UNIVERSITY OF KWAZULU-NATAL

COMPUTER-BASED PRODUCTIVITY ESTIMATION OF ACADEMIC STAFF USING THE FUZZY ANALYTIC HIERARCHY PROCESS AND FUZZY TOPSIS METHOD

By

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Abstract

Universities generally use a human-intensive approach such as peer evaluations, expert judgments, group interviews or a weighting system to estimate academic productivity. This study develops an algorithmic approach by integrating the fuzzy Multi-Criteria Decision Making (MCDM) and the fuzzy TOPSIS methods to estimate productivity of academic staff at tertiary institutions. Currently, evaluations are done in the conventional manner and as a result, the outputs are difficult to quantify. There are no standard methods in evaluating the outputs and the estimates are therefore hard to validate. It is therefore suggested that a data intensive approach (also referred to as algorithmic approach) be adopted. An algorithmic approach is empirical and will produce results that are easily quantifiable. The algorithmic approach allows for the IS Principles of data collection, processing, analysis and interpretation to be easily applied. If an algorithmic approach were adopted, it would generally revolve around the numeric-value approach, which produces a precise measure of productivity. Recently however, the software engineering domain had to also consider non-numeric attributes (also referred to as linguistic expressions) such as very low, low, high and very high for productivity estimation (Odeyale *et al.*, 2014). The imprecise nature of these attributes constitutes uncertainty in their interpretation and therefore could not be measured or quantified appropriately in the past. It is now possible to do so using fuzzy logic and fuzzy sets. Since academic departments are constantly faced with imprecision and uncertainty, an algorithmic fuzzy-based decision model is the most suitable approach that can be used to estimate productivity. The nature of duties performed by academic staff lends itself more efficiently to a qualitative rather than a quantitative evaluation (Chaudhari *et al.*, 2012). These qualitative evaluations are reliant on human judgment and could be described using linguistic expressions such as weak, average, good and excellent (Khan *et al.*, 2011). In this study, a fuzzy MCDM method called Fuzzy Analytic Hierarchy Process (FAHP) is used to estimate productivity of academic staff. Choosing the most preferred alternative, ranking and selection will be done using the fuzzy TOPSIS method. The Design Science Research Methodology (DSRM) was used to develop a fuzzy-based productivity estimation system using these two methods. The results of the study indicated that the fuzzy-based system produced results that were more reliable than conventional methods. Future research should however explore how fuzzy logic and fuzzy set theory could be integrated into other productivity estimation techniques such as the DEA and SAW models.

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LIST OF ACRONYMS USED IN THIS THESIS

AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
AI	Artificial Intelligence
BNP	Best Non-Fuzzy Performance value
CC_i	Closeness Coefficient
CI	Consistency Index
CQPA	Centre for Quality Promotion and Assurance
CR	Consistency Ratio
DS	Design Science
DEA	Data Envelopment Analysis
DSR	Design Science Research
DSRM	Design Science Research Methodology
FAHP	Fuzzy Analytic Hierarchy Process
FIS	Fuzzy Inference System
FNIS	Fuzzy Negative Ideal Solution
FOOM	Fuzzy Object-Oriented Modeling
FPIS	Fuzzy Positive Ideal Solution
FTOPSIS	Fuzzy Technique for Order Preference by Similarity to Ideal Solution
HEQC	Higher Education Quality Committee
IC	Intellectual Capital
ICCC	Intra Class Correlation Coefficient
ICCI	Intra Class Correlation Index
IRRS	Inter-Rater Reliability Score
KMO	Kaiser-Meyer-Olkin
MCDM	Multi-Criteria Decision Making

NQF	National Quality Framework
NRM	Network Relationship Map
PMS	Performance Management Systems
RI	Random Index
SAQA	South African Qualifications Authority
SAW	Simple Additive Weighting
SPSS	Statistical Package for Social Sciences
TAM	Technology Acceptance Model
TFPR	Triangular Fuzzy Positive Reciprocal
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
UIS	User Interface Satisfaction
UML	Unified Modeling Language

Chapter 1

BACKGROUND AND CONTEXT

1.1 Introduction

Productivity can be defined as a measure of how efficient individuals and systems are in converting inputs into meaningful outputs (Mullins, 2005). In a university, the inputs are people, equipment, time and money. The outputs are expected to be high quality graduates who will play a meaningful role in society. In order to determine whether a university is producing high quality graduates, it is important to measure the performance of academic staff in terms of their effectiveness and efficiency.

Efficiency refers to the level and quality of service that is obtained from a given amount of resources (Gates & Stone, 1997). Effectiveness relates to the extent to which a university can meet the demands of students, faculties, local communities and a nation (Coccia, 2008). Measuring the efficiency and effectiveness is synonymous to estimating the productivity of academic staff. There are many benefits to having reliable and proper productivity estimates. Therefore, it is critically important that the efficiency and effectiveness (that is, productivity) be appropriately measured in order to provide reliable and acceptable estimates.

Productivity estimation may be used at a university to maximize the output of staff by utilising limited resources such as people, equipment, time and money optimally (Mezrich & Nagy, 2007). It can also be used to identify personnel (without subjectivity and bias) who are due for promotion and rate a university in terms of research outputs and publications. In order to maximize output, researchers have shown a keen interest in estimating the productivity of academic staff to improve their organisational behaviour and influence strategic change (Coccia, 2008). Organisational behaviour is a field of study that is concerned with what people do in an organisation and how their behaviour can impact the performance of an organisation (Nelson & Quick, 2010). According to Mullins (2005), strategic change involves an attempt to change the current mode of thinking so that an organisation can act by taking advantage of opportunities as well as cope with challenges. Before strategic change can be effected, the performance of academic staff and academic departments has to firstly be evaluated (Gates & Stone, 1997).

The core duties performed by academic staff are teaching and supervision, research and innovation, writing and publication, consultancy, community engagement and services rendered to the University (Mohamad *et al*., 2008).

It is important to evaluate the performance of academic staff in these core areas to improve the quality of education. According to Koslowski (2006), evaluating the quality of higher education is important due to increased competition between universities to attract students. Students will generally choose a university that offers quality education (Al-Jammal & Al-Khasawneh, 2012). Thomson (2008) conducted a series of interviews with universities across the United States and Europe regarding productivity at universities. The findings indicated that a common evaluation and assessment technique applicable to all universities in a geographical area should be developed. This will lead to the development of national standards from which each institution can be benchmarked.

A national standard can also be helpful to programmes that are due for reviews. A national standard is also required when accreditation is required for certain qualifications. All this can only be achieved with proper and effective productivity estimates. According to Lissoni *et al*. (2011), proper assessment techniques can also assist in identifying academic staff who are due for promotion. Proper assessment methods can reduce subjectivity and bias to determine which academics should be promoted. Productivity estimation models can also be used to forecast the number and quality of personnel that are required in the future.

Due to the current economic crisis, many universities are forced to operate on a limited budget and this can impact on recruitment of personnel and spending on resources such as equipment (Nelson & Quick, 2010). Institutions are now placed in a situation where they need to 'do more with less'. Proper estimation techniques can help in this regard. Accurate metrics are also required by the state to identify high performing universities so that these institutions can be funded appropriately (Coccia, 2008). A university is generally regarded as high performing if its research output, publications and throughput rates are higher than the norm. High performing universities will generally receive a higher funding by the state when compared to poor performing universities (Al-Jammal & Al-Khasawneh, 2012). Proper estimation techniques can also assist in rating a university in terms of its research and publications (Mohamad *et al*., 2008).

The prestige of a university increases when it's rating increases (Lissoni *et al*., 2011). The need for reliable measuring techniques has therefore become paramount when estimating the overall productivity of a university.

1.2 The Problems Associated with Current Estimation Models

Universities have acknowledged that there are many benefits in having reliable and effective metrics when estimating the productivity of academic staff and academic departments (Mohamad *et al*., 2008). The most important benefit is that management can use reliable metrics to maximize the output of academic staff and an academic department by utilizing limited resources (such as people, equipment, time and money) optimally (Mezrich & Nagy, 2007). Most universities are using the precise numeric-value method, peer evaluations, group interviews, weighting methods and expert judgment to evaluate the performance of academic staff. Universities however acknowledge that the conventional manner in which these methods are implemented generally produce estimates that are difficult to quantify (Chaudhari *et al*., 2012). Since most of the current methods are human intensive, a judgmental approach is adopted and the evaluators will have diverse opinions during the decision-making process. In order to get a fair and consistent evaluation from all evaluators regarding common criteria, a group decision-making method that uses fuzzy logic and fuzzy set theory is therefore proposed. A fuzzy-based approach will synthesize all diverse opinions and produce the best possible outcome (Reddy, 2012).

Some universities are using a computerised Performance Management Systems (PMS) to estimate productivity of academic staff. However, inputs into this PMS system generally revolve around numeric values. The numeric-value approach is most suited in an industrial environment where the inputs (such as number of workers, hourly rate, material cost and amount of output) are precise and deterministic, that is, these inputs are quantitative. The precise numeric-value approach is however not suitable to evaluate all the key performance areas of an academic since most of the attributes to be measured are qualitative (Chaudhari *et al*., 2012). Where academics are faced with imprecision, uncertainty and a lack of knowledge in a particular area, the precise numeric-value approach becomes inefficient and ineffective (Mohaghegh, 2000). Evaluating this imprecision and uncertainty is therefore reliant on human judgment. This evaluation could best be described using linguistic expressions and not the precise numeric-value approach (Khan *et al.*, 2011). The linguistic expressions can be represented using a number or an interval. However, a number or an interval representation does not mimic how the human mind interprets linguistic values and therefore cannot deal with imprecision and uncertainty. In order to overcome this, it is suggested that fuzzy logic using fuzzy sets be used instead of numbers or intervals. Fuzzy set theory is a modeling tool that can address this uncertainty, imprecision and lack of information (Mohaghegh, 2000). In crisp sets an object either belongs to a set or does not belong to a set. However, in fuzzy logic, an object will always belong to a set to a certain degree. This approach called fuzzy-based decision methods takes both the numeric-values approach as well as linguistic expressions into consideration when estimating productivity (Zadeh, 1994).

Universities that do not use a computerised Performance Management System (PMS) will usually adopt a group decision-making method involving a panel (Kaplan & Norton, 1996). The panel will generally use some weighting method during the performance evaluation of an academic. However, other methods such as expert judgment and peer evaluations may also be used. Peer evaluations will generally involve panel interviews as well the assessment of documentation and resources of an academic or an academic department (Mezrich & Nagy, 2007). Using peer evaluations and expert judgment in the conventional manner can be useful only to a certain extent. It can help make some judgment about the quality and merit of an academic project or some completed research. The reviewer is generally knowledgeable about the problem at hand and can therefore provide valid opinions about projects under review. Peer evaluations can help detect shortcomings in past projects. These shortcomings can be avoided when developing similar projects in the future. Expert judgment method involves experts who have vast knowledge about past experiences in a certain area and can apply their knowledge to evaluate key performance areas (Koslowski, 2006). The expert's knowledge may be required when appraising a departmental project. The expert may also be required to review and rate papers that are due for publication. The expert may also provide valuable information and opinions so that an academic department can improve in areas that require attention.

Group decision-making involving a panel, peer evaluations and expert judgment methods are very useful and cannot be done away with (Kaplan & Norton, 1996). However, the conventional manner in which they are implemented, does not adequately allow for the principles of IS (such as data collection, processing, data validation, data verification, output reliability as well as data analysis and interpretation) to be appropriately applied. This is because imprecise and vague attributes are being measured to produce deterministic outputs using the precise-value method. As a result, these techniques (when implemented in the conventional manner) cannot adopt an empirical or algorithmic approach and the estimation is therefore not explicit and repeatable. These estimations are not easily quantifiable and may produce unreliable estimates. The evaluator may also choose to assign scores or weights to key performance areas. For example, an academic is allocated a score of 30 if a minimum of 50 hours community engagement is performed. The problem with such a system is that an academic who has performed 51 hours of community engagement will attain the same score (30) as an academic who was done 100 hours of community engagement. The problem with the weighting method is that an academic is not credited for the extra hours he or she has worked in a key performance area. In other words, the degree to which an academic has performed is not taken into consideration. In order to overcome these deficiencies, group decision-making involving a panel, peer evaluations and expert judgment have to be integrated with more reliable techniques that use fuzzy logic and fuzzy set theory so that the estimates can be more efficiently quantified.

1.3 The need for quantitative indicators in productivity estimation

Every department should have a mission and a vision for the future (Al-Turki & Duffuaa, 2003). The vision and mission should be linked to the objectives of the department. Performance indicators in the form of numerical or quantitative identifiers should indicate how well the objectives of the department could be met (Pritchard *et al.,* 1990).

According to Bashir and Thompson (2001), productivity is broadly defined as the ratio of outputs generated from a system to the inputs provided to create the outputs. With regard to academic productivity, society is concerned about what they are getting from higher education institutions (that is, the output) in terms of the amount of resources that are put in. This output has to be appropriately measured using quantitative techniques. The efficiency and effectiveness (namely productivity) of an academic department can be meaningfully described if it can be appropriately measured using quantitative indicators in order to examine the extent to which the goals and the mission of an institution have been met (Mezrich & Nagy, 2007). However, unlike a manufacturing industry where the output is tangible and easily quantifiable, measuring productivity of an academic institution is difficult because the output is non-homogeneous and intangible (Mohamad *et al*., 2008). This study therefore focuses on developing an effective algorithmic fuzzy-based model that uses quantitative techniques to estimate productivity of academic staff and academic departments. This new technique should be able to integrate current methods with an appropriate model that will use fuzzy logic and fuzzy sets.

1.4 Research objectives

This study:

- Investigates the need for adopting proper techniques to estimate productivity of academic staff and academic departments;
- Examines the benefits of having reliable metrics available to management;
- Examines the effectiveness of productivity estimation methods that are currently being used;
- Investigates how conventional methods (such as the numerical value, peer evaluation, expert judgment and weighting techniques) can be more effective when integrated with fuzzy logic and fuzzy sets;
- Uses a multi-criteria decision-making (MCDM) model called the fuzzy Analytic Hierarchy Process (AHP) and the fuzzy TOPSIS method as a basis for the development of a fuzzy-based system to estimate productivity of academic staff and academic departments;
- Uses the Design Science Research (DSR) methodology to develop the model;
- Demonstrates how the model can be mapped into an object-oriented programming language;
- Tests and evaluates the functionality of the model; and
- Uses the model to develop a software package to estimate the productivity of academic staff as well as the productivity of academic departments.

1.5 The Research Design

The aim of this study is to develop a fuzzy-based productivity estimation model for academics staff and academic departments. This study adopts a positivist constructivist paradigm incorporating a design science methodology to develop the model. According to Simon (1969: 55), "natural sciences and social sciences try to understand reality while design science attempts to create things that serve human purposes." 'Design theories' provide explicit details on 'how to do something' that corresponds to 'kernel theories'. This study will use the kernel theory and design theory approach to solve the IS problem. In other words, theories from the social, behavioural and natural sciences will be used to create the artifact, that is, a computerised model to estimate the productivity of academic staff and academic departments at a university.

1.6 Rationale for the study

The researcher carried out a preliminary investigation at the three leading universities in KwaZulu-Natal on how productivity of academic staff is estimated. The researcher discovered that Durban and Mangosuthu University of Technologies use a manual (non-computerised) method such as the examination of resources and the weighting system. However, the quality assurance unit at these institutions indicated that due to the imprecise and uncertain attributes that were being measured, current evaluation methods are inefficient and unreliable to a large extent. The University of KwaZulu-Natal has a computerised Performance Management System (PMS), but the quality unit at this institution indicated that this system is not being fully utilized by academic departments. This is due to the inefficiency of the computerised system because precise values are being used to rate qualitative attributes.

As a result of these shortcomings, the researcher decided to explore other models of productivity estimation that could be used by academic departments. After an in-depth literature review and an in-depth survey on productivity estimation methods at universities, the researcher decided that an algorithmic fuzzy-based approach is the most appropriate technique that should be employed. This is a unique technique that can easily be used to evaluate imprecise and fuzzy attributes. The fuzzy-based approach is best suited for a university environment because most of the attributes being measured lend themselves more to a qualitative rather than a quantitative evaluation. However, the fuzzy-based model is most effective when it is integrated with the current methods of evaluation (such as peer, panel and expert evaluations) that rely on human judgment. The rationale for conducting this study is to therefore encourage management at a university to implement a fuzzy-based productivity estimation system. This will be done by demonstrating to management the efficiency and effectiveness of the newly developed system.

1.7 Outline of chapters

The study is broken down into the following chapters:

Chapter 1 deals with the background of the study, the research problem, a fuzzy-based solution to this problem, the objectives and the rationale for carrying out this study.
Chapter 2 outlines the literature review that supports the study by providing a motivation as to why this research is important. It also provides a motivation as to why a new productivity estimation model needs to be developed.
Chapter 3 discusses how the new productivity estimation model is developed using the design science research methodology (DSRM).
Chapter 4 explores an object-oriented approach to modeling imprecise and fuzzy data.
Chapter 5 demonstrates how the developed model is implemented using the IT department at Durban University of Technology. The case study method is employed.
Chapter 6 evaluates the functionality of the system by observing and measuring how well the solution supports the problem.
Chapter 7 discusses the results of the survey that was administered to academic staff at DUT.
Chapter 8 provides a conclusion of the study with recommendations for future research.

1.8 Conclusion

This chapter puts the entire study into context by focusing on the problems relating to productivity estimations methods that are currently being employed at universities. An algorithmic fuzzy-based solution is suggested to solve these problems. The research objectives and the rationale for conducting this study were also focused upon. Chapter 2 provides an in-depth literature review that provides a justification for conducting this study.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

IS practitioners and researchers are constantly engaged in developing better productivity estimation models in order to maximize output (Mezrich & Nagy, 2007). However, most of their development efforts are concentrated in an industrial and business environment where the inputs are precise and deterministic (Sun, 2010). The outputs in an industrial and business environment are tangible, which makes quantifying and productivity estimation easier. Universities on the hand are constantly faced with attributes that are uncertain and imprecise (Lee, 2010). As a result, the outputs are intangible and therefore difficult to estimate. Computerised Performance Management Systems (PMS) that can be used to estimate the productivity of academic staff have been developed. These systems are inefficient to a large degree because the inputs and outputs are expected to be precise values (Jahanshahaloo *et al.*, 2006). The precise-value method is not suitable in an environment where the attributes to be measured are imprecise and uncertain (such as an academic department). IS practitioners and researchers are therefore using estimation models from industry and integrating these with fuzzy set theory in order to address issues of imprecision and uncertainty (Tsaur *et al.*, 2002). The Fuzzy Analytic Hierarchy Process (FAHP), which uses a multi-criteria decision- making (MCDM) method is one such example. Academic staff are constantly faced with many conflicting criteria before a decision is made and therefore a MCDM method is chosen (the MCDM model is discussed in section 2.2). The Analytic Hierarchy Process (AHP) is a structured technique designed to organise and analyse complex decisions. This technique provides a framework for (Saaty, 1980):

a) Structuring a decision problem.
b) Representing and quantifying the elements of the problem.
c) Relating the elements to overall goals.
d) Evaluating alternate solutions.

An academic department is generally evaluated using a top-down approach (Mohamad *et al.*, 2008). Although the processing of the AHP is bottom-up, the general structure is developed in a top-down manner with the goal on top and the alternatives at the bottom (Nikoomaran *et al.*, 2009). The top down structure of the AHP can therefore form the basis for the development of an effective productivity estimation model applicable to academic departments. The AHP allows pair-wise comparisons of elements (based on human judgment) and is represented using precise values attained from a nominal scale such as the one indicated in Table 2-1 (Chang, 1996). These precise values will be used to determine priorities or weights. These priorities (or weights) will be used to develop the fuzzy performance matrix from which the best alternative can be selected. However, using precise values for the ratings and weights is not suitable for an academic department because uncertain and imprecise criteria are evaluated. This deficiency can be overcome by using fuzzy data for the ratings and weights in the AHP (Nikoomaran *et al*., 2009). Fuzzy set theory is a modeling tool that can address the imprecision, uncertainty and lack of information that universities constantly face (Mohaghegh, 2000). Fuzzy logic and fuzzy set theory is discussed in section 2.6.2. In order to rank the alternatives, the fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method will be used. The classical TOPSIS method uses precise data. Jahanshahaloo *et al*. (2006) extended the classical TOPSIS method to include fuzzy data. The fuzzy TOPSIS methods will therefore be used in this study to rank and select the best alternatives. The fuzzy TOPSIS method is discussed in section 2.7.

In order for the developed model to be accepted by academic staff, it must be easy to use and useful. The Technology Acceptance Model (TAM) by Davis (1989) will be used to determine the extent to which the developed model can be accepted by the academic staff at DUT.

2.2 A MCDM approach on Academic Department Productivity Estimation Problem

The multi-criteria decision making (MCDM) approach considers many criteria before a decision can be made (Tseun-Ho *et al.* 2012). In deciding whom to appoint as the leader of an academic department for example, one may use age, academic qualifications, research publications, administrative duties, external engagement and experience as the key criteria to make a choice. It is not expected that all applicants for the post will be highly rated in all key performance areas (that is, in all the criteria). An academic may be highly rated for research publications but he or she may be failing in effectively performing administrative duties. A trade-off between the various criteria is therefore necessary before a decision can be made. An MCDM approach helps in determining the trade-off by quantifying each criterion and ranking all the alternatives. This can be achieved when evaluating the degree to which an academic has performed in each of the key productivity areas using a fuzzy-based approach. Since many criteria are used in an evaluation, a MCDM (fuzzy-based) approach using the AHP will be used to rate an academic in terms of his or her overall performance as well as rate an academic department as a whole.

Haarstrich and Lazarevska (2009) identify the main steps that are involved in solving a MCDM problem. These are:

1. Problem identification. Universities acknowledge that the conventional manner in which these methods are implemented generally produce estimates that are difficult to quantify (Chaudhari *et al*., 2012). Based on an extensive literature survey, the researcher decided that in order for current methods to be effective, it has to be integrated with a model that uses fuzzy logic and fuzzy set theory.
2. Defining relevant attributes. The conceptual approach to maximizing academic productivity involves the evaluation of intellectual capital (IC). Intellectual capital evaluation involves human, organisational and relational capital inputs. These terms are defined and discussed in the section 2.3.
3. Extracting relevant criteria related to the attributes from (2) above. Voon *et al*. (2011) identifies the following six criteria to be evaluated in order to maximize academic productivity. These are administration, curriculum development, technology transfer, research and innovation, teaching and external engagement.
4. Discussing and proposing alternatives. This step involves building the hierarchy and is depicted in Figure 2-3.
5. Allocating weights for the criteria (Shahroudi & Rouydel, 2012). This process is discussed in section 2.4.
6. Synthesizing and ranking the alternatives. This process is discussed in detail in section 2.4.

The classical MCDM method has been used extensively in environments where the inputs are precise (tangible) and the outputs are deterministic (Tsaur *et al*., 2002). However since the output of an academic's productivity is intangible and non-deterministic, a fuzzy-based MCDM approach using fuzzy TOPSIS will be used to estimate the productivity of academic staff (Chaudhari *et al*., 2012).

2.3 Intellectual Capital Evaluation

By evaluating the productivity of all academic departments, the intellectual capital of a university is also being evaluated (Youndt *et al*., 2004). Intellectual capital is defined as the sum of all knowledge resources that a university possesses (Lee, 2010). It is important to evaluate the intellectual capital of a university so that it can be benchmarked against other higher education institutions. Intellectual capital is categorised into the following three main constructs (Youndt *et al*., 2004):

- Human capital: This refers to the knowledge level of researchers and staff at the university.
- Organisational capital: This refers to the sum of all the creative abilities a university possesses. This includes the knowledge a university possesses in order to establish its own vision, organisational culture, management philosophy, strategies, processes, working systems and information technologies.
- Relational capital: This refers to the sum of all assets that makes it possible for a university to interact with its environment. The relational capital includes interaction with society, shareholders, industries and official institutions.

Lee (2010) proposed a conceptual framework for intellectual capital (IC) evaluation at a university. The framework is depicted in Figure 2-1.

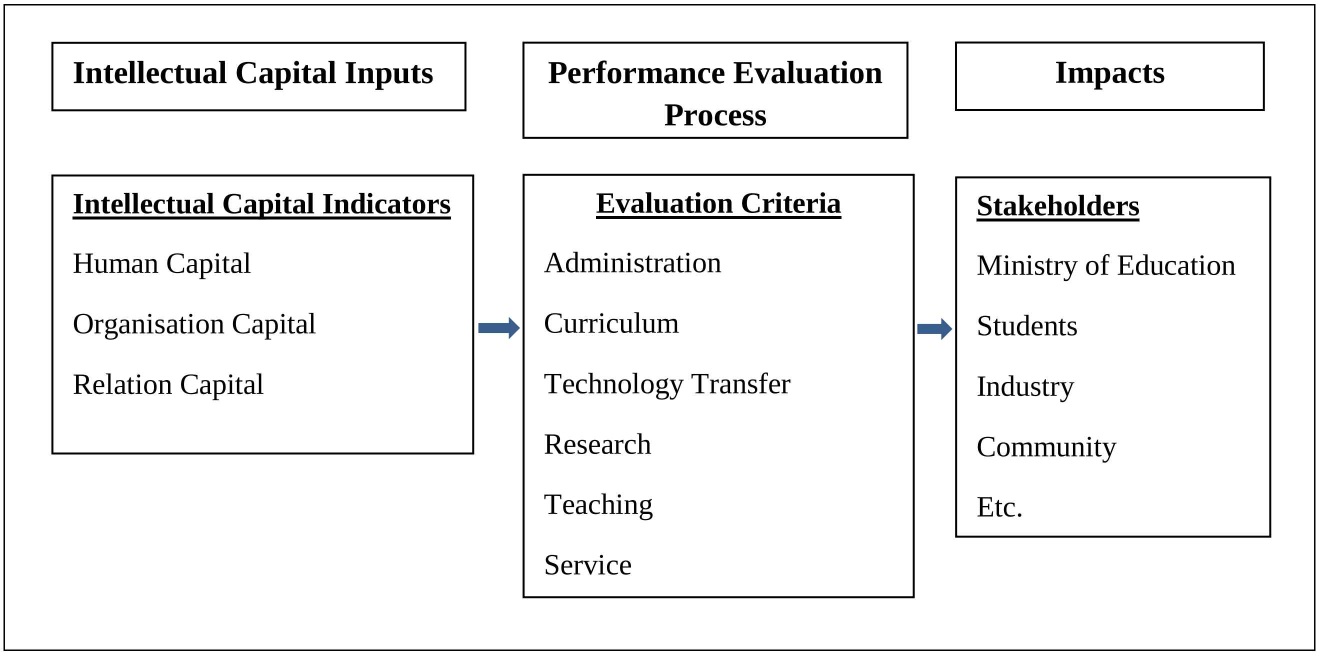


Figure 2-1: Incorporating IC in an academic department evaluation (Lee, 2010)

Although this framework was originally developed by Lee (2010) to evaluate the productivity of a university as a whole, it can however, also be used to evaluate the productivity of an academic department. This means that an academic department can also be evaluated in terms of its intellectual capital inputs, performance evaluation processes and its impact on the various stakeholders as indicated in Figure 2-1. Academic departments are generally evaluated in a top-down approach. The IC framework can be adapted into a hierarchical top-down structure when designing the evaluation model (the structure is depicted in Figure 2-3). This study will use the AHP as a basis for the development of the new fuzzy-based system.

2.4 The Analytic Hierarchy Process (AHP)

The purpose of this section is to describe in detail how the AHP can be used as a multi-criteria decision making (MCDM) technique. By having a good understanding on how this method works, it becomes easier to show how fuzzy logic and fuzzy set theory can be integrated into this model.

The analytic hierarchy process (AHP) is a structured technique designed to organise and analyse complex decisions. This technique was developed by Saaty (2008) in the early 70's and has been continuously refined. It can be applied in a variety of situations, including higher education. The AHP does not strive to produce the correct solution, but rather the optimal solution from many alternatives. The elements of the problem are firstly quantified and the best solution is then selected when the alternatives are compared. The general structure of the AHP is depicted in Figure 2-2.

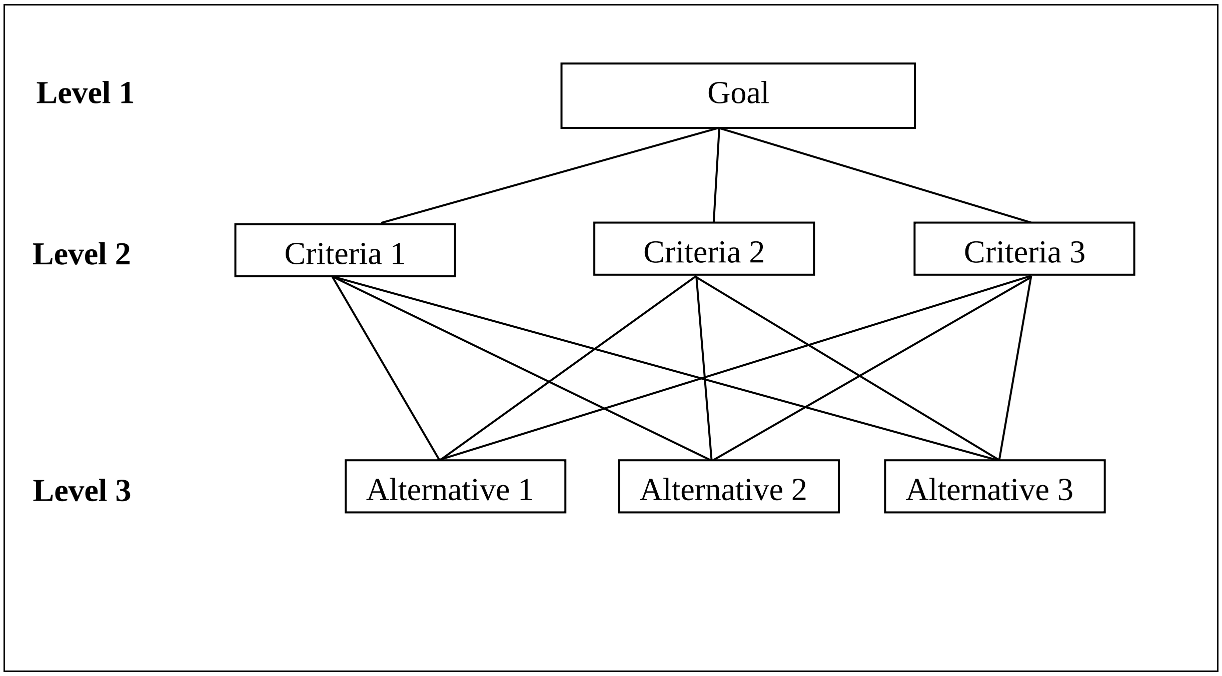


Figure 2-2: General Structure of the hierarchy (Saaty, 2008)

This structure enables decision-makers to decompose a large complicated problem into many smaller elements as indicated in Figure 2-2. In other words, a large problem is broken up into many criteria and sub-criteria as well as many alternatives. For purposes of illustration, a three-level hierarchy is depicted. The number of sub-criteria under a criteria has an impact on the reliability of the results. This was confirmed by a study conducted by Tseun-Ho *et al.* (2012) which indicated that a criteria that had more sub-criteria produced results that were less reliable than a criteria that had fewer sub-criteria. The following four steps are followed when using the AHP to make a decision (Saaty, 2008):

- Define the problem properly and then determine the knowledge that will be required to solve this problem;

- The decision hierarchy is then structured with the goal at the top of the hierarchy, the criteria to be used during evaluation is executed in level 2 and the alternatives to be chosen are usually in the lowest level;
- A set of pair-wise comparison matrices is then constructed. An element in an upper level is used to compare the elements in the level immediately below with respect to the upper element; and
- Use priorities from the comparisons to weight the priorities in the level immediately below. This must be done for every element. The weighed values for each element are then added to gain a global priority for each element. This process of weighing and adding is continued until the final priorities of the alternatives in the last level are obtained. In order to make comparisons of priorities, numbers or quantitative measures are required. These numbers will indicate by how many times more important or dominant one element is when compared to another for a certain criterion or property. Such a scale was developed by Saaty (1980) and is depicted in the Table 2-1:

Intensity of importance	**Definition**	**Explanation**
1	Equal Importance	Two activities make equal contribution to an objective
2	Weak or slight	
3	Moderate importance	Experience and judgment slightly favour one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgment strongly favour one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favoured very strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favouring one activity over another is the highest possible order of affirmation
Reciprocals	If activity i has one of the above non-zero numbers assigned to it when compared to activity j , then j has the reciprocal value when compares with i	See explanation below on reciprocal values

1.1-1.9	If the activities are very close	It may be difficult to assign the best value but when compared with other contrasting activities, the size of the small numbers would not be too noticeable, yet they can still indicate the relative importance of the activities

Table 2-1: The fundamental scale of absolute numbers (Saaty 1980)

Table 2-1 can be explained using the following example. Which key performance activity is more important? The absolute values are attained from the scale in Table 2-1.

	Administration	**Service**	**Research**	**Teaching**
Administration	1	9	5	1/6
Service	1/9	1	1/3	1/9
Research	1/5	3	1	1/3
Teaching	6	9	3	1

Table 2-2: Which key performance activity is more important?

The intersection between the row-value for Administration and the column-value for Service is 9. This means that Administration is 9 times more important than Service. Conversely, the intersection between the row-value for Service and the column-value for Administration is $\frac{1}{9}$. It means that Service is 9 times less important than Administration. The priorities for the key performance activities are obtained by adding each row and dividing by the total sum of all values in the matrix.

The AHP uses pair-wise comparisons to determine priorities as indicated in Table 2-2. These priorities are calculated based on absolute values, which produce precise estimates (Saaty, 2008). However, academic staff are constantly faced with imprecision and uncertainty which therefore requires a fuzzy logic approach (and not the absolute or precise-value approach) (Nikoomaran *et al.*, 2009). In other words, fuzzy numbers and not absolute numbers are required for the pair-wise comparisons. The fuzzy numbers can be attained using two methods. The first method uses a Saaty scale (Table 2-2) with absolute values to obtain the fuzzy numbers. The second approach involves directly using a fuzzy scale that can convert linguistic values into fuzzy numbers as shown in Table 2-3. This study will show how fuzzy values can be incorporated with the pair-wise comparisons in order to address imprecision, ambiguities and uncertainties.

Fuzzy number	**Linguistic Scale**	**Scale of fuzzy numbers**
$\tilde{9}$	Perfect	(8, 9, 10)
$\tilde{8}$	Absolute	(7, 8, 9)
$\tilde{7}$	Very good	(6, 7, 8)
$\tilde{6}$	Fairly good	(5, 6, 7)
$\tilde{5}$	Good	(4, 5, 6)
$\tilde{4}$	Preferable	(3, 4, 5)
$\tilde{3}$	Not bad	(2, 3, 4)
$\tilde{2}$	Weak advantage	(1, 2, 3)
$\tilde{1}$	Equal	(1, 1, 1)

Table 2-3: An example of membership function of linguistic scale (Sun, 2010)

2.5 Evaluating performance of academic departments using the AHP

This section combines the intellectual capital (IC) structure (Figure 2-1) with the hierarchical structure (Figure 2-2) to develop a framework that can be used to evaluate the productivity of academic departments (Lee, 2010). The framework is depicted in Figure 2-3:

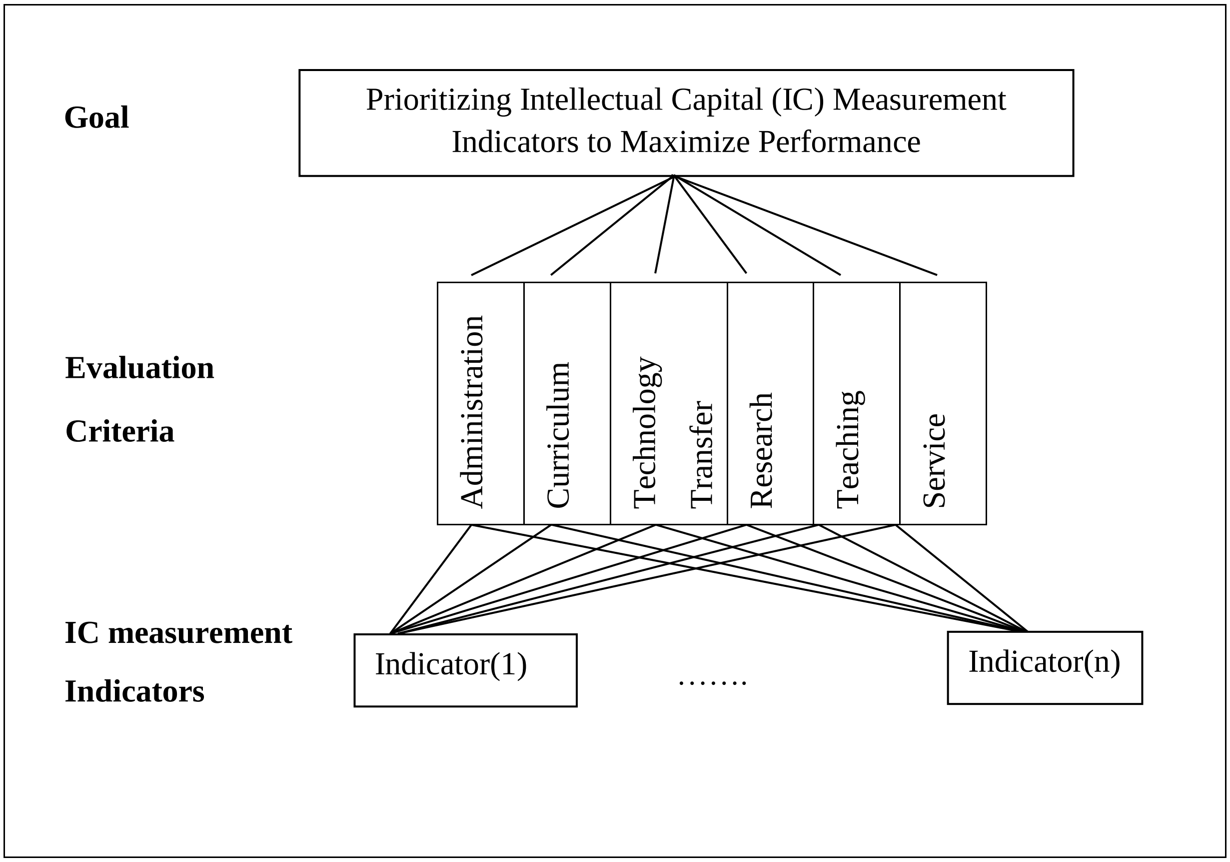


Figure 2-3: The AHP structure for maximizing performance (Lee, 2010)

This structure conceptualizes the transformation process of intangible resources (such as human, organisation and relational capital) when carrying out different activities (such as teaching, research and community engagement) in order to produce different outputs. These six key performance criteria are used at Taiwan University and may however differ from one higher education institution to another (Lee, 2010). This hierarchy structure (Figure 2-3) can be used in the following two ways:

- It can be used to prioritise intellectual capital (IC) measurement indicators, which contribute to maximizing the productivity of an academic department; and
- It can be used to estimate the productivity of an academic. This is done by changing the goal in Figure 2-3 to something like: Rank each academic staff member according to his/her productivity. The IC measurement indicators (row 3) will also have to be changed to include the names of the academics in a department. For example, Indicator (1) to Indicator (n) can be changed to names of academics.

The AHP is used extensively to solve multi-criteria decision making (MCDM) problems in many different business contexts where the inputs are tangible and deterministic. The AHP is however criticized by some researchers for the following reasons (Cheng, 1999):

- The AHP is mainly used in an environment that involves crisp decision applications. In other words, the AHP does not naturally lend itself to solving MCDM problems in an environment where the key performance criteria are imprecise and uncertain (such as an academic department);
- Much criticism is leveled against the estimation scales that are sometimes deemed unbalanced;
- Since the AHP considers the criteria being used as certain, it does not take uncertainty into account when evaluating the performance of the alternatives;
- The AHP does not take imprecision into account during the ranking process; and
- Some decisions rely heavily on human judgment and this may lead to inaccurate results.

In order to overcome these deficiencies, it is important to integrate fuzzy decision methods and fuzzy set theory with the AHP (Nikoomaran *et al*., 2009).

2.6 Fuzzy logic and fuzzy set theory

The aim of this study is to develop a fuzzy based productivity estimation model for academic departments. This section therefore presents a detailed explanation on fuzzy logic and fuzzy set theory. Knowledge on fuzzy logic and fuzzy set theory is required for the development of the model (Sun, 2010). This section also provides a motivation as to why a fuzzy logic and not a crisp binary logic approach is necessary for a qualitative evaluation of academic departments. A discussion on fuzzy inference systems is also presented. This section concludes by presenting a discussion on fuzzy TOPSIS which is required for ranking and selection.

2.6.1 Introduction

The productivity estimation system for an academic department will be based upon the mathematical theory of fuzzy logic and fuzzy sets by Zadeh. Zadeh, (1994) extended the concept of Boolean logic to form a new type of logic called fuzzy logic. Boolean logic allows for a member to either belong to a set (True) or not to belong to a set (False). Fuzzy logic on the other hand is multi-valued. It relates to classes of objects where membership is a matter of degree (Yager, 1996). The underlying concept regarding fuzzy logic and fuzzy set theory is that of a linguistic variable where the values are words rather than numbers. In essence, fuzzy logic is computing with words rather than numbers (Khan *et al.*, 2011). Words are however less precise than numbers but are preferred in certain contexts because they are closer to human intuition. Computing with words increases the tolerance for imprecision and thereby reduces the cost for finding a solution. The basic concept underlying fuzzy logic computing is the use of fuzzy if-then rules (or fuzzy rules). A rule-based system is the heart of Artificial Intelligence (AI) and will form the basis for the development of a productivity estimation model for academic departments (Yadav & Singh, 2011).

2.6.2 Fuzzy logic

Fuzzy logic is a convenient method that can be used to map an input space into an output space using fuzzy rules (or if-then rules). The concepts "input space" and "output space" is best described using the following example. "You tell me how good the research presentation was and I will rate it." These concepts are depicted in Figure 2-4 and Figure 2-5 respectively.

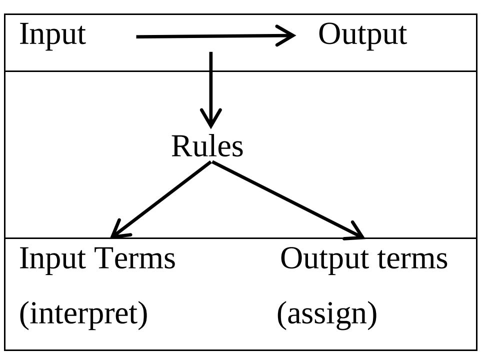


Figure 2-4: A General Case

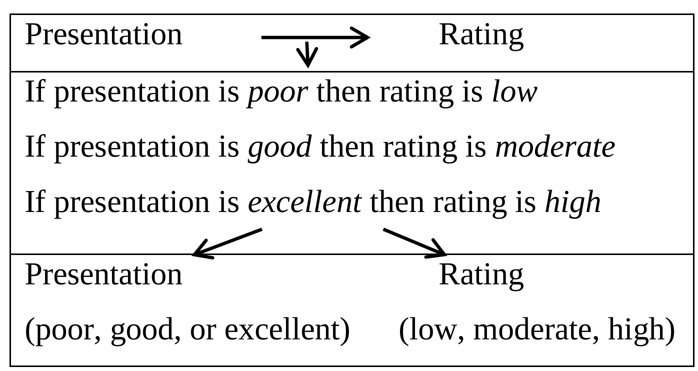


Figure 2-5: A Specific example

Figure 2-4 presents a general case and Figure 2-5 presents a specific example. All rules (if-then or fuzzy rules) indicated in Figure 2-5 are executed in parallel. The terms (such as poor, good, excellent, low, moderate and high) are adjectives that need to be described. For example, what does the words 'poor' or 'high' mean. A fuzzy inference is also required to convert the input space into an output space. A fuzzy inference is a method that interprets the values in the input vector and assigns values to the output vector based on fuzzy rules (Chaudhari *et al.*, 2012). Fuzzy inference systems are discussed in detail in section 2.6.8.

In order to understand the concept of fuzzy logic, it is important to understand what a fuzzy set is (Sun, 2010). A fuzzy set is a set without a crisp clearly defined boundary. A fuzzy set can also contain elements with a partial degree of membership. The concept of a fuzzy set is best illustrated by describing what a classical set is. A classical set will wholly include or wholly exclude an element (Bobillo & Straccia, 2011). For example, 'Saturday' and 'Thursday' will wholly belong to the classical set called 'days of the week'. Other elements like humans, cows and snakes will therefore be wholly excluded from this classical set called 'days of the week'. Now consider a set called 'week-end'. Most people would agree that only 'Saturday' and 'Sunday' would belong to this set. Some people may however feel that the week-end starts on late Friday evening and ends on early Monday morning. Friday evening and Monday morning will therefore have partial membership of the set 'week-end'. As a result, the set 'week-end' does not have a crisp and clearly defined boundary and will therefore constitutes uncertainty or fuzziness. This uncertainty or fuzziness makes the set 'week-end' a fuzzy set. In fuzzy logic, the truth is a matter of degree. In this example, Friday evening and Monday morning belongs to the set 'week-end' to a certain degree. A fuzzy set is therefore an extension of a classical set.

2.6.3 Fuzzy logic and Boolean logic

Fuzzy logic is preferred over Boolean logic in certain situations. This is explained using the following example: One of the core duties of an academic is be involved in community and external engagements (Al-Turki & Duffuaa, 2003). Consider an example where an academic is required to spend a minimum of 50 hours in community engagement. This can be described using Boolean logic and fuzzy logic as follows:

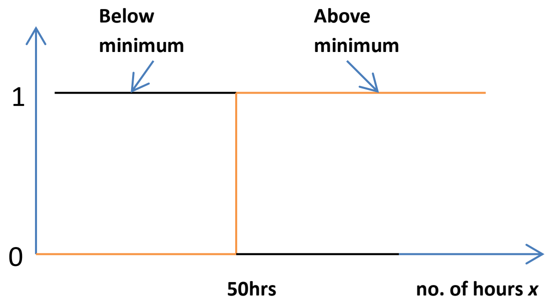


Figure 2-6: A binary-logic performance measure

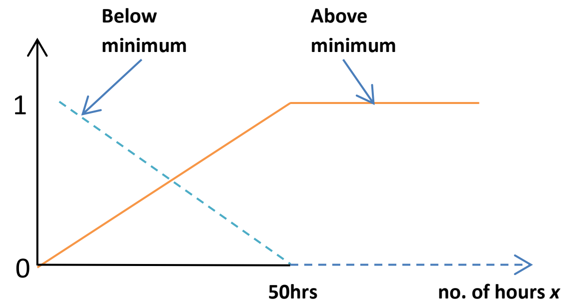


Figure 2-7: A fuzzy-logic performance measure

Academics involvement in community engagement is depicted in Figure 2-6 using Boolean logic. According to Figure 2-6, two academics that were engaged in 49 hours and 51 hours of community involvement respectively will produce two different results in Boolean logic although the difference is only 2 hours between them. The first value (49 hours) will belong to the set 'below minimum' only since this value is <50. The second value (51) will belong to the set 'above minimum' only since this value is >50. Although the first academic did 49 hours of community work, it does not indicate the degree to which the academic was involved in community engagement.

Using fuzzy logic (Figure 2-7), the academics that did 49 and 51 hours of community work would belong to both the sets 'below minimum' and 'above minimum'. The fuzzy logic in Figure 2-7 indicates the degree of community engagement the academics were involved in. As the number of hours increase, the membership grade within the 'above minimum' set increases and the membership grade within the 'below minimum' set decreases. Unlike Boolean logic, the fuzzy logic representation of academic departments is therefore preferred because it indicates the degree to which an academic was involved in community engagement. The output would also produce similar results for similar inputs.

In Figures 2-6 and 2-7 the x-axis represents the universe of discourse, that is, the range of all possible values that the variable x can assume. The y-axis in Figure 2-6 represents whether an object is in a set or not, that is, the value 1 if the object belongs or 0 if it does not belong in the set. This is called a crisp set. The y-axis in Figure 2-7 represents the membership value of the fuzzy set. It indicates the degree to which an object belongs to the set, that is, it can take the value 1 or 0 or any value between 0 and 1. The curve in each graph is known as a membership function and is given the designation of μ. For example, from Figure 2-6, the following can be attained: Below minimum can be represented as $\mu = 0$ and above minimum can be represented as $\mu = 1$. From Figure 2-7, the following can be attained from the graph 'Above minimum': Very close to minimum requirement can be represented as $\mu = 0.9$ and far from minimum requirement can be represented as $\mu = 0.1$.

2.6.4 A mathematical representation of a fuzzy set

A fuzzy set can be represented mathematically as follows (Yager, 1996): Let A represent 'below minimum' or 'above minimum' and X represents the universe of discourse, then for a crisp set (Figure 2-6),

$$f_A(x)\colon X \longrightarrow \{0, 1\}, \text{ where } f_A(x) = \begin{cases} 1, & if\ x \in A \\ 0, & if\ x \notin A \end{cases} \tag{2.1}$$

A fuzzy set as indicated in Figure 2-7 can be mathematically represented as follows: Fuzzy set *A* of universe *X* is defined by the function $\mu_A(x)$ and is called the membership function of set *A* and is represented as follows (Yager, 1996):

$$\begin{cases} \mu_A(x)\colon X \longrightarrow [0,1], \text{where } \mu_A(x) = \begin{cases} 1, & if\ x \in A; \\ 0, & if\ x \notin A; \end{cases} \\ 0 < \mu_A(x) < 1\ if\ x \text{ is partly in } A. \end{cases} \tag{2.2}$$

This set allows for a continuum of possible choices.

2.6.5 Fuzzy logic membership functions

The simplest membership functions are the ones that are formed using straight lines. The triangular and trapezoidal are two such examples (Bobillo & Straccia, 2011). These functions are also the most commonly used membership functions because of its simplicity. The trapezoidal membership function is simply a triangular membership function that has been truncated. Both these functions are depicted in Figures 2-8 and 2-9 respectively.

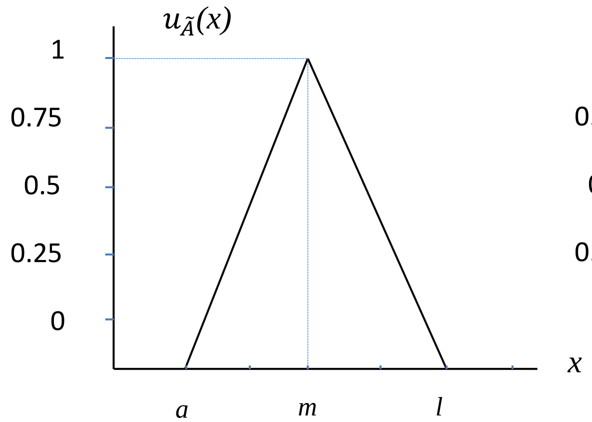


Figure 2-9: Triangular membership

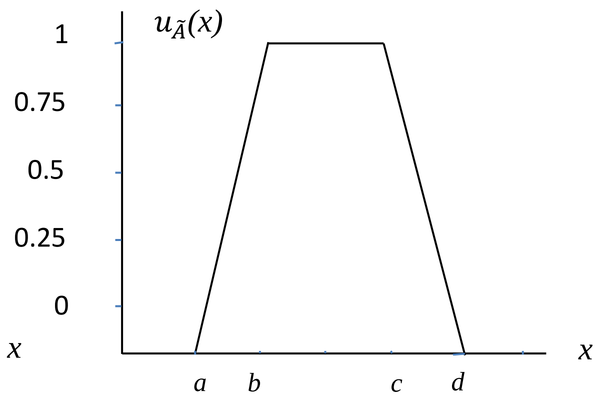


Figure 2-8: Trapezoidal membership

This study will be using the triangular membership function. The triangular membership function is described below. From Figure 2-9, let $\tilde{A}$ be a triangular fuzzy number $\tilde{A}$ with the triplet (a, m, l). The central value is m, the left spread is a, and the right spread is l. This triangular membership can be defined as:

$$u_{\tilde{A}}(x) = \begin{cases} \frac{x-a}{m-a}, & a \leq x \leq m, \\ \frac{l-x}{l-m}, & m \leq x \leq l, \\ 0, & otherwise \end{cases} \tag{2.3}$$

Figure 2-10 shows an α-cut of a triangular fuzzy number for the fuzzy performance score $\tilde{x}_{ij}$. Each value of $\tilde{x}_{ij}$ is a triangular fuzzy number and is represented as $\tilde{x}_{ij}$ = (x_{ij}, α_{ij}, β_{ij}).

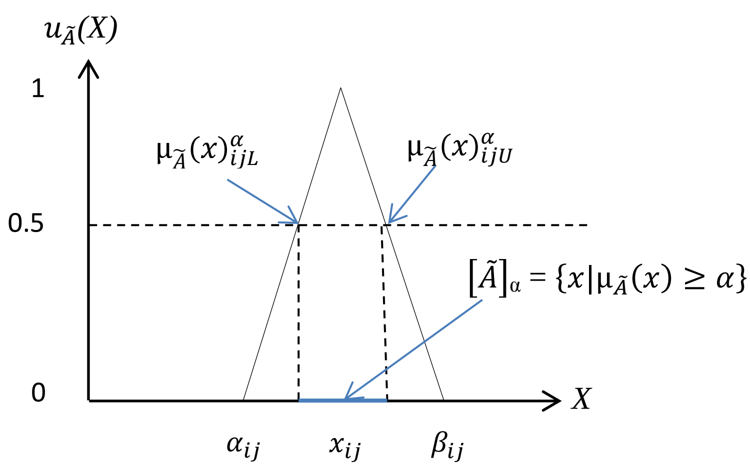


Figure 2-10: A triangular fuzzy number with the $\boldsymbol{\alpha}$-cut for $\mu_{\boldsymbol{A}^{\sim}}(\boldsymbol{x})$

The α-cut of a fuzzy set $\tilde{A}$ is a crisp subset of X and is denoted by:

(2.4) $$[\tilde{A}]_\alpha = \{x | \mu_{\tilde{A}}(x) \geq \alpha\}$$

where $\mu_{\tilde{A}}(x)$ is the membership function of $\tilde{A}$ and $\alpha \in [0,1]$. The lower limit of the α-cut is represented as $[\tilde{A}]_\alpha^L$ and the upper limit is represented as $[\tilde{A}]_\alpha^U$. If $\tilde{A} = \left[[\tilde{A}]_\alpha^L, [\tilde{A}]_\alpha^U\right]$, then by choosing α = 1, the central value of $\tilde{A}$ is attained. If $\tilde{A} = \left[[\tilde{A}]_\alpha^L, [\tilde{A}]_\alpha^U\right]$, then by choosing α = 0, the left and right spreads of $\tilde{A}$ are attained. If $\tilde{A}$ is a triangular fuzzy number and $\tilde{A}_\alpha^L > 0$ and $\tilde{A}_\alpha^U \leq 1$ for $\in [0,1]$, then $\tilde{A}$ is called a normalised positive triangular number. A fuzzy set $\tilde{A}$ is normal if and only if $[\mu_{\tilde{A}}(x)]_x^U = 1$ (Jahanshahaloo *et al*., 2006).

Since this study will be using triangular fuzzy values, some operations that will be used in the model development are presented. Let $\tilde{A}_1 = (l_1, m_1, u_1)$ and $\tilde{A}_2 = (l_2, m_2, u_2)$ represent two triangular fuzzy numbers. The following operations can be expressed (Sun, 2010):

- Addition of fuzzy numbers:

$$\tilde{A}_1 \oplus \tilde{A}_2 = (l_1, m_1, u_1) \oplus (l_2, m_2, u_2)$$
$$= (l_1 + l_2, m_1 + m_2, u_1 + u_2)$$

- Multiplication of fuzzy numbers:

$$\tilde{A}_1 \otimes \tilde{A}_2 = (l_1, m_1, u_1) \otimes (l_2, m_2, u_2)$$
$$= (l_1 l_2, m_1 m_2, u_1 u_2) \text{ for } l_1 l_2 > 0;\ m_1 m_2 > 0;\ u_1 u_2 > 0$$

- Subtraction of fuzzy numbers:

$$\tilde{A}_1 \ominus \tilde{A}_2 = (l_1, m_1, u_1) \ominus (l_2, m_2, u_2)$$
$$= (l_1 - u_2, m_1 - m_2, u_1 - l_2)$$

- Reciprocal of the fuzzy number:

$$\tilde{A}^{-1} = (l_1, m_1, u_1)^{-1} = (1/u_1, 1/m_1, 1/l_1) \text{ for } l_1 > 0;\ m_1 > 0;\ u_1 > 0$$

- Division of fuzzy numbers: Let $\tilde{A} = (a_1, a_2, a_3)$ and $\tilde{B} = (b_1, b_2, b_3)$, then

$$\frac{\tilde{A}}{\tilde{B}} = \left(\frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1}\right).$$

From Figure 2-8, let $\tilde{A}$ represent a trapezoidal fuzzy number as (a, b, c, d) such that $a < b < c < d$.

This trapezoidal membership can be described as:

$$(2.5) \qquad u_{\tilde{A}}(x) = \begin{cases} 0, & (x < a) \text{ or } (x > d), \\ \frac{x-a}{b-a}, & (a \le x \le b), \\ 1, & (b \le x \le c), \\ \frac{d-x}{d-c}, & (c \le x \le d), \end{cases}$$

Operations involving trapezoidal fuzzy numbers will not be discussed because this study will be using triangular fuzzy numbers in the model development. The purpose of depicting the trapezoidal function with its mathematical definition is to show that there are other ways of representing fuzzy numbers (and not only using triangular membership functions) (Chaudhari *et al.*, 2012).

2.6.6 Logical operators used in fuzzy logic

There are many logical operators that can be used in fuzzy logic. These operators are a superset of the standard Boolean logic. Consider the following standard Boolean truth tables below.

A	**B**	**A and B**	**A or B**	**Not A**
0	0	0	0	1
0	1	0	1	1
1	0	0	1	0
1	1	1	1	0

Table 2-4: The AND, OR and NOT operators

In Boolean logic, the AND as well as the OR are the most commonly used operators. Boolean logic indicates whether an element either belongs to a set or does not belong to a set. Fuzzy logic reasoning is however a superset of Boolean logic. This means that Boolean logic can be used to indicate the degree to which an element belongs to a set when the *min* and *max* operators are used (Bobillo & Straccia, 2011). For all fuzzy values, that is 0, 1 and all real values between 0 and 1, the *min(A,B)* instead of A AND B and *max(A,B)* instead of A OR B are used. NOT A becomes 1-A. With the *min* and the *max* operators, the results of Table 2-4 remain the same, yet the values are interpreted as fuzzy values.

2.6.7 If-then rules in fuzzy logic

The basic concept underlying fuzzy logic computing is the use of fuzzy if-then rules (or fuzzy rules) (Chaudhari *et al*., 2012). A fuzzy if-then rule takes the following form:

If x is A then y is B

with A and B being linguistic values that are defined by fuzzy sets on the ranges (universe of discourse) X and Y respectively. The '*x is A*' part is called the antecedent or premise and the '*y is B*' is called the consequent or conclusion. Applying the result to the consequent is called the implication. The following example demonstrates these rules:

If presentation is excellent then rating is high

The antecedent part is '*If presentation is excellent*' while the consequent is '*then rating is high*'. The antecedent is a conditional statement and is denoted using '==' while the consequent is an assignment statement and is denoted using '='. It is therefore better to write the above statement as: *If presentation == excellent then rating = high*

The value for *presentation* is the current value between 0 and 1 while the output (in this case *high*) is an entire fuzzy set. This fuzzy set *high* will later be defuzzified so that only one crisp value is attained. The discussions regarding fuzzy rules and the use of operators (such as *min* and *max*) are encapsulated using an example in Figure 2-11.

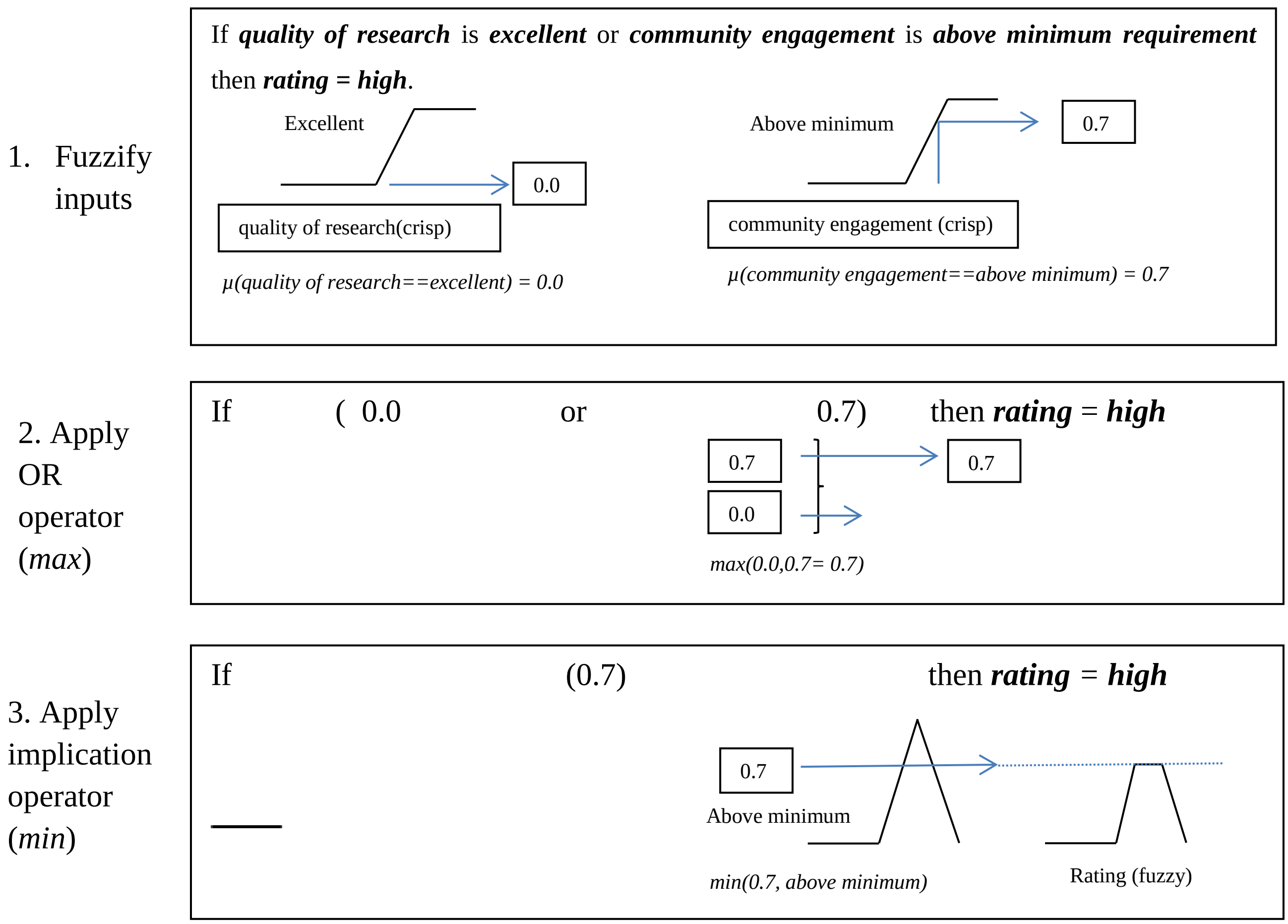


Figure 2-11: Implementing the if-then rules using an example

The steps in Figure 2-11 are explained as follows:

1. Fuzzify inputs: All fuzzy statements in the antecedent need to be resolved to a degree between 0 and 1.
2. Apply fuzzy operators: Multiple parts of the antecedent should be resolved using the fuzzy logical operators so that the entire antecedent is resolved to a single value between 0 and 1.
3. Apply the implication method: The output fuzzy set is shaped by using the degree of support for the entire rule. The consequent assigns the entire fuzzy set to the output.

If the antecedent is true to some degree of membership then the consequent is also true for the same degree. This is indicated as follows:

$$0.2\, p \longrightarrow 0.2\, q \text{ (partial antecedent provide partial implication).}$$

If there is more than one part to the antecedent, then all parts are calculated to a single value using logical operators. If there is more than one part in the consequent, then all the consequents are affected equally. A fuzzy set specified by the consequent is then assigned to the output. The fuzzy set is then modified using the implication function to the degree specified by the antecedent using truncation or 'chopping off'. One way of doing this is by applying the *min* function.

2.6.8 Fuzzy Inference Systems

Fuzzy inference relates to the process that can be formulated in order to map the input into an output using fuzzy logic (Chaudhari *et al*., 2012). Fuzzy inference systems (or fuzzy rule-based systems) will use a linguistic rule base in conjunction with the fuzzy inference process in order to produce the output as indicated in the Figure 2-12.

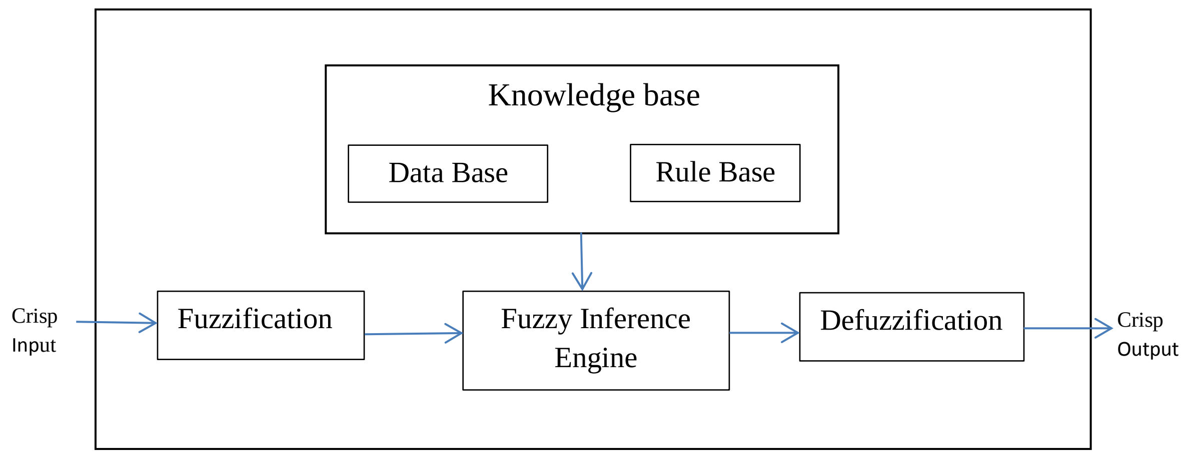


Figure 2-12: Architecture of a fuzzy system (Khan *et al*., 2011)

The components of a fuzzy system depicted in Figure 2-12 are described as follows (Khan *et al*., 2011):

a) The knowledge base comprises a data-base which contains membership functions of the linguistic terms and a rule base which contains a collection of fuzzy rules.
b) A fuzzy inference engine which produces the fuzzy outputs by combining the fuzzy inputs which follows the relations defined in the rule base.

c) The fuzzification and defuzzification modules which fuzzifies crisp inputs into fuzzy data and then defuzzifies the processed data into crisp outputs.

The two most commonly used fuzzy inference systems are Mamdani (also called linguistic fuzzy systems) and Sugeno-type systems (Tsaur *et al.*, 2002). In the Mamdani fuzzy systems, the antecedent and consequent are fuzzy propositions and the rules of this system will take the following form. *r*: if X_1 is A_{i1} and if X_2 is X_{i2} and…and if X_n is A_{in} then $Y\ is\ B_i$. This means that B_i is a fuzzy proposition. In Sugeno fuzzy systems, the antecedent are fuzzy propositions and the consequent is a crisp function of the variables in the antecedent. Rules in Sugeno systems are of the form: *r*: if X_1 is A_{i1} and if X_2 is X_{i2} and…and if X_n is A_{in} then $Y_i = f_i(X_i)$, where the consequent is usually a linear function which combines the systems inputs.

Clearly, these two systems vary in the manner in which the crisp output is determined after the fuzzification process. The Mamdani approach uses defuzzification to produce the crisp output. The Sugeno inference system uses weighted average to produce the crisp output. The Sugeno-type systems have the advantage of low computational costs and high accuracy. However, the Mamdani inference systems are the most commonly used system because they can be easily interpreted by humans (Chaudhari *et al.*, 2012). The Mamdani inference system was proposed by Ebrahim Mamdani when he attempted to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from human operators. Mamdani's method was based on fuzzy algorithms developed by Lotfi Zadeh (Zadeh, 1994). The concept of a Mamdani inference system is best described using the following example. Consider the following two inputs, three-rule and one output system pertaining to an academic department:

If *quality of research* is *weak* or *community engagement* is *poor* then rating is *low*.
If *quality of research* is *good* then rating is *average*.
If *quality of research* is *excellent* or *community engagement* is *good* then rating is *high*.
The situation above is illustrated in Figure 2-13.

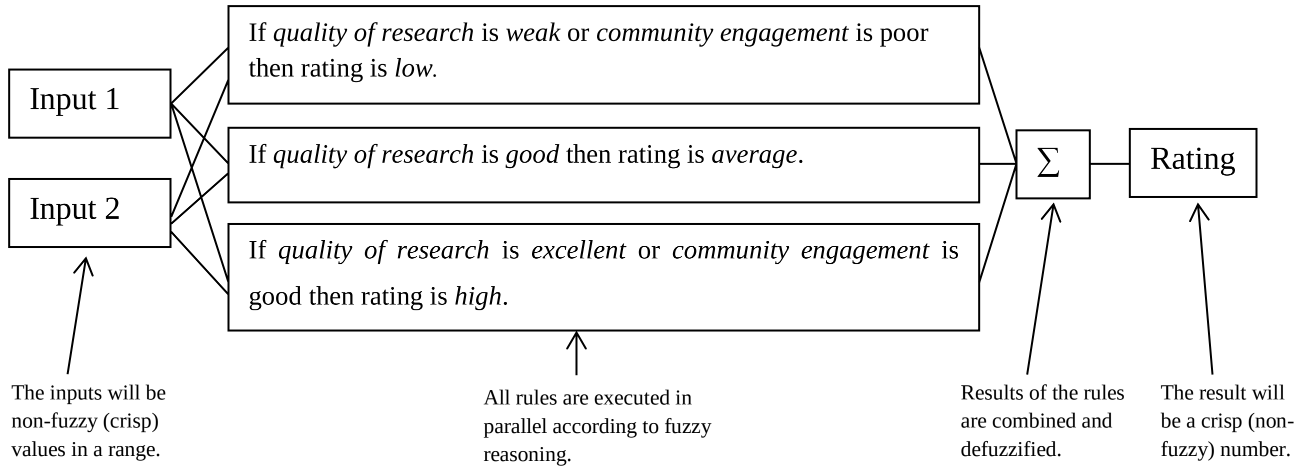


Figure 2-13: A two input, three-rule and single output system

In a fuzzy-based system, processing is always done from the left to the right in a parallel manner. In this example, information flows from two inputs to a single output (from left to right). Figure 2-13 will be used in combination with Figure 2-14 to explain in detail what a fuzzy inference system is.

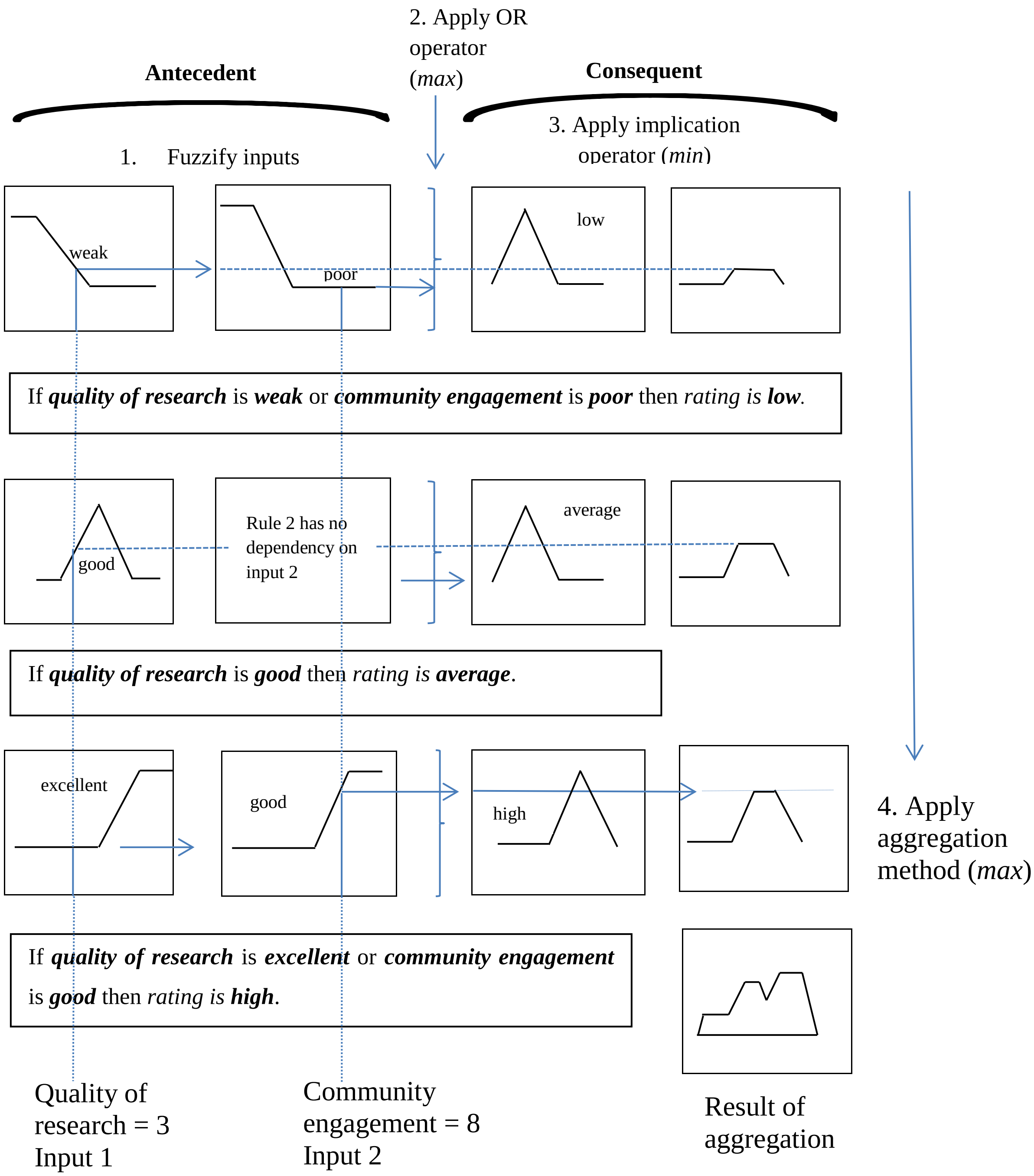


Figure 2-14: An example to explain a fuzzy inference system

There are five parts in the inference system as indicated in Figure 2-14. These are:

1. Fuzzification of inputs:

For the purposes of explanation, 'quality of research = 3' and 'community engagement = 8' are chosen as inputs. These inputs have to firstly be fuzzified. The inputs are crisp numerical values between 0 and 10 (in this case input 1 = 3 and input 2 = 8) and the outputs are fuzzy values between 0 and 1. Fuzzification of the outputs is done using a lookup table that will contain the crisp inputs and its fuzzy value equivalence. For example, in Figure 2-14, the value for 'community engagement = 8' is fuzzified into a value 0.7.

2. The AND as well as the OR operators are applied in the antecedent:

After fuzzification of the inputs, it is known to what degree each part of the antecedent has been satisfied (for each rule) (Chaudhari *et al*., 2012). If the antecedent (for a rule) has more than one part, the fuzzy operator is applied so that a single value is attained for the complete antecedent (for that particular rule). This value will be applied to the output function. An example where the AND as well as the OR operators are used is depicted in Figures 2-11 and 2-14.

3. Implication takes place from antecedent to consequent:

Before the implication method can be applied, proper weighting has to be applied to each rule (Osman *et al*., 2013). The consequent is always a fuzzy set represented by linguistic characteristics attributed to it. The input for the implication method is a single fuzzy value and the output is a fuzzy set (for that particular rule). The consequent is then reshaped using a single value from the consequent (that is, the fuzzy triangular representation for each rule in Figure 2-14). Implication for each rule is then implemented. This is done using the *min* (minimum) operator that truncates the output fuzzy set and the *prod* (product) operator that scales the output of the fuzzy set. This is represented inside the last square for each rule in Figure 2-14.

4. Aggregation is done on all fuzzy outputs:

In order to make decisions, the implication for each rule has to be combined. This is referred to as aggregation. Aggregation is a process where all fuzzy sets for each rule are combined into a single fuzzy set (Khan *et al*., 2011). Aggregation is done once just prior to defuzzifiction. Aggregation is supported by *max* (maximum), *probor* (probabilistic or) and *sum* (the sum of the output set for each rule). Since aggregation is commutative, the order in which the rules are implemented is not important. Aggregation is indicated in the last square at the bottom right hand corner of Figure 2-14.

5. Defuzzification is carried out to attain a single value:

The aggregation process produces a fuzzy set with many values (Osman *et al*., 2013). Defuzzification has to therefore take place in order to select a single crisp value. The Mamdani inference system uses the method of defuzzification (to produce the single crisp output) and is supported by most programming languages that support fuzzy logic (Chaudhari *et al*., 2012). The most popular method in selecting a single value is the centroid calculation that returns the centre of the area (or centroid method) under the curve (Tsaur *et al*., 2002). This is depicted in Figure 2-15. There are however other methods that can be used to produce a single output. These methods are the bisector, middle of maximum (the average of the maximum values of the output sets), largest of the maximum values, and the smallest of the maximum values. This study will use the centroid method for defuzzification.

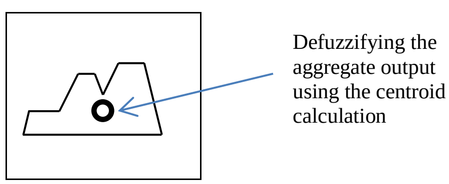


Figure 2-15: Defuzzification using the centroid calculation (Tsaur *et al*., 2002)

2.6.9 Conclusion

This section provided a detailed explanation of fuzzy logic and fuzzy set theory. A justification as to why fuzzy logic is preferred over Boolean logic in certain contexts is also presented. This section also provided a detailed description of a fuzzy inference system (FIS), which forms the backbone for solving fuzzy-based problems. Fuzzy logic and fuzzy set theory will be used in the development of an Artificial Intelligence (AI) system to estimate the productivity of an academic department. This system should also be able to do rankings and selections from many feasible alternatives. Selections and ranking are important for rating academic staff in terms of their overall performance as well as for promotion purposes. The technique that will be used in this study is called fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution).

2.7 Technique for order preference by similarity to ideal solution (TOPSIS)

The decision-making process aims to choose the optimal option from many feasible alternatives. Most decisions are chosen when the alternatives are quantified using precise values and then ranked in some numerical order. The most preferable method that can be employed for choosing the best alternative is the TOPSIS (Technique for order preference by similarity to ideal solution) method because it is a simple technique to program and implement (Tsaur *et al*., 2002). The conventional TOPSIS could only handle precise data. However, not all data that require processing are precise and absolute. The attributes in an academic department lend themselves more to a qualitative rather than a quantitative evaluation because imprecise, uncertain and fuzzy inputs have to be measured. Therefore the conventional TOPSIS method has to be adapted to handle fuzzy requirements. Awasthi *et al*. (2011) proposed a method to extend the conventional TOPSIS method in order to process fuzzy inputs. This method is discussed in detail in section 2.7.2.

2.7.1 A MCDM model and conventional TOPSIS

In order to understand how the fuzzy TOPSIS works, knowledge of a MCDM environment and the conventional TOPSIS method is important (Chen, 2010).

In a MCDM environment, decision-makers are concerned about the following (Ding, 2011):

- From many feasible alternatives, the most preferred one is chosen.
- Ranking the alternatives in some order (possibly in terms of importance).
- Screening the alternatives when the final decision needs to be made.

The MCDM problem does not aim to choose the ‘correct’ solution, but rather the most efficient or optimal one given all the criteria and alternatives. The general matrix format of a MCDM problem is (Jahanshahaloo *et al*., 2006):

$$
\begin{array}{cc}
 & \begin{array}{cccc} \boldsymbol{C_1} & \boldsymbol{C_2} & \cdots & \boldsymbol{C_n} \end{array} \\
\begin{array}{c} \boldsymbol{A_1} \\ \boldsymbol{A_2} \\ \vdots \\ \boldsymbol{A_m} \end{array} & \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}
\end{array}
$$

$$\boldsymbol{W} = [w_1, w_2 \dots, w_n]$$

where $A_1, A_2 \dots, A_m$ are the alternatives that decision makers can choose from, $C_1, C_2 \dots, C_n$ are criteria with which the alternative performance are measured, x_{ij} is the rating of alternative A_i for criterion C_j and w_j is the weight of criterion C_j.

The steps involved in a MCDM model are as follows (Saaty, 2008):

1) The evaluation criteria for the system are established and these are related to the goals.
2) Alternate solutions are generated.
3) The alternate solutions are evaluated in terms of the criteria.
4) A normative multi-criteria analysis method is applied.
5) An optimal solution is selected.
6) If the chosen solution is not acceptable, then new information should be gathered and the next iteration of multi-criteria optimization is entered into.

Steps (1) and (5) are performed by decision makers (such as upper management or the quality assurance department at a university) while the other steps are determined by an IS engineer whose responsibility is to develop the solution. When selections or rankings are required, weights for the criteria have to firstly be calculated and then the conventional TOPSIS is applied using crisp values.

The TOPSIS is a multi-criteria method that can identify solutions from a given number of alternatives (Tsaur *et al*., 2002). A chosen optimal solution defines points that have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution (at the same time). The positive ideal solution is regarded as the maximal benefit solution because it contains the best values for the criteria while the negative ideal solution has the worst values of the criteria. The basic idea of TOPSIS is diagrammatically represented in Figure 2-16 (Tsaur *et al*., 2002).

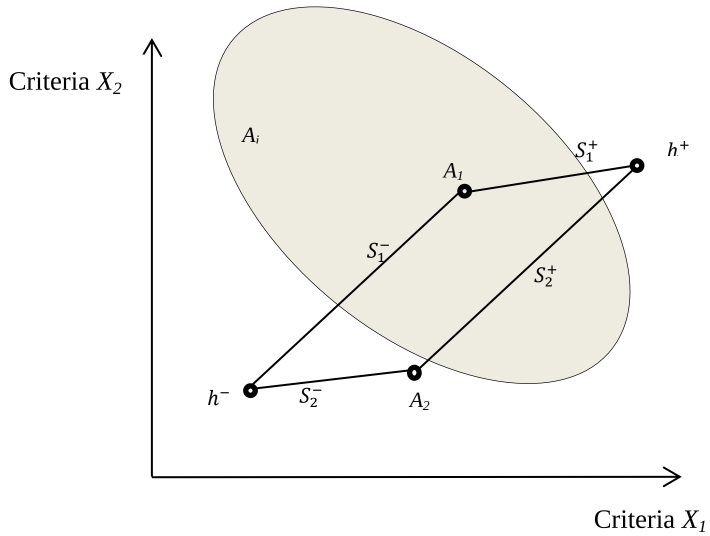


Figure 2-16: Representation of TOPSIS with two criteria (Tsaur *et al*., 2002)

In Figure 2-16, the objective space for two criteria, X_1 and X_2 are depicted. The positive ideal solution is indicated by $h^+$and the negative ideal solution is indicated by h^-. The two alternatives are A_1 and A_2. The distance between A_1 and h^+ and the distance between A_1 and h^- is S_1^+ and S_1^- respectively. The distance between A_2 and h^+ and the distance between A_2 and h^- is S_2^+ and S_2^- respectively. The distance between h^+ (the ideal solution) and A_1 is shorter than the distance between h^+ (the ideal solution) and A_2. At the same time, A_1 is further from the negative ideal solution than A_2. Therefore A_1 is preferred.

The conventional TOPSIS approach has the following steps (Bhutia & Phipon, 2012):

1) The normalised decision matrix is calculated. The normalised value n_{ij} is calculated as follows:

   (2.6) $$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}(x_{ij})2}}, \quad i = 1, 2, \dots, m; \; j = 1, 2, \dots, n$$

2) The weighted normalised decision matrix is calculated. The weighted normalised value v_{ij} is calculated as: $v_{ij} = w_j n_{ij}$, $i = 1, 2, \dots, m$; $j = 1, 2, \dots, n$ where w_j is the weight of the i^{th} attribute or criterion, and $\sum_{j=1}^{n} w_j = 1$.

3) The positive ideal and negative ideal solutions are the determined as follows:

(2.7) $A^{+} = \{v_1^{+}, \ldots\ldots\ldots v_n^{+}\} = \{(\max_j v_{ij} \mid i \in I), (\min_j v_{ij} \mid i \in J)\},$

(2.8) $A^{-} = \{v_1^{-}, \ldots\ldots\ldots v_n^{-}\} = \{(\min_j v_{ij} \mid i \in I), (\max_j v_{ij} \mid i \in J)\}$ where I is associated with the benefit criteria and J is associated with the cost criteria.

4) The separation measures are then calculated using the *n*-dimensional Euclidean distance. The separation for each alternative from the ideal solution is:

(2.9) $$d_i^{+} = \left\{\sum_{j=1}^{n}\left(v_{ij} - v_j^{+}\right)^2\right\}^{1/2}, i = 1, 2, \ldots, m;$$

Similarly, the separation from the negative ideal solution is:

(2.10) $$d_i^{-} = \left\{\sum_{j=1}^{n}\left(v_{ij} - v_j^{-}\right)^2\right\}^{1/2}, i = 1, 2, \ldots, m;$$

5) The relative closeness to the ideal solution is then calculated. The relative closeness of alternative A_i with respect to A^+ is defined as:

(2.11) $R_i = d_i^{-}/(d_i^{+} + d_i^{-}), i = 1, \ldots., m$. Since $d_i^{-} \geq 0$ and $d_i^{+} \geq 0$, $R_i \in [0,1]$.

6) The preference order is then ranked.

This conventional TOPSIS method was designed to operate on precise and deterministic data. However in the real world, most of the data are not so deterministic and precise. An academic department for example is constantly faced with attributes that are imprecise and fuzzy. Awasthi *et al*. (2011) therefore extended the original TOPSIS method to handle imprecise and fuzzy data. This method is generally referred to as fuzzy TOPSIS.

2.7.2. TOPSIS method with fuzzy data

Like the conventional TOPSIS method, the fuzzy TOPSIS method also selects the optimal solution that is closest to the positive ideal solution and farthest to the negative ideal solution (at the same time) (Tsaur *et al*., 2002). In order to achieve this, it is necessary use a formula that calculates the distance between two triangular fuzzy numbers. This is determined as follows: Let $\tilde{a} = (a_{1,} a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$ be two fuzzy triangular numbers. Using the vertex method, the distance between these two triangular fuzzy numbers is given by (Fenton & Wang, 2006):

(2.12) $d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}([(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2])}$. This formula is required in step 7 of the fuzzy TOPSIS method.

The following steps are used in the fuzzy TOPSIS method (Awasthi *et al.*, 2011):

Step 1: Assign ratings to the criteria and the alternatives:

The fuzzy decision matrix represents *j* alternatives, that is, $(A_1, A_2 \ldots, A_j)$ from which decision-makers (such as an evaluation panel of a university) have to choose against *n* criteria, that is, $(C_1, C_2 \ldots, C_j)$ such as Administration, Teaching and Supervision, Research and Innovation, Writing and Publication, Consultancy as well as Community Engagement (Fenton & Wang, 2006). The criteria are $C_1, C_2 \ldots, C_n$ with which the alternatives are measured. The weight $\widetilde{w}_i$ $(i = 1, 2, 3, \ldots, m)$ is the weight of the criterion and is always a normalised fuzzy number. The performance ratings of each decision-maker $D_k (k = 1, 2, \ldots, K)$ for each alternative $A_j (j = 1, 2, 3, \ldots, n)$ with respect to criteria $C_i (i = 1, 2, 3, \ldots, m)$ are denoted by:

(2.13 $\tilde{R}_k = \tilde{x}_{ijk} (i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n;\ k = 1, 2, \ldots, K)$ with membership function $\mu_{\tilde{R}_k(x)}$.

Step 2: The aggregate fuzzy ratings for each criteria and the alternatives are computed:

If the fuzzy rating of all the decision-makers is a triangular fuzzy number and is denoted as $\tilde{R}_k$=(a_k, b_k, c_k), $k = 1, 2, \ldots, K$ then the aggregate fuzzy rating of all decision-makers is given by:

(2.14) $\tilde{R}$ = (a, b, c), $k = 1, 2, \ldots, K$ with $a = \min_k \{a_k\}, b = \frac{1}{K}\sum_{k=1}^{K} b_k$, and $c = \max_k \{c_k\}$. If the fuzzy rating and importance weight of the k^{th} decision-maker are $\tilde{x}_{ijk}$= $(a_{ijk}, b_{ijk}, c_{ijk})$ and $\widetilde{w}_{ijk}$=$(w_{jk1}, w_{jk2}, w_{jk3})$, $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$ then the aggregated fuzzy rating $(\tilde{x}_{ij})$ of alternatives with respect to each criterion are given by:

(2.15) $\tilde{x}_{ij} = (a_{ij,} b_{ij}, c_{ij})$ where $a_{ij} = \min_k \{a_{ijk}\}$, $b_{ij} = \frac{1}{K}\sum_{k=1}^{K} b_{ijk}$ and $c_{ij} = \max_k \{c_{ijk}\}$.

The aggregated fuzzy weights ($\tilde{w}_{ij}$) of each criterion are calculated as:

(2.16) $\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3})$ where $w_{j1} = \min_k \{w_{jk1}\}$, $w_{j2} = \frac{1}{K}\sum_{k=1}^{K} w_{jk2}$ and $w_{j3} = \max_k \{w_{jk3}\}$.

Step 3: The fuzzy decision matrix is computed as follows:

$$\widetilde{\boldsymbol{D}} = \begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \dots & \boldsymbol{C_n} \\ \boldsymbol{A_1} & \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \boldsymbol{A_2} & \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{A_m} & \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{bmatrix} \quad i = 1, 2, \dots, m; j = 1, 2, \dots, n$$

$$\widetilde{W} = [\tilde{w}_1, \tilde{w}_2, \dots\dots, \tilde{w}_n]$$

Step 4: The fuzzy decision matrix is normalised:

The fuzzy decision matrix is normalised using a using a linear scale transformation to bring all criteria scales into a common comparable scale. The normalised fuzzy decision matrix is given by:

(2.17) $\tilde{R} = [\tilde{r}_{ij}]_{m \times n}$ where $\tilde{R}_{ij} = \left(\frac{a_{ij}}{c_j}, \frac{b_{ij}}{c_j}, \frac{c_{ij}}{c_j}\right)$ and $c_j = \max_i \ c_{ij}$ (benefit criteria)

$\tilde{R}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right)$ and $a_j^- = \min_i \ a_{ij}$ (cost criteria)

Step 5: The weighted normalised matrix ($\tilde{V}$) is computed:

This is achieved by multiplying the weights ($\tilde{w}_j$) of the evaluation criteria with the normalised fuzzy decision matrix $\tilde{r}_{ij}$. It means:

(2.18) $\tilde{V} = [\tilde{v}_{ij}]_{m \times n} \ \ i = 1, 2, \dots, m; \ j = 1, 2, \dots, n \ where \ \tilde{v}_{ij} = \tilde{r}_{ij}(\times)\tilde{w}_{ij}$.

Step 6: The fuzzy positive ideal (FPIS) and the fuzzy negative ideal (FNIS) solutions are computed as follows:

(2.19) $A^* = (\tilde{v}_1^*, \dots, \tilde{v}_n^*)$ where $\tilde{v}_j^* = \max_i \{v_{ij3}\}$, $i = 1, 2, \dots, m; \ j = 1, 2, \dots, n$

(2.20) $A^{-} = (\tilde{v}_1, \ldots, \tilde{v}_n)$ where $\tilde{v}_j^{-} = \min_i \{v_{ij1}\},\ i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n$

Step 7: The distance of each alternative from FPIS and FNIS is computed.

The distance (d_i^*, d_i^-) of each of the weighted alternative $i = 1, 2, \ldots, m$ from the FPIS and FNIP is computed as follows:

(2.21) $d_i^* = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^*),\ i = 1, 2, \ldots, m$ and

(2.22) $d_i^- = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^-),\ i = 1, 2, \ldots, m$ where $d_v(\tilde{a}, \tilde{b})$is the distance between two fuzzy numbers $\tilde{a}$ and $\tilde{b}$.

Step 8: The closeness coefficient (CC_i) of each alternative is computed.

The closeness coefficient (CC_i) represents the distances to the FPIS (A^*) and the FNIS (A^-) simultaneously. The coefficient (CC_i) of each alternative is computed using the following equation:

(2.23) $$CC_i = \frac{d_i^-}{(d_i^- + d_i^+)},\ i = 1, 2, \ldots, m$$

Step 9: The alternatives are ranked.

In step 9, the alternatives are ranked in decreasing order according to the coefficient (CC_i). The optimum solution is closest to the FPIS and farthest to the FNIS (Mohammadi *et al*., 2011).

Sections 2.7.1and 2.7.2 described in detail the convention TOPSIS and the fuzzy TOPSIS methods. Since the fuzzy TOPSIS method will be used for ranking and selection, a numerical example with fuzzy requirements is presented in the next section using this technique.

2.7.3 A numerical example using fuzzy TOPSIS

The following numerical example illustrates how the fuzzy TOPSIS can be used in the decision-making process using fuzzy data.

Suppose the IT department at a University wishes to appoint a Head of Department. There are three applicants (alternatives A_1, A_2, A_3) for the post. It was decided that a committee of four academics (decision-makers D_1, D_2, D_3, D_4) will conduct the interviews. The committee decided that all three applicants will be interviewed on the following four criteria: research (C_1), teaching skills (C_2), administration (C_3) and external engagement (C_4). The committee decided to use linguistic assessment scales from Tables 2-5 and 2-6 for the alternatives and criteria respectively. These scales are attained from a triangular fuzzy ratio scale indicated in Figure 2-17.

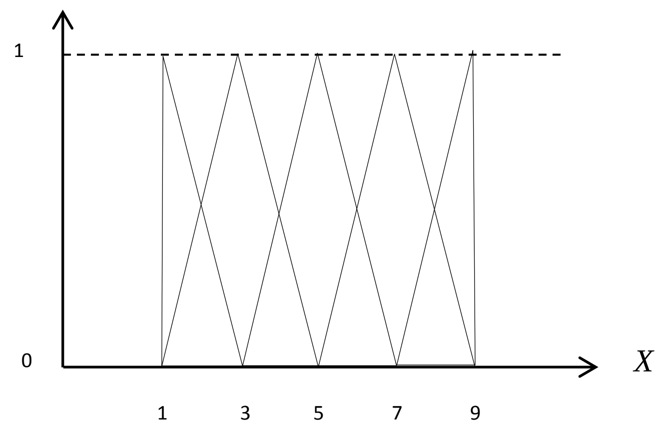


Figure 2-17: Triangular fuzzy ratio scales

Linguistic term	Membership function
Very weak (VW)	(1,1,3)
Weak (W)	(1,3,5)
Average (A)	(3,5,7)
Good (G)	(5,7,9)
Very Good (VG)	(7,9,9)

Table 2-5: Linguistic terms for alternative ratings

Linguistic term	Membership function
Very Low (VL)	(1,1,3)
Low (L)	(1,3,5)
Medium (M)	(3,5,7)
High (H)	(5,7,9)
Very High (VH)	(7,9,9)

Table 2-6: Linguistic terms for criteria ratings

After the committee rated the criteria using Table 2-6 the linguistic assessments for the 4 criteria were obtained. These assessments are indicated in Table 2-7.

Criteria	**Decision-makers**			
	D_1	D_2	D_3	D_4
C_1	H	H	VH	H
C_2	H	VH	VH	H
C_3	VH	VH	H	VH
C_4	H	H	VH	H

Table 2-7: Linguistic assessments for the 4 criteria

The aggregate fuzzy weight $\widetilde{w}_{ij}$ of each criterion is calculated using the following equations: $w_{j1} = \min_k \{w_{jk1}\}$, $w_{j2} = \frac{1}{K}\sum_{k=1}^{K} w_{jk2}$ and $w_{j3} = \max_k \{w_{jk3}\}$. For example, C_1 is 'research' and the aggregate fuzzy weight for this criterion is given by $\widetilde{w}_j = (w_{j1}, w_{j2}, w_{j3})$ where: $w_{j1} = \min_k(5, 5, 7, 5) = 5$, $w_{j2} = \frac{1}{4}\sum_{k=1}^{4}(7 + 7 + 9 + 7) = 7.5$ and $w_{j3} = \max_k(9, 9, 9, 9) = 9$. The remaining three aggregate weights can be calculated using the same equations and all the results are indicated in Table 2-8.

Criteria	Weight
C_1	(5, 7.5, 9)
C_2	(5, 8, 9)
C_3	(5, 8.25, 9)
C_4	(5, 7.5, 9)

Table 2-8: Aggregate fuzzy weights

The committee used Table 2-5 to assess the alternatives in terms of the criteria and the results are indicated in Table 2-9.

Criteria	Alternatives											
	A_1				A_2				A_3			
	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4
C_1	A	VG	A	W	G	VG	G	W	W	G	VG	VG
C_2	VG	A	W	A	A	G	VG	VW	VG	A	W	G
C_3	VW	W	G	G	A	VG	VW	A	G	VG	VG	G
C_4	VG	G	VG	W	A	VW	W	G	VG	A	G	G

Table 2-9: Linguistic assessments for the 3 alternatives

The aggregate fuzzy weights of the alternatives are then calculated. For example, the rating C_1 (research) for alternative A_1 using the assessments of the four decision-makers is calculated as follows:

$$a_{ij} = \min_k (3, 7, 3, 1) = 1,\ b_{ij} = \frac{1}{4}\sum_{k=1}^{4}(5 + 9 + 5 + 3) = 5.5 \text{ and } c_{ij} = \max_k(7, 9, 7, 5) = 9.$$

The aggregate ratings for the remaining alternatives can be calculated using the same equations and all the results are indicated in Table 2-10.

Criteria	Alternatives		
	A_1	A_2	A_3
C_1	(1, 5.5, 9)	(1, 6.5, 9)	(1, 7, 9)
C_2	(1, 5.5, 9)	(1, 5.5, 9)	(1, 6, 9)
C_3	(1, 4.5, 9)	(1, 5, 9)	(5, 8, 9)
C_4	(1, 7, 9)	(1, 4, 9)	(3, 7, 9)

Table 2-10: Aggregate fuzzy decision matrix

The next step involves normalising the fuzzy decision matrix. Since all the criteria are benefit criteria, the following equation is used: $\tilde{R}_{ij} = \left(\frac{a_{ij}}{c_j}, \frac{b_{ij}}{c_j}, \frac{c_{ij}}{c_j}\right)$ with $c_j = \max_i c_{ij}$ (benefit criteria). For example, the normalised value of $A_1$for criteria C_1 is calculated as follows: $c_j = \max_i(9, 9, 9)$ $= 9$ and $\tilde{r}_{ij} = \left(\frac{1}{9}, \frac{5.5}{9}, \frac{9}{9}\right) = (0.11, 0.61, 1)$. The other normalised values are calculated using the same equations and all the computations are indicated in Table 2-11.

Criteria	Alternatives		
	A_1	A_2	A_3
C_1	(0.11, 0.61, 1)	(0.11, 0.72, 1)	(0.11, 0.78, 1)
C_2	(0.11, 0.61, 1)	(0.11, 0.61, 1)	(0.11, 0.76, 1)
C_3	(0.11, 0.5, 1)	(0.11, 0.56, 1)	(0.56, 0.89, 1)
C_4	(0.11, 0.78, 1)	(0.11, 0.44, 1)	(0.33, 0.78, 1)

Table 2-11: Normalised fuzzy decision matrix for alternatives

The fuzzy weighted matrix is then calculated using the following equation: $\tilde{v}_{ij} = \tilde{r}_{ij}(\times)\tilde{w}_{ij}$. The $\tilde{r}_{ij}$ values are obtained from Table 2-11 and the $\tilde{w}_{ij}$ values are obtained from Table 2-8. For example, the fuzzy weight for alternative of A_1 with respect to criterion C_1 is calculated as: $\tilde{v}_{ij} = (0.11, 0.61, 1) \times (5, 7.5, 9) = (0.55, 4.58, 9)$. Likewise, the other fuzzy weighted matrix values are calculated and are indicated in Table 2-12. In order to compute the fuzzy positive ideal solution (A^*) and the fuzzy ideal negative solution (A^-) the following equations are used:

$$A^* = (\tilde{v}_1^*, \cdots, \tilde{v}_n^*) \text{ where } \tilde{v}_j^* = \max_i\{v_{ij3}\},\ i = 1, 2, \ldots, m; j = 1, 2, \ldots, n$$

$$A^- = (\tilde{v}_1, \cdots, \tilde{v}_n^*) \text{ where } \tilde{v}_j^- = \min_i\{v_{ij1}\},\ i = 1, 2, \ldots, m; j = 1, 2, \ldots, n$$

After applying the above equations, the results are indicated in the last two columns of Table 2-12.

Criteria	Alternatives			FNIS (A^{-})	FPIS ($*$)
	A_1	A_2	A_3		
C_1	(0.55, 4.58, 9)	(0.55, 5.4, 9)	(0.55, 5.85, 9)	(0.55, 0.55, 0.55)	(9, 9, 9)
C_2	(0.55, 4.88, 9)	(0.55, 4.88, 9)	(0.55, 6.08, 9)	(0.55, 0.55, 0.55)	(9, 9, 9)
C_3	(0.55, 4.13, 9)	(0.55, 4.62, 9)	(2.8, 7.34, 9)	(0.55, 0.55, 0.55)	(9, 9, 9)
C_4	(0.55, 5.85, 9)	(0.55, 3.3, 9)	(1.65, 5.85, 9)	(0.55, 0.55, 0.55)	(9, 9, 9)

Table 2-12: Weighted normalised alternatives, FPIS and FNIS

The next step involves computing the distance of each alternative from the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS). For example, for alternative A_1 and criterion C_1, the distance is calculated using the distance formula as follows (Fenton & Wang, 2006): $d_v(A_1, A^{*}) = \sqrt{\frac{1}{3}([(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2])}$

$$= \sqrt{\frac{1}{3}([(0.55 - 0.55)^2 + (4.58 - 0.55)^2 + (9 - 0.55)^2])}$$

$$= \underline{5.41}$$

$$d_v(A_1, A^{-}) = \sqrt{\frac{1}{3}([(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2])}$$

$$= \sqrt{\frac{1}{3}([(0.55 - 9)^2 + (4.58 - 9)^2 + (9 - 9)^2])}$$

$$= \underline{5.51}$$

The rest of the calculations are obtained in a similar manner and all the results are indicated in Table 2-13.

Criteria	d^{-}			d^{*}		
	A_1	A_2	A_3	A_1	A_2	A_3
C_1	5.41	5.63	5.76	5.51	5.30	5.21
C_2	5.48	5.48	5.83	5.43	5.43	5.16
C_3	5.30	5.42	6.39	5.63	5.50	3.71
C_4	5.76	5.13	5.79	5.21	5.88	4.62

Table 2-13: Distance $\boldsymbol{d_v(A_i, A^{*})}$ and $\boldsymbol{d_v(A_i, A^{-})}$ for alternatives

The distance d_i^{*} and d_i^{-} are then calculated using the following equations:

$d_i^{*} = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^{*}), i = 1, 2, \ldots, m$ and $d_i^{-} = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^{-}), i = 1, 2, \ldots, m$. In other words, these equations determine the sum of each column of Table 2-5(i). The closeness coefficient is calculated using the following equation: $CC_i = \frac{d_i^-}{(d_i^- + d_i^+)}$ $i = 1, 2, \ldots, m$. For example, for the alternative A_1, the closeness coefficient is: $CC_i = \frac{d_i^-}{(d_i^- + d_i^+)} = \frac{21.78}{(21.78+21.95)} = 0.50$. The remaining calculations for d_i^*, d_i^- and CC_i are indicated in Table 2-14.

	A_1	A_2	A_3
d_i^-	21.95	21.66	23.77
d_i^*	21.78	22.11	18.70
CC_i	0.50	0.51	0.44

Table 2-14: Closeness coefficient (CC_i) for the three alternatives

The last step involves ranking the alternatives. The largest CC_i value is ranked number one indicating that it is the optimal solution. Therefore A_2 is the best alternative that should therefore be chosen as Head of the Information Technology Department.

2.8 Conclusion

In chapter 1, problems relating to productivity estimation methods currently being used at universities were discussed. This chapter (chapter 2) provided a detailed discussion on why a fuzzy-based multi-criteria decision making (MCDM) method is most suitable for estimating productivity of academic departments. A motivation is also provided as to why the fuzzy Analytic Hierarchy Process (AHP) is chosen for developing the productivity estimation model (Lee, 2010). Since the model development is fuzzy-based, a detailed explanation on fuzzy logic and fuzzy set theory was provided. A detailed comparison was also made between the conventional and extended TOPSIS methods. A numerical example was also presented using this technique. This chapter formed the basis for developing the productivity estimation model using the Design Science Research Methodology (DSRM) which is discussed in chapter 3.

Chapter 3

MODEL DEVELOPMENT USING DESIGN SCIENCE RESEARCH METHODOLOGY (DSRM)

3.1 Introduction

Design science research methodology (DSRM) culminates in the creation and evaluation of some artifact with the intention of solving an IS problem (Hevner *et al*., 2004). An artifact can constitute a construct, method, model or an instantiation. According to Winter, (2008), constructs are the 'language' that specifies the problems and solutions while models will use this language to specify the problem and solutions. Methods provide a description of the processes that are required to solve the problem. Instantiation is defined as problem-specific aggregates of constructs, methods and models (Kuechler & Vaishnavi, 2008). IS is an applied research discipline that makes use of theories from other disciplines (such as natural, behavioural and social sciences) to solve problems at the intersection of IT and an organisation (Peffers *et al*., 2008). According to Simon (1969: 55), "natural sciences and social sciences try to understand reality while design science attempts to create things that serve human purposes." Kuechler and Vaishnavi (2008) refer to the natural, behavioural and social science theories as 'kernel' theories that present novel techniques to designing IS solutions. 'Design theories' provide explicit details on 'how to do something' that corresponds to 'kernel theories'. This study will use the kernel theory and design theory approach to solve the IS problem. In other words, theories from the social, behavioural and natural sciences will be used to create the artifact, that is, a computerised model to estimate the productivity of academic staff and academic departments at a university.

3.2 The activities necessary in Design Science Research Methodology

The aim of design science research methodology is to develop a commonly accepted framework based on design science (DS) principles (Kuechler & Vaishnavi, 2008). The broad DS principles are the conceptual principles that define what design science research is, the practice rules for design science research and the processes that are involved for conducting and presentation of the research (Peppers *et al*., 2008). These principles were used in developing a common framework for conducting design science research. The framework was developed using a consensus building approach based on accepted elements from previously conducted research

(Winter, 2008). This consensus building approach resulted in six activities that are recommended when conducting design science research. These activities are as follows (Peffers *et al*., 2008):

1. Problem identification and motivation:

This activity clearly defines the specific research problem and presents a solution to the problem. The problem should be conceptually articulated so that the complexity of the problem is captured. The resource requirement for this activity is knowledge of the problem and why it is important that this problem be solved. With regard to this study, the research problem and solution are as follows: Universities are constantly faced with uncertain and imprecise attributes that are difficult to evaluate using conventional methods (Mohamad *et al*., 2008). This viewpoint is further supported by the results of a research questionnaire that was sent out to academic staff to elicit their opinions regarding current evaluation methods (Chapter 7). The results in Figure 7-7 generally indicate that respondents feel that current evaluation methods are ineffective since and unreliable estimates are produced. Unreliable metrics usually leads to inaccurate productivity estimation of an academic department. The proposed solution to this problem is the development of a fuzzy-based model that can be integrated with current methods so that efficient and effective estimates are obtained. Besides improved productivity estimation of academic staff and academic departments, efficient and reliable estimates may also lead to scarce resources such as personnel, equipment, time and money to be optimally utilized.

2. Define the objectives for a solution:

The objectives are inferred from the problem definition and knowledge about circumstances regarding the problem (Peppers *et al*., 2008). It is important to be realistic about what is possible and feasible regarding the objectives. A description on how the new artifact can help solve the problem is also required. The resources required for this activity includes a thorough knowledge of the problems and possible solutions. The main objectives of this study are to:

- Investigate why current productivity estimation methods are inefficient and ineffective.

- Investigate how conventional methods (such as the numerical value, peer evaluation, expert judgment and weighting techniques) can be more effective when integrated with a model that is fuzzy-based (Mohamad *et al*., 2008).
- Create an artifact that uses a multi-criteria decision making (MCDM) model called the Analytic Hierarchy Process (AHP) and the fuzzy TOPSIS method as a basis for the development of a fuzzy-based system to estimate productivity of academic staff and academic departments.

3. Design and development:

This activity involves creating the artifact (Peffers *et al*., 2008). This activity firstly determines the functionality and architecture of the artifact and then the actual artifact is created. The requirements for this activity include knowledge of theories that can be used in the solution. In this study fuzzy logic and fuzzy set theory applied to the Analytic Hierarchy Process (AHP) will used in the development of the artifact. The fuzzy TOPSIS methods will be used for ranking and selection.

4. Demonstration:

After the artifact has been developed, it must demonstrate how it can be used to solve the IS problem. This activity usually involves simulation, case studies and experimentation. In this study, the IT department at Durban University of Technology will be used as a case study when implementing the model.

5. Evaluation:

This activity involves observing and measuring how well the solution supports the problem (Peffers *et al*., 2008). The requirement for this activity is knowledge of analysis techniques and relevant metrics. Many evaluation techniques can be used for this activity. This includes comparing the objectives to the actual observed results, quantitative performance measures, client feedback and simulation. Empirical evidence and logic proof can also be used to determine whether the solution satisfactorily solves the IS problem. Based on evaluation results, the researcher will determine whether it is necessary to iterate back to activity 3 to improve on the functionality of the artifact. Quantitative performance techniques and client feedback will be the main evaluation methods for this study. A quantitative assessment involving conventional methods and the artifact will be compared. Client feedback involves academic staff using the new system and comparing its' usefulness with conventional techniques.

6. Communication:

The research problem, the artifact indicating its utility and the artifact design should be communicated to relevant stakeholders. In this study, the productivity estimation problem and the solution to the problem will be communicated to upper management at Durban University of Technology. The intention is to make management aware that there are problems in current productivity estimation methods and a solution to the problem is available. The research problem and the solution will also be published in scholarly journals.

The six activities in Figure 3-1 depict the DSRM process for the productivity estimation problem of academic departments (Peffers *et al*., 2008).

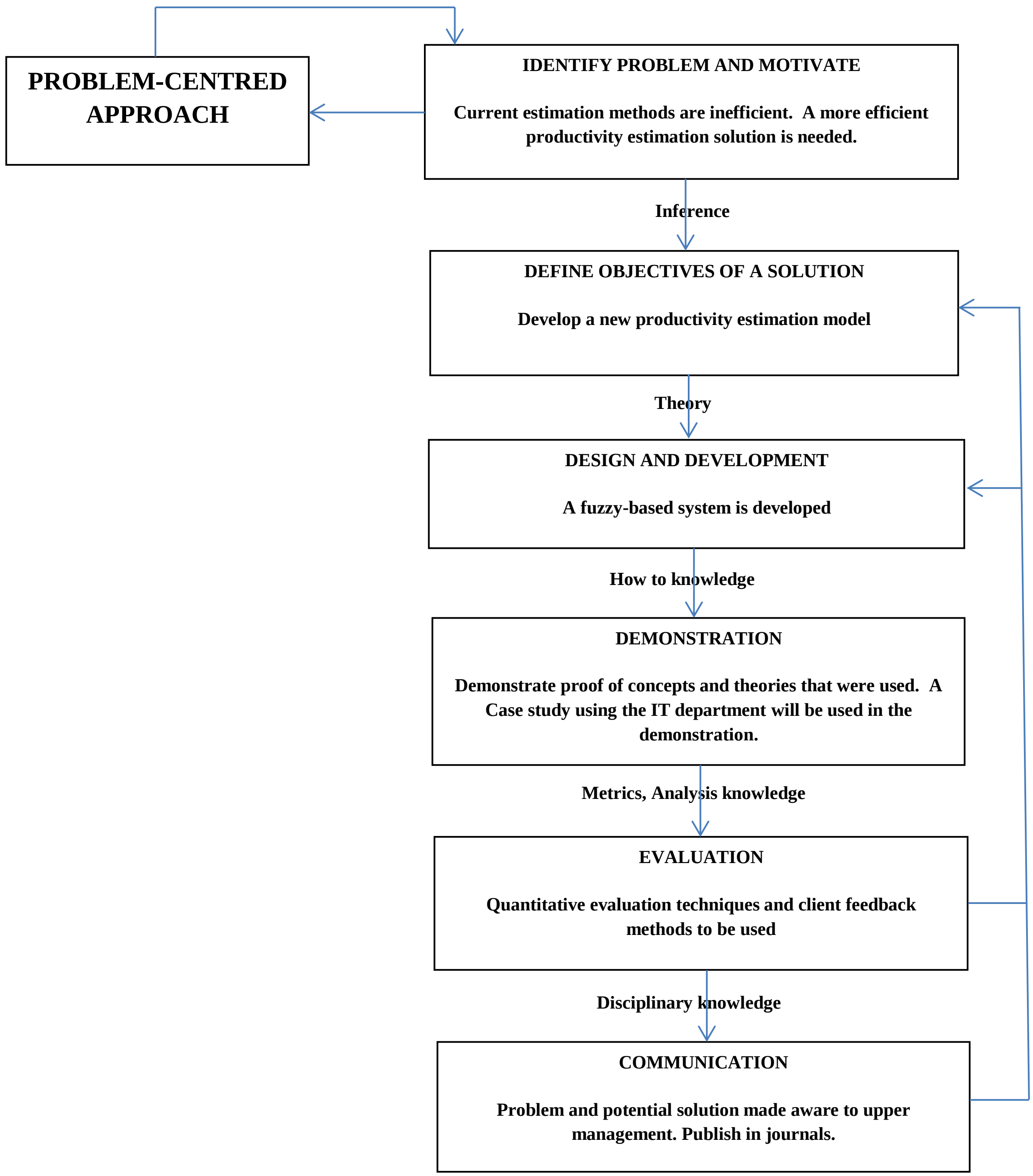


Figure 3-1: DSRM for academic department productivity estimation (Peffers *et al*., 2008)

3.3 Model Development

A multi-criteria decision making (MCDM) method called the Analytic Hierarchy Process (AHP) as well as a selection and ranking method called Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) as the basis for the development of the model is proposed. The AHP and TOPSIS techniques were designed for an industrial environment where the attribute to be measured are precise and deterministic. However, in some situations, the attributes to be measured are imprecise and uncertain. Academic staff and academic departments for example are constantly faced with imprecision and uncertainty which therefore requires a fuzzy logic approach (and not a precise-value approach) (Nikoomaran *et al*., 2009). In order to overcome this deficiency, this study will show how fuzzy logic and fuzzy set theory can be integrated with the conventional AHP and TOPSIS methods during the design and development stages. The design and development of the model (artifact) encompasses the third activity (depicted in Figure 3-1) in the Design Science Research Methodology (DSRM).

3.3.1 Methodology for productivity estimation of academic departments

Since most of the criteria to be evaluated are human intensive, the results are based on personal judgments and are therefore subjective (Shahroudi & Rouydel, 2012). One such example of subjectivity or personal judgment is: 'rate this research publication in terms of poor, good or excellent'. In this study, all subjective evaluation criteria will be referred to as intangibles. An academic department will also have objective criteria that require evaluation. One such example is: 'how many hours do you lecture per week?' In this study, the objective criteria will be referred to as tangibles.

The methodology for the productivity estimation model is diagrammatically depicted in the flowchart (Figure 3-2). The steps on the methodology are discussed below the flowchart.

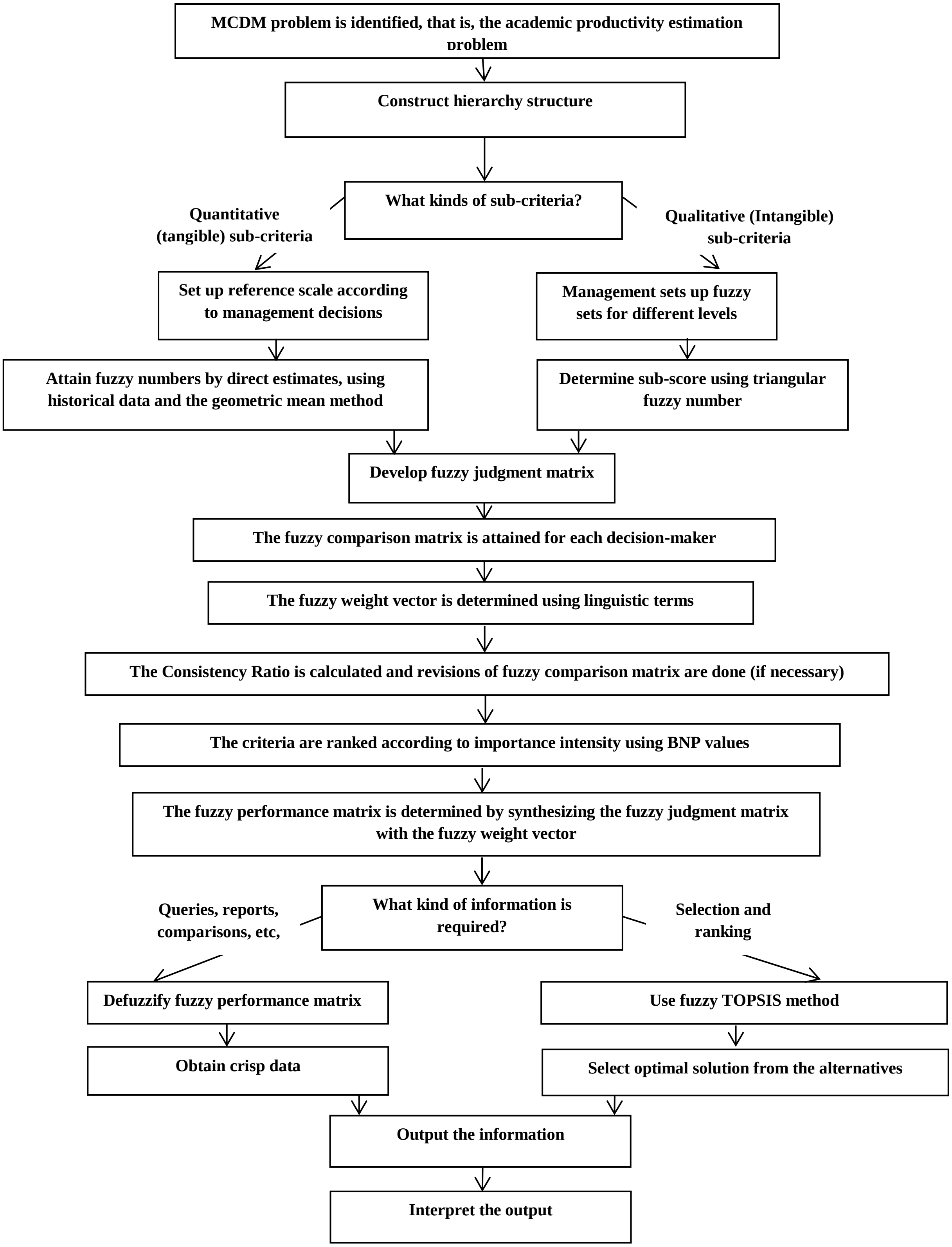


Figure 3-2: Methodology for productivity estimation for academic staff

Each step of the methodology (Figure 3-2) is discussed below:

1. Problem Identification:

This step of the development (problem identification) was completed in section 3.2 using design science research methodology.

2. The development of the hierarchical structure:

The general structure for the productivity estimation hierarchy is depicted in Figure 3-3.

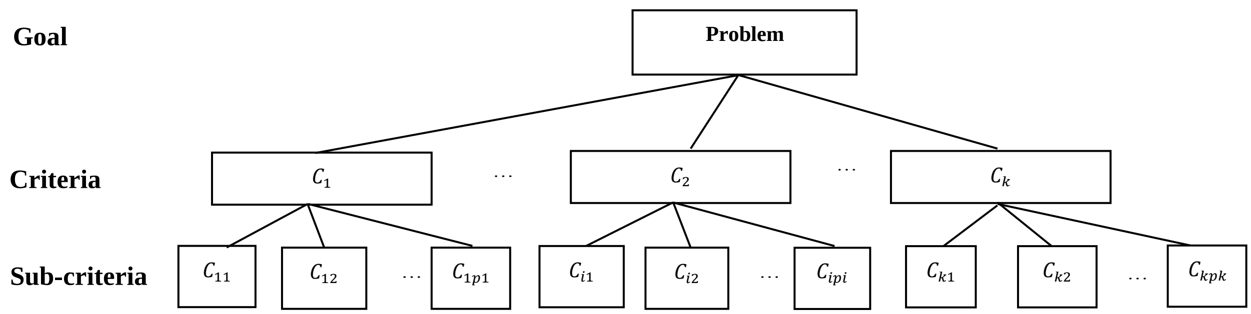


Figure 3-3: The General AHP Hierarchy Structure

The evaluation for the MCDM problem is bottom-up with the alternatives in the lowest level and the sub-criteria immediately above the alternatives. Each alternative is firstly measured using the sub-criteria. Each criterion (that is, each key performance attributes) combines with the sub-scores in order to attain the overall goal. An example of a criterion is $C_1$and an example of a sub-criterion is C_{11}as indicated in Figure 3-3.

3. Identify tangible and intangible operational indicators:

When estimating productivity of academic staff or an academic department as a whole, the attributes to be measured lend themselves more to a qualitative rather than a quantitative evaluation. As a result, most of the attributes to be measured are intangible. However, there are some tangible attributes (or quantitative attributes) that require evaluation. The artifact development will also show how tangible and intangible sub-criteria are handled in the AHP (sun, 2010).

4. Evaluate the tangible sub-criteria

The ratings of alternatives are fuzzy numbers and are measured using the sub-criteria. Sub-criteria that are tangible (that is, with precise ratings) have to therefore be normalised into fuzzy numbers. Ding (2011) therefore two methods of converting the tangible sub-criteria into fuzzy numbers. The first method involves using the triangular fuzzy numbers directly if the sub-criteria can be appropriately estimated. For example, if the average teaching load of an academic is 10 lectures per week, with a minimum of 6 lectures and a maximum of 14 lectures, then this value (10) can be subjectively represented using triangular fuzzy numbers as $(6, 10, 14)$. The second approach uses historical data. Let $x_1,\ x_1, \ldots, x_k$ represent *H* (that is, the average number of hours for community engagement) for *k* periods, then the geometric mean method can be used to express Has a fuzzy number (L, M, U), where:

(3.1) $$L = \min_i \{x_i\},\ M = \left[\prod_{i=1}^{k} x_i\right]^{1/k} \text{ and } U = \max_i \{x_i\}$$

For example if the 4 historical data available for *H* with respect to an alternative (such as A_1) are 8, 12, 13, and 10, then after evaluation, the fuzzy triangular number is $(8, \sqrt[4]{8X10X12X13}, 13)$ = $(8, 10.57, 13)$.

5. Evaluate the intangible sub-criteria

Intangible sub-criteria lend themselves more to a qualitative rather than a quantitative evaluation. These sub-criteria are difficult to evaluate because they are imprecise and vague. As a result, the evaluation is reliant on human judgment and decision-makers will have many diverse viewpoints for an alternative. A panel or a group with subjective judgments normally carries out the evaluation of an academic department. Therefore, in order to attain a more consistent outcome, a group decision method is proposed. Each decision-maker (D_p) grades each alternative (A_i) on the same sub-criteria (C_{jk}). This approach enables an alternative (A_i) to attain many grades $(\tilde{G}_{ijkp})$ from all the decision-makers (Tsaur *et al.*, 2002). The matrix below shows the group decision method using intangible sub-criteria.

$$\begin{bmatrix} & \boldsymbol{D_1} & \boldsymbol{D_2} & \cdots & \boldsymbol{D_t} \\ \boldsymbol{A_1} & \tilde{G}_{1jk1} & \tilde{G}_{1jk2} & \cdots & \tilde{G}_{1jkt} \\ \boldsymbol{A_2} & \tilde{G}_{2jk1} & \tilde{G}_{2jk2} & \cdots & \tilde{G}_{2jkt} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{A_n} & \tilde{G}_{njk1} & \tilde{G}_{njk2} & \cdots & \tilde{G}_{njkt} \end{bmatrix}$$

$$where\ i = 1,2,\dots,n;\ j = 1,2,\dots,m;\ k = 1,2,\dots,q;\ p = 1,2,\dots,t$$

A grade of alternate *i* with respect to decision-maker *p* on a sub-criterion *jk* is represented by$\left(\tilde{G}_{ijkp}\right)$. The fuzzy number $\left(\tilde{G}_{ijk}\right)$ from $\left(\tilde{G}_{ijkp}\right)$ represent the sub-score of alternative *i* with respect to the sub-criterion jk. The fuzzy number $\left(\tilde{G}_{ij}\right)$ represent a score of alternate *i* with respect to criterion j. Each element in the matrix has the subscript jk that indicates that the same sub-criterion is being evaluated by all decision-makers (D_t) for each alternative (A_n) under the criteria *j* (Tsaur *et al*., 2002). With$\left(\tilde{G}_{ijkp}\right)$, a fuzzy number for an intangible sub-criterion can be composed as follows: Let *L*, *M*, and *U* represent the lower middle and upper limits of a triangular fuzzy number. The lowest (*L*) and highest (*U*) score of all p decision-makers are taken as the lower and upper limits respectively. The middle value (*M*) between the lowest and highest is calculated. The fuzzy number for an intangible sub-criterion can therefore be derived as follows (Tsaur *et al*., 2002):

(3.2) $$\left(\tilde{G}_{ijkp}\right) = \left(L_{ijkp}, M_{ijkp}, U_{ijkp}\right)$$

(3.3) $$L_{ijk} = \min\left(L_{ijkp}\right) \text{ with } p = 1,2,\dots,t$$

(3.4) $$M_{ijk} = \frac{\left(\sum_{p=1}^{t} M_{ijkp}\right)}{p} \text{ with } p = 1,2,\dots,t$$

(3.5) $$U_{ijk} = \max\left(U_{ijkp}\right) \text{ with } i = 1,2,\dots,t$$

Therefore the fuzzy number for an intangible sub-criterion is represented as:

(3.6) $$\left(\tilde{G}_{ijk}\right) = \left(L_{ijk}, M_{ijk}, U_{ijk}\right).$$

6. The fuzzy judgment matrix is obtained:

This step will judge the alternatives by examining the scores of the criteria. The sub-scores for all sub-criteria (C_{jk}) belonging to the same criterion (C_j) of each alternative (A_j) are added and are represented as$(\tilde{G}_{ij})$ (Tsaur *et al.*, 2002). This process is carried out for every criterion that has sub-criteria. This calculation is derived as follows:

(3.7) $$\tilde{G}_{ij} = \sum_{k=1}^{q} \tilde{G}_{ijk}, \ k = 1, 2, \ldots, q$$

where q is the number of sub criteria for each criteria (C_j). After applying this equation, the following decision matrix is derived (Sun, 2010):

$$\begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \cdots & \boldsymbol{C_m} \\ \boldsymbol{A_1} & \tilde{G}_{11} & \tilde{G}_{12} & \cdots & \tilde{G}_{1m} \\ \boldsymbol{A_2} & \tilde{G}_{21} & \tilde{G}_{22} & \cdots & \tilde{G}_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{A_n} & \tilde{G}_{n1} & \tilde{G}_{n2} & \cdots & \tilde{G}_{nm} \end{bmatrix}$$

This matrix is then normalised so that the values can be matched with the weight vectors (the calculation of weights is discussed in step 7). The normalisation of each criterion (C_j) is done using the following equation (Chen & Hwang, 1992; Tsaur et al., 2002):

(3.8) $$\tilde{a}_{ij} = \frac{\tilde{G}_{ij}}{\sqrt[2]{\sum_{i=1}^{n} (\tilde{G}_{ij})^2}}$$ and the normalised matrix is now:

$$\boldsymbol{A} = \begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \cdots & \boldsymbol{C_m} \\ \boldsymbol{A_1} & \tilde{a}_{11} & \tilde{a}_{12} & \cdots & \tilde{a}_{1m} \\ \boldsymbol{A_2} & \tilde{a}_{21} & \tilde{a}_{22} & \cdots & \tilde{a}_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{A_n} & \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & \tilde{a}_{nm} \end{bmatrix}$$

The judgment score of alternate (A_i) with respect to (C_j) is denoted by $\tilde{a}_{ij}$.

7. The fuzzy performance vector is determined:

The overall fuzzy performance vector is attained when each alternative takes all the criteria into consideration. This is achieved when the fuzzy judgment matrix is multiplied by the fuzzy weight vector. The fuzzy judgment matrix was derived in step 6 above. The fuzzy weight vector has to be determined. There are many methods that can be used to attain the fuzzy weight vector. The two most popular ones are the use of absolute values from a Saaty scale that can be converted into fuzzy numbers. The second technique is the geometric mean method (Osman *et al.*, 2013). The first method is discussed in sections 7.1 and 7.2 below. The geometric mean method uses linguistics values of the decision-makers to evaluate the criteria. This method is discussed in section 7.3. Although both methods have been successfully implemented, the nature of the problem should be taken into consideration before deciding on which technique to adopt (Osman *et al.*, 2013). If it can be determined that decision-makers can get a more objective trade-off among all the criteria, then the first method should be used, otherwise the second method should be used (Tseun-Ho *et al.*, 2012).

7.1 The fuzzy weight vector is determined using a Saaty scale with absolute values

The relative importance among the criteria is determined using a weight vector. This is achieved in the AHP with pair-wise comparisons of elements (based on human judgment) and is represented using precise values attained from a nominal scale such as the one indicated in Table 2-1 (Saaty, 2008). These precise values will be used to determine priorities or weights that will be used to select the best alternative. However, using precise values of individual decision-makers does not provide a credible evaluation of an intangible attribute. In order to address this deficiency, the scores of all decision-makers (a group decision method) based on triangular fuzzy numbers is proposed (Sun, 2010).

In order to achieve such triangular fuzzy numbers, a scale (see Table 2-1) with precise ratings to carry out pair-wise comparisons of the criteria is used. This is indicated as follows (Saaty, 2008):

$$\boldsymbol{D_p} = \begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \cdots & \boldsymbol{C_m} \\ \boldsymbol{C_1} & b_{11p} & b_{12p} & \cdots & b_{1mp} \\ \boldsymbol{C_2} & b_{21p} & b_{22p} & \cdots & b_{2mp} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{C_m} & b_{m1p} & b_{m2p} & \cdots & b_{mmp} \end{bmatrix}$$

If C_1 represents "teaching" and C_2 represents "administration" and using a value of 9 in a Saaty scale means that teaching is 9 times more important than administration. The converse means that administration is 9 times less important than teaching, that is, the value for (administration, teaching) is $\frac{1}{9}$ (the reciprocal value). The "equally preferred" values are $b_{11p,}$ b_{22p},..., b_{mmp} and will yield a value of 1. The above situation can be represented as follows (Sun, 2010): $b_{jep} = {b_{ejp}}^{-1}$ if $j \neq e$ and b_{jep} = 1 if j = e (j = 1, 2...m and e = 1, 2….m) where a decision-maker D_p measures the relative importance between criteria e and j. In order to attain triangular fuzzy numbers from all the decision makers, the following equations are used:

$$(3.9) \quad L_{je} = \min\left(b_{jep}\right) \text{ with } p = 1, 2, \dots, t;\ j = 1, 2, \dots, m \text{ and } e = 1, 2, \dots, m$$

$$(3.10) \quad M_{je} = \frac{\left(\sum_{p=1}^{t} b_{jep}\right)}{p} \text{ with } p = 1, 2, \dots, t;\ j = 1, 2, \dots, m \text{ and } e = 1, 2, \dots, m$$

$$(3.11) \quad U_{je} = \max\left(b_{jep}\right) \text{ with } p = 1, 2, \dots, t;\ j = 1, 2, \dots, m \text{ and } e = 1, 2, \dots, m$$

The fuzzy numbers are now represented as:

$$(3.12)\ \left(\tilde{b}_{je}\right) = \left(L_{je}, M_{je}, U_{je}\right),\ j = 1, 2, \dots, m;\ e = 1, 2, \dots, m.$$

The score $\left(\tilde{b}_{je}\right)$ indicates the comprehensive judgment scores of all decision-makers regarding all the criteria and is represented in the matrix as:

$$\boldsymbol{D} = \begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \dots & \boldsymbol{C_m} \\ \boldsymbol{C_1} & \tilde{b}_{11} & \tilde{b}_{12} & \dots & \tilde{b}_{1m} \\ \boldsymbol{C_2} & \tilde{b}_{21} & \tilde{b}_{22} & \dots & \tilde{b}_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{C_m} & \tilde{b}_{m1} & \tilde{b}_{m2} & \dots & \tilde{b}_{mm} \end{bmatrix}$$

The purpose of using a Saaty scale (Table 2-1) is to show that the criteria have varying degrees of importance. It is therefore important to acquire weights or priorities ($\widetilde{w}_j$) that correspond to a criterion (C_j). The following equation is used to calculate these weights (Rana *et al*., 2012):

$$(3.13) \qquad \widetilde{w}_j = \frac{\sum_{e=1}^{m} \tilde{b}_{je}}{\sum_{j=1}^{m} \sum_{e=1}^{m} \tilde{b}_{je}},\ j = 1, 2, \dots, m \text{ and } e = 1, 2, \dots, m$$

The criteria weights ($\widetilde{w}_j$) collectively will make up the fuzzy weight vector $W = (\widetilde{w}_1, \widetilde{w}_2, \dots, \widetilde{w}_m)$.

7.2 Synthesize the fuzzy judgment matrix with the fuzzy weight vector:

The next step involves calculating the fuzzy performance matrix. However, before the fuzzy performance matrix is calculated, the pair-wise comparison matrix will have to be checked for inconsistencies in the decision-makers choices (Lee, 2010). Consistency checking is discussed in number 8 below. After the pair-wise comparison matrix has been checked for any consistencies (and revisions implemented), the fuzzy performance matrix is calculated by multiplying the fuzzy judgment matrix by the fuzzy weight vector. The fuzzy-judgment matrix provides an overall score of alternate A_i with respect to criteria C_j. However, the relative weights between each criterion are not taken into consideration. The fuzzy judgment matrix and the fuzzy weight vector have to therefore be synthesized and this is done by multiplying each criterion weight $\widetilde{w}_j$ to its corresponding criterion of the fuzzy judgment matrix as indicated below (Lee, 2010).

$$\boldsymbol{H} = \begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \cdots & \boldsymbol{C_m} \\ \boldsymbol{A_1} & \widetilde{w}_1\tilde{a}_{11} & \widetilde{w}_2\tilde{a}_{12} & \cdots & \widetilde{w}_m\tilde{a}_{1m} \\ \boldsymbol{A_2} & \widetilde{w}_1\tilde{a}_{21} & \widetilde{w}_2\tilde{a}_{22} & \cdots & \widetilde{w}_m\tilde{a}_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{A_n} & \widetilde{w}_1\tilde{a}_{n1} & \widetilde{w}_2\tilde{a}_{n2} & \cdots & \widetilde{w}_m\tilde{a}_{nm} \end{bmatrix} = \begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \cdots & \boldsymbol{C_m} \\ \boldsymbol{A_1} & \tilde{h}_{11} & \tilde{h}_{12} & \cdots & \tilde{h}_{1m} \\ \boldsymbol{A_2} & \tilde{h}_{21} & \tilde{h}_{22} & \cdots & \tilde{h}_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{A_n} & \tilde{h}_{n1} & \tilde{h}_{n2} & \cdots & \tilde{h}_{nm} \end{bmatrix}$$

The fuzzy performance score with alternate (A_i) corresponding to (C_j) with fuzzy numbers (L_{ij}, M_{ij}, U_{ij}) is denoted by $\tilde{h}_{ij}$. The overall fuzzy performance scores of each alternative with all criteria are represented by H.

7.3 The fuzzy weight vector is determined using linguistic values:

The first step involves constructing pair-wise comparison matrices among all the criteria as indicated below. These matrices indicate the judgment scores of all decision-makers regarding all the criteria. The decision-makers will use a linguistic scale (like the one depicted in Table 3-1) to rate all the criteria.

$$
\boldsymbol{D} = \begin{array}{c} \\ \boldsymbol{C_1} \\ \boldsymbol{C_2} \\ \vdots \\ \boldsymbol{C_m} \end{array}
\begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \cdots & \boldsymbol{C_m} \\ \boldsymbol{C_1} & 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1m} \\ \boldsymbol{C_2} & \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{C_m} & \tilde{a}_{m1} & \tilde{a}_{m2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \cdots & \boldsymbol{C_m} \\ \boldsymbol{C_1} & 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1m} \\ \boldsymbol{C_2} & \frac{1}{\tilde{a}_{12}} & 1 & \cdots & \tilde{a}_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{C_m} & \frac{1}{\tilde{a}_{1m}} & \frac{1}{\tilde{a}_{2m}} & \cdots & 1 \end{bmatrix}
$$

where

$$
\tilde{a}_{ij} = \begin{cases} \tilde{9}^{-1}, \tilde{8}^{-1}, \tilde{7}^{-1}, \tilde{6}^{-1}, \tilde{5}^{-1}, \tilde{4}^{-1}, \tilde{3}^{-1}, \tilde{2}^{-1}, \tilde{1}^{-1}, \tilde{1}, \tilde{2}, \tilde{3}, \tilde{4}, \tilde{5}, \tilde{6}, \tilde{7}, \tilde{8}, \tilde{9} & i \neq j \\ 1 & i = j \end{cases}
$$

The next step involves using the geometric mean technique to define the fuzzy geometric mean and fuzzy weights of each criterion as follows (Sun, 2010):

$$
\tilde{r}_i = (\tilde{a}_{i1} \otimes \ldots \otimes \tilde{a}_{ij} \otimes \ldots \otimes \tilde{a}_{in})^{1/n} \tag{3.14}
$$

$$
\tilde{w}_i = \tilde{r}_i \otimes [\tilde{r}_1 \oplus \ldots \oplus \tilde{r}_i \oplus \ldots \oplus \tilde{r}_n]^{-1} \tag{3.15}
$$

where $\tilde{a}_{ij}$ is a fuzzy comparison value of dimension *i* to criterion *j*. Thus $\tilde{r}_i$ is a geometric mean of fuzzy comparison value of the criterion *i* to each criterion. The fuzzy weight of the i^{th} criterion is $\tilde{w}_i$ and can be indicated as a triangular fuzzy number as $\tilde{w}_i = (lw_i, mw_i, uw_i)$ where lw_i, mw_i and uw_i stands for the lower, middle and upper values of the fuzzy number.

Linguistic scale for importance	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Just equal	(1, 1, 1)	(1, 1, 1)
Equally important (EI)	(1/2, 1, 3/2)	(2/3, 1, 2)
Weakly more important (WMI)	(1, 3/2, 2)	(1/2, 2/3, 1)
Strongly more important (SMI)	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)
Very strongly more important (VSMI)	(2, 5/2, 3)	(1/3, 2/5, 1/2)
Absolutely more important (AMI)	(5/2, 3, 7/2)	(2/7, 1/3, 2/5)

Table 3-1: Linguistic terms for criteria ratings

The next step involves calculating the fuzzy performance matrix. However, before the fuzzy performance matrix is calculated, the pair-wise comparison matrix will have to be checked for inconsistencies in the decision-makers choices (Rostamy *et al.*, 2012). Consistency checking is discussed in section 8 below. After the pair-wise comparison matrix has been checked for any inconsistencies (and revisions implemented), the fuzzy performance matrix is calculated by multiplying the fuzzy judgment matrix with the fuzzy weight vector (Ramik & Korviny, 2013). The fuzzy judgment matrix has to be synthesized with the fuzzy weight vector during the multiplication process. Synthesizing is done by multiplying each criterion weight $\widetilde{w}_i$ to its corresponding criterion of the fuzzy judgment matrix. This process is discussed in section 7.2.

8. Consistency test of the fuzzy pair-wise comparison matrix

Since the criteria to be measured are vague and imprecise, the evaluations are reliant on human judgment. As a result of the varying viewpoints from different decision-makers, the AHP does not demand perfect consistency but allows for a small measure of inconsistency (Ramik & Korviny, 2013). A Consistency Ratio (CR) ≤ 10% (or CR ≤ 0.1) is considered acceptable (Osman *et al*., 2013). If the CR is > 10% (or CR > 0.1) then the pair-wise judgments will have to be revised by the decision-makers. The consistency of the pair-wise comparison matrix has to therefore be measured, checked and revised (if necessary) before the fuzzy performance matrix is calculated (Rostamy *et al.*, 2012).

In order to measure consistency, a triangular fuzzy positive reciprocal (TFPR) matrix is used. The elements of a TFPR matrix are positive triangular positive numbers $\tilde{a}_{ij}$= (a_{ij}^L, a_{ij}^M, a_{ij}^U) where

$a_{ij}^L > 0$ and by using the formula for the reciprocal of fuzzy numbers, that is, $\left(\frac{\tilde{1}}{\tilde{a}} = (\frac{1}{a^U}, \frac{1}{a^M}, \frac{1}{a^L})\right)$, the following matrix is constructed:

$$\tilde{A} = \begin{bmatrix} (1,1,1) & (a_{12}^L, a_{12}^M, a_{12}^U) & \cdots & (a_{1n}^L, a_{1n}^M, a_{1n}^U) \\ (\frac{1}{a_{12}^U}, \frac{1}{a_{12}^M}, \frac{1}{a_{12}^L}) & (1,1,1) & \cdots & (a_{2n}^L, a_{2n}^M, a_{2n}^U) \\ \vdots & \vdots & \ddots & \vdots \\ (\frac{1}{a_{1n}^U}, \frac{1}{a_{1n}^M}, \frac{1}{a_{1n}^L}) & (\frac{1}{a_{2n}^U}, \frac{1}{a_{2n}^M}, \frac{1}{a_{2n}^L}) & \cdots & (1,1,1) \end{bmatrix}$$

Using triangular fuzzy numbers are considered to be the most appropriate technique in group decision making. This is so because a^L is interpreted as the minimum possible values, a^U is interpreted as the maximum possible value and a^M is the geometric mean, that is, the mean value or the most possible value of all decision makers. Hence triangular fuzzy numbers can therefore be effectively used to measure the consistency of the pair-wise comparison matrix.

When calculating the Consistency Ratio (CR), Saaty's absolute value method is adapted in order to take fuzzy requirements into consideration. Saaty's method is chosen as a reference because it can handle multiple criteria with ease as well as calculate the weights and Consistency Index (CI) without cumbersome mathematics. His method uses the eigenvector method to determine the weights of the various criteria by implementing a pair-wise reciprocal comparison matrix (Odeyale *et al*., 2014). The largest eigenvector is defined as λ_{max} of matrix A and the weight w_i as a component of the normalised vector corresponding to λ_{max} where $w_i = \frac{r_i}{(r_1 + r_2 + \cdots + r_n)}$ and r_i is the geometric mean of each row with $r_i = \left[\prod_{j=1}^{n} a_{ij}\right]^{1/n}$ (Aly & Vrana, 2008). The consistency of the pair-wise comparisons can be assessed through calculating the consistency ratio (CR) from the consistency index and the random (RI) as follows:

(3.16) $$\mathrm{CI} = \frac{\lambda_{\max - n}}{n-1}$$

(3.17) $$\mathrm{CR} = \frac{CI}{RI}$$

The random index values provide different values for *n* (that is, *n* = the number of factors or criteria) as indicated in Table 3-2.

N	1	2	3	4	5	6	7	8	9	10	11	12
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.58

Table 3-2: The random index RI for number of factors/criteria *n*

The value in this table is simply a look-up table for the values of *n* from 1 to 12 (Rostamy *et al.*, 2012). These values have been determined experimentally and have been universally accepted. The demonstration in Chapter 5 will therefore make use of this table.

The λ_{max} value for absolute values is a single precise value. The λ_{max} value for fuzzy inputs is computed as the modal value of the resulting fuzzy number and fuzzy operations are used in all the calculations. Annexure C shows detailed calculations involving Saaty's method to calculate the weights and the CR for precise values. The purpose of Annexure C is to demonstrate the steps involved when precise values are involved so that this technique can be adapted to take fuzzy data into consideration.

9. Apply fuzzy TOPSIS method for ranking and selection:

The fuzzy performance matrix H in step 7 above was derived after applying fuzzy logic and fuzzy set theory to the AHP. Since each element of the matrix is a triangular fuzzy number, it will be used as the input for the fuzzy TOPSIS method (for selection and ranking). The fuzzy TOPSIS method was discussed in detail in section 2.7.2.

10. Selecting the optimal solution:

This step in the model development selects the optimal solution from all the alternatives with respect to all the criteria. The ranking and selection process is incorporated in the discussion on fuzzy TOPSIS in section 2.7.2.

11. Defuzzify the fuzzy performance matrix:

Defuzzification is a technique that converts fuzzy numbers into crisp real values in order to determine the best non-fuzzy performance (BNP) value (Tsaur *et al.*, 2002). Although there are many methods of accomplishing this, the most popular method is the Centre-of-Area method (also called the centroid method). This method is popular because it is simple to implement.

Also, the analyst's personal judgment is not required when this equation is used (Zhao & Govind, 1991). The equation for defuzzification is:

$$BNP_{ij} = \frac{[(U_{ij} - L_{ij}) + (M_{ij} - L_{ij})]}{3} + L_{ij} \quad \text{(3.18)}$$
(Tsaur *et al.*, 2002)

In this study, the centroid method will be used for defuzzification to:

- Rank each performance criteria according to its importance intensity. This is done in section 5.5.5 (e)
- Evaluate the performance of an academic based on each criterion. A BNP value will indicate how an academic has performed when a certain criteria is considered. This is discussed in section 5.6. For example: "Show the evaluation of alternative A_1 on "Administration". This evaluation can be attained from the fuzzy performance matrix if alternative A_1 represents an academic and criteria C_1 represent "Administration". The fuzzy performance score for the academic with respect to Administration is therefore $h_{ij.}$ Defuzzification of the fuzzy data $\tilde{h}_{ij}$ will be done using the BNP equation.

3.4 Conclusion

In Chapter 2, a detailed discussion was provided as to why a fuzzy-based multi-criteria decision making method is most suitable for estimating productivity of academic staff. This chapter (chapter 3) discussed in detail the methodology for developing a productivity estimation model of academic staff and academic departments using a fuzzy-based approach. A design science research methodology (DSRM) with six activities was proposed. The design was accomplished using a Multi-Criteria Decision Making (MCDM) method called Fuzzy Analytic Hierarchy Process (FAHP) and a ranking and selection method called Fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). The first three activities of the design science research (DSR) approach were adopted in the model development phase. The demonstration activity (4th activity) will show how the model can be used to solve the productivity estimation problem of academic staff and an academic department. This activity is discussed in Chapter 5. However, before the demonstration activity, it is imperative to show how imprecise and fuzzy data can be modeled using fuzzy objects in an object-oriented programming environment. A fuzzy object-oriented approach to programming is therefore discussed in chapter 4.

Chapter 4

MODELING IMPRECISE DATA USING A FUZZY OBJECT-ORIENTED APPROACH

4.1 Introduction

An object-oriented approach can be described as a software engineering principle that aims to create a representation of real-world objects and maps it into a software solution. These real-world objects are viewed as separate entities having their own state and can only be modified by procedures (or methods) within the object.

The aim of object-oriented methods is to create artifacts by applying a large number of rules. The classical object-oriented approach takes into consideration precise and deterministic data. However, not all data that require processing are precise and deterministic (Lee *et al*., 1999). An academic department for example lends itself more to a qualitative rather than a quantitative evaluation. In this case, most of the evaluation criteria are imprecise and fuzzy. The classical object-oriented approach to software development has to therefore be extended to accommodate these imprecise and fuzzy requirements (Tsaur *et al*., 2002). This approach is referred to as fuzzy object-oriented approach to software development.

The purpose of this chapter is to determine how imprecise data for productivity estimation of academic departments can be modeled using a fuzzy object-oriented approach. This chapter therefore examines the important features of the classical object-oriented approach and then discusses how these features can be extended to accommodate fuzzy requirements.

4.2 Using fuzzy logic to extend the classical object-oriented paradigm

This section describes how the classical object-oriented approach to programming can be extended to incorporate requirements that are imprecise or fuzzy. The classical UML (Unified Modeling Language) used in this section is also extended to accommodate fuzzy requirements. The discussion will focus on the following important dimensions:

- The extended class formed by grouping objects that have similar properties into a fuzzy class;

- The encapsulated fuzzy rules in the fuzzy class that describes the relationship between attributes;
- The range that an attribute (with linguistic value) can take;
- An evaluation of the membership function contained in a fuzzy class by taking both static and dynamic properties into consideration; and
- A modeling of the uncertain fuzzy associations between classes.

These dimensions will be discussed using the problem domain relating to productivity estimation of academic departments. In order to address these dimensions, a good knowledge of fuzzy objects and fuzzy classes is essential.

4.2.1 Fuzzy objects and classes

An object is described as fuzzy if its behaviour is non-deterministic (Dwibedy *et al*., 2013). Fuzziness can be described using a linguistic term such low, high and very high or some value such as 0.8 degree. Generally, an object is fuzzy if at least one of its attributes is a fuzzy set or a fuzzy value.

A fuzzy class can be described as an encapsulation of a fuzzy set of objects. In a fuzzy class, objects may have similar attributes, similar relationships and similar operations. For example, in the academic productivity estimation domain, a class *Important Project* will be modeled as a fuzzy class to indicate the degree to which a project is important. A fuzzy class in fuzzy object-oriented modeling has properties that can be classified as static or dynamic (Lee *et al*., 1999). Attributes, identifiers and operations are classified as static because they exist for its lifetime. On the other hand, dynamic properties such fuzzy rules and fuzzy relationships are short-lived (Chaudhari *et al*., 2010). The degree of membership of an instance of a fuzzy class will therefore depend on these properties, especially the values of the attributes and the values of the link attributes (link attributes and associations are discussed in section 4.3.3) (Dwibedy *et al*., 2013). Static and dynamic properties of a fuzzy class are depicted in Table 4-1.

Fuzzy Class	
Static	**Dynamic**
identifiers fuzzy attribute operation	fuzzy relationship fuzzy rules

Table 4-1: Static and Dynamic properties of a fuzzy class (Dwibedy *et al*., 2013).

The domain of an attribute describes the set of all values an attribute may take, irrespective of which class it falls into. A fuzzy class can therefore be formed when it is intentionally defined using a fuzzy domain and a fuzzy range (Dwibedy *et al*., 2013). The range of an attribute is defined as the set of allowed values that a member of a class may take for the attribute. In fuzzy object-oriented modeling, the fuzziness in the range is described using some linguistic term (that is, fuzzy sets) or some value to indicate fuzzy degrees (Dwibedy *et al*., 2013). An example that can use fuzzy sets to describe fuzziness in a range is the following: The class *Research Ratings* may have an attribute called *conference presentation* that will use linguistic terms such as *excellent*, *good* or *average* to rate a presentation. An example that will use a fuzzy value to describe the degree of fuzziness of an attribute is the following: The degree to which an academic may publish the required minimum number of papers in a semester is 0.7. Fuzzy rules (also called if-then rules) can also be applied to deal with imprecision and fuzziness where a rules conditional and/or conclusion part contains linguistic variables (Chaudhari *et al*., 2012). For example, the class *Research Ratings* may have the following fuzzy rule: If presentation is *excellent* then rating is *high*. In this example, fuzzy rules will be used to describe the internal relationships between attributes in a class. Fuzzy rules can also be used to describe the external relationship between two classes. From a programming perspective, it is important to understand to what level fuzzy values, fuzzy sets and fuzzy rules can be applied in an object-oriented paradigm in order to solve a problem. These levels of fuzziness are discussed in the next section.

4.2.2 The three levels of fuzziness

In this section the three levels of fuzziness relating to fuzzy classes and fuzzy objects on fuzzy data is discussed. These levels of fuzziness provide details on the structure of fuzzy objects and fuzzy classes when compared to classical objects and classes. The three levels of fuzziness are as follows (Dwibedy *et al*., 2013):

- Fuzziness in terms of the extent to which a class belongs in the data model and fuzziness on the content (in terms of attributes) of the class. This is modeled by firstly indicating the attribute or class name followed by the words WITH *mem* DEGREE, where $0 \leq mem \leq 1$. An example would be PUBLICATION TARGET *WITH 0.7 DEGREE*;
- Fuzziness relating to instances of a class. This is modeled by including an additional attribute μ in the class to indicate the instance membership degree to the class. Using Unified Modeling Language (UML), a fuzzy class is differentiated from the second level of fuzziness by using a dashed-outline rectangle; and
- Fuzziness relating to attribute values of an instance of a class. In order to indicate this type of fuzziness, the keyword *FUZZY* is placed in front of the attribute.

The following example in Figure 4-1 depicts the three levels of fuzziness.

Details of Academic
ID
Name
FUZZY Age
Community Engagement *WITH 0.7 DEGREE*
μ

Figure 4-1: The three levels of fuzziness on the class Details of Academic

The three levels of fuzziness depicted in Figure 4-1 can be represented in the classes below.

```
public class Academic {

    private int id;
    private String name;
    private FuzzyAge age;
    private final Double communityEngagement = 0.7;

    public Academic(int id, String name, FuzzyAge age) {
```

```java
        this.id = id;
        this.name = name;
        this.age = age;
    }
}

/*
Represents a Fuzzy component
 */
public class FuzzyAge{

    private boolean isYoung ;
    private boolean isMiddleAge ;
    private boolean isOld ;

    public FuzzyAge(boolean isYoung, boolean isMiddleAge, boolean isOld) {
        this.isYoung = isYoung;
        this.isMiddleAge = isMiddleAge;
        this.isOld = isOld;
    }
}
```

The following section describes the various kinds of relationships that can be formed during software development. The relationships used in the classical object-oriented approach are discussed first followed by a discussion on the fuzzy object-oriented approach. These relationships are then depicted using a Unified Modeling Language (UML). A segment code in Java is suggested for each relationship using both the classical and fuzzy object-oriented approaches.

4.2.3 Different types of relationships between classes in fuzzy object-oriented programming

This section describes how the relationships between classes and objects can be extended to accommodate fuzzy requirements (Lee, 2010). Implementation of the model with fuzzy requirements will be done in Java. Java was chosen since it has a built-in garbage collection system that handles memory management intrinsically, whereas an object-oriented programming languages like C++ requires the programmer to allocate and de-allocate memory manually. The built-in garbage collection system in Java therefore makes programming easier and more efficient. Unlike C++, applications developed in Java are platform independent. This means that large Java projects may be built on multiple OS platforms over their entire project lifecycle. As a result, it avoids any unnecessary association with the platform on which the program was originally built.

For each relationship, the following approach is used in the discussion:

1) The relationship is described using the classical object-oriented approach.
2) The UML (Unified Modeling Language) for this relationship (classical approach) is then depicted.
3) A program segment in Java for the relationship (classical approach) is suggested.
4) The relationship using the extended object-oriented (fuzzy) approach is described.
5) The UML for this fuzzy object-oriented relationship is depicted.
6) A program segment in Java (by extending the classical program segment in 3 above) of the fuzzy relationship is suggested.

a) Association

Associations describe the connections that exist among class instances (Schildt, 2010). A role is generally assigned to each class taking part in the association. The association is therefore a direct link where one class will use another. The UML notation for the classical object-oriented association relationship is the following: ⟶ An example of such an association is an Academic being associated with a Faculty.

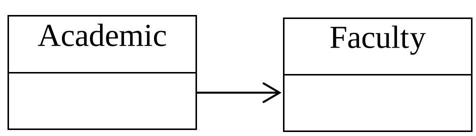


Figure 4-2: An example of a classical object-oriented association

The classical object-oriented association for the example in Figure 4-2 can be coded in Java as follows:

```
/*
  Displaying an association between Faculty and Academic
 */
public class Faculty {

    private Academic academic;
}
```

```java
public class Academic {

    private int id;
    private String name;
    private FuzzyAge age;
    private final Double communityEngagement = 0.7;

    public Academic(int id, String name, FuzzyAge age) {
        this.id = id;
        this.name = name;
        this.age = age;
    }
}
```

Associations and links establish relationships between objects and classes (Lee *et al*., 1999). A link can be described as a physical or conceptual connection between instances. Certain and precise knowledge about an association is not always available as most knowledge are generally imprecise and uncertain. Imprecision implies that an object participates in an association to some extent whereas uncertainty refers to the confidence degree of an association (Lee *et al*., 1999). In order to represent imprecision of an association, fuzzy object-oriented modeling introduces a special link attribute that indicates how intensely an object participates in an association. This usually takes the form of a fuzzy truth table such as *true*, *fairly true* and *very true*. A link between *x* and *y* for an instance of *R* (the association) can be represented as follows:

$$(link\ attribute, \langle x,y \rangle, degree\ of\ participation, \tau)$$

The $\langle x,y \rangle$ link value is described in the *degree of participation*. This value is a linguistic term such as *very high, high or low*. The value τ indicates the confidence level of the fuzzy association whose value is a fuzzy truth-value. This representation can be further explained using the following example depicted in UML.

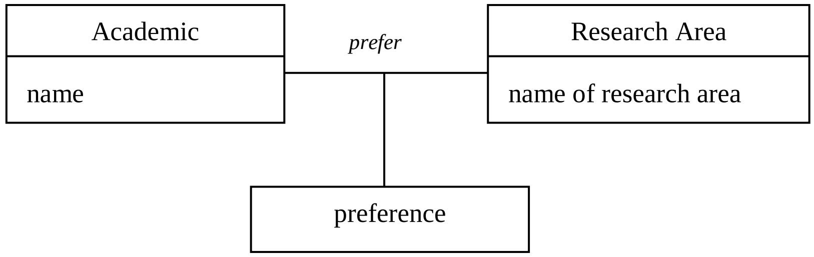


Figure 4-3: An example of a fuzzy association

The following example is represented using the canonical form $(link\ attribute, \langle x,y \rangle, degree\ of\ participation, \tau)$ and Figure 4-3. Suppose an academic identifies his preference for a research area and the intensity of his preference. Since there is no certainty about the academics choice, there is no certainty about the academics choice, a link attribute called *preference* is introduced. The link attribute *preference* is associated with *prefer* which indicates the degree of preference. Suppose a link between X (Academic) and object-oriented programming (Research Area) is depicted as follows: $(preference, \langle X, object-oriented\ programming \rangle, strong, true)$. This means that it is true that X strongly prefers *object-oriented programming*.

A fuzzy association using the above example can be coded in Java as follows:

```
public class FuzzyAcademic {

    private String name;

    // a FuzzyAge is also used to illustrate the dependency of FuzzyAge on
       FuzzyAcademic
    private FuzzyAge age;
    private PreferenceOfRA pref;

    // this is used to for illustrating composition
    private Faculties faculties;


    public FuzzyAcademic(String name, FuzzyAge age, String pref, String
      researchArea, String facultyName) {
        this.name = name;
        this.age = age;
        this.pref = new PreferenceOfRA(pref,researchArea);
        this.faculties = new Faculties(facultyName);
    }

    /*
        E.g FuzzyAcademic fa = new FuzzyAcademic(John, new
        FuzzyAge(false,true,false), "very high", "fuzzy decision making",
        "Computer Science");

     */
}

public class PreferenceOfRA {

    private String pref;
    private String researchArea;

    public PreferenceOfRA(String pref, String researchArea) {
        this.pref = pref;
```

```
        this.researchArea = researchArea;
    }
}
public class ResearchArea {

    private String name;

    public ResearchArea(String name) {
        this.name = name;
    }
}
```

b) Aggregation

Aggregation is a special case of association (Schildt, 2010). Aggregation exhibits a 'has-a' association since an object from one class will have objects of another class. It captures the whole-part relationship. Unlike association, aggregation always insists on direction. The UML notation for aggregation using the classical object-oriented approach is the following: The following is an example of the aggregation relationship: University aggregate Chancellor. This means that a university 'has-a' Chancellor. Even without a Chancellor, a university can exist. However, the Faculties cannot exist without a University. This is a special case of aggregation (called composition) that is discussed below. Using the example above, the class diagram for aggregation using classical object-oriented programming is as follows:

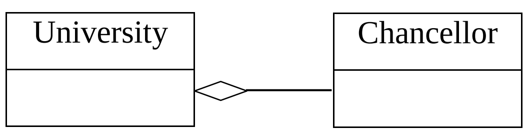


Figure 4-4: An example of a classical aggregation relationship

A Java class for aggregation for the example in Figure 4-4 using the classical object-oriented approach is represents as follows:

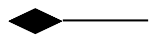
```
public class University {

    private Chancellor chancellor;
    public String getChancellorName()
    {
        return chancellor.getName();
    }
}
public class Chancellor {
    private String name;

    public Chancellor(String name) {
```

```
        this.name = name;
    }

    public String getName() {
        return name;
    }
}
```

A restricted aggregation is called composition (Schildt, 2010). If the contained object cannot exist without the existence of the container object then this is called composition. Consider the example where the container object is University and the contained object is Faculties then the faculties cannot exist if the university does not exist. The lifetime of the object Faculties is attached to the lifetime of the University. The UML notation for composition using classical object-oriented programming is the following:  It is the same shape as aggregation but the diamond is solid. Using the example, the class diagram for composition can be represented as follows:

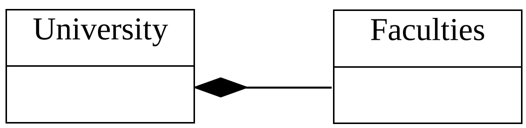


Figure 4-5: An example of a classical composition relationship

The example in Figure 4-5 can be mapped in Java as follows:

```
public class University {

    private final Faculties faculties[];
    private String name;

    public University(String name, int noOfFaculties) {

        this.name = name;
        // Faculties is encapsulated within University. The outside world has
           no access to a Faculty without a University
        this.faculties = new Faculties[noOfFaculties];
    }
}


public class Faculties {

    private String name;

    public Faculties(String name) {
        this.name = name;
```

```
    }
}
```

The classical object-oriented approach to aggregation can be extended to take imprecise and fuzzy requirements into consideration. Every instance of an aggregate can be projected into a set of instances of constituent parts (Dwibedy *et al*., 2013). If a class is aggregated from fuzzy constituent parts then the aggregated class is also fuzzy with membership [0,1]. Using UML, a dashed diamond denotes a fuzzy aggregate relationship. Figure 4-6 shows a fuzzy aggregate relationship.

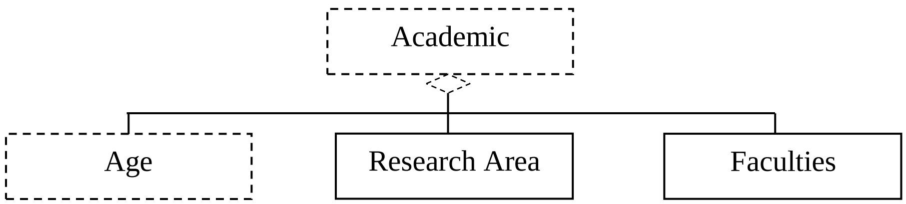


Figure 4-6: A fuzzy aggregate relationship

From Figure 4-6 the class Academic is aggregated from the classes Age, Research Area and Faculties. Since at least one of the constituent classes (in this case Age) is fuzzy, it means that the aggregate class Academic will now become fuzzy.

Refer to the class FuzzyAcademic in (a) that also represents the fuzzy aggregation.

c) Generalisation

Generalisation exhibits an 'is-a' relationship between classes (Schildt, 2010). It uses specialised classes to build taxonomy of classes. Common structures and behaviour from specialised classes is used to build the generalised class. In a broader sense, it can be thought of as inheritance with an emphasis on similarities between objects or classes. One class is a general description of a set of other classes. The purpose of generalisation is to reduce complexities by replacing objects or entities that perform similar functions with a single object or construct. Generalisation is useful when an application is required to be broadened in order to encompass a wider domain of objects that are of the same or different type. Programming languages will handle generalisation through variables, parameterization, generics and polymorphism. The UML notation for generalisation is as follows: The generalisation relationship is demonstrated using the following example. Consider the three classes called Person, Academic Staff and Administration Staff. An Academic Staff as well as an Administration Staff is a Person. Therefore there is a general relationship between Academic Staff and Person as well as Administration Staff and Person. This can be depicted using UML as follows:

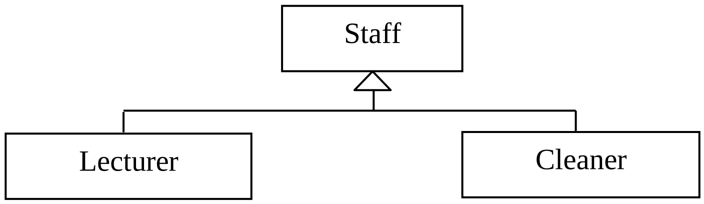


Figure 4-7: An example of a classical generalisation relationship

The following program segment shows how the classical generalisation relationship can be coded.

```
public class Staff {

    protected String name;
    protected int age;
    protected int id;

    public Staff(String name, int age, int id) {
        this.name = name;
        this.age = age;
        this.id = id;
    }

    public String getName() {
        return name;
    }

    public void setName(String name) {
        this.name = name;
    }
}


public class Lecturer extends Staff {

    private double salary;

    public Lecturer(String name, int age, int id, double salary) {
        super(name, age, id);
        this.salary = salary;
```

```
    }
}
public class Cleaner extends Staff {

    private double wages;

    public Cleaner(String name, int age, int id, int wages) {
        super(name, age, id);
        this.wages = wages;
    }
}
```

The fuzzy generalisation relationship can be attained by utilizing the inclusion degree of objects to the class (Dwibedy *et al*., 2013). Since a subclass is a specialisation of the superclass, an object that belongs to the subclass must also belong to the superclass. If the superclass is fuzzy, then a subclass produced from this superclass is also fuzzy. This means that the subclass-superclass relationship is also fuzzy. In essence, a class is a subclass of another class with membership degree of [0,1] at that particular moment. A dashed triangular arrowhead is applied to represent fuzzy generalisation. Figure 4-8 shows a fuzzy generalisation relationship. These classes will have instances that belong to classes that have membership degree [0,1].

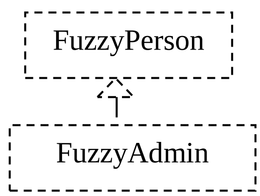


Figure 4-8: A fuzzy generalisation relationship

The following program segment shows the coding of the above example (Figure 4-8) for a fuzzy generalisation relationship.

```
/*
    A Fuzzy example of generalisation
 */
public class FuzzyPerson {

    protected String name;
    protected FuzzyAge age;

    public FuzzyPerson(String name, FuzzyAge age) {
        this.name = name;
        this.age = age;
    }
}
```

```java
public class FuzzyAdmin extends FuzzyPerson{

    private int adminNumber;

    public FuzzyAdmin(String name, FuzzyAge age, int adminNumber) {
        super(name, age);
        this.adminNumber = adminNumber;
    }
}
```

d) Dependency

When two classes have a semantic relationship between each other, then a change in the target class will necessitate a change in the source class (Schildt, 2010). This means that a change in structure or behaviour of the target class will require modification of the source class. The UML notification for dependency is as follows:-------> The dependency relationship is demonstrated using the UML as follows:

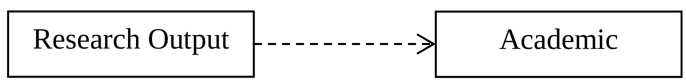


Figure 4-9: A classic dependency relationship

From Figure 4-9, the source is Research Output and the target is Academic. The classical dependency relationship (Figure 4-9) can be coded in Java as follows:

```java
/*
   Example of Dependency
 */
public class Academic {

    private String name;

    // here it is noted, that the research output is dependent on the
       academic.
    // (i.e a new academic will have a different research output)
    private int researchOutput;

    public Academic(String name, int researchOutput) {
        this.name = name;
        this.researchOutput = researchOutput;
    }
}
```

The fuzzy dependency relationship between classes does not require instances to be considered (Dwibedy *et al*., 2013). A fuzzy dependency relationship is a relationship to a certain degree of possibility. If the source class has the first level of fuzziness (levels of fuzziness was discussed in section 4.3.2) then the target class must also be fuzzy with the first level of fuzziness. The degree of possibility of the target class is attained from the source class. This means that the degree of possibility of both the source and target classes will eventually be the same. For example, both the source and the target in the figure below will have a possibility of 0.6 DEGREE.

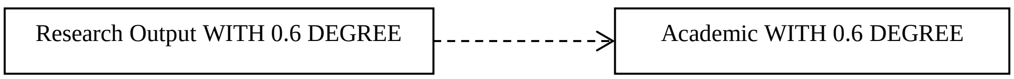


Figure 4-10: An example of a fuzzy dependency relationship

A fuzzy dependency relationship is coded in the class FuzzyAcademic in (a).

4.3 Polymorphism

An important characteristic of the object-oriented paradigm is polymorphism. The term polymorphism means ‘many shapes’. From a programming perspective, polymorphism means requesting that the same operation be performed on many different types of things (Schildt, 2010). Consider a program that requires three different stacks (a first-in, last-out data structure), one for integer values, one for floating-point values and one for characters. When non-object-oriented programming is used, three different stack routines will be required. However, in object-oriented programming, because of polymorphism, a single general stack routine can be created that works for all three situations. Knowledge of one provides knowledge of the other two.

In classical object-oriented programming, many methods have been devised to support polymorphism viz. overloading, coercions, parameter polymorphism and inclusion polymorphism. Fuzzy object-oriented modeling (FOOM) adopts inclusion polymorphism. When inclusion polymorphism is adopted, a function that operates on a range of types is allowed as determined by the subtyping principle. Suppose S is a subtype of T. Subtyping occurs when substituting an object of type S whenever an object of type T occurs without producing any type mismatch errors. This means that with inclusion polymorphism in FOOM and the subtyping principle, a function of a particular type will be able to operate on any subtype. The following class is an example of polymorphism.

```
public class PolyExample {

    // classical OOP
    private Staff cleaner = new Cleaner("Tom",25,123456,500);

    // fuzzy
    // fuzzyPerson = Jerry who is middle aged and has an AdminNo of 986
    private FuzzyPerson fuzzyPerson = new FuzzyAdmin("Jerry", new
            FuzzyAge(false,true,false), 986);
}
```

The classes used in this example refers to the previously mentioned classes.

4.4 Conclusion

Chapter 3 discussed in detail the methodology for developing a productivity estimation model for academic staff and academic departments. This model is required to be implemented into an object-oriented programming language when developing the fuzzy-based system. This chapter (chapter 4) therefore provided an overview of the most important features of the classical object-oriented (which supports crisp data) approach to programming such as abstraction, information hiding, inheritance and encapsulation. The discussion then focused on how the classical object-oriented approach can be extended to consider fuzzy requirements with a special emphasis on the different types of relationships between classes and objects. Polymorphism as an important characteristic of object-oriented programming was also discussed. Chapter 5 demonstrates how the developed model can be implemented in an empirical study. The results were attained using Java.

Chapter 5

AN EMPIRICAL STUDY: ACADEMIC PRODUCTIVITY ESTIMATION AT A UNIVERSITY

5.1 Introduction

This chapter firstly discusses the goals, policies and key performance areas regarding evaluation and productivity estimation at Durban University of Technology (DUT). It then demonstrates how the model developed in Chapter 3 and its implementation in an object-oriented language described in Chapter 4 can be used to estimate productivity of academic staff and academic departments by adhering to DUT policies and requirements. This is the 4th activity of the design science research methodology (DSRM).

A case study method involving the Information Technology Department at DUT will be used in the demonstration. This chapter however does not discuss how evaluation and productivity estimation is presently being implemented at DUT as this aspect has already been discussed in Chapters 1 and 2. Evaluation methods currently employed at DUT are also dealt with in the research questionnaire which is discussed in detail in Chapter 7. This chapter therefore focuses on demonstrating how the new model can be applied.

5.2 The Centre for Quality Promotion and Assurance

The Durban University of Technology has a centre called 'The Centre for Quality Promotion and Assurance (CQPA)' (Sattar, 2012). This centre is responsible for implementing policies regarding evaluations and productivity estimation of academic departments. It is expected that all departments adhere to the goals and policies of CQPA. The short-term goals of this centre are to:

- Monitor on an annual basis the quality of education across the university in all departments and sectors;
- Implement programme reviews of academic departments;
- Evaluate academic departments in order to determine their readiness for national review and accreditation of existing programmes; and

- Provide support in the form of suggestions and advice to academic departments in areas that require attention.

The long-term goals of this centre are to:

- Secure and safeguard academic standards of learning programmes;
- Promote, develop and sustain a culture of quality in the review and evaluation of learning programmes;
- Encourage all staff to take responsibility for the quality assurance processes; and
- Promote self-evaluation at all levels in order to foster self-improvement on a continuous basis.

These short-and-long term goals have been formulated by upper management in conjunction with the Higher Education Quality Committee (HEQC), the South African Qualifications Authority (SAQA) and professional bodies such as the Engineering Council of South Africa (Sattar, 2012). The scope of CQPA embraces all sectors of the university and its main function is to evaluate to what extent the goals mentioned above have been achieved. These goals are measured against six key performance areas (or criteria). These key performance areas are discussed in detail in the next section.

5.3 Key performance criteria with tangible and intangible sub-criteria

The six key performance criteria as required by CQPA are Administration (C_1), Teaching and Supervision (C_2), Research and Innovation (C_3), Writing and Publication (C_4), Consultancy (C_5) as well as Services Rendered and External Engagement (C_6). Some of the key criterion also has sub-criteria (Sattar, 2012). The sub-criteria (operational indicators) for Administration (C_1) are:

- Competency in managing and administering academic programmes (C_{11}); and
- Contribution to administration in the department (C_{12}).

The sub-criteria (operational indicators) for Teaching and Supervision (C_2) are:

- Teaching load (C_{21});
- Participation in planning and development of programmes and study material (C_{22});
- Quality of teaching emphasizing the use of new and emerging technologies (C_{23});

- Peer and student evaluations of academics' teaching performance (C_{24});
- Co-curricular involvement (C_{25});
- Supervision of student projects (C_{26}); and
- Number of Masters and PhD students supervised (C_{27}).

The sub-criteria (operational indicators) for Research and Innovation (C_3) are:

- Level of involvement in research project/s (C_{31});
- Number of National and International Conference Presentations attended (C_{32});
- Number of papers presented at National and International Conferences (C_{33});
- Networking with researchers outside DUT (C_{34}); and
- Evidence of funding received (C_{35}).

The sub-criteria (operational indicators) for Writing and Publications (C_4) are:

- Number of accredited/recognized/non-accredited articles published (C_{41});
- Involvement with Scholarly and Academic writing (C_{42}); and
- Other writing (C_{43}).

The sub-criterion (operational indicators) for Consultancy (C_5) is:

- Level of involvement with industries (C_{51}).

The sub-criteria (operational indicators) for Services and External Engagement (C_6) are:

- Services rendered to academic department such as head of a committee, etc. (C_{61});
- Involvement in External Examination and Moderation (C_{62});
- Involvement in generating income (3rd stream) from outside DUT (C_{63});
- Voluntary services rendered (C_{64}); and
- Member of professional, cultural, religious or other bodies (C_{65}).

According to DUT evaluation guidelines, there are six (6) key performance indicators (main criteria) and twenty-three (23) operational indicators (sub-criteria) as discussed above (Sattar, 2012). Five (5) of these are tangible operational indicators namely, C_{21}, $C_{27,}$ $C_{32,}$ $C_{33,}$ C_{41} while the remaining eighteen (18) are intangible operational indicators. Since C_2, C_3 and C_4 have some sub-criteria that are tangibles, these key performance indicators cannot be described as being purely intangible. C_1, C_5 and C_6 are purely intangible criteria since none of their sub-criteria are tangible. The Centre for Quality Promotion and Assurance usually has four members on a panel that will conduct the evaluations. In this demonstration, these members will be referred to as decision-makers and are identified as D_1, D_2, D_3 and D_4. For the purpose of illustration, the performance of three academics (alternatives A_1, A_2, A_3) from the Information Technology department will be evaluated for the demonstration.

5.4 Objectives of the demonstration

The objectives of this demonstration are to implement the methodology (discussed in Chapter 3) into an object-oriented programming language called Java (discussed in Chapter 4) to:

- Estimate the productivity of the three academics from the IT department by showing their performance in the 6 key performance areas. Such information may be required by management to estimate the overall performance of an academic;
- Show the strongest and weakest performance areas of each academic. Such information may be required by management to assist academics in areas that require attention;
- Compare the performance of the three academics (with each other) in each of the key performance areas. This information may be required when management needs to delegate duties to academics according to their strengths. For example, an academic that has performed the best in research and innovation (when compared to the other academics) may be chosen to head the research unit at the department;
- Show the overall performance of all academics in all key performance areas. This information is required when the productivity estimation of an entire department is required. Such information is generally required when the Dean or Head of Department are required to present an annual report on the state of an academic department (Sattar, 2012). The kind of information required includes research outputs, conference attendance and presentations, articles published, supervision of Masters and PhD students, 3^{rd} -stream income and external engagement;
- Rank the three academics in terms of all 6 key performance areas. Such information may be required for promotion purposes. Some universities also provide incentives or awards

when an academic has excelled. Ranking and selecting academics in a fair manner is therefore important. Such information is necessary when deciding who should be promoted or rewarded;

- Rank all departments in a faculty in order to identify the best and worst performing departments. Such information may be required when incentives are required to be awarded to the best performing departments. Such information may be also required to assist departments that require assistance to improve their productivity; and
- Compare the performance of an academic against the average performance of the department that the academic belongs to.

These objectives were formulated from the results a survey (Chapter 7) of academics from the Durban University of Technology where respondents were asked about what they expect from an efficient and effective productivity estimation model. The researcher accommodated most of the respondent's expectations and requirements when the system was being developed. The researcher also elicited the view of management and CQPA on what additional functionality should be included in the new system. An adequate amount of preliminary information has now been provided to start the demonstration.

5.5 The evaluation

The Centre for Quality Promotion and Assurance (CQPA) at Durban University of Technology evaluates each academic department every three years (Sattar, 2012). This demonstration will therefore focus on estimating the productivity of academics between 2011 and 2013. The demonstration will not include 2014 since the data collection process of academics has been not completed for 2014.

5.5.1 Develop the Hierarchy Structure

A hierarchy structure that indicates the six major criteria and twenty-three sub-criteria (as discussed in section 5.3) with the goal in level 1 and the alternatives in level 4 is firstly developed. The structure is shown in Figure 5-1.

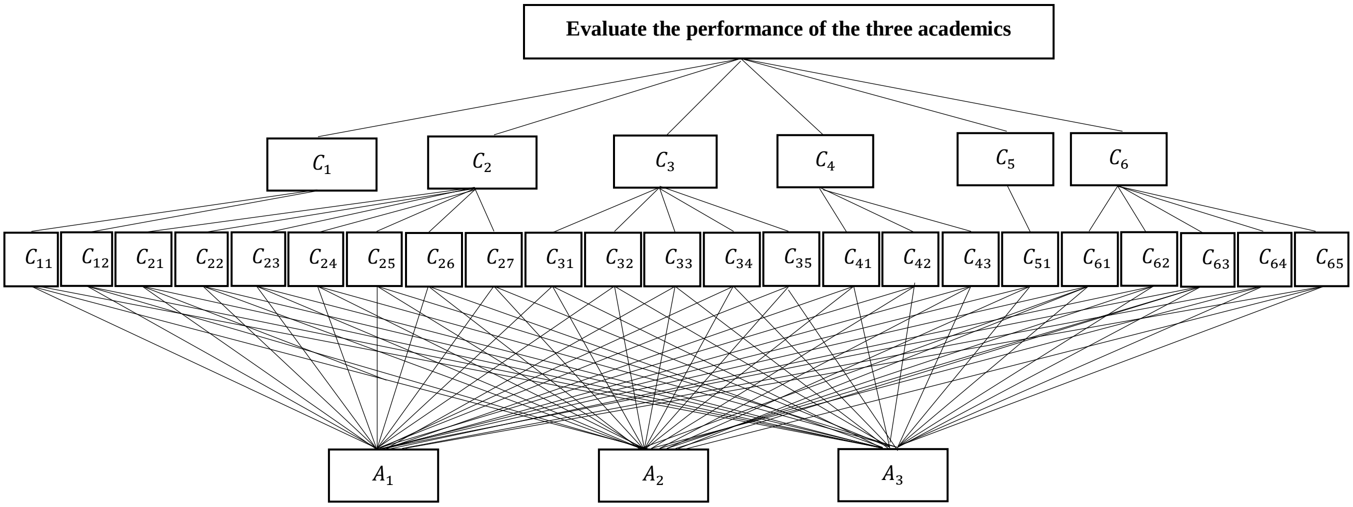


Figure 5-1: Hierarchy Structure for academic department estimation problem

The problem is solved bottom up. Each criterion (that is, each key performance attributes) combines with the sub-scores in order to attain the overall goal. The alternatives can then be ranked according to each academic's overall performance. The objectives discussed in section 5.4 will be addressed at the end of the demonstration.

5.5.2 Convert precise ratings of tangible sub-criteria into fuzzy numbers

The researcher collected real quantitative (tangible) data from the IT department on the three academics (A_1, A_2 and A_3) for the period 2011 to 2013. Table 5-1 indicates the actual quantitative data for the following tangible sub-criteria: Teaching load in terms of number of lectures per week (C_{21}), number of Masters and PhD students supervised in one year (C_{27}), number of national and International Conferences attended during (C_{32}), number of papers presented at national and International Conferences (C_{33}) and number of accredited/recognized/non-accredited articles published (C_{41}).

	C_{21}			C_{27}			C_{32}			C_{33}			C_{41}		
	2011	2012	2013	2011	2012	2013	2011	2012	2013	2011	2012	2013	2011	2012	2013
A_1	12	11	12	1	2	2	1	2	3	1	1	1	2	3	3
A_2	11	13	12	2	2	2	2	2	1	2	2	1	3	2	3
A_3	10	12	12	1	1	2	3	2	2	1	2	2	1	3	2

Table 5-1: Actual quantitative data attained from the IT department

The quantitative data is then transformed into fuzzy numbers. By using the geometric mean method (equation 3.1), these quantitative data can be expressed as fuzzy numbers (Ding, 2011). Teaching load (C_{21}) for example can be expressed as a fuzzy number as follows: $L = \min_i \{x_i\} = 11$, $M = \left[\prod_{i=1}^{k} x_i\right]^{1/k} = \sqrt[3]{12X11X12} = 11.7$ and $U = \max_i \{x_i\} = 12$. The quantitative values for C_{21} expressed as a fuzzy number is therefore (11, 11.7, 12). The other fuzzy numbers for the quantitative values in Table 5-1 can also be attained by analogy using the same method. The sub-score for all the quantitative (tangible) criteria are indicated in Table 5-2. The following Java method was used to convert quantitative inputs into fuzzy numbers.

```
/**
 * Convert an array of quantitative values into a fuzzy.FuzzyNumber
 * @param values Array of quantitative values
 * @return fuzzy.FuzzyNumber
 */
public FuzzyNumber quantitativeToFuzzy(String values[])
{
    Arrays.sort(values);
    double min = Double.parseDouble(values[0]);
    double max = Double.parseDouble(values[values.length-1]);
    double geometricMean = geometricMean(values);
    return new FuzzyNumber(min,geometricMean,max);
}
```

	C_{21}	C_{27}	C_{32}	C_{33}	C_{41}
A_1	(11, 11.7, 12)	(1, 1.6, 2)	(1, 1.8, 3)	(1, 1, 1)	(2, 2.6, 3)
A_2	(11, 12, 13)	(2, 2, 2)	(1, 1.6, 2)	(1, 1.6, 2)	(2, 2.6, 3)
A_3	(10, 11.3, 12)	(1, 1.3, 2)	(2, 2.3, 3)	(1, 1.6, 2)	(1, 1.8, 3)

Table 5-2: Sub-scores with respect to tangible criteria C_{21}, C_{27}, C_{32}, C_{33}, and C_{41}

5.5.3 The intangible sub-criteria are measured

According to DUT evaluation guidelines, 18 of the sub-criteria are intangibles as discussed in section 5.3 (Sattar, 2012). Since the intangible sub-criteria lend themselves more to a qualitative evaluation, they cannot be quantified as was done for tangible sub-criteria in section 5.5.2. Intangible (qualitative) sub-criteria are reliant on human judgment with subjective viewpoints and the decision-makers will have diverse opinions regarding the alternatives. Therefore, in order to attain a more consistent outcome, a group decision method is used. The Centre for Quality Promotion and Assurance has a panel of four evaluators (D_1, D_2, D_3 and D_4) that will be responsible for grading each academic in a department.

The panel decided to use a linguistic assessment scale from Table 5-3 for the alternatives and the sub-criteria. These scales are attained from a triangular fuzzy ratio scale indicated in Figure 5-2.

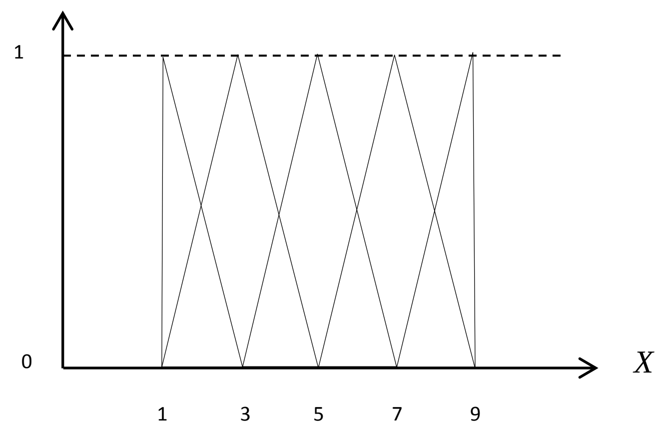


Figure 5-2: Triangular fuzzy ratio scales

Linguistic term	Membership function
Very weak (VW)	(1,1,3) or $\tilde{1}$
Weak (W)	(1,3,5) or $\tilde{3}$
Average (A)	(3,5,7) or $\tilde{5}$
Good (G)	(5,7,9) or $\tilde{7}$
Very Good (VG)	(7,9,9) or $\tilde{9}$

Table 5-3: Linguistic terms for alternatives

The following Java method was used to convert the linguistic terms from Figure 5-3 into fuzzy numbers.

```
/**
     * Converts a linguistic code to its corresponding fuzzy.FuzzyNumber
     * @param code Linguistic term code
     * @return The fuzzy.FuzzyNumber corresponding to the linguistic code
     */
    public FuzzyNumber linguisticToFuzzy(String code)
    {
        switch(code)
        {
            case "VW":
                return new FuzzyNumber(1,1,3);
            case "W":
                return new FuzzyNumber(1,3,5);
            case "A":
                return new FuzzyNumber(3,5,7);
            case "G":
                return new FuzzyNumber(5,7,9);
            case "VG":
                return new FuzzyNumber(7,9,9);
        }
        throw new IllegalArgumentException("Invalid linguistic code used");
    }
```

The decisions of the panel regarding the intangible sub-criteria for criteria C_1 are indicated in Table 5-4.

A_i	C_{11}				C_{12}			
	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4
A_1	G	VG	G	G	G	VG	VG	G
A_2	A	G	G	A	G	VG	G	G
A_3	G	VG	G	VG	G	VG	VG	VG

Table 5-4: Grades of each academic with regard to C_{11} and C_{12}

By using equations 3.2 to 3.5, the four decision-makers sub-scores for C_{11} and C_{12} are integrated. A detailed method for attaining the sub-score for C_{11} with regard to alternative A_1 is presented. The same method will apply when calculating all the other sub-scores. The four decision-makers choices for C_{11} with regard to A_1 is G, VG, G and G respectively are shown in Table 5-4. These linguistic values are equivalent to the fuzzy numbers indicated in Figure 5.2 as follows: G_{1111} = (5, 7, 9), G_{1112} = (7, 9, 9), G_{1113} = (5, 7, 9) and G_{1114} = (5, 7, 9) respectively. By applying equation 3.3, that is, $L_{ijk} = \min\left(L_{ijkp}\right)$, the following is attained: $L_{111} = \min(5,7,5,5) = 5$. By applying equation 3.4, that is, $M_{ijk} = \frac{\left(\sum_{p=1}^{t} M_{ijkp}\right)}{p}$ the following is atained: $M_{111} = \frac{\left(\sum_{p=1}^{t} M_{ijkp}\right)}{p} = \frac{7+9+7+7}{4} = \frac{30}{4} = 7.5$. By applying equation 3.5, that is, $U_{ijk} = \max\left(U_{ijkp}\right)$, the following is attained: $U_{111} = \max\left(U_{ijkp}\right) = \max(9, 9, 9, 9) = 9$. The fuzzy number attained is therefore $G_{111} = (5, 7.5, 9)$. All other sub-scores can be attained in the same way and the results for C_{11} and C_{12} are depicted in Table 5-5.

A_i	C_{11}	C_{12}
A_1	(5, 7.5, 9)	(5, 8, 9)
A_2	(3, 6, 9)	(5, 7.5, 9)
A_3	(5, 8, 9)	(5, 8.5, 9)

Table 5-5: Sub-scores of each academic with regard to C_{11} and C_{12}

The following Java methods were used to convert the linguistic values into fuzzy numbers:

```
/**
     * Convert an array of qualitative values into a fuzzy.FuzzyNumber
     * @param decisions Array of decisions which are linguistic terms
     * @return fuzzy.FuzzyNumber
     */
    public FuzzyNumber qualitativeToFuzzy(String [] decisions)
    {
        double minArray[] = new double[decisions.length];
        double geoMeanArray[] = new double[decisions.length];
        double maxArray[] = new double[decisions.length];

        for(int i=0;i<decisions.length;i++)
        {
            // Converting the linguistic term to a Fuzzy number, then extract
               each component
            minArray[i] = linguisticToFuzzy(decisions[i]).getMin();
            geoMeanArray[i] = linguisticToFuzzy(decisions[i]).getMean();
            maxArray[i] = linguisticToFuzzy(decisions[i]).getMax();
        }

        return new FuzzyNumber(getMinValue(minArray),
                      getAverage(geoMeanArray), getMaxValue(maxArray));
    }
/**
     * Determines the maximum value from the given array of values
     * @param values Array of values
     * @return Maximum value in the values array
     */
    public double getMaxValue(double [] values)
    {
        Arrays.sort(values);
```

```java
        return values[values.length-1];
    }

    /**
     * Determines the minimum value from the given array of values
     * @param values Array of values
     * @return Minimum value in the values array
     */
    public double getMinValue(double [] values)
    {
        Arrays.sort(values);
        return values[0];
    }

    /**
     * Calculates the geometric mean of a given array
     * @param data Array of values
     * @return Geometric mean
     */
    public double geometricMean(double[] data) {

        if (data.length == 0)
            return 0;
        // calculates the product
        double geoMean = 1.0;
        for (int i = 0; i < data.length; i++) {
            geoMean *= data[i];
        }
        // raise the product to 1/(the number of elements in data)
        geoMean = Math.pow(geoMean, 1.0 / (double) data.length);
        // rounding off to one decimal place
        geoMean = (double) Math.round(geoMean * 10) / 10;
        return geoMean;
    }
```

The decisions of the panel regarding the intangible sub-criteria for criteria C_2 are indicated in Table 5-6.

A_i	C_{22}				C_{23}				C_{24}				C_{25}				C_{26}			
	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4
A_1	A	G	G	W	VG	G	G	VG	W	A	G	G	A	VG	G	G	VG	W	G	G
A_2	G	G	VG	VG	W	A	VG	G	G	G	A	G	A	G	VG	A	G	G	W	A
A_3	VG	A	G	A	G	VG	A	A	W	G	G	VG	G	G	A	G	G	VG	W	G

Table 5-6: Grades of each academic with regard to C_{22}, C_{23}, C_{24}, C_{25} and C_{26}

By using equations 3.2 to 3.5, the four decision-makers sub-scores for C_{22}, C_{23}, C_{24}, C_{25} and C_{26} are integrated. The method is identical to the method used to attain the sub-scores for C_{11} and

C_{12} (see computations above). The sub-scores for criteria C_2 are therefore presented without showing the calculations. These sub-scores are indicated in Table 5-7.

A_i	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}
A_1	(1, 5.5, 9)	(5, 8, 9)	(1, 5.5, 9)	(3, 7, 9)	(1, 6.5, 9)
A_2	(5, 8, 9)	(1, 6, 9)	(3, 6.5,9)	(3, 6.5, 9)	(1, 5.5, 9)
A_3	(3, 6.5, 9)	(3, 6.5, 9)	(1, 6.5, 9)	(3, 6.5, 9)	(1, 6.5, 9)

Table 5-7: Sub-scores of each academic with regard to C_{22}, C_{23}, C_{24}, C_{25} and C_{26}

The decisions of the panel regarding the intangible sub-criteria for criteria C_3 are indicated in Table 5-8.

A_i	C_{31}				C_{34}				C_{35}			
	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4
A_1	A	VG	A	G	W	A	G	G	A	G	G	A
A_2	VG	G	G	G	G	A	G	G	VG	A	G	G
A_3	G	VG	G	A	A	G	A	A	G	VG	G	A

Table 5-8: Grades of each academic with regard to C_{31}, C_{34} and C_{35}

By using equations 3.2 to 3.5, the four decision-makers sub-scores for C_{31}, C_{34}, and C_{35} are integrated. The sub-scores are presented in Table 5-9.

A_i	C_{31}	C_{34}	C_{35}
A_1	(3, 6.5, 9)	(1, 5.5, 9)	(3, 6, 9)
A_2	(5, 7.5, 9)	(3, 6.5, 9)	(3, 7, 9)
A_3	(3, 7, 9)	(3, 5.5, 9)	(3, 7, 9)

Table 5-9: Sub-scores of each academic with regard to C_{31}, C_{34} and C_{35}

The decisions of the panel regarding the intangible sub-criteria for criteria C_4 are indicated in Table 5-10.

A_i	C_{42}				C_{43}			
	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4
A_1	A	G	G	A	G	G	A	A
A_2	G	VG	G	G	G	VG	G	A
A_3	A	W	G	A	W	A	A	A

Table 5-10: Grades of each academic with regard to C_{42} and C_{43}

By using equations 3.2 to 3.5, the four decision-makers sub-scores for C_{42} and C_{43} are integrated. These sub-scores are presented in Table 5-11.

A_i	C_{42}	C_{43}
A_1	(3, 6, 9)	(3, 6, 9)
A_2	(5, 7.5, 9)	(3, 7, 9)
A_3	(1, 5, 9)	(1, 4.5, 7)

Table 5-11: Sub-scores of each academic with regard to C_{42} and C_{43}

The decisions of the panel regarding the intangible sub-criteria for criteria C_5 are indicated in Table 5-12.

A_i	C_{51}			
	D_1	D_2	D_3	D_4
A_1	A	A	G	A
A_2	W	A	W	W
A_3	G	A	G	G

Table 5-12: Grades of each academic with regard to C_{51}

By using equations 3.2 to 3.5, the four decision-makers sub-scores for C_{51} are integrated. These sub-scores are presented in Table 5-13.

A_i	C_{51}
A_1	(3, 5.5, 9)
A_2	(1, 3.5, 7)
A_3	(3, 6.5, 9)

Table 5-13: Sub-scores of each academic with regard to C_{51}

The decisions of the panel regarding the intangible sub-criteria for criteria C_6 are indicated in Table 5-14.

A_i	C_{61}				C_{62}				C_{63}				C_{64}				C_{65}			
	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4
A_1	G	A	G	G	A	VG	G	G	G	A	VG	G	G	G	G	A	G	VG	G	G
A_2	W	A	A	W	A	G	G	A	A	G	G	W	W	G	G	A	G	A	W	A
A_3	VG	G	VG	G	G	A	G	G	A	G	VG	G	VG	G	G	G	VG	G	G	G

Table 5-14: Grades of each academic with regard to C_{61}, C_{62}, C_{63}, C_{64} and C_{65}

By using equations 3.2 to 3.5, the decision makers sub-scores for C_{61}, C_{62}, C_{63}, C_{64} and C_{65} are integrated. The sub-scores for criteria C_6 are presented in Table 5-15.

A_i	C_{61}	C_{62}	C_{63}	C_{64}	C_{65}
A_1	(3, 6.5, 9)	(3, 7, 9)	(3, 7, 9)	(3, 6.5, 9)	(5, 7.5, 9)
A_2	(1, 4, 7)	(3, 6, 9)	(1, 5.5, 9)	(1, 5.5, 9)	(1, 5, 9)
A_3	(5, 8, 9)	(3, 6.5, 9)	(3, 7, 9)	(5, 7.5, 9)	(5, 7.5, 9)

Table 5-15: Sub-scores of each academic with regard to C_{61}, C_{62}, C_{63}, C_{64} and C_{65}

5.5.4 The fuzzy judgment matrix is attained

In order to attain the fuzzy judgment matrix, the sub-scores for each main criterion using equation 3.7 are firstly added. However, the sub-scores for the quantitative (tangible) sub-criteria that were computed in section 5.5.2 has to be firstly be included before the addition process can begin. This means that the tangible (quantitative) sub-criteria C_{21}, C_{27}, C_{32}, C_{33} and C_{41} will have to be combined with the intangible (qualitative) sub-criteria under the main criteria C_2, C_3, and C_4. Criteria C_1, C_5, and C_6 does not have tangible (quantitative) sub-criteria and will therefore remain the same. After combining the tangible with the intangible sub-scores, Tables 5-16, 5-17 and 5-18 are attained.

A_i	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}	C_{27}
A_1	(11, 11.7, 12)	(1, 5.5, 9)	(5, 8, 9)	(1, 5.5, 9)	(3, 7, 9)	(1, 6.5, 9)	(1, 1.6, 2)
A_2	(11, 12, 13)	(5, 8, 9)	(1, 6, 9)	(3, 6.5, 9)	(3, 6.5, 9)	(1, 5.5, 9)	(2, 2, 2)
A_3	(10, 11.3, 12)	(3, 6.5, 9)	(3, 6.5, 9)	(1, 6.5, 9)	(3, 6.5, 9)	(1, 6.5, 9)	(1, 1.3, 2)

Table 5-16: Tangible and intangible sub-scores under criterion C_2

A_i	C_{31}	C_{32}	C_{33}	C_{34}	C_{35}
A_1	(3, 6.5, 9)	(1, 1.8, 3)	(1, 1, 1)	(1, 5.5, 9)	(3, 6, 9)
A_2	(5, 7.5, 9)	(1, 1.6, 2)	(1, 1.6, 2)	(3, 6.5, 9)	(3, 7, 9)
A_3	(3, 7, 9)	(2, 2.3, 3)	(1, 1.6, 2)	(3, 5.5, 9)	(3, 7, 9)

Table 5-17: Tangible and intangible sub-scores under criterion C_3

A_i	C_{41}	C_{42}	C_{43}
A_1	(2, 2.6, 3)	(3, 6, 9)	(3, 6, 9)
A_2	(2, 2.6, 3)	(5, 7.5, 9)	(3, 7, 9)
A_3	(1, 1.8, 3)	(1, 5, 9)	(1, 4.5, 7)

Table 5-18: Tangible and intangible sub-scores under criterion C_4

Equation 3.7 ($\tilde{G}_{ij} = \sum_{k=1}^{q} \tilde{G}_{ijk}$) is now used to add all the sub-scores of each alternative that belongs to the same criteria. Detailed steps for the calculations involving C_1 are shown. Using equation 3.7 and Table 5.5 the following for C_1 is attained:

$$\tilde{G}_{11} = \tilde{G}_{111} \oplus \tilde{G}_{112} = (5, 7.5, 9) + (5, 8, 9) = (10, 15.5, 18)$$

$$\tilde{G}_{21} = \tilde{G}_{211} \oplus \tilde{G}_{212} = (3, 6, 9) + (5, 7.5, 9) = (8, 13.5, 18)$$

$$\tilde{G}_{31} = \tilde{G}_{311} \oplus \tilde{G}_{312} = (5, 8, 9) + (5, 8.5, 9) = (10, 16.5, 18)$$

The results for C_2, C_3, C_4, C_5, and C_6 can be attained by analogy and all the results are presented as a matrix below.

$$\begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} \\ \boldsymbol{A_1} & (10, 15.5, 18) & (23, 45.8, 59) & (9, 20.8, 31) & (8, 14.6, 21) & (3, 5.5, 9) & (17, 34.5, 45) \\ \boldsymbol{A_2} & (8, 13.5, 18) & (26, 46.5, 60) & (13, 24.2, 31) & (10, 17.1, 21) & (1, 3.5, 7) & (7, 26, 43) \\ \boldsymbol{A_3} & (10, 16.5, 18) & (22, 45.1, 59) & (12, 23.4, 32) & (3, 11.3, 19) & (3, 6.5, 9) & (21, 36.5, 45) \end{bmatrix}$$

The following Java method was used to add all the sub-criteria under a single criteria.

```java
/**
     * Perform calculations to combine all the sub-criteria into a single
     * Fuzzy Number
     * @return
     */
    public FuzzyNumber calculateFuzzyNumber()
    {
        double totalMin = 0;
        double totalGeoMean = 0;
        double totalMax = 0;

        for(int i=0; i<mSubCriteria.length; i++)
        {
            totalMin += mSubCriteria[i].getFuzzyNumber().getMin();
            totalGeoMean += mSubCriteria[i].getFuzzyNumber().getMean();
            totalMax += mSubCriteria[i].getFuzzyNumber().getMax();
        }
        return new FuzzyNumber(totalMin,totalGeoMean,totalMax);
    }
```

The matrix is now normalised by using equation 3.8 and the formula for division of fuzzy numbers, that is, $\frac{\tilde{A}}{\tilde{B}} = (\frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1})$. A detailed calculation for the normalising process for C_1 is shown. The same method will be used to normalise the other criteria.

$$\tilde{a}_{11} = \frac{\tilde{G}_{ij}}{\sqrt[2]{\sum_{i=1}^{n} (\tilde{G}_{ij})^2}} = \frac{(10,\ 15.5,\ 18)}{(16.248,\ 26.358,\ 31.177)} = \left(\frac{10}{31.177}, \frac{15.5}{26.358}, \frac{18}{16.248}\right) = (0.32,\ 0.59,\ 1.11)$$

$$\tilde{a}_{21} = \frac{\tilde{G}_{ij}}{\sqrt[2]{\sum_{i=1}^{n} (\tilde{G}_{ij})^2}} = \frac{(8,\ 13.5,\ 18)}{(16.248,\ 26.358,\ 31.177)} = \left(\frac{8}{31.177}, \frac{13.5}{26.358}, \frac{18}{16.248}\right) = (0.26,\ 0.51,\ 1.11)$$

$$\tilde{a}_{31} = \frac{\tilde{G}_{ij}}{\sqrt[2]{\sum_{i=1}^{n} (\tilde{G}_{ij})^2}} = \frac{(10,\ 16.5,\ 18)}{(16.248,\ 26.358,\ 31.177)} = \left(\frac{10}{31.177}, \frac{16.5}{26.358}, \frac{18}{16.248}\right) = (0.32,\ 0.63,\ 1.11)$$

The rest of the calculations can be deduced by analogy and the complete fuzzy judgment matrix is depicted below.

$$\begin{array}{cc} & \begin{array}{cccccc} \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} \end{array} \\ \begin{array}{c} \boldsymbol{A_1} \\ \boldsymbol{A_2} \\ \boldsymbol{A_3} \end{array} & \begin{bmatrix} (0.32, 0.59, 1.11) & (0.22, 0.58, 1.44) & (0.17, 0.53, 1.56) & (0.23, 0.58, 1.60) & (0.21, 0.60, 2.06) & (0.22, 0.61, 1.61) \\ (0.26, 0.51, 1.11) & (0.25, 0.59, 1.46) & (0.24, 0.61, 1.56) & (0.28, 0.68, 1.60) & (0.07, 0.38, 1.61) & (0.09, 0.46, 1.54) \\ (0.32, 0.63, 1.11) & (0.21, 0.57, 1.44) & (0.22, 0.59, 1.61) & (0.09, 0.45, 1.44) & (0.21, 0.71, 2.06) & (0.27, 0.65, 1.61) \end{bmatrix} \end{array}$$

5.5.5 Calculating the CR, the Fuzzy Performance Matrix and ranking the criteria

The overall fuzzy performance matrix is attained when each alternative takes all the criteria into consideration. This is achieved when the fuzzy judgment matrix is multiplied by the fuzzy weight vector. The fuzzy judgment matrix was derived in section 5.5.4. The fuzzy weight vector has to now be determined. In this section, the fuzzy weight vector for each individual pairwise comparison matrix (for each decision-maker) is computed. This fuzzy weight vector is required when calculating the Consistency Ratio (CR) of each pair-wise comparison matrix. These fuzzy weight vectors are computed in sections 5.5.5 (a), 5.5.5 (b) and 5.5.5 (c) below. It is also necessary to compute the fuzzy weight vector that will be used to calculate the overall fuzzy performance matrix. In order to attain this, a comprehensive pair-wise comparison matrix is constructed by integrating the different opinions of the four decision-makers from which this fuzzy weight vector is computed. This fuzzy weight vector is computed in section 5.5.5 (d) below. In this study, two methods were discussed on how fuzzy weights can be attained. These methods are discussed in steps 7.1, 7.2 and 7.3 of Chapter 3. The first method uses a scale with absolute numbers and the second method uses a linguistic value scale for fuzzy requirements. This study will use the geometric mean method with linguistic values to calculate the weights and evaluate the criteria. This method is chosen because the fuzzy weights can be easily attained by adapting Saaty's absolute value technique for fuzzy requirements. Saaty's absolute method is discussed in Annexure C. The consistency ratio for each of the four pair-wise comparison matrices is firstly calculated in order to determine their acceptability.

a) A fuzzy weight vector is computed for calculating the CR

Four comparison matrices (because there are four decision-makers) have to be constructed, one for each decision-maker. A fuzzy weight vector has to be computed for each comparison matrix as this vector is required when calculating the Consistency Ratio (CR) of each comparison matrix. The following linguistic fuzzy scale (Table 5-19) is used for evaluation of the level of importance (or level of intensity importance) of the criteria by the four panel members.

Linguistic scale for importance	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Just equal	(1, 1, 1)	(1, 1, 1)
Equally important (EI)	(1/2, 1, 3/2)	(2/3, 1, 2)
Weakly more important (WMI)	(1, 3/2, 2)	(1/2, 2/3, 1)
Strongly more important (SMI)	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)
Very strongly more important (VSMI)	(2, 5/2, 3)	(1/3, 2/5, 1/2)
Absolutely more important (AMI)	(5/2, 3, 7/2)	(2/7, 1/3, 2/5)

Table 5-19: Linguistic terms for intensity importance

All the steps are provided when calculating the fuzzy weight vector for the first decision-maker (D_1) regarding the six criteria. The same method is used to calculate the fuzzy weights of the remaining three decision-makers, therefore detailed calculations will not be shown for D_2, D_3, and D_4.

The formula to calculate the reciprocal of a fuzzy number is: $\frac{1}{(a,\ b,\ c)} = (\frac{1}{c}, \frac{1}{b}, \frac{1}{a})$. This formula will be used to attain a pair-wise comparison matrix of all the criteria for the choices of the first decision-maker (D_1) by using Table 5-19 as follows:

$$\boldsymbol{D_1} = \begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} \\ \boldsymbol{C_1} & (1,1,1) & (\frac{2}{3},1,2) & (\frac{2}{5},\frac{1}{2},\frac{2}{3}) & (2,\frac{5}{2},3) & (\frac{2}{3},1,2) & (2,\frac{5}{2},3) \\ \boldsymbol{C_2} & (\frac{1}{2},1,\frac{3}{2}) & (1,1,1) & (\frac{1}{2},\frac{2}{3},1) & (\frac{3}{2},2,\frac{5}{2}) & (\frac{3}{2},2,\frac{5}{2}) & (\frac{3}{2},2,\frac{5}{2}) \\ \boldsymbol{C_3} & (\frac{3}{2},2,\frac{5}{2}) & (1,\frac{3}{2},2) & (1,1,1) & (\frac{5}{2},3,\frac{7}{2}) & (\frac{5}{2},3,\frac{7}{2}) & (\frac{2}{3},1,2) \\ \boldsymbol{C_4} & (\frac{1}{3},\frac{2}{5},\frac{1}{2}) & (\frac{2}{5},\frac{1}{2},\frac{2}{3}) & (\frac{2}{7},\frac{1}{3},\frac{2}{5}) & (1,1,1) & (\frac{1}{2},\frac{2}{3},1) & (\frac{5}{2},3,\frac{7}{2}) \\ \boldsymbol{C_5} & (\frac{1}{2},1,\frac{3}{2}) & (\frac{2}{5},\frac{1}{2},\frac{2}{3}) & (\frac{2}{7},\frac{1}{3},\frac{2}{5}) & (1,\frac{3}{2},2) & (1,1,1) & (\frac{3}{2},2,\frac{5}{2}) \\ \boldsymbol{C_6} & (\frac{1}{3},\frac{2}{5},\frac{1}{2}) & (\frac{2}{5},\frac{1}{2},\frac{2}{3}) & (\frac{1}{2},1,\frac{3}{2}) & (\frac{2}{7},\frac{1}{3},\frac{2}{5}) & (\frac{2}{5},\frac{1}{2},\frac{2}{3}) & (1,1,1) \end{bmatrix}$$

The computations of the matrix in normalised form as well as all the other calculations are depicted in the matrix below. An explaination on how these calculations are derived is discussed below the matrix. The following Java code was used to normalise the matrix.

```
    /**
     * Normalises the given matrix
     * @param alternatives
     */
    public void normaliseMatrix(Alternative[] alternatives)
    {
        double a1,a2,a3;
        a1 =0;
        a2 =0;
        a3 =0;

        double [][] bValues = calculateBValues(alternatives);

        // loop through each alternative's criteria
        for(int alt=0; alt<alternatives.length; alt++)
        {
            for(int cols=0; cols<alternatives[0].getCriteriaArray().length;
                cols++)
            {
                // get the fuzzy components of the fuzzy number that's being
                   normalised
                a1 =
alternatives[alt].getCriteriaArray()[cols].getFuzzyNumber().getMin();
                a2 =
alternatives[alt].getCriteriaArray()[cols].getFuzzyNumber().getMean();
                a3 =
alternatives[alt].getCriteriaArray()[cols].getFuzzyNumber().getMax();

                FuzzyNumber normalisedFuzzyNumber = new FuzzyNumber(
(a1/bValues[2][cols]) , (a2/bValues[1][cols]), (a3/bValues[0][cols]) );

                // replace fuzzy number with normalised fuzzy number

alternatives[alt].getCriteriaArray()[cols].setFuzzyNumber(normalisedFuzzyNumb
er);
            }
        }

    }
```

	C_1	C_2	C_3	C_4	C_5	C_6	$weights\ (PV)$
C_1	(1, 1, 1)	(0.67, 1.00, 2.00)	(0.40, 0.50, 0.67)	(2.00, 2.50, 3.00)	(0.67, 1.00, 2.00)	(2.00, 2.50, 3.00)	(0.11, 0.19, 0.33)
C_2	(0.50, 1.00, 1.50)	(1, 1, 1)	(0.50, 0.67, 1.00)	(1.50, 2.00, 2.50)	(1.50, 2.00, 2.50)	(1.50, 2.00, 2.50)	(0.12, 0.21, 0.34)
C_3	(1.50, 2.00. 2.50)	(1.00, 1.50, 2.00)	(1, 1, 1)	(2.50, 3.00, 3.50)	(2.50, 3.00, 3.50)	(0.67, 1.00, 2.00)	(0.16, 0.27, 0.45)
C_4	(0.33, 0.40,0.50)	(0.40, 0.50, 0.67)	(0.29, 0.33, 0.40)	(1, 1, 1)	(0.50, 0.67, 1.00)	(2.50, 3.00, 3.50)	(0.07, 0.11, 0.18)
C_5	(0.50, 1.00, 1.50)	(0.40, 0.50, 0.67)	(0.29, 0.33, 0.40)	(1.00, 1.50, 2.00)	(1, 1, 1)	(1.50, 2.00, 2.50)	(0.08, 0.14, 0.23)
C_6	(0.33, 0.40, 0.50)	(0.40, 0.50, 0.67)	(0.50, 1.00, 1.50)	(0.29, 0.33, 0.40)	(0.40, 0.50, 0.67)	(1, 1,1)	(0.05, 0.09, 0.14)
Sum	(4.16, 5.80, 7.50)	(3.87, 5.00, 7.01)	(2.98, 3.83, 4.97)	(8.29, 10.33, 12.40)	(6.57, 8.17, 10.67)	(9.17, 11.50,14.50)	
$Sum * PV$	(0.46, 1.10, 2.55)	(0.46, 1.05, 2.38)	(0.48, 1.03, 2.24)	(0.58, 1.14, 2.23)	(0.53, 1.14, 2.35)	(0.46, 1.03, 2.03)	
λ_{max}	(2.96, 6.50, 13.78)						

In order to calculate the weight vector, equations 3.14 and 3.15 are used.

By using equation 3.14, the 6th root (because there are 6 criteria) of the product of each row as follows are attained: $\tilde{r}_i = (\tilde{a}_{i1} \otimes \ldots \otimes \tilde{a}_{ij} \otimes \ldots \otimes \tilde{a}_{in})^{\frac{1}{n}}$

$$\tilde{r}_1 = (1\text{x}0.67\text{x}0.4\text{x}2\text{x}0.67\text{x}2, 1\text{x}1\text{x}0.5\text{x}2.5\text{x}1\text{x}2.5, 1\text{x}2\text{x}0.67\text{x}3\text{x}2\text{x}3)^{\frac{1}{6}}$$

$$= ((0.72)^{\frac{1}{6}}, (3.13)^{\frac{1}{6}}, (24)^{\frac{1}{6}})$$

$$= (0.95, 1.21, 1.70)$$

By using the same method, the other $\tilde{r}_i$ values are obtained. These are:

$$\tilde{r}_2 = (0.97, 1.32, 1.69)$$

$$\tilde{r}_3 = (1.36, 1.73, 2.23)$$

$$\tilde{r}_4 = (0.60, 0.71, 0.88)$$

$$\tilde{r}_5 = (0.66, 0.89, 1.12)$$

$$\tilde{r}_6 = (0.44, 0.57, 0.71)$$

The fuzzy weight ($\widetilde{w}_1$) for the first row is calculated using equation 3.15 as follows:

$$\widetilde{w}_i = \frac{\tilde{r}_i}{[\tilde{r}_1 \oplus \ldots \oplus \tilde{r}_i \oplus \ldots \oplus \tilde{r}_n]}$$

$$\widetilde{w}_1 = \frac{\tilde{r}_1}{[\tilde{r}_1 \oplus \tilde{r}_2 \oplus \tilde{r}_3 \oplus \tilde{r}_4 \oplus \tilde{r}_5 \oplus \tilde{r}_6]}$$

$$= \frac{(1.08,1.21,1.70)}{(1.08,1.21,1.70)+(0.97,1.32,1.69)+(1.36,1.73,2.23)+(0.60,0.71,0.88)+(0.66,0.89,1.12)+(0.44,0.57,0.71)}$$

$$= \frac{(1.08,1.21,1.70)}{(5.12,6.43,8.37)}$$

$= (0.11, 0.19, 0.34)$ (that is, fuzzy weight for $\tilde{r}_1$).

This fuzzy weight $(0.11, 0.19, 0.34)$ is attained by applying the formula for division of fuzzy numbers (that is, $\frac{\tilde{A}}{\tilde{B}} = (\frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1})$. The weights for the other rows are calculated in the same way and all the weights are indicated in the matrix above. The following Java methods were used for the calculations:

```java
/**
 * Calculate the 6th root of the product of each row of a given decision
 * maker matrix
 * @param decisionMakerMatrix
 * @return array of roots corresponding to each row
 */
public FuzzyNumber[] calculateRoots(FuzzyNumber[][] decisionMakerMatrix)
{
    // initialize variables to 1 since we're using the product of each
       row
    double min = 1;
    double mean = 1;
    double max = 1;
    FuzzyNumber roots[] = new FuzzyNumber[decisionMakerMatrix.length];
    double n = decisionMakerMatrix.length;

    // rows
    for(int i=0; i<decisionMakerMatrix.length; i++)
    {
        // columns
        for(int j=0; j<decisionMakerMatrix[0].length; j++)
        {
            min *= decisionMakerMatrix[i][j].getMin();
            mean *= decisionMakerMatrix[i][j].getMean();
            max *= decisionMakerMatrix[i][j].getMax();
        }
        roots[i] = new FuzzyNumber(Math.pow(min,(1/n)),
        Math.pow(mean,(1/n)), Math.pow(max,(1/n)));

        // reset variables for next row
        min = mean = max = 1;
    }

    return roots;
}
```

```
    /**
     * Calculates the weight vector given the roots
     * @param roots
     * @return weight vector
     */
    public FuzzyNumber[] calculateWeightVector(FuzzyNumber[] roots)
    {
        FuzzyNumber[] weights = new FuzzyNumber[roots.length];

        // the denominator
        FuzzyNumber sumOfRoots = addRoots(roots);

        for(int i=0; i<weights.length; i++)
        {
            weights[i] = new FuzzyNumber(roots[i].getMin()   /
sumOfRoots.getMax(),    // a1/b3
                                         roots[i].getMean() /
sumOfRoots.getMean(),   // a2/b2
                                         roots[i].getMax()   /
sumOfRoots.getMin());   // a3/b1
        }
        return weights;
    }
```

b) Calculating and checking the Consistency Ratio

Detailed steps are provided for calculating the Consistency Ratio (CR) of the first decision-maker (*D_1*) regarding the six criteria. The same method is used to calculate the CR of the remaining 3 decision-makers. The resultant calculations for *D_1* are indicated in the final matrix in section 5.5.5 (a).

The Consistency Ratio (CR) is determined using Saaty's original method. His original method with absolute values is illustrated in Annexure C using an example. Saaty's absolute value technique is adapted to calculate the CR for fuzzy requirements. The λ_{max} value for absolute values is a single precise value. The λ_{max} value for fuzzy inputs is computed as the modal value of the resulting fuzzy number. However, fuzzy operations and not absolute value operations are used in all the calculations for fuzzy requirements. All the calculations are indicated in the final matrix in section 5.5.5 (a). It is important to emphasize that not all the choices of the decision-makers produced consistent pair-wise comparison matrices the first time round. The choices had to be revised until consistency matrices were attained. Calculating the CR is a four-step process.

The first step requires that the pair-wise comparison values in each column be added together as the sum value. Each sum value is then multiplied by the respective weight from the Priority

Vector (*PV*). The sum value for C_1 is $(4.16, 5.80, 7.50)$ and the respective weight vector is $(0.11, 0.19, 0.34)$. The product $(Sum \text{ X } PV)$ is $(4.16, 5.80, 7.50) \text{ X } (0.11, 0.19, 0.34) = (0.46, 1.10, 2.55)$. The $(Sum \text{ X } PV)$ for the other 5 criteria are calculated in the same manner and are indicated in the matrix above. The second step involves adding all the $Sum \text{ X } PV$ values to get the λ_{max} value, that is, $\lambda_{max} = (2.96, 6.50, 13.78)$ in the matrix. The modal value 6.50 is the resultant value of λ_{max}. The Consistency Index (CI) is calculated in the third step as follows: $CI = \frac{(\lambda_{max} - n)}{(n-1)}$ with n representing the number of factors/criteria. In this case n = 6 for the 6 different criteria being compared. Therefore $CI = \frac{(\lambda_{max} - n)}{(n-1)} = \frac{(6.50 - 6)}{(6-1)} = \frac{0.50}{5} = 0.1$. The CR is calculated by dividing the CI by a Random Index (RI) that is attained from a lookup table (Table 5-20). Since n = 6, the RI value is 1.24 from the lookup table. The Consistency Ratio (CR) = $\frac{CI}{RI} = \frac{0.50}{1.24} =$ <u>0.08</u>. Since CR ≤ 0.1, the decision-maker's (D_1) pair-wise comparisons are consistent. This comparison is therefore acceptable. The following Java method was used to calculate the Consistency Ratio.

```java
/**
 * Calculates the consistency ratio for a given matrix.
 * @param lamdaMax The lamdaMax FuzzyNumber
 * @param dimensions The number of criteria used
 * @return consistency ratio
 */
public double calculateConsistencyRatio(FuzzyNumber lamdaMax, int
              dimensions) {

    // consistency ratio
    double cr =0;
    double ci =0;
    ci = (lamdaMax.getMean() - dimensions) / (dimensions-1);
    cr = ci / Constants.RANDOM_INDEX_TABLE[dimensions];
    return cr;
}
```

Refer to K1 in Annexure K for the methods that calculates sum of columns, $Sum \text{ X } PV$ and λ_{max} (that is, lambdaMax).

N	1	2	3	4	5	6	7	8	9	10	11	12
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.58

Table 5-20: Random Index table (RI)

c) Calculating the weights and Consistency Ratio of the remaining decision-makers

The fuzzy weight vector and the Consistency Ratio for the first decision-maker (D_1) were computed in sections 5.5.5 (a) and 5.5.5 (b). The same methods will be employed to compute the fuzzy weights and CR for the remaining decision-makers (D_2, D_3, D_4). It is therefore not necessary to show detailed calculations in this section as the results are attained by analogy.

The second decision-maker (D_2) made the following choices regarding all 6 criteria from Table 5-19.

$$\boldsymbol{D_2} = \begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} \\ \boldsymbol{C_1} & (1,1,1) & (\frac{1}{2},1,\frac{3}{2}) & (\frac{2}{7},\frac{1}{3},\frac{2}{5}) & (\frac{2}{5},\frac{1}{2},\frac{2}{3}) & (\frac{2}{3},1,2) & (\frac{2}{3},1,2) \\ \boldsymbol{C_2} & (\frac{2}{3},1,2) & (1,1,1) & (\frac{1}{2},1,\frac{3}{2}) & (\frac{3}{2},2,\frac{5}{2}) & (\frac{1}{3},\frac{2}{5},\frac{1}{2}) & (\frac{3}{2},2,\frac{5}{2}) \\ \boldsymbol{C_3} & (\frac{5}{2},3,\frac{7}{2}) & (\frac{2}{3},1,2) & (1,1,1) & (\frac{1}{2},1,\frac{3}{2}) & (\frac{5}{2},3,\frac{7}{2}) & (\frac{2}{3},1,2) \\ \boldsymbol{C_4} & (\frac{3}{2},2,\frac{5}{2}) & (\frac{2}{5},\frac{1}{2},\frac{2}{3}) & (\frac{2}{3},1,2) & (1,1,1) & (\frac{1}{2},\frac{2}{3},1) & (\frac{1}{2},1,\frac{3}{2}) \\ \boldsymbol{C_5} & (\frac{1}{2},1,\frac{3}{2}) & (2,\frac{5}{2},3) & (\frac{2}{7},\frac{1}{3},\frac{2}{5}) & (1,\frac{3}{2},2) & (1,1,1) & (\frac{1}{2},1,\frac{3}{2}) \\ \boldsymbol{C_6} & (\frac{1}{2},1,\frac{3}{2}) & (\frac{2}{5},\frac{1}{2},\frac{2}{3}) & (\frac{1}{2},1,\frac{3}{2}) & (\frac{2}{3},1,2) & (\frac{2}{3},1,2) & (1,1,1) \end{bmatrix}$$

The computations of the fuzzy weight vector in normalised form as well as all other calculations for the Consistency Ratio (CR) are depicted in the matrix below.

$$\begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} & \boldsymbol{weights\ (PV)} \\ \boldsymbol{C_1} & (1,1,1) & (0.50,1.00,1.50) & (0.29,0.33,0.40) & (0.40,0.50,0.67) & (0.67,1.00,2.00) & (0.67,1.00,2.00) & (0.06,0.12,0.25) \\ \boldsymbol{C_2} & (0.67,1.00,2.00) & (1,1,1) & (0.50,1.00,1.50) & (1.50,2.00,2.50) & (0.33,0.40,0.50) & (1.50,2.00,2.50) & (0.09,0.18,0.33) \\ \boldsymbol{C_3} & (2.50,3.00,3.50) & (0.67,1.00,2.00) & (1,1,1) & (0.50,1.00,1.50) & (2.50,3.00,3.50) & (0.67,1.00,2.00) & (0.12,0.23,0.47) \\ \boldsymbol{C_4} & (1.50,2.00,2.50) & (0.40,0.50,0.67) & (0.67,1.00,2.00) & (1,1,1) & (0.50,0.67,1.00) & (0.50,1.00,1.50) & (0.08,0.15,0.30) \\ \boldsymbol{C_5} & (0.50,1.00,1.50) & (2.00,2.50,3.00) & (0.29,0.33,0.40) & (1.00,1.50,2.00) & (1,1,1) & (0.50,1.00,1.50) & (0.08,0.17,0.30) \\ \boldsymbol{C_6} & (0.50,1.00,1.50) & (0.40,0.50,0.67) & (0.50,1.00,1.50) & (0.67,1.00,2.00) & (0.67,1.00,2.00) & (1,1,1) & (0.07,0.15,0.31) \\ \boldsymbol{Sum} & (6.67,9.00,12.00) & (4.97,6.50,8.84) & (3.25,4.66,6.80) & (5.07,7.00,9.67) & (5.67,7.07,10.00) & (4.84,7.00,10.50) & \\ \boldsymbol{Sum * PV} & (0.40,1.08,3.00) & (0.45,1.17,2.92) & (0.39,1.07,3.20) & (0.41,1.05,2.90) & (0.45,1.20,3.00) & (0.34,1.05,3.25) & \\ \boldsymbol{\lambda_{max}} & (2.44,6.62,18.27) & & & & & & \end{bmatrix}$$

The modal value from λ_{max} is 6.62. The *CI* is calculated as follows: $CI = \frac{(\lambda_{max} - n)}{(n-1)} = \frac{(6.62-6)}{(6-1)} = \frac{0.62}{5} = \underline{0.12}$. The Consistency Ratio (CR) $= \frac{CI}{RI} = \frac{0.12}{1.24} = 0.099$. Since CR ≤ 0.1, the comparison matrix for D_2 is consistent and is therefore acceptable.

The third decision-maker (D_3) made the following choices regarding all 6 criteria from Table 5-19.

$$
D_3 = \begin{array}{c|cccccc}
 & C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \\
\hline
C_1 & (1,1,1) & (\frac{3}{2},2,\frac{5}{2}) & (2,\frac{5}{2},3) & (\frac{2}{5},\frac{1}{2},\frac{2}{3}) & (\frac{2}{3},1,2) & (\frac{2}{3},1,2) \\
C_2 & (\frac{2}{5},\frac{1}{2},\frac{2}{3}) & (1,1,1) & (\frac{1}{2},1,\frac{3}{2}) & (\frac{1}{2},1,\frac{3}{2}) & (\frac{1}{3},\frac{2}{5},\frac{1}{2}) & (\frac{1}{2},1,\frac{3}{2}) \\
C_3 & (\frac{1}{3},\frac{2}{5},\frac{1}{2}) & (\frac{2}{3},1,2) & (1,1,1) & (\frac{1}{2},1,\frac{3}{2}) & (\frac{1}{2},1,\frac{3}{2}) & (\frac{2}{3},1,2) \\
C_4 & (\frac{3}{2},2,\frac{5}{2}) & (\frac{2}{3},1,2) & (\frac{2}{3},1,2) & (1,1,1) & (\frac{1}{2},\frac{2}{3},1) & (\frac{1}{2},1,\frac{3}{2}) \\
C_5 & (\frac{1}{2},1,\frac{3}{2}) & (2,\frac{5}{2},3) & (\frac{2}{3},1,2) & (1,\frac{3}{2},2) & (1,1,1) & (\frac{1}{2},1,\frac{3}{2}) \\
C_6 & (\frac{1}{2},1,\frac{3}{2}) & (\frac{2}{3},1,2) & (\frac{1}{2},1,\frac{3}{2}) & (\frac{2}{3},1,2) & (\frac{2}{3},1,2) & (1,1,1)
\end{array}
$$

The computations for the fuzzy weight vector in normalised form as well as all other calculations for the Consistency Ratio (CR) are depicted in the matrix below.

	C_1	C_2	C_3	C_4	C_5	C_6	weights (PV)
C_1	(1, 1, 1)	(1.50, 2.00, 2.50)	(2.00, 2.50, 3.00)	(0.40, 0.50, 0.67)	(0.67, 1.00, 2.00)	(0.67, 1.00, 2.00)	(0.10, 0.19, 0.39)
C_2	(0.40, 0.50, 0.67)	(1, 1, 1)	(0.50, 1.00, 1.50)	(0.50, 1.00, 1.50)	(0.33, 0.40, 0.50)	(0.50, 1.00, 1.50)	(0.06, 0.12, 0.24)
C_3	(0.33, 0.40, 0.50)	(0.67, 1.00, 2.00)	(1, 1, 1)	(0.50, 1.00, 1.50)	(0.50, 1.00, 1.50)	(0.67, 1.00, 2.00)	(0.07, 0.14, 0.30)
C_4	(1.50, 2.00,2.50)	(0.67, 1.00, 2.00)	(0.67, 1.00, 2.00)	(1, 1, 1)	(0.50, 0.67, 1.00)	(0.50, 1.00, 1.50)	(0.08, 0.17, 0.37)
C_5	(0.50, 1.00, 1.50)	(2.00, 2.50, 3.00)	(0.67, 1.00, 2.00)	(1.00, 1.50, 2.00)	(1, 1, 1)	(0.50, 1.00, 1.50)	(0.09, 0.21, 0.41)
C_6	(0.50, 1.00, 1.50)	(0.67, 1.00, 2.00)	(0.50, 1.00, 1.50)	(0.67, 1.00, 2.00)	(0.67, 1.00, 2.00)	(1, 1,1)	(0.07, 0.16, 0.39)
Sum	(4.23, 5.90, 7.67)	(6.51, 8.50, 12.50)	(5.34, 7.50, 11.00)	(4.07, 6.00, 8.67)	(3.67, 5.07, 8.00)	(3.84, 6.00,9.50)	
Sum * PV	(0.42, 1.12, 2.99)	(0.39, 1.02, 3.00)	(0.37, 1.05, 3.30)	(0.33, 1.02, 3.21)	(0.33, 1.06, 3.28)	(0.27, 0.96, 3.71)	
λ_{max}	(2.11, 6.23, 19.49)						

The modal value from λ_{max} is 6.23. The CI is calculated as follows: $CI = \frac{(\lambda_{max}-n)}{(n-1)} = \frac{(6.23-6)}{(6-1)} = \frac{0.23}{5} = \underline{0.046}$. The Consistency Ratio (CR) $= \frac{CI}{RI} = \frac{0.046}{1.24} = 0.037$. Since CR ≤ 0.1, the comparison matrix for D_3 is consistent and is therefore acceptable.

The fourth decision-maker (D_4) made the following choices regarding all 6 criteria from Table 5-19.

$$
D_4 = \begin{array}{c} \\ \boldsymbol{C_1} \\ \boldsymbol{C_2} \\ \boldsymbol{C_3} \\ \boldsymbol{C_4} \\ \boldsymbol{C_5} \\ \boldsymbol{C_6} \end{array}
\begin{array}{cccccc}
\boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} \\
\end{array}
$$

$$
\begin{array}{c|cccccc}
 & \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} \\
\hline
\boldsymbol{C_1} & (1,1,1) & (\frac{1}{2},1,\frac{3}{2}) & (\frac{3}{2},2,\frac{5}{2}) & (\frac{2}{5},\frac{1}{2},\frac{2}{3}) & (\frac{2}{3},1,2) & (\frac{2}{3},1,2) \\
\boldsymbol{C_2} & (\frac{2}{3},1,2) & (1,1,1) & (2,\frac{5}{2},3) & (\frac{1}{2},1,\frac{3}{2}) & (1,\frac{3}{2},2) & (\frac{1}{2},1,\frac{3}{2}) \\
\boldsymbol{C_3} & (\frac{2}{5},\frac{1}{2},\frac{2}{3}) & (\frac{1}{3},\frac{2}{5},\frac{1}{2}) & (1,1,1) & (\frac{1}{2},1,\frac{3}{2}) & (\frac{1}{2},1,\frac{3}{2}) & (1,\frac{3}{2},2) \\
\boldsymbol{C_4} & (\frac{3}{2},2,\frac{5}{2}) & (\frac{2}{3},1,2) & (\frac{2}{3},1,2) & (1,1,1) & (\frac{1}{2},\frac{2}{3},1) & (\frac{1}{2},1,\frac{3}{2}) \\
\boldsymbol{C_5} & (\frac{1}{2},1,\frac{3}{2}) & (\frac{1}{2},\frac{2}{3},1) & (\frac{2}{3},1,2) & (1,\frac{3}{2},2) & (1,1,1) & (\frac{1}{2},1,\frac{3}{2}) \\
\boldsymbol{C_6} & (\frac{1}{2},1,\frac{3}{2}) & (\frac{2}{3},1,2) & (\frac{1}{2},\frac{2}{3},1) & (\frac{2}{3},1,2) & (\frac{2}{3},1,2) & (1,1,1)
\end{array}
$$

The computations for the fuzzy weight vector in normalised form as well as all other calculations for the Consistency Ratio (CR) are depicted in the matrix below.

	C_1	C_2	C_3	C_4	C_5	C_6	***weights*** (***PV***)
C_1	(1, 1, 1)	(0.50, 1.00, 1.50)	(1.50, 2.00, 2.50)	(0.40, 0.50, 0.67)	(0.67, 1.00, 2.00)	(0.67, 1.00, 2.00)	(0.08, 0.17, 0.35)
C_2	(0.67, 1.00, 2.00)	(1, 1, 1)	(2.00, 2.50, 3.00)	(0.50, 1.00, 1.50)	(1.00, 1.50, 2.00)	(0.50, 1.00, 1.50)	(0.09, 0.21, 0.42)
C_3	(0.40, 0.50, 0.67)	(0.33, 0.40, 0.50)	(1, 1, 1)	(0.50, 1.00, 1.50)	(0.50, 1.00, 1.50)	(1.00, 1.50, 2.00)	(0.06, 0.14, 0.26)
C_4	(1.50, 2.00,2.50)	(0.67, 1.00, 2.00)	(0.67, 1.00, 2.00)	(1, 1, 1)	(0.50, 0.67, 1.00)	(0.50, 1.00, 1.50)	(0.08, 0.17, 0.38)
C_5	(0.50, 1.00, 1.50)	(0.50, 0.67, 1.00)	(0.67, 1.00, 2.00)	(1.00, 1.50, 2.00)	(1, 1, 1)	(0.50, 1.00, 1.50)	(0.08, 0.17, 0.35)
C_6	(0.50, 1.00, 1.50)	(0.67, 1.00, 2.00)	(0.50, 0.67, 1.00)	(0.67, 1.00, 2.00)	(0.67, 1.00, 2.00)	(1, 1,1)	(0.07, 0.16, 0.36)
Sum	(4.57, 6.50, 9.17)	(3.67, 5.07, 8.00)	(6.34, 8.17, 11.50)	(4.07, 6.00, 8.67)	(4.34, 6.17, 9.50)	(4.17, 6.50,9.50)	
Sum $*$ ***PV***	(0.37, 1.10, 3.21)	(0.33, 1.06, 3.28)	(0.38, 1.14, 2.99)	(0.33, 1.02, 3.29)	(0.35, 1.05, 3.32)	(0.29, 1.04, 3.42)	
λ_{max}	(2.05, 6.41, 19.51)						

The modal value from λ_{max} is 6.41. The *CI* is calculated as follows: $CI = \frac{(\lambda_{max} - n)}{(n-1)} = \frac{(6.41-6)}{(6-1)}$ $= \frac{0.41}{5} = \underline{0.082}$. The Consistency Ratio (CR) $= \frac{CI}{RI} = \frac{0.082}{1.24} = 0.066$. Since CR ≤ 0.1, the comparison matrix for D_4 is consistent and is therefore acceptable. It is important that all the comparison matrices are consistent so that the results of the fuzzy weight vectors are reliable. Therefore, when inconsistent comparison matrices were attained, the decision-makers were asked to revise their choices.

d) Computing the fuzzy weight vector from the comprehensive comparison matrix

In section (c) above, the individual comparison matrix for each decision-maker is computed in order to attain the fuzzy weight vector (for each comparison matrix) because it was required in the calculation of the Consistency Ratio (CR). The varying opinions of the four decision-makers has to still be integrated into a single comprehensive comparison matrix in order to attain the comprehensive weight vector that is required when calculating the fuzzy performance matrix.

Equation (2.14) is used to integrate the four comparison matrices into one comprehensive matrix from which the weight vector can be attained. Here $\tilde{x}_{12}$ is calculated and the remaining scores can be attained by analogy. From the comparison matrices D_1, D_2, D_3 and D_4, the fuzzy values for $\tilde{x}_{12}$ are (0.67, 1.00, 2.00), (0.50, 1.00, 1.50), (1.50, 2.00, 2.50) and (0.50, 1.00, 1.50) respectively. By applying equation 2.14, that is, $a = \min\limits_{k} \{a_k\}$, $b = \frac{1}{K}\sum_{k=1}^{K} b_k$, and $c = \max\limits_{k} \{c_k\}$ the following is attained:

$$a_{12} = \min(0.67, 0.50, 1.50, 0.50) = 0.50$$

$$b_{12} = \frac{1.00+1.00+2.00+1.00}{4} = \frac{5}{4} = 1.25$$

$$c_{12} = \max(2.00, 1.50, 2.50, 1.50) = 2.50 \text{ and therefore } \tilde{x}_{12} = (0.50, 1.25, 2.50).$$

The rest of the fuzzy numbers are attained in the same way. In section 5.5.5 (a) the method that should be used to calculate the fuzzy weight vector was already discussed. The same method is used to calculate the fuzzy weight vector of the comprehensive comparison matrix. The completed matrix with the comprehensive fuzzy weight vector is depicted in the matrix below.

$$\begin{array}{c} \\ \boldsymbol{C_1} \\ \boldsymbol{C_2} \\ \boldsymbol{C_3} \\ \boldsymbol{C_4} \\ \boldsymbol{C_5} \\ \boldsymbol{C_6} \end{array}
\begin{array}{ccccccc} \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} & \boldsymbol{weights\,(PV)} \\
\left[\begin{array}{c} (1,1,1) \\ (0.40, 0.88, 2.00) \\ (0.33, 1.48, 3.50) \\ (0.33, 1.60, 2.50) \\ (0.50, 1.00, 1.50) \\ (0.33, 0.85, 1.50) \end{array}\right.
& \begin{array}{c} (0.50, 1.25, 2.50) \\ (1,1,1) \\ (0.33, 0.97, 2.00) \\ (0.40, 0.75, 2.00) \\ (0.40, 1.54, 3.00) \\ (0.40, 0.75, 2.00) \end{array}
& \begin{array}{c} (0.29, 1.33, 3.00) \\ (0.50, 1.29, 3.00) \\ (1,1,1) \\ (0.29, 0.83, 2.00) \\ (0.29, 0.67, 2.00) \\ (0.50, 0.92, 1.50) \end{array}
& \begin{array}{c} (0.40, 1.00, 3.00) \\ (0.50, 1.50, 2.50) \\ (0.50, 1.50, 3.50) \\ (1,1,1) \\ (1.00, 1.50, 2.00) \\ (0.29, 0.83, 2.00) \end{array}
& \begin{array}{c} (0.67, 1.00, 2.00) \\ (0.33, 1.07, 2.50) \\ (0.50, 2.00, 3.50) \\ (0.50, 0.67, 1.00) \\ (1,1,1) \\ (0.40, 0.88, 2.00) \end{array}
& \begin{array}{c} (0.67, 1.38, 3.00) \\ (0.50, 1.50, 2.50) \\ (0.67, 1.12, 2.00) \\ (0.50, 1.50, 3.50) \\ (0.50, 1.25, 2.50) \\ (1,1,1) \end{array}
& \left.\begin{array}{c} (0.05, 0.17, 0.75) \\ (0.04, 0.18, 0.71) \\ (0.04, 0.20, 0.78) \\ (0.04, 0.15, 0.60) \\ (0.05, 0.17, 0.62) \\ (0.04, 0.13, 0.54) \end{array}\right]
\end{array}$$

The fuzzy weights are:

$$W = (\widetilde{w}_1, \widetilde{w}_2, \widetilde{w}_3, \widetilde{w}_4, \widetilde{w}_5, \widetilde{w}_6)$$

$$=\{(0.05, 0.17, 0.75), (0.04, 0.18, 0.71),$$
$$(0.04, 0.20, 0.78), (0.04, 0.15, 0.60), (0.05, 0.17, 0.62), (0.04, 0.13, 0.54)\}$$

The following Java methods were used in the computation of the fuzzy weights.

```
/**
     * Calculates the weight for a given row given the matrices D1, D2, D3
     * and D4
     * @param xij
     * @return weight value for row xij
     */
    public FuzzyNumber extractWeight(FuzzyNumber[] xij)
    {
        double [] minArray = new double [xij.length];
        double [] meanArray = new double [xij.length];
        double [] maxArray = new double [xij.length];

        // create 3 arrays that temporarily store each component of the fuzzy
           numbers in row Xij
        for(int i=0; i<xij.length;i++)
        {
            minArray[i] = xij[i].getMin();
            meanArray[i] = xij[i].getMean();
            maxArray[i] = xij[i].getMax();
        }

        Task1 task1 = new Task1();
        double weightMin = task1.getMinValue(minArray);
        double weightMean = task1.getAverage(meanArray);
        double weightMax = task1.getMaxValue(maxArray);

        return new FuzzyNumber(weightMin,weightMean,weightMax);
    }
```

e) Rank the performance criteria

After the fuzzy weights have been computed, the six criteria are ranked according to their importance intensity as decided by the four decision-makers collectively. In order to achieve this, each fuzzy weight vector has to be defuzzified into a crisp value. This is attained by applying equation (3.18) to calculate the Best Non-Fuzzy Performance value (*BNP*). The calculations for the first fuzzy weight ($\widetilde{w}_1$) is shown and the rest is determined by analogy.

$$BNP_{ij} = \frac{[(U_{ij} - L_{ij}) + (M_{ij} - L_{ij})]}{3} + L_{ij}$$

$$BNP_{w_1} = \frac{[(U_{w_1} - L_{w_1}) + (M_{w_1} - L_{w_1})]}{3} + L_{w_1}$$

$$= \frac{[(0.75 - 0.05) + (0.17 - 0.05)]}{3} + 0.05$$

$$= \underline{0.32}$$

By analogy, w_2 = 0.31, w_3 = 0.34, w_4 = 0.26, w_5 = 0.28 and w_6 = 0.24. Since the largest crisp (*BNP*) value is w_3 = 0.34, it can be concluded that the decision-makers feel that the most important criterion that is considered when evaluating an academic is C_3 (that is, Research and Innovation). The least important criterion is C_6 (that is, Services rendered and External Engagement) since w_6 has the lowest *BNP* value. The following Java method was used in the calculation of the BNP values.

```
/**
     * Calculate the corresponding BNP value of a fuzzy number
     * @param fuzzyNumber
     * @return BNP value
     */
    public double fuzzyToBNP(FuzzyNumber fuzzyNumber)
    {

        double bnp = ((fuzzyNumber.getMax()-fuzzyNumber.getMin()) +
                     (fuzzyNumber.getMean()-fuzzyNumber.getMin())) /3.0
                     + fuzzyNumber.getMin();
        return bnp;
    }
```

The ranking and weights of all six criteria are indicated in Table 5-21.

Criteria	**Weights**	**BNP**	**Rank**
Administration	$(0.05, 0.17, 0.75)$	0.32	2
Teaching and Supervision	$(0.04, 0.18, 0.71)$	0.31	3
Research and Innovation	$(0.04, 0.20, 0.78)$	0.34	1
Writing and Publication	$(0.04, 0.15, 0.60)$	0.26	5
Consultancy	$(0.05, 0.17, 0.62)$	0.28	4
Services Rendered and Ext. Engagement	$(0.04, 0.13, 0.54)$	0.24	6

Table 5-21: Fuzzy Weights, BNP value and Ranking of the Criteria

f) Compute the Fuzzy Performance Matrix

The fuzzy performance matrix is achieved by combining the fuzzy judgment matrix with the fuzzy weight vector. The fuzzy judgment vector was computed in section 5.5.4 and the fuzzy weight vector was computed in section 5.5.5 (d). The fuzzy judgment matrix and the fuzzy weight vector have to therefore be synthesized during the multiplication process. This is done by multiplying each criterion weight $\widetilde{w}_j$ to its corresponding criterion of the fuzzy judgment matrix as indicated below.

$$H = \begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} \\ \boldsymbol{A_1} & \widetilde{w}_1\tilde{a}_{11} & \widetilde{w}_2\tilde{a}_{12} & \widetilde{w}_3\tilde{a}_{13} & \widetilde{w}_4\tilde{a}_{14} & \widetilde{w}_5\tilde{a}_{15} & \widetilde{w}_6\tilde{a}_{16} \\ \boldsymbol{A_2} & \widetilde{w}_1\tilde{a}_{21} & \widetilde{w}_2\tilde{a}_{22} & \widetilde{w}_3\tilde{a}_{23} & \widetilde{w}_4\tilde{a}_{24} & \widetilde{w}_5\tilde{a}_{25} & \widetilde{w}_6\tilde{a}_{26} \\ \boldsymbol{A_3} & \widetilde{w}_1\tilde{a}_{31} & \widetilde{w}_2\tilde{a}_{32} & \widetilde{w}_3\tilde{a}_{33} & \widetilde{w}_4\tilde{a}_{34} & \widetilde{w}_5\tilde{a}_{35} & \widetilde{w}_6\tilde{a}_{36} \end{bmatrix}$$

$$= \begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} \\ \boldsymbol{A_1} & (0.32, 0.59, 1.11) & (0.22, 0.58, 1.44) & (0.17, 0.53, 1.56) & (0.23, 0.58, 1.60) & (0.21, 0.60, 2.06) & (0.22, 0.61, 1.61) \\ \boldsymbol{A_2} & (0.26, 0.51, 1.11) & (0.25, 0.59, 1.46) & (0.24, 0.61, 1.56) & (0.28, 0.68, 1.60) & (0.07, 0.38, 1.61) & (0.09, 0.46, 1.54) \\ \boldsymbol{A_3} & (0.32, 0.63, 1.11) & (0.21, 0.57, 1.44) & (0.22, 0.59, 1.61) & (0.09, 0.45, 1.44) & (0.21, 0.71, 2.06) & (0.27, 0.65, 1.61) \\ & \otimes & \otimes & \otimes & \otimes & \otimes & \otimes \\ Weights & (0.05, 0.17, 0.75) & (0.04, 0.18, 0.71) & (0.04, 0.20, 0.78) & (0.04, 0.15, 0.60) & (0.05, 0.17, 0.62) & (0.04, 0.13, 0.54) \end{bmatrix}$$

The multiplication of the first criteria C_1 with the respective fuzzy weight $(\widetilde{w}_1)$ are performed as follows:

$$\tilde{h}_{11} = (0.32, 0.59, 1.11) \otimes (0.05, 0.17, 0.75) = (0.32 \otimes 0.05,\ 0.59 \otimes 0.17,\ 1.11 \otimes 0.75)$$

$$= (0.02, 0.10, 0.83)$$

$$\tilde{h}_{21} = (0.26, 0.53, 1.11) \otimes (0.05, 0.17, 0.75) = (0.26 \otimes 0.05,\ 0.53 \otimes 0.17,\ 1.11 \otimes 0.75)$$

$$= (0.01, 0.09, 0.83)$$

$$\tilde{h}_{31} = (0.32, 0.63, 1.11) \otimes (0.05, 0.17, 0.75) = (0.32 \otimes 0.05,\ 0.63 \otimes 0.17,\ 1.11 \otimes 0.75)$$

$$= (0.02, 0.11, 0.83)$$

The rest is deduced by analogy and the complete fuzzy performance matrix is:

$$\begin{bmatrix} & \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} \\ \boldsymbol{A_1} & (0.02, 0.10, 0.83) & (0.01, 0.10, 1.02) & (0.01, 0.11, 1.22) & (0.01, 0.09, 0.96) & (0.01, 0.10, 1.28) & (0.01, 0.08, 0.87) \\ \boldsymbol{A_2} & (0.01, 0.09, 0.83) & (0.01, 0.11, 1.04) & (0.01, 0.12, 1.22) & (0.01, 0.10, 0.96) & (0.00, 0.06, 1.00) & (0.00, 0.06, 0.83) \\ \boldsymbol{A_3} & (0.02, 0.11, 0.83) & (0.01, 0.10, 1.02) & (0.01, 0.12, 1.26) & (0.00, 0.07, 0.86) & (0.01, 0.12, 1.28) & (0.01, 0.08, 0.87) \end{bmatrix}$$

The fuzzy performance matrix was attained using the following Java methods.

```
/**
     * Convert a Fuzzy Judgement matrix to a Fuzzy Performance Matrix by
     * multiplying each column with the corresponding
     * fuzzy weight vector element. Once this method is called,
     * alternatives[] will now represent the Fuzzy Performance Matrix
     * @param alternatives the fuzzy judgement matrix
     * @param weights the fuzzy weight vector
     */
    public void convertToFuzzyPerformanceMatrix(Alternative[] alternatives,
                FuzzyNumber[] weights)
    {

        double min,mean,max=mean=min=0;
        DecimalFormat df = new DecimalFormat("#.00");
        String format;

        // rows
        for(int i=0; i<alternatives.length; i++)
        {
            // columns
            for(int j=0; j<alternatives[0].getCriteriaArray().length; j++)
            {
                FuzzyNumber Cij =
                alternatives[i].getCriteriaArray()[j].getFuzzyNumber();

                // multiplication is done on values that are rounded to two
                   decimal place
                try {
                    min = (Double)df.parse(df.format(Cij.getMin()))*
(Double)df.parse(df.format(weights[j].getMin()));
                    mean = (Double)df.parse(df.format(Cij.getMean()))*
(Double)df.parse(df.format(weights[j].getMean()));
                    max = (Double)df.parse(df.format(Cij.getMax()))*
(Double)df.parse(df.format(weights[j].getMax()));
                } catch (ParseException e) {
                    e.printStackTrace();
                }


                // replace the value at position Cij with the product of Cij
                   and it's corresponding weight
                alternatives[i].getCriteriaArray()[j].setFuzzyNumber(new
                FuzzyNumber(min,mean,max));
            }
        }
    }
```

5.6 Using the Fuzzy Performance Matrix to meet the objectives

The purpose of section 5.5.5 was to compute the fuzzy performance matrix. This section will demonstrate how the fuzzy performance matrix can be used to meet the objectives stated in section 5.4. In order to meet the objectives, the fuzzy performance matrix has to be defuzzified by using equation 3.18 and analysed. The defuzzification for the first fuzzy value is shown and the rest is determined by analogy. The Java method to compute the BNP value is shown in section (e).

$$BNP_{ij} = \frac{[(U_{ij} - L_{ij}) + (M_{ij} - L_{ij})]}{3} + L_{ij}$$

$$BNP_{11} = \frac{[(U_{11} - L_{11}) + (M_{11} - L_{11})]}{3} + L_{11}$$

$$= \frac{[(0.83 - 0.02) + (0.10 - 0.02)]}{3} + 0.02$$

$$= \underline{0.32}$$

The fuzzy performance matrix as well as Table 5-22 is shown with all the BNP values for the matrix.

$$\begin{array}{c} \\ \boldsymbol{A_1} \\ \boldsymbol{A_2} \\ \boldsymbol{A_3} \end{array} \begin{array}{cccccc} \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} \end{array}$$

$$\begin{array}{c} \boldsymbol{A_1} \\ \boldsymbol{A_2} \\ \boldsymbol{A_3} \end{array} \begin{bmatrix} (0.02, 0.10, 0.83) & (0.01, 0.10, 1.02) & (0.01, 0.11, 1.22) & (0.01, 0.09, 0.96) & (0.01, 0.10, 1.28) & (0.01, 0.08, 0.87) \\ (0.01, 0.09, 0.83) & (0.01, 0.11, 1.04) & (0.01, 0.12, 1.22) & (0.01, 0.10, 0.96) & (0.00, 0.06, 1.00) & (0.00, 0.06, 0.83) \\ (0.02, 0.11, 0.83) & (0.01, 0.10, 1.02) & (0.01, 0.12, 1.26) & (0.00, 0.07, 0.86) & (0.01, 0.12, 1.28) & (0.01, 0.08, 0.87) \end{bmatrix}$$

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.32	0.38	0.44	0.35	0.46	0.32
A_2	0.31	0.38	0.45	0.36	0.36	0.30
A_3	0.32	0.38	0.46	0.31	0.47	0.32

Table 5-22: BNP values for the Fuzzy Performance matrix

A discussion follows on how the objectives indicated in section 5.4 can be met:

Objective 1: Determine the overall performance of an academic.

The following code segment determines the overall performance of an academic.

```
/**
     * Return comments about each alternative's performance, based on the
     * average of each criteria in the BNP matrix
     * @param bnpMatrix
     * @param avgCriteria
     * @return
     */
    public String analysisOfBnpValues(double [][]bnpMatrix, double []
           avgCriteria)
    {
        String comments ="";
        int score=0;

        // used for rounding to two decimal places
        DecimalFormat df = new DecimalFormat("#.00");
        double criteriaValue =0;

        // rows correspond to each alternative
        for(int i=0; i<bnpMatrix.length; i++)
        {
            comments +="Alternative "+(i+1)+":\t";
            score = 0;

             // columns correspond to each criteria
            for(int j=0; j<bnpMatrix[0].length; j++)
            {
                try {
                    criteriaValue =
                    (Double)df.parse(df.format(bnpMatrix[i][j]));
                } catch (ParseException e) {
                    e.printStackTrace();
                }

                // count number of criteria, alternative i has a value
                   greater than the average
                if(criteriaValue >= avgCriteria[j])
                {
                    score++;
                }
            }

            if(score<=2)
            {
                comments += "Weak performer"+"\n";
            }
            else if(score==3)
            {
                comments += "Average performer"+"\n";
            }
```

```
            else if(score==4)
            {
                comments += "Good performer"+"\n";
            }
            else if(score>=5)
            {
                comments += "Very good performer"+"\n";
            }
        }

        return comments;
    }
```

Table 5-22 can provide a general idea about an academic's overall performance by looking at the overall BNP values in all performance areas. Since the BNP values for academic A_1 in five performance areas is fairly high, one can conclude that this academic generally performs well. However, academic A_1 need to improve in Research and Innovation (C_3) since the BNP value for this criterion is the lowest when compared to the other academics. Likewise, one can conclude that academic A_2 is an average performer since most of the BNP values are below the average score for each criteria. Improvement is however required in Administration (C_1), Consultancy (C_5) and Services Rendered and External Engagement (C_6) since this academic has attained the lowest BNP values for these three criteria. Academic A_3 has the largest BNP values in five of the six performance area. One can therefore conclude that academic A_3 is a high performer. However, this academic needs to improve in Writing and Publication (C_4).

Objective 2: To determine the strongest and weakest performance areas of an academic.

The following code segment computes the weakest and strongest performance areas of an academic.

```
/**
     * Display which alternative scored the highest and lowest in for the
     * given criteria
     * @param bnpMatrix
     * @param criteria using values between [1-6]
     */
    public void displayStrongestAndWeakest(double [][]bnpMatrix, int
                criteria)
    {

        double min = bnpMatrix[0][criteria-1];
        double max = bnpMatrix[0][criteria-1];
```

```java
        int minAlternative, maxAlternative = minAlternative = 0;
        boolean isAllEqual =true;

        // rows correspond to each alternative
        for(int i=1; i<bnpMatrix.length; i++)
        {
            if(bnpMatrix[i][criteria-1] < min)
            {
                min =  bnpMatrix[i][criteria-1];
                minAlternative = i;
            }

            if(bnpMatrix[i][criteria-1] > max)
            {
                max =  bnpMatrix[i][criteria-1];
                maxAlternative = i;
            }

            // comparing raw values
            if(bnpMatrix[i-1][criteria-1] != bnpMatrix[i][criteria-1])
            {
                isAllEqual = false;
            }
        }

        if(isAllEqual)
        {
            System.out.println("All alternatives have performed equally");
        }
        else
        {
            System.out.println("The weakest alternative in criteria
            "+criteria+" is: A"+(minAlternative+1));
            System.out.println("The strongest alternative in criteria
            "+criteria+" is: A"+(maxAlternative+1));

            // delegation of duties
            System.out.println("Therefore, alternative A"+(maxAlternative+1)
            +" should help alternative A"+(minAlternative+1));
        }
    }
```

In order to determine the weakest and strongest performance areas, the BNP values of each column of Table 5-22 are analysed. The higher values will indicate the strengths while the lower values will indicate the weaknesses of an academic. Academic A_1 for example has the lowest BNP value (0.44) for Research and Innovation (C_3) but has fairly large BNP values for Administration (C_1), Teaching and Supervision (C_2) as well as Services Rendered and External Engagement (C_6). This means that academic A_1 performs poorly in Research and Administration (when compared to the other academics) but his strengths are in Administration, Teaching and

Supervision as well as Services Rendered and External Engagement. Such information is important when management wants to improve all performance areas of an academic. Academic A_3 with the highest BNP value (0.46) for Research and Innovation may therefore be asked to assist academic A_1 who is lacking in this area of performance.

Objective 3: To delegate duties to academics according to their strengths.

The Java methods to achieve this is contained in objective 2.

The Head of a Department may for example have difficulty in selecting an academic to take charge of an important area such as Research. However, by using Table 5-22, academic A_3 has the highest BNP value (0.46) for Research and Innovation (C_3). This academic can therefore be chosen to head the Research and Innovation area of the department.

Objective 4: Select a delegation from all academic departments

The Java methods to achieve this is contained in objective 2.

Upper management for example may require a delegation to be selected from all departments to attend a conference on Writing and Publication (C_4). The best performing academic can be selected by determining the largest BNP value for Writing and Publication from each academic department. The IT department will therefore select academic A_2 since this academic has the largest BNP value (0.36) for Writing and Publication when compared to the other academics in the department.

Objective 5: Show the overall performance of all academics in all key areas

For this objective, the quantitative data is presented. Refer to Annexure K for Java coding that achieves this.

Such information may be required by the Dean when compiling the annual report. The information required is more quantitative (tangible) in nature. The Head of Department may request the following information from the computer system which will have Table 5-1 data stored for each academic in a department. Some of the information required is as follows: number of publications, number of conferences attended, projects completed and the number of Masters and PhD students that have graduated in a department.

Objective 6: Rank academics in terms of all six key performance areas

Such information is required for promotion purposes or when the best performing academics are required to be selected for incentives and awards. Ranking and selecting academics in a fair manner is therefore very important. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for fuzzy data is used for ranking and selection. This technique is discussed in detail in section 2.7. In the demonstration, the three academics (A_1, A_2, A_3) are ranked using the fuzzy TOPSIS approach.

Since the fuzzy performance matrix has been attained, it means that the first five steps of the fuzzy TOPSIS method have been accomplished. In the sixth step, the fuzzy positive ideal solution (FPIS) called (A^*) and the fuzzy ideal negative solution (FNIS) called (A^-) are computed by applying equations 2.19 and 2.20 which are:

$$A^* = (\tilde{v}_1^*, \ldots, \tilde{v}_n^*) \text{ where } \tilde{v}_j^* = \max_i\{v_{ij3}\},\ i = 1,2,\ldots,m;\ j = 1,2,\ldots,n$$

$$A^- = (\tilde{v}_1, \ldots, \tilde{v}_n) \text{ where } \tilde{v}_j^- = \min_i\{v_{ij1}\},\ i = 1,2,\ldots,m;\ j = 1,2,\ldots,n$$

After applying these equations, the (FPIS) and (FNIS) are attained as indicated in the matrix below.

	$\boldsymbol{C_1}$	$\boldsymbol{C_2}$	$\boldsymbol{C_3}$	$\boldsymbol{C_4}$	$\boldsymbol{C_5}$	$\boldsymbol{C_6}$
$\boldsymbol{A_1}$	(0.02, 0.10, 0.83)	(0.01, 0.10, 1.02)	(0.01, 0.11, 1.22)	(0.01, 0.09, 0.96)	(0.01, 0.10,1.28)	(0.01, 0.08, 0.87)
$\boldsymbol{A_2}$	(0.01, 0.09, 0.83)	(0.01, 0.11, 1.04)	(0.01, 0.12, 1.22)	(0.01, 0.10, 0.96)	(0.00, 0.06, 1.00)	(0.00, 0.06, 0.83)
$\boldsymbol{A_3}$	(0.02, 0.11, 0.83)	(0.01, 0.10, 1.02)	(0.01, 0.12, 1.26)	(0.00, 0.07, 0.86)	(0.01, 0.12, 1.28)	(0.01, 0.08, 0.87)
$\boldsymbol{FNIS}\ (\boldsymbol{A^-})$	(0.01, 0.01, 0.01)	(0.01, 0.01, 0.01)	(0.01, 0.01, 0.01)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)	(0.00, 0.00, 0.00)
$\boldsymbol{FPIS}\ (\boldsymbol{A^*})$	(0.83, 0.83, 0.83)	(1.04, 1.04, 1.04)	(1.26, 1.26, 1.26)	(0.96, 0.96, 0.96)	(1.28, 1.28, 1.28)	(0.87, 0.87, 0.87)

The next step involves computing the distance of each alternative from the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS) by applying equation 2.12. For example, for alternative A_1 and criterion C_1, the distance is calculated using the distance formula as follows:

$$d_v(A_1, A^*) = \sqrt{\frac{1}{3}([(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2])}$$

$$= \sqrt{\frac{1}{3}([(0.02-0.01)^2 + (0.10-0.01)^2 + (0.83-0.01)^2])}$$

$$= \underline{0.48}$$

$$d_v(A_1, A^-) = \sqrt{\frac{1}{3}([(a_1-b_1)^2 + (a_2-b_2)^2 + (a_3-b_3)^2])}$$

$$= \sqrt{\frac{1}{3}([(0.02-0.83)^2 + (0.10-0.83)^2 + (0.83-0.83)^2])}$$

$$= \underline{0.63}$$

The rest of the calculations are obtained in a similar manner and all the results are indicated in Table 5-23.

Criteria	d^-			d^*		
	A_1	A_2	A_3	A_1	A_2	A_3
C_1	0.48	0.48	0.48	0.63	0.64	0.63
C_2	0.60	0.60	0.60	0.77	0.81	0.81
C_3	0.74	0.74	0.76	1.04	1.03	1.03
C_4	0.56	0.56	0.45	0.74	0.74	0.76
C_5	0.74	0.41	0.74	1.00	1.07	0.99
C_6	0.50	0.48	0.50	0.67	0.69	0.67
d_i^-	3.62	3.27	3.53	-	-	-
d_i^*	-	-	-	4.85	4.98	4.89

Table 5-23: Distance $\boldsymbol{d_v(A_i, A^*)}$ and $\boldsymbol{d_v(A_i, A^-)}$ for alternatives

The distance d_i^* and d_i^- are then calculated using equations 2.21 and 2.22, that is, the equations $d_i^* = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^*)$, $i = 1, 2, \dots, m$ and $d_i^- = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^-)$, $i = 1, 2, \dots, m$ respectively. In other words, these equations determine the sum of each column of Table 5-23. The closeness coefficient is calculated using equation (2.23), that is, $CC_i = \frac{d_i^-}{(d_i^- + d_i^+)}$ $i = 1, 2, \dots, m$. For example, for the alternative A_1, the closeness coefficient is: $CC_i = \frac{d_i^-}{(d_i^- + d_i^+)} = \frac{4.85}{(4.85+3.62)} = 0.57$. The remaining calculations for d_i^*, d_i^- and CC_i are shown in Table 5-24.

	A_1	A_2	A_3
d_i^-	3.62	3.27	3.53
d_i^*	4.85	4.98	4.89
CC_i	0.57	0.60	0.58

Table 5-24: Closeness coefficient ($\boldsymbol{CC_i}$) for the three alternatives

The last step involves ranking the alternatives from Table 5-22. The largest CC_i is ranked number one indicating that it is the optimal solution. Therefore academic A_2 is the best alternative, followed by A_3 and then A_1. The desired satisfaction degree of fuzzy TOPSIS is 1. Table 5-25 shows the gap degree of each academic, that is, how far from the desired fuzzy TOPSIS value (which is 1) each academic has performed. This information is necessary so that academic will know by how much they can improve. This is done in conjunction with analysing the BNP values indicated in Table 5-22. The gap degree is calculated using the following formula:

$$CC_i^+ = \frac{d_i^+}{\left(d_i^+ + d_i^-\right)}$$

The gap degree for A_1 is calculated and the other values can be deduced by analogy.

$$CC_i^+ = \frac{3.62}{(3.62+4.85)}$$

$$= \underline{0.43}$$

	d_i^*	d_i^-	Gaps degree of CC_i^+	Satisfaction degree of CC_i^-
A_1	4.85	3.62	0.43	0.57
A_2	4.98	3.27	0.40	0.60
A_3	4.89	3.53	0.42	0.58

Table 5-25: Closeness coefficients to aspired level among different academics

The program segment that ranks academic staff using the Fuzzy TOPSIS method is shown below.

```
public class Task7 {

    /**
     * Calculate the FNIS- vector
     * @param alternatives
     * @return
     */
    public FuzzyNumber[] getFNISAneg(Alternative[] alternatives)
    {
        double min =0;
        FuzzyNumber [] fnisNeg = new
        FuzzyNumber[alternatives[0].getCriteriaArray().length];
```

```
        // columns
        for(int j=0; j<alternatives[0].getCriteriaArray().length; j++)
        {
            min =
            alternatives[0].getCriteriaArray()[j].getFuzzyNumber().getMin();
            // rows
            for(int i=0; i<alternatives.length; i++)
            {
                // find the lowest min value from all alternatives

if(alternatives[i].getCriteriaArray()[j].getFuzzyNumber().getMin() < min)
                {
                    min =
alternatives[i].getCriteriaArray()[j].getFuzzyNumber().getMin();
                }
            }
            // repeat the lowest min
            fnisNeg[j] = new FuzzyNumber(min,min,min);
        }
        return fnisNeg;
    }

    /**
     * Calculate the FNIS* vector
     * @param alternatives
     * @return
     */
    public FuzzyNumber[] getFNISApos(Alternative[] alternatives)
    {
        double max =0;
        FuzzyNumber [] fnisPos = new
FuzzyNumber[alternatives[0].getCriteriaArray().length];

        // columns
        for(int j=0; j<alternatives[0].getCriteriaArray().length; j++)
        {
            max =
alternatives[0].getCriteriaArray()[j].getFuzzyNumber().getMax();
            // rows
            for(int i=0; i<alternatives.length; i++)
            {
                // find the highest max value from all alternatives

if(alternatives[i].getCriteriaArray()[j].getFuzzyNumber().getMax() > max)
                {
                    max =
alternatives[i].getCriteriaArray()[j].getFuzzyNumber().getMax();
                }
            }
            // repeat the highest max
            fnisPos[j] = new FuzzyNumber(max,max,max);
        }
        return fnisPos;
    }


    /**
```

```
     * Calculate the distace of an alternative for a given criteria from the
     * fuzzy ideal
     * @param alternative Fuzzynumber for an alternative for a given criteria
     * @param a the FNISA- or FNISA* of a given criteria
     * @return
     */
    public double calculateDv(FuzzyNumber alternative, FuzzyNumber a)
    {

        double dv =0;

        dv = Math.sqrt((1/3.0)*( Math.pow(alternative.getMin()-a.getMin(),2)
+
                                 Math.pow(alternative.getMean()-
a.getMean(),2) +
                                 Math.pow(alternative.getMax()-a.getMax(),2)
));

        return dv;
    }

    /**
     * Calculate the d* vector using the a- values
     * @param alternatives
     * @param fnisaX
     * @return
     */
    public double[][] calculateDx(Alternative[] alternatives, FuzzyNumber[]
fnisaX)
    {
        // the dPos values for all alternatives for each criteria
        double dPos[][]= new
double[alternatives.length][alternatives[0].getCriteriaArray().length];

        // rows
        for(int i=0; i<alternatives.length; i++)
        {
            // columns to calculate the d* values for each criteria
            for(int j=0; j<alternatives[0].getCriteriaArray().length; j++)
            {
                dPos[i][j] =
calculateDv(alternatives[i].getCriteriaArray()[j].getFuzzyNumber(),fnisaX[j])
;
            }
        }
        return dPos;
    }


    /**
     * Sums the columns of the dX matrix
     * @param dX
     * @return
     */
    public double [] calcualteDi(double [][] dX)
    {
        double sum;
```

```
        double diSum[] = new double[dX.length];

        // rows
        for(int i=0; i<dX.length; i++)
        {
            sum  = 0;
            // columns to calculate the d* values for each criteria
            for(int j=0; j<dX[0].length; j++)
            {
                sum+= dX[i][j];
            }
            diSum[i] = sum;
        }
        return diSum;
    }

    /**
     * Calculates the Closeness Coefficient CCI for the alternatives
     * @param dNeg vector of the di- values
     * @param dPos vector of the di+ values
     * @return
     */
    public double[] calculateCCi(double []dNeg, double []dPos)
    {
        double cciValues[] = new double[dNeg.length];

        for(int i=0; i< dNeg.length; i++)
        {
            cciValues[i] = (dPos[i]) /(dNeg[i]+dPos[i]);
        }
        return cciValues;
    }
```

Objective 7: Rank all departments in a faculty

The Java method to achieve this is shown below.

```
    /**
     * Calculates the average CCI value
     * @param cciValues
     * @return
     */
    public double calculateAvgCCI(double[] cciValues)
    {
        DecimalFormat df = new DecimalFormat("#.00");
        return
Double.valueOf(df.format(DoubleStream.of(cciValues).sum()/cciValues.length));
    }
```

Such information may be required when incentives are required to be awarded to the best performing departments in a Faculty. Information of this nature is also necessary when the high performing departments are required to assist those (departments) that require improvement in their productivity. In order to achieve this, the collective performance of an academic has to be determined. The closeness coefficient values (CC_i^-) in Table 5-25 indicate the satisfaction degree of each academic. Since all academic staff in the different departments are evaluated against the same criteria, the average score of all the closeness coefficient of a department can be used to determine its collective performance. The average performance of an academic department is calculated as follows: average $= \frac{\sum_{i=1}^{m} CC_i^-}{m} \quad i = 1, 2, \ldots, m$ (where m represents the number of academics in a department). If the IT department has only the three academics used in the demonstration then the average score $= \frac{\sum_{i=1}^{m} CC_i^-}{m} = \frac{CC_1^- + CC_2^- + CC_3^-}{3} = \frac{0.57+0.60+0.58}{3} = 0.58$. Each department score can therefore be computed in a similar manner and all scores can be ranked to determine the best and worst performing departments.

Objective 8: Comparing the performance of an academic against the average score of the department (that the academic belongs to).

The following method was used to compare the score of each academic against the average score the department.

```
/**
     * Returns the comparison of the CCI scores for each alternative to the
     * department average CCI score
     * @param cciValues the CCI scores of all alternatives
     * @param avgCCI the department's average CCI score
     */
    public String displayAlternativeComparison(double[] cciValues, double
            avgCCI) {

        String str ="";
        for(int i=0; i<cciValues.length; i++)
        {
            if(cciValues[i] < avgCCI)
            {
                str+="Alternative "+(i+1)+" has scored below the average\n";
            }
            else if(cciValues[i] > avgCCI)
            {
                str+="Alternative "+(i+1)+" has scored above the average\n";
            }
            else
```

```
            {
                str+="Alternative "+(i+1)+" has a score equal to the
                average\n";
            }
            str+= "\n";
        }

        return str;
    }
```

The performance scores of the three academics as well as the average performance score of the IT department (assuming that only three academics belong to the IT department) have already been calculated in objectives 6 and 7 respectively. These scores are indicated in Table 5-26.

$\boldsymbol{A_i}$	**Satisfaction degree of $\boldsymbol{CC_i^-}$**	**Average score of the IT dept.**
$\boldsymbol{A_1}$	0.57	0.58
$\boldsymbol{A_2}$	0.60	0.58
$\boldsymbol{A_3}$	0.58	0.58

Table 5-26: Comparison of each academic to the average score of the department

From Table 5-26, it can be deduced that A_1 has performed slightly below the average score of the department, A_2 has performed above average while the performance of A_3 is average.

5.7 Conclusion

Chapter 4 provided an overview of the most important features of the classical object-oriented approach that are generally used when implementing a solution. This chapter demonstrated how the model was programmed into an object-oriented programming language called Java. It also demonstrated the functionality of the newly developed system by determining whether the objectives indicated in section 5.4 have been met. Four panel members form the Centre for Quality Promotion and Assurance (CQPA) were used to evaluate three academics from the IS departments. As required by upper management and CQPA, five quantitative (tangible) and eighteen qualitative (intangible) sub-criteria as well as six main criteria were used in the evaluation. The results of the demonstration indicated that all objectives indicated in section 5.4

have been met. However, it is important to evaluate this new system in order to determine its efficiency and reliability. Evaluating the artifact is the next activity of the Design Science Research Methodology (DSRM). This activity is discussed in Chapter 6.

Chapter 6

EVALUATING AND TESTING THE ARTIFACT

6.1 Introduction

Evaluation of the artifact is the 5^{th} activity of the Design Science Research Methodology (DSRM). This activity involves observing and measuring how well the solution supports the problem. Many evaluation techniques can be used for this activity. This includes developing instruments to evaluate the usefulness (or utility) of the artifact, comparing the objectives to the actual observed results, quantitative performance measures and client feedback. All four of these techniques were used in the evaluation of the newly developed fuzzy-based model.

A design science (DS) approach for developing research instruments to evaluate the utility of the artifact was firstly adopted. A quantitative assessment involving conventional evaluation methods was then compared with the newly developed system. A usability study involving client feedback is the last evaluation technique that was used to ascertain the opinions of academic staff regarding the new system in terms of its usefulness and functionality. The evaluation of the newly developed artifact took the following form:

- A design science (DS) approach for evaluating the utility of the artifact was conducted using IS research instruments;
- The newly developed fuzzy-based model was compared with the conventional AHP method in terms of the criteria weights;
- Presently, the Durban University of Technology (DUT) uses a manual weighting system to evaluate academic staff. This manual weighting system was compared to the newly developed fuzzy-based model. The purpose was to determine how the evaluation results of the new system compare with the results of the conventional manual weighting system; and
- A demonstration was presented to members of the Center for Quality Promotion and Assurance (CQPA) as well as the staff of the IT department at the Durban University of Technology. Their opinions regarding the functionality and usefulness of the new system were elicited through a questionnaire.

6.2 A Design Science approach to evaluation of the artifact

A design science (DS) approach should not only focus on developing IS applications but the emphasis should also be on developing research instruments that can be used to evaluate the usefulness (or utility) of the artifact. Previously, the emphasis on designing IS instruments only focused on how well the instrument captures the construct of the artifact (that is, its validity and reliability). However, the focus should also be on the practical utility of the instrument in order to determine the usefulness of the artifact (Baskerville *et al.*, 2009). By placing emphasis on the practical utility of the instruments, the results of the artifact can be readily corroborated and the quality and usefulness of the findings is improved. This section therefore uses a design science approach to instrument development in order to evaluate amongst other things, the utility of the artifact. Figure 6-1 depicts an iterative approach to the development of research instruments using multiple research methods in order to design and evaluate the instruments. The purpose of this section is to therefore demonstrate how most of the methods presented in Figure 6-1 have been adopted in this study.

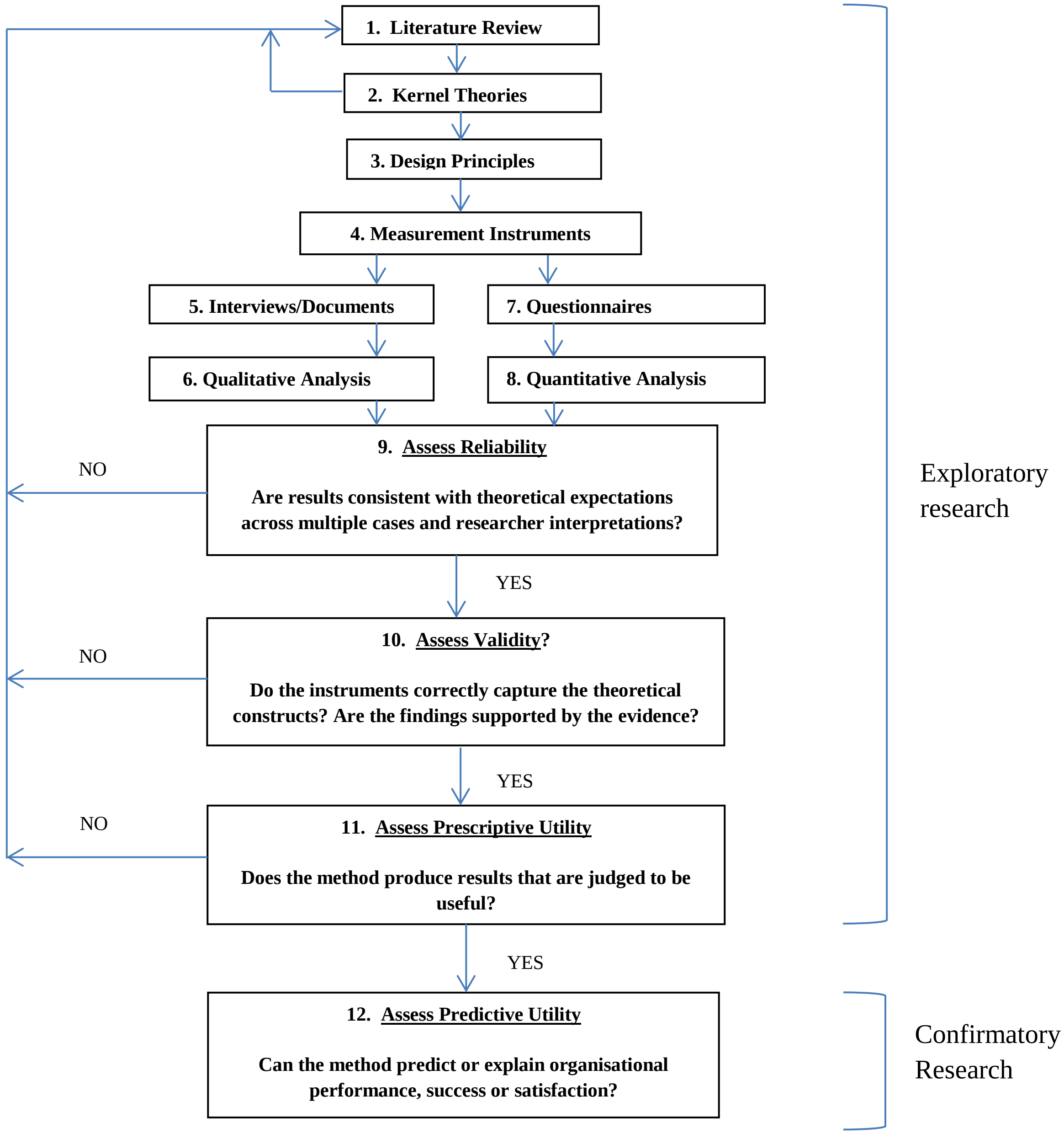


Figure 6-1: DSR approach to developing instruments (Hevner *et al.*, 2004)

The design science research approach to developing instruments would ensure that the process is grounded in theory in order to establish its reliability and utility. The outputs of the iterative approach (Figure 6-1) should also be easily corroborated by experts in IS design. This approach is in contrast to the traditional approach where a short pilot test is applied and a lengthy statistical process undertaken (McLaren *et al.*, 2011). The approach will evaluate the descriptive and prescriptive properties of the research instrument, which is absent when the traditional approach is adopted. A design science approach to developing an instrument involves determining 'how well the research instrument works' rather than only determining its reliability and validity (Hevner *et al*., 2004). To determine how well an instrument works, many research methods are employed. These methods involve examining the evaluation results of the instrument and corroborating it with the quantitative outputs attained from field experiments and case studies (Baskerville *et al*., 2009). Figure 6-1 emphasizes many aspects of instrument development from data collection and analysis, theory building and verifying emerging theories in the real world. The iterative process ensures that methods and theories are continually evaluated and refined until the findings are consistent with the gathered evidence. The end result is a confirmatory research technique that can be used to predict the utility of the research instrument when evaluating the usefulness of the artifact. The design science approach to developing and designing research instruments was used to evaluate the utility of the productivity estimation model (Chapter 3) and its implementation (Chapter 5).

The design science approach requires the following properties (Hevner *et al*., 2004):

- It should be theoretically grounded: Convincing theoretical arguments must be justified when measuring the outputs. In this study, the artifact was developed based on the fuzzy AHP model using Zadeh's (1994) fuzzy logic and fuzzy set theory approach. This approach resulted in the development of the fuzzy performance matrix (the output) in order to meet the objectives mentioned in section 5.4. The results were defuzzified into absolute values using the best non-fuzzy performance (BNP) value. The results can therefore be deemed as being reliable and credible since it was developed using a theoretical approach. Further, a theoretical approach was used to ascertain the scoring patterns (inputs) of the evaluators. The Consistency Ratio (CR) was used in the fuzzy-based system and the intra class correlation index was used in the conventional weighting system to determine the scoring patterns of the evaluators (Ramik & Korviny, 2013). The theoretical approach in determining the scoring patterns (inputs) resulted in outputs that were reliable and acceptable. The calculation of the CR is discussed in section 3.3 (step 8) and the calculation of the intra class correlation index is discussed in sections 6.4.3 and 6.5.2;

- Readily corroborated: This activity ensures that the measurement outputs are reliable and valid by corroborating the results with other evidence (as indicated in Figure 6-1). In this study, corroboration was done using experts from DUT in various areas such as CQPA, IS, Computer Science, Computer Programming, Database Design and Networks. Their responses were elicited through interviews and questionnaires; and
- Actionable: As indicated in Figure 6-1, the measuring approach must have descriptive and prescriptive utility. This means that the methods must produce results that are judged to be useful. In this study, the descriptive and prescriptive properties were used to explain or predict whether the newly developed system is able to improve productivity estimation of academic departments. The research instruments should also be able to predict whether the newly developed system can fit in the organisation and whether any corrective measure (such as the improvement of IS capabilities) may be required so that the newly developed system can be deemed useful. In order to determine whether the new system can fit in the university, it must firstly be accepted by evaluators, academic staff and management. The results of the surveys on evaluators (section 6.5.3) and academic staff (Figures 7-7 and 7-8) predicted that a new computerised fuzzy-based system is necessary in order to improve productivity estimation at DUT. Further, a usability study was conducted on academic staff from the IT department in order to elicit their views on the newly developed system. This was done through a questionnaire (Refer to Annexure B for the questionnaire). The results indicated that academic staff were satisfied with the performance of the system in terms of user interface and the capabilities of the system. The researcher also elicited the views of IS experts at DUT to determine whether any corrective measures were required in the university environment to accommodate the new system. The most important views revolved around strategies that may be necessary for CQPA and academic staff to adapt from a culture of manual evaluation to a culture of a computerised evaluation system.

Using the flowchart (Figure 6-1), the process of evaluating the artifact using instruments are described as follows: A design science approach was adopted to develop the model (Chapter 3). The researcher consulted many scholarly articles on fuzzy logic and fuzzy set theory (such as articles by Zadeh (1994), Lee (1999), Lee (2010) and Rana (2012)) that formed the backbone of the fuzzy-based system. Kernel theories from mathematics (based on fuzzy logic and fuzzy set theory by Zadeh (1994)), computer science and behavioral science were used in the design of the system. The kernel theories used in the development included fuzzy logic and fuzzy set theory that was discussed in sections 2.6, 3.1 and 3.2. The researcher therefore felt that it was necessary to adopt a design science approach which entails developing instruments that can be used in the evaluation of usefulness of the artifact.

As shown in Figure 6-1, research instrument design for IS evaluation required several iterations that satisfied the requirements for reliability, validity and prescriptive utility. During the various development stages of the fuzzy-based system, the outputs of the evaluation instruments were compared to the expected results of fuzzy-based systems contained in scholarly literature. The comparison of outputs from the research instruments with the expected outputs ensured that the research instruments were well-grounded in theory. This process was continuously carried out throughout the development of the artifact. The researcher also compared the output of the model at various stages based on the results of the research questionnaires (that is, the expectations and requirements of academic staff as indicated in Figures 7-7 and 7-8). The instrument that was developed is a questionnaire that contains both structured and semi-structured questions. The purpose of this questionnaire was to determine whether the outputs of the model are in keeping with the outputs that were expected from academic staff and CQPA. This questionnaire is contained in Annexure A. The researcher also developed a semi-structured research instrument (questionnaire) to elicit the views of CQPA to compare the results of the conventional weighting system with the results of the new fuzzy-based model. This questionnaire is contained in section 6.5.3. A usability study was also conducted to elicit the view of respondents on whether the developed system was able to meet their (the respondent's) expectations. The questionnaire for the usability study is contained in Annexure B and the results of the study is discussed in section 6.6

This section demonstrated how a design science approach can be used not only for the design of an IS application but also the design of research instruments that can evaluate the utility of the IS application. Besides evaluating the utility of the application, it is also important to evaluate its efficiency and reliability. The rest of this chapter focuses on evaluating the newly developed system in terms of its efficiency and reliability using quantitative techniques.

6.3 Comparing conventional AHP with fuzzy AHP

Productivity estimation models for academic departments have been developed in the past using absolute (crisp) values (such as conventional AHP and conventional TOPSIS) as inputs. In this section, the results of conventional AHP are firstly examined and then compared with fuzzy AHP in terms of their criteria weights. In order to acquire valid results, the same hierarchy (Figure 5-1) and similar data for both the conventional and fuzzy AHP models were used. If for example, the first evaluator (decision-maker) D_1 chose the linguistic value ‘Equally Important (EI)’ from Table 5-19 for fuzzy AHP, then it is expected that the same evaluator will choose “Equal Importance” from Table 2-1 for conventional AHP. However, when discrepancies arose, the evaluators were asked to revise their choices.

6.3.1 Using absolute values to rate the criteria

In sections 5.5.5(a) and 5.5.5(c) the choices of the four decision-makers (D_1, D_2, D_3, D_4) using fuzzy AHP was shown. The choices of the four decision-makers using absolute values from Table 2-1 for conventional AHP are as follows:

$$\boldsymbol{D_1} = \begin{array}{c} \\ \boldsymbol{C_1} \\ \boldsymbol{C_2} \\ \boldsymbol{C_3} \\ \boldsymbol{C_4} \\ \boldsymbol{C_5} \\ \boldsymbol{C_6} \end{array} \begin{array}{c} \begin{array}{cccccc} \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} \end{array} \\ \begin{bmatrix} 1 & 1 & \frac{1}{5} & 7 & 1 & 7 \\ 1 & 1 & \frac{1}{7} & 5 & 5 & 5 \\ 5 & 7 & 1 & 9 & 9 & 1 \\ \frac{1}{7} & \frac{1}{5} & \frac{1}{9} & 1 & \frac{1}{7} & 9 \\ 1 & \frac{1}{5} & \frac{1}{9} & 7 & 1 & 5 \\ \frac{1}{7} & \frac{1}{5} & 1 & \frac{1}{9} & \frac{1}{5} & 1 \end{bmatrix} \end{array}$$

$$\boldsymbol{D_2} = \begin{array}{c} \\ \boldsymbol{C_1} \\ \boldsymbol{C_2} \\ \boldsymbol{C_3} \\ \boldsymbol{C_4} \\ \boldsymbol{C_5} \\ \boldsymbol{C_6} \end{array} \begin{array}{c} \begin{array}{cccccc} \boldsymbol{C_1} & \boldsymbol{C_2} & \boldsymbol{C_3} & \boldsymbol{C_4} & \boldsymbol{C_5} & \boldsymbol{C_6} \end{array} \\ \begin{bmatrix} 1 & 1 & \frac{1}{9} & \frac{1}{5} & 1 & 1 \\ 1 & 1 & 1 & 5 & \frac{1}{7} & 5 \\ 9 & 1 & 1 & 1 & \frac{1}{9} & 1 \\ 5 & \frac{1}{5} & 1 & 1 & \frac{1}{7} & 1 \\ 1 & 7 & 9 & 7 & 1 & 1 \\ 1 & \frac{1}{5} & 1 & 1 & 1 & 1 \end{bmatrix} \end{array}$$

$$
D_3 = \begin{array}{c} \\ C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \end{array}
\begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array}
$$

$$
\begin{array}{c} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \end{array}
\begin{bmatrix}
1 & 5 & 7 & \frac{1}{5} & 1 & 1 \\
\frac{1}{5} & 1 & 1 & 1 & \frac{1}{7} & 1 \\
\frac{1}{7} & 1 & 1 & 1 & 1 & 1 \\
5 & 1 & 1 & 1 & \frac{1}{7} & 1 \\
1 & 7 & 1 & 7 & 1 & 1 \\
1 & 1 & 1 & 1 & 1 & 1
\end{bmatrix}
$$

$$
D_4 = \begin{array}{c} \\ C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \end{array}
\begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array}
$$

$$
\begin{array}{c} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \end{array}
\begin{bmatrix}
1 & 1 & 5 & \frac{1}{5} & 1 & 1 \\
1 & 1 & 7 & 1 & 3 & 1 \\
\frac{1}{5} & \frac{1}{7} & 1 & 1 & 1 & \frac{1}{3} \\
5 & 1 & 1 & 1 & \frac{1}{3} & 1 \\
1 & \frac{1}{3} & 1 & 3 & 1 & 1 \\
1 & 1 & 3 & 1 & 1 & 1
\end{bmatrix}
$$

The four scores of the decision-makers using the geometric mean method are calculated. The computation for x_{12} is shown in detail and the remaining scores can be deduced by analogy. From the comparison matrices D_1, D_2, D_3 and D_4 above, the values for x_{12} are 1, 1, 5 and 1. By applying equation 3.1, the following is attained: $\left[\prod_{i=1}^{k} x_i\right]^{1/k} = \sqrt[4]{1X1X5X1} = 1.50$. The remaining values are computed using the same method and the complete comparison matrix is presented below (section 6.3.2). The weights are also shown in the matrix. The method for calculating the weights is described below the matrix.

6.3.2 Calculating weights using conventional AHP

	C_1	C_2	C_3	C_4	C_5	C_6	6^{rd} root of prod	Weight
C_1	1	1.50	0.94	0.49	1.00	1.63	1.018	0.176
C_2	0.67	1	1.00	2.24	0.74	2.24	1.164	0.202
C_3	1.06	1.00	1	1.73	1.00	0.76	1.058	0.183
C_4	1.37	0.45	0.58	1	0.18	1.73	0.691	0.120
C_5	1.00	1.34	1.00	1.00	1	1.50	1.123	0.195
C_6	0.61	0.45	1.32	0.58	0.67	1	0.720	0.125
sum							5.774	

Saaty's absolute value method is used to calculate the weights from the comparison matrix as follows: The 6^{th} root is calculated by multiplying the values in each row and then computing the n^{th} (in this case, the 6^{th} root since there are 6 criteria) root of the product. The values of the 6^{th} root are then added. The weights for each criterion are calculated as follow:

$w_1 = \frac{1.018}{5.774} = 0.176$; $w_2 = \frac{1.164}{5.774} = 0.202$; $w_3 = \frac{1.058}{5.774} = 0.183$; $w_4 = \frac{0.691}{5.774} = 0.120$;
$w_5 = \frac{1.123}{5.774} = 0.195$; $w_6 = \frac{0.720}{5.774} = 0.12$

6.3.3 Ranking the criteria weights

The criteria weights for the conventional AHP are then ranked as follows:

Criteria	Weights	Rank
Administration	0.176	4
Teaching and Supervision	0.202	1
Research and Innovation	0.183	3
Writing and Publication	0.120	6
Consultancy	0.195	2
Services Rendered and Ext. Engagement	0.125	5

Table 6-1: Ranking the Criteria for Conventional AHP

6.3.4 A comparison between conventional and fuzzy AHP in terms of criteria weights

The rankings for fuzzy AHP (Table 5-21) and conventional AHP (Table 6-1) in the following graph are depicted so that a comparison of the criteria weights can be made. A discussion then follows.

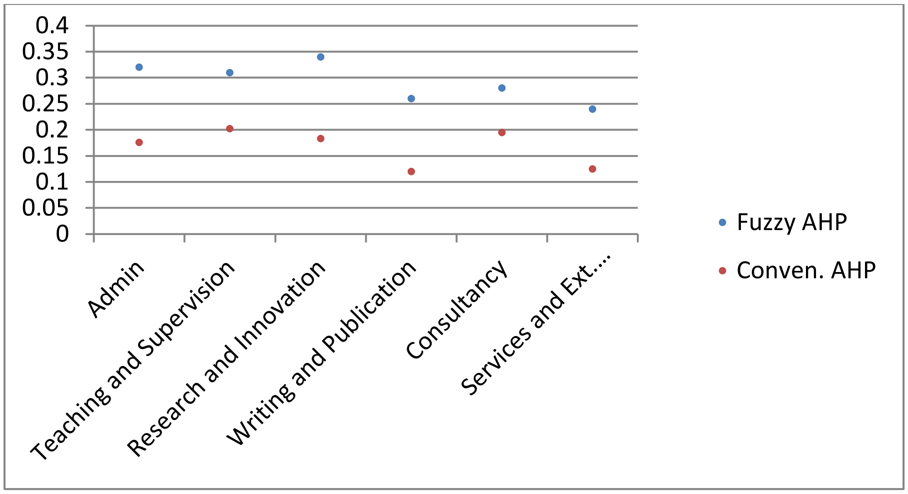


Figure 6-2: Comparison of fuzzy AHP and conventional AHP in terms of weights

From the graph, it is shown that the decision-makers feel that the three most important criteria for fuzzy AHP are Research and Innovation, Administration as well as Teaching and Supervision. For conventional AHP, their choices for the three most important criteria are Teaching and Supervision, Consultancy as well Research and Innovation. In both cases, the results indicate that Research and Innovation as well as Teaching and Supervision are among the more important criteria that must be considered when evaluating academic staff.

In fuzzy AHP and conventional AHP, Services Rendered and External Engagement are ranked towards the bottom indicating that this criterion is not as important when compared to the other criteria. However, the major discrepancies for both approaches revolve around the following:

- The criteria ranked number one is different in both cases; and
- Consultancy is ranked number 4 for fuzzy AHP indicating that it is not as important when compared to the top 3 ranked criteria. However, Consultancy is quite important (ranked number 2) when conventional AHP is implemented.

These discrepancies arose because the decision-makers choices for conventional AHP are precise values from a deterministic scale, which can produce misleading results. For example, the evaluators were faced with a dilemma as to what value to choose when they felt that one criteria is "more or less equal in importance" when compared to another. From the Saaty scale (Table 2-

1) for absolute values, the values 1, 2, 3 and 4 are available to the 4 evaluators for the choice "more or less equal in importance". A pessimistic decision-maker may therefore assign a score of 1 while an optimistic decision-maker may assign a score of 4 for the same criteria. This situations caused fuzziness in the decision-making process and could however be easily handled using fuzzy AHP.

For fuzzy AHP, most of the evaluators will therefore most likely choose only one linguistic value "Equally important" (Table 5-19) represented by the triangular fuzzy number $\left(\frac{1}{2}, 1, \frac{3}{2}\right)$ with its fuzzy reciprocal value $\left(\frac{2}{3}, 1, 2\right)$. In other words, conventional AHP have exact values for the various choices whereas in the fuzzy AHP method there are intervals between two numbers that will encompass the most likely values (or choices). Hence the discrepancies mentioned above.

In this empirical study, one can therefore conclude that the weights for fuzzy AHP with linguistic values are more reliable as the evaluators will take less risky decisions when compared to conventional AHP. One can also conclude that the performance matrix for conventional AHP will be less reliable when compared to fuzzy AHP as the weights are used in the computation of the performance matrix. In this study, it is therefore not necessary to compute the performance matrices for both approaches to show which one is more reliable.

This section compared the weights of the conventional AHP with the weights of the fuzzy AHP using the same criteria and the same evaluators. The fuzzy AHP approach proved to be more reliable when compared to the conventional AHP approach. This is attributed to the fact that a fuzzy logic approach was adopted to evaluate the qualitative criteria and not an absolute (crisp) value approach.

6.4 The manual evaluation system using weights

The present method of evaluation allocates weights (or scores) to each sub-criterion for every academic. The scores of all the sub-criteria under a main criterion are then added to attain a score for that criterion. The final score for each academic is acquired by adding the scores of all six criteria.

This section compares the newly developed fuzzy-based system with the manual weighting system that is currently adopted at DUT. In order to achieve a valid comparison, the same decision-makers (D_1, D_2, D_3 and D_4) were asked to evaluate the performance of the same three academics (A_1, A_2, and A_3) using the same sub-criteria and criteria mentioned in section 5.3 (that is, the same criteria and sub-criteria that was used for fuzzy AHP). The following approach is adopted in this section:

- The evaluators were asked to rate the six criteria in terms of their importance intensity;
- A reliability score and an intra-correlation index are calculated to determine whether the scoring patterns for the criteria are acceptable;
- The weights for the criteria are calculated;
- The 4 decision-makers were asked to evaluate the 3 academics using the manual weighting system that is presently in use at DUT;
- A reliability score and an intra-correlation index are calculated to determine whether the scoring patterns of the evaluators regarding the evaluation of the 3 academics are acceptable;
- The decision-makers were asked to fill in a short open-ended questionnaire. The purpose was to elicit their opinions regarding the manual weighting system and the newly developed system in terms of the inputs. Their opinions are then analysed and discussed; and
- A comparison was made between the manual weighting system and the newly developed system using quantitative techniques in terms of the objectives mentioned in section 5.4.

6.4.1 Rating the six criteria using absolute values

For fuzzy AHP, a comprehensive pair-wise comparison matrix was used to calculate the weights in order to determine the rankings of the six criteria. The use of a comprehensive pair-wise comparison matrix is not possible when using the current method of evaluation at DUT, that is, the manual weighting system. Determining the rankings of the criteria in terms of "importance intensity" is not mandatory with the current evaluation system. However, the 4 evaluators were asked to rank the criteria so that a comparison can be made with the rankings (of the criteria) of the fuzzy AHP. Rating the criteria was done using absolute values to indicate the weights of the criteria as determined by each evaluator. Since there are six criteria, there will be six levels of "importance intensity". The "most important" criterion is indicated using the value 1 and the "least important" criterion is indicated using the value 6. After the evaluators made their choices, the following results as indicated in Table 6-2 was attained.

Criteria	D_1	D_2	D_3	D_4
Administration	2	2	3	2
Teaching and Supervision	1	1	2	3
Research and Innovation	4	3	1	1
Writing and Publication	5	6	4	4
Consultancy	3	4	5	6
Services Rendered and Ext. Engagement	6	5	6	5

Table 6-2: Ranking the criteria using absolute values

6.4.2 Calculating the reliability scores for the ratings

Before analysing the absolute value method for rating the criteria, the reliability of the scoring patterns of the evaluators are determined. This is achieved by calculating the mean and standard deviation scores of the 4 evaluators for each criterion. The results of the reliability test for the data from Table 6-2 are indicated in Table 6-3.

Descriptives

			Statistic	Std. Error
Administration	Mean		2.2500	.25000
	95% Confidence Interval for Mean	Lower Bound	1.4544	
		Upper Bound	3.0456	
	5% Trimmed Mean		2.2222	
	Median		2.0000	
	Variance		.250	
	Std. Deviation		.50000	
Teaching and Supervision	Mean		1.7500	.47871
	95% Confidence Interval for Mean	Lower Bound	.2265	
		Upper Bound	3.2735	

	5% Trimmed Mean		1.7222	
	Median		1.5000	
	Variance		.917	
	Std. Deviation		.95743	
Research and Innovation	Mean		2.2500	.75000
	95% Confidence Interval for Mean	Lower Bound	-.1368	
		Upper Bound	4.6368	
	5% Trimmed Mean		2.2222	
	Median		2.0000	
	Variance		2.250	
	Std. Deviation		1.50000	
Writing and Publication	Mean		4.7500	.47871
	95% Confidence Interval for Mean	Lower Bound	3.2265	
		Upper Bound	6.2735	
	5% Trimmed Mean		4.7222	
	Median		4.5000	
	Variance		.917	
	Std. Deviation		.95743	
Consultancy	Mean		4.5000	.64550
	95% Confidence Interval for Mean	Lower Bound	2.4457	
		Upper Bound	6.5543	
	5% Trimmed Mean		4.5000	
	Median		4.5000	
	Variance		1.667	
	Std. Deviation		1.29099	
Services Rendered and Ext. Engagement	Mean		5.5000	.28868
	95% Confidence Interval for Mean	Lower Bound	4.5813	
		Upper Bound	6.4187	
	5% Trimmed Mean		5.5000	
	Median		5.5000	
	Variance		.333	
	Std. Deviation		.57735	

Table 6-3: Reliability scores for the 4 evaluators

The results from Table 6-3 indicate a 95% Confidence Interval for the Mean. Since the data sets are not normal, Mann Whitney tests were used to determine whether there was a significant difference in the mean values (using the central value comparison of the distributions). All of the p-values for the different combinations of raters per variable have p-values > level of significance of 0.05. This indicates that there was a high degree of acceptability and consistency scoring by the 4 evaluators.

6.4.3 Calculating the intra class correlation index

Intra class correlations are used when quantitative measurements are made on units that are organised into groups. In this case the 4 decision-makers (evaluators) would belong to such a group. It describes how strongly units in the same group resemble each other. In this case all 4 evaluators (decision-makers) have many years of experience in conducting evaluations which indicates that they resemble each other due to their expertise. Intra class correlations are generally used to quantify the degree to which individuals with a fixed degree of relatedness resemble each other in terms of some quantitative traits. Intra class correlations are generally applied when an assessment of consistency or reproducibility of quantitative measurements by different observers measuring the same quantity is required. Refer to Annexure F for an explanation on how intra class correlations are calculated. The intra class coefficient was calculated using SPSS version 21.0. The results are indicated in Table 6-4.

Intra class Correlation Coefficient

	Intra class Correlation[b]	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	.808[a]	.499	.966	17.812	5	15	.000
Average Measures	.944[c]	.799	.991	17.812	5	15	.000

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. The estimator is the same, whether the interaction effect is present or not.

b. Type C intra class correlation coefficients using a consistency definition-the between-measure variance is excluded from the denominator variance.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Table 6-4: Results of the intra class correlation coefficient

The results from Table 6-4 indicate that the single measures intra class correlations are high (significant as $p < 0.05$). This means that the evaluators rated the criteria in a similar manner. Now that the reliability and the intra class correlation coefficients have indicated acceptable results, the weights of the six criteria can be computed.

6.4.4 Calculating the weights using absolute values

The geometric mean method was used in Saaty's method to calculate the weights for conventional and fuzzy AHP. In order for the results to be valid, the geometric mean method is also used in the calculation of the weights for the manual evaluation system from Table 6-2. The calculation for the first criteria (Administration) is as follows: $\left[\prod_{i=1}^{k} x_i\right]^{1/k} = \sqrt[4]{2X2X3X2}$ = 2.213. The rest are determined by analogy and the weight for each criterion is indicated in Table 6-5.

Criteria	Weight
Administration	2.213
Teaching and Supervision	1.861
Research and Innovation	1.861
Writing and Publication	4.680
Consultancy	4.356
Services Rendered and Ext. Engagement	5.477

Table 6-5: Criteria weights using absolute values

For fuzzy AHP, the calculation of criteria weights involving all four evaluators (group decision) is necessary. In other words, ranking the criteria in terms of 'intensity importance' involving all members of the evaluation panel is necessary to determine the fuzzy performance matrix. The fuzzy performance matrix was used to address the objectives in section 5.4. However, for the manual weighting system, it is not mandatory that the four evaluators collectively rank the criteria. Some departments may however want to rank the six criteria. The purpose of requesting the evaluators to rank the criteria (for the manual weighting system) was to make a comparison between the criteria ranking of fuzzy AHP and the criteria ranking of the current manual system in use. Since the fuzzy weights in terms of the BNP values (Table 5-21) are normalised with values between 0 and 1, the absolute values in Table 6-5 were also converted into values between 0 and 1. The comparisons are indicated in Figure 6-3.

6.4.5 A comparison of the criteria weights

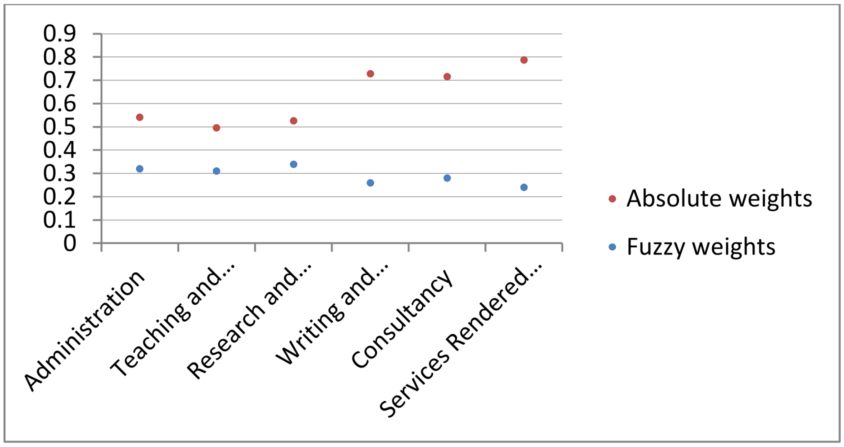


Figure 6-3: Comparing fuzzy weights with absolute value weights

From Figure 6-3, the largest BNP values indicate the most important criteria for fuzzy AHP and the smallest value for absolute weights indicate the most important criteria. For both fuzzy and absolute value weights, Research and Innovation, Administration as well as Teaching and Supervision ranks among the most important. In both cases, Services Rendered and External Engagement is ranked the lowest. The discrepancy revolves around the order of the "importance intensity" for the first 3 criteria in both cases. This is due to the fuzziness in the evaluator's decisions regarding Teaching and Supervision as well as Research and Innovation when absolute values were used to rate the six criteria. Although there are no major discrepancies in the overall results for both methods, fuzzy AHP is more reliable (Lee, 2010). This is due to the fact that the use of linguistic values limits or eradicates the uncertainty that evaluators experience when using absolute values to rate the criteria.

Although the reliability score and the intra class coefficient correlation shows good ratings, the evaluation system itself is not preferred when the results of the experiment as well as the opinions of academic staff (as indicated in Figure 7-7) regarding the manual weighting system are taken into consideration. Therefore, one can also conclude that the scoring patterns of evaluators have little or no bearing in the type of system that is used for the evaluation of academic staff.

6.5 Evaluating academic performance using weights (absolute values)

This section used the manual weighting system to evaluate the 3 academics. The actual data provided by the 4 evaluators is used to analyse the merits and demerits of the manual weighting system. This evaluation system is then compared to the fuzzy AHP method in terms of how the objectives mentioned in section 5.4 are met.

6.5.1 The approach adopted in collecting the actual data

The 4 decision-makers (D_1, D_2, D_3 and D_4) were asked to evaluate the 3 academics (that is, alternatives A_1, A_2 and A_3) using the current method of evaluation (that is, the manual weighting system). Of the 23 sub-criteria, 18 are qualitative (intangible) and 5 are quantitative (tangible) sub-criteria. It was advised that the 18 intangible sub-criteria be evaluated according to the following guidelines: <40% = 'weak', 40% to 49% = 'fair', 50% to 59% = 'average', 60% to 69% = 'good', 70% to 79% = 'very good' and ≥ 80% = 'excellent'. However, the evaluators are not bound by these guidelines. The data for the 5 quantitative (tangible) sub-criteria are absolute values and the evaluation required simple computations. These quantitative scores were simply calculated by the evaluators and then entered in Table 6-6. For example, since the average teaching load (C_{21}) for A_1 is 11.67, a score of 2 is awarded to this academic (see C_{21} in column 1 of Table 6-6 on the criteria to determine the scores for teaching load). Table 6-6 contains all the scores of the 4 evaluators (decision-makers).

Criteria and sub-criteria	Academics (Alternatives)												
	Max weight	A_1				A_2				A_3			
		D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4
Administration (C_1)	**10**	6	8	7	6	5	7	6	5	6	8	8	7
Managing and administering academic programmes (C_{11})	**5**	3	4	3	3	2	3	3	2	3	4	4	3
Contribution to administration in the department (C_{12})	**5**	3	4	4	3	3	4	3	3	3	4	4	4
Teaching and Supervision (C_2)	**20**	$15\frac{1}{2}$	15	17	$15\frac{1}{2}$	$13\frac{1}{2}$	14	15	14	12	$12\frac{1}{2}$	11	12
Teaching load (C_{21}). *(If load ≤ 5 then score = 1. If load > 5 then score = 2)*	**2**	2	2	2	2	2	2	2	2	2	2	2	2

Planning and developing programmes and study material (C_{22})	**4**	2	3	3	1	3	3	3.5	3.5	3.5	2	3	2
Quality of teaching using new and emerging technologies (C_{23})	**2**	2	1.5	1.5	2	0.5	1	2	1.5	1	1.5	1	1
Peer and student evaluation of teaching performance (C_{24})	**2**	0.5	1	1.5	1.5	1.5	1	1.5	1	0.5	1	1.5	2
Co-Curricular involvement (C_{25})	**1**	0.5	1	1	1	0.5	1	1	0.5	1	1	0.5	1
Supervision of student projects (C_{26})	**3**	2.5	0.5	2	2	2	2	1	1.5	2	3	1	2
Number of Masters/PhD supervisions (C_{27}). *(2 points per student with max 6)*	**6**	6	6	6	6	4	4	4	4	2	2	2	2
Research and Innovation (C_3)	**25**	$13\frac{1}{2}$	$20\frac{1}{2}$	16	17	$22\frac{1}{2}$	20	20	$21\frac{1}{2}$	20	$23\frac{1}{2}$	$20\frac{1}{2}$	17
Level of involvement in research project/s (C_{31})	**14**	7	13	8	10	12	11	10	11	10	13	11	8
Number of Conf. Present. attended (C_{32}). *(1 pt. per Con. with max of 2)*	**2**	2	2	2	2	2	2	2	2	2	2	2	2
Number of papers presented at Conf. (C_{33}). *(1 pt. per paper with max of 5).*	**5**	3	3	3	3	5	5	5	5	5	5	5	5
Networking with researchers outside DUT (C_{34})	**2**	0.5	1	1.5	1.5	1.5	1	1.5	2	1	1.5	1	1
Evidence of funding received (C_{35})	**2**	1	1.5	1.5	0.5	2	1	1.5	1.5	2	2	1.5	1
Writing and Publication (C_4)	**20**	$17\frac{1}{2}$	$17\frac{1}{2}$	17	16	$15\frac{1}{2}$	$16\frac{1}{2}$	$15\frac{1}{2}$	15	12	$11\frac{1}{2}$	14	$12\frac{1}{2}$
Accredited/ recognized/ non-accredited articles published (C_{41}). *(Acc.: 3 pts. per art. with max of 12; rec/non-acc.: 1 pt. per art. with max of 3)*	**15**	14	14	14	14	12	12	12	12	10	10	10	10
Involvement with Scholarly and Academic Writing (C_{42})	**3**	1.5	2	2	1	2	2.5	2	2	1.5	0.5	2.5	1.5
Other Writing (C_{43})	**2**	2	1.5	1	1	1.5	2	1.5	1	0.5	1	1.5	1
Consultancy (C_5)	**10**	5	5.5	6	5	2	5	3	2	7	5.5	6	7
Level of involvement with industry (C_{51})	**10**	5	5.5	6	5	2	5	3	2	7	5.5	6	7

Services Rendered and External Engagement (C_6)	**15**	10	10	$11\frac{1}{2}$	$10\frac{1}{2}$	$7\frac{1}{2}$	10	9	6	$11\frac{1}{2}$	10	12	$11\frac{1}{2}$
Services rendered such as head of a committee, etc. (C_{61})	**4**	2.5	2	3	2.5	1	2	2	1.5	3	2.5	3	2.5
Involvement in External Examination and Moderation (C_{62})	**4**	2	3	2	2.5	2.5	3	3	2	3	2	2.5	3
Involvement in generating 3rd stream income (C_{63})	**3**	2	1.5	3	2	1.5	2	2	0.5	1.5	2	3	2.5
Voluntary Services rendered to the community (C_{64})	**2**	2	1.5	2	2	0.5	2	1.5	1	2	1.5	2	1.5
Member of professional, cultural, religious and other bodies (C_{65})	**2**	1.5	2	1.5	1.5	2	1	0.5	1	2	2	1.5	2
TOTAL	**100**	$67\frac{1}{2}$	76	$74\frac{1}{2}$	70	66	$72\frac{1}{2}$	$68\frac{1}{2}$	$63\frac{1}{2}$	$68\frac{1}{2}$	71	$71\frac{1}{2}$	67

Table 6-6: Evaluating the 3 academics using the manual weighting system

Before an analysis of the manual weighting system can be made, the rating patterns of the evaluators were determined using the intra class correlation coefficient. This is necessary to determine whether the ratings are acceptable.

6.5.2 Calculating the inter-rater reliability score

The intra class correlation coefficient is an index of the reliability of the ratings for a typical, single judge (evaluator). This coefficient is employed when most of the data are collected using only one judge (evaluator) at a time. However, when more than one judge is used (in this case, 4 evaluators) an inter-rater reliability score had to be calculated on a subset of the data. SPSS calls this statistic the ‘single measure intra class correlation’. This procedure was therefore implemented 3 times (since there are 3 academics that are evaluated). The results using SPSS for academic A_1 are as follows:

Reliability Statistics

Cronbach's Alpha	N of Items
.987	4

Table 6-7: Reliability score for Academic $\boldsymbol{A_1}$

Intra class Correlation Coefficient

	Intra class Correlation[b]	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	.949[a]	.907	.976	75.824	22	66	.000
Average Measures	.987[c]	.975	.994	75.824	22	66	.000

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. The estimator is the same, whether the interaction effect is present or not.

b. Type C intra class correlation coefficients using a consistency definition-the between-measure variance is excluded from the denominator variance.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Table 6-8: Intra class correlation coefficient for Academic $\boldsymbol{A_1}$

The results for academic A_2 are as follows:

Reliability Statistics

Cronbach's Alpha	N of Items
.992	4

Table 6-9: Reliability score for Academic $\boldsymbol{A_2}$

Intra class Correlation Coefficient

	Intra class Correlation[b]	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	.969[a]	.943	.985	125.880	22	66	.000
Average Measures	.992[c]	.985	.996	125.880	22	66	.000

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. The estimator is the same, whether the interaction effect is present or not.

b. Type C intra class correlation coefficients using a consistency definition-the between-measure variance is excluded from the denominator variance.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Table 6-10: Intra class correlation coefficient for Academic $\boldsymbol{A_2}$

The results for academic A_3 are as follows:

Reliability Statistics

Cronbach's Alpha	N of Items
.985	4

Table 6-11: Reliability score for Academic $\boldsymbol{A_3}$

Intra class Correlation Coefficient

	Intraclass Correlation[b]	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	.943[a]	.896	.973	67.118	22	66	.000
Average Measures	.985[c]	.972	.993	67.118	22	66	.000

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. The estimator is the same, whether the interaction effect is present or not.

b. Type C intra class correlation coefficients using a consistency definition-the between-measure variance is excluded from the denominator variance.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Table 6-12: Intra class correlation coefficient for Academic A_3

The Cronbach's Alpha for each academic exceeds the minimum recommended value of 0.70. The single measures intra class correlations for each academic is very high (significant as $p < 0.05$). This means that the raters rated the various dimensions per academic in a similar manner. Now that the ratings are acceptable, an analysis of the scoring can take place.

6.5.3 Evaluators opinions regarding the manual weighting system

After the decision-makers completed their evaluations, the researcher prepared a short open-ended questionnaire in order to elicit their opinions regarding the conventional weighting scoring system in terms of the inputs. The evaluators have been using the manual weighting system for many years and the researcher felt their responses to the questionnaire will therefore be more reliable and credible. Their inputs should therefore be regarded as expert opinions. The following questions were asked:

1. What difficulties (if any) did you experience when evaluating the 5 quantitative (tangible) sub-criteria?
2. What difficulties (if any) did you experience when evaluating the 18 qualitative (intangible) sub-criteria?
3. What is your general opinion regarding this method of evaluation?

The differences between tangible and intangible sub-criteria were explained in the questionnaire. From the responses, none of the evaluators experienced any problems regarding the evaluations of the tangible sub-criteria since this required simple computations. However, the evaluators generally felt that they were not clear about what scores to assign for each intangible sub-criterion or criterion. This implies that the evaluators were faced with uncertainty and fuzziness in the decision-making process. If for example, they felt that the performance for Consultancy was 'average', then according to the guidelines, this academic should be given a score between 50% and 59%. The decision-makers mentioned that they were at a dilemma as to what score to choose between 50% and 59%. This point is further highlighted when the choices of D_1 and D_2 in table 6-6 are examined. These decision-makers D_1 and D_2 felt that the performance of A_1 is 'average' for Consultancy.

However, D_1 assigned a score of 5 (or 50%) and D_2 assigned a score of 5.5 (or 55%) for the same academic (A_1), a difference of 5% implying fuzziness and uncertainty in the scoring system. These inconsistent scores for the sub-criteria will therefore have an accumulative effect and unreliable results will eventually be produced when determining the overall performance of an academic. The evaluators also felt that this manual weighting system is time-consuming because of their indecisions regarding the choices of the scores.

The decision-makers also mentioned that evaluations using the new system (when compared to the present system in use) was easier to use because absolute values were not required but linguistic values such as 'very weak', 'weak', 'average', 'good' and 'very good' were used as inputs. The indecisions on their part were reduced and it also took less time to do the evaluations. Also, the 2 decision-makers who chose the values 5 (or 50%) and 5.5 (or 55%) respectively for the criteria Consultancy can now choose only one linguistic value 'average' using the fuzzy-based system in order to avoid deviations of the scores. Using linguistic values is therefore more reliable and less risky when compared to using the weighting scoring system. This is so because a linguistic value will have intervals between two numbers that will encompass the most likely values (or choices). The evaluators however expressed their concerns as to how all the linguistic inputs can be computed and consolidated in order to attain a performance measure of each academic. Such a system has now been developed. The fuzzy-based model was developed in Chapter 3 and its implementation was demonstrated in Chapter 5.

6.5.4 Comparing the two systems in terms of the objectives indicated in section 5.4

This section compares the results of the conventional weighting system with the results of the newly developed fuzzy-based system in terms of the objectives indicated in section 5.4. The scores for the 4 evaluators (for the manual weighting system) have to firstly be consolidated by computing the averages for each criterion (with respect to each alternative) before the comparisons can be made. The performance score for A_1 in terms of C_1 (Administration) for example is calculated as follows: $\frac{6+8+7+6}{4}$ = 6.75. The rest of the calculations can be deduced by analogy and are indicated in Table 6-13.

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	6.75	15.75	16.75	17.00	5.40	10.50
A_2	5.75	14.13	21.00	15.63	3.00	8.13
A_3	7.25	11.88	20.21	12.50	6.40	11.25

Table 6-13: Results of the manual weighting system

In section 5.6, the fuzzy performance matrix was calculated and the equivalent BNP values are indicated in Table 6-14.

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.32	0.38	0.44	0.35	0.46	0.32
A_2	0.31	0.38	0.45	0.36	0.36	0.30
A_3	0.32	0.38	0.46	0.31	0.47	0.32

Table 6-14: BNP values for the Fuzzy Performance matrix

Table 6-13 and Table 6-14 indicate the evaluation scores of the manual weighting system and the scores of the fuzzy-based system with respect to the six criteria. The results of these two tables will be used to show the differences between the two evaluation methods. This will be done by focusing on the extent to which each method is able to address each objective mentioned in section 5.4. The comparisons between the two evaluation methods will show disparities. Some of these disparities will overlap (or will be similar) for some for the objectives. The researcher therefore chose 5 of the most important objectives for discussion.

Objective 1: Determine the overall performance of an academic

This is achieved by examining the row values for each academic in both tables. When the manual weighting system (Table 6-13) was used for the evaluation, the results indicated that academic A_1 generally performed well in 5 of the performance areas. However, this academic (A_1) had the lowest score for Research and Innovation (C_3). When the fuzzy AHP method was used in the evaluation, academic A_1 performs well in 5 areas besides Research and Innovation (C_3) where the BNP value is the lowest when compared to the other academics. This means that there is concurrence for both evaluation methods regarding the general performance of A_1.

The results of the manual weighting system indicated that academic A_2 is an average performer (when compared to the other 2 academics) since he had the lowest performance values in 3 areas that is, Administration (C_1), Consultancy (C_5) and Services rendered and External Engagement (C_6). The fuzzy AHP (Table 6-14) also indicated that A_2 has the lowest scores for the same three criteria. The results of both evaluation methods therefore concur with each other for academic A_2.

Both evaluation methods indicate that academic A_3 is generally a good performer since he has the highest rating in 5 performance areas when compared to the other 2 academics. However, the disparity lies with the criteria in which this academic (A_3) performed poorly. The results of the manual weighting system indicated that this academic (A_3) requires improvement in Teaching and Supervision (C_2) while the results of the fuzzy AHP method indicated that this academic needs to improve in Writing and Publication (C_4).

One can therefore conclude that there is not much disparity in the evaluation results when both methods are compared but the discrepancy lies with the performance area that requires improvement for academic A_3. The disparity can be attributed to the inconsistent scoring patterns for the manual weighting system and fuzzy AHP method for academic A_3. When the scoring patterns for academic A_3 with respect to Teaching and Supervision (C_2) as well as Writing and Publication (C_4) are analysed, they do not resemble each other in both methods. Hence the disparity regarding which performance area requires improvement for academic A_3. The reasons for the scoring not resembling each other are discussed in section 6.5.5 (the conclusion section).

Objective 2: To determine the strongest and weakest performance areas of an academic

In order to determine this, the values in each column for both tables are examined. Table 6-15 indicates the strongest and weakest performance areas for all 3 academics using both evaluation methods.

	Strongest Performance area (weighting system)	Strongest Performance area (Fuzzy AHP)	Weakest Performance area (weighting system)	Weakest Performance area (fuzzy AHP)
$\boldsymbol{A_1}$	C_2 and C_4	C_1, C_2 and C_6	C_3	C_3
$\boldsymbol{A_2}$	C_3	C_2 and C_4	C_1, C_5 and C_6	C_1, $C_5$and C_6
$\boldsymbol{A_3}$	C_1, C_5 and C_6	C_1, C_2, C_3, C_5 and C_6	C_2 and C_4	C_4

Table 6-15: Strongest and Weakest performance areas

From Table 6-15, it is evident that both evaluation methods generally concur with each other for most of the criteria and alternatives (academics). Both evaluation methods identify academic A_1 as having criterion C_2 as a strength and criterion C_3 as a weakness. Both evaluation methods identify C_1, C_5 and C_6 as weaknesses for A_2. Both methods are able to identify academic A_3 as having strengths in most performing areas when compared to the other two academics.

However, the disparity revolves around the results for academic A_2 where there is little concurrence between the two evaluation methods on the strengths of A_2. This is due to the fact that the three criteria (C_2, C_3 and C_4) are allocated the most percentage points that is, 65% (20% for C_2, 25% for C_3 and 20% for C_4) when compared to the other three criteria. This high allocation of scores for each of these criteria means that the scoring patterns of evaluators will be more divergent for the manual weighting system. In other words, evaluators have a wider range of absolute values from which to choose a score. This deduction was confirmed by the results of a survey of evaluators in section 6.5.3.

One would however argue why A_1 and A_3 showed more convergence (for both evaluation methods) than A_2 although the same criteria are used for evaluating all academics. The reason is that the scoring pattern for A_2 using the manual weighting system did not closely resemble the scoring pattern when fuzzy AHP was used. Therefore the results for the two evaluation methods (for A_2) are not similar when the strengths are taken into consideration.

One should however, take note that where the scoring by evaluators has a potential to be divergent, then linguistic values (that is, a fuzzy-based approach) should be used as discussed in 6.5.3 above. Further, C_2, C_3 and C_4 have the most sub-criteria when compared to the other three criteria. This will further compound the degree of reliability during the evaluation process. This was confirmed by a study conducted by Tseun-Ho *et al.* (2012) which indicated that a criteria that had more sub-criteria produced results that were less reliable than a criteria that had fewer sub-criteria when the manual weighting system is used. It is for these reasons there is a disparity on the strengths and weaknesses for A_2 as indicated in Table 6-15.

Objective 3: To delegate duties to academics according to their strengths

As discussed for objective 2 above, C_2, C_3 and C_4 showed more divergence between the two evaluation methods because these criteria were allocated the most percentage points. It is however noticeable that C_1 and C_6 showed more convergence because these criteria were allocated lesser percentage points, that is, 10% for C_1 and 15% for C_6 (as indicated in Table 6-6). Therefore if the Head of Department wishes to appoint an academic to head the Administration (C_1) section of the department then A_3 should be chosen because this academic has scored the highest when both evaluation methods were used. In other words both methods showed convergence for C_1 indicating that this choice (A_3) is fairly reliable for both evaluation methods. However, if an academic is required to be chosen to head the Research (C_3) section, then A_2 is chosen when the manual weighting system is used and A_3 is chosen when fuzzy AHP is used.

This discrepancy is due to the reasons discussed under objective 2. Therefore choosing A_3 is more reliable using fuzzy AHP when compared to A_2 where the manual weighting system was used. A similar argument can be made when selecting academics in the other criteria.

Objective 4: Show the overall performance of all academics in all key areas

Such information may be required by the Dean when compiling the annual report. The information required is more quantitative (tangible) in nature. The Head of Department may request the following information from the computer system which will have Table 5-1 data stored for each academic in a department. Some of the information required is as follows: number of publications, number of conferences attended, projects completed and the number of Masters and PhD students that have graduated in a department. This is one of the instances where there are no disparities of the results for both evaluation methods since quantitative data is being manipulated. The output is therefore the same for both evaluation methods.

Objective 5: Rank academics in terms of all six key performance areas

In order to rank academics in all six key performance areas using the manual weighting system, the total average score of the 4 evaluators is calculated. For academic A_1, the average score is calculated as follows: $A_1 = \frac{67.5+76+74.5+70}{4} = 72$. The average scores for the other two academics are calculated in an identical manner. These are $A_2 = 67.5$ and $A_3 = 69.5$. Therefore, the rankings are as follows: Number 1 = A_1, Number 2 = A_3 and Number 3 = A_2. For fuzzy AHP, the ranking was done in section 5.6 using the Fuzzy TOPSIS method. The results attained were Number 1 = A_2, Number 2 = A_3 and Number 3 = A_1. When the results of the rankings are compared, both evaluation methods ranked A_3 as second. The disparity lies with the ranking of A_1 and A_2 although there is a small difference between the three average scores when the manual weighting system is used. However, the small differences in scores are significant especially in terms of promotion and awards. The reason for the disparity in the scores for A_1 and A_2 using both methods are explained in the conclusion of this section.

6.5.5 Conclusion

The results generally indicated that there were concurrences between both evaluation methods. There are however a few disparities that were addressed in section 6.5.4. For quantitative (or tangible) sub-criteria, the results of both evaluation methods produced the same results. One such situation was discussed for objective 4. The major discrepancies revolved around the qualitative (or intangible) sub-criteria and criteria. This was due to the fact that qualitative sub-criteria and criteria were evaluated using quantitative values, which produced unreliable results. The following factors also contributed to unreliable results being produced when the manual weighting system was used:

- The manual weighting system did not take the "importance intensity" of the criteria when the evaluators assigned scores to each sub-criterion or each criterion. This is not a mandatory requirement when this evaluation system is used. The fuzzy AHP on the other hand requires that the fuzzy weight vector for each criterion be firstly calculated and then ranked according to "importance intensity". The weight of each criterion is used in the computation of the fuzzy performance matrix from which the ratings of academics (for each criteria and overall performance) can be determined. This produced more reliable results;
- The evaluators were uncertain or fuzzy about what scores to assign to the sub-criteria or criteria when the manual weighting system was used in the evaluation. This was indicated by the survey results in section 6.5.3 above. The fuzzy AHP method on the other hand used linguistic values that limited or eradicated uncertainty and fuzziness;
- The personality of the evaluators will have an impact on the results when the manual weighting evaluation system is used. If for example, according to the guidelines, an "average" rating for a criterion should attain a score between 50% and 59%, then a pessimistic evaluator may assign a score of 51% and an optimistic evaluator may assign a score of 58% for "average". The difference of 7% therefore has a bearing on the reliability of the scoring. This can easily be resolved by using "average" as a linguistic value in fuzzy AHP that will encompass the most likely value; and
- A survey of the evaluators was carried out to ascertain their opinions on both evaluation methods (refer to section 6.5.3). They indicated that the manual weighting process was

time consuming and that they experienced fuzziness about what choices to make. On the other hand, evaluating academic staff using the fuzzy AHP required linguistic values to be input which is less confusing and took less time. As a result, the outputs attained were more reliable.

When the overall results of both evaluation methods are considered, the fuzzy AHP produced results that were more reliable when compared to the manual weighting system. The researcher also wanted to subject historical data to the newly developed system. The purpose is to ascertain whether the results of the fuzzy AHP system concur with historical decisions in terms of awards and promotion as well as strengths and weaknesses of academic staff. However, such historical data was not available and the researcher therefore used current data in the evaluations and comparisons.

A survey of academic staff was carried out to ascertain the opinions of academic staff on the manner in which present evaluation methods are implemented. The results in Figure 7-7 indicated that academics are generally unhappy with how evaluations are currently taking place at DUT. The results of the comparisons of the two evaluation methods coupled with the results of the survey of academic staff will provide greater impetus for management to consider implementing the newly developed system. However, it is also important that academic staff themselves accept the newly developed evaluation system. A usability study was therefore conducted to ascertain their opinions on the User Interface Satisfaction (UIS) as well as the functionality and capabilities of the newly developed system.

6.6 A usability study on the new system

This section elicited the opinions of academic staff from the IT department on the newly developed system. The purpose of this survey was to:

- Elicit the responses from academic staff on whether the newly developed system was able to meet their requirements in terms of the systems capabilities and functionality;
- Elicit the responses from the participants on User Interface Satisfaction (UIS) regarding the newly developed system; and

- Determine the extent to which the new system was able to meet the objectives indicated in section 5.4.

The researcher chose the IT department for the survey because most academic staff from this department are experienced in areas such as programming, the design and development of software and databases, networking and IS. Their inputs were necessary in improving aspects relating to user interface as well as the functionality of the developed system.

Twenty-eight (28) staff members from the IT department participated in the survey. Each participant was given a questionnaire to complete (Refer to Annexure B for the questionnaire). The participants were required to fill in the questionnaire during or after their interaction with the newly developed system. The results of the survey are indicated in Table 6-16. The results for questions (a) to (e) relate to User Interface Satisfaction (UIS). The results for questions (f) to (j) relate to the capabilities and functionality of the new system.

Statements	**Results of the Study in terms of the number of responses for each category**				
	Strongly Agree	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
a) The positioning of messages on the screen is consistent.	15 (or 54%)	4 (or 14%)	6 (or 21%)	3 (or 11%)	Nil
b) The prompts for input is clear.	13 (or 46%)	7 (or 25%)	4 (or 14%)	3 (or 11%)	1 (4%)
c) The system gives error messages that clearly tell me how to fix problems.	6 (or 21%)	10 (36%)	4 (or 14%)	5 (or 18%)	3 (or 11%)
d) The organisation of information are clearly laid out and are visually appealing.	16 (or 58%)	6 (or 21%)	6 (or 21%)	Nil	Nil
e) The terminology used is clear.	12 (or 43%)	6 (or 22%)	2 (or 7%)	6 (or 21%)	2 (or 7%)
f) The system is capable of effectively creating a computerised portfolio of an academic.	8 (or 29%)	13 (or 46%)	4 (or 14%)	2 (or 7%)	1 (or 4%)
g) The system is able to fairly rank and select candidates who are due for:					

• An award.	5 (or 18%)	12 (or 43%)	7 (or 25%)	4 (or 14%)	Nil
• A promotion.	13 (or 46%)	6 (or 21%)	6 (or 21%)	2 (or 7%)	1 (or 4%)
h) The system is able to monitor and process the performance of an academic in terms of the core strategic goals such as:					
• Teaching and Supervision.	10 (or 36%)	13 (46%)	3 (11%)	1 (4%)	1 (4%)
• Research and Innovation.	13 (or 46%)	6 (or 21%)	5 (or 18%)	3 (or 11%)	1 (or 4%)
• Administration.	11 (or 39%)	7 (or 25%)	6 (or 21%)	4 (or 14%)	Nil
• Writing and Publication.	12 (or 43%)	8 (or 29%)	7 (or 25%)	1 (or 4%)	Nil
• Consultancy.	8 (or 29%)	13 (or 46%)	5 (or 18%)	1 (or 4%)	1 (or 4%)
• External engagement.	9 (or 32%)	11 (or 39%)	8 (or 29%)	Nil	Nil
i) The system is capable of easily identifying the:					
• Strengths and	18 (or 64%)	6 (or 22%)	4 (or 14%)	Nil	Nil
• Weaknesses of an academic.	20 (or 71%)	5 (or 18%)	2 (or 7%)	1 (or 4%)	Nil
j) With the new system, it is easier to input the data using linguistic values such as 'very weak', 'weak', 'average', 'good' and 'very good' rather than using precise values.	19 (or 68%)	7 (or 25%)	2 (or 7%)	Nil	Nil

Table 6-16: Results of Usability Study

The overall results indicate that most of the respondents felt that their expectations in terms of user interface and functionality of the system have been met. This can be deduced when the number of responses for the columns "Strongly Agree" and "Agree" are examined. The number of responses in these columns are the largest for most of the statements. This indicates that the majority of respondents “Strongly Agree” or “Agree” with most of the statements, indicating a high level of acceptability for the newly developed system. However, the results of the study also indicated that there were some areas that could be improved upon.

Close to 30% of the respondents felt that the system was not very effective in informing the user on how to fix errors and close to 28% of the respondents felt that the terminologies indicated on the screen were not very clear. The researcher took note of this when improvements of the system was implemented. The respondents however indicated a high level of satisfaction on the other aspects relating to user interface such as positioning of messages on the screen, layout of information and prompts for data inputs.

The rest of the questions focused on the capability and functionality of the system. Around 70% of respondents “Strongly Agreed” or “Agreed” that the system was effective in evaluating academic staff in terms of the core strategic goals of the university such as Teaching and Learning, Research and Innovation, Administration, Writing and Publication, Consultancy and External Engagement.

One of the objectives (or functionality) of the system is to identify the strengths and weaknesses of an academic. For this objective, the results indicated a very high level of satisfaction among respondents as 86% felt that the system was successful in correctly identifying the strengths and 89% felt that the system was capable of correctly identifying the weaknesses of respondents. A fairly large percentage of respondents were satisfied on how the system was able to select candidates for an award (61%) and a promotion (67%). However, selecting candidates for an award or a promotion ranks the lowest when compared to the other capabilities of the system. Those respondents who were successful in attaining an award or a promotion using the conventional evaluation system therefore “Strongly Disagreed” or “Disagreed” with the new system of evaluation. This is confirmed by the results in Figure 7-5 which indicated that 29% of respondents were evaluated using the conventional evaluation system when they applied for a promotion. These respondents are therefore reluctant to be subjected to a new system of evaluation which they are not familiar with.

The most important result of the study indicated that 93% of respondents preferred the new system because it was easier to input the data using linguistic values (such as ‘very weak’, ‘weak’, ‘average’, ‘good’ and ‘very good’) instead of using precise values. This was also deduced when the results of the open-ended question (question 10 of the questionnaire in Annexure B) was analysed. The analysis of the open-ended question also concluded that it was the first time that respondents were able to input linguistic values which resulted in the monitoring and processing of an academic’s performance in terms of the core strategic goals of the university, the identification and strengths and weaknesses as well as the ranking and selection of candidates for an award or a promotion.

It can be concluded that the results of the usability study indicates a high level of satisfaction amongst respondents in terms of user interface and capabilities of the system. The results of the usability study also assisted in identifying some minor weaknesses in the system, which the researcher improved on.

6.7 Conclusion

Chapter 5 demonstrated the functionality of the newly developed fuzzy-based system. The purpose of this chapter (chapter 6) was to test the efficiency and reliability of the new system. The following methodology was used in the evaluation: The design science approach to instrument development to determine the usefulness (or utility) of the artifact, comparing the objectives to the actual observed results, quantitative performance measures and client feedback. The newly developed fuzzy-based model was firstly compared with the conventional AHP method in terms of the criteria weights. The results indicated that the fuzzy-based system was more reliable because linguistic values were used when compared to the conventional AHP method which used precise (or absolute) values. The current evaluation system (that is, the manual weighting system) was then compared with the newly developed fuzzy-based system in terms of performance and reliability. In both cases, similar data and the same evaluators were used in the experiment in order to attain valid results. The results indicated that both evaluation methods were not vastly different. Both methods did not show any difference in the results for quantitative sub-criteria and criteria. However, there were some discrepancies for qualitative sub-criteria and criteria. These discrepancies revolved around which criteria was ranked number one, the ranking of the alternatives and the identification of strengths and weakness of the three academics (alternatives).

In terms of these discrepancies, the manual weighting system was not reliable for the following reasons: (1) The evaluations using the manual weighting system was time consuming and as a result, the evaluators experienced fatigue and confusion during the evaluation process. (2) The manual weighting system did not take the "importance intensity" of the criteria when the evaluators assigned scores to each sub-criterion or each criterion. (3) The evaluators were uncertain or fuzzy about what scores to assign to the sub-criteria or criteria. (4) The personality of the evaluators had an impact on the results. The optimistic evaluator assigned higher scores while the pessimistic evaluator assigned lower scores. (5) The number of sub-criteria had a bearing on the results of the manual weighting system. Criteria that had fewer sub-criteria produced more reliable results that criteria that had more sub-criteria. (6) The amount of weights allocated to each criteria and sub-criteria also has an impact on the results. Criteria and sub-criteria that were allocated higher weights produced results that were more divergent when compared to criteria and sub-criteria that were allocated fewer weights.

All these shortcomings of the manual weighting system were easily resolved using linguistic values for the newly developed fuzzy-based system. The fuzzy-based system therefore proved to be more reliable than the manual weighting system. Further, the results of the usability study of academic staff from the IT department indicated the following results regarding the new fuzzy-based system: (1) An academic who applied for a promotion or an award was fairly rated. (2) The strengths and weaknesses of an academic were correctly identified. (3) An academic's performance in terms of the cores strategic goals of the university such as Teaching and Learning, Research and Innovation, Administration, Writing and Publication, Consultancy and External Engagement was easily monitored and processed.

The system was developed using data collected from academic staff at DUT. Chapter 7 discusses the approach that was adopted in collection and analyzing the data.

Chapter 7

THE RESEARCH APPROACH, STATISTICAL ANALYSIS AND REGRESSION MODELS

7.1 Introduction

Before developing the model, the researcher conducted a survey of academic staff at DUT to ascertain the following:

- The methods that are currently used to evaluate the performance of academic staff and their opinions regarding these methods;
- The opinions of academic staff regarding the development of a new computerised evaluation system; and
- What contributions the academic staff can make in the development of the new system.

This survey took the form of a questionnaire containing both open and closed-ended questions. This questionnaire is contained in Annexure A. Based on the results of the survey, a fuzzy-based productivity estimation model was developed. After the model was developed, the researcher conducted a usability study to ascertain the opinions of academic staff regarding the functionality and effectiveness of the newly developed. In this regard, the academic staff from the IT department was surveyed. The questionnaire for the usability study is contained in Annexure B and the results are discussed in section 6.6.

This chapter focuses on the approach that was adopted when designing and developing the first questionnaire contained in Annexure A as well as the collection, analysis and presentation of the primary data. Thereafter, the results of the survey are analysed and discussed. This chapter also developed two regression models based on the most important objectives of the study. This section concludes with a discussion on the TAM with a view to establish what factors (independent and dependent) are necessary so that management, CQPA and academic staff can accept the newly developed system.

7.2 The Research Approach

A quantitative and qualitative approach was adopted for the survey questionnaire (refer to Annexure A for the questionnaire). The objectives of the quantitative sections (questions 1 to 9) of the questionnaire were to elicit the following:

- General information such as status, faculty, years of service and number of evaluations. These questions were asked in questions 1 to 7. The purpose of these questions is to put the answers in context in terms of the study;
- The respondent's opinions regarding the current and proposed methods of evaluations are elicited in question 8. These are Likert-type questions where respondents are required to indicate their degree of agreement or disagreement using numbers 1 to 5. The number 1 indicates "strongly agree" and the number 5 indicates "strongly disagree"; and
- Their opinions regarding what constitute an effective productivity estimation model for the evaluation of academic staff. The academic staff was required to rank the functionality of an effective productivity estimation model from "least important" to "most important". Information about ranking is elicited in question 9.

Questions 10 and 11 are qualitative in nature. A qualitative approach was adopted for these two questions because the researcher wanted the respondents to think freely in order to express their opinions on what they expect from an effective evaluation system. The objectives of the qualitative sections (questions 10 and 11) were to elicit the following from the respondents:

- Information regarding their opinions on what constitutes an effective productivity estimation model;
- What form the inputs should take and how the processed information should be presented; and
- Respondents were also asked to make any general comments that could be taken into consideration when developing the productivity estimation model.

7.3 Testing the questionnaire

The target population for this research was the academic staff at the Durban University of Technology (DUT). All academic staff at DUT undergoes some form of evaluation from management and the Centre for Quality Promotion and Assurance (CQPA). It was imperative that the questionnaire be firstly tested with a few staff members before distributing these to the academic staff, that is, the population. Five academics were chosen. They were chosen on the following basis:

- A Lecturer in Communications who assisted with the appropriate use of grammar and language;
- Two Lecturers with at least twenty (20) years' experience who have undergone at least 3 evaluations; and
- Two Lecturers in IT that are skilled in programming and technical aspects such database design and online data capturing and processing.

The objective of this exercise was to test the following:

- The suitability of the language used. The Lecturer in Communication corrected the grammatical errors and also advised that some questions were technical in nature and respondents who do not have a strong IT background will experience problems in answering some of the questions. One of the technical questions was removed and two were rephrased so that these could be easily comprehended;
- Whether appropriate questions regarding past and current evaluation methods were asked in the questionnaire. The two lecturers with at least 20 years experience suggested that questions relating to SAQA (South African Quality Assurance) requirements and the principles of the National Quality Framework (NQF) be included in the questionnaire; and
- Whether a computerised productivity estimation model can be developed for academic staff and academic departments. The two respondents with advanced knowledge in programming and technical aspects raised some concerns about the ability of the proposed computer program to capture all functional requirements.

7.4 Population

The main objective of the questionnaire was to elicit the opinions of academic staff regarding present evaluation methods and the development of a new productivity estimation model based on their experiences. The information required was elicited by a survey. Bryman (2004) defines a population as the universe of units from which a sample is selected. Since all academics have undergone performance evaluation at some stage or the other (or will be evaluated in the future), the population in this study is therefore all academic staff from the 6 faculties at DUT. The population size for this study was 499 academic staff members. Since the population size is fairly small, the researcher decided to survey the entire population in order to get as many responses as possible (that is, the census).

7.5 Distribution of the questionnaire

The researcher attempted to distribute the questionnaire online using Google documents. According to Wright (2005), online distribution makes data capturing and data processing easier. However, online distribution was tried at the satellite campus in Pietermaritzburg and the response rate was low. Five (5) respondents from the Pietermaritzburg campus with a staff of eight one (81) completed the questionnaire online. In addition to online data collection, the researcher therefore decided to make hardcopies of the questionnaire for the respondent to fill in manually.

For manual distribution, the questionnaires were hand delivered to the Deans of each Faculty. They were very cooperative and agreed to assist in the data distribution and collection process. Each Dean assigned the task to a member of their respective faculty to distribute and collect the questionnaires. The researcher gave the respondents one week to complete the process. A total of 100 completed questionnaires were collected from a population of 499. This means that just above 20% of completed questionnaires were collected. The breakdown of the returns is as follows:

Faculty	Number of returns
1) Accounting and Informatics	14
2) Applied Sciences	28
3) Arts	22
4) Economic and Management Sciences	19
5) Engineering	6
6) Health Sciences	11

Table 7-1: Breakdown of returns

7.6 Ethical Considerations

The respondents were given the assurance of confidentiality. This assurance was clearly mentioned in a consent form that was attached to each questionnaire. It was also important to emphasize that their participation in the study was voluntary. In addition to other relevant information, the informed consent form contained the following:

- The name of the researcher;
- The name of the supervisor;
- The name of the institution supporting the research;
- The objectives of the study; and
- That the respondents' participation is voluntary and that he or she can withdraw from the study at any time.

It is important to emphasize that the questionnaire did not request for the respondent's name, ID number, address or any other information that could identify the respondent. This further helped in keeping all information confidential.

A staff list for each faculty was obtained and handed to the Dean of each faculty. This helped in keeping track on who the questionnaire was given to and who returned the completed ones. This helped to ensure that the responses are valid.

7.7 Statistical Analysis: Statement of findings, interpretation and discussion of the data

Sections 7.1 to 7.6 discussed the research approach, the design of the questionnaire (research instrument) and the methodology that was adopted in gathering the primary data. This section presents the results of the survey after the primary data was captured and analysed. The Statistical Package for Social Sciences version 21.0 (SPSS) was used for the analysis. The results are presented as descriptive statistics in the form of graphs, cross tabulations and other figures for the data that was collected. Inferential techniques include the use of correlations and chi square test values which are interpreted using the p-values are also presented.

7.7.1 A comparison of the respondents with the population

Since the focus of this study is to estimate the productivity of academic departments, only Junior and Senior Lecturers, Associate Professors and Professors were surveyed. In other words, academics that are subject to evaluations are surveyed in this study. Table 7-2 describes the demographics of Durban University in terms of status and faculties regarding academic staff. The table also indicates how the collected responses compare with the population for all six faculties.

Comparison Of The Sample With The Population							
Faculty	**Accounting and Informatics**	**Applied Sciences**	**Arts**	**Economic & Management Sciences**	**Engineering**	**Health Sciences**	**Total**
Total staff complement	96	72	82	85	80	84	499
Total responses collected	14	28	22	19	6	11	100
Percentage	14.6%	38.9%	26.8%	22.4%	7.5%	13%	20%
Number of Junior Lecturers	2	3	3	4	4	2	18
Number of Lecturers	67	44	52	49	36	56	304
Numbers of Senior Lecturers	24	17	21	25	33	23	143
Number of Associate Professors	1	6	5	4	4	1	21
Number of Professors	2	2	1	3	3	2	13

Table 7-2: Comparison of the sample with the population

Table 7-2 indicates that Lecturers make up the largest complement (304 or 61%) of the total number of academic staff at DUT. Junior Lecturers making up the smallest complement (18 or 3.6%). The total number of academics that are Senior Lecturers, Associate Professors and

Professors is 177 (or 35.5%). This indicates that more than one third of DUT academics have a high level of experience in teaching and research. The table also indicates that from a population of 499 academics from all six faculties, just over 20% of respondents completed the questionnaire. Most of the responses were from the Faculty of Applied Sciences (38.9%) while the least number of responses came from the Faculty of Engineering (7.5%). Close to 50% of the responses came from the Faculties of Arts (26.8%) and Economic and Management Sciences (22.4%).

7.7.2 The objectives of the questionnaire (research instrument)

It is important to show to what extent the results of the survey are able to address the objectives of the questionnaire. The objectives of the questionnaire are to:

- Examine the present state of academic evaluation and productivity estimation at Durban University of Technology (DUT);
- Elicit the opinions of the academic staff on the evaluation and productivity estimation methods that are currently being used at DUT; and
- Elicit the opinions of the academic staff regarding the development of a new computerised productivity estimation model.

7.7.3 The Research Instrument

The research instrument consisted of 28 items with a level of measurement at a nominal or an ordinal level. The questionnaire was divided into 4 sections which measured various themes as illustrated below:

Question 1 to 7: These questions were asked to get information on the demographics of each department at DUT. This type of information helped to put the study in perspective.

Question 8: This question elicited the opinions of the respondent's regarding current and proposed methods of evaluation at DUT.

Question 9: This question elicited the opinions of academic staff on what constitutes an effective productivity estimation model.

Question 10 and 11: These questions are qualitative in nature. The purpose was to elicit responses from academic staff regarding the inputs, outputs as well as what functions the system should be able to perform.

7.7.4 Reliability Statistics

The two most important aspects of precision are reliability and validity. Reliability is computed by taking several measurements on the same subjects. A reliability coefficient of around 0.70 is considered as “acceptable”. Refer to Annexure D for an explanation on how reliability is calculated. The results for reliability are presented in Table 7-3.

Section	**Reliability**
Question 8 (13 items): Opinions on current and proposed evaluation methods.	0.859
Question 9 (4 items): Opinions on what constitutes an effective productivity estimation model.	0.600
Overall	0.693

Table 7-3: Results of the reliability scores in the questionnaire

The reliability score for question 8 exceeded the recommended value of 0.70 which indicates that the scoring of the respondents was reliable (for question 8). However the score for question 9 was lower than the recommended value of 0.70. This is due to the fact that this question has fewer items (four) and the reliability was therefore expected to be on the lower side. The overall score (0.693) is close to the recommended score of 0.7. It indicates that there was a high (overall) degree of acceptability and consistency scoring for the research.

7.7.5 Descriptive statistics

Descriptive statistics will be used to describe the organising and summarizing of the quantitative data that was collected. This summarised information is required for more constructive research after a detailed analysis has been undertaken. The frequency distributions for questions 1 to 7 are presented below.

a) Distribution in terms of status

Figure 7-1 describes the characteristics of the respondents in terms of status.

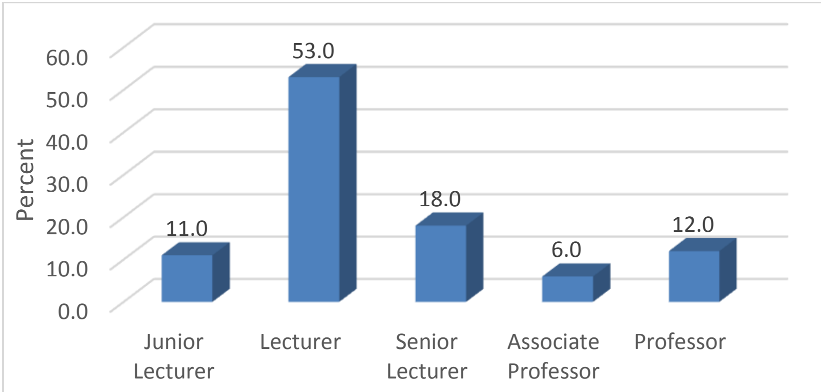


Figure 7-1: Description in terms of status

Most of the respondents were Junior Lecturers, Lecturers or Senior Lecturers. These categories of academics are evaluated more often by management or CQPA.

b) Distribution in terms of faculties

Table 7-1 describes the characteristics of the respondents in terms of faculties they belong to. However, a detailed discussion is presented in terms of why the response rate differed in the various faculties.

Half of the respondents (50%) were either from the Faculties of Applied Sciences or Arts. The fairly large percentage is attributed to the fact that departments in these faculties have been undergoing evaluations during the last 2 years. Their recent experiences in evaluations could have motivated them to respond the questionnaire. This is in contrast to the Faculty of Engineering (where the response rate was only 6%) where a new round of evaluations will only begin from 2015.

c) Distribution in terms of frequency of evaluations

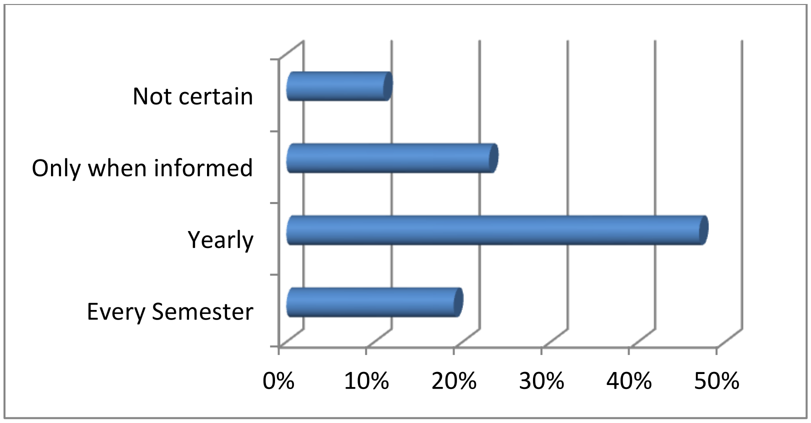


Figure 7-2: Description in terms of how often evaluations take place

Forty seven (47) of the respondents are evaluated on a yearly basis and nineteen (19) are evaluated every semester. This means that 66 (around two thirds) of the respondents undergo some form of evaluation at least once a year. The results indicate that evaluation and productivity estimation play an integral part in measuring the performance of academic staff at DUT. Just over 20% of respondents were evaluated only when they are informed about it. A general interpretation from the responses (Figure 7-2) indicates that departments in the various faculties are at liberty to evaluate academic staff either on a semester or yearly basis or on an *ad hoc* basis. Those respondents who were not certain (10%) are academic staff that have been recently employed at DUT and are not yet aware about evaluation procedures in the department or faculty. This corresponds to the results in Figure 7-3 which indicates that 10% of academic staff is employed at DUT for less than 5 years.

d) Distribution in terms of experience

Figure 7-3 describes the respondents experience in terms of the number of years of service at DUT.

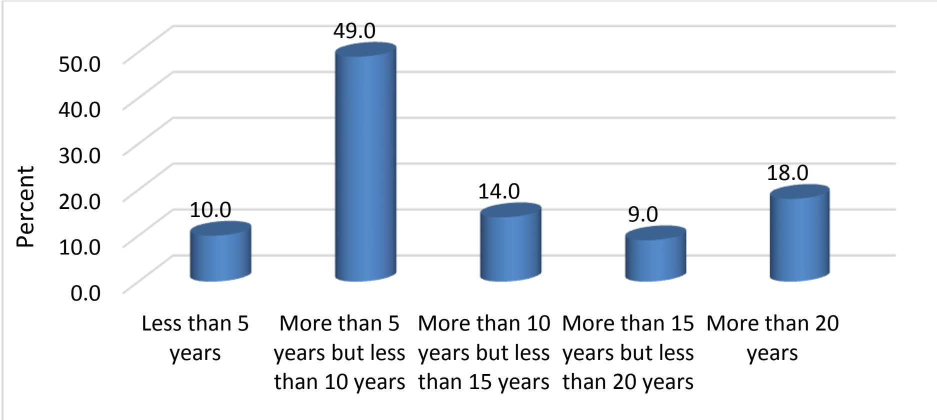


Figure 7-3: Description in terms of number of year service at DUT

Since 10% of respondents are employed for less than 5 years, it means that at least 90% of the respondents are employed at DUT for 5 years or longer. Clearly DUT has a teaching staff that is reasonably experienced and who have undergone some form of evaluations while at DUT. This is confirmed by the results in Figure 7-4 which indicated that more than 70% of respondents have undergone at least one evaluation per year. Since most respondents have undergone at least one evaluation, it is expected that their opinions regarding present evaluation methods (question 8) and what constitutes an efficient productivity estimation model (question 9) will be useful in developing the model.

e) Distribution in terms of number of evaluations

Figure 7-4 describes the number of evaluations that academic staff have undergone while employed at DUT.

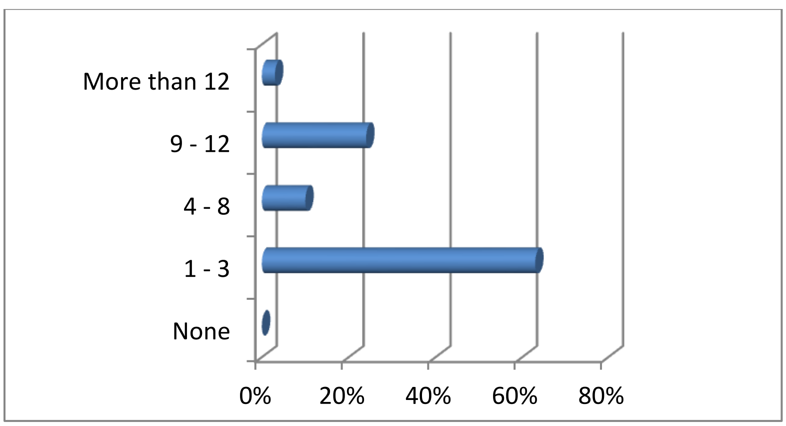


Figure 7-4: Description in terms of number of evaluations at DUT

Figure 7-4 indicates that every respondent has undergone at least one evaluation. The fact that most respondents have undergone between 1 and 3 evaluations (63%) indicate that this group of academics are employed at DUT for the least number of years when compared to the other categories. This is further confirmed by the results indicated in Figure 7-3 that shows that most respondents (close to 60%) have been employed at DUT for less than 10 years (that is, 10% for less than 5 years and 49% between 5 and 10 years as indicated in Figure 7-3). The most experienced respondents at DUT (close to 18% as indicated in Figure 7-4) have the most number of evaluations (more than 12 as indicated in Figure 7-4). It is therefore expected that this group will provide the most valuable information regarding current evaluation methods (question 8) and the development of an effective productivity estimation model (question 9).

f) Distribution in terms of reasons for evaluations having taken place

Figure 7-5 describes the reasons why respondents were evaluated.

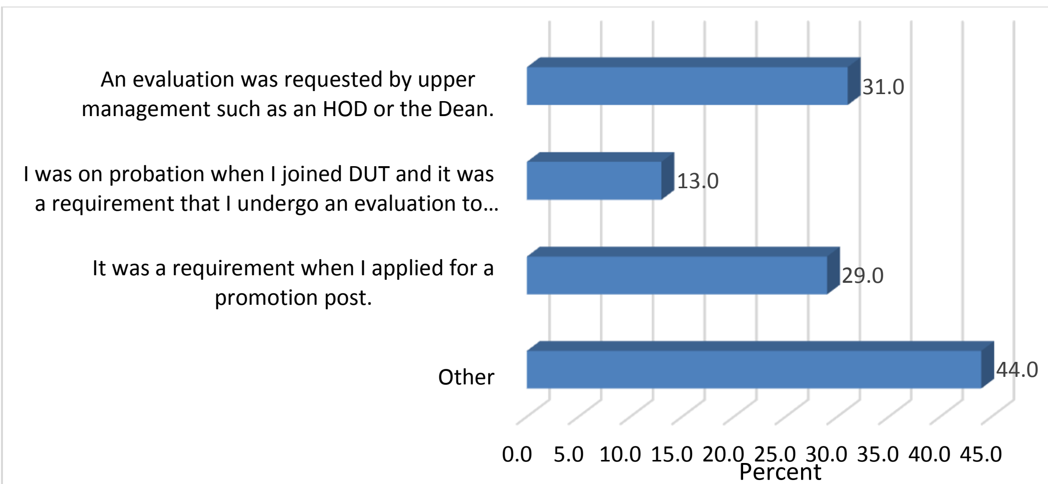


Figure 7-5: Description in terms of reasons for evaluations

Sixty four percent (64%) of respondents were specific about why they were being evaluated. Further analysis revealed that a majority of the 'other' respondents indicated that they were evaluated by the Centre for Quality Promotion and Assurance (CQPA). Some respondents indicated that they were evaluated when they applied for a transfer from one department to another while others were evaluated when they applied for a transfer from campus to another.

g) Distribution in terms of evaluation methods

Figure 7-6 describes the type of evaluation methods that the respondents have undergone.

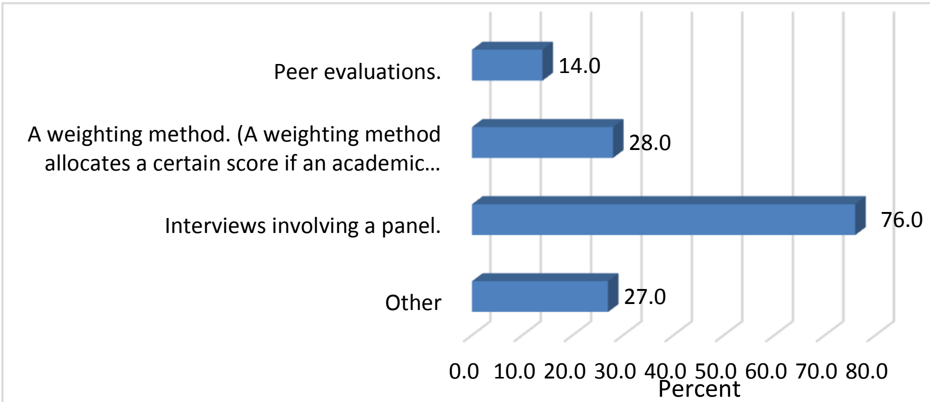


Figure 7-6: Description in terms of evaluation methods

Over three-quarter (76.0%) of the respondents were subjected to interviews by a panel. This is a common form of evaluation that involves questions being asked to the respondent. If the evaluation is for promotion purposes, then the same questions are generally asked to all applicants. The weighting method (28% of respondents) is usually combined with the panel interview (76% of respondents). Each panel member will ask a question and the entire panel will independently assign a weight or a score to a criteria or sub-criteria. The scores are added at the end of the interview and a discussion then takes place so that all evaluators come to an agreement on the final score. Since the total of these two percentages (76% and 28%) exceeds 100%, it means that some respondents chose both options.

The Centre of Quality Promotion and Assurance (CQPA) encourage peer evaluations of academic staff. This is however not a very popular method as only 14% of respondents have undergone such a method of evaluation. This question also had the 'other' option that was open-ended with 27% of respondents having chosen this option. Most of the respondents for the 'other' option were from the Engineering, Arts and Health Sciences faculties. Besides the standard methods of evaluation prescribed by CQPA, these faculties have additional methods of evaluations. A few respondents from the Engineering faculty were evaluated based on a demonstration of a new artifact they developed. Some members from the Drama department were evaluated based on some theatre production while some respondents from the Health Sciences Faculty were evaluated based on some innovative and ground-breaking research.

This section described the results of the survey for questions 1 to 7 of the research questionnaire. In order to address the objectives of the remainder of the questions, inferential techniques are used. Inferential techniques include the use of correlations and chi square test values, which are interpreted using the p-values.

7.7.6 Factor and statistical analysis for questions 8 and 9

This section discusses:

- Factor analysis;
- The tests required before factor analysis can be implemented;
- The results after implementing the factor analysis procedure; and
- An analysis of the survey results.

Factor analysis is a statistical technique whose main goal is data reduction or duplication from a set of correlated variables. Correlated variables are represented with a smaller set of "derived" variables. In other words, one variable can represent many other variables. The main purpose of factor analysis is to help put objects (or people) into smaller manageable categories. Factor analysis can therefore be used to establish whether multiple measures do, in fact, measure the same thing. If so, they can then be combined and summarised to create a new variable to capture the "essence" of items.

Before the factor analysis procedure can take place, two requirements have to be met. These are:

- The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy should be greater than 0.50. Refer to Annexure G for an explanation on how the KMO test is conducted; and
- The Bartlett's Test of Sphericity should be less than 0.05. Refer to Annexure G for an explanation on how the Bartlett's Test of Sphericity is conducted.

a) Analysis of question 8

Table 7-4 presents the results (for question 8) of the KMO and Bartlett tests for the data.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.505
Bartlett's Test of Sphericity	Approx. Chi-Square	1546.228
	Df	78
	Sig.	.000

Table 7-4: KMO and Bartlett's Test for question 8

The results of the KMO test yields a value of 0.505 which is > 0.50 and the result of the Bartlett test yields a value of 0.000 which is < 0.05. Both requirements have been met and the factor analysis procedure was therefore implemented. The results of the factor analysis procedure are indicated in Table 7-5.

Statement	Component		
	1	2	3
Creating a computerised portfolio of an academic makes evaluation and productivity estimation easier.	.339	.064	.640
Rating a university in terms of its research output in all its' departments collectively can be easily done using a computerised production estimation system	.206	-.041	.821
Current evaluation methods are effective in meeting SAQA (South African Quality Assurance) requirements.	.590	.486	.302
Current evaluation methods are able to meet the principles (such as standards, quality and excellence) of the National Quality Framework.	.532	.353	.343
Present evaluation methods at DUT are capable of benchmarking academic productivity.	.518	.698	.063
Current evaluation methods are successful in measuring an academic's productivity (that is, an academic's efficiency and effectiveness).	.671	.525	.197
Current evaluation methods are able to determine whether minimum standards in terms of departmental requirements can be met.	.774	.168	.387
Present methods of evaluation are successful in measuring the productivity of an academic department as a whole.	.924	.013	.159
Present methods of evaluation are able to fairly select candidates who are due for promotion.	.669	.244	-.157
Current evaluation methods can be used to determine whether an academic is due for a merit award.	.194	.886	.000
Current evaluation methods are effective in monitoring and processing performance in terms of the core strategic goals such as teaching and learning, research and external engagement.	.165	.735	.264
Present evaluation methods have been successful in identifying the strengths and weaknesses of academic staff in terms of these core strategic goals.	.112	.943	.058

Table 7-5: Results of factor analysis for question 8

Table 7-5, indicates that the variables that constituted question 8 was loaded along 3 components. This implies that respondents identified certain aspects of the sub-themes as belonging to other sub-sections. The theme for the first column can be summarised as whether current evaluation methods are able to estimate productivity of academic staff so that minimum standards pertaining to a department and external bodies can be met. The theme for the second column is whether current evaluation methods can monitor and process an academic's performance in terms of the core strategic goals as well as for promotion or awards. The theme for the third column is whether a computerised system can make evaluation easier in terms of creating a portfolio of academic staff and rating a university in terms of its research outputs.

Figure 7-7 presents the results of the scoring patterns of the respondents for question 8. The categories “Strongly Agree” and “Agree” has been collapsed into a single category called “Agree”. The categories “Strongly Disagree” and “Disagree” has been collapsed into a single category called “Disagree”. The category “Neutral” remains the same. This is allowed due to the acceptable levels of reliability. The results are first presented using summarised percentages for the variables (that constitute each section) and then described.

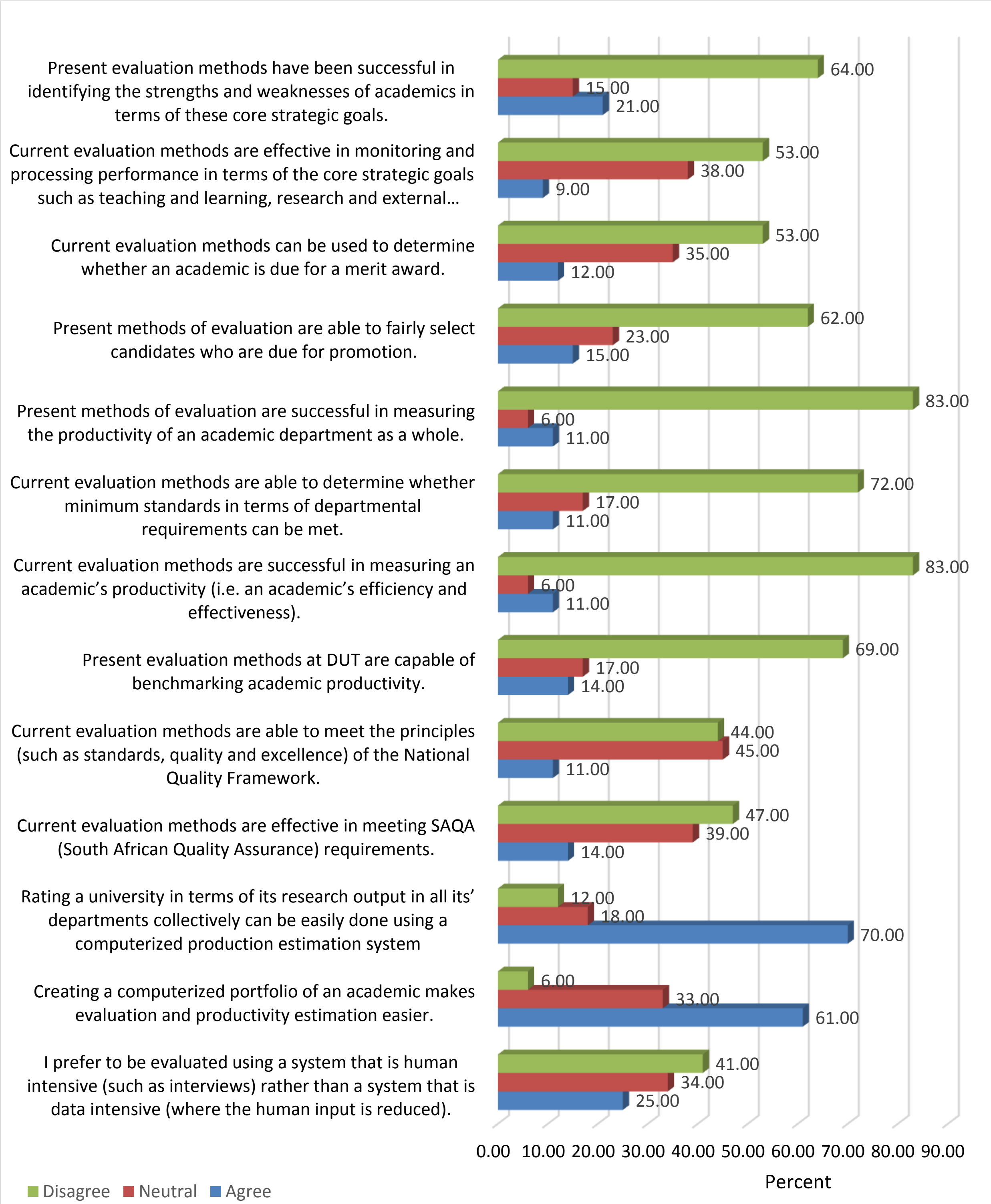


Figure 7-7: Results of scoring patterns for question 8

Evaluation and productivity estimation plays an integral part in measuring the performance of academic staff at the Durban University of Technology. This is clearly demonstrated by the results depicted in Figures 7-3 and 7-4, which indicates that at least 70% of respondents have undergone some kind of evaluation. However, respondents are unhappy about the evaluation methods that are currently implemented at DUT. The results from Figure 7-7 indicate that more than half the respondents feel that current evaluation methods cannot identify strengths and weaknesses of academic staff. They also feel that current evaluation methods cannot efficiently determine whether an academic is due for a merit award and that current procedures are unable to fairly select candidates who are due for promotion.

Estimating productivity of academic departments is difficult due to the qualitative nature of the attributes to be measured (Lee, 2010). Presently, quantitative techniques are being used to measure qualitative attributes. The outputs are therefore inefficient and unreliable. It is for these reasons that 83 % of respondents agreed that current estimation methods are unreliable and inefficient. They feel that the development of a new system is therefore necessary as 61% of respondents indicated that creating a computerised portfolio of an academic makes evaluation and productivity estimation easier and more efficient. Academic staff members are constantly involved in research and publications.

Presently, a system does not exist at DUT that can collectively rate an academic department or the university as a whole in terms of its research and publications. This is confirmed by the results from Figure 7-7 which indicates that 70% of respondents agree that a computerised system can effectively be used to rate a university in terms of its research outputs. The results for the first 4 questions from Figure 7-7 indicates that more than 50% of respondents have remained neutral (for these questions). The reasons could be attributed to the fact that respondents have been subjected to only one method of evaluation method (that is, the manual weighting system) and therefore cannot make a comparison with any other evaluation techniques. Their best option was to therefore remain neutral. It is necessary to comment on why a small percentage of respondents prefer the status quo, that is, the current evaluation methods. For example, 15% agree that present evaluation methods are able to fairly select candidates that are due for promotion and 12% agree that current methods are effective in selecting academics for a merit award. This is attributed to the fact that this small group of respondents succeeded in acquiring a merit award or a promotion after being evaluated with the current methods. This is confirmed by the results indicated in Figure 7-5 that shows 29% of respondents were evaluated because they applied for a promotion. These respondents are therefore reluctant to be subjected to a new system of evaluation. An unexpected result of the survey indicated that only 33% of respondents prefer a system that is data intensive. A data intensive system will normally involve a computerised system. This contradiction may be attributed to the fact that respondents were not able to differentiate between a data intensive and a human intensive system. When one examines the overall results of the survey, it is clear that respondents are unhappy about current evaluation methods. The overall response also indicates that an effective computerised productivity estimation system should be implemented. Such a system has now been developed (Chapter 3) and demonstrated (Chapter 5).

b) Analysis of question 9

Table 7-7 presents the results (for question 9) of the KMO and Bartlett tests for the data.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.540
	Approx. Chi-Square	173.286
Bartlett's Test of Sphericity	Df	6
	Sig.	.000

Table 7-6: KMO and Bartlett's Test for question 9

The results of the KMO test yields a value of 0.540 which is > 0.50 and the result of the Bartlett test yields a value of 0.000 which is < 0.05. Both requirements have been met and the factor analysis procedure was therefore implemented. The results of the factor analysis procedure are indicated in Table 7-7.

Rotated Component Matrix[a]

Statement	Component	
	1	2
An effective productivity estimation model should be able to correctly rank personnel for promotion.	.577	.730
The model should be able to monitor and process an academic staff's performance in terms of the core strategic goals such as teaching and learning, research and external engagement.	.945	.051
The model should be able to identify the strengths and weaknesses in terms of the core strategic goals.	.907	-.181
The model should be able to create a portfolio of an academic so that evaluation and estimation productivity is made easier.	-.313	.886

Table 7-7: Results of factor analysis for question 9

The principle component analysis was used as the extraction method, and the rotation method was Varimax with Kaiser Normalisation (Refer to Annexure H for an explanation on how the rotated component matrix is determined). This is an orthogonal rotation method that minimizes the number of variables that have high loadings on each factor. It simplifies the interpretation of the factors. The rotation converged in 3 iterations. Factor analysis showed inter-correlations between variables. Items of questions that loaded similarly imply measurement along a similar factor. An examination of the content of items loading at or above 0.5 (and using the higher or highest loading in instances where items cross-loaded at greater than this value) effectively measured along the various components. This question (question 9) loaded along 2 sub-components. The theme for the first component (column 1) relates to the importance intensity of a new computerised model in terms of promotion, academics performance as well as identifying strengths and weaknesses of academics. The theme for the second component (column 2) relates to the importance intensity of developing a model to create portfolios of academic staff in order to make productivity estimation easier.

Figure 7-8 presents the results of the scoring patterns of the respondents for question 9.

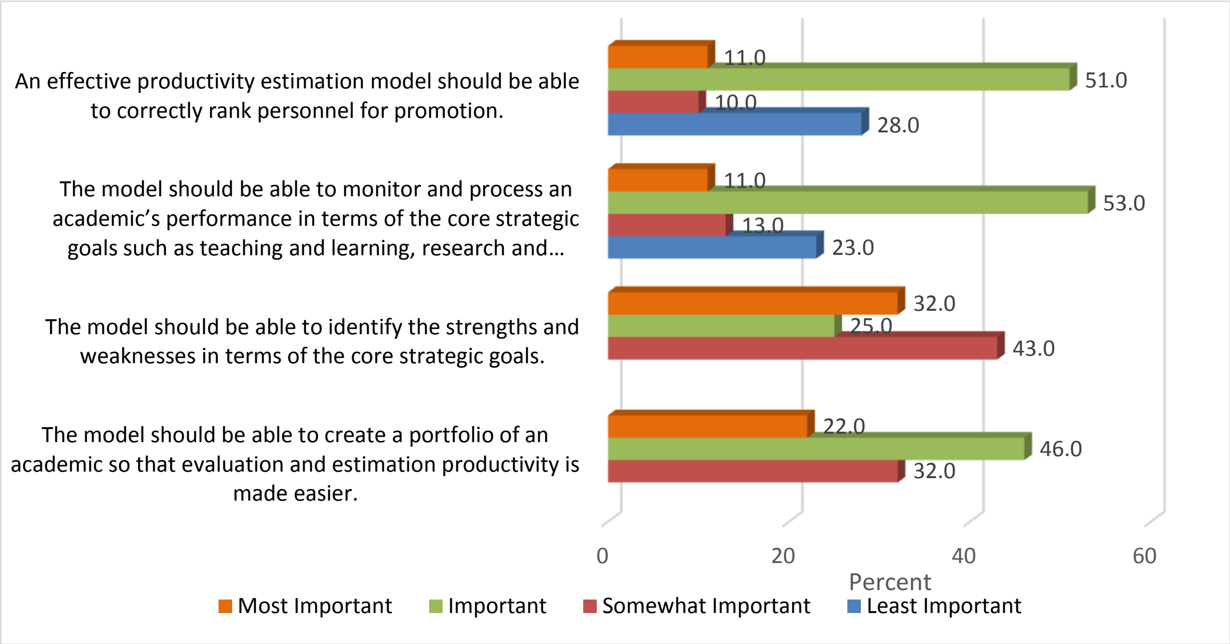


Figure 7-8: Results of scoring patterns for question 9

The overall results in Figure 7-8 indicate that the third statement has a lower level of importance when compared to the other statements (Refer to Table 7-8 for the overall rankings of the 4 statements). This means that according to the respondents, correctly identifying personnel for promotion, monitoring performance in terms of core strategic goals and creating a portfolio for each academic are the most important attributes that should be considered first when creating a productivity estimation model. However, all 4 attributes were taken into consideration when developing the model. The overall ranking of the 4 statements are indicated in Table 7-8.

Statement	Percent	Rank
The model should be able to create a portfolio of an academic so that evaluation and estimation productivity is made easier.	68	1
The model should be able to monitor and process an academic's performance in terms of the core strategic goals such as teaching and learning, research and external engagement.	64	2
An effective productivity estimation model should be able to correctly rank personnel for promotion.	62	3
The model should be able to identify the strengths and weaknesses in terms of the core strategic goals.	57	4

Table 7-8: Ranking the statements from "Most Important" to "Least Important"

In order to determine the overall ranking of these statements, the scores of "Most Important" and the scores of "Important" were combined. These rankings are indicated in Table 7-8. In order to determine the significance between the statements, bivariate correlation measures were calculated. Refer to Annexure I on how bivariate correlations are calculated. Table 7-9 indicates the relationships between the four statements. The following keys are used in the table:

X1: "The model should be able to create a portfolio of an academic so that evaluation and estimation productivity is made easier."

X2: "The model should be able to identify the strengths and weaknesses in terms of the core strategic goals."

X3: "The model should be able to monitor and process an academic's performance in terms of the core strategic goals such as teaching and learning, research and external engagement."

X4: "An effective productivity estimation model should be able to correctly rank personnel for promotion."

Correlations

			X1	X2	X3	X4
Spearman's rho	X1	Correlation Coefficient	1.000			
		Sig. (2-tailed)	.			
		N	100			
	X2	Correlation Coefficient	-.390**	1.000		
		Sig. (2-tailed)	.000	.		
		N	100	100		
	X3	Correlation Coefficient	-.189	.810**	1.000	
		Sig. (2-tailed)	.059	.000	.	
		N	100	100	100	
	X4	Correlation Coefficient	.340**	.360**	.589**	1.000
		Sig. (2-tailed)	.001	.000	.000	.
		N	100	100	100	100

**. Correlation is significant at the 0.01 level (2-tailed).

Table 7-9: Results of the correlations between variables

Most of the relationships in Table 7-9 indicate a high degree of correlation between the 4 factors. This means that although the level of importance between the four factors differ to a small degree (as indicated in Table 7-8), all four factors are significant and therefore should be taken into consideration when developing the productivity estimation model. The correlation between "The model should be able to create a portfolio of an academic so that evaluation and estimation productivity is made easier" (X1) and "An effective productivity estimation model should be able to correctly rank personnel for promotion" (X4) is moderate relationship (0.340). Academics are required to develop a manual portfolio while employed at the Durban University of Technology. This manual process is cumbersome and could easily be simplified using a computerised system. Also, ranking and selecting personnel for promotion using current methods are not successful as indicated in the results of the survey (Figure 7-7). The relationship between X1 and X4 therefore indicates that the development of a computerised system that is able to create portfolios of academic staff can make the process of selecting and ranking personnel for promotion easier. The correlation between “The model should be able to identify the strengths and weaknesses in terms of the core strategic goals” (X2) and “An effective productivity estimation model should be able to correctly rank personnel for promotion” (X4) is also moderate (0.360). This means that that a newly developed computerised system should be effective when identifying the strengths and weaknesses of academic staff as these attributes are important when ranking and selecting personnel for promotion. The correlations between “The model should be able to monitor and process an academic’s performance in terms of the core strategic goals such as teaching and learning, research and external engagement” (X3) and “An effective productivity estimation model should be able to correctly rank personnel for promotion” (X4) is strong (0.589) when compared to the correlations discussed above. This means that the newly developed system should consider teaching and learning, research and external engagement as very significant criteria when ranking and selecting personnel for promotion.

Table 7-9 indicates that “The model should be able to identify the strengths and weaknesses in terms of the core strategic goals” (X2) and “The model should be able to monitor and process an academic’s performance in terms of the core strategic goals such as teaching and learning, research and external engagement” (X3) is the strongest relationship when compared to all other correlations (0.810). According to the results of Figure 7-7, respondents feel that current evaluation methods are unable to effectively identify the strengths and weaknesses of academic staff and as a result, their performance cannot be effectively monitored and processed according to the core strategic goals. The newly developed system should therefore be able to identify the strengths and weaknesses in order to effectively monitor and process the performance of academic staff.

c) Analysis of question 10

Question 10 is qualitative in nature. The objectives of this question were to elicit the following from the respondents:

- Information regarding their opinions on what constitutes an effective productivity estimation model;

- What form the inputs should take and how the processed information should be presented; and
- Respondents were also asked to make any general comments that could be taken into consideration when developing the productivity estimation model.

The methodology that is used for analysing qualitative data involves the examination, identification and interpretation of patterns and themes in textual data. These patterns and themes will help answer the research question at hand. In this study, questions 10.1, 10.2 and 10.3 were individually analysed and interpreted. Question 10.1 elicited information on the functionality of the system (that is, what the model is expected to do). The underlying themes and patterns that emerged for question 10.1 are indicated in Table 7-10.

Patterns/themes	**Percent**
Method should fairly/accurately evaluate productivity.	97
Identify areas of weaknesses	79
Identify areas of strengths	73
Determine promotion and awards	65
It should be accurate, realistic and reliable	64

Table 7-10: Results on the functionality of a proposed evaluation model

From the results indicated in Figure 7-7, most respondents are concerned that current methods evaluate academics unfairly and inaccurately. It is for this reason that 97% of respondents want a new system that can rate academics fairly and 64% of respondents feel that the system should be realistic and reliable (results from Table 7-10). This is further confirmed by the results indicated in Figure 7-7 where 62% of respondents agreed that current methods could easily lend themselves to bias. The results also indicate that areas of weaknesses and strengths are relatively high (79% and 73%). When the new system was being developed, all the themes and patterns indicated in Table 7-9 was taken into consideration. Section 5.6 demonstrated that the strengths and weaknesses of academics could be accurately identified using the new system. The system has also proven to be reliable and accurate as demonstrated in Chapter 5.

Question 10.2 elicited information from respondent’s on what form the inputs should take. The underlying themes and pattern are indicated in Table 7-11.

Inputs	Percent
Words such as weak, good and very good	64
Values within a range for each category	35
Weights	33

Table 7-11: Results on the form of the inputs

The current method of evaluation involves individual evaluators assigning weights to the sub-criteria and criteria. These weights take the form of absolute values or values that may be contained within a range such as “Average = 50 to 59” and “Excellent ≥ 80”. These values are then added after the evaluation has been completed. The group of evaluators will then discuss the assessments until a score has been assigned through consensus. The results in Table 7-11 indicate that respondents are unhappy about these forms of inputs. These results also concur with the results of a survey of evaluators (section 6.5.3) that indicated that numeric values as a form of input should be avoided when evaluating qualitative data. Most respondents preferred linguistic values such as weak, good, very good and excellent as a form of input. When the new system was being developed, the researcher used fuzzy logic and fuzzy set theory that uses linguistic values as inputs.

Question 10.3 elicited information from respondents on what forms the outputs should take. The underlying themes and patterns are indicated in Table 7-12.

Form of output	Percent
Reports	78
Clearly laid out, easy access of information	68
Output in the form of graphs, charts	64
Outputs using words such as good, average, weak, etc.	62

Table 7-12: Results on the form of the outputs

Most respondents prefer the output from the computerised system to be in the form of reports. The other forms of output are also popular and the researcher therefore decided to use many different methods for the outputs.

7.7.7 Hypothesis Testing

The traditional approach to reporting a result requires a statement of statistical significance using a p-value. A p-value is generated from a test statistic**.** A significant result is indicated with "$p < 0.05$" using Pearson's Chi Square Tests (Refer to Annexure E for a description on how the Chi Square Tests are carried out). These values are highlighted with an * indicated in Table 7-13. In the Table below, Col 2 = Status; Col 3 = Faculty; Col 4 = How often does evaluation take place in your faculty (also consider CQPA evaluations); Col 5 = How many completed years of service do you have; Col 6 = How many evaluations did you have while employed at DUT (also consider CQPA evaluations).

Pearson Chi Square Tests		Status	Faculty	Evaluation Frequency	years of service	Number of evaluations
I prefer to be evaluated using a system that is human intensive (such as interviews) rather than a system that is data intensive (where the human input is reduced).	Chi-square	42.615	56.091	36.775	40.878	14.464
	Df	8	10	6	8	6
	Sig.	.000*	.000*	.000*	.000*	.025*
Creating a computerised portfolio of an academic makes evaluation and productivity estimation easier.	Chi-square	140.792	138.329	61.341	97.108	53.879
	Df	8	10	6	8	6
	Sig.	.000*	.000*	.000*	.000*	.000*
Rating a university in terms of its research output in all its' departments collectively can be easily done using a computerised production estimation system	Chi-square	70.863	77.905	52.057	97.456	51.919
	Df	8	10	6	8	6
	Sig.	.000*	.000*	.000*	.000*	.000*
Current evaluation methods are effective in meeting SAQA (South African Quality Assurance) requirements.	Chi-square	50.828	77.602	64.342	66.999	24.043
	Df	8	10	6	8	6
	Sig.	.000*	.000*	.000*	.000*	.001*
Current evaluation methods are able to meet the principles (such as standards, quality and excellence) of the National Quality Framework.	Chi-square	44.516	82.568	53.341	40.425	29.264
	Df	8	10	6	8	6
	Sig.	.000*	.000*	.000*	.000*	.000*
Present evaluation methods at DUT are capable of benchmarking academic productivity.	Chi-square	111.485	129.729	36.722	69.290	13.968
	Df	8	10	6	8	6
	Sig.	.000*	.000*	.000*	.000*	.030*
Current evaluation methods are successful in measuring an academic's productivity (that is, an academic's efficiency and effectiveness).	Chi-square	110.252	143.373	67.544	76.428	26.100
	Df	8	10	6	8	6
	Sig.	.000*	.000*	.000*	.000*	.000*
Current evaluation methods are able to determine whether minimum standards in terms of departmental requirements can be met.	Chi-square	77.543	125.222	110.005	78.919	11.446
	Df	8	10	6	8	6
	Sig.	.000*	.000*	.000*	.000*	0.076
Present methods of evaluation are successful in measuring the productivity of an academic department as a whole.	Chi-square	110.252	143.373	67.544	76.428	26.100
	Df	8	10	6	8	6
	Sig.	.000*	.000*	.000*	.000*	.000*
Present methods of evaluation are able to fairly select candidates who are due for promotion.	Chi-square	46.183	72.714	29.155	40.058	40.417

	Df	4	5	3	4	3
	Sig.	.000*	.000*	.000*	.000*	.000*
Current evaluation methods can be used to determine whether an academic is due for a merit award.	Chi-square	47.736	77.060	16.919	28.099	17.011
	Df	4	5	3	4	3
	Sig.	.000*	.000*	.001*	.000*	.001*
Current evaluation methods are effective in monitoring and processing performance in terms of the core strategic goals such as teaching and learning, research and external engagement.	Chi-square	33.896	45.518	15.040	18.637	24.458
	Df	4	5	3	4	3
	Sig.	.000*	.000*	.002*	.001*	.000*
Present evaluation methods have been successful in identifying the strengths and weaknesses of academics in terms of these core strategic goals.	Chi-square	47.098	51.327	8.144	22.264	12.264
	Df	4	5	3	4	3
	Sig.	.000*	.000*	.043*	.000*	.007*
An effective productivity estimation model should be able to correctly rank personnel for promotion.	Chi-square	85.416	116.308	119.194	80.135	42.932
	Df	12	15	9	12	9
	Sig.	.000*	.000*	.000*	.000*	.000*
The model should be able to monitor and process an academic's performance in terms of the core strategic goals such as teaching and learning, research and external engagement.	Chi-square	111.343	148.233	80.134	91.446	27.835
	Df	12	15	9	12	9
	Sig.	.000*	.000*	.000*	.000*	.001*
The model should be able to identify the strengths and weaknesses in terms of the core strategic goals.	Chi-square	68.210	94.214	60.241	63.008	67.128
	Df	8	10	6	8	6
	Sig.	.000*	.000*	.000*	.000*	.000*
The model should be able to create a portfolio of an academic so that evaluation and estimation productivity is made easier.	Chi-square	65.925	153.445	46.269	83.387	39.790
	Df	8	10	6	8	6
	Sig.	.000*	.000*	.000*	.000*	.000*

Table 7-13: Results of Pearson Chi Square Tests

Pearson's Chi Square tests looked at whether there were any differences in the options per statement. The null hypothesis states that there is no difference in the frequencies for each option for each question. A second Chi square test was performed to determine whether there was a statistically significant relationship between the variables (rows versus columns). The null hypothesis states that there is no association between the two. The alternate hypothesis indicates that there is an association. All values less than 0.05 imply that the distributions are skewed in one direction. A result from Table 7-13 can be described as follows: The p-value between "I prefer to be evaluated using a system that is human intensive (such as interviews) rather than a system that is data intensive (where the human input is reduced)" and col 3, that is, "Faculty" is 0.000 (which is less than the significance value of 0.05). This means that there is a significant relationship between the variables. That is, the faculty to which the respondent belongs does play a role in terms of how respondents wished to be evaluated. All other significant relationships can be described in a similar manner. Since there are too many relationships that are significant, only a few are highlighted are described.

The p-value for the cross tabulation of “Creating a computerised portfolio of an academic makes evaluation and productivity estimation easier” and col 2, that is, “Status” is 0.000 (which is < 0.05) indicates that the status of the respondents does play a role on whether the choice of a system to create a computerised portfolio of academics will make productivity estimation easier.

The p-value for the cross tabulation of “Current evaluation methods can be used to determine whether an academic is due for a merit award” and col 4, that is, “How often does evaluation of academics take place in your faculty?” is 0.001 (which is < 0.05). This means that there is a significant relationship between the frequency of evaluations in a faculty and whether present evaluation systems can be used to determine if an academic is due for a merit award. The implication is that some academics may not apply for a merit award in order to avoid being evaluated by a system that they are not happy with.

The p-value for the cross tabulation between “Current evaluation methods are effective in monitoring and processing performance in terms of the core strategic goals such as teaching and learning, research and external engagement” and col 5, that is, “how many years of service do you have at DUT” is 0.001 (which < 0.05). This indicates that there is a significant relationship between these two statements. The implication is that the number of years of service academics have at DUT may determine their response regarding performance in terms of the core strategic goals.

The p-value for the cross tabulation between “Present evaluation methods at DUT are capable of benchmarking academic productivity” and col 6, that is, “How many evaluations did you have while at DUT” is 0.030 (which is < 0.05). The implication is that their decision on whether current evaluation methods can benchmark academic productivity will be based on the number of evaluations they have undergone.

This section used Pearson’s Chi Square tests to determine whether there was a significant relationship between variables (row versus columns). The results indicated that there were too many significant relationships that can be discussed. The researcher therefore only chose 5 relationships as discussed in the paragraph above. All other significant relationships can be discussed along similar lines.

7.7.8 Correlations

Bivariate correlation was also performed on the (ordinal) data. Refer to Annexure I on how bivariate correlations are calculated.

The results indicate the following patterns: Positive values indicate a directly proportional relationship between the variables and a negative value indicates an inverse relationship. All significant relationships are indicated by a * or **. The correlation results are indicated in Table 7-14. Since the amount of text was too large to fit in the row and column headings, it was decided that a unique key with keywords be used to represent each statement. The keys with the keywords are indicated in Table 7-13.

Statement	Key
I prefer to be evaluated using a system that is human intensive (such as interviews) rather than a system that is data intensive (where the human input is reduced).	S1 (Human intensive)
Creating a computerised portfolio of an academic makes evaluation and productivity estimation easier.	S2 (Computerised portfolio)
Rating a university in terms of its research output in all its' departments collectively can be easily done using a computerised production estimation system	S3 (Rating a university)
Current evaluation methods are effective in meeting SAQA (South African Quality Assurance) requirements.	S4 (SAQA requirements
Current evaluation methods are able to meet the principles (such as standards, quality and excellence) of the National Quality Framework.	S5 (NQF framework)
Present evaluation methods at DUT are capable of benchmarking academic productivity.	S6 (Benchmark productivity)
Current evaluation methods are successful in measuring an academic's productivity (that is, an academic's efficiency and effectiveness).	S7 (Efficiency and Effectiveness)
Current evaluation methods are able to determine whether minimum standards in terms of departmental requirements can be met.	S8 (Minimum standards)
Present methods of evaluation are successful in measuring the productivity of an academic department as a whole.	S9 (Productivity of Department)
Present methods of evaluation are able to fairly select candidates who are due for promotion.	S10 (Selection for promotion)
Current evaluation methods can be used to determine whether an academic is due for a merit award.	S11 (Merit Awards)

Current evaluation methods are effective in monitoring and processing performance in terms of the core strategic goals such as teaching and learning, research and external engagement.	S12 (Strategic goals)
Present evaluation methods have been successful in identifying the strengths and weaknesses of academics in terms of these core strategic goals.	S13 (Strengths and weaknesses)
An effective productivity estimation model should be able to correctly rank personnel for promotion.	S14 (Ability to Rank for promotion)
The model should be able to monitor and process an academic's performance in terms of the core strategic goals such as teaching and learning, research and external engagement.	S15 (Ability to monitor performance)
The model should be able to identify the strengths and weaknesses in terms of the core strategic goals.	S16 (Ability to identify strengths and weaknesses)
The model should be able to create a portfolio of an academic so that evaluation and estimation productivity is made easier.	S17 (Ability to create portfolio)

Table 7-14: Keys used to represent each statement

		S1 Human intensive	**S2 Comp. portfolio**	**S3 Rating**	**S4 SAQA**	**S5 NQF**	**S6 Bench-mark**	**S7 Efficiency & Effectiv.**	**S8 Min. Standards**	**S9 Dept. Product.**	**S10 Promotion**	**S11 Merit Awards**
S1 Human intensive	Correlation Coefficient	1.000										
	Sig. (2-tailed)											
	N	100										
S2 Compt. Portflio	Correlation Coefficient	-.109	1.000									
	Sig. (2-tailed)	.280										
	N	100	100									
S3 Rating	Correlation Coefficient	-.241*	.045	1.000								
	Sig. (2-tailed)	.016	.655									
	N	100	100	100								
S4 SAQA	Correlation Coefficient	-.252*	.281**	-.017	1.000							
	Sig. (2-tailed)	.011	.005	.870								
	N	100	100	100	100							
S5 NQF	Correlation Coefficient	-.220*	-.012	.291**	.421**	1.000						
	Sig. (2-tailed)	.028	.903	.003	.000							
	N	100	100	100	100	100						
S6 Bench mark	Correlation Coefficient	-.275**	.224*	-.043	.762**	.581**	1.000					
	Sig. (2-tailed)	.006	.025	.674	.000	.000						
	N	100	100	100	100	100	100					
S7 Efficiency & Effectiveness	Correlation Coefficient	-.296**	-.025	-.068	.593**	.459**	.731**	1.000				
	Sig. (2-tailed)	.003	.803	.499	.000	.000	.000					

	N	100	100	100	100	100	100	100				
S8 Min. Standards	Correlation Coefficient	-.265**	.169	.099	.319**	.515**	.513**	.795**	1.000			
	Sig. (2-tailed)	.008	.092	.326	.001	.000	.000	.000				
	N	100	100	100	100	100	100	100	100			
S9 Dept. Productivity	Correlation Coefficient	-.296**	-.025	-.068	.593**	.459**	.731**	1.000**	.795**	1.000		
	Sig. (2-tailed)	.003	.803	.499	.000	.000	.000		.000			
	N	100	100	100	100	100	100	100	100	100		
S10 Promotion	Correlation Coefficient	-.064	-.106	-.237*	.012	.236*	.274**	.576**	.343**	.576**	1.000	
	Sig. (2-tailed)	.527	.292	.017	.905	.018	.006	.000	.000	.000		
	N	100	100	100	100	100	100	100	100	100	100	
S11 Merit Awards	Correlation Coefficient	-.209*	.114	-.115	.451**	.344**	.550**	.479**	.222*	.479**	.419**	1.000
	Sig. (2-tailed)	.036	.257	.256	.000	.000	.000	.000	.026	.000	.000	
	N	100	100	100	100	100	100	100	100	100	100	100

*. Correlation is significant at the 0.05 level (2-tailed) and **. Correlation is significant at the 0.01 level (2-tailed).

Table 7-15: Results of Correlations between variables

The complete correlation results for all variables are indicated in Annexure J. However, an abbreviated table (Table 7-15) that contains the correlations for discussion is shown. The correlation value for factors between S6 and S2, that is, “Present evaluation methods at DUT are capable of benchmarking academic productivity” and “Creating a computerised portfolio of an academic makes evaluation and productivity estimation easier” is 0.224. This is a directly related proportionality. Respondents agree that the establishment of a computerised evaluation system will help benchmark academic productivity. Negative values imply an inverse relationship. That is, the variables have an opposite effect on each other. The relationship between S2 and S1 is an inverse relationship.

Creating a computerised portfolio of an academic is more data intensive rather than human intensive. However, the results in Figure 7-7 indicate that most respondents prefer a human intensive system rather than a data intensive one. This implies that there is a contradiction regarding respondent’s choices for this question and therefore an inverse relationship was attained. This is the underlying pattern (that is, the contradictions) since most of the results in the S1 column yielded negative results. The reason for this contradiction is that respondents could not differentiate between a human intensive and a data intensive system. The methods that are employed to rate academics for merit awards and promotions are generally a contentious issue.

The correlation between S11 and S10 is therefore fairly high (0.419) indicating that current methods are ineffective in rating academics for awards as indicated in Figure 7-7. The correlation between the principles of the National Quality Framework (NQF) and rating an academic department in terms of its research outputs is also fairly high (0.281). This indicates that both an academic department and the NQF are expected to be benchmarked against high standards, quality and excellence which cannot be achieved using current evaluation methods as indicated in Figure 7-7. Similarly all correlations (direct or inverse) can be discussed.

Discussing all the correlations in Table 7-15 is not necessary but patterns and themes can be determined by examining most of the relationships. The underlying theme that emerges from Table 7-15 indicates that respondents are generally unhappy with the current evaluation methods and that alternative techniques are therefore necessary.

7.7.9 Regression Models

This section focuses on how a model can be formulated by associating a chosen dependent variable with associated independent variables. In order to do so, a dependent variable which captures the essence of the study as well as independent variables that have an impact on the dependent variable are identified (Bryman, 2004). This study presents the formulation of two such models. The first model pertains to the main aim of the study. The second model pertains to respondents opinions on whether current evaluation methods are capable of efficiently estimating the productivity of academic staff.

The aim of this study is to develop a computerised fuzzy-based productivity estimation system that is efficient and reliable. The researcher has therefore identified the second statement of question 8, that is, “Creating a computerised portfolio of an academic makes evaluation and productivity estimation easier” as the dependent variable. According to the results of the survey, current methods are difficult to implement because qualitative attributes are being measured using quantitative techniques. This difficulty produces results that are inaccurate and unreliable. This is confirmed by the results of the survey discussed in section 7.8.6. Linked to the dependent variables are the four independent variables (the first 4 statements of question 9 in the research questionnaire), that is, “An effective productivity estimation model should be able to correctly rank personnel for promotion”, “The model should be able to monitor and process an academic’s performance in terms of the core strategic goals such as teaching and learning, research and external engagement", "The model should be able to identify the strengths and weaknesses in terms of the core strategic goals" and "The model should be able to create a portfolio of an academic so that evaluation and estimating productivity is made easier". These 4 statements are in essence the aims of the study which was accomplished by developing the fuzzy-based system. After entering the dependent and the independent variables in SPSS, a summary of the model in Table 7-16 is attained. A discussion follows below the table.

Model Summary

Model B	R C	R Square d	Adjusted R Square e	Std. Error of the Estimate f
1	.806[a]	.649	.634	.457

Table 7-16: Summary of the model

From Table 7-16, the following points (highlighted in red) are discussed as follows:

- Correlation Coefficient: This is indicated as a in the table. It represents the correlation coefficient between the dependent and independent variables;
- Predictors (constants): These are: The model should be able to create a portfolio of an academic so that evaluation and estimation productivity is made easier. The model should be able to monitor and process an academic's performance in terms of the core strategic goals such as teaching and learning, research and external engagement. An effective productivity estimation model should be able to correctly rank personnel for promotion. The model should be able to identify the strengths and weaknesses in terms of the core strategic goals;
- Model: This is indicated as b in the table. SPSS allows you to specify multiple models in a single regression command. This tells you the number of the model being reported;
- R: This is indicated as c in the table. R is the square root of R-Squared and is the correlation between the observed and predicted values of dependent variable;
- R-Square: This is indicated as d in the table. R-Square is the proportion of variance in the dependent variable which can be predicted from the independent variables. This value indicates that 64.9% of the variance in the dependent variable can be predicted from the independent variables. R-Square is also called the coefficient of determination;

- Adjusted R-Square: This is indicated as e in the table. As predictors (or independent variables) are added to the model, each predictor will explain some of the variance in the dependent variable simply due to chance. One could continue to add predictors to the model which would continue to improve the ability of the predictors to explain the dependent variable, although some of this increase in R-Square would be simply due to chance variation in that particular sample. The adjusted R-Square attempts to yield a more honest value to estimate the R-Squared for the population. The value of R-Square was 0.649, while the value of Adjusted R-Square was 0.634; and
- Error of the Estimate: This is indicated as f in the table. The standard error of the estimate, also called the root mean square error, is the standard deviation of the error term, and is the square root of the Mean Square Residual (or Error).

Table 7-17 indicates whether the independent variables can reliably predict the dependent variable.

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F g	Sig. H
1	Regression	36.631	4	9.158	43.920	.000[b]
	Residual	19.809	95	.209		
	Total	56.440	99			

Table 7-17: Can the independent variables reliably predict the dependent variable?

Table 7-17 indicates the F (column g) and Sig (column h) values after computation. The F-value is 43.920. The p-value associated with this F value is 0.000. These values are used to answer the question "Do the independent variables reliably predict the dependent variable?" The p-value is compared to the alpha level (typically 0.05) and, if smaller, it can be concluded that the predictors can be used to give a good indication of performance since the significance value is less than 0.05. In this case, since the p-value is less than 0.05, the independent variables predict the dependent variable.

The results of the computations for the relationship between the dependent and the independent variables are indicated in Table 7-18.

Coefficients[a]

		Unstandardised Coefficients		Standardised Coefficients		
	I	J	k	l	m	N
	Model	B	Std. Error	Beta	t	Sig.
1	(Constant)	4.382	.309		14.161	.000
	An effective productivity estimation model should be able to correctly rank personnel for promotion.	-.548	.064	-.739	-8.548	.000
	The model should be able to monitor and process an academic's performance in terms of the core strategic goals such as teaching and learning, research and external engagement.	.090	.088	.115	1.022	.309
	The model should be able to identify the strengths and weaknesses in terms of the core strategic goals.	-.196	.089	-.224	-2.204	.030
	The model should be able to create a portfolio of an academic so that evaluation and estimation productivity is made easier.	-.124	.080	-.120	-1.543	.126

Dependent Variable: Creating a computerised portfolio of an academic makes evaluation and productivity estimation easier.

Table 7-18: Relationship between the dependent and independent variables

Column i shows the predictor variables. The first variable represents the constant, also referred to in textbooks as the Y intercept, the height of the regression line when it crosses the Y-axis. In other words, this is the predicted value of the dependent variable when all other variables are 0.

Column j indicates the β values. These are the values for the regression equation for predicting the dependent variable from the independent variable. These are called unstandardised coefficients because they are measured in their natural units. As such, the coefficients cannot be compared with one another to determine which one is more influential in the model, because they can be measured on different scales. The regression equation can be presented in many different ways, for example: Let LHS $= Y_{predicted}$ and $X_1 =$ "An effective productivity estimation model should be able to correctly rank personnel for promotion", $X_2 =$ "The model should be able to monitor and process an academic's performance in terms of the core strategic goals such as teaching and learning, research and external engagement", X_3 = "The model should be able to identify the strengths and weaknesses in terms of the core strategic goals", X_4 = "The model should be able to create a portfolio of an academic so that evaluation and estimation productivity is made easier". The column of estimates (coefficients or parameter estimates, from here on labeled coefficients) provides the values for b_0, b_1, b_2, b_3 and b_4 for this equation. Expressed in terms of the variables used in this example, the regression equation is:

$$Y_{predicted} = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4$$

$$= 4.382\text{-}0.548X_1\text{+}0.090X_2\text{-}0.196X_3\text{-}0.124X_4$$

These estimates tell you about the relationship between the independent variables and the dependent variable. These estimates indicate the amount of increase in the dependent variable that would be predicted by a 1 unit increase in the predictor. This can be explained as follows: "An effective productivity estimation model should be able to correctly rank personnel for promotion" - The coefficient (parameter estimate) which is -0.548. So, for every unit increase in "An effective productivity estimation model should be able to correctly rank personnel for promotion", a 0.548 unit decrease in "Creating a computerised portfolio of an academic makes evaluation and productivity estimation easier" is predicted, holding all other variables constant. It does not matter at what value you hold the other variables constant, because it is a linear model. "The model should be able to monitor and process an academic's performance in terms of the core strategic goals such as teaching and learning, research and external engagement" - For every unit increase in "The model should be able to monitor and process an academic's performance in terms of the core strategic goals such as teaching and learning, research and external engagement", there is a 0.090 unit increase in the predicted "Creating a computerised portfolio of an academic makes evaluation and productivity estimation easier" scores, holding all other variables constant. A similar reasoning can be adopted for the other two independent variables.

Column k indicates the standard errors (Std. Error) associated with the coefficients. The standard error is used for testing whether the parameter is significantly different from 0 by dividing the parameter estimate by the standard error to obtain a t-value (see the column with t-values and p-values).

Column l indicates Beta values which are the standardised coefficients. These are the coefficients that you would obtain if you standardised all of the variables in the regression, including the dependent and all of the independent variables, and ran the regression. By standardising the variables before running the regression, all of the variables has to be put on the on the same scale and then it is possible to compare the magnitude of the coefficients to see which one has more of an effect. It is noticeable that the larger betas are associated with the larger t-values.

Columns m and n indicate the t and Sig. values respectively. These columns provide the t-value and 2 tailed p-value used in testing the null hypothesis that the coefficient/parameter is 0. Coefficients having p-values less than alpha are statistically significant for a two tail test. For example, for alpha equal to 0.05, coefficients having a p-value of 0.05 or less would be statistically significant (that is, you can reject the null hypothesis and say that the coefficient is significantly different from 0). In this model, the values highlighted in yellow show significant non-zero coefficients.

The second model focuses on the respondent’s opinions on whether current productivity estimation methods are efficient and effective. For this model, the researcher identified the following statement as the dependent variable: “Current evaluation methods are successful in measuring an academic’s productivity (that is, an academic’s efficiency and effectiveness)”. The independent variables entered into SPSS are indicated in Table 7-19.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Present methods of evaluation are successful in measuring the productivity of an academic department as a whole. Current evaluation methods are effective in monitoring and processing performance in terms of the core strategic goals such as teaching and learning, research and external engagement. Present evaluation methods have been successful in identifying the strengths and weaknesses of academics in terms of these core strategic goals. Current evaluation methods are able to determine whether minimum standards in terms of departmental requirements can be met.[b]	.	Enter

Table 7-19: Variables entered

The dependent variable is as follows:

a. Dependent Variable: Current evaluation methods are successful in measuring an academic's productivity (that is, an academic's efficiency and effectiveness).

b. All requested variables entered.

Table 7-20 indicates the constants that are used in the model.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.967[a]	.936	.933	.234

Table 7-20: Summary of the model with constants used

a. Predictors: (Constant). Present methods of evaluation are successful in measuring the productivity of an academic department as a whole. Current evaluation methods are effective in monitoring and processing performance in terms of the core strategic goals such as teaching and learning, research and external engagement. Present evaluation methods have been successful in identifying the strengths and weaknesses of academics in terms of these core strategic goals. Current evaluation methods are able to determine whether minimum standards in terms of departmental requirements can be met.

Table 7-21 determines whether the independent variables can reliably predict the dependent variables.

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	75.730	4	18.933	347.233	.000[b]
	Residual	5.180	95	.055		
	Total	80.910	99			

Table 7-21: Can the independent variables reliable predict the dependent variable?

a. Dependent Variable: Current evaluation methods are successful in measuring an academic's productivity (that is, an academic's efficiency and effectiveness).

b. Predictors: (Constant). Present methods of evaluation are successful in measuring the productivity of an academic department as a whole. Current evaluation methods are effective in monitoring and processing performance in terms of the core strategic goals such as teaching and learning, research and external engagement. Present evaluation methods have been successful in identifying the strengths and weaknesses of academics in terms of these core strategic goals. Current evaluation methods are able to determine whether minimum standards in terms of departmental requirements can be met.

Table 7-22 determines the relationship between the dependent and independent variables.

Coefficients[a]

Model	Unstandardised Coefficients		Standardised Coefficients	T	Sig.
	B	Std. Error	Beta		
(Constant)	-1.059	.149		-7.089	.000
Current evaluation methods are effective in monitoring and processing performance in terms of the core strategic goals such as teaching and learning, research and external engagement.	-.298	.054	-.290	-5.506	.000
Present evaluation methods have been successful in identifying the strengths and weaknesses of academics in terms of these core strategic goals.	.822	.041	.747	20.233	.000
Current evaluation methods are able to determine whether minimum standards in terms of departmental requirements can be met.	.342	.095	.289	3.624	.000
Present methods of evaluation are successful in measuring the productivity of an academic department as a whole.	.431	.070	.426	6.150	.000

Table 7-22: Relationship between the dependent and independent variables

a. Dependent Variable: Current evaluation methods are successful in measuring an academic's productivity (that is, an academic's efficiency and effectiveness).

The regression model can be represented in the form of an equation as follows:

Let LHS $= Y_{predicted}$ and $X_1 =$ "Current evaluation methods are effective in monitoring and processing performance in terms of the core strategic goals such as teaching and learning, research and external engagement", $X_2 =$ "Present evaluation methods have been successful in identifying the strengths and weaknesses of academics in terms of these core strategic goals", $X_3 =$ "Current evaluation methods are able to determine whether minimum standards in terms of departmental requirements can be met", $X_4 =$ "Present methods of evaluation are successful in measuring the productivity of an academic department as a whole". The column of estimates (coefficient or parameter estimates) provide the values for b_0, b_1, b_2, b_3 and b_4 for this equation. Expressed in terms of the variables used in this example, the regression equation is:

$$Y_{predicted} = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4$$

$$= -1.0594 - 0.289X_1 + 0.822X_2 + 0.342X_3 + 0.431X_4$$

The equation can be explained as follows: For every unit increase in "Current evaluation methods are effective in monitoring and processing performance in terms of the core strategic goals such as teaching and learning, research and external engagement" a 0.289 unit decrease in "Current evaluation methods are successful in measuring an academic's productivity (that is, an academic's efficiency and effectiveness)" is predicted. For every unit increase in "Present evaluation methods have been successful in identifying the strengths and weaknesses of academics in terms of these core strategic goals", a 0.822 increase in "Current evaluation methods are successful in measuring an academic's productivity (that is, an academic's efficiency and effectiveness)" is predicted. A similar reasoning can be adopted for the other two independent variables.

7.7.10 Regression models and the TAM

Productivity estimation and evaluation of academic staff is presently done using the conventional manual system (that is, a non-computerised manual weighting system) at the Durban University of Technology. The aim of this study was to develop a computerised fuzzy-based system that is able to estimate productivity of academic staff. The system was successfully developed and evaluated. However, in order for the new computerised system to be accepted, it should be useful and easy to use. For the developed system to be useful, the requirements of management, the Center for Quality Performance and Assurance (CQPA) and academic staff (as identified by the research questionnaire) should be considered. The model should also be easy to use for it to be accepted. This section therefore discusses the Technology Acceptance Model with a view to establish what factors (independent and dependent) are necessary so that management, CQPA and academic staff can accept the newly developed system.

a) The Technology Acceptance Model

The Technology Acceptance Model (TAM) suggests that when users are presented with new technologies, two important factors will influence their decision, namely (Safeena *et al*., 2010):

- Perceived usefulness; and
- Perceived ease-of-use.

Perceived ease of use and perceived usefulness predict attitudes toward use of technology. Attitude toward use predicts the behavioural intention to use the technology. Finally intention predicts the actual use of the technology (Davis, 1989). If the technology is indeed useful and easy to use, then the individual will accept the technology. The converse will however also be true. If the technology is not useful and is difficult to use, then the user will reject the technology. A user will either accept or reject the technology. The main dependent constructs for the TAM are behavioural intention to use and system usage. The main independent constructs are perceived usefulness and perceived ease of use. The Technology Acceptance Model is depicted in Figure 7-9.

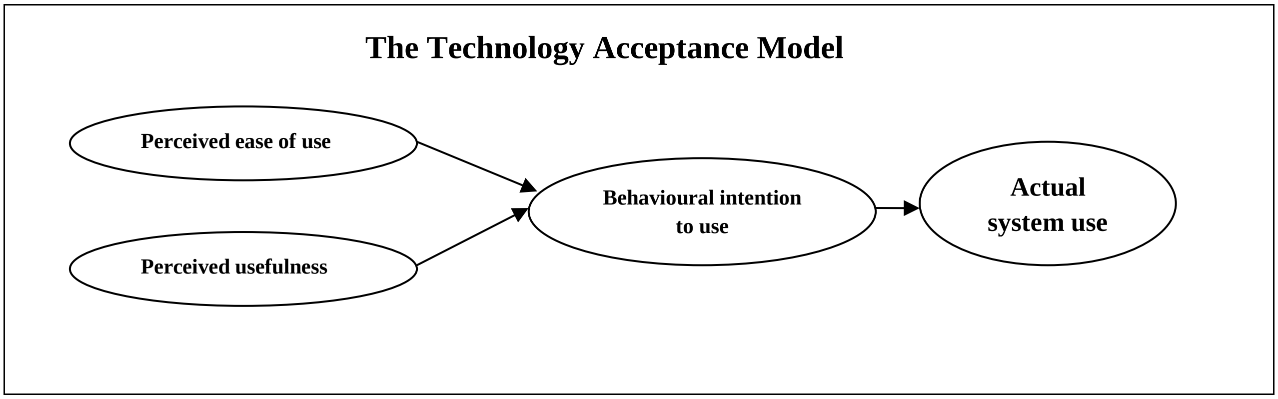


Figure 7-9: The Technology Acceptance Model (Davis, 1989)

The results of the survey of the 4 evaluators from CQPA indicated that current productivity estimation methods are time-consuming and difficult to implement (refer to section 6.5.3 for the survey). The results in Figure 7-7 also indicated that respondents (academic staff) are unhappy about the manner in which current evaluation methods are implemented and that a computerised system is preferred. Such a computerised system was therefore developed. It needs to be determined whether the TAM can determine whether such a system is useful and can be accepted by the users.

With regard to the first regression model, the 4 independent statements identified by the researcher are as follows: "An effective productivity estimation model should be able to correctly rank personnel for promotion", "The model should be able to monitor and process an academic's performance in terms of the core strategic goals such as teaching and learning, research and external engagement", "The model should be able to identify the strengths and weaknesses in terms of the core strategic goals" and "The model should be able to create a portfolio of an academic so that evaluation and estimating productivity is made easier". The results of survey (Figure 7-7 and Table 7-8) indicated that respondents perceive that a new system that takes these statements into consideration will be easy to use and will be useful. This concurs with the independent factors of the TAM, which are perceived ease of use and perceived usefulness.

The researcher identified the second statement of question 8 (from the research questionnaire), that is, "Creating a computerised portfolio of an academic makes evaluation and productivity estimation easier" as the dependent variable. Academics are required to develop a manual portfolio while employed at the Durban University of Technology. This manual process is cumbersome and could easily be simplified using a computerised system. A fairly high percentage (61% as indicated in Figure 7-7) of the respondents therefore agreed with this statement. This indicates that 61% of respondents have an intension to use a computerised productivity estimation system that can easily create a portfolio an academic. This deduction will therefore concur with the dependent factor in the TAM (Figure 7-9), which is behavioural intension to use the system.

The TAM states that for a technology to be accepted, it must not only be easy to use, but it must also be useful. In other words, the newly developed system should adequately address the requirements of management, CQPA and academic staff for it to be useful. These requirements were elicited through the research questionnaire and formulated into objectives as indicated in section 5.4.

A usability study was conducted to elicit the views of academic staff on whether their requirements (or objectives of the system) were adequately addressed. Refer to Annexure B for the questionnaire and section 6.6 for the results of the usability study. The results of the usability study indicated that respondents were satisfied with the user interface (in terms of ease of use) and the capabilities of the newly developed system (in terms of its usefulness). The new system will be useful in processing and monitoring the performance of academic staff in terms of the core strategic goals of the university, the identification of strengths and weaknesses and the ranking and selection of candidates for an award or a promotion.

It can therefore be concluded that since the developed system is easy to use and is useful, it will be accepted by the users. This will lead to the actual use of the system once upper management have approved its implementation in all academic departments.

7.8 Conclusion

Chapter 6 focused on testing the efficiency and reliability of the developed system. This chapter (chapter 7) focused on the research instrument, the research approach based on the Design Science Research Methodology (DSRM) as well as the analysis and presentation of the survey results. The presentation of the analysed results was done using descriptive statistics. Inferential techniques were also necessary in the analysis. This included the use of correlations and chi square tests which were interpreted using p-values. Two regression models were also developed by associating chosen dependent variables that are associated with the independent variables. These variables were associated with the dependent and independent variables of the TAM with a view to establish what factors (independent and dependent) are necessary so that management, CQPA and academic staff can accept the newly developed system. Based on the results of the study, a fuzzy-based productivity estimation system was developed using the Design Science

Research DSRM. Chapter 8 is the last chapter that focused on the summary of the results and recommendations.

Chapter 8

SUMMARY AND RECOMMENDATIONS

8.1 Introduction

This chapter presents an overview of the research conducted. The overview summarizes the results of the research questionnaires, the reasons for choosing a fuzzy-based methodology for the model development, suggestions for future research, the limitations of the study, recommendations as well as the effectiveness and functionality of the newly developed system. This chapter concludes with a discussion on communication (that is, how the artifact can be communicated to management and other stakeholders) which is the last (6^{th}) activity of the Design Science Research Methodology (DSRM).

8.2 Objectives of the study

The main objectives of the study were to:

- Ascertain from academic staff their opinions regarding evaluation methods that are currently used at the Durban University of Technology (DUT);
- Elicit the opinions of academic staff on the development of a new computerised productivity estimation model;
- Develop a computerised fuzzy-based system based on the requirements of academic staff; and
- Evaluate the developed system using:
    a. A design science approach to instrument development to establish the utility of the new system,
    b. Interviews to elicit the opinions of the evaluators on current evaluation methods and the new system,
    c. Quantitative techniques in order to compare the reliability of the new system with current evaluation methods,
    d. A usability study to ascertain from academic staff their views on the effectiveness and functionality of the new system.

8.3 Findings and discussions

The results of the survey (Figure 7-7) indicated that academic staff are generally unhappy about how current evaluation methods are implemented. The main areas of dissatisfaction revolve around the identification of strengths and weaknesses, unreliable techniques that are used to rank academics for promotion and awards as well as the inability of current methods to monitor and process performance in terms of the core strategic goals of the university. The results from Figure 7-8 indicated that a computerised productivity estimation system would be able to address these shortcomings. After an in-depth literature review, the researcher decided that an algorithmic fuzzy-based approach was the most appropriate technique to be implemented when developing the computerised system. The Design Science Research Methodology (DSRM) was adopted in the development of the system.

The academic productivity estimation model was efficiently developed using fuzzy-AHP, which was capable of easily accommodating both objective (tangible) and subjective (intangible) factors. Problems susceptible to educational, social, political, economic and technical factors that require linguistic variables can be efficiently solved using the Fuzzy Analytic Hierarchy Process (FAHP). The criteria and the alternatives are determined at the beginning and are depicted in the top-down hierarchy structure. The alternatives are at the lowest level with the sub-criteria and criteria above the alternatives.

Fuzzy AHP computes the best alternative (or optimal solution) by using a weighting process. The fuzzy AHP approach allows for pair-wise comparisons of elements (based on human judgment) and was represented using linguistic values attained from an 'intensity importance' fuzzy scale (Table 5-19). These values were used to determine priorities or weights. These weights in conjunction with other mathematical computations such as the fuzzy judgment (which uses a linguistic scale for the alternatives as indicated in Table 5-3) and the fuzzy performance matrices were used to select the best alternative. This approach is preferred because linguistic values can efficiently mimic how the human mind interprets imprecision and uncertainty. Further, the use of linguistic values is easier to input. This was ascertained from the results of a survey of the 4 evaluators (refer to section 6.5.3 for the results). Each linguistic variable is represented using an interval between two numbers that will contain the most likely value. This makes the choices (inputs) of the evaluators more reliable.

The researcher also made a comparison of criteria weights between the conventional AHP and fuzzy AHP methods using similar data. The same decision-makers and the same academics (alternatives) were used so that the experiment was valid. The results of the experiment showed that the results were not vastly different for most of the criteria. However, the major discrepancy revolved around which criteria was ranked number one. This discrepancy was due to many choices being available to the decision-makers when an 'intensity importance' is chosen from the Saaty scale of absolute values (Table 2-1) for conventional AHP. This means that evaluators were at a dilemma as to what rating to assign to a criterion. The solution to the problem was that the indecisions were resolved by using linguistic values for fuzzy AHP. The experiment showed that fuzzy AHP is more reliable than conventional AHP when implemented in an environment that is uncertain and fuzzy such as an academic department. It should however be mentioned that conventional AHP and fuzzy AHP should not be seen as competitors with each other. Both approaches are reliable depending on the type of criteria/factors (tangible or intangible) used in the problem domain. If all the sub-criteria and criteria in a problem domain are tangible, then conventional AHP should be used. If the problem domain has at least one intangible sub-criterion or criteria, then fuzzy AHP should be used.

A comparison was also made between the current method (manual weighting system) of evaluation and the newly developed model. Similar data for both the manual weighting method and the fuzzy AHP system was used. The experiment also used the same evaluators. Using the same evaluators and similar data ensured that the comparisons were valid. After completing the manual evaluation, the opinions of the evaluators regarding these two methodologies were elicited using a questionnaire (this survey is discussed in section 6.5.3). The results of the survey indicated that the evaluators experienced much indecision or fuzziness in their choices when the manual weighting method was used. They also found the manual weighting system to be time-consuming when inputting or assigning weights. In order to resolve issues relating to speedy input of data, fuzziness and indecisions, the new system was developed to accept linguistic values. A linguistic value will have intervals between two numbers that will encompass the most likely values (or choices) in order to eliminate or eradicate indecisions and to speedily improve the input of data.

The results of the manual weighting system and the fuzzy AHP method concurred with each other in terms of the quantitative (tangible) sub-criteria and criteria. There were however some disparities between the two evaluation methods that involved qualitative (or intangible) sub-criteria and criteria. The findings indicated that these disparities were due to the fact that qualitative sub-criteria and criteria were evaluated using quantitative techniques. As a result, the manual weighting method was not as reliable as the fuzzy AHP method. The fact that the weighting or "importance intensity" of each criteria was not taken into consideration for the manual weighting system made this method of evaluation even more inefficient when compared to the fuzzy AHP (where ranking the "importance intensity" of the criteria is mandatory). Other factors such as the personality of the evaluators, the amount of weights allocated to each sub-criterion and criteria as well as the number of sub-criteria under each criterion also had an impact on the results. The optimistic evaluators assigned higher scores while the pessimistic evaluators assigned lower scores that resulted in disparities in the results for the same sub-criteria and criteria. Sub-criteria and criteria that were allocated higher weights produced more unreliable results. Also, the criteria that had more sub-criteria produced more unreliable results when compared to criteria that had fewer sub-criteria. All these limitations for the manual weighting system could easily be resolved if linguistic values are used for fuzzy AHP. When the overall results of both evaluation methods are considered in terms of the qualitative (intangible) sub-criteria and criteria, the fuzzy AHP produced results that were more reliable when compared to the manual weighting system.

The researcher also conducted a usability study on the academic staff from the Information IT department. The purpose of the study was to elicit the views on whether the developed system was able to meet the requirements of academic staff in terms of User Interface Satisfaction (UIS) and the functionality and capabilities of the new system. The purpose of the usability study was to also determine whether the system was able to meet the objectives mentioned in section 5.4. The results of the study indicated that the respondents were satisfied that the system was able to efficiently process and monitor performance in terms of the core strategic goals of the university, correctly identify the strengths and weaknesses as well as fairly rank and select an academic for an award or a promotion. The system was also successful in meeting the objectives indicated in section 5.4

8.4 Suggestions for future research

A fuzzy-based method was chosen to develop the model because the criteria that are required to evaluate academic staff lend themselves more to a qualitative rather than a quantitative evaluation. However, there are certain gaps that have emerged from the study which future research could explore.

This study did not take into account the evaluator's degree of confidence and risk issues in terms of the criteria during the decision-making process. In other words, a sensitivity analysis study was not incorporated in the development of the model. A sensitivity analysis study can determine the influence of the fuzzy criteria weights on the decision-making process. Future studies could therefore extend the model to include a sensitivity analysis study.

Section 5.6 calculated the gap degree of each academic, that is, how far from the desired fuzzy TOPSIS value (which is 1) each academic has performed at. This information is necessary so that each academic will know by how much they can improve. However, this study did not compute the gap degree in each criterion. Future studies can therefore explore how to improve the gaps in each criterion based on the Network Relationship Map (NRM) as well as the complex relationships among the evaluation criteria. In other words, the NRM can be used not only to find out the most important performance criterion but it can also be used to measure the relationships among the evaluation criteria.

Inconsistencies in the decision-making process usually lead to inconsistent results. In this study, it was therefore necessary to test for inconsistencies in the pair-wise comparison matrix using Saaty's (1980) method. When inconsistencies arose, the evaluators were asked to revise their decisions so that a consistency comparison matrix could be established. Saaty's method works efficiently for a small number of criteria as required in this study (only six criteria). However, some departments at DUT may require additional criteria for evaluation of academic staff as discussed in section 7.7.5(g). As a result, the number of criteria against which academics are evaluated will therefore increase for these departments. As the number of criteria increases, the number of comparisons increases and as a result, the number of inconsistencies will also increase. Saaty's method will therefore be inefficient for establishing a pair-wise comparison matrix for a large number of criteria. Establishing a pair-wise comparison matrix requires $\frac{n\times(n-1)}{2}$ judgments for n criteria using Saaty's method. Future research should therefore explore how a new technique called fuzzy linguistic preference relations (sometimes called Fuzzy LinPreRa) can be incorporated in the model to test for inconsistencies in the pair-wise comparison matrix. This method works efficiently for a large number of criteria by reducing the number of pair-wise comparisons to $(n-1)$.

This study used only the fuzzy TOPSIS method for ranking and selection. Ranking and selection is necessary for the recruitment of personnel, promotion and determining who qualifies for an award. Historically, selecting candidates for promotion and awards has been a contentious issue. The process of ranking and selection is therefore critically important in terms of fairness and reliability. The results of the questionnaire survey (refer to Figure 7-7) indicated that most respondents are unhappy about the current methods that are employed for recruitment, promotion and awards. Future studies can therefore explore and incorporate in this model other multi-criteria approaches such as the Analytic Network Process (ANP) and the fuzzy outranking methods in order to determine ranking and selection. The comparisons of the various methods may increase the level of accuracy in order to select the most suitable and appropriate personnel (for recruitment, promotion or an award) more fairly.

The researcher chose the Multi-Criteria Decision Making (MCDM) model called the Analytic Hierarchy Process (AHP) as a basis for developing the productivity estimation system of academic departments using a fuzzy logic approach. However, there are other MCDM models that can be used for estimation, such as the Data Envelopment Analysis (DEA) and the Simple Additive Weighting (SAW) models. Future research should explore the possibility of adapting these models for evaluations in a university environment as well as determine how fuzzy logic and fuzzy set theory can be integrated into these models. Further, the results of these models can be compared in order to establish which one performs most efficiently in a particular problem domain that requires a qualitative evaluation.

There are other areas in a university environment that also lend themselves to a qualitative evaluation. The human resources, maintenance and security departments are such examples and can therefore be efficiently evaluated using a fuzzy-based system. Future research can also explore these avenues.

8.5 Limitations of the study

In this study, the criteria that were used to evaluate academic staff from the six faculties have been restricted to Administration, Teaching and Learning, Research and Innovation, Writing and Publication, Consultancy as well as Services Rendered and External Engagement (as required by upper management and the Centre for Quality Promotion and Assurance or CQPA). Some departments in certain faculties however have different or additional criteria in order to evaluate academic staff. In addition to the standard criteria, the Drama Department for example evaluate academic staff according to the number and quality of theatre productions while certain departments in the Health Sciences, Applied Sciences and Engineering faculties evaluate academic staff according to some scientific innovations or discoveries. This was confirmed by the results discussed in section 7.7.5(g). Such criteria have not been taken into consideration because the quality unit has decided on a common set of criteria that is applicable to all academic staff. For future research, the development of the model could be extended to take into consideration the specific evaluation criteria of each department.

The developed system was successful in performing the following tasks:

- Creating a portfolio of each academic;
- Monitoring and processing an academic’s performance in terms of the core strategic goals such as teaching and learning, research and external engagement;
- Ranking academic staff for awards and promotion; and
- Identifying strengths and weaknesses of academic staff.

However, from the results indicated in Figure 7-7, respondents would prefer additional functionality such as:

- The ability of the system to benchmark the performance of DUT staff with other universities; and
- Determine whether the evaluations using the developed system are capable of meeting the standards required by bodies such as the National Quality Framework (NQF) and the South African Quality Assurance (SAQA).

The newly developed system only focused on the requirements of each department, CQPA and upper management at DUT. Future development should therefore focus on how evaluations of academic staff can be benchmarked against the requirements of these external institutions.

When calculating the fuzzy weights, the consistency ratio (CR) was also computed and checked. When the CR was inconsistent, the decision-makers were asked to revise their choices so that consistent results were attained. The results with the original choices would therefore be different when compared to the results of this study where revisions were necessary. Requesting evaluators to revise their decisions can therefore be construed as interference and may influence the results.

8.6 Recommendations

Developing the linguistic scale is a subjective task and may differ from one individual to another as well as from one group to another. The results may differ according to the linguistic scale being used. In order to address this, it is recommended that a common linguistic scale be used based on consensus of all departments and CQPA.

The researcher elicited the views of IS experts at DUT to determine whether any corrective measures were required in the university environment to accommodate the new system. The most important views revolved around strategies that may be necessary for CQPA and academic staff to adapt from a culture of manual evaluation to a culture of a computerised evaluation system. It is therefore recommended that a team be formed to implement the necessary strategies that can enable CQPA and academic staff to accept the new system.

It is recommended that the system be first piloted in one chosen department to address problems that may occur. All problems encountered should be properly documented in order to make the researcher's task easier when implementing corrective measures. It is advised that the system only become available to all departments once all corrective measures have been implemented and the new system functions smoothly.

8.7 Conclusion

The aim of this study was to develop a fuzzy-based system that is capable of reliably estimating productivity in terms of the core strategic goals of the university and the requirements of respondents at DUT. These requirements were ascertained from a research survey that the academic staff at DUT had to complete. The system was successfully developed using a Multi-Criteria Decision Making (MCDM) model called the Fuzzy Analytic Hierarchy Process (FAHP) and fuzzy TOPSIS method. A Design Science Research Methodology (DSRM) was adopted in the development. This chapter summarised the following:

- The results of the research survey;
- The reasons for adopting a fuzzy logic approach to developing the system as compared to a binary logic approach (or a precise value method);
- A design science (DS) approach to developing research instruments in order to determine the utility (usefulness) of the developed system;
- The results of a comparative study between current evaluation methods and the developed system in order to determine it's (the new system) reliability and efficiency. The techniques used in the evaluation included comparing the objectives with the actual observed results, quantitative performance measures as well as client feedback;
- The results of the usability study in order to determine whether the developed system was capable of meeting the objectives discussed in section 5.4; and
- Suggestions for future research, limitations of the study as well as recommendations were also discussed.

The results of the survey indicated that a computerised productivity estimation model will be able to efficiently identify strengths and weaknesses of an academic, reliably rank and select an academic for a promotion or an award as well as effectively monitor and process performance of academic staff in terms of the core strategic goals of the university.

The researcher felt that a fuzzy-based AHP methodology using linguistic values was the most appropriate approach (as compared to the precise or binary value approach) in developing the computerised system since the shortcomings of current evaluation methods can be efficiently accommodated using this technique. The fuzzy-based system was capable of easily accommodating both tangible (objective) and intangible (subjective) criteria. Further, this approach was preferred because linguistic values can efficiently mimic how the human mind interprets imprecision and uncertainty.

The results of the comparative study indicated that there was no difference between current evaluation methods and the newly developed fuzzy-based system in terms of the tangible (objective) criteria. However, the fuzzy-based system produced more reliable results in terms of identifying strengths and weaknesses of an academic, identifying personnel for awards and promotion in a more fair and unbiased manner as well as monitoring and processing an academic's performance in terms of the core strategic goals such as teaching and learning, research and external engagement.

The results of the usability study indicated that the new system was able to meet the requirements of academic staff in terms of User Interface Satisfaction (UIS) as well as its functionality and capabilities. The system was able to efficiently process and monitor an academic's performance in terms of the core strategic goals of the university, correctly identify the strengths and weaknesses as well as fairly rank and select candidates who are due for an award or a promotion. The system was also able to meet all objectives indicated in section 5.4.

Although the fuzzy-based system generally proved to be more reliable than the current evaluation methods, the researcher identified limitations in this study which future research can address. These include extending the study to accommodate the following:

- A sensitivity analysis involving the criteria;
- The gap degree in each criterion using the Network Relationship Map (NRM); and
- Using a more efficient technique called the fuzzy LinPreRa method to calculate the Consistency Ratio (CR) as the number of criteria increases (instead of Saaty's method for fewer criteria).

The development of the new system was communicated to the academic staff of the IT department as well as upper management. This is the last activity (6^{th}) of the Design Science Research Methodology (DSRM) called communication. It is hoped that management will consider implementing this new evaluation system as soon as possible.

8.8 Final conclusion

Chapter 7 discussed the research instrument, the research approach as well as the analysis and presentation of the survey results. This chapter presented an overview of the research conducted. The overview summarized the results of the research questionnaires, the reasons for choosing a fuzzy-based methodology for the model development, suggestions for future research, the limitations of the study, recommendations as well as the effectiveness and functionality of the newly developed system.

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ANNEXURE A Research Questionnaire

RESEARCH QUESTIONNAIRE

Title: Computer-based Productivity Estimation of Academic staff using the Fuzzy Analytic Hierarchy Process and Fuzzy TOPSIS method

Presently, most universities are using non-algorithmic methods such as panel interviews, peer evaluations, expert judgment or a weighting system to estimate the productivity of academic staff. This researcher is interested in establishing the effectiveness of these estimation methods. The purpose of this questionnaire is to therefore:

- Examine the present state of academic staff evaluation and productivity estimation at Durban University of Technology (DUT);
- Elicit the opinions of academic staff on the evaluation and productivity estimation methods that are currently being used at DUT; and
- Elicit the opinions of academic staff regarding the development of a new computerised productivity estimation model.

Indicate your choice with an X.

1. Status:

1.1 Junior Lecturer	
1.2 Lecturer	
1.3 Senior Lecturer	
1.4 Associate Professor	
1.5 Professor	
1.6 Other (Specify)	

2. Faculty:

2.1 Accounting and Informatics	
2.2 Applied Sciences	
2.3 Arts	
2.4 Economic and Management Sciences	
2.5 Engineering	
2.6 Health Sciences	

3. How often does evaluation of academics take place in your faculty? (Also take into consideration Centre for Quality Promotion and Assurance (CQPA) evaluations.)

3.1 Every semester	
3.2 Yearly	
3.3 Only when we are informed that an evaluation needs to be done	
3.4 Not certain	

4. How many completed years of service do you have at DUT?

4.1 Less than 5 years	
4.2 More than 5 years but less than 10 years	
4.3 More than 10 years but less than 15 years	
4.4 More than 15 years but less than 20 years	
4.5 More than 20 years	

5. How many evaluations did you have while serving as an academic at DUT? (Also take into consideration Centre for Quality Promotion and Assurance (CQPA) evaluations.)

5.1 None	
5.2 1-3	
5.3 4-8	
5.4 9-12	
5.5 More than 12	

6. If you were evaluated, what were the reason/s for the evaluation/s? (You may choose more than one option if necessary.)

6.1 It was a requirement when I applied for a promotion post.	
6.2 I was on probation when I joined DUT and it was a requirement that I undergo an evaluation to become a permanent staff member.	
6.3 An evaluation was requested by upper management such as an HOD or the Dean.	
6.4 Other (Specify):	

7. What evaluation method/s were employed? (You may choose more than one option if necessary). Do not answer this question if you were not evaluated.

7.1 Interviews involving a panel.	
7.2 Peer evaluations.	
7.3 Expert judgment. (This method involves an expert who has vast knowledge about past experiences in a certain area and can apply this knowledge to evaluate a key performance area.)	
7.4 A weighting method. (A weighting method allocates a certain score if an academic has met the requirement in a key performance area. For example, a score of 30 is allocated if an academic has done a minimum of 50 hours of community engagement.)	
7.5 Other. Specify what other method/s	

8. Current and proposed evaluation methods. Indicate your choice with an "X".	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
a) I prefer to be evaluated using a system that is human intensive (such as interviews) rather than a system that is data intensive (where the human input is reduced).					
b) Creating a computerised portfolio of an academic makes evaluation and productivity estimation easier.					
c) Rating a university in terms of its research output in all its' departments collectively can be easily done using a computerised production estimation system					
d) Current evaluation methods are effective in meeting SAQA (South African Quality Assurance) requirements.					
e) Current evaluation methods are able to meet the principles (such as standards, quality and excellence) of the National Quality Framework.					
f) Present evaluation methods at DUT are capable of benchmarking academic productivity.					
g) Current evaluation methods are successful in measuring an academic's productivity (that is, an academic's efficiency and effectiveness).					
h) Current evaluation methods are able to determine whether minimum standards in terms of departmental requirements can be met.					
i) Present methods of evaluation are successful in measuring the productivity of an academic department as a whole.					

j) Present methods of evaluation are able to fairly select candidates who are due for promotion.					
k) Current evaluation methods can be used to determine whether an academic is due for a merit award.					
l) Current evaluation methods are effective in monitoring and processing performance in terms of the core strategic goals such as teaching and learning, research and external engagement.					
m) Present evaluation methods have been successful in identifying the strengths and weaknesses of academics in terms of these core strategic goals.					

9. Rank the following statements by indicating the degree of importance using an "X". The number "1" indicates "least important" and the number "4" indicates "most important".

Statement	Least important			Most important
	1	2	3	4
An effective productivity estimation model should be able to correctly rank personnel for promotion.				
The model should be able to monitor and process an academic's performance in terms of the core strategic goals such as teaching and learning, research and external engagement.				
The model should be able to identify the strengths and weaknesses in terms of the core strategic goals.				
The model should be able to create a portfolio of an academic so that evaluation and estimation productivity is made easier.				

10. What do you expect from a computerised production estimation model (regarding academic departments) in terms of its:

10.1 Functionality: (that is, what the model should be able to do.

____

____

____

10.2 Inputs: (that is, what form the inputs should take.)

____

____

____

10.3 Outputs: (that is, how the processed information should be presented on screen.)

____

____

____

11. Any other comments:

____

____

____

ANNEXURE B Questionnaire for Usability Study

RESEARCH QUESTIONNAIRE FOR USABILITY STUDY

Title: Computer-based Productivity Estimation of Academic staff using the Fuzzy Analytic Hierarchy Process and Fuzzy TOPSIS method

Presently, most universities are using non-algorithmic methods such as panel interviews, peer evaluations, expert judgment or a weighting system to estimate the productivity of academic staff. The researcher already conducted a survey to establish the effectiveness of these estimation methods. The purpose of the survey was to:

- Examine the present state of academic staff evaluation and productivity estimation at Durban University of Technology (DUT);
- Elicit the opinions of academic staff on the evaluation and productivity estimation methods that are currently being used at DUT; and
- Elicit the opinions of academic staff regarding the development of a new computerised productivity estimation model.

The results of the survey indicated that current productivity estimation methods are unable to meet the requirements of academic staff at DUT and that a computerised evaluation system should be developed. A computerised fuzzy-based system was therefore developed to meet the requirements of academic staff. The purpose of this questionnaire is to elicit the views of academic staff on the extent to which the new system is able to meet their (academic staff) requirements.

Indicate your choice with an X in the circle.

12. Status:

1.1 Junior Lecturer		◯
1.2 Lecturer		◯
1.3 Senior Lecturer		◯
1.4 Associate Professor		◯
1.5 Professor		◯
1.6 Other (Specify)		◯

13. Faculty:

2.1 Accounting and Informatics	◯

2.2 Applied Sciences	◯
2.3 Arts	◯
2.4 Economic and Management Sciences	◯
2.5 Engineering	◯
2.6 Health Sciences	◯

14. How often does evaluation of academics take place in your faculty? (Also take into consideration Centre for Quality Promotion and Assurance (CQPA) evaluations.)

3.1 Every semester	◯
3.2 Yearly	◯
3.3 Only when we are informed that an evaluation needs to be done	◯
3.4 Not certain	◯

15. How many completed years of service do you have at DUT?

4.1 Less than 5 years	◯
4.2 More than 5 years but less than 10 years	◯
4.3 More than 10 years but less than 15 years	◯
4.4 More than 15 years but less than 20 years	◯
4.5 More than 20 years	◯

16. How many evaluations did you have while serving as an academic at DUT? (Also take into consideration Centre for Quality Promotion and Assurance (CQPA) evaluations.)

5.1 None	◯
5.2 1-3	◯
5.3 4-8	◯
5.4 9-12	◯
5.5 More than 12	◯

17. If you were evaluated, what were the reason/s for the evaluation/s? (You may choose more than one option if necessary.)

6.1 It was a requirement when I applied for a promotion post.	◯
6.2 I was on probation when I joined DUT and it was a requirement that I undergo an evaluation to become a permanent staff member.	◯
6.3 An evaluation was requested by upper management such as an HOD or the Dean.	◯
6.4 Other (Specify):	◯

18. What evaluation method/s were employed? (You may choose more than one option if necessary). Do not answer this question if you were not evaluated.

7.1 Interviews involving a panel.	◯
7.2 Peer evaluations.	◯
7.3 Expert judgment. (This method involves an expert who has vast knowledge about past experiences in a certain area and can apply this knowledge to evaluate a key performance area.	◯
7.4 A weighting method. (A weighting method allocates a certain score if an academic has met the requirement in a key performance area. For example, a score of 30 is allocated if an academic has done a minimum of 50 hours of community engagement.)	◯
7.5 Other. Specify what other method/s.	◯

Questions 8.1 to 8.5 relate to User Interface Satisfaction (UIS) regarding the new system.

8. Indicate your choice with an "X" in the circle.	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
8.1 The positioning of messages on the screen is consistent.	◯	◯	◯	◯	◯
8.2 The prompts for input is clear.	◯	◯	◯	◯	◯
8.3 The system gives error messages that clearly tell me how to fix problems.	◯	◯	◯	◯	◯
8.4 The organisation of information are clearly laid out and are visually appealing.	◯	◯	◯	◯	◯
8.5 The terminology used is clear.	◯	◯	◯	◯	◯

Questions 9.1 to 9.5 relate the functionality and capability of the system.

9. Indicate your choice with an "X" in the circle.	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
9.1 The system is capable of effectively creating a computerised portfolio of an academic.					
9.2 The system is able to fairly rank and select candidates who are due for:					
9.2.1 An award.					
9.2.2 A promotion.					
9.3 The system is able to monitor and process the performance of an academic in terms of the core strategic goals such as:					
i. Teaching and Supervision.					
ii. Research and Innovation.					
iii. Administration.					
iv. Writing and Publication.					
v. Consultancy.					
vi. External engagement.					
b. The system is capable of easily identifying the:					
i. Strengths and					
ii. Weaknesses					
of an academic.					
9.5 With the new system, it is easier to input the data using linguistic values such as 'very weak', 'weak', 'average', 'good' and 'very good' rather than using precise values.					

10. Any further comments:

ANNEXURE C Saaty's absolute values method to calculate the Consistency Ratio (CR)

The purpose of this section is to demonstrate the steps involved in computing the weight vector (or priority vector) and the Consistency Index (CI) using Saaty's precise value method because the same steps can be used to compute the weight vector and the CI for fuzzy inputs (Saaty, 1980).

This process is best described using the following example. Consider a comparison matrix that has the following criteria: experience, education and personality. By using the fundamental scale of absolute numbers from Table 2-1, the following comparisons can be made: Suppose a decision-maker decides that education "is extremely strongly preferred" over experience. According to the scale in Table 2-1, the value 9 should therefore be used. Conversely, the reciprocal value (experience over education) is 1/9 = 0.11. If the decision-maker decides that personality is "moderately plus important" over experience, then according to the scale in Table 2-1, the value 4 should be used. Conversely, the reciprocal value (experience over personality) is 1/4 = 0.25. If the decision-maker decides that education is "weak" over personality, then the value 2 is used from Table 2-1. Conversely, the reciprocal value (personality over education) is 1/5 = 0.2. All these pair-wise comparisons are indicated in Table A-1. The "equally preferred" values mean that each criterion is compared with itself and therefore takes the value 1. Since there are three criteria, the matrix is 3X3.

	Experience	**Education**	**Personality**
Experience	1.00	0.11	0.25
Education	9.00	1.00	2.00
Personality	4.00	0.50	1.00

Table A-1: Pair-wise comparisons of criteria

The next step is to multiply the values in each row and then calculate the n^{th} root of the product. The n^{th} root is then normalised to get the appropriate weights. The Consistency Ratio (CR) is then calculated and checked. These calculations are indicated in Table A-2 and then explained below the table.

	Experience	Education	Personality	3rd root of product	Priority Vector (PV) (or weights)
Experience	1.00	0.11	0.25	0.31	0.07
Education	9.00	1.00	2.00	2.62	0.63
Personality	4.00	0.5	1.00	1.26	0.30
Sum	14.00	1.61	3.25	4.19	1.000
Sum*PV	1.04	1.01	0.98		
$\boldsymbol{\lambda_{max}}$	1.04+1.01+0.98 = 3.03				
CI =	0.015				
CR =	0.03				

Table A-2: Steps involved in calculating the Consistency Ratio (CR)

The 3^{rd} root is calculated by multiplying the values in each row and calculating the n^{th} (in this case, it is the 3^{rd} root since there are 3 criteria) root of the product. The values of the 3^{rd} root are then added. The weights (also referred to as priority vectors) for each criterion are calculated as follows:

Experience: $\frac{0.31}{4.19} = 0.07$

Education: $\frac{2.62}{4.19} = 0.63$

Personality: $\frac{1.26}{4.19} = 0.30$

When calculated correctly, the sum of all priority vectors will equal to 1.

The Consistency Ratio (CR) provides information to the decision-maker on how consistent the pair-wise comparisons were. The following steps are followed when calculating the CR.

- The pair-wise comparison values are added in each column and each sum is then multiplied by the respective weight for the respective criteria as follows:

  Experience: (1.00 + 9.00 + 4.00) = 14 X 0.07 = 1.04

  Education: (0.11 + 1.00 + 0.50) = 1.61 X 0.63 = 1.01

  Personality: (0.25+ 2.00 +1.00) = 3.25X 0.30 = 0.98;

- The Sum*PV values are then added together to get a value known as *lambda-max* (or λ_{max}) as follows: (1.04 + 1.01 + 0.98) = 3.03. Unlike the weights, the λ_{max} value does not necessarily add up to 1;
- The Consistency Index (CI) is then calculated using the following formula:

  CI = $\frac{\lambda_{max}-n}{n-1}$ where *n* represents the number of criterion (in this case *n* = 3).

  CI = $\frac{3.03-3}{3-1}$ = $\frac{0.03}{2}$ = 0.015; and
- Lastly, the Consistency Ratio (CR) is calculated by dividing the Consistency Index (CI) by a Random Index (RI) which is determined from a lookup table (indicated in Table A-3). Since *n* = 3 (number of criteria), the value of RI from Table A-3 is 0.58. Therefore CR = $\frac{CI}{0.580}$ = $\frac{0.015}{0.580}$ = 0.03.

N	1	2	3	4	5	6	7	8	9	10	11	12
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.58

Table A-3: The random index RI for number of factors/criteria *n*

Since CR < 0.1, it means that the comparison matrix is consistent and can therefore be used for further calculations.

ANNEXURE D Cronbach's Alpha

Cronbach's alpha measures how well a set of items (or variables) measures a single uni dimensional latent construct (Johnson & Bhattacharyya, 2006). When data have a multidimensional structure, Cronbach's alpha will usually be low. Technically speaking, Cronbach's alpha is not a statistical test - it is a coefficient of reliability (or consistency).

Cronbach's alpha can be written as a function of the number of test items AND the average inter-correlation among the items. Below, for conceptual purposes, the formula for the standardised Cronbach's alpha is shown:

$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N-1) \cdot \bar{c}}$$

Here N is equal to the number of items, c-bar is the average inter-item covariance among the items and v-bar equals the average variance.

One can see from this formula that if you increase the number of items, you increase Cronbach's alpha. Additionally, if the average inter-item correlation is low, alpha will be low. As the average inter-item correlation increases, Cronbach's alpha increases as well.

This makes sense intuitively - if the inter-item correlations are high, then the items are measuring the same underlying construct. This is really what is meant when someone says they have "high" or "good" reliability. They are referring to how well their items measure a single unidimensional latent construct.

Thus, if you have multi-dimensional data, Cronbach's alpha will generally be low for all items. In this case, run a factor analysis to see which items load highest on which dimensions, and then take the alpha of each subset of items separately.

ANNEXURE E Chi Square Test

A chi-square test is any statistical hypothesis test in which the test statistic has a Chi-Square distribution when the null hypothesis is true, or any in which the probability distribution of the test statistic (assuming the null hypothesis is true) can be made to approximate a chi-square distribution as closely as desired by making the sample size large enough (Johnson & Bhattacharyya, 2006).

Specifically, a chi-square test for independence evaluates statistically significant *differences* between proportions for two or more groups in a data set.

Chi-square test statistic:

$$\chi^2 = \frac{(f_o - f_e)^2}{f_e}$$

$$df = (r-1)(c-1)$$

ANNEXURE F Calculating the intra class correlation index

Intra class correlations (ICC) are used when quantitative measurements are made on units that are organised into groups (Ionan *et al*., 2014). It describes how strongly units in the same group resemble each other. Intra class correlations are generally used to quantify the degree to which individuals with a fixed degree of relatedness resemble each other in terms of some quantitative traits. Intra class correlations are generally applied when an assessment of consistency or reproducibility of quantitative measurements by different observers measuring the same quantity is required .

The ICC is calculated using the following formula (Ionan *et al*., 2014):

$$ICC = \frac{\sigma^2(b)}{\sigma^2(b) + \sigma^2(w)} \quad [1]$$

where $\sigma^2(w)$ is the pooled variance within subjects, and $\sigma^2(b)$ is the variance of the trait between subjects.

It is easily shown that $\sigma^2(b) + \sigma^2(w)$ = the total variance of ratings, that is, the variance for all ratings, regardless of whether they are for the same subject or not (Ionan *et al*., 2014). Hence the interpretation of the ICC as the proportion of total variance accounted for by within-subject variation.

Equation [1] would apply if the true values are known, $\sigma^2(w)$ and $\sigma^2(b)$. But the true values are rarely known, and must instead estimate them from sample data. For this all available information should be used; this adds terms to Equation [1].

The $\sigma^2(b)$ for example reflects the variance of true trait levels between subjects. Since it is unlikely that individuals would know the true trait level of a subject, it is therefore necessary to estimate it from the subject's mean rating across the raters who rate the subject. Each mean rating is subject to sampling variation or deviation from the subject's true trait level, or its' surrogate (the mean rating that would be obtained from a very large number of raters). Since the actual mean ratings are often based on two or a few ratings, these deviations are appreciable and inflate the estimate of between-subject variance.

There are usually three classes of ICC. In the first case, raters for each subject are selected at random. The same raters rate each case. These are a random sample. In the third case, the same raters rate each case. These are the only raters.

The amount and correct for this extra, error variation can be estimated. If all subjects have k ratings, then for case 1, the ICC the extra variation is estimated as (1/k) s^2(w), where s^2(w) is the pooled estimate of within-subject variance. When all subjects have k ratings, s^2(w) equals the average variance of the k ratings of each subject (each calculated using k-1 as denominator). The ICC is attained as follows:

- Estimate σ^2(b) as [s^2(b) - s^2(w)/k], where s^2(b) is the variance of subjects' mean ratings;
- Estimate σ^2(w) as s^2(w); and
- Use Equation [1]

Each of the three cases are now discussed:

Case 1: One has a pool of raters. For each subject, one randomly samples from the rater pool k different raters to rate this subject. Therefore the raters who rate one subject are not necessarily the same as those who rate another. This design corresponds to a 1-way Analysis of Variance (ANOVA) in which Subject is a random effect, and Rater is viewed as measurement error.

Case 2: The same set of k raters rate each subject. This corresponds to a fully-crossed (Rater × Subject), 2-way ANOVA design in which both Subject and Rater are separate effects. In Case 2, the Rater is considered a random effect; this means the kraters in the study are considered a random sample from a population of potential raters. Case 2 ICC estimates the reliability of the larger population of raters.

Case 3: This is like Case 2, a fully-crossed, 2-way ANOVA design. But here one estimates the ICC that applies only to the k raters. Since this does not permit generalisation to other raters, the Case 3 ICC is not often used.

ANNEXURE G KMO Measure of Sampling and the Bartlett's Test of Sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.888
Bartlett's Test of Sphericity	Approx. Chi-Square	6230.901
	Df	91
	Sig.	.000

This table shows two tests that indicate the suitability of your data for structure detection. The **Kaiser-Meyer-Olkin Measure of Sampling Adequacy** is a statistic that indicates the proportion of variance in your variables that might be caused by underlying factors (Williams *et al.*, 2010). High values (close to 1.0) generally indicate that a factor analysis may be useful with your data. If the value is less than 0.50, the results of the factor analysis probably won't be very useful.

Bartlett's test of sphericity tests the hypothesis that your correlation matrix is an identity matrix, which would indicate that your variables are unrelated and therefore unsuitable for structure detection. Small values (less than 0.05) of the significance level indicate that a factor analysis may be useful with your data.

ANNEXURE H Rotated factor matrix

Factor	1	2	3
1	.837	.516	.184
2	-.497	.856	-.140
3	-.230	.026	.973

The factor transformation matrix describes the specific rotation applied to your factor solution (Costello & Osborne, 2005). This matrix is used to compute the rotated factor matrix from the original (unrotated) factor matrix. Smaller off-diagonal elements correspond to smaller rotations. Larger off-diagonal elements correspond to larger rotations

ANNEXURE I Pearson's Bivariate Correlation

Bivariate correlation measures the relationship between the two variables (Hauke & Kossowski, 2011). This is achieved in terms of the strength between the two variables which can range from absolute value 1 to 0. The stronger the relationship, the closer the value is to 1. The relationship can be positive or negative. In a positive relationship, as one value increases, another value increases with it. In a negative relationship, as one value increases, the other one decreases. For example, the positive relationship of .90 can represent positive correlation between the hot weather temperatures and the sales of ice. The hotter the weather, the more ice is sold. The negative correlation can be found between going on the shopping spree and your savings.

The strength between two variables is calculated using Pearson Correlation Coefficient and is represented by the symbol *r* relationship. The value *r* can range from -1.0 to +1.0 where the – and the + signs indicates "direction". This value measures the linear relationship only. The symbol *r* represents the following (Hauke & Kossowski, 2011):

$$r = \frac{\text{degree to which X \& Y vary together}}{\text{degree to which X \& Y vary seperately}}$$

$$r = \frac{\text{covariance of X \&Y}}{\text{variance of X \& Y}}$$

The Pearson *r* formula is as follows:

$$r = \frac{SP}{\sqrt{SS_X SS_Y}}$$

Where SP = "Sum of Products" and SS = "Sum of Squared Deviations"

$$SP = \Sigma(X-\overline{X})(Y-\overline{Y});\ SS_X=\Sigma(X-\overline{X})^2;\ SS_y=\Sigma(Y-\overline{Y})^2$$

The variance interpretation of *r* is as follows:

r^2 = % of variance in Y explained by its linear relationship with X (and vice versa)

r^2 = *"Coefficient of determination"*

% of *shared variance* between X & Y

% of variance in Y *predicted* by X

The factors that affect the size of *r* are the following:

- $r \approx 0$ could mean many things;
- No relationship at all between X & Y;
- *Non-linear* relationship between X & Y;
- *Restricted range* on X and/or Y; and
- *Outlier* may be causing problem

ANNEXURE J Results of Correlations between variables

CORRELATIONS

		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17
S1	Correlation Coefficient	1.000																
	Sig. (2-tailed)																	
	N	100																
S2	Correlation Coefficient	-.109	1.000															
	Sig. (2-tailed)	.280																
	N	100	100															
S3	Correlation Coefficient	-.241*	.045	1.000														
	Sig. (2-tailed)	.016	.655															
	N	100	100	100														
S4	Correlation Coefficient	-.252*	.281**	-.017	1.000													
	Sig. (2-tailed)	.011	.005	.870														
	N	100	100	100	100													
S5	Correlation Coefficient	-.220*	-.012	.291**	.421**	1.000												
	Sig. (2-tailed)	.028	.903	.003	.000													
	N	100	100	100	100	100												
S6	Correlation Coefficient	-.275**	.224*	-.043	.762**	.581**	1.000											
	Sig. (2-tailed)	.006	.025	.674	.000	.000												
	N	100	100	100	100	100	100											
S7	Correlation Coefficient	-.296**	-.025	-.068	.593**	.459**	.731**	1.000										
	Sig. (2-tailed)	.003	.803	.499	.000	.000	.000											
	N	100	100	100	100	100	100	100										
S8	Correlation Coefficient	-.265**	.169	.099	.319**	.515**	.513**	.795**	1.000									
	Sig. (2-tailed)	.008	.092	.326	.001	.000	.000	.000										
	N	100	100	100	100	100	100	100	100									
S9	Correlation Coefficient	-.296**	-.025	-.068	.593**	.459**	.731**	1.000**	.795**	1.000								
	Sig. (2-tailed)	.003	.803	.499	.000	.000	.000		.000									
	N	100	100	100	100	100	100	100	100	100								
S10	Correlation Coefficient	-.064	-.106	-.237*	.012	.236*	.274**	.576**	.343**	.576**	1.000							
	Sig. (2-tailed)	.527	.292	.017	.905	.018	.006	.000	.000	.000								
	N	100	100	100	100	100	100	100	100	100	100							
S11	Correlation Coefficient	-.209*	.114	-.115	.451**	.344**	.550**	.479**	.222*	.479**	.419**	1.000						
	Sig. (2-tailed)	.036	.257	.256	.000	.000	.000	.000	.026	.000	.000							
	N	100	100	100	100	100	100	100	100	100	100	100						
S12	Correlation Coefficient	-.285**	.114	.302**	.451**	.684**	.550**	.479**	.654**	.479**	-.035	.558**	1.000					
	Sig. (2-tailed)	.004	.257	.002	.000	.000	.000	.000	.000	.000	.726	.000						

	N	100	100	100	100	100	100	100	100	100	100	100	100					
S13	Correlation Coefficient	-.306**	-.061	.167	.700**	.602**	.723**	.601**	.372**	.601**	.142	.796**	.796**	1.000				
	Sig. (2-tailed)	.002	.544	.098	.000	.000	.000	.000	.000	.000	.157	.000	.000					
	N	100	100	100	100	100	100	100	100	100	100	100	100	100				
S14	Correlation Coefficient	.291**	-.679**	-.196	-.446**	-.265**	-.365**	-.327**	-.425**	-.327**	-.048	-.513**	-.513**	-.417**	1.000			
	Sig. (2-tailed)	.003	.000	.051	.000	.008	.000	.001	.000	.001	.634	.000	.000	.000				
	N	100	100	100	100	100	100	100	100	100	100	100	100	100	100			
S15	Correlation Coefficient	.294**	-.269**	-.453**	-.563**	-.681**	-.507**	-.411**	-.488**	-.411**	-.053	-.137	-.563**	-.477**	.589**	1.000		
	Sig. (2-tailed)	.003	.007	.000	.000	.000	.000	.000	.000	.000	.600	.174	.000	.000	.000			
	N	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100		
S16	Correlation Coefficient	.221*	-.129	-.490**	-.100	-.713**	-.285**	-.240*	-.504**	-.240*	-.175	.004	-.507**	-.238*	.360**	.810**	1.000	
	Sig. (2-tailed)	.027	.201	.000	.321	.000	.004	.016	.000	.016	.081	.965	.000	.017	.000	.000		
	N	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	
S17	Correlation Coefficient	.101	-.129	.385**	-.295**	.251*	-.178	-.477**	-.161	-.477**	-.422**	-.415**	.186	-.097	.340**	-.189	-.390**	1.000
	Sig. (2-tailed)	.318	.199	.000	.003	.012	.077	.000	.110	.000	.000	.000	.063	.335	.001	.059	.000	
	N	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

*. Correlation is significant at the 0.05 level (2-tailed) and **. Correlation is significant at the 0.01 level (2-tailed).

ANNEXURE K Java Files, Classes and Methods

(K1): Methods to calculate the sum of each column, sum of columns, Sum x PV and λ_{max} (that is, lambdaMax).

```
/**
     * Calculates the sum of each column and returns it as a vector
     * @param decisionMakerMatrix
     * @return
     */
    public FuzzyNumber[] calculateSum(FuzzyNumber[][] decisionMakerMatrix) {

        FuzzyNumber sumOfCriteria [] = new
        FuzzyNumber[decisionMakerMatrix[0].length];
        double sumOfMin, sumOfMean, sumOfMax;

        // columns
        for(int i=0; i<decisionMakerMatrix[0].length; i++)
        {
            sumOfMin = sumOfMean = sumOfMax =0;
            // rows
            for(int j=0; j<decisionMakerMatrix.length; j++)
            {
                sumOfMin += decisionMakerMatrix[j][i].getMin();
                sumOfMean += decisionMakerMatrix[j][i].getMean();
                sumOfMax += decisionMakerMatrix[j][i].getMax();
            }
            sumOfCriteria[i] = new FuzzyNumber(sumOfMin, sumOfMean,sumOfMax);
        }

        return sumOfCriteria;
    }

    /**
     * Calculates the Sum*PV for each criteria
     *
     *
     * @param sumOfCriteria
     * @param weightVector
     * @return
     */
    public FuzzyNumber[] calculateSumTimesPV(FuzzyNumber[] sumOfCriteria,
        FuzzyNumber[] weightVector) {

        FuzzyNumber sumTimesPV[] = new FuzzyNumber[weightVector.length];

        for(int i=0; i<weightVector.length; i++)
        {
            sumTimesPV[i] = new
            FuzzyNumber(sumOfCriteria[i].getMin()*weightVector[i].getMin(),
                    sumOfCriteria[i].getMean()*weightVector[i].getMean(),
                    sumOfCriteria[i].getMax()*weightVector[i].getMax());
        }
```

```
        return  sumTimesPV;
    }

    /**
     * Returns the LambdaMax value by adding all the valeus from the Sum*PV
vector
     * @param sumTimesPV
     * @return LambdaMax
     */
    public FuzzyNumber calculateLambdaMax(FuzzyNumber[] sumTimesPV) {

        double lMaxMin, lMaxMean, lMaxMax=lMaxMin=lMaxMean=0;
        DecimalFormat df = new DecimalFormat("#.00");

        for(int i=0; i<sumTimesPV.length; i++)
        {
            lMaxMin += Double.valueOf(df.format(sumTimesPV[i].getMin()));
lMaxMin = Double.valueOf(df.format(lMaxMin));
            lMaxMean+= Double.valueOf(df.format(sumTimesPV[i].getMean()));
lMaxMean = Double.valueOf(df.format(lMaxMean));
            lMaxMax+= Double.valueOf(df.format(sumTimesPV[i].getMax()));
lMaxMax = Double.valueOf(df.format(lMaxMax));
        }
        return new FuzzyNumber(Double.valueOf(df.format(lMaxMin)),
                Double.valueOf(df.format(lMaxMean)),
                        Double.valueOf(df.format(lMaxMax)));
    }
```

(K2) Fuzzy Alternatives

```
package fuzzy;

import utilities.Constants;

/**
 * Represents an fuzzy.Alternative
 */
public class Alternative {

    private String mName;
    private Criteria mCriteria[];
    //private FuzzyNumber fuzzyNumber;

    public Alternative(String name)
    {
        mName = name;
        setupCriteria();
    }

    /**
     * Initializes mCriteria with blank criterion and their respective sub-
criteria
     */
    private void setupCriteria() {
```

```java
        mCriteria = new Criteria[Constants.CRITERIA_INFO.size()];
        for(int i=0; i< Constants.CRITERIA_INFO.size();i++)
        {
            mCriteria[i] = new Criteria("C"+(i+1));
        }

    }

    public String getName() {
        return mName;
    }

    public void setName(String mName) {
        this.mName = mName;
    }

    /**
     * Retrieve the fuzzy.Criteria with the given label
     * @param label
     * @return
     */
    public Criteria getCriteria(String label) {

        for(int i=0; i< mCriteria.length; i++)
        {
            if(mCriteria[i].getLabel().equals(label))
            {
                return mCriteria[i];
            }
        }
        return null;
    }

    /**
     * Display the entire vector represented by this alternative
     * @return
     */
    public String toString()
    {

        String str ="";

        str += "\n";

        // display fuzzy numbers for each criteria
        for(int j=0; j<mCriteria.length; j++)
        {
            str +=mCriteria[j].getFuzzyNumber().toString()+" \t\t";
        }

        return str;
    }

    public Criteria[] getCriteriaArray() {
        return mCriteria;
    }
```

```
    public void setCriteria(Criteria[] mCriteria) {
        this.mCriteria = mCriteria;
    }



   /* public FuzzyNumber getFuzzyNumber() {
        return fuzzyNumber;
    }*/
}
```

(K3) Fuzzy Criteria

```
package fuzzy;

import utilities.Constants;

/**
 * Represents a fuzzy.Criteria
 */
public class Criteria {

    private String mLabel;
    private SubCriteria mSubCriteria[];
    private FuzzyNumber mFuzzyNumber;

    public Criteria(String label)
    {
        mLabel = label;
        setupSubCriteria();
    }

    /**
     * Initializes each sub-criteria with their appropriate type
     */
    private void setupSubCriteria() {

        // determine the number of sub-criteria from CRITERIA_INFO
        int size = Constants.CRITERIA_INFO.get(mLabel);
        mSubCriteria = new SubCriteria[size];
        for(int i=0; i<mSubCriteria.length; i++)
        {
            mSubCriteria[i] = new SubCriteria(mLabel+(i+1));
        }
    }

    /**
     * Perform calculations to combine all the sub-criteria into a single
Fuzzy Number
     * @return
     */
    public FuzzyNumber calculateFuzzyNumber()
    {
        double totalMin = 0;
        double totalGeoMean = 0;
```

```java
        double totalMax = 0;

        for(int i=0; i<mSubCriteria.length; i++)
        {
            totalMin += mSubCriteria[i].getFuzzyNumber().getMin();
            totalGeoMean += mSubCriteria[i].getFuzzyNumber().getMean();
            totalMax += mSubCriteria[i].getFuzzyNumber().getMax();
        }
        return new FuzzyNumber(totalMin,totalGeoMean,totalMax);
    }

    /**
     * If the fuzzy.FuzzyNumber was not previously calculated, this method
will calculate it then return it
     * @return
     */
    public FuzzyNumber getFuzzyNumber()
    {
        //TODO: Becareful here
        if(mFuzzyNumber==null)
        {
            mFuzzyNumber = calculateFuzzyNumber();
            return mFuzzyNumber;
        }
        return mFuzzyNumber;
    }

    public String getLabel() {
        return mLabel;
    }

    public void setLabel(String mLabel) {
        this.mLabel = mLabel;
    }

    /**
     * Determine the sub-criteria given the label
     * @param label
     * @return
     */
    public SubCriteria getSubCriteria(String label) {
        for(int i=0; i< mSubCriteria.length; i++)
        {
            if(mSubCriteria[i].getLabel().equals(label))
            {
                return mSubCriteria[i];
            }
        }
        return null;
    }

    public void setSubCriteria(SubCriteria[] mSubCriteria) {
        this.mSubCriteria = mSubCriteria;
    }

    public void setFuzzyNumber(FuzzyNumber fuzzyNumber) {
        this.mFuzzyNumber = fuzzyNumber;
```

```
    }

    public SubCriteria[] getSubCriteriaArray() {
        return mSubCriteria;
    }
}
```

(K4) Represents a Decision Maker and the 6 criteria

```
package fuzzy;

/**
 * Represents a Decision Maker regarding the 6 criteria
 */
public class DecisionMaker {

    /* Global variables */

    private String mName;
    // square matrix
    private FuzzyNumber [][] mMatrix;

    public DecisionMaker(String name, int dimension) {
        mName = name;
        mMatrix = new FuzzyNumber[dimension][dimension];
    }

    /* Getters and Setters */
    public String getName() {
        return mName;
    }

    public void setName(String name) {
        this.mName = name;
    }

    public FuzzyNumber[][] getMatrix() {
        return mMatrix;
    }

    public void setMatrix(FuzzyNumber[][] matrix) {
        this.mMatrix = matrix;
    }
}
```

(K5) Represents a Fuzzy Number

```
package fuzzy;

import java.text.DecimalFormat;

/**
 * This class represents a Fuzzy number
 */
```

```java
public class FuzzyNumber  {

    double mMin;
    double mMean;
    double mMax;
    DecimalFormat df = new DecimalFormat("#.00");

    public FuzzyNumber(double min, double mean, double max)
    {
        mMin = Double.valueOf(df.format(min));
        mMean = Double.valueOf(df.format(mean));
        mMax = Double.valueOf(df.format(max));
    }

    // copy constructor
    public FuzzyNumber (FuzzyNumber fuzzyNumber)
    {
        this.mMin = Double.valueOf(df.format(fuzzyNumber.getMin()));
        this.mMean = Double.valueOf(df.format(fuzzyNumber.getMean()));
        this.mMax = Double.valueOf(df.format(fuzzyNumber.getMax()));
    }

    public String displayValues()
    {
        String fuzzyNumber = "Min = "+mMin+"\nMean = "+ mMean +"\nMax =
"+mMax;
        return fuzzyNumber;
    }

    public String toString()
    {
        //String fuzzyNumber = "("+String.format("%.2f",mMin)+","+
String.format("%.2f",mMean) +","+String.format("%.2f",mMax)+")";

        DecimalFormat df = new DecimalFormat("#.00");
        String fuzzyNumber = "("+Double.valueOf(df.format(mMin))+","+
Double.valueOf(df.format(mMean))+","+Double.valueOf(df.format(mMax))+")";
        return fuzzyNumber;
    }


    public double getMin() {
        return Double.valueOf(df.format(mMin));
    }

    public void setMin(double mMin) {
        this.mMin = mMin;
    }

    public double getMean() {
        return Double.valueOf(df.format(mMean));
    }

    public void setMean(double mGeoMean) {
        this.mMean = mGeoMean;
    }
```

```
    public double getMax() {
        return Double.valueOf(df.format(mMax));
    }

    public void setMax(double mMax) {
        this.mMax = mMax;
    }
}
```

(K6) Represents a sub-criteria

```
package fuzzy;

import utilities.Constants;

/**
 * Represents a sub-criteria
 */
public class SubCriteria {

    private String mLabel;
    // Type can either be Quantitative of Qualitative
    private String mType;
    private FuzzyNumber mFuzzyNumber;


    /**
     * When creating a sub-criteria only the label is required. The type will
be determined via the Constants class
     * and the fuzzy.FuzzyNumber will be set later
     * @param label
     */
    public SubCriteria(String label)
    {
        mLabel = label;
        if(Constants.QUANTITATIVE.contains(label))
        {
            mType = "QUANTITATIVE";
        }
        else if(Constants.QUALITATIVE.contains(label))
        {
            mType = "QUALITATIVE";
        }
    }

    /* Getters and Setters */
    public String getLabel() {
        return mLabel;
    }

    public void setLabel(String mLabel) {
        this.mLabel = mLabel;
    }

    public String getType() {
```

```
        return mType;
    }

    public void setType(String mType) {
        this.mType = mType;
    }

    public FuzzyNumber getFuzzyNumber() {
        return mFuzzyNumber;
    }

    /**
     * The fuzzy.FuzzyNumber is only created when it's set
     * @param mFuzzyNumber
     */
    public void setFuzzyNumber(FuzzyNumber mFuzzyNumber) {
        this.mFuzzyNumber = new
FuzzyNumber(mFuzzyNumber.getMin(),mFuzzyNumber.getMean(),mFuzzyNumber.getMax(
));
    }
}
```

(K7) Normalisation

```
package tasks;

import fuzzy.Alternative;
import fuzzy.FuzzyNumber;

/**
 */
public class Task2
{
    /**
     * Normalises the given matrix
     * @param alternatives
     */
    public void normaliseMatrix(Alternative[] alternatives)
    {
        double a1,a2,a3;
        a1 =0;
        a2 =0;
        a3 =0;

        double [][] bValues = calculateBValues(alternatives);

        // loop through each alternative's criteria
        for(int alt=0; alt<alternatives.length; alt++)
        {
            for(int cols=0; cols<alternatives[0].getCriteriaArray().length;
cols++)
            {
                // get the fuzzy components of the fuzzy number that's being
normalised
```

```
                a1 =
alternatives[alt].getCriteriaArray()[cols].getFuzzyNumber().getMin();
                a2 =
alternatives[alt].getCriteriaArray()[cols].getFuzzyNumber().getMean();
                a3 =
alternatives[alt].getCriteriaArray()[cols].getFuzzyNumber().getMax();

                FuzzyNumber normalisedFuzzyNumber = new FuzzyNumber(
(a1/bValues[2][cols]) , (a2/bValues[1][cols]), (a3/bValues[0][cols]) );

                // replace fuzzy number with normalised fuzzy number

alternatives[alt].getCriteriaArray()[cols].setFuzzyNumber(normalisedFuzzyNumb
er);
            }
        }

    }


    /**
     * Calulate b1,b2,b3 for each criteria
     * @param alternatives
     * @return
     */
    public double [][] calculateBValues(Alternative [] alternatives)
    {
        // each column represents a criteria which has 3 b values
        double [][] bValues = new
double[3][alternatives[0].getCriteriaArray().length];
        double b1, b2, b3 =b1=b2=0;

        for(int cols=0; cols<alternatives[0].getCriteriaArray().length;
cols++)
        {
            // add each component of the fuzzy numbers by row
            for(int rows=0; rows<alternatives.length; rows++)
            {
                b1 +=
Math.pow(alternatives[rows].getCriteriaArray()[cols].getFuzzyNumber().getMin(
),2);
                b2 +=
Math.pow(alternatives[rows].getCriteriaArray()[cols].getFuzzyNumber().getMean
(), 2);
                b3 +=
Math.pow(alternatives[rows].getCriteriaArray()[cols].getFuzzyNumber().getMax(
), 2);
            }

            // find the square root of the values used in the division
            b1 = Math.sqrt(b1); b2 = Math.sqrt(b2); b3 = Math.sqrt(b3);

            bValues[0][cols] = b1;
            bValues[1][cols] = b2;
            bValues[2][cols] = b3;

            b1=b2=b3=0;
```

```
        }
        return bValues;

    }

}
```

ANNEXURE L Informed Consent form to participant

UNIVERSITY OF KWAZULU-NATAL

SCHOOL OF MANAGEMENT, IT and GOVERNANCE

Dear Respondent,

PhD Research Project
Researcher: Steven Parbanath (Tel: 0338458800)
Supervisor: Professor M Maharaj (Office Telephone Number: 0312608003)

I, **Steven Parbanath**, am a PhD student, at the School of IT, Management and Governance, of the University of KwaZulu-Natal. You are invited to participate in a research project entitled "**Computer-based Productivity Estimation of Academic staff using the Fuzzy Analytic Hierarchy Process and Fuzzy TOPSIS method"**.

The aim of this study is to investigate:

- Why the fuzzy-based approach is the most effective method in estimating productivity of an academic department; and
- How the estimates of a fuzzy based approach compares to the estimates of conventional methods.

Through your participation I hope to:

- Understand the present methods that are adopted to evaluate the performance of academic staff;
- Elicit your opinions regarding the development of a new fuzzy-based model; and
- Ascertain what contributions you can provide in the development of the new model.

The results of the survey are intended to develop a new fuzzy-based model that is more effective and efficient than conventional models.

Your participation in this project is voluntary. You may refuse to participate or withdraw from the project at any time with no negative consequence. There will be no monetary gain from participating in this survey. Confidentiality and anonymity of records identifying you as a participant will be maintained by the School of IS and Technology, UKZN.

If you have any questions or concerns about completing the questionnaire or about participating in this study, you may contact me or my supervisor at the numbers listed above.

The survey should take you about **25** minutes to complete. I hope you will take the time to complete this survey.

Sincerely.

Investigator : S Parbanath   Date : 15 February 2013

ANNEXURE M Consent of participant

<u>CONSENT</u>

I……………………………………………………………………….... (full names of participant) hereby confirm that I understand the contents of this document and the nature of the research project, and I consent to participating in the research project.

I understand that I am at liberty to withdraw from the project at any time, should I so desire.

SIGNATURE OF PARTICIPANT DATE

……………………………………………………………………………………………….

ANNEXURE N Permission to conduct research at DUT campus

DUT
DURBAN UNIVERSITY OF TECHNOLOGY

FACULTY OF ACCOUNTING & INFORMATICS

8 September 2014

University Of KwaZulu-Natal

Ethics Committee

<u>Re: SUPPORT TO UNDERTAKE RESEARCH ON THE DUT CAMPUS: S PARBANATH</u>

I hereby support Mr S Parbanath, a PhD student at UKZN (student number 210555757) to undertake research at the Durban University of Technology (DUT). His topic "Computer-based Productivity Estimation of Academic staff using Fuzzy Analytic Hierarchy Process and Fuzzy TOPSIS method" is of interest to the University since the system he is developing can be used to estimate the productivity of academic staff at DUT.

Thanking you.

DUT
DURBAN UNIVERSITY OF TECHNOLOGY

DEPARTMENT OF FINANCE & INFORMATION MANAGEMENT

DR PAUL GREEN
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ANNEXURE O Letter of approval from UKZN to conduct the study

UNIVERSITY OF
KWAZULU-NATAL
INYUVESI
YAKWAZULU-NATALI

30 September 2014

Mr Steven Parbanath 210555757
School of Management, IT and Governance
Westville Campus

Dear Ms Parbanath

Protocol reference number: HSS/1207/014M
Project Title: Computer-based Productivity estimation of Academic staff using Fuzzy Analytic Hierarchy Process and Fuzzy TOPSIS method

Full Approval – Expedited

This letter serves to notify you that your application in connection with the above has now been granted **Full Approval**

Any alterations to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project; Location of the Study, Research Approach/Methods must be reviewed and approved through an amendment /modification prior to its implementation. Please quote the above reference number for all queries relating to this study. PLEASE NOTE: Research data should be securely stored in the school/department for a period of 5 years.

The ethical clearance certificate is only valid for a period of 3 years from the date of issue. Thereafter Recertification must be applied for on an annual basis.

Best wishes for the successful completion of your research protocol

Yours faithfully

Dr Shenuka Singh (Chair)
Humanities & Social Science Research Ethics Committee

/pm

cc Supervisor: Professor M Maharaj
cc Academic Leader: Professor Brian McArthur
cc School Admin: Ms Angela Pearce

Humanities & Social Sciences Research Ethics Committee
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