Renewables and energy storage to optimise the amount of electrical energy consumed in a building.

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January 2022

In fulfilment of a Master of Science (Electrical Engineering), College of Agriculture, Engineering and Science, University of KwaZulu-Natal

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DECLARATION 1 - PLAGIARISM

As the candidate's supervisor, I agree to the submission of this dissertation.

Supervisor: Dr A. G. Swanson

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I, Ulika Devina Naidoo, declare that:

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2. This thesis has not been submitted for any degree or examination at any other university.

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Acknowledgements

This dissertation is dedicated to my parents, Karna and Chandra Naidoo, for allowing me to study, the continued support, and boundless inspiration. Thank you for listening, and proofreading.

To my sister, Varisha Naidoo, for questioning me at every step, and lending your financial expertise to ensure the accuracy of calculated inflation and interest rates, a massive thank you. Thanks to Hivash and Cruz for their motivation.

A special thanks to my supervisor, Dr Andrew Swanson, for helping me refine the topic, his motivation, and continued guidance during the development of this dissertation.

Abstract

The rising cost of electricity and fuel, along with the looming threat of load shedding has frustrated not only the business owner but the homeowner as well. The need to reduce costs, and the growing pressure for companies and individuals to become more environmentally friendly, is becoming more apparent. To reduce costs and the effects of load shedding, and to become more sustainable, the integration of renewable energy is a clear solution.

The solution has led to the investigation of a hybrid system that uses grid-supplied power and renewable energy supplied power which will achieve an effective and efficient optimization of cost.

This dissertation is centred on minimising the total cost of ownership over twenty years. This is done by comparing different optimisation algorithms and identifying a cost-effective way of integrating a source of renewable energy, specifically solar energy, with an existing grid-supplied building.

The zoning of buildings was found to have an impact on the total cost of ownership as the tariffs were different. By developing a function, the efficiency of a system was quantified based on the load, and what type of building it was. The load has a direct impact on the total cost of ownership. The electrical energy used in a building, and the property type, whether industrial, commercial or residential zone, affects the optimisation algorithm that is used.

To minimise the total cost of ownership over twenty years, consideration was given to trade-offs between the available solar, oversizing the PV installation, the cost of electricity at different hours and the use of a storage system. To ensure that the total cost of ownership was correct, financial equations for growing annuity and the prescribed rates for assets, maintenance, and electricity were used. Further to this, South African energy tariffs, actual prices of inverters, solar panels, batteries and solar data of South Africa was used. MATLAB was the application of choice of software due to its optimisation capabilities.

Examples of each type of building were analysed to find the optimisation that returned the lowest TCO. Particle Swarm Optimisation, when used for industrial buildings produced the lowest TCO, while smaller loads from commercial buildings and a residential housing, showed that the lowest TCO came from Teaching-Learning Based Optimisation. In each case, the fastest and slowest optimisation technique was Pattern Search and Firefly Optimisation respectively.

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List of Acronyms

Abbreviations	Full Description
ABC	Artificial Bee Colony
AC	Alternating Current
ACO	Ant Colony Optimisation
BBO	Biogeography Based Optimisation
CAPEX	Capital Expenditure
CFC's	Chlorofluorocarbons
CH4	Methane
CMAO	Covariance Matrix Adaptation Optimisation
CO_2	Carbon Dioxide
CSP	Concentrating Solar Power
DC	Direct Current
DEO	Differential Evolution Optimisation
DER	Distributed Energy Resources
DG	Distribution Grid
DOD	Depth of Discharge
EDLC	Electrochemical Double Layer Capacitors
EMS	Energy Management System
EOLEX	End Of Life Expenditure
ESD	Energy Storing Device
ESS	Energy Storage Systems
ETS	Electric Thermal Storage
FA	Firefly Algorithm
GA	Genetic Algorithm
H	High
HS	Harmony Search
IT	Information Technology
IWO	Invasive Weed Optimisation
L	Low
LA	Lead Acid
LM	Load Modelling
M	Moderate
N	Negligible
N2O	Nitrous oxide
OPEX	Operational Expenditure
PS	Pattern Search
PSO	Particle Swarm Optimisation
PV	PhotoVoltaic
RE	Renewable Energy
RES	Renewable Energy Sources
SA	South Africa
SAURAN	Southern African Universities Radiometric Network
SC	SuperCapacitor

SCEO	Shuffled Complex Evolution Optimisation
SDLC	Software Development Life Cycle
SMES	Superconducting Magnetic Energy Storage
SOC	State Of Charge
TCO	Total Cost of Ownership
TES	Thermal Energy Storage
TOC	Total Ownership Cost
VH	Very High

1 Chapter 1 – Introduction

1.1 Research Question

There is a vast interest to incorporate renewable energy partly or completely. This is brought on by factors such as global warming, uncertain electricity supply, the decreasing prices of renewable energy technology, and the option to reduce expenses. Companies that manufacture solar renewable systems suggest the sizing of a renewable energy system to allow for usage during peak demand periods. Basic design guides inform individuals on how to make the right choice with regards to solar energy systems and panels that are big enough to power all appliances or to cover usage [1] [2] [3]. The general process is to find the energy usage of a building, and the peak sun hours. Then the energy used is divided by the peak sun hours, and further divided by the efficiency of panels and inverter used [4] [5] [6] [7] [8].

Among the issues associated with electricity generated by coal are the processing effects on the environment, the rising CO_2 levels, increasing coal costs, the maintenance of electrical substations and the emission of harmful waste from these substations. There have been several different investigations into the methods of renewable energy and the integration of renewable energy into the grid [9] [10]. This research has focused on renewable energy based on the geographical positioning within South Africa and the appropriate storage required.

Research into how the energy is being stored in microgrids, batteries, and the possibility of supercapacitors have been analysed. DC microgrids could be advantageous as there is no voltage conversion between renewable energies and a DC bus [11].

The different types of renewable energy have different types of integration issues [10]. Hydro-electric energy, although being used in South Africa, has been omitted as it was not within the confines of this research. The table below, adapted from [10], mentions some of the integration issues. Solar integration is considered as it is easily accessible in South Africa and requires less land space (solar panels mounted onto the roofs of buildings).

Table 1: Renewable Energy and their Integration Issues

Type of Renewable Energy	Integration Issues
Solar	Power electronics. Integration into the electricity supply grid. System optimisation.
Hydrogen	Electric interfaces. Fuel cell integration. Fuelling systems. Storage systems.
Wind	Wind-grid integration. Transmission planning.

Integration has two main issues: the existing electricity networks cannot grow fast enough to keep up with supply being demanded, and renewable energies have natural uncertainties [12]. This research has used multiple algorithms to minimise the Total Cost of Ownership (TCO) and provide the lowest TCO solution.

The solution to cater for total energy usage in a building, or to cater for peak usage, is to size a system that can reduce the required amount of electricity being used from the grid. This reduces the cost of electricity from the grid, but not the total cost of the system. From research and algorithms, the cost associated with the implementation of a solar energy system is incomplete when only total energy usage is considered. The total cost of ownership of a renewable system must consider the capital, maintenance, replacement, and the cost of electricity from the grid. The TCO should consider the financial trade-offs between storage systems and time of use tariffs, as well as the rates of inflation and growth.

This research considered achieving financial optimization of a building's energy consumption by:

- Which algorithm provided the lowest TCO?
- Which algorithm provided the fastest results?
- Does the TCO size for peak power from solar panels?

1.2 Hypothesis

This dissertation is centred around a function that uses multiple optimisation algorithms. The trade-offs between the cost of making a building energy-efficient versus the current cost of electricity, as well as the costs of the integration of renewable energy was considered.

1. Design – the intention is to use solar energy as a source and build a qualitative analysis on how to store this energy most cost-effectively.
    a. There are two required user inputs: the average load over twenty-four hours, and the type of building, e.g. residential, commercial, or industrial.
    b. The external inputs are inverter size and price, PhotoVoltaic (PV), sizes and price, battery sizes and price, and the cost of electricity at off-peak, standard, and peak times.

2. Function – to provide a way for business owners and homeowners to do a quick analysis of the most cost-effective way to make their building energy efficient. The functions allow for different optimisation algorithms to consider user-specific data and output the most cost-effective option. This output should consider all inputs and constraints. The solution should provide information on which Inverter size, PV sizes, and battery size would ultimately result in saving money for twenty years.

The stored renewable energy was allowed to discharge when electricity from the grid is at peak prices and when the state of charge of the battery is above the minimum. The charging of the storage device shall occur with renewable energy or at off-peak times. If the renewable energy is not sufficient, the stored energy is discharged and should result in a lower running cost.

The hypothesis is that the use of optimisation algorithms would result in a lower TCO that can be achieved with the implementation of solar energy. The storage of this energy, and the integration with the grid is a part of the function, and current methods will be used to calculate the size of the PV system cater for the maximum load. Each example load will be analysed against multiple optimisation algorithms, and lowest cost TCO found. The TCO is dependent on both the algorithm and load/ type of building. Ancillary hypothesis is that maximisation of PV would not result in a cost-optimised system.

1.3 Importance of Study and Contribution

Consideration of a hybrid storage system (batteries and Supercapacitor, SC,) was analysed as an optimisation design and was compared to a single storage system. Batteries are more commonly used as they have a long lifespan, low initial cost, and high energy density [13]. However, some disadvantages inhibit them from supplying sudden changes in load or power. The disadvantages are low power density and slow response [13]. This differs from a SC which has fast charging and discharging time and a long-life cycle. With this, the notion that a SC can reduce battery stress is introduced.

A SC also stores energy using static charge whereas the battery uses electrochemical processes. When a supercapacitor is being used, it can cause the total energy efficiency in the system to change. The load directly impacts on the converter and storage devices' efficiency, highlighting the need for cross-analysis between storage devices and how it is integrated into the system based on load requirements. The use of optimisation algorithms would allow for a system's efficiency to be quantified based on what storage components are used and how it is integrated into a residential or commercial building.

1.4 Methodology

The research is based on analysis and case studies of buildings in SA. Once conclusive results were found, algorithms that consider trade-offs were incorporated to find the total cost of ownership.

The research has been divided into the following main sections:

1. Background research into solar energy.
2. Different methods of storage of the energy produced by solar energy were considered.
3. The development of a total cost of ownership equation which compromised of many other equations such as the lifespan, cost, and efficiency of the equipment.
4. Research and incorporation of different optimisation algorithms.
    a. The algorithms included the time of use tariffs of electricity in eThekwini.
    b. The algorithm incorporated the total cost of ownership equation and used different optimisation algorithms.
    c. The explanation of the code, and decision diagrams of the code.
5. Results of case studies are presented using the load information of each of the building types: industrial, commercial, and residential.

1.5 Dissertation Structure

This dissertation has six chapters:

- Chapter one, which culminates here, is the introduction that contains the research question, hypothesis, the importance of the study, the contribution it can offer, along with the methodology.
- Chapter two is the literature review, which gives background theory, the current problem and solution, economic benefits, and load modelling.
- Chapter three is a detailed component of the dissertation which is the total cost of ownership and tariffs. The total cost of ownership and tariff section consists of theory, equations, and different storage options. The equations include cost, efficiency, losses, and include the financial equation for a growing annuity.
- Chapter four discusses optimisation. Optimisation options are considered and discussed. The algorithms are explained, and decision flow diagrams are included.

- Chapter five encompasses optimisation results based on existing load profiles. To achieve a more accurate result, real data was used. The load information for three industrial, three commercial, and one residential building was used.
- Chapter six includes both conclusions and recommendations for further studies. While references can be found in the seventh section.

2 Chapter 2 - Literature Review

2.1 Introduction

This literature review assists in identifying the problem and verifying whether the problem still exists. Research into optimisation of integration of renewable energy exists, however a gap exists in the comparison of different optimisations to achieve the lowest TCO.

2.2 Related Research

There have been several different investigations into the methods of renewable energy, and the integration of renewable energy into the grid.

The study in India, [9], focuses on historical and present renewable energy utilisation. The government policies are included, along with the challenges of renewable integration. The study details policy implementation and divides the challenges of renewable energy sources into four areas: technological, managerial, user awareness, as well as research and development. The issues of grid stability, lack of skilled individuals, lack of data, and funding are some of the issues are underlined in [9]. In the Colorado specific research, [10] the renewable efficiency and integration issues were investigated.

The battery storage study that explores flexibility constraints, [14], focuses on a battery being used to counteract load fluctuations (for load following). The energy management approach from [14] indicated that battery storage leads to an increased cost, but a more reliable system. The research done in [15] concentrates on the implementation of renewable energy microgrids to a grid extension in South Africa.

The economics surrounding renewable energy is not as well known. Similar to integration and storage questions, there are many subsections within the economic impact of renewable energy. The policies mentioned in, [9], support the growth of renewable energy sources by providing incentives, such as tax reduction and reduced electricity rates. A Californian study of the financial side of using renewable energy sources evaluates the purchase agreements in place, identified gaps in the market, and it emphasises the need to analyse and optimally design an renewable energy system [16]. An investigation was conducted within households in South Africa, to analyse the effect of electric geysers on energy consumption [17]. The simulations run in [17], replaced the electric geysers with solar geysers and heat pumps. Further to this, the tariff structure was used. The findings from [17] were that efficient appliances must be used, implementing the time-of-use tariffs would benefit the consumer (reduction of the monthly bill) and the utility (reduction of peak demand), supports the hypothesis.

While [18] focuses on optimisation of a hybrid system with the issues of intermittent supply of renewable energy, cost reduction, and a degree of flexibility, it only uses a genetic algorithm. A single focus algorithm study was also done in [19] where the particle swarm optimisation algorithm was used to present a cost-efficient method with multiple renewable energy sources including solar energy and wind energy. Particle swarm optimisation, artificial bee colony algorithm, and firefly algorithm are looked at in [20].However the focus of research done in [20] is to optimise wind energy over energy supplied by the grid, to include a battery and its end of life cost, and to charge the battery when the wind is in surplus. The total cost of ownership is not mentioned in [20].

The total cost of ownership of the transformer alone, including the inflation rate, is considered in [21]. A solar home total cost of ownership is discussed in [22]. The focus being the reliability of components. However optimisation of the total cost is not considered. A lithium-ion storage for a solar energy system is proposed in [23]. The total cost of ownership in [23] uses the minimum solar available for sizing instead of the maximum, which is traditionally used. Though [23] considers the total cost of ownership with two values of solar energy available, the minimum and maximum optimisation is not considered.

In [24] the investigation into the effect of a battery scheduling in a time-of-use tariff scenario, total cost of ownership and different optimisation methods were not considered. A genetic algorithm approach is used in [25]. It incorporates renewable energy, and energy storage, with the power grid. While real data for a building is used, along with the ability to sell electricity to the grid in [25], the total cost of ownership and different optimisations are not considered. Based on the genetic algorithm that aims to minimise cost, of both solar and wind, is studied in [26]. Though it considers real building and weather data, this does not consider total cost of ownership, with inflation rates, or various optimisation algorithms.

The concept of zero net energy buildings which is where the total energy generated from renewable energy is equal to the energy consumed, is being promoted. A discussion in [27] based on the differential evolution algorithm and zero net energy buildings found that by scheduling appliances and avoiding peak hours saves on the electricity bill and allows for selling electricity to the grid. Research in [27] did not consider total cost of ownership, nor did it compare multiple optimisation algorithms.

The proposal of a hybrid design including wind, solar, and fuel cells was done in [28] where optimisation was done to minimise the error between the responses of the actual system and the reference systems. Similar to the previous research, total cost of ownership and optimisation was not considered.

The research done in this dissertation is different from above literature as it not only considers the optimisation of renewable energy by multiple algorithms, but it also includes tariffs from the utility, and emphasises the economic aspects to focus on a lower total cost of ownership.

2.3 Background Theory

The impact of climate change, depletion of fossil fuels, and technological advancement have led to increased electricity usage [29]. Rising temperatures, caused by climate change have significantly increased the power demand for cooling technologies [30]. The level of CO_2 has reached 410 parts per million. The global temperature has risen by 1.0°C since 1880, and the sea level is said to have increased by roughly 3.3 millimetres per year [31] [32]. The greenhouse effect, which results in the warming of the Earth's atmosphere, has five leading contributing gases: Nitrous oxide (N_2O), Methane (CH_4), Chlorofluorocarbons (CFC's), and Carbon Dioxide (CO_2) as well as water vapour (H_2O). Water vapour is essential due to the feedback mechanism it provides in the way of clouds and precipitation. Nitrous oxide is produced by soil cultivation, fossil fuel combustion, nitric acid production, and biomass burning [31]. Methane is both natural and human-made: the decomposition of landfills, rice cultivation, and manure management. CFC's have been banned and successfully regulated in most countries. CO_2 is a heat-trapping gas and thus does not allow heat to escape the Earth's atmosphere. CO_2 is also produced through natural processes such as respiration and volcanic eruptions. However, humans have increased the CO_2 level by burning fossil fuels (to supply energy) and deforestation. The greenhouse effect has resulted in the Earth becoming warmer in some regions. This results in increased evaporation and precipitation, together with the unfortunate consequence of certain regions becoming dryer [31]. This climate change may benefit some areas where crops can thrive. However, crops in other areas may suffer from increased temperatures. The trapping of heat within the atmosphere has also caused rising sea levels as it melts glaciers and other ice [31].

The electricity demand has increased significantly in South Africa and Africa. The population growth combined with an increased standard of living implies a significant increase in the demand for affordable electricity. Economic changes influence the increase in infrastructures such as buildings, roads, telecommunications, transport, and energy. Political stability entices more investments to the continent and South Africa. This advanced economy is unintentionally centred on energy – the driving force of manufacturing, transport, and industrial growth. Economic growth often ends with wealth for the country – as people become wealthy, their desires increase, and consequently, their energy usage rises. The rate of urbanisation has also caused a surge in energy consumption as between 2010 and 2015, the household energy consumption rate increased by 4.2% compounded annually [33].

South Africa is often referred to as the economic hub of the continent. Among the issues associated with electricity generated by coal are the effects on the environment, the rising CO_2 levels, along with increasing coal costs, the maintenance of electrical substations and the emission of harmful waste from these substations [34] [35].

The economic benefits that can encourage individuals or companies to invest resources in renewable energy are based on the country's policies. A simple way to do this is to introduce an increase in electricity prices during high demand times [36]. A constant supply of renewable energy is not possible if there are no storage devices. A hybrid model, consisting of both renewable and non-renewable energy and a storage unit, should be considered to solve this problem. Renewable energy can supply electricity, or if it is not used then the storage bank can be charged. The storage unit has three main actions: being unused, being charged or being discharged, i.e. supplying energy [36]. Non-renewable energy can be used when renewable energy cannot be harnessed, and the storage system is uncharged. Hence, there would be a reduction in $CO_{2.}$

With the current increased demand for electricity, there needs to be an analysis of the existing system – to make it efficient, sustainable and independent of imported energy needs. India has a ministry dedicated to new and renewable energy. This ministry is tasked with identifying the potential of renewable energy integration into its current system. The focus of the ministry is to promote research into residential and commercial demands and allows for subsidising Renewable Energy Sources (RES) [34].

The Government of India introduced five-year plans. However, it was only in the late 1980s that part of the budget went towards RES [34]. India made headlines in 1984 when a sector of the ministry of energy began promoting privately owned grid-connected wind energy conversion systems, which then began receiving subsidies two years later. Further to this, India began implementing tax exemption on the sale of generated power and allowed for large scale wind energy harnessing by providing relief on customs [34].

An isolated microgrid design was done in one area of KwaZulu-Natal [15]. Research in [15] was based on one specific area, and the data used to simulate results were averages of surrounding areas and did not include of uMhlabuyalingana Municipality (uMkanyakude District). While using the Homer simulation software to produce proposed results, the mock-up took a diesel generator, a DC to AC converter and vice versa into account while neglecting the surge capacities. While [15] highlighted some limitations, it also highlighted the importance of the Electric Distance Limit and the transmission powerline length required [15].

There are two main concerns with renewable energy implementation: reliability and cost. A grid-connected combination of renewable power generation with storage and conventional generation is referred to as a hybrid energy system or a microgrid. The optimum microgrid would be an arrangement of solar, storage, and grid-supplied power, to achieve power reliability and minimise the system's cost. The hybrid system should provide an optimal balance between energy demand and the total cost of the system.

The cost of capital associated with the implementation of renewable energy is high, the cost of solar panels, invertors, the storage of energy, and installation should be considered. The upfront capital cost although high, is minimal when savings are considered over twenty years. The TCO should consider costs and savings over a specific time, the costs should be holistic and include assets. The TCO for a twenty-year period considers the cost of capital, maintenance, electricity, and the replacement costs.

This research is focused on renewable energy based on the geographical positioning within South Africa and how storage takes place while taking cost benefits into account. When considering solar energy, it is common knowledge that the three immediate benefits are: it is an inexhaustible supply, is accessible at no cost, and has no pollution yields when transforming the energy. However solar energy is inconsistent in its reliability as it is weather dependent. The storage analysis, and the possibility of oversizing, to account for tariffs and weather, is considered. Under sizing may save on initial capital but may result in unreliable power while oversizing means a high capital expenditure and a surplus of energy. The balance between the two has be to investigated.

2.4 Microgrids and Storage

The advancement of technology, along with the increased demand for electricity, and the diverse energy generation methods, has led to the need to diversify the grid. With Distributed Energy Resources (DER), allowing for small-scale units of local generation connected to the grid at a distribution level transforms the grid to a bi-directional flow of power [37]. DERs can include renewable and non-renewable energy generation, typical examples being solar units, wind turbines, batteries, and electric vehicles.

A microgrid is a low voltage distribution network that includes multiple loads, storage devices and DERs [14]. Research into how the energy is stored in microgrids, batteries and the possibility of solar storage is also analysed. DC microgrids could be advantageous as there is no voltage conversion between renewable energies and a DC bus [11]. However, a microgrid would need a management system for monitoring and controlling the bi-directional flow of energy. This also has a higher efficiency of power transmission and mitigates the harmonic interference that would normally be encountered in AC-DC microgrids [35]. Battery storage provides a suitable solution as it can both store and generate a charge at an increased expense. Microgrids optimisation can be categorised into two categories: load following constraints and flexibility or regulatory constraints. Load following constraints is the equality between the net load and generation and deals with the energy balance and the ramping required to follow load changes [14]. Flexibility constraints ensure a microgrid has a sufficient reserve to react to the short-term responses (e.g. solar power), load fluctuations and smooth the power output.

The role of energy storage is critical when considering renewable energy deployment. The storage facility can also be used to accommodate the fluctuations of available solar energy. Due to the importance of storage, it is predicted that the price of installed battery storage could fall by 50 – 66% in the next few years [38].

Many off-grid systems form multiple isolated microgrids. Integration due to economic or technical reasons did not occur. These isolated microgrids often face high fuel and electricity costs, to reduce these costs, the need for Energy Storage Systems (ESS), becomes evident. Due to ESS being expensive Lead-Acid batteries are utilised as storage. Lead-Acid batteries have a short life expectancy as they have a low energy density, self-discharge, and leakage of charge.

An alternative form of short-term energy storage is Superconducting Magnetic Energy Storage (SMES). SMES are efficient and can handle load spikes and variations but work best with a hydrogen fuel cell [39]. SMES have Zero electrical losses, but only if liquid nitrogen or helium cooling systems are used. This proves that the SMES method is costly and not practical yet.

Electric Thermal Storage (ETS) is cheaper [40], and ETS's allow for efficient use of electricity. The thermal storage capabilities manage the electric power output separately from the thermal heat output [40]. The ability to control microgrids is done by an Energy Management System (EMS), which determines the optimal use of DER's, which allows for control of the net import and export from the main grid. The types of ETS systems are determined by how storage occurs, the placement of the storage and the conversion of electric energy [37] [40]. Storage can occur in a solid or liquid state, and the placement could be central or closer to the system/ device using the most electricity. Conversion of electricity into thermal energy can be done by a heating element or a heat pump. Many of the newer housing developments in South Africa use heat pumps for geysers, bringing down the amount of electricity used and reducing the cost for the end-user.

2.4.1 Thermal Storage

The research into concentrated solar power stations shows that there is more energy in the sun's heat than in the sun's light. However, the effects of erosion, thermal properties and heat transfers are yet to be fully researched [41]. The uncertainty of the capture and transfer of solar energy/ heat adds to the challenge of microgrid energy management. Concentrating Solar Power (CSP) stations have high storage efficiency due to the power station containing Thermal Energy Storage (TES) [42]. TES uses sensible heat, which is different from latent heat and thermal chemical storage, as sensible heat stores the heat energy through the change of temperature of the liquid heat storage medium. The TES can either have a single or a dual tank heat storage. A CSP station can maintain several hours of electrical output power, even in the absence of sunlight, or in reduced sunlight, and TES allows for a power supply to be scheduled [42].

The SAM software developed by the United States Renewable Energy Laboratory can simulate the CSP power station's characteristics. However, more than 90 input parameters are required, which increases the chances of incorrect results [42]. These factors make this technology less desirable.

2.4.2 Batteries

Batteries are typically contained in a metal or plastic case. There are two separate pathways in a battery; one is the electric circuit through which electrons flow – supplying the load, and the other is where ions move between the cathode, positive terminal, and anode, the negative terminal. These terminals are known as electrodes. There is a barrier between these positive and negative terminals called the separator. The electrolyte is the medium in which charge flows between the electrodes. The collector is responsible for conducting the charge to the outside of the battery [43]. A battery generates electricity when the anode undergoes oxidation while the cathode undergoes a reduction reaction – the anode creates electrons which the cathode absorbs. This action produces electricity. However, when a substance at either electrode runs out, the battery would no longer produce electricity.

Table 2: Table of the composition of a Lead Acid battery, adapted from [44].

Lead Acid	Cathode	Anode	Electrolyte
Material	Lead dioxide	Gray lead	Sulfuric acid
Full Charge	Lead oxide, electrons are added to the positive plate.	Lead, electrons are removed from the negative plate.	Strong sulphuric acid.
Discharged	Electrons move from the cathode to the anode.	Lead turns to lead sulphate.	Weak sulphuric acid.

Table 3: Table of the composition of a Lithium-Ion battery, adapted from [23].

Lithium-ion	Cathode	Anode	Electrolyte
Material	Aluminium foil. Metal oxides from cobalt, nickel, manganese, iron, and aluminium.	Carbon-based.	Lithium salt in an organic solvent.
Full Charge	Metal oxide structure	Lithium ions migrate here.	
Discharged	Lithium ions move back.	Mainly carbon	

Non-rechargeable batteries or, primary batteries, and rechargeable batteries, secondary batteries, produce electricity in the same way. The only difference is that the chemical reaction in a rechargeable battery is reversible. When an external source is applied to a rechargeable battery, the electrons flow from negative to positive, thus restoring the batteries charge. Primary batteries can store more energy than secondary. Batteries are more responsive than a combustion engine, fuel cell, or steam engine as these require minutes or hours to warm up and build up power [44]. Being environmentally friendly, batteries run clean, quietly, do not vibrate, and at end of life can be recycled, unlike generators, substations, and fuel cells. While being more efficient than a fuel cell, Lithium-Ion, (Li-ion) is 99% efficient whereas a fuel cell is up to 60% efficient [44]. Batteries can become more cost-effective if the charging is done at off-peak times or when the cost of electricity is lower. If battery charging is done through the electricity grid, the cost of using electricity from the battery would be comparatively higher than the cost of electricity from the grid. Low maintenance is another attraction to the use of batteries. The complete maintenance of batteries includes the cleaning of the corrosion build up on the exposed terminals along with intermittent performance checks [44]. The drawing of charge that results in a full discharge causes strain to the battery and results in a loss of some battery capacity.

2.4.2.1 Lead Acid Batteries

Lead Acid (LA), batteries were invented by Gaston Plante in 1859, the grid structure is made of a lead alloy to add mechanical strength and improve electrical properties [44]. A LA battery can provide between two hundred and three hundred discharge and charge cycles. The grid corrosion on the positive electrode and the depletion of the active material is the reason for the shorter life cycle.

Table 4: Advantages and disadvantages of lead acid batteries, adapted from [44].

Advantages	Disadvantages
Inexpensive and simple to manufacture; a low cost per watt-hour.	Must be stored in a charged condition to prevent sulfation.
Low self-discharge.	Slow charge, between 14 -16 hours.
Capable of high discharge currents, high specific power.	Poor weight-to-energy ratio, low specific energy.
Temperature performance is good; in high and low temperatures.	Limited cycle life.
Well understood technology.	No low state of charge cut-out.

2.4.2.2 Lithium-Ion Batteries

The research toward a non-rechargeable lithium-ion battery began in 1912 by G.N. Lewis. However, it was not commercially available until the 1970s. It was only in 1991 that the first rechargeable Li-ion battery was commercialised by Sony [44].

Table 5: Advantages and disadvantages of lithium-ion batteries, adapted from [23].

Advantages	Disadvantages
Long cycle life, maintenance-free.	Requires a protection circuit to prevent thermal runaway.
High capacity (up to 100%), low internal resistance, and good efficiency (up to 98%).	High voltage and high-temperature cause degradation.
Short charge times.	Expensive to manufacture, higher cost. (Higher than LA batteries.)
Low self-discharge.	
High energy density- compact and lightweight.	

2.4.2.3 A summary of Lead Acid and Lithium-Ion Batteries

Although the LA battery has a lower purchase price and installation cost compared to Li-ion. The Li-ion has a much longer lifespan than can potentially even out the cost. The Li-ion battery also has a higher energy density when compared to a LA battery of the same size and the Li-ion can hold more charge [45]. The depth of discharge for a Li-ion battery is 80-90 % and a LA battery is 50% respectively. A 90% depth of discharge means a 10% state of charge. This means that Li-ion batteries have a higher effective capacity than the LA option [45] [46]. Self-discharge is the loss of charge due to internal chemical reactions of the battery without a connection between the electrodes. Self-discharge of the Li-ion is 5% on the first day and 4-5% per month thereafter, whereas the self-discharge of the LA battery is 5% per month. The image below is a visual representation of the depth of discharge and the state of charge for both battery types Li-ion, and LA.

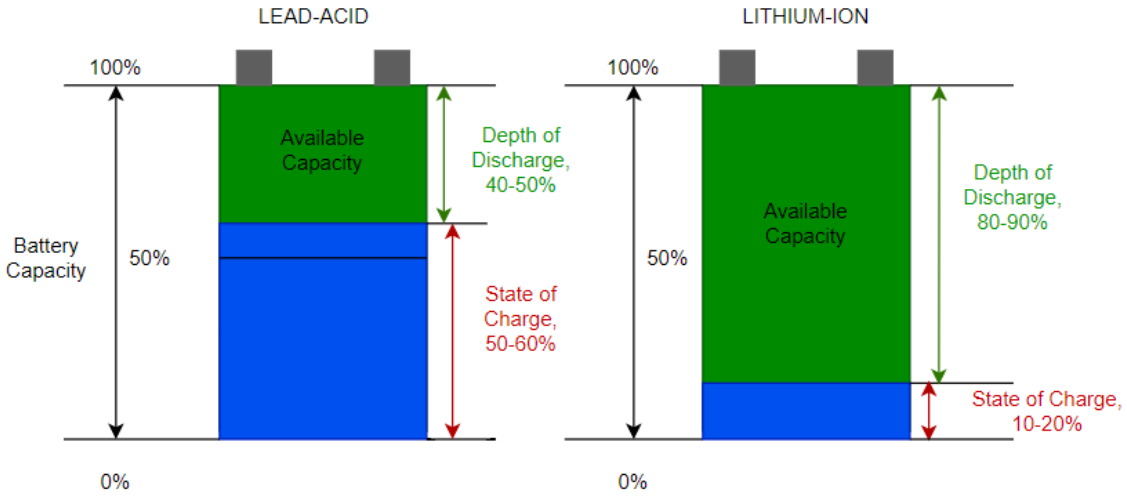

Figure 1: The Depth of Discharge and State of Charge for both, a Lead Acid and Lithium-Ion Battery, adapted from [46].

In a daily charge/discharge cycle, the recommended maximum depth of discharge is 40% for a LA battery, while for the Li-ion is recommended depth of discharge is 70-80%. Efficiency is important when considering batteries because the higher efficiencies mean faster charging, and a higher effective capacity. The efficiency of a LA is 80-85% as compared to the Li-ion of roughly 95%.

2.4.3 Supercapacitors

Capacitors are like batteries as they both store electrical energy. However, they work in entirely different ways. A capacitor is more straightforward than a battery as it does not produce electrons. A capacitor only stores electrons. A capacitor consists of two metal plates separated by a dielectric, or a non-conducting substance [47]. The material used as the dielectric determines what type of capacitor it is and for what it is best suited. There are various capacitor types.

Table 6: The capacitor dielectric types and what they are most suited for.

Dielectric Type	Best Use
Air	Often used in radio circuitry
Glass	For high voltage applications
Ceramic	High-frequency applications
Supercapacitors (SC)	High power-consuming applications

The difference between a capacitor and a battery is that a capacitor can discharge completely in a fraction of a second while a battery would take minutes to hours to discharge [47]. Similarly, a supercapacitor takes a few seconds to recharge and withstand unlimited charge cycles. Supercapacitors have a higher energy density than conventional capacitors but lower than batteries.

Supercapacitors have a symmetric construction: two electrodes and a membrane that acts as a dielectric. This forms two electrical double layers on each of the electrodes – one for each electrode interface [48]. Supercapacitors are also known as Electrochemical Double Layer Capacitors (EDLC). Like conventional capacitors, the material selection of supercapacitors determines the electrical properties of the supercapacitor. The electrode's surface directly determines the supercapacitor's capacity as the charge storage in a double-layer is a surface process [48]. Due to the surface being a determining factor, carbon was used as an electrode material from the beginning. Similarly, the choice of electrolyte determines the maximum allowed voltage for a supercapacitor.

For a battery to generate the equivalent power generated by a supercapacitor, the battery would need to be more significant. The oversizing of a lead-acid battery would mean that the overall system mass and cost would increase. Lead-acid batteries are heavy and while non-polluting in use, they do contain hazardous lead. They can also not withstand as many charge-discharge cycles [48]. A hybrid system consisting of both batteries and supercapacitors can reduce costs significantly. However, these batteries must be chosen carefully because if a standard lead-acid battery is chosen the rapid charging and discharging would destroy the lead electrodes [48] so it would be better to use a battery with a larger capacity.

The supercapacitor has a 100% depth of discharge, and 50% self-discharge in a month if not used [44]. A supercapacitor can be charged and discharged millions of times and has an average lifespan of twenty years. However, to maintain this lifespan, voltages should not be higher than recommended by the manufacturers.

Table 7: Advantages and disadvantages of Supercapacitors, adapted from [44].

Advantages	Disadvantages
Very long cycle life.	Low specific energy.
Low resistance means high load currents; high specific power.	High self-discharge.
Fast charge; a few seconds.	Low cell voltage, requires a series connection.
Overcharge is not an issue.	High cost.
Low-temperature independent.	

2.4.4 Integration to the Grid

The deployment of renewable energy sources creates numerous risks: voltage and power fluctuations due to the unpredictable supply, frequencies being mismatched (where the frequency of generated power does not match the frequency of the AC grid), and harmonics, which are caused by nonlinear loads and which affect the power quality [39]. While the unpredictable supply cannot be controlled, with a battery it can be reduced, the frequency can be matched using either power conditioning or instrumentation equipment. Harmonics can be limited by either filters or an inverter.

The different types of Renewable Energy (RE) have different types of integration issues [35]. Integration has two main issues: the existing electricity networks cannot grow fast enough to keep up with supply, and renewable energies have natural uncertainties [12].

Based on case dependent parameters such as hydro, gas or coal, cost-effectiveness and efficiency, combinations of power sources can be formed to achieve uninterrupted power. In much of the research done to date, fuel prices, advances in technology, and climate changes over time have not been considered. However, recent design studies have proven that the optimal design solution is a hybrid energy system [49]. With solutions being built with the long-term aim of twenty years of gradual integration. If the integration of renewable energy into the grid is carried out in phases, uncontrollable circumstances can be analysed and solutions sought. Expenses in the form of fuel and the initial capital outlay can be reduced while research into technology, demand patterns, and the climate continues.

2.5 Economic benefits

The main problem in South Africa is the dependency on a fossil-fuel-based energy provision system that is state-owned. Since the energy provider is state-owned, a monopolistic energy policy has been embedded into the country. South Africa is the gateway into Africa and is also one of the most attractive destinations for RE investment [50]. As a developing country, there is a need to encourage and focus on economic progress; however, this progress is controlled by economic activity and population shifts. RE can aid this by allowing for sustainable development.

India, a developing country, is currently using solar and wind-based energy as their primary sources of energy. This is determined by the weather patterns of the different geographic locations within the country [34].

In South Africa, the set targets to improve efficiency were not met, and neither was more specific policies put into place. In August of 2011, South Africa announced the launch of a competitive bidding process for RE. The bids contained project structure, legal qualifications, land, environmental, financial, technical, and economic development credentials [51]. The agreements that were signed provided a sovereign guarantee in case Eskom defaulted. In this four-round bidding process, prices continued to decrease as increased competition and equipment prices declined. This resulted in South Africa using competitive tenders and auctions to benefit the country [51].

In [50] a comprehensive analysis of the benefits of implementing RE in three provinces in S.A.: Northern Cape, Western Cape and Eastern Cape. The study takes the projects, (only wind and solar), that was to be operational by 2018 and elaborates on the economic progress and the social cohesion and human development that resulted from these RE projects. The upliftment of these rural areas, within the Northern Cape, Western Cape and Eastern Cape, would take place in the form of employment during the construction and later through the maintenance of the RE plant. The possibility of income generation through leasing land from farmers and increasing the level of education for the local community was discussed. [50].

The study mentioned above took the geographical standing of these provinces into account and assessed what infrastructure was in place. However, energy storage was not considered, and a discussion on the integration into the grid was also omitted. While clean energy is necessary and would create more jobs, it is pertinent that all forms of RE are considered, and the best is chosen, along with the most suitable storage method.

The possibility of a building reducing the final total cost of ownership is the centre of this analysis. This includes minimising the capital expenditure, the operational expenditure (maintenance), and the replacement costs. There are trade-offs to each of these costs. While minimising the capital expenditure, the operational expenditure in terms of the cost of electricity would increase. On the other hand, while trying to minimise the operational expenditure and replacement costs, the capital expenditure would increase.

2.6 Load Modelling

Load modelling (LM) allows the user to develop a mathematical formula that can approximate load behaviours [52]. LM has added complexity due to its dependence on many components; dynamic loads, weather, capacitors, and cabling, among other things. Load Models consists of two categories: dynamic and static as well as two types of approaches to load modelling (measurement-based and component-based).

There are two main steps in LM: selecting a load structure and identifying the load model parameters. The physical behaviours of loads and their associated mathematical relation fall under the component-based approach, while the measurement-based modelling approach is based on data that is directly obtained from the network [52]. While this means that the data used is from the existing network and can thus be used on any load. The drawback is that it may only be relevant to a network at one location.

The mathematical equations can describe the relationship between power, voltage and frequency at a given bus bar [53].

2.6.1 Importance of Load Modelling

With a continued increase in demand, the delivery of energy must be effective. The use of a dynamic model is preferred as it is more accurate when considering the dynamics of the system and can be used to ensure more accurate voltage stability [53]. Voltage stability is an essential subset of the power system stability as it can remain at an acceptable voltage regardless of operating conditions or a disturbance. P-V and Q-V curves are used as a method of assessing voltage stability. The composition of a load is dependent on the day, month, season and weather.

2.6.2 Load Models to be used

To ensure accuracy, load models used in this dissertation are of buildings in eThekwini. This information was gathered from the eThekwini electricity department.

2.7 Current Problems and Solutions

In South Africa, people are often victims of Load Shedding or coal mining strikes [54] [55]. This has led to a loss of revenue by many companies. Some companies resort to the purchasing of expensive generators that require maintenance, and the purchasing of and burning of fuel which leads to pollution. The rising cost of electricity and fuel, along with the looming threat of load shedding, has frustrated the business owner and the homeowner. Many have made attempts to make homes and businesses "off-the-grid" where parts or sections of buildings are dependent on renewable energy. The cost of electricity has led to many homes using solar geysers, gas stoves and heaters to decrease consumption.

For South Africa to contribute to the decline of CO_2 being produced, worldwide steps need to be taken based on South Africa's uniqueness. Having a vast geographical profile gives rise to the idea that each terrestrial biome of South Africa can optimise a different source of renewable energy, e.g. wind, water, and solar.

2.8 Conclusion

The above literature gives insight into how to optimise renewable energy to form a hybrid system. Although the research previous done into optimisation of renewable energy, TCO is not considered. Where a TCO method was proposed, there was no optimisation. Storage of renewable energy mentioned above did not include TCO or multiple optimisation algorithms.

The research done in this dissertation is different from above literature as it not only considers the optimisation of renewable energy by multiple algorithms, but also includes tariffs from the utility, and includes the annuity equation to emphasis the economic aspects to focus on a lower total cost of ownership.

3 Chapter 3 - Total Cost of Ownership & Tariffs

3.1 Introduction

Total Cost of Ownership (TCO), or Total Ownership Cost (TOC), is a concept that analyses the real cost. TCO was initially used in an Information Technology (IT), research and advisory company that considered the total costs of owning and managing IT infrastructure [56]. The Capital Expenditure, (CAPEX), for hardware and software for IT, was roughly only 20% of the total cost during lifetime use [57]. The TCO approach considers the initial investment, the costs for maintenance, and replacement of parts, end of life, and unexpected malfunctioning [58]. TCO is essentially the sum of CAPEX, Operational Expenditure (OPEX), and End Of Life Expenditure (EOLEX), which is usually omitted. The most common mistake is to minimise CAPEX where the focus should be on minimising TCO.

OPEX is separated into two subgroups: controlled OPEX and risk. In this context, the risk is the product of the probability of an unexpected malfunction, part of the system, and the consequences the malfunction would have in a product's role [57]. Therefore, the need to control the risk can be achieved by reducing the probability and the consequences.

TCO is relevant when considering building efficiency to calculate the number of years it would take to start allowing for savings/ profit to be made.

An electricity tariff is the amount of money charged to the consumer for the supply of electrical energy. The tariff is dependent on a few factors: type of load; the time the load is supplied; the power factor of the load; and the amount of energy consumed [59]. The type of customer is most commonly classified into three types: commercial, industrial, and residential. Industrial consumers use more energy than residential and thus have a higher tariff. The tariff is also determined by demand. At peak times there is a higher tariff than at off-peak or standard times. Lastly, more energy consumed means a higher cost.

Once detailed information around the cost of installation and maintenance is made available, an informed decision can be made. The decision would ideally choose low-cost suppliers favouring low price suppliers [56].

The end goal is to remain in a period of "money saved". Total electricity cost over n years is calculated using the growth annuity formulae, to be discussed in Objective Function section. The TCO is the outcome of the optimisation and is dependent on the number of years. Below, n is the number of years:

$$\text{Projected Savings} = \text{Cost of Electricity for n years} - \text{TCO for n years} \tag{1}$$

The TCO and specifically, the risk must be considered. TCO is not merely the summation of CAPEX, OPEX and EOLEX. Each of these summands are comprised of hidden costs such as:

- CAPEX not only includes the physical items but also the cost of erection,
- OPEX takes running costs and downtime into account,
- EOLEX looks for lifetime replacement of all product items, ranging from PV panels, and batteries to the cables, and switches. the

It is important to note that PV system degradation rates are higher based on the worst-performing modules.

3.2 TCO Equations

3.2.1 Overview

The Distribution Grid (DG) has a much lower initial investment. However, the maintenance and operational costs push the OPEX much higher than a fully solar or a hybrid solution [60]. Below is a comparison between a DG, a solar and a hybrid (generator and solar) solution adapted from [60]:

Table 8: Comparative analysis for three solutions of electricity generation.

Comparison of \ Solution	DG Solution	Solar Power	Hybrid Solution
Battery back-up time	4 – 8 hours	3 – 5 days	1 – 2 days
Environmental Impact	Noise & air pollution.	Green.	Less noise & air pollution.
Required Operation and Maintenance	Coal, oil, parts and fees.	Routine maintenance.	Coal, oil, parts and fees.
Operation and Maintenance Cost	High	Low	Medium
Reliability	Medium	High	High
Initial Investment	Low	High	High

3.2.2 TCO Equation for Hybrid System

The TCO equation, from [57] is:

$$\mathrm{TCO} = C_e + \sum_{\mathrm{year}=1}^{n} \left[\frac{C_{pm} + C_{cm} + C_{op} + C_{sd} + C_r}{(1+i)^{\mathrm{year}}}\right] + \frac{C_{eol}}{(1+i)^n} \qquad (2)$$

Where:
C_e = cost of erection (including components, installation and infrastructure)
C_{pm} = preventive maintenance costs / year
C_{cm} = corrective maintenance costs / year
C_{op} = operational costs / year
C_{sd} = shut down costs / year
C_r = repair costs / year
C_{eol} = end of life costs
I = inflation / year

Reflection at a later stage allows for changes in the formulae where the power that cannot be produced by the PV panels is C_{power}, and the power that can be saved is $C_{powersaving}$.
OPEX is a cost that fluctuates based on uncontrolled risks. In equation 2, the uncontrolled costs are C_{op}, C_{sd}, C_r, and C_{eol}. The recommendation of replacing a battery after four years of use falls under C_{eol}. Asset management is vital in balancing performance, finance and risk. Risk can be defined as:

$$\mathrm{Risk} = \mathrm{Probability} * \mathrm{Consequences} \qquad (3)$$

A commonly used asset management tool is the Risk Management Matrix, adopted from [57]:

Table 9: Risk Management Matrix.

Probability of Occurrence		**Consequences**			
	Frequency (times/occurrence)	Catastrophic	Severe	Serious	Moderate
Daily	1000	VH	VH	VH	H
Weekly	100	VH	VH	H	M
Monthly	10	VH	VH	H	M
Yearly	1	VH	H	M	L
Frequently	0,1	VH	H	M	L
Probable	0,01	H	M	L	N
Possible	0,001	H	M	L	N
Not Likely	0,0001	M	L	N	N
Almost Impossible	0,00001	L	L	N	N

The risk is indicated as Very High (VH), High (H), Moderate (M), Low (L), and Negligible (N). In the matrix, all consequences can be categorised.

The lifetime or lifespan of a product is how long the product can operate while performing the desired function at the required rate of reliability. Every product ages and with ageing the efficiency decreases.

3.2.3 PV Panel TCO

PV panels or modules are chosen generally, by two driving factors the efficiency at which sunlight is converted into electricity and how this efficiency changes over time. The degradation rate is also known as the power decline over time [61]. Degradation of solar panels is most often caused by Potential Induced, Light, Ultraviolet, Moisture Degradation, and cell cracks. It is ultimately caused by environmental factors such as temperature, humidity, and irradiance. Potential Induced Degradation is when there is ion mobility between the semiconductor and any other element – driven by voltage potential and leakage current. The degradation rate is of importance as this can be used to determine the power production decrease, which directly impacts the financial risk.

Initially, it was understood that a PV panel lifespan is 20 years and degraded by 1% every year, reaching an efficiency of 80% after 20 years of use.

Using the data recovered from field tests and literature, the average degradation rate is 0.8%/year and 0.5%/year as a median value [61]. Due to the studies and the cumulative testing that supports warranties, products can be in the field for more than 25 years and may continue to perform at a reasonable rate. The majority of data, 78%, shows the degradation rate of less than 1%/year. This excludes thin-film degradation rates as they are statically closer to 1% degradation per year.

In conclusion, the TCO can consider that solar panels can last 20 years and upwards. For the maximum lifespan of a solar panel, there has to be proper and regular maintenance. The best way to ensure the long life of a solar panel, and to optimise the power produced, is to ensure it is always clean. Thoroughly washing the panel with a hose often means dirt would not build up. There are also biodegradable soap options, setting up an automated sprinkler system or hiring a solar panel cleaning company. There is a small risk the panels can malfunction or not be operational, for this reason, the risk factor is be omitted. Thus the TCO for PV panels are:

$$\mathrm{TCSP} = \mathrm{SP_{cap}} + \mathrm{SP_{main}} \qquad (4)$$

Where:
TCSP = Total Cost of Solar Panels [currency]
SP_{cap} = Solar Panel Capital [currency]
SP_{main} = Solar Panel Maintenance [currency]

As a panel ages, there is a power loss that must be considered. A PV panel receives solar irradiation and converts it into electrical energy. Nevertheless, this electrical energy output depends on the operating voltage and is generally considered to be only 18% of the total solar power [62]. The following equation, from [62], is the electrical output of a PV panel:

$$\mathrm{P_{ele}} = \mathrm{V} * \mathrm{I} \leq 0.18 * \mathrm{P_{sol}} \qquad (5)$$

Where:
P_{ele} = electrical power output [W]
V = Operating voltage of the PV panel [V]
I = Current of the panel [A]
P_{sol} = Total solar power [W]

To take degradation into account, the formula can become:

$$\mathrm{P_{ele,d}} = \mathrm{V} * \mathrm{I} * \left(\frac{98.2}{100}\right)^{\mathrm{n}-1} \qquad (6)$$

Where:
$P_{ele,d}$ = Electrical Power output including degradation percentage [W]
V = Operating voltage of the PV panel [V]
I = Current of the panel [A]
n = number of years the panel has been in use for

3.2.4 Inverter TCO

A solar inverter's average lifespan is ten years with regular maintenance, including cleaning, and inspection. It is recommended that the inverter is chosen between 90 to 110% of the maximum technical output of the solar panels [63].

Essentially the TCO of an inverter is the same as the TCO of the solar panel;

$$TCI = I_{cap} + I_{main} \quad (7)$$

Where:
TCI = Total Cost of the Inverter [currency]
I_{cap} = Initial Capital for Inverter [currency]
I_{main} = Maintenance for Inverter [currency]

Inverter efficiency is the amount of DC power that is converted into AC power when there are losses due to heat, standby losses (independent of the output power), and load losses (load dependent) [64] [65]. The formula is

$$\eta_{inv} = \frac{P_{AC}}{P_{DC}} \quad (8)$$

Where:
η_{inv} = inverter efficiency
P_{AC} = AC power in watts
P_{DC} = DC power in watts

There are different types of efficiency classification for inverters: peak, European, and California Energy Commission. Peak efficiency is the maximum efficiency that an inverter can achieve based on the power output. The European and California Energy Commission rankings are similar as they both use weighting factors, both using numbers based on the inverter operation at different power outputs in Europe and California respectively [65] [66].

The inverter efficiency is dependent on the quality of the sine wave, a high-quality sine wave inverter can achieve upwards of 90% efficiency while lower quality sine wave inverters can achieve between 75 -85%. This value can be found on the inverters datasheet.

3.2.5 Cable TCO

Cables, just like all other components, have a lifespan. As the cable is used, its efficiency is reduced each year. The formula below, from [57], is used to calculate the total cost of cables:

$$CT = Cl + Cj \quad (9)$$

Where:
Cl is the cost of the length of the cable used.
Cj is the value of joule losses during N years and is defined as:

$$Cj = \left(i_{max}^2 * R * l * N_p * N_c\right) * (T * P + D) * \frac{\sum_{n=1}^{N}[r^{n-1}]}{(1 + \frac{i}{100})} \quad (10)$$

Where:
Imax = max load in the first year [A]
R = cable AC resistance per unit length [Ω]
L = cable length
Np = number of phase conductors per circuit

Nc = number of circuits carrying the same type and value of the load
T = operating time at max joule losses [h]
P = cost of 1Wh [currency]
I = discounting rate used to compute present values [pu]
N = economic life [number of years]

3.2.6 The Tariffs

The tariffs charged are first divided by building type. The tariffs are then further divided by hour and load. The figures below are from the Tariff Booklet 2021 – 22, [67].

Table 10: Low Demand Season Tariff hour classification from [67].

Low demand season			
Time periods	**Mon – Fri**	**Saturday**	**Sunday**
22h00 - 06h00	Off-peak	Off-peak	Off-peak
06h00 - 07h00	Standard	Off-peak	Off-peak
07h00 - 10h00	Peak	Standard	Off-peak
10h00 - 12h00	Standard	Standard	Off-peak
12h00 - 18h00	Standard	Off-peak	Off-peak
18h00 - 20h00	Peak	Standard	Off-peak
20h00 - 22h00	Standard	Off-peak	Off-peak

Table 11: High Demand Season Tariff hour classification from [40].

High demand season			
Time periods	**Mon – Fri**	**Saturday**	**Sunday**
22h00 - 06h00	Off-peak	Off-peak	Off-peak
06h00 - 07h00	Peak	Off-peak	Off-peak
07h00 - 09h00	Peak	Standard	Off-peak
09h00 - 12h00	Standard	Standard	Off-peak
12h00 - 17h00	Standard	Off-peak	Off-peak
17h00 - 18h00	Peak	Off-peak	Off-peak
18h00 - 19h00	Peak	Standard	Off-peak
19h00 - 20h00	Standard	Standard	Off-peak
20h00 - 22h00	Standard	Off-peak	Off-peak

3.2.6.1 Residential Tariffs

Residential premises are those defined by the bylaws and that generally consume more than 1000 kWh per month. The Network Access Charge is based on the inverter size; the amount below must be multiplied by the inverter size.

Table 12: Residential Tariffs from [67].

Energy charge, non-seasonal (c/kWh)			Service Charge (R) per month	Network Access Charge (R/kVA) per month
Peak	Standard	Off-peak		
305.77	152.76	113.15	164.67	Inverter size * 17.83

3.2.6.2 Commercial Tariffs

Commercial tariffs are designed for businesses with a maximum demand equal to or less than 100 kVA. The Network Access Charge is the same for all seasons but a minimum of a 50 kVA inverter.

Table 13: Commercial Tariffs from [67].

Energy charge, June to August (c/kWh)			Service Charge (R) per month	Network Access Charge (R/kVA) per month
Peak	Standard	Off-peak		
408.58	204.43	99.59	432.67	Inverter size * 87.20
Energy charge, September to May (c/kWh)			**Network Demand Charge (R) per month**	**Network Access Charge (R) per month**
Peak	Standard	Off-peak	Maximum load of every month * 87.20	Inverter size *28.98*12
201.58	162.17	94.33		

3.2.6.3 Industrial Tariffs

This tariff is for consumers with a demand greater than 100 kVA. In addition to the amounts below, there is a Network Demand Charge, at R kVA based on the actual demand of electricity where the Network Access Charge is based on the highest demand recorded.

Table 14: Industrial Tariffs from [67].

Energy charge, June to August (c/kWh)			Service Charge (R) per month	Network Access Charge (R/kVA) per month
Peak	Standard	Off-peak		
407.85	131.44	76.51	5105.00	Inverter size * 109.64

<table>
<tr><th colspan="3">Energy charge, September to May (c/kWh)</th><th colspan="2">Network Demand Charge, NDC, (R) per month</th><th>Network Access Charge, NAC, (R) per month</th></tr>
<tr><td>Peak</td><td>Standard</td><td>Off-peak</td><td colspan="2" rowspan="2">Maximum load of every month * 109.64</td><td rowspan="2">Maximum load of every month * 36.01</td></tr>
<tr><td>140.62</td><td>100.33</td><td>67.75</td></tr>
<tr><th colspan="4">Ancillary Network Access Charge</th><th colspan="2">Voltage Surcharge</th></tr>
<tr><td colspan="4">ANAC = Inverter Size * 20.67 * 12;</td><td colspan="2">VoltageSurcharge = 0.225 * (NDC + NAC + ANAC)</td></tr>
</table>

3.3 Storage Systems

3.3.1 Battery TCO

Batteries vary in many properties that affect the storage system capabilities and end costs. These properties include weight, state of charge/ discharge, degradation properties and cost [68]. Both lead-acid and lithium-ion batteries have high energy density but low power density capabilities, and can be seen in the figure below which has been adapted from [69]. A battery has a higher energy density than a capacitor. In comparison, a capacitor has a higher power density than a battery – a capacitor can give off energy more quickly than a battery, but a battery stores more energy than a capacitor.

Batteries are rated as ampere-hours, or Ah. Ah is a measure of electrical charge where the measure of electrical energy in kilowatt-hours, kWh. To convert between the two, the following formulae can be used:

$$\mathrm{kWh} = (\mathrm{Ah} * \mathrm{V}) * \frac{1}{1000} \qquad (11)$$

Where:
kWh = electrical energy in a battery
Ah = ampere-hours (rated for battery)
V = voltage (rated for battery)

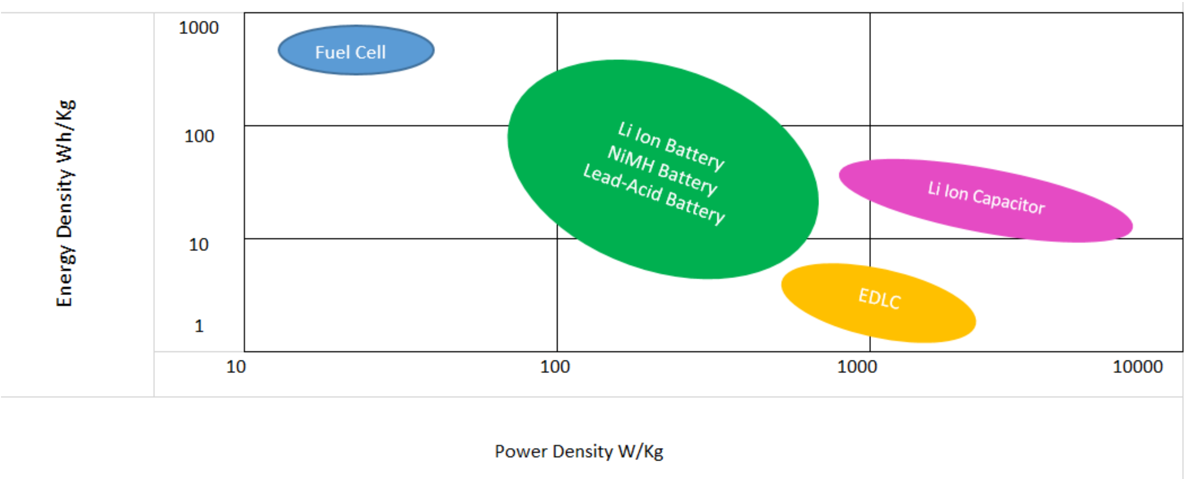

Figure 2: The relationship between energy density and power density.

Figure 2 shows a fuel cell, a lithium-ion (Li-Ion), Nickel-metal Hydride (NiMH), and Lead Acid, LA, a battery, a lithium-ion battery, and a supercapacitor (or EDLC).

Due to the uncertainty and intermittence of sunlight, a storage device is used to ensure electrical stability. The cycles and depth of charging and discharging affect the lifespan of batteries [70]. When batteries are at the maximum number of cycles, they must then be replaced. This means that the State of Charge (SOC), and the charging and discharging would affect the lifespan of a battery. When considering a PV system, the sizing of the system directly influences the battery life. The total degradation can be calculated using Miner's law of cumulative degradation.

SOC is the opposite of Depth of Discharge (DOD), as the DOD is the used power, and the SOC is the remaining power of a battery [71].

Miner's rule is a commonly used cumulative damage model for failures caused by fatigue. It includes k as the amount of stress levels, the degradation given by D, is at the j^{th} stress, Sj and the average number of cycles to failure is Nj [72]. The formula is given by:

$$D = \sum_{j=1}^{k} \left(\frac{n_j}{N_j}\right) \qquad (12)$$

Where:
n_j = number of cycles accumulated at stress S_j
D = is the fraction of life consumed by exposure to the cycles at different levels of stress

The number of cycles to failure, Nj, can also be given by the formula below taken from [73]:

$$N_j = N^{\#} * e^{\frac{-v^{\#} * Q_J}{kT}} \qquad (13)$$

Where:
$V^{\#}$ = activation damage voltage
Q_j = discharge during a cycle of type j

When the Degradation (D) reaches unity, there is structural failure [73]. Essentially it is evaluating the amount of degradation at each stress level and adding the proportions together. For a chemical cell, a battery, the industry standard that defines the DOD, is often a percentage using the following formula:

$$\mathrm{DoD} = \left(\frac{\mathrm{Q}}{\mathrm{Q}^{\#}}\right) \qquad (14)$$

Where:
$Q^{\#}$ = value the battery manufacturer assumes the battery to be fully discharged
Q = the charge

A rough timeframe of when the battery should be replaced can be done using the battery's cycles before requiring a replacement,. This allows for factoring in the purchasing of replacement batteries to be worked into the TCO. A lead-acid battery lifespan is roughly five years, while a lithium-ion is about ten years [68]. A shorter battery lifespan can be directly related to how frequently the battery is charged or discharged and if the battery exceeds its SOC or DOD.

Then DOD is essentially a percentage of the battery that has been used if a battery has a max capacity of 50kWh and discharges 30kW in 1 hour then at the end of the hour the DOD is:

$$DoD = \left(\frac{Q}{Q^{\#}}\right) = \left(\frac{30 * 1}{50}\right) = 0.6, 60\%$$

When it reaches unity or 100%, the battery is fully discharged.

Lithium-Ion batteries allow for a greater discharge than Lead Acid batteries. Cycle life is a good initial indication of battery charge/ discharge duration. If a battery has a cycle life of 3650, that means the battery can fully charge/ discharge twice daily for a full 5-year duration. Most batteries cannot be drained of all their energy as it can cause irreversible damage to the battery itself [74]. The cycle life tends to decrease as the DOD increases.

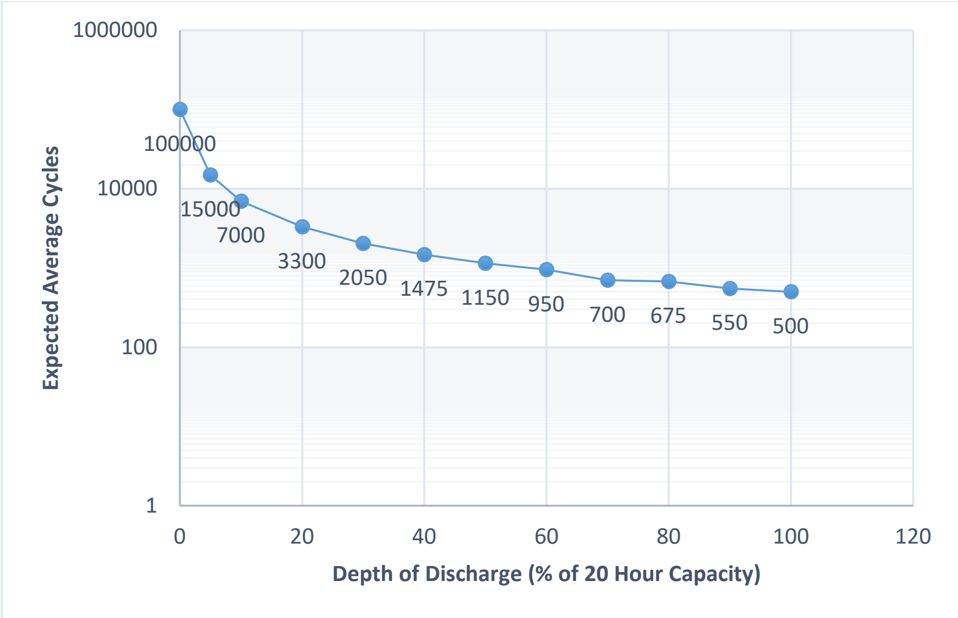

Figure 3: Relationship between the cycle life and the depth of discharge, adapted from [74].

DOD is related to SOC by the following equation:

$$SOC_{min} = (1 - DoD) * C_{bat} \qquad (15)$$

Where:
C_{bat} is the total capacity of the battery in Wh.

The batteries go through two phases, namely charging and discharging.
To discharge the battery, the following equation is used:

$$SOC_{bat} = SOC_{bat} - selfdis - \frac{P_{dc} * n_{dis}}{C_{bat}} \qquad (16)$$

Where:
SOC_{bat} is the state of charge of the battery
Selfdis is the self-discharging the battery experiences, around 5% per month
P_{dc} is the DC power in the battery
n_{dis} is the discharging efficiency of the battery
C_{bat} is the total capacity of the battery in Wh

The DC power is calculated by:

$$P_{dc} = n_{ac} * P_{bat} \qquad (17)$$

The power of the battery is calculated by:

$$P_{bat} = (SOC_{bat} - SOC_{min}) * C_{bat} \qquad (18)$$

Where:
SOC_{min} is the minimum state of charge of the battery.

The charging equation used is:

$$SOC_{bat} = SOC_{bat} - selfdis + \frac{P_{dc} * n_{ch}}{C_{bat}} \qquad (19)$$

Where:
N_{ch} is the discharging efficiency of the battery.
However, in the charging equation, the power is calculated differently:

$$P_{dc} = -n_{ac} * P_{bat} \qquad (20)$$

3.3.2 Supercapacitors

A supercapacitor (SC) can also be referred to as an EDLC, or an ultracapacitor. SC can charge and discharge at a remarkable rate, unlike batteries. Supercapacitors have a longer lifespan and withstand many more discharges, more than 500 times any battery [75] [76], along with this the energy is stored in an SC not chemical but an electrostatic field. For a greater impact in a battery's lifetime, a larger SC is used [75].

3.3.3 Replacement Comparison

The table below, adapted from [68], comprises reviews of multiple studies on LA, Li-Ion and supercapacitors.

Table 15: Lifespan and Cost Analysis for LA, Li-Ion, and Supercapacitor adapted from [10].

		Efficiency (%)	Life Time (in years)	Trade Period (in years)
LA Battery	Min	60	5	5
	Max	90	16	6
Li-Ion Battery	Min	78	5	10
	Max	99	16	10
Supercapacitor	Min	70	8	-
	Max	98	20	-

3.4 Objective Function

To compare future cash flows to current cash flows, the future cash flows must be discounted using an appropriate discount factor. The discount factor used in the calculations below is

3.94% [77]. (This is the interest rate which cash deposits are currently earning.) To ensure comparability across the various elements (cost of electricity, maintenance, and replacement costs) over time, appropriate inflation rates must be used [78]. Based on the information found in [79], differing inflation rates have been used for: utilities, maintenance, and durable items. The cost of electricity falls under the utility inflation rate. The maintenance of items has a different inflation rate. Durable items are defined as items that do not require frequent replacement, examples are home appliances, consumer electronics, furniture, toys, and cars [80]. A battery, or SC, falls into the durable good category. To validate the various inflation estimates, inflationary estimates used in the study have been sourced from [79]. Both the interest (discount factor) and inflation rates used are as at the end of 2020.

$$\mathrm{TCO} = \mathrm{Capital} + \mathrm{Maintenance} + \mathrm{Replacement} + \mathrm{Electricity} \tag{21}$$

The TCO equation above is then broken down into each of its components: capital, maintenance, replacement, and electricity. The capital equation:

$$\mathrm{Capital} = \mathrm{Inverter} + \mathrm{PV} + \mathrm{Battery} \tag{22}$$

Where battery can be either LA or Li-Ion or a SC. The next equation is the maintenance equation:

$$\mathrm{Maintenance} = \frac{\mathrm{P}}{\mathrm{r} - \mathrm{g}} * \left(1 \left(\frac{1 + \mathrm{g}}{1 + \mathrm{r}}\right)^{\mathrm{n}}\right) \tag{23}$$

Where maintenance cost is between 1 and 1.5% of the initial cost [81]. Using the equation for the present value of a growing annuity:
P is the first payment: $0.015 * (\mathrm{Inverter} + \mathrm{PV})$
r is the discount factor rate per period
g is the growth rate or inflation rate
and n is the number of periods, maintenance is conducted annually.

Specific to maintenance, r is 3.94%, g is 3.7%, and n is 20.

The next equation to be considered is the replacement of items with a lifespan of fewer than twenty years:

$$\mathrm{Replacement} = \frac{\mathrm{Inverter} * (1 + \mathrm{g})^{\mathrm{n}}}{(1 + \mathrm{r})^{\mathrm{n}}} + \frac{\mathrm{Battery} * (1 + \mathrm{g})^{\mathrm{n}}}{(1 + \mathrm{r})^{\mathrm{n}}} \tag{24}$$

Where the replacement values are specific to each type of battery or SC. The inflate rate, g, is 3.4%, while the discount factor, r, is 3.94%, and n is the number of years the item is projected to be replaced in.

For the LA option, the equation becomes:

$$\text{Replacement} = \frac{\text{Inverter} * (1+g)^{10}}{(1+r)^{10}} + \frac{\text{Battery} * (1+g)^{5}}{(1+r)^{5}} + \frac{\text{Battery} * (1+g)^{10}}{(1+r)^{10}} + \frac{\text{Battery} * (1+g)^{15}}{(1+r)^{15}} \tag{25}$$

For the Li-ion option the equation becomes:

$$\text{Replacement} = \frac{\text{Inverter} * (1+g)^{10}}{(1+r)^{10}} + \frac{\text{Battery} * (1+g)^{10}}{(1+r)^{10}} \tag{26}$$

And lastly, for the SC option, the replacement equation becomes:

$$\text{Replacement} = \frac{\text{Inverter} * (1+g)^{10}}{(1+r)^{10}} \tag{27}$$

The last part of the TCO equation to be derived is electricity.
For the increasing cost of electricity, the equation for the present value of a growing annuity can be used.

$$\text{Electricity} = \frac{P}{r-g} * \left(1 + \left(\frac{1+g}{1+r}\right)^{n}\right) \tag{28}$$

Where P is the electricity cost. The cost of electricity is calculated with PV consideration (the available solar), the load, the tariff, and the storage battery condition DOD.
r is the discount factor per period
g is the growth rate or inflation rate
and n is the number of periods, in the case of electricity it is monthly

Specific to the electricity equation above: r is 3.94%, g is 2.7% per annum – 0.225% for monthly, and n is 240, as electricity is paid monthly.

3.5 Data Used

The following section compromises the array used in the code. The data used is from various stores in South Africa.

To choose the inverter, the following sizes, prices and connection fee is used. The connection fee is based on the building type, the service charge, network access charge, network demand charge, the ancillary network access charge, and the voltage surcharge. shows all the information gathered for inverter sizes used in the code; column one is the brand of the inverter, column two is the inverter size, while column three and four is the price of the inverter and the total connection cost for twenty years respectively.

Table 16: Table of data of the inverters used from [52].

Brand	Inverter Size (kVA)	Inverter Price	Total Twenty Year Connection Fee (NAC*size*20*12)
1	8.2	R 62 456.01	R 139 905.12
2	8	R 42 107.80	R 136 492.80
3	6	R 31 160.00	R 102 369.60
3	5	R 29 061.45	R 85 308.00
4	4.6	R 33 147.40	R 78 483.36
3	4	R 25 609.15	R 68 24.64
3	3.6	R 25 645.72	R 61 421.76
3	3	R 22 895.95	R 51 184.80
3	2.5	R 20 506.70	R 42 654.00
3	1.5	R 15 238.01	R 25 592.40

Table 17 below shows the brand, size of solar panels, and the price of solar panels. This real data was taken from [82] to be able to provide the most accurate TCO.

Table 17: Table of PV sizes and prices from [82].

Brand	Size (in VA)	Price
5	380	R 3 749.64
5	340	R 2 323.00
5	330	R 2 249.00
5	325	R 2 491.00
5	315	R 2 294.00
5	270	R 1 966.01
5	250	R 1 897.99
5	150	R 1 654.00
5	140	R 1 541.00
5	120	R 1 582.00
5	100	R 1 318.00
5	90	R 1 284.00
5	80	R1 415.50
5	50	R 822.00
5	20	R 442.70
5	10	R 180.00

The table that follows is the brand, size (in Ah and kW), and the price of LA batteries. To convert Ah to kW, using batteries with a voltage of 12:

$$\text{kWh} = \frac{\text{size in Ah} * \text{voltage}}{1000} \qquad (29)$$

Table 18: Necessary information of LA batteries from [82].

Brand	Size (in Ah)	Capacity (in kWh)	Price
6	230	2.76	R 7 146.50
7	100	1.2	R 3 188.20
8	96	1.152	R 2 722.69
9	75	0.9	R 9 338.51
7	65	0.78	R 2 406.00
9	55	0.66	R 7 400.49
8	50	0.6	R 1 642.56
8	40	0.48	R 1 364.21
10	26	0.312	R 1 179.90
10	18	0.216	R 851.20

Next is a table of information on Li-ion batteries. This follows the format of the LA battery table.

Table 19: Table showing the brand, size, and price of Li-ion batteries from [82].

Brand	Size (in Ah)	Capacity (in kWh)	Price
11	310	3.72	R 36 615.85
11	218	2.616	R 27 119.00
12	200	2.4	R 23 766.14
11	150	1.8	R 18 630.00
11	108	1.296	R 12 349.00
11	104	1.248	R 13 291.00
12	100	1.2	R 11 316.40
11	82	0.984	R 11 115.00
12	75	0.9	R 10 563.06
11	44	0.528	R 5 711.00
12	40	0.48	R 6 224.40
11	22	0.264	R 3 166.00
12	20	0.24	R 3 232.85
12	10	0.12	R 1 638.75

Supercapacitors are measured in Farads. To get to kWh, a few calculations must take place. All SC's considered are 12V.

First, the electrical charge in Coulombs is required:

$$Q = C * V \quad (30)$$

Where:
Q is the electrical charge in Coulombs,
C is the capacitance in Farads.
And V is the voltage of the capacitor.

Once this is calculated the kWh can be found after converting to Ah. To convert to Ah:

$$Ah = \frac{Q}{3600} \quad (31)$$

Thereafter the following equation is used.

$$kWh = \frac{\text{size in Ah} * \text{voltage}}{1000} \quad (32)$$

The table that follows has capacitance and price as listed from [83].

Table 20: Supercapacitor values and prices from [83]

Brand	Capacitance (in F)	Q = C*V (in Coulombs)	Ah = Q/3600	Capacity (in kWh)	Price
14	1	12	0.00333333	0.00004	R 320.75
14	5	60	0.01666667	0.0002	R 917.28
15	87	1044	0.29	0.00348	R 551.73
15	100	1200	0.33333333	0.004	R 651.99
15	112	1344	0.37333333	0.00448	R 743.57
16	1280	15360	4.26666667	0.0512	R 900.04
13	0.22	2.64	0.00073333	0.0000088	R 137.89
14	0.9	10.8	0.003	0.000036	779.06

Table 21: The sizes and prices listed below are from [84].

Brand	Capacity (in kWh)	Price
17	0.465	R 7 173.25
17	0.50	R 7 578.04
17	1	R 858.04
17	3	R41 004.44
17	3.55	R48 521.92
17	5.9	R80642.32

3.6 The Current Method of Calculation

As mentioned in Chapter 1 – Introduction, the current method proposed by companies and governments advise users to size a PV system to cater for the maximum load. This method would be referred to as "the current method". The following method and equations are adapted from [4], these equations were used to compare to the TCO from optimisation.

1. Calculate the average daily usage of a system.
2. Find the peak sun hours in the chosen location.
3. Calculate the PV size using the following formula:

$$PV\ Size = \frac{\text{Daily kWh}}{Average\ sun\ hours} * 1.15(\text{efficiency factor}) \tag{33}$$

The average sun hours for Durban, South Africa is 4.0 to 4.9 hours, from [85], the average of 4.45 should be used.

4. The inverter size is half of the PV size.

$$Inverter\ Size = \frac{\text{PV Size}}{2} \tag{34}$$

The following additions to the sizing system were made to ensure a more complete answer of TCO is found.

5. A battery should be able to provide for one day with no PV and be sized accordingly.

$$Battery\ Size = \ Daily\ kWh \tag{35}$$

6. The battery would only discharge at peak times.
7. The values of the inverter, PV, and battery should then be used in the function to get TCO.

3.7 Conclusion

For a TCO equation to be accurate and all modules must be considered on an individual basis. Each part of the system comes with degradation and lifespan. The losses from component to component, PV to the inverter to a battery, was considered. The cost of a replacement part must be calculated at the future cost.

4 Chapter 4 – Optimisation

4.1 Optimisation options and decision

Various routes can be used to optimise a specific problem. Optimisation is making the best or most effective decision regarding a situation or a resource. For this discussion, the resource that is being optimised is capital or money. The goal is to propose a cost-saving scenario for buildings that is based explicitly on the efficiency and integration of renewable sources.

There are trade-offs between oversizing the building requirements to produce and store surplus energy but at the expense of increased initial capital, maintenance, and the possible replacement costs at a later date. For example, PV panels can be used for twenty years, whereas batteries are often replaced after five years. The different optimisation algorithms took this into account.

There are many optimisation algorithms available, the ones that are used when analysing the case studies are explained below.

4.1.1 Graphical Construction

The graphical construction method is generally based on satisfying the average value of demand and generally based on only two decision variables. Using an optimisation constraint, it shows the graphical solution. While being easy to understand, its major downfall is the variable number limitation [86].

4.1.2 The Iterative Method

The iterative method is the software development of a large application, broken down into smaller pieces. An iterative algorithm was used in 1998, in [87], to determine the capacity required for a stand-alone system. The algorithm allowed for the objective function, the total annual cost, to be minimised while minimising the magnitude difference between the generated power and the power demand.

The procedure adapted from [87] is:

1. Selection from the available sizes of renewable energy and storage.
2. Increasing the size of the PV panels, so that the system is balanced or has surplus energy.
3. Repeating the previous step, to store energy for a specific number of hours or possibly for days using the batteries for storage.
4. Calculating the total system cost for each combination of steps 2 and 3.
5. Choosing the most appropriate combination – either the lowest cost or the ability to store surplus energy.

The iterative method is essentially the start of a software development as it progressively becomes more complex until the system is complete. The iterative model is the implementation of a part of the Software Development Life Cycle (SDLC), that starts off being focused and simple yet develops into a complex program [88] [89].

It is essentially implementing small sets of requirements from the object that slowly evolves [89]. A specific section is completed, reviewed, and the next step is decided on – this is the first iteration. This continues until the full set of requirements, and the objective is met. There are five stages to the iterative method: requirements, design, implementation, testing, and review [88] [89]. The requirement phase is where the objective is divided into smaller, meaningful parts. The iteration that is carried out is crucial to optimal design decisions. Unit testing is done at each iteration this ensures that implementation is smoother. The review is necessary to determine if the developed iteration/ piece of code meets the requirement. The iterative model uses incremental prototyping at each iteration. The decision to move forward or reject the iteration [89] is made before the following iteration. The iterative model allows for a more precise understanding of requirements, more testing, and a dedicated design phase, optimised code [88].

Deterministic and heuristic optimisation techniques are used for optimisation. Deterministic is the use of a gradient that results in convergence around a point, usually a local minimum. A heuristic approach is to minimise or maximise the objective function where the function can be calculated. A hybrid method is a combination of where the heuristic method is used to determine a global minimum region. The determinist locates the minimum point within the region. Below is an image that illustrates the difference between global and local minimums and maximums.

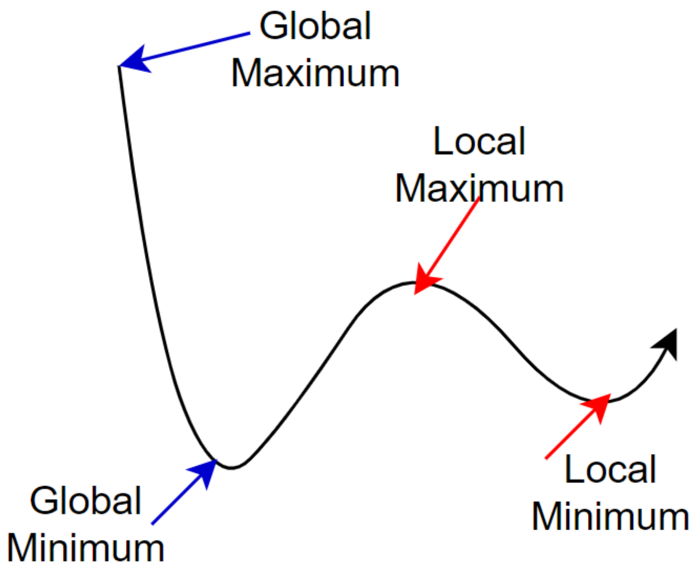

Figure 4: Illustration of the difference between global and local minimums and maximums, made by researcher.

4.1.3 Particle swarm

Particle Swarm Optimisation (PSO) is a form of intelligent optimisation. Introduced by Kennedy and Eberhart in the early 1990s, it is a metaheuristic algorithm, or independent problem algorithm, based on swarm intelligence [90]. PSO is a learning, iterative algorithm. There are many variations of the classical algorithm that was first introduced: the linear-decreasing inertia weight, the constriction factor weight, the dynamic inertia and maximum velocity reduction, and the hybrid models [90].

A PSO algorithm can also be described as a swarm of candidate solutions. Each possible solution has a personal best solution and a global best solution. This is based on personal or cognitive behaviour that is gained by its own experience. Global or social behaviour is where the neighbours of the personal solution have tried choices and thus have gained experience or knowledge of choices. The actual best solution is a combination of the pieces of both the personal and global best solutions.

There are five primary stages to a PSO;

- Problem definition – what is to be minimised/maximised
- Parameters of PSO
- Initialisation
- The main loop of PSO
- The results.

PSO is similar to the genetic algorithm as both techniques move from a set of points to another set of points in a single iteration, using deterministic and heuristic rules. While a PSO is continuous, the genetic algorithm is discrete [91].

4.1.4 Genetic algorithm

A Genetic Algorithm (GA) is an optimisation technique used to solve non-linear, non-differential optimisation problems. GAs are global search heuristic that use the iterative technique [92]. This concept was inspired by evolutionary biology and starts with a generation of candidate solutions tested against the objective function. The different phases of the generation of a solution include:

- Selection – the best performing solution is retained,
- Crossover – the combination of the common points of two solutions are used to form new solutions,
- Mutation – the initial solution is changed by random values; this prevents local minimums.

These three phases are repeated until the algorithm converges, either by a fixed number of iterations, or the objective function is no longer changing or changing by a small value.

PSO and GA are quite similar as optimisation techniques. Both are based on evolutionary methods which means that within each iteration, points change from having one set of data to another.

4.1.5 Pattern Search Optimisation

Pattern Search (PS) is the process whereby the objective function is run until an optimal point is reached. The objective function either decreases or remains the same from a particular point in the sequence or to the next set of values for the variables. The variables begin in the iteration at the value set by the user, x_0 [93]. The optimisation works by using a mesh method, a mesh of size 1, with the PS algorithm, adds the pattern vectors to the initial point.

If $x_0 = [1\ 1]$, it follows that:

$$[1\ 0] + x0 = [2\ 1], [0\ 1] + x0 = [1\ 2], [-1\ 0] + x0 = [0\ 1], and\ [0\ -1] + x0 = [1\ 0] \quad (36)$$

The objective function is calculated at the mesh points and uses the mesh points that result in a smaller value of the objective function than at the initial x_0 points. The values of the variables at these mesh points are used.

4.1.6 Surrogate Optimisation

The surrogate optimisation method is the use of a function that estimates another function [93]. To minimise the objective function, surrogate optimisation is where the surrogate of a function is evaluated on points. The lowest value of the approximation function is used as the minimum of the objective function.

4.1.7 Pare to Search Optimisation

This algorithm is the use pattern search to iteratively minimise the objective function. Similar to how the mesh of PS optimisation works, starting at the x_0 once a pattern is found that outputs the minimum value of the objective function [93]. The objective function at this minimum point gives the variable values.

4.1.8 Ant Colony Optimisation for Continuous Domains

The Ant Colony Optimisation (ACO) method was inspired by the behaviour of ants [94] [95]. This algorithm is based on the interactions and communication methods that are used by ants. Ants leave trails of pheromones, the strength of the pheromone suggests a route that is preferred [94]. The preferred route is often the shortest path to food from the nest. The ACO was first developed by Marco Dorigo in 1992, [94] [95]. ACO works to optimise an objective function by updating a pheromone trail by using a mathematical formula to calculate the total pheromone in the region. A random search area is selected with each iteration and the pheromone strength compared to the previous iteration until an optimal solution is found.

4.1.9 Artificial Bee Colony Optimisation

Inspired by the behaviour of bees swarming to find food, the Artificial Bee Colony (ABC) algorithm was formed. There are three types of bees in ABC optimisation: scout bees, employed bees, and onlooker bees [95]. The employed bee search for food and pass this information of quality and quantity, onto onlooker bees [96]. The onlooker bee uses the information provided by the employed bee to pick out a food source to investigate, once an onlooker bee begins its search it becomes an employed bee. A scout bee is an employed bee whose food source was abandoned. The scout bees conduct random searches within the search space [95] [96]. This process is a probability approach and is repeated until an optimum food source, or solution is found.

4.1.10 Bee Algorithm Optimisation

The Bee Algorithm (BA) is similar to the ABC optimisation. However, it does not use probability and instead uses fitness evaluation. Scout bees search for food and even after finding some, they continue further in hope of better food. The scout bees share this information of food with the bees in the hive through a dance known as the “waggle dance” [97]. The “waggle dance” allows for the scout bees to share knowledge of the food source, distance from the hive, and the direction of the source. The algorithm allows for the most promising, optimised solutions, to be investigated. Each area around the proposed location is investigated in more detail to either select improved optimisation or keep the current variable values.

4.1.11 Biogeography Based Optimisation

Proposed by Dan Simon in 2008, Biogeography Based Optimisation (BBO), was inspired by biogeographic concepts of the evolution of new species, migration of species, and the extinction of species [98]. The optimisation technique is based on a mathematical model that defines how species immigrate and emigrate to a suitable habitat. BBO is a probabilistic approach, the chance that a candidate shares a feature with the population is related to its fitness. The greater the fitness of a candidate, the smaller chance it has of sharing a feature with the population. This feature fitness comes to an end when an optimal solution is found.

4.1.12 Covariance Matrix Adaptation Optimisation

The Covariance Matrix Adaptation Optimisation (CMAO) was introduced in 2001 [99] [100]. CMAO is a numeric optimisation technique that encompasses evolutionary strategies. The best values are found by the repeated variation (relationship between recombination and mutation), and selection (new candidates are generated from the existing parents). If the new candidates give a more optimised solution, then these candidates give rise to new solutions, they become parents to a new generation. This process is continued until an optimised solution is found.

4.1.13 Differential Evolution Optimisation

The difference of solutions used to create new solutions is the simplest explanation of Differential Evolution Optimisation (DEO) [100]. The DEO is where new candidates are found by using existing candidates and applying a mathematical formula. The candidate that gives the more optimal solution is retained. Until the objective function is optimised the iterations shall continue.

4.1.14 Firefly Algorithm Optimisation

Although based on Fireflies that send signals to attract the opposite sex, the Firefly Algorithm (FA) is a mathematical model that assumes single-sex and any firefly can attract other fireflies. Introduced by Xin-She Yang in 2008 [101], the FA works on the basis that the brighter a firefly is, the more attractive it is. The brightness is associated with the objective function [102]. The algorithm finds the optimal position based on the attractive level of a firefly, if a new firefly is less attractive than an existing one, the new firefly would stay in its current position.

4.1.15 Harmony Search Optimisation

Inspired by musicians, Harmony Search (HS) is a random search technique that has an initial number of randomly generated solutions [103]. These initial solutions form the HS memory which is then adjusted according to a pitch rate, forming mutations, or new solutions. The new solution is evaluated and if the fitness is better, it replaces the HS memory value. This progresses until an optimal solution is found.

4.1.16 Real-Coded Simulated Annealing Optimisation

Real-Coded Simulated Annealing (RCSA) is a probabilistic technique for approximating the optimum of an objective function. This is the model of minimising the system energy by heating material and slowly lowering the temperature to reduce defects [93]. A new randomly generated point is given at every iteration. The distribution between the new and current point is proportional to the temperature. Candidates that lower the objective are accepted, along with candidates that raise the objective but are within a certain probability (this avoids a local minimum) [93]. As the temperature, or iterations decrease, the algorithm converges on an optimised solution.

4.1.17 Shuffled Complex Evolution Optimisation

The Shuffled Complex Evolution Optimisation (SCEO) is used for global optimisation and compromises of both probabilistic and deterministic approaches, clustering, systematic evolution, and competitive evolution [104]. The SCEO calculates the initial population size, creates a random set of candidates in a space, investigates the objective, categorise the candidates, in an array, in ascending order according to the function, and sorts these candidates so the first has the smallest objective function result [105]. Next, the population is divided and modified, these modified values are substituted into the array. If these new candidates meet the criteria the operation stops, if not it returns to the outcome before population division [105].

4.1.18 Invasive Weed Optimisation

Weeds are invasive plants that are robust, can adapt, and are random. Invasive Weed Optimisation (IWO) is the optimisation designed to mimic weed growth [106]. The optimisation is limited to population initialisation or the number of seeds in space. Each seed can grow into a plant and produce its own seeds, dependent on its fitness. The fitness of the seed leads to more fit plants surviving and weaker, less optimal plants, dying off [107]. The notion of competition is achieved as if the maximum population size is reached, and the least fit plant is removed from the population. This continues until an optimum solution is found or the maximum iterations are reached.

4.1.19 Teaching-Learning Based Optimisation

The Teaching-Learning Based Optimisation (TLBO) is influenced by the interactions between teachers and learners in a class [108]. The teacher imparts knowledge on a learner, the learner in turn improves, or modifies this knowledge, and sometimes passes it onto another learner. This is done in a mathematical model where the fitness for each learner is calculated, the teaching phase is where the learners' initial fitness is compared to the fitness after teaching, and the optimal value is used [109]. The learner phase is where knowledge is shared between learners and the fitness of learners are recalculated and the optimum solution chosen. This is repeated until the objective function is optimised.

4.2 MATLAB Code Explained

4.2.1 Iterative Method

The start is user input data where the data is the load for a year. The user is then required to enter the type of building; residential, commercial, or industrial.

The inverter choices, sizes, and prices, are gathered externally and exist as an array in the code. The inverter price takes the network connection charge into account. This implies that when the type of building changes, the network access charge is different.

The first loop is the inverter loop, and this uses the maximum load value. It first checks if any exact values match an inverter size, and if that is false, it finds the closest value inverter.

The chosen inverter size then goes through a loop multiplying the inverter size by 0.6 to 1.4, stepping in 0.2. This has two purposes: to allow for variations of inverter and the solar panels chosen. These "new" inverter values loop through the inverter array and the exact or closest match is found. The solar panel choices, sizes, and prices are gathered externally and exist as an array in the code. Similar to the inverter, variations are allowed. This is used in the loop where the solar panels are chosen.

The battery information (LA, Li-Ion, and SC) is considered by the code and the size and price are saved as an array. The inverter efficiency, along with charging and discharging efficiency for all types of storage is considered separately. The SOC and the self-discharge amounts are also noted and considered concerning each storage choice. The charging of the energy storage device (ESD) is determined by the hour of the day and the SOC of the ESD. If it is a peak hour, determined by an array saved in the code, the SOC is checked. If it is above the minimum SOC the ESD discharges. If it is below the minimum state of charge the ESD is idle. If it is not a peak hour, and the SOC is less than the maximum SOC the ESD charges. While if the state of charge is equal to or greater than the maximum state of charge, the ESD is left idle if it is not a peak hour.

The maximum available battery, LA, Li-Ion, and SC, size is found, and multiples of it are considered. A loop is entered with the condition, a storage size to be less than an option from the array of thirty created, to iterate through each of the inverter sizes made by the multiplication loop earlier. The code then checks if the required battery is less than the largest battery size it enters the loop which outputs a single battery that is exactly or closest to the required power. If the required power is less than twice the maximum battery size, it enters a loop that comprises every battery combination. It then finds the battery combination that is an exact match or closest to the required power.

The tariffs for each building type, from eThekwini Municipality (2021), are entered into the code [67], residential, along with commercial and industrial tariffs at low and high demand periods. The hours are entered into the code and the relevant tariff option is applied to them: peak, standard, and off-peak are entered. The corresponding monetary values for these hours are put into the code. The consumption is calculated by using the user load input values and multiplying it by the corresponding tariff, building and hour dependent. This is summed, multiplied by the number of years, in this case, twenty years, and this is then divided by interest compounded annually.

The data from the South African Universities Radiometric Network (SAURAN) is unit data. To have the correct available solar, this data is multiplied by the values in the five PV options which is plotted against the user input load. The solar data alone is also plotted in 3D so the variation for each month can be easily seen. Further to this, there is a plot of the load for every month of the year.

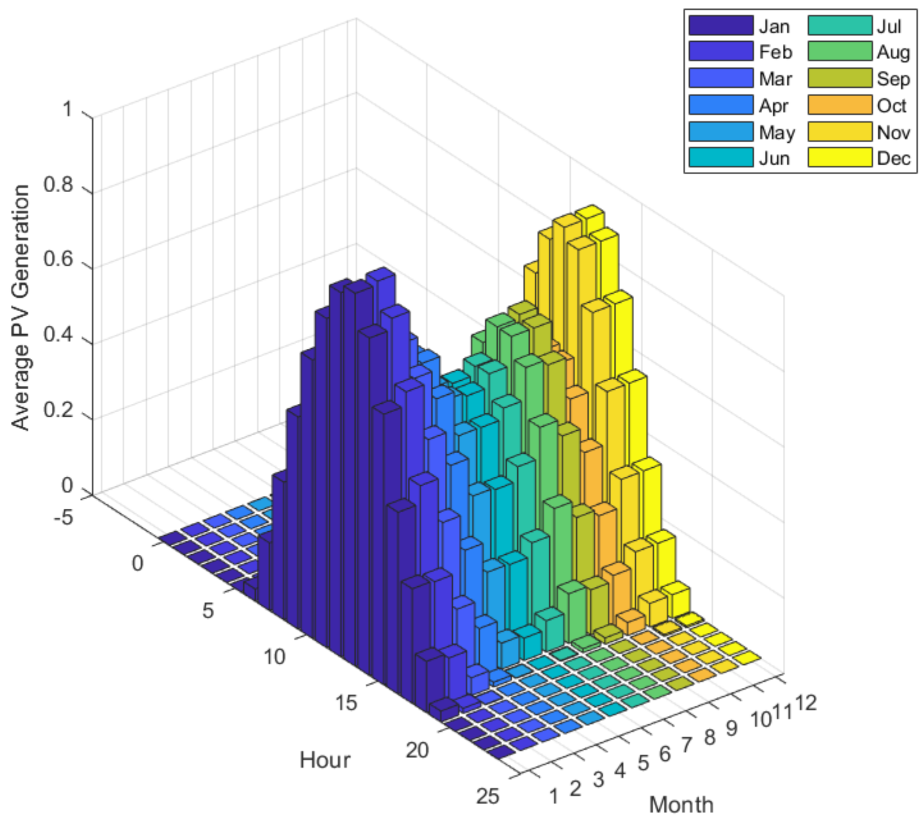

Figure 5: SAURAN unit data - the average solar generation for each hour of each month.

The plotted load is subtracted from the SAURAN data, this subtraction is done to identify a solar deficiency. This allows for the use of electricity required to supplement the shortfall of the solar to be calculated. Each ESD had individual loops for calculating the cost of electricity. This was done by first considering which building type, the month of the year, and the hour of the day. Each load value specific to month and hour was used in each ESD loop. This allowed for self-discharge and losses to be calculated as accurately as possible. The remaining capacity of the storage option was then used to subtract the difference between the available solar and load. This value was then multiplied by the cost of electricity at that hour: peak, off-peak, or standard, and that month: high or low demand. This resulted in an array that consisted of summed electricity cost for each hour of each month for each ESD choice.

The last part of the code is a function that is based on the TCO. This function passes in the inverter options, the PV options, the lead-acid battery options, the lithium-ion options, the supercapacitor options, along the three storage options associated with electricity cost. Within the function, there are two loops to iterate through the options of the inverter and PV and the ESD options. Five calculations take place: the maintenance, capital, replacement, electricity, and the total of the maintenance, capital, replacement, and electricity. All these calculations are based on twenty-years years of operation. This was done for all three storage options, and the function is made to return the minimum of the three.

4.2.2 Decision Flow Diagram of the Manual Iteration

The diagram that follows illustrates the progression of the code.

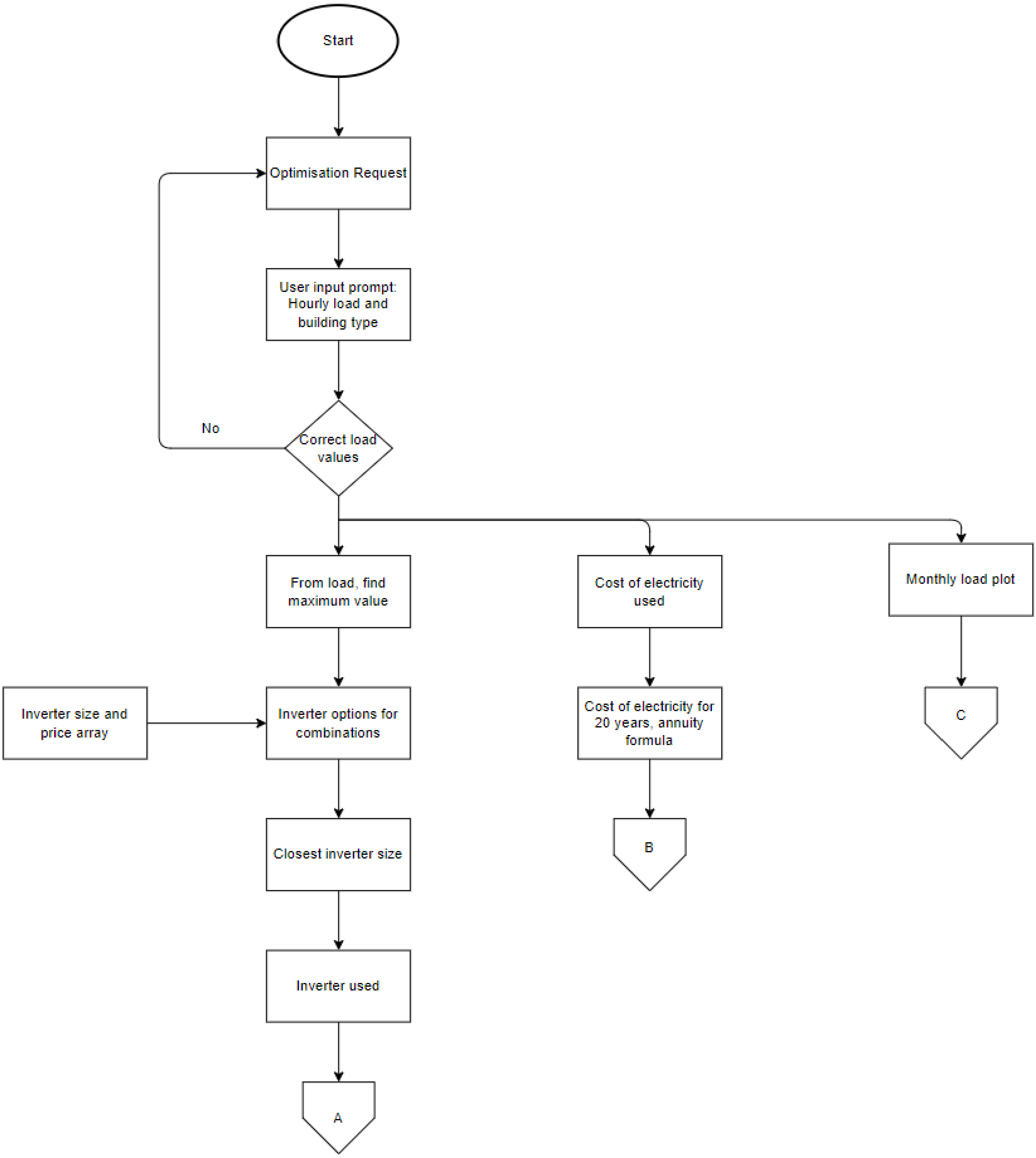

Figure 6: Part one of the decision flow diagram - load input, inverter choice, cost of electricity calculation and monthly load plot.

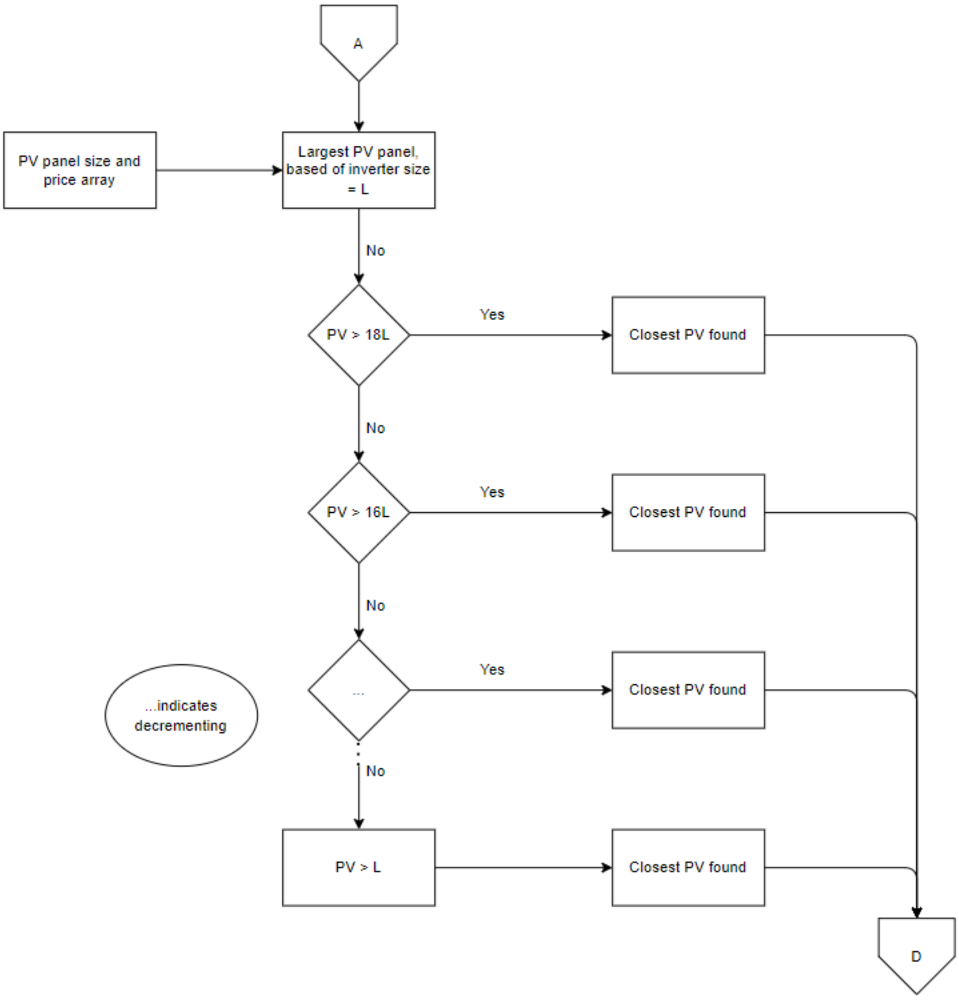

Figure 7: Part two of the decision flow diagram – how PV is chosen.

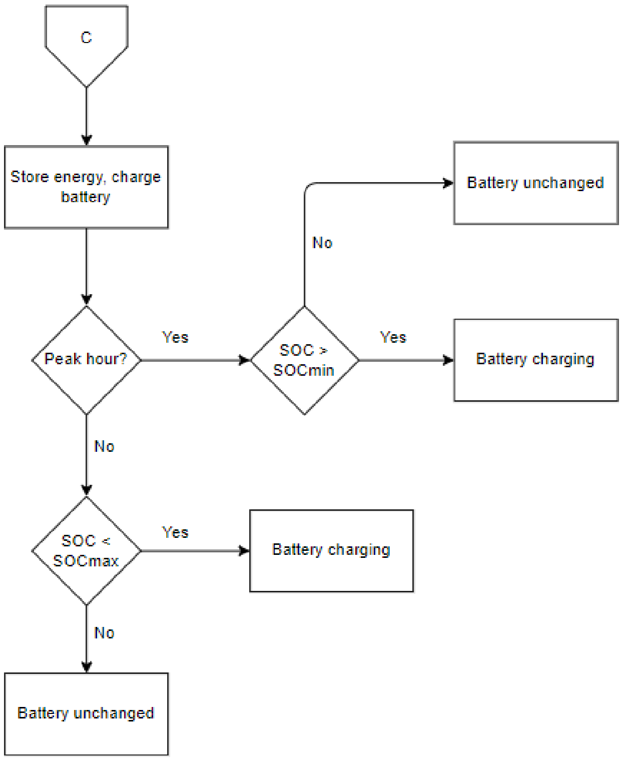

Figure 8: Part three of the decision flow diagram - battery charging.

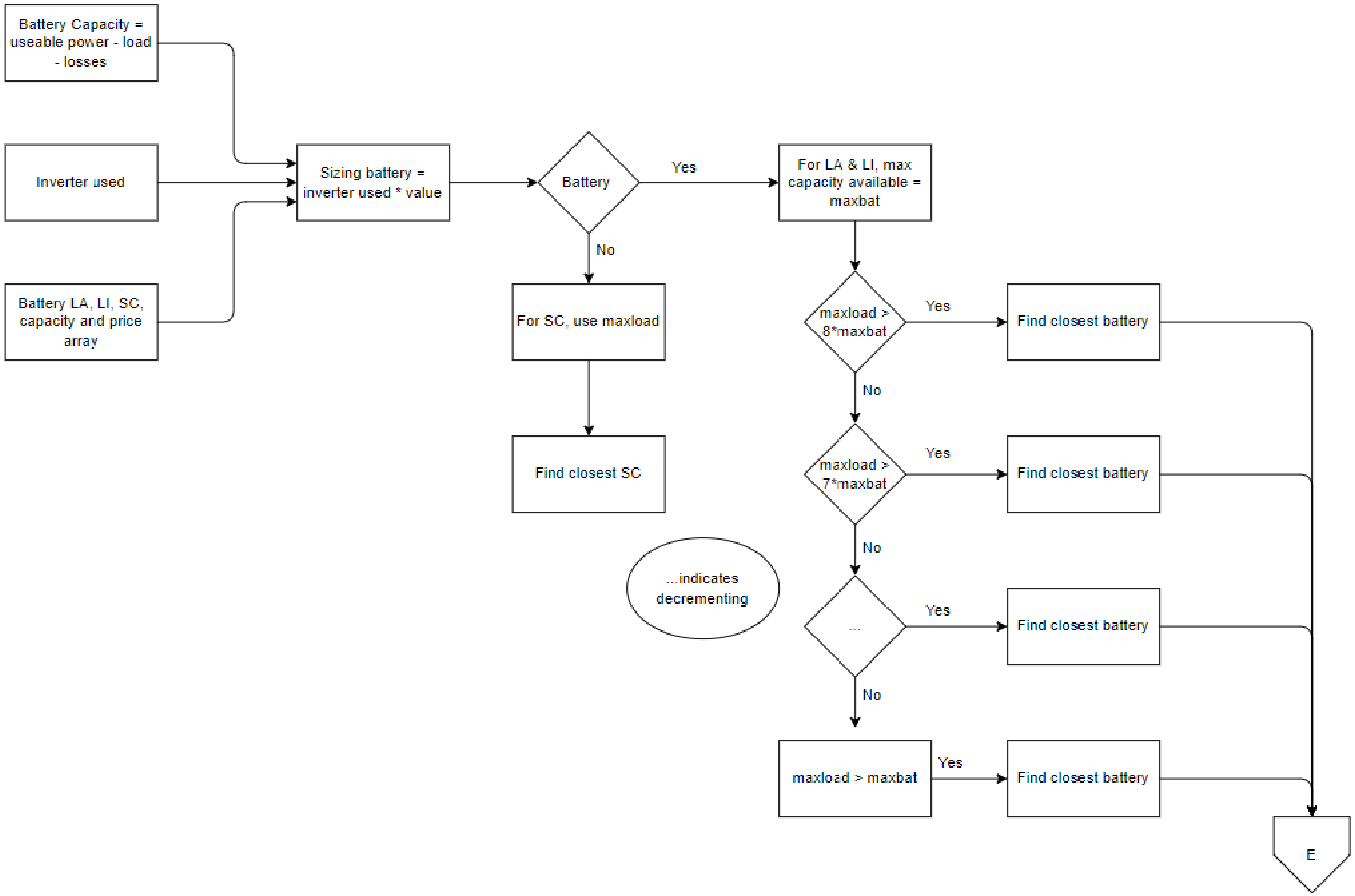

Figure 9: Part four of the decision flow diagram - battery choice.

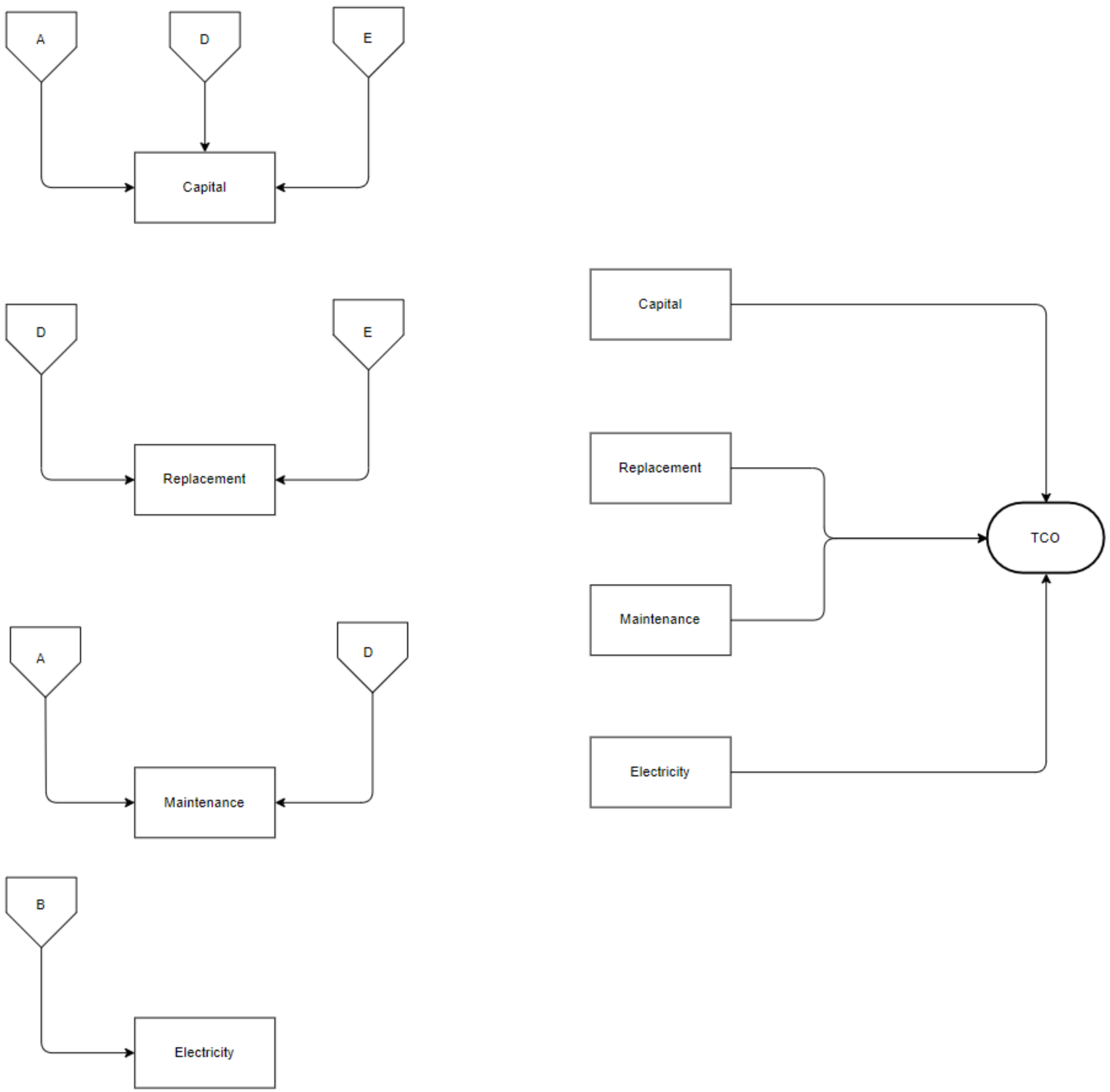

Figure 10: Part five of the decision flow diagram - TCO calculation.

4.2.3 Optimisation Function

The function that was developed to run through each optimisation works similarly to the iteration method above. It requires the load, type of building, and SAURAN data.

Using the data of cost and size of an inverter, PV, along with the cost and capacity of an LA battery, an LI battery, and a SC, equations were developed to cost any of the above based on the values from the function. The capital and replacement costs were calculated using the same equations in the iterative method. Values were summed and where a replacement was necessary the growth annuity formula was used for the appropriate number of years.

The value that was multiplied by the SAURAN data, to find the available useable PV, was the smaller value between the inverter and PV size. The total cost of electricity without PV and batteries was calculated using the tariff rates for the appropriate building type.

The battery charge and discharge loops have one addition as compared to the one used for iteration: there is an if condition where if the SOC of the battery is less than the difference between the load and PV the SOC remains the same, otherwise the SOC is given a value of zero. This is to ensure the system is not sized in a way to sell to the grid.

The next if statement is to allow for the suitable calculations of grid charges dependent on the building type. The service charge, network access charge, network demand charge, the ancillary network access charge, and the voltage surcharge are all calculated based on the value of the inverter of the maximum load required for an hour in the month and the building type. These calculations were done using the formula from the eThekwini tariff booklet [67] and can be found in The Tariffs.

The next loop calculated the different electricity costs based on the SOC of the battery, the type of battery, the efficiency of the inverter, and the load. The cost was found by first checking the SOC of the battery and subtracting the losses of the battery. Next, the load was subtracted from the available PV which was first multiplied by the inverter efficiency. The value that remained was multiplied by the cost of electricity at the particular hour, this was summed to give the total amount required from the grid, in kW and Rands.

The total grid required amount in Rands was then applied to the growth annuity formula to give the cost of electricity for twenty years. The maintenance cost was calculated using the maintenance formula with the growth annuity formula.

The final TCO was the sum of the capital, replacement, grid required electricity and maintenance. The TCO and the value of the inverter, PV, and battery was returned at the output of the function.

4.2.4 Decision Flow Diagram of the Optimisation Function

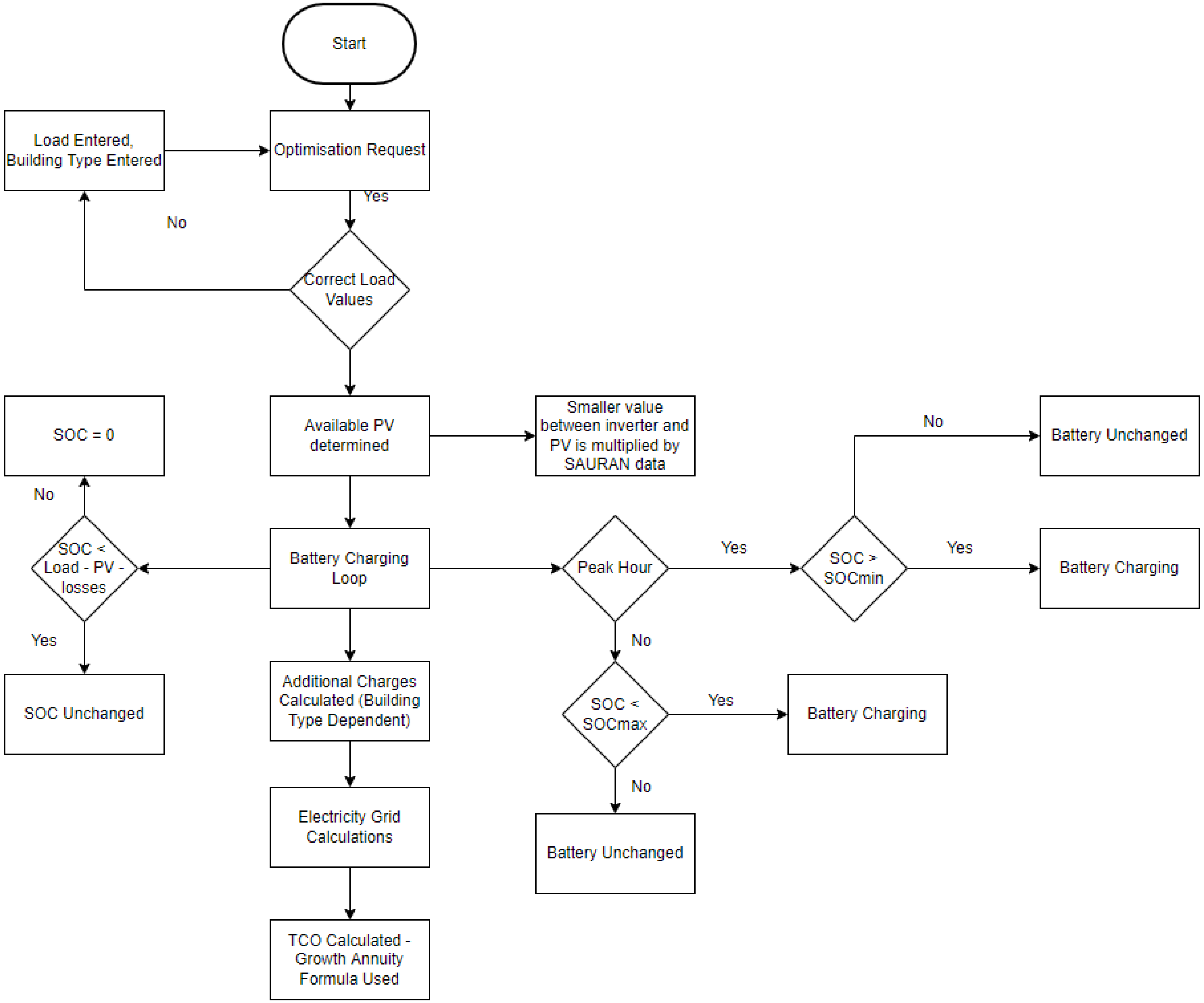

Figure 11: Decision diagram of the function used for algorithms.

4.2.5 Outcome of the Code

Once the minimum TCO is found, the output is the following information:

- The annual electric bill without PV
- The annual electricity cost with PV
- The inverter choice size
- The PV choice size
- The storage of choice
- The storage choice size
- The total cost of electricity, with PV, over twenty years
- The total annual savings of electricity
- The total saving on electricity for twenty years

5 Chapter 5 – Case Study & Optimisation Results

The data used in this dissertation was provided by the eThekwini municipality electricity department. For confidentiality reasons, the names of companies/ malls/residences were changed.

The raw data supplied was the power consumed every thirty minutes, to get this into hourly data, every two values of thirty minutes were summed. Every value of the same hour was summed and the total divided by the number of days in the month. The input of load, per hourly average per month, was used.

5.1 Example 1

5.1.1 Site Information

This example data is from an industrial paper plant in Durban, for confidential purposes, this factory was referred to as factory 1.

Table 22: Site information of Example 1.

Location	Durban, South Africa
Time Zone	Africa/ Johannesburg

5.1.2 Average Electric Energy Consumption

The table that follows is the hourly monthly average consumption of factory 1.

Table 23: Monthly Consumption of factory 1.

Month	Hourly Monthly Average (in kW)
January	41 035.93
February	36 929.91
March	31 621.29
April	7 244.96
May	21 642.59
June	4 958.67
July	14 812.86
August	32 764.56
September	34 831.33
October	24 537.30
November	42 519.21
December	34 704.92

Table 24: Electric Consumption from the grid for Example 1.

Hourly Monthly Average	Annual Consumption	Annual Peak Demand Month
27 300.29kW	7 862 485kW	November at 43 370kW

5.1.3 Load Profile of Example 1

Below is an image of the load profile of the factory used in Example 1.

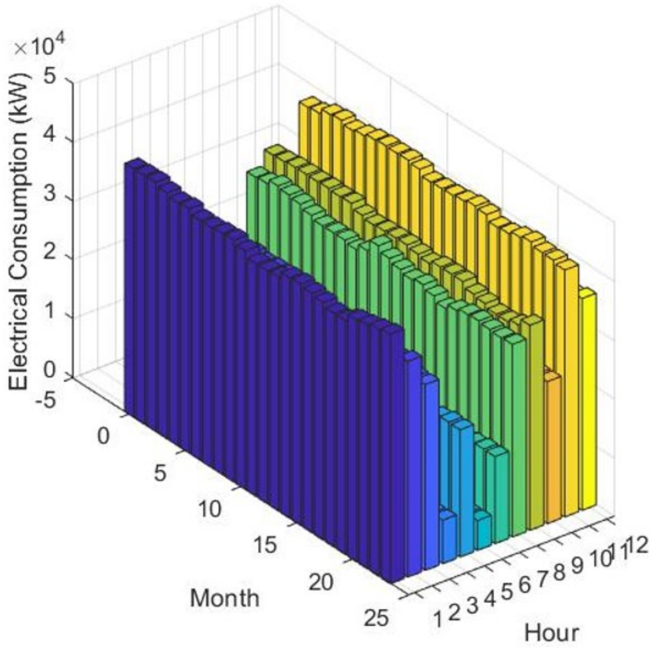

Figure 12: Plotted profile of factory 1- Hourly Monthly Average Electrical Consumption

5.1.4 Base System Electric Bill

The following table shows the interpreted electric bill for each month.

Table 25: Electric Bill (Grid supplied only) of Example 1

Month	Monthly Electricity Costs
January	R138 148 998.3
February	R125 305 412.1
March	R106 447 570.6
April	R24 427 829.79
May	R72 856 013.11
June	R16 719 163.04
July	R49 864 911.14
August	R110 304 848.8
September	R117 488 259.2
October	R83 526 335.32
November	R144 078 675.7
December	R116 678 956.1
Annual Total	R1 105 846 973

5.1.5 Comparison of Optimisation Algorithms Results

Different algorithms have been formulated and the results of each algorithm, for Example 1, is below. The electricity cost for twenty years without PV was calculated at R411 789 908 511.58.

Table 26: Results of Example 1 using multiple algorithms. Where an upper bound was required, the value of 20 000 was used.

Algorithm	Time taken for solution in seconds	TCO	Savings for 20 years (Electricity-TCO)	Inverter, PV, Battery values
Iteration (Manual optimisation)	390.12	R403 884 453 061.16	R7 905 455 450.42	5 000.00 VA 1 520.00 W 13 860.00 Wh
Particle Swarm	74.00	R403 736 956 284.15	R8 052 952 227.43	5 282.13 VA 1 725.46 W 13 350.12 Wh
Genetic Algorithm	39.43	R403 759 353 814.88	R8 030 554 696.70	3 281 VA 1 767.78 W 8 293 Wh
Pattern Search Optimisation	13.36	R403 851 696 440.70	R7 938 212 070.88	3.54 VA 1 W 3.22 Wh
Surrogateopt	24.05	R403 883 174 414.88	R7 906 734 096.70	6 478.31 VA 1 643.80 W 16 375.11 Wh
Paretosearch	120.38	R403 813 730 935.97	R7 976 177 575.61	943.02 VA 936.60 W 2 810.15 Wh
Ant Colony Optimisation for Continuous Domains	17.04	R403 884 705 550.21	R7 905 202 961.37	5 296.74 VA 1 724.42 W 13 386.79 Wh
Artificial Bee Colony	180.04	R403 736 974 315.64	R8 052 934 195.94	5 286.89 VA 1 706.21 W 13 358.94 Wh
Bee Algorithm	143.03	R403 885 825 846.74	R7 904 082 664.84	5 575.12 VA 1 768.50 W 14 085.84 Wh
Biogeography Based	52.63	R403 736 981 047.38	R8 052 927 464.20	5 355.59 VA 1 725.46 W 13 535.79 Wh
Matrix Adaptation	64.48	R403 783 359 891.11	R8 006 548 620.47	5 262.06 VA 1W 13 194.36 Wh
Differential Evolution	48.52	R403 827 404 522.64	R7 962 503 988.95	6 527.68 VA 2 796.12 W 19 273.26 Wh

Firefly Algorithm	259.53	R403 736 957 219.50	R8 052 951 292.08	5 282.16 VA 1 719.93 W 13 350.11 Wh
Harmony Search	15.05	R403 736 961 055.25	R8 052 947 456.33	5 286.48 VA 1 723.20 W 13 359.57 Wh
Real-Coded Simulated Annealing	393.22	R403 736 964 118.66	R8 052 944 392.93	5 266.46 VA 1 714.64 W 13 309.55 Wh
Shuffled Complex Evolution	68.25	R403 736 956 284.15	R8 052 952 227.43	5 282.13 VA 1 725.47 W 13 350.12 Wh
Invasive Weed Optimisation	34.63	R403 907 020 665.12	R7 882 887 846.46	1 622.56 VA 3 114.34 W 3 817.28 Wh
Teaching-learning based Optimisation	59.01	R403 736 957 888.50	R8 052 950 623.09	5 275.40 VA 1 726.65 W 13 332.90 Wh

5.1.6 Current Method of Calculation

Using the daily average for factory 1 is 21 541.05kWh.

Table 27: Results of TCO and related values using the method that is currently used.

Factory 1	
PV Size	5 566.79W
Inverter Size	2 783.39VA
Battery Capacity	21 541.05Wh
TCO	R404 795 820 060.94

5.1.7 Findings of Example 1

Below is a visual representation of the TCO's and the time it took to find a solution.

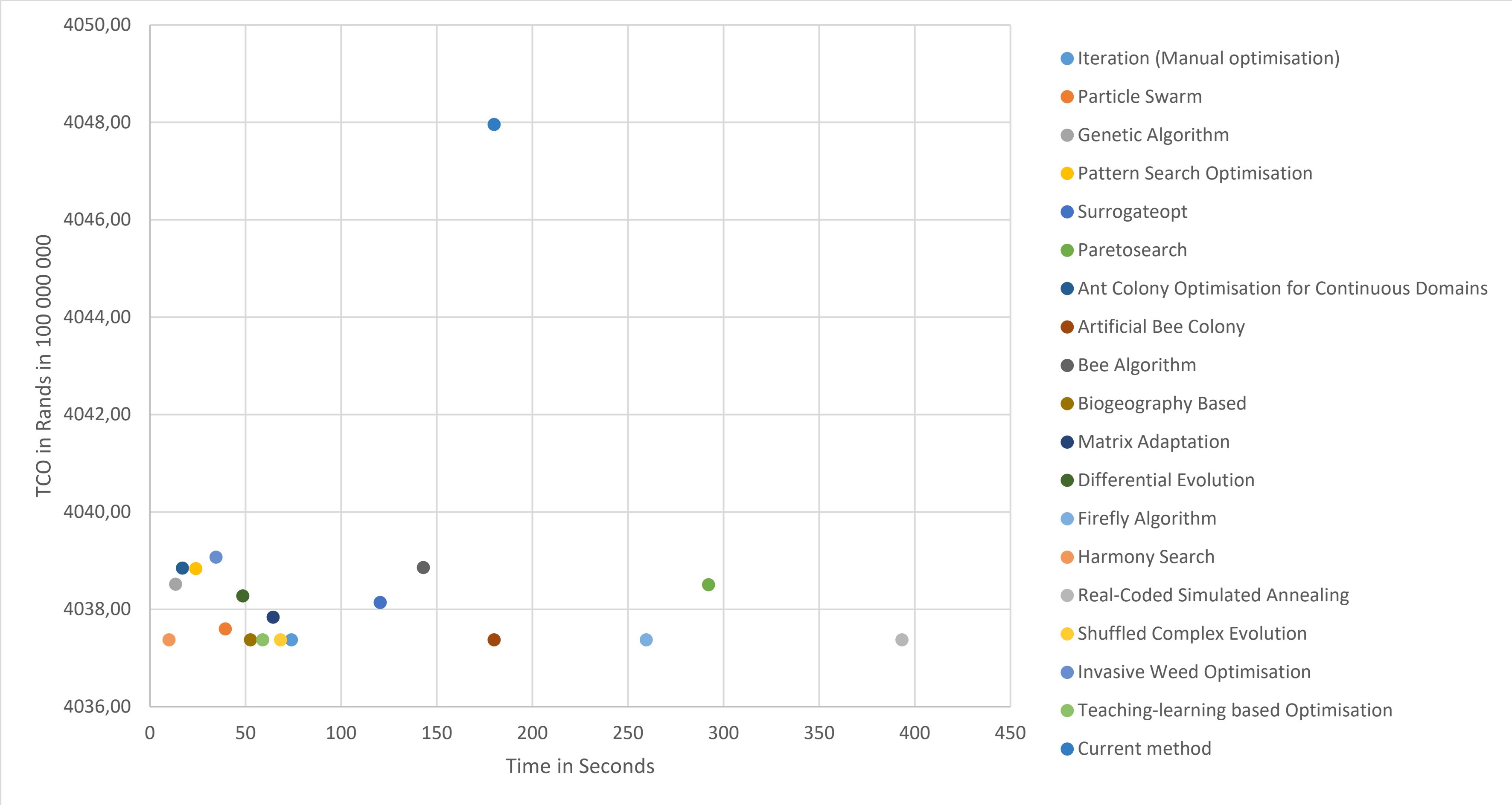

Figure 13: Time vs TCO for Example 1.

The fastest algorithm was Pattern Search at 13.36 seconds, while the slowest at 393.22 seconds was Real-Coded Simulated Annealing. The average time taken was 105.21 seconds. The lowest TCO at R403 736 956 284.15 is obtained from PSO and SCEO, while IWO had the highest TCO at R403 907 020 665.12. PSO took 74.00 seconds and SCEO took 68.25 seconds, a difference of 5.75. Both had values of 5 282.13 for an inverter, 13 350.12 for a battery. While the PV values differed by 0.01, for PSO to have 1 725.46 and SCEO to have 1 725.47.

Comparing the current method used, the TCO is R404 795 820 060.94. This is a difference of R1 055 863 776.79. This large difference supports the hypothesis, the maximising of PV does not give the lowest total cost of ownership. The TCO has lower values with smaller differences when different optimisation techniques are used.

While PS is the fastest optimisation, the difference in TCO is R4 771.10 between PS and PSO/SCEO. PS has values giving a larger inverter and battery, while PSO and SCEO have a large PV value. The difference in time between PSO and SCEO is more than half the time for HS. The difference is almost a minute between PS and SCEO, 58.20 seconds. Although there is a time difference to the solution, the difference in TCO cannot be ignored. The most suitable optimisation method is SCEO.

Table 28: System Overview Analysis of Example 1.

Lowest Net Cost System Architecture	**Inverter Size - 5 282.13VA** PV Size - **1 725.47VA** **Battery, SC, Capacity - 13 350.12Wh**
Annual Electric Bill	R1 105 846 973.05
Annual Electricity Cost with PV	R13 039 261.34
Projected Annual Savings	R402 647 611.37
Total System Capital	R552 357.55
Annual PV payment	R20 186 847 814.21
Discount Rate	3.94%
Inflation	Electricity – 2.7% Maintenance – 3.7% Battery – 3.34%
Projected TCO for 20 years	R403 736 956 284.15
Projected Electric Bill for 20 years	R411 789 908 511.58
Projected Lifetime Total 20 Saving	R8 052 952 227.43

The figures below, Figure 14 and Figure 15 show monthly data for the SCEO solution. The load can be seen in orange at the top, along with the LA and LI capacity. The SC capacity is on the bottom left, while the available PV is blue at the bottom, and around the available PV is the required energy from the grid-dependent on each type of storage. These figures show the average hourly data for January and June.

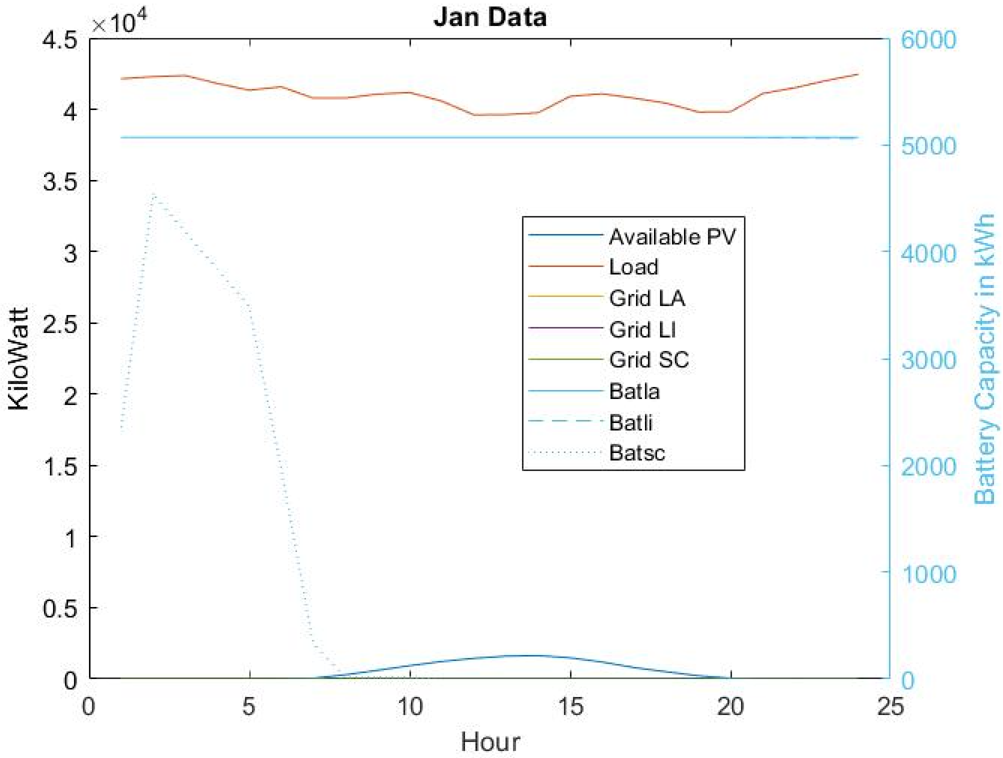

Figure 14: SCEO January Data for Example 1.

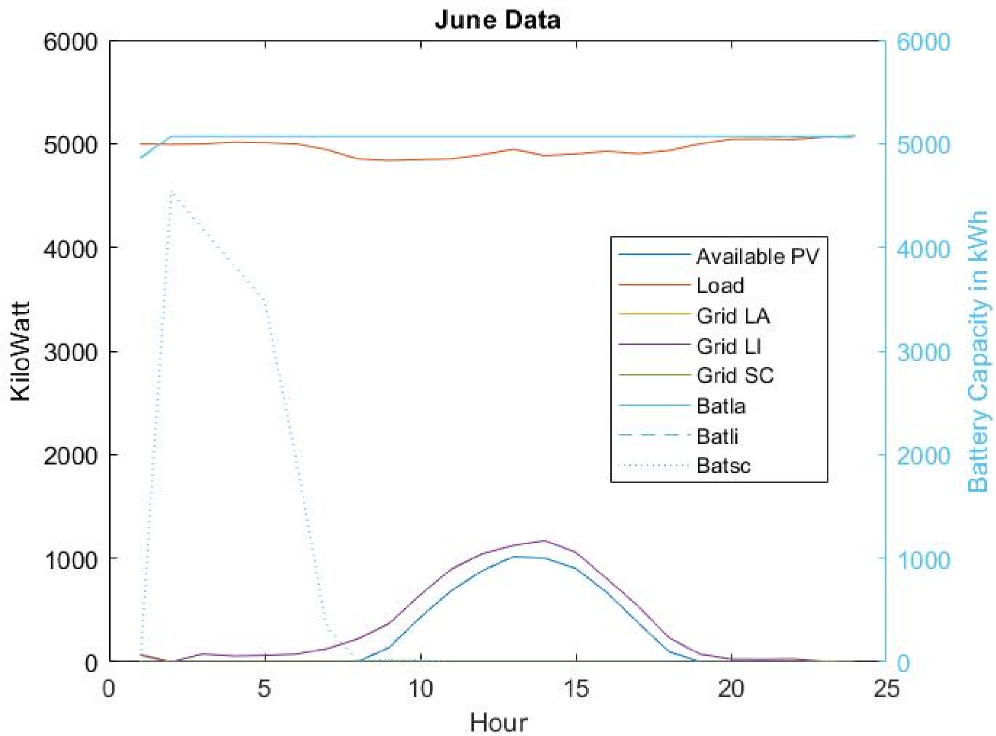

Figure 15: SCEO June Data for Example 1.

5.2 Example 2

5.2.1 Site Information

This example data is from an industrial car plant in Durban, for confidential purposes, this factory was referred to as factory 2.

Table 29: Site information of Example 2.

Location	Durban, South Africa
Time Zone	Africa/ Johannesburg

5.2.2 Average Electric Energy Consumption

The table that follows is the hourly monthly average consumption of factory 2.

Table 30: Monthly Consumption of factory 2factory 1.

Month	Hourly Monthly Average (in kW)
January	18 094.97
February	26 797.52
March	24 009.03
April	7 013.07
May	16 142.06
June	22 196.53
July	21 268.52
August	21 572.13
September	22 642.80
October	25 406.58
November	26 446.13
December	16 185.16

Table 31: Electric Consumption from the grid for Example 2.

Hourly Monthly Average	Annual Consumption	Annual Peak Demand Month
20 647.88kW	5 946 588kW	February at 33 073.66kW

5.2.3 Load Profile of Example 2

Below is an image of the load profile of the factory used in Example 2.

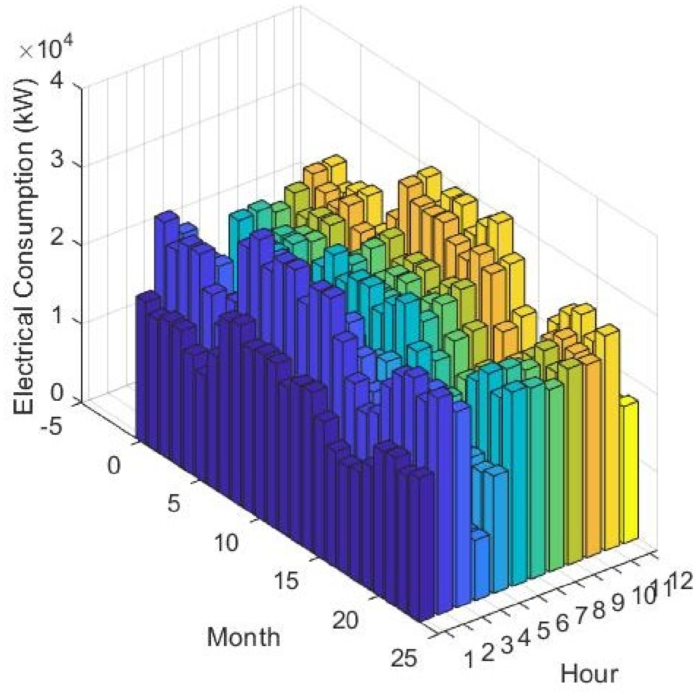

Figure 16: Plotted profile of factory 2 - Hourly Monthly Average Electrical Consumption.

5.2.4 Base System Electric Bill

The following table shows the interpreted electric bill for each month.

Table 32: Electric Bill (Grid supplied only) of Example 2.

Month	Monthly Electricity Costs (in R)
January	62 249 431.12
February	91 807 326.92
March	82 343 412.57
April	23 517 974.43
May	55 605 342.35
June	75 301 247.71
July	71 805 764.90
August	73 421 364.60
September	76 563 359.74
October	86 689 112.24
November	90 530 221.50
December	54 772 873.02
Annual Total	844 607 431.12

5.2.5 Comparison of Optimisation Algorithms Results

Different algorithms have been formulated and the results of each algorithm, for Example 2, are tabulated below. R314 510 800 558.57 was the calculated cost of electricity for twenty years, without PV.

Table 33: Results of Example 2 using multiple algorithms. Where an upper bound was required, the value of 30 000 was used.

Algorithm	Time taken for solution in seconds	TCO	Savings for 20 years (Electricity-TCO)	Inverter, PV, Battery values
Iteration (Manual optimisation)	124.01	R306 345 156 159.01	R8 167 644 399.56	8 200.00 VA 1 770.00 W 2 100.00 Wh
Particle Swarm	55.06	R306 142 845 827.85	R8 367 954 730.83	8 128.83 VA 1 709.38 W 20 544.89 Wh
Genetic Algorithm	42.55	R306 145 589 373.64	R8 365 211 184.93	7 590.00 VA 1 706.96 W 19 198.00 Wh
Pattern Search Optimisation	9.03	R306 284 180 347.43	R8 226 620 211.14	3.54 VA 1.00 W 3.22 Wh
Surrogateopt	26.38	R306 142 937 935.87	R8 367 862 622.70	8 062.07 VA 1 728.07 W 20 372.71 Wh
Paretosearch	81.91	R306 144 432 728.38	R8 366 367 830.19	7 760.07 VA 1 714.27 W 19 604.20 Wh
Ant Colony Optimisation for Continuous Domains	36.61	R306 142 863 413.03	R8 367 937 145.56	8 094.55 VA 1 709.46 W 20 458.26 Wh
Artificial Bee Colony	126.68	R306 142 849 343.52	R8 367 951 215.05	8 130.23 VA 1 701.92 W 20 548.05 Wh
Bee Algorithm	31.42	R306 163 931 314.15	R8 346 869 244.43	5 457.93 VA 1 675.17 W 13 801.03 Wh
Biogeography Based	37.17	R306 145 540 439.14	R8 365 260 119.43	9 921.59 VA 1 709.15 W 25 075.94 Wh
Matrix Adaptation	38.77	R306 151 084 038.40	R8 359 716 520.17	7 228.85 VA 1 782.88 W 18 126.30 Wh
Differential Evolution	34.21	R306 407 348 445.16	R8 103 452 368.47	742.06 VA 2 376.87 W 7 479.56 Wh

Firefly Algorithm	182.69	R306 142 849 032.66	R8 367 951 525.91	8 127.96 VA 1 707.32 W 20 541.83 Wh
Harmony Search	13.04	R306 144 600 769.98	R8 366 199 788.59	7 725.99 VA 1 702.08 W 19 524.56 Wh
Real-Coded Simulated Annealing	60.14	R306 143 658 465.76	R8 367 142 092.81	7 895.56 VA 1 695.20 W 19 946.75 Wh
Shuffled Complex Evolution	77.93	R306 142 845 832.23	R8 367 954 726.34	8 128.83 VA 1 709.39 W 20 544.88 Wh
Invasive Weed Optimisation	21.84	R306 243 441 248.23	R8 267 359 310.34	5 881.42 VA 3 196.56 W 15 655.42 Wh
Teaching-learning based Optimisation	57.67	R306 142 846 031.78	R8 367 954 526.79	8 128.61 VA 1 711.50 W 20 544.34 Wh

5.2.6 Current Method of Calculation

Using the daily average for factory 2 is 16 242.32kWh.

Table 34: Results of TCO and related values using the method that is currently used.

Factory 2	
PV Size	4 197.45W
Inverter Size	2 098.73VA
Battery Capacity	16 242.32Wh
TCO	R306 719 546 401.80

5.2.7 Findings of Example 2

Below is a visual representation of the TCO's and the time it took to find a solution.

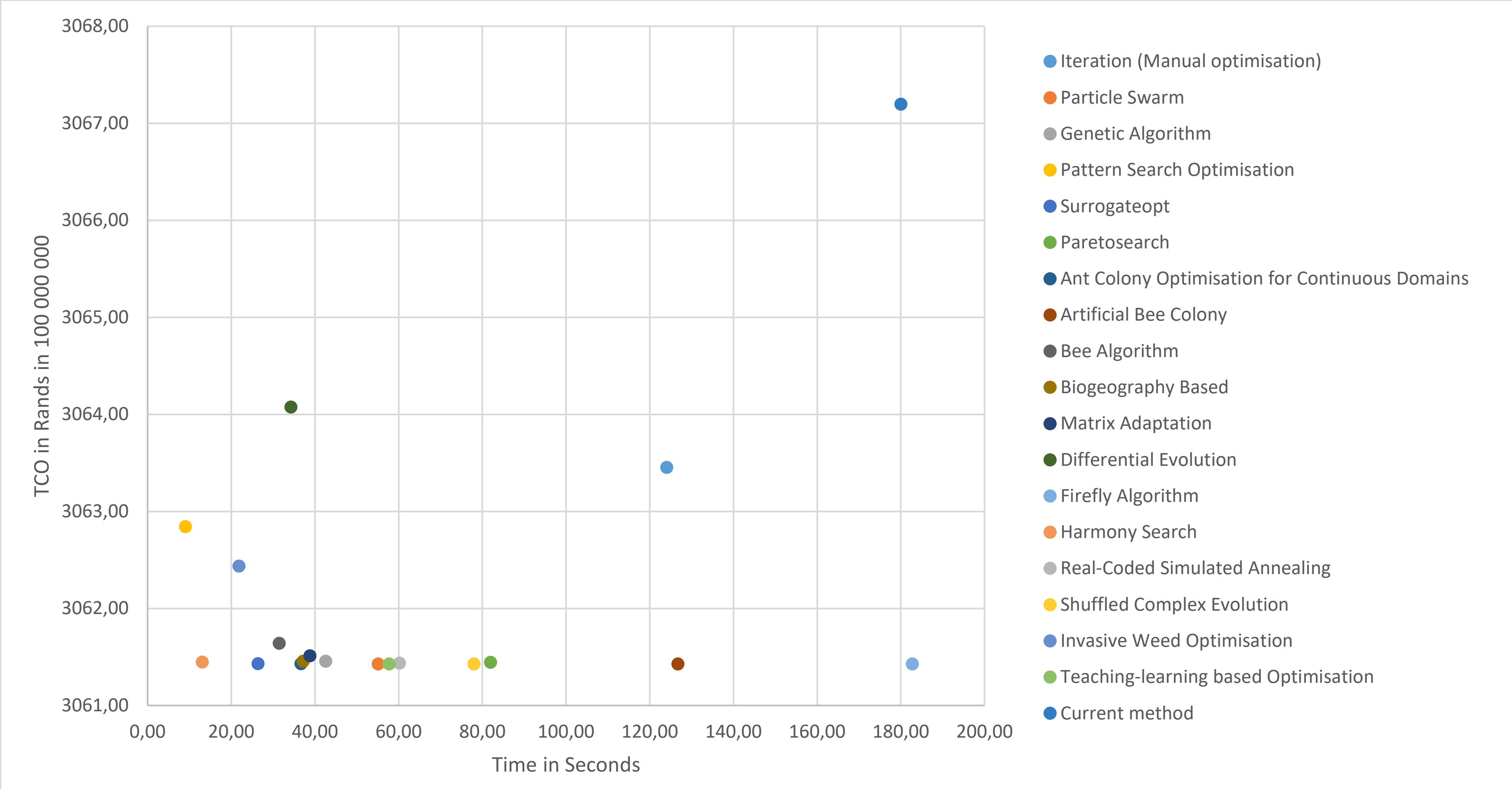

Figure 17: Time vs TCO for Example 2.

The fastest algorithm was Pattern Search at 9.03 seconds, while the slowest at 182.69 seconds was Firefly Algorithm. The lowest TCO at R306 142 845 827.85 was obtained from PSO, while Differential Evolution had the highest TCO at R306 407 348 445.16. PSO took 55.06 seconds, and the values were 8 128.83 for an inverter, 1 709.38 for PV, and 20 544.89 for batteries.

Comparing the current method used, the TCO is R306 719 546 401.80. This is a difference of R576 700 573.95. While Pattern Search is the fastest optimisation, the difference in TCO is R141 334 519.58 between Pattern Search and PSO. HS has values giving a larger inverter and battery, while PSO and SCEO have a large PV value. Although there is a time difference to the solution, the difference in TCO cannot be ignored. The most suitable optimisation method is PSO.

Table 35: System Overview Analysis of Example 2Example 1.

Lowest Net Cost System Architecture	**Inverter Size - 8 128.83VA** PV Size - **1 709.38 VA** **Battery, SC, Capacity - 20 544.89Wh**
Annual Electric Bill	R844 607 431.12
Annual Electricity Cost with PV	R9 846 906.10
Projected Annual Savings	R418 397 736.54
Total System Capital	R561 553.69
Annual PV payment	R15 307 142 291.39
Discount Rate	3.94%
Inflation	Electricity – 2.7% Maintenance – 3.7% Battery – 3.34%
Projected TCO for 20 years	R306 142 845 827.74
Projected Electric Bill for 20 years	R314 510 800 558.57
Projected Lifetime Total 20 Saving	R8 367 954 730.83

With PSO being chosen as the most suited optimisation for Example 2, a substantial saving on electricity could be made. The figures below show monthly data for the SCEO solution. The load can be seen in orange at the top, along with the LA and LI capacity. The SC capacity is on the bottom left, while the available PV is blue at the bottom, and around the available PV is the required energy from the grid-dependent on each type of storage. These figures show the average hourly data for January and June.

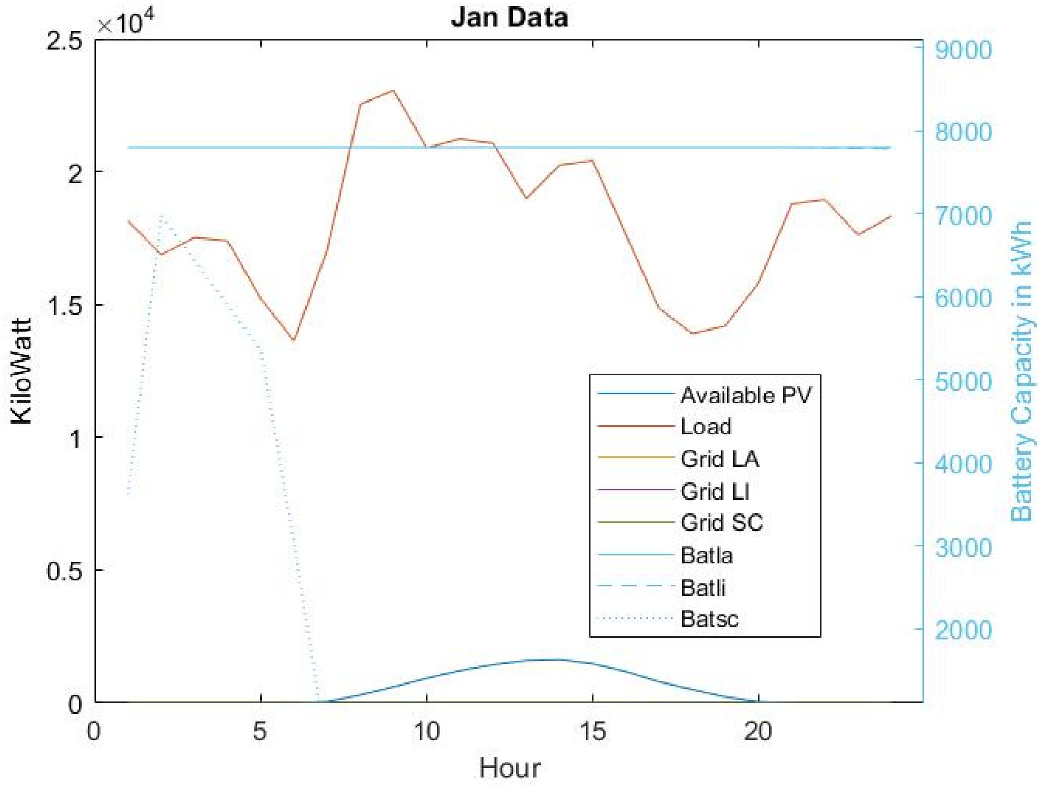

Figure 18: PSO January Data for Example 2

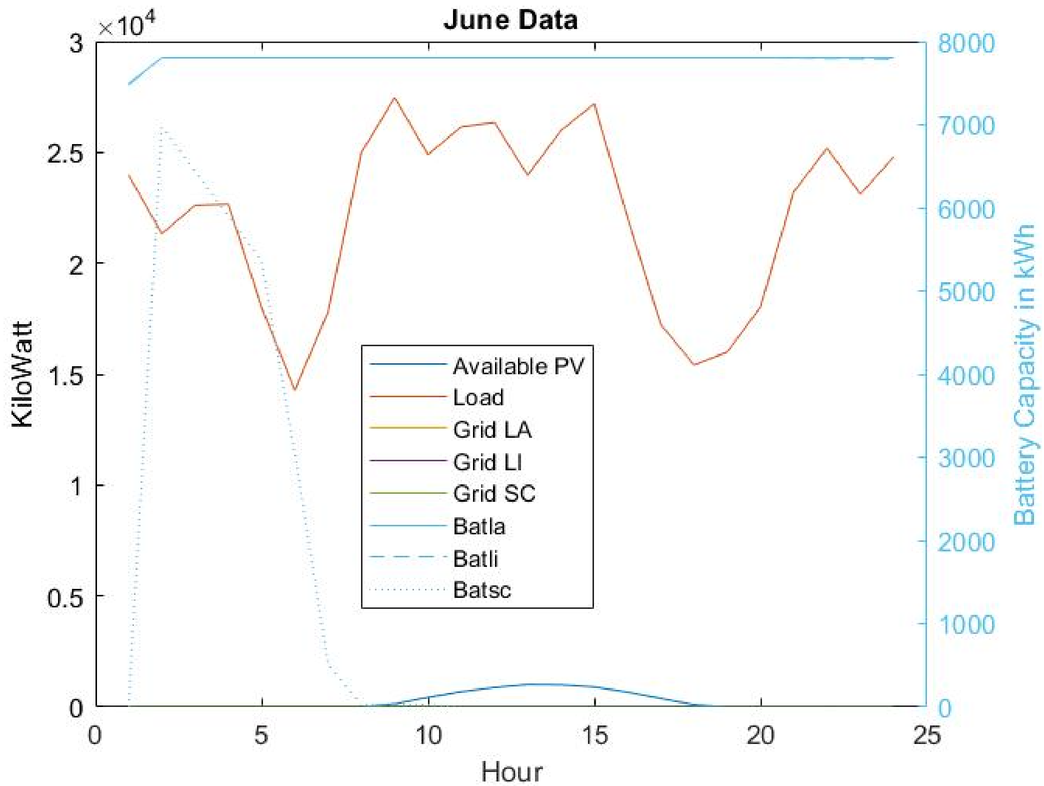

Figure 19: PSO June Data for Example 2.

5.3 Example 3

5.3.1 Site Information

This example data is from an industrial plant in Durban, for confide purposes, this factory was referred to as factory 3.

Table 36: Site information of Example 3.

Location	Durban, South Africa
Time Zone	Africa/ Johannesburg

5.3.2 Average Electric Energy Consumption

The table that follows is the hourly monthly average consumption of factory 3.

Table 37: Monthly Consumption of factory 3.

Month	Hourly Monthly Average (in kW)
January	6 692.63
February	6 827.29
March	6 167.85
April	3 623.98
May	4 898.36
June	5 409.90
July	6 068.48
August	6 101.31
September	6 304.25
October	6 551.36
November	7 195.13
December	34 521.61

Table 38: Electric Consumption from the grid for Example 3.

Hourly Monthly Average	Annual Consumption	Annual Peak Demand Month
8 363.52kW	2 408 692.00kW	December at 46 583.54kW

5.3.3 Load Profile of Example 3

Below is an image of the load profile of the factory used in Example 3. It should be noted that the December consumption is almost seven times any other month.

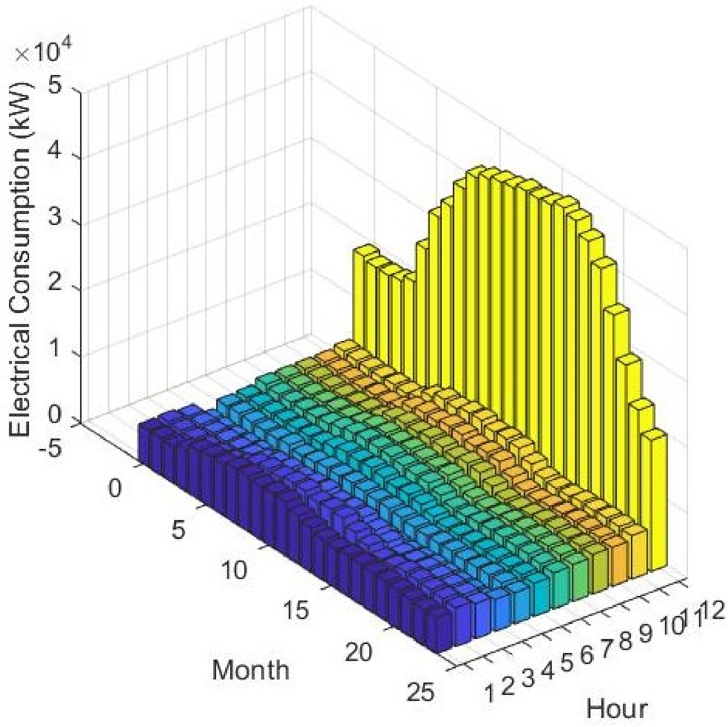

Figure 20: Plotted profile of factory 3 - Hourly Monthly Average Electrical Consumption.

5.3.4 Base System Electric Bill

The following table shows the interpreted electric bill for each month.

Table 39: Electric Bill (Grid supplied only) of Example 3Example 2.

Month	Monthly Electricity Costs
January	R23 212 991.39
February	R23 696 915.20
March	R21 260 253.40
April	R12 174 779.17
May	R16 621 858.37
June	R18 602 629.61
July	R20 958 223.03
August	R21 017 959.66
September	R21 718 183.00
October	R22 637 936.78
November	R24 880 733.56
December	R124 041 203.37
Annual Total	R350 823 666.44

5.3.5 Comparison of Optimisation Algorithms Results

Different algorithms have been formulated and the results of each algorithm, for Example 3, is tabulated below. Electricity for twenty years, without, PV, was calculated to be R130 638 007 812.92.

Table 40: Results of Example 3Example 2 using multiple algorithms. Where an upper bound was required, the value of 30 000 was used.

Algorithm	Time taken for solution in seconds	TCO	Savings for 20 years (Electricity-TCO)	Inverter, PV, Battery values
Iteration (Manual optimisation)	112.14	R124 213 060 190.63	R6 424 947 622.29	3 600.00 VA 1 700.00 W 9 840.00 Wh
Particle Swarm	36.14	R124 127 134 711.75	R6 510 873 101.17	3 909.33 VA 1 709.10 W 9 880.50 Wh
Genetic Algorithm	21.60	R124 127 142 835.11	R6 510 864 977.81	3 938.00 VA 1 709.20 W 9 953.00 Wh
Pattern Search Optimisation	6.16	R124 220 541 489.68	R6 417 466 323.24	3.54 VA 1.00 W 3.22 Wh
Surrogateopt	16.84	R124 127 616 658.43	R6 510 391 154.50	4 288.61 VA 1 626.67 W 10 852.49 Wh
Paretosearch	62.46	R124 127 826 453.43	R6 510 181 359.49	3 714.22 VA 1 711.09 W 9 386.09 Wh
Ant Colony Optimisation for Continuous Domains	23.07	R124 127 135 005.79	R6 510 872 807.13	3 910.90 VA 1 710.39W 9 884.40 Wh
Artificial Bee Colony	89.02	R124 127 143 032.38	R6 510 864 780.54	3 913.73 VA 1 719.54 W 9 889.53 Wh
Bee Algorithm	20.61	R124 131 363 617.72	R6 506 644 195.20	3 621.29 VA 2 041.94 W 9 126.54 Wh
Biogeography Based	22.05	R124 127 845 337.20	R6 510 162 241.62	4 577.66 VA 1 679.51 W 11 569.62 Wh
Matrix Adaptation	33.12	R124 202 764 329.62	R6 435 243 483.30	1 531.76 VA 1.00 W 3 783.65 Wh
Differential Evolution	24.45	R124 714 791 035.56	R5 923 216 777.36	3 491.23 VA 4 566.29 W 20 869.07 Wh
Firefly Algorithm	138.97	R124 127 135 170.67	R6 510 872 642.25	3 911.45 VA 1 710.18 W 9 885.74 Wh

Harmony Search	10.44	R124 127 319 227.75	R6 510 688 585.17	3 829.22 VA 1 701.97 W 9 676.90 Wh
Real-Coded Simulated Annealing	42.95	R124 127 245 193.99	R6 510 762 618.93	3 923.48 VA 1 753.52 W 9 920.89 Wh
Shuffled Complex Evolution	61.58	R124 127 134 711.72	R6 510 873 101.20	3 909.33 VA 1 709.17 W 9 880.50 Wh
Invasive Weed Optimisation	15.55	R124 472 215 766.29	R6 165 792 046.63	5 458.54 VA 33.29 W 29 273.26 Wh
Teaching-learning based Optimisation	44.13	R124 127 137 296.94	R6 510 870 515.98	3 909.70 VA 1 702.80 W 9 880.80 Wh

5.3.6 Current Method of Calculation

Using the daily average for factory 3factory 1 is 6 599.16kWh.

Table 41: Results of TCO and related values using the method that is currently used.

Factory 3	
PV Size	1 705.40W
Inverter Size	852.70VA
Battery Capacity	6 599.16Wh
TCO	R124 279 654 822.05

5.3.7 Findings of Example 3

A visual representation of the time taken for a solution plotted against TCO.

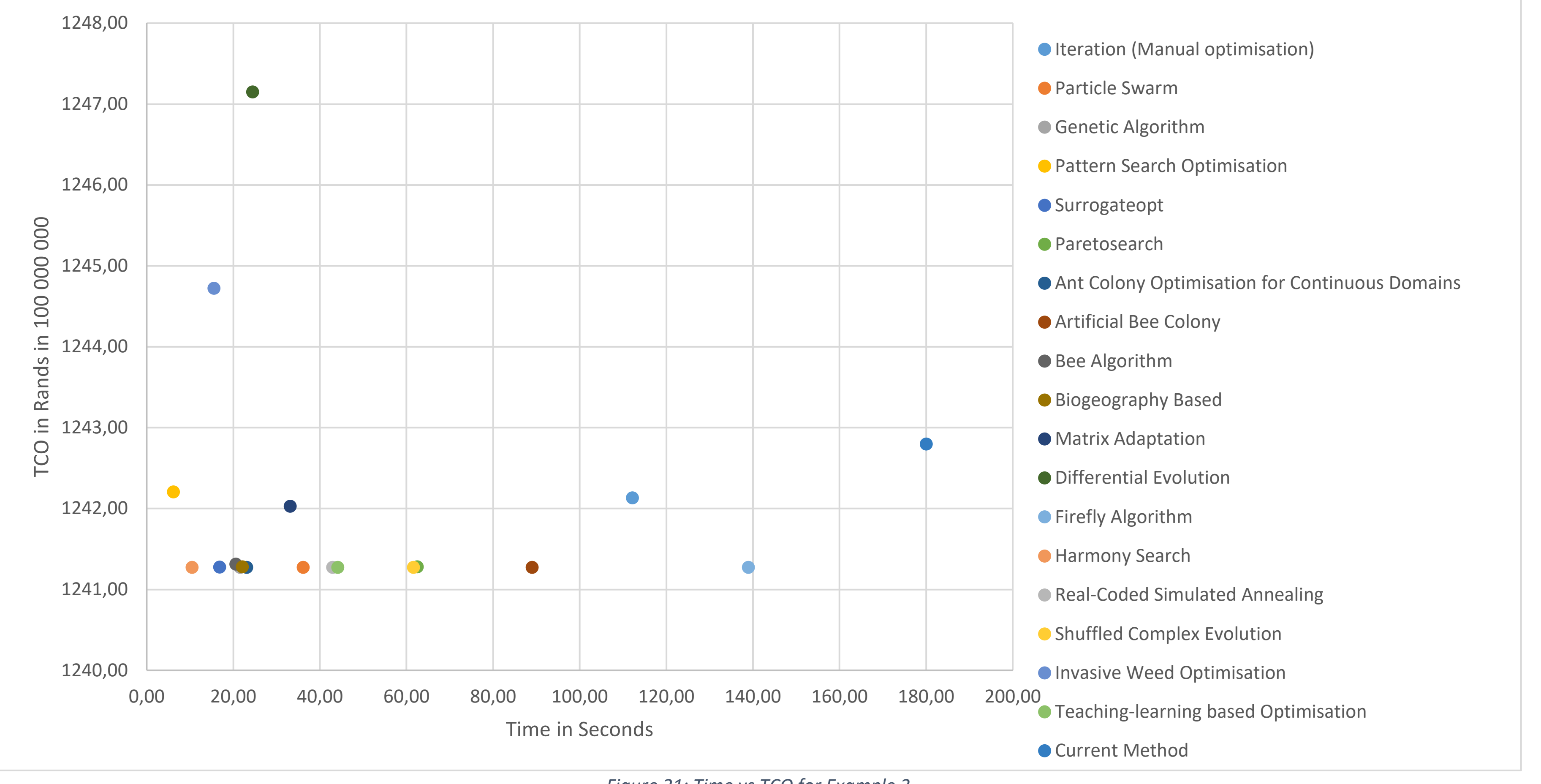

Figure 21: Time vs TCO for Example 3.

The fastest algorithm was Pattern Search at 6.16 seconds and a TCO of R124 220 541 489.68. While the slowest algorithm was FA at 138.97 seconds and a TCO of R124 127 135 170.67. The average time taken was 44.12 seconds. The lowest TCO at R124 127 134 711.75 was obtained from PSO at 36.14. Differential Evolution had the highest TCO at R124 714 791 035.56.

Comparing the current method used, the TCO is R124 279 654 822.05. This is a difference of R152 520 110.30. This means the maximising of PV does not give the lowest total cost of ownership. The TCO has lower values with smaller differences when different optimisation techniques are used.

The difference in time between PSO and Pattern Search is 37.96, however, this does not justify the TCO difference, the most suitable optimisation method is PSO.

Table 42: System Overview Analysis of Example 3.

Lowest Net Cost System Architecture	**Inverter Size - 3 909.33VA** PV Size - **1 709.10VA** **Battery, SC, Capacity - 9 880.50kWh**
Annual Electric Bill	R350 823 666.44
Annual Electricity Cost with PV	R4 033 663.84
Projected Annual Savings	R325 543 655.06
Annual PV payment	R6 206 356 735.59
Discount Rate	3.94%
Inflation	Electricity – 2.7% Maintenance – 3.7% Battery – 3.34%
Projected TCO for 20 years	R124 127 134 711.75
Projected Electric Bill for 20 years	R130 638 007 812.92
Projected Lifetime Total 20 Saving	R6 510 873 101.17

With PSO being chosen as the most suited optimisation for Example 3Example 1, a substantial saving on electricity could be made. The figures below show monthly data for the PSO solution. The load can be seen in orange at the top, along with the LA and LI capacity. The SC capacity is on the bottom left, while the available PV is blue at the bottom, and around the available PV is the required energy from the grid-dependent on each type of storage. These figures show the average hourly data for January and June. The drop in available PV from summer in January, Figure 22, is higher than the available PV in June, Figure 23.

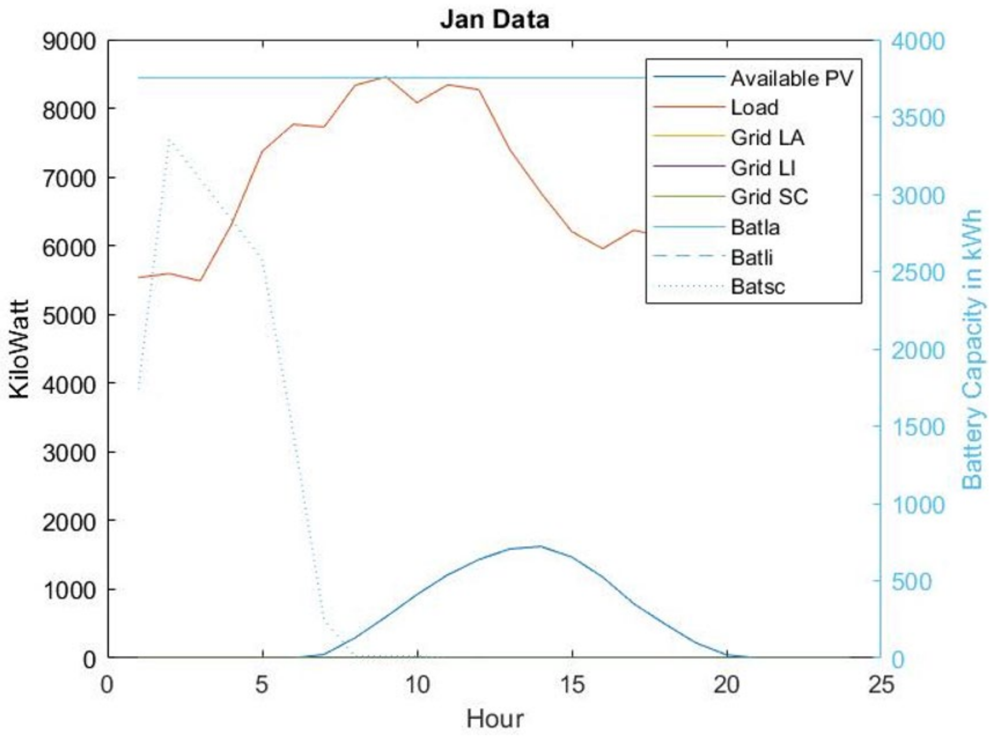

Figure 22: PSO January Data for Example 3.

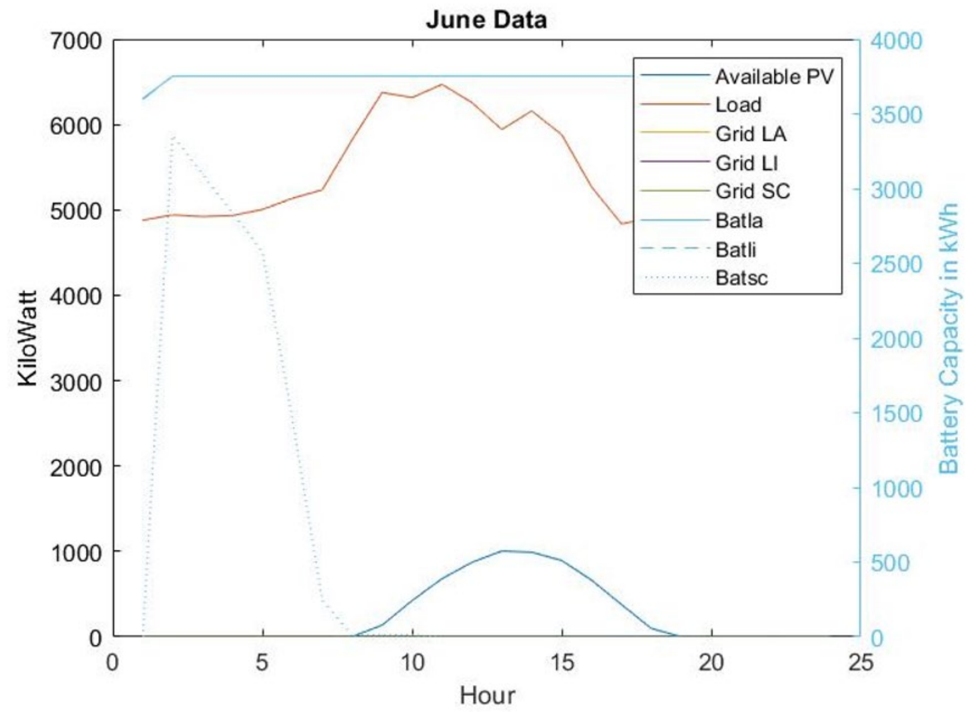

Figure 23: PSO June Data for Example 3.

5.4 Example 4

5.4.1 Site Information

This example data is from a shopping complex in Durban, for confidential purposes, this complex was referred to as shopping complex 1.

Table 43: Site information of Example 4.

Location	Durban, South Africa
Time Zone	Africa/ Johannesburg

5.4.2 Average Electric Energy Consumption

The table that follows is the hourly monthly average consumption of shopping complex 1.

Table 44: Monthly Consumption of shopping complex 1.

Month	Hourly Monthly Average (in kW)
January	67 335.59
February	62 423.02
March	55 475.01
April	38 237.33
May	37 698.59
June	40 352.94
July	40 569.92
August	42 015.74
September	46 727.65
October	51 334.73
November	14 270.04
December	15 342.94

Table 45: Electric Consumption from the grid for Example 2Example 4.

Hourly Monthly Average	Annual Consumption	Annual Peak Demand Month
42 648.62kW	12 282 803.71kW	January at 87 057.34kW

5.4.3 Load Profile of Example 4

Below is an image of the load profile used in Example 4.

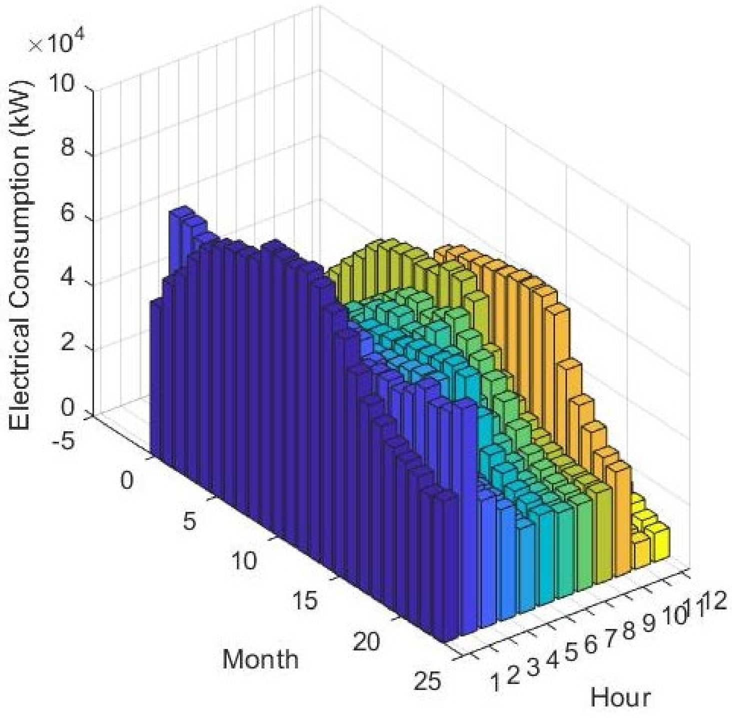

Figure 24: Plotted profile of shopping complex 1 - Hourly Monthly Average Electrical Consumption.

5.4.4 Base System Electric Bill

The following table shows the interpreted electric bill for each month.

Table 46: Electric Bill (Grid supplied only) of Example 4.

Month	Monthly Electricity Costs (in Rands)
January	231 717 331.80
February	207 927 470.36
March	191 187 522.81
April	131 521 857.40
May	131 820 750.54
June	141 795 435.21
July	141 488 488.25
August	147 084 697.55
September	161 601 684.28
October	183 620 576.50
November	50 703 501.19
December	55 129 423.72
Annual Total	1 775 598 739.61

5.4.5 Comparison of Optimisation Algorithms Results

Different algorithms have been formulated and the results of each algorithm, for Example 4, is tabulated below. Without PV the cost of electricity for twenty years is R661 188 808 537.44.

Table 47: Results of Example 4 using multiple algorithms. Where an upper bound was required, the value of 55 000 was used.

Algorithm	Time taken for solution in seconds	TCO	Savings for 20 years (Electricity-TCO)	Inverter, PV, Battery values
Iteration (Manual optimisation)	94.15	R32 147 135 114.89	R629 041 673 422.55	19 400.00 VA 1 900.00 W W 47 040.00 Wh
Particle Swarm	44.33	R31 478 132 480.53	R629 710 676 056.91	19 253.90 VA 1 863.46 W 48 662.48 Wh
Genetic Algorithm	53.16	R32 418 926 121.89	R628 769 882 415.55	6 594.00 VA 2 017.19 W 16 715.00 Wh
Pattern Search Optimisation	6.97	R32 164 346 381.88	R629 024 462 155.56	3.70 VA 1.00 W 3.34 Wh
Surrogateopt	18.17	R31 480 414 943.46	R629 708 393 593.98	20 272.23 VA 1 771.04 W 51 244.64 Wh
Paretosearch	62.40	R31 479 356 429.00	R629 709 452 108.44	19 967.55 VA 1 852.36 W 50 453.92 Wh
Ant Colony Optimisation for Continuous Domains	19.45	R31 478 142 628.18	R629 710 665 909.26	19 282.38 VA 1 864.04 W 48 734.40 Wh
Artificial Bee Colony	87.53	R31 478 154 494.41	R629 710 654 043.03	19 286.07 VA 1 876.56 W 48 742.77 Wh
Bee Algorithm	27.13	R31 947 391 106.12	R629 241 417 431.32	4 277.55 VA 2 514.01 W 10 351.38 Wh
Biogeography Based	24.00	R31 478 273 440.65	R629 710 535 096.79	19 073.91 VA 1 878.68 W 48 207.11 Wh
Matrix Adaptation	32.09	R31 493 163 288.48	R629 695 645 248.96	19 305.90 VA 2 382.39 W 48 501.72 Wh
Differential Evolution	26.42	R32 172 381 358.16	R629 016 427 179.28	8 516.81 VA 5 037.02 W 22 478.72 Wh
Firefly Algorithm	129.42	R31 478 136 052.13	R629 710 672 485.31	19 250.14 VA 1 863.13 W 48 653.47 Wh

Harmony Search	10.01	R31 490 194 876.12	R629 698 613 661.32	17 658.56 VA 1 987.77 W 44 628.39 Wh
Real-Coded Simulated Annealing	46.99	R31 478 516 051.97	R629 710 292 485.47	19 646.16 VA 1 848.54 W 49 653.72 Wh
Shuffled Complex Evolution	64.98	R31 478 130 516.20	R629 710 678 018.24	19 246.96 VA 1 866.43 W 48 644.95 Wh
Invasive Weed Optimisation	16.56	R33 288 089 229.01	R627 900 719 308.43	32 493.16 VA 4 903.36 W 54 293.17 Wh
Teaching-learning based Optimisation	46.05	R31 478 134 447.09	R629 710 674 090.35	19 259.04 VA 1 865.38 W 48 675.52 Wh

5.4.6 Current Method of Calculation

Using the daily average for shopping complex 1 is 33 651.52kWh.

Table 48: Results of TCO and related values using the method that is currently used.

shopping complex 1	
PV Size	8 696.46W
Inverter Size	4 348.24VA
Battery Capacity	33 651.52Wh
TCO	R35 420 135 071.19

5.4.7 Findings of Example 4

The time taken for a solution plotted against the TCO in Rands is below.

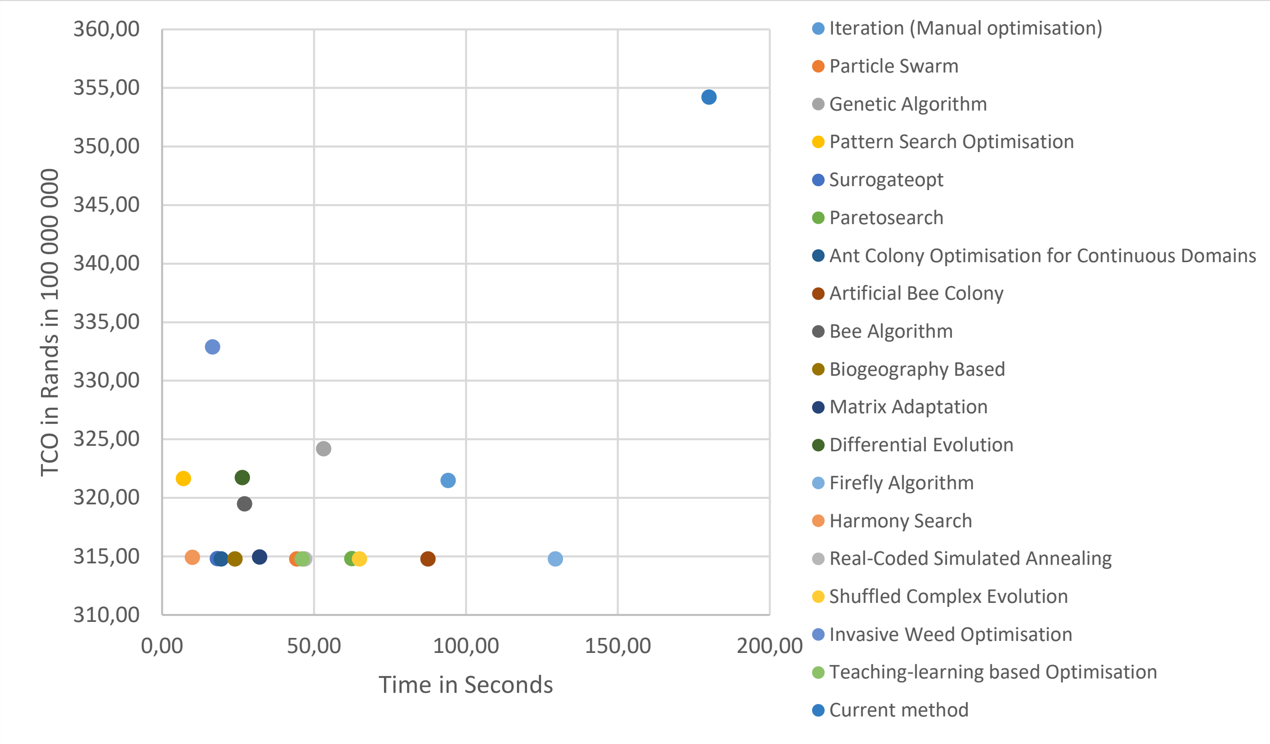

Figure 25: Time vs TCO for Example 4.

The lowest TCO came from the SCEO, at 64.98 seconds and R31 478 130 516.20. At 6.97 seconds, pattern search was the fastest yet third-highest TCO after GA and DE. The average time taken for the optimisation algorithms was 44.22 seconds. DE has the highest TCO from the optimisation methods, however, this R32 172 381 358.16, remains R2 132 045 842.18 above the TCO obtained from the method more freely available.

Table 49: Tabulation of results of Example 4 Inverter, PV, and Battery value ranges.

Value Ranking	Inverter	PV	Battery
Highest	32 493.16	5 037.02	54 293.17
Lowest	3.70	1.00	3.34
SCEO	19 246.96	1 866.43	48 644.95

It should also be noted there is a small difference between PSO and SCEO, the difference being R1 964.33. The values of PSO are 19 253.90, 1 863.46, and 48 662.48 for an inverter, PV and a battery respectively. The time taken for the optimisation algorithms PSO and SCEO to run to completion, is 44.33 and 64.98, a difference of 20.65 seconds. Furthermore, the PSO time is closer to the average time taken for the optimisations to run, the difference in the value of TCO is smaller and can be disregarded as SCEO takes a third more time to run. The most suitable optimisation method is PSO at a TCO of R31 478 132 480.53

Table 50: System Overview Analysis of Example 4Example 1.

Lowest Net Cost System Architecture	Inverter Size - 19 253.90VA PV Size - 1 863.46VA Battery, SC, Capacity - 48 644.95kWh
Annual Electric Bill	R 1 775 598 739.61
Annual Electricity Cost with PV	R 26 123 969.73
Projected Annual Savings	R31 485 533 802.85
Annual PV payment	R1 573 906 624.02
Discount Rate	3.94%
Inflation	Electricity – 2.7% Maintenance – 3.7% Battery – 3.34%
Projected TCO for 20 years	R31 478 132 480.53
Projected Electric Bill for 20 years	R661 188 808 537.44
Projected Lifetime Total 20 Saving	R201 692 115.60

The figures below show monthly data for the SCEO solution. The load can be seen in orange at the top, along with the LA and LI capacity. The SC capacity is on the bottom left, while the available PV is blue at the bottom, and around the available PV is the required energy from the grid-dependent on each type of storage. These figures show the average hourly data for January and June.

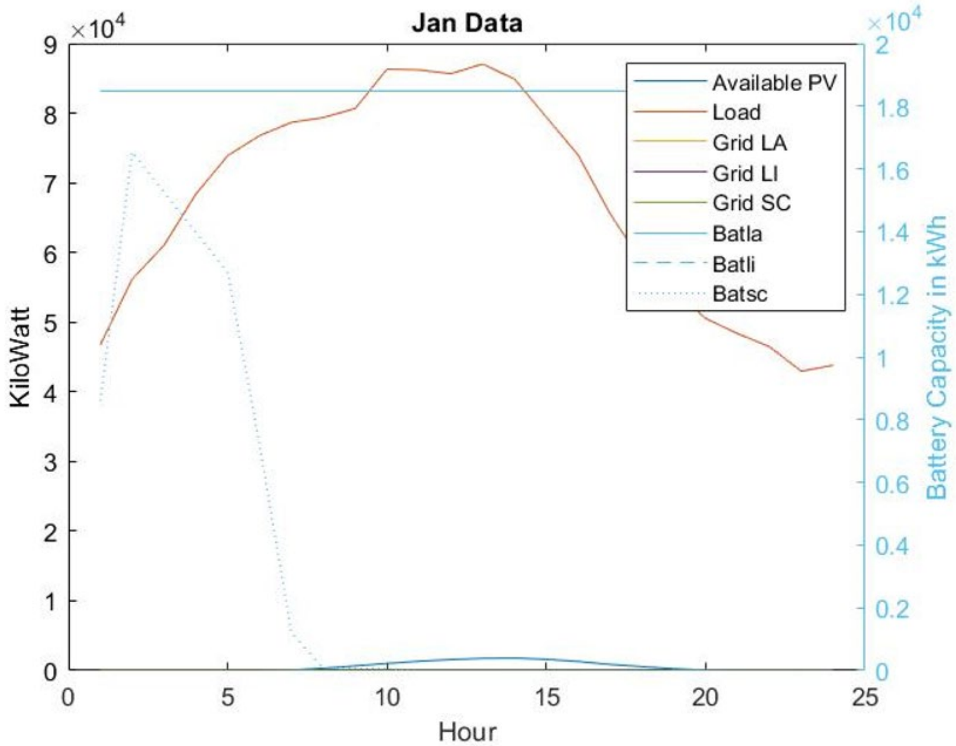

Figure 26: PSO January Data for Example 4.

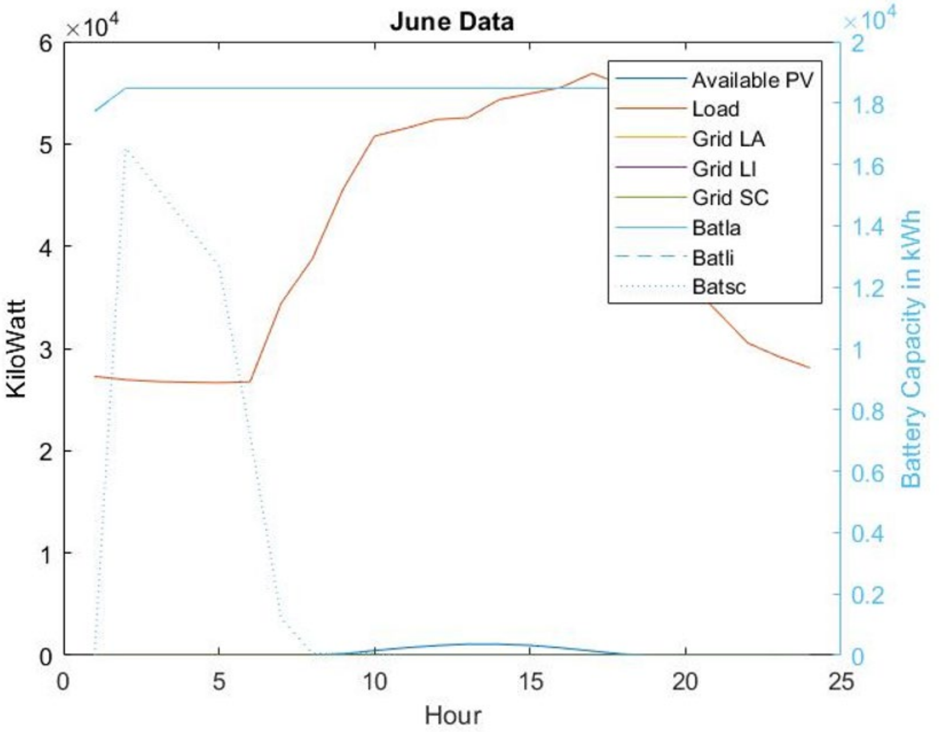

Figure 27: PSO January Data for Example 4.

5.5 Example 5

5.5.1 Site Information

This example data is from a shopping complex in Durban, for confident purposes, this complex was referred to as shopping complex 2.

Table 51: Site information of Example 5.

Location	Durban, South Africa
Time Zone	Africa/ Johannesburg

5.5.2 Average Electric Energy Consumption

The table that follows is the hourly monthly average consumption of shopping complex 2.

Table 52: Monthly Consumption of shopping complex 2.

Month	Hourly Monthly Average (in kW)
January	786.84
February	761.35
March	744.17
April	554.81
May	525.93
June	573.14
July	573.52
August	593.64
September	633.65
October	670.56
November	702.30
December	436.36

Table 53: Electric Consumption from the grid for Example 5.

Hourly Monthly Average	Annual Consumption	Annual Peak Demand Month
629.14kW	180 563.50kW	January at 1 127.32kW

5.5.3 Load Profile of Example 5

Below is an image of the load profile of the factory used in Example 5.

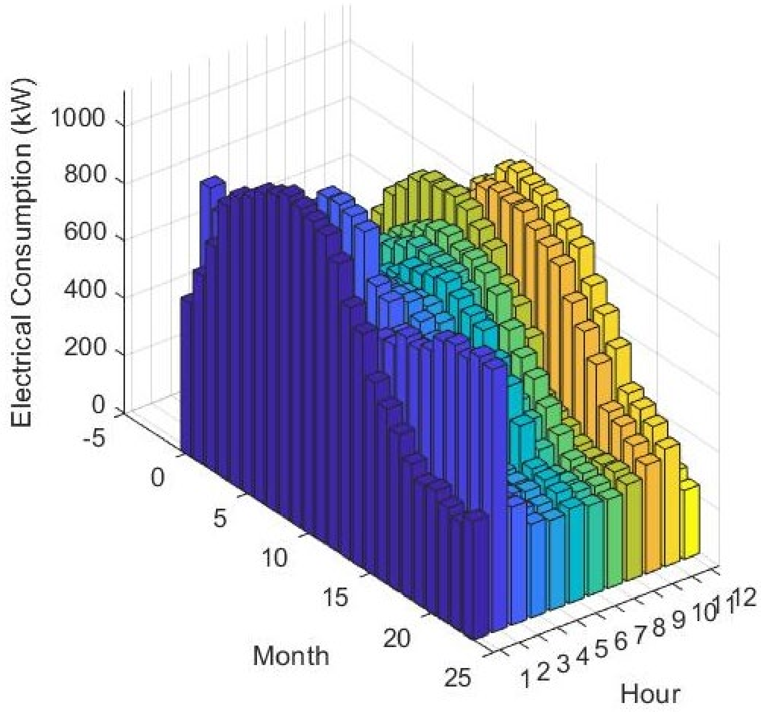

Figure 28: Plotted profile of shopping complex 2 - Hourly Monthly Average Electrical Consumption.

5.5.4 Base System Electric Bill

The following table shows the interpreted electric bill for each month.

Table 54: Electric Bill (Grid supplied only) of Example 5.

Month	Monthly Electricity Costs (in Rands)
January	2 683 912.31
February	2 527 740.74
March	2 588 889.80
April	1 957 683.01
May	1 853 592.27
June	2 049 389.77
July	2 022 819.29
August	2 104 681.27
September	2 216 925.38
October	2 413 618.95
November	2 519 028.30
December	1 587 190.85
Annual Total	26 525 471.94

5.5.5 Comparison of Optimisation Algorithms Results

Different algorithms have been formulated and the results of each algorithm, for Example 5, is tabulated below. The calculated value of electricity for twenty years with no PV was R9 877 426 019.68.

Table 55: Results of Example 5 using multiple algorithms. Where an upper bound was required, the value of 2 000 was used.

Algorithm	Time taken for solution in seconds	TCO	Savings for 20 years (Electricity-TCO)	Inverter, PV, Battery values
Iteration (Manual optimisation)	98.14	R498 191 059.62	R9 379 234 960.06	1 500.00 VA 460.00 W 1 200.00 Wh
Particle Swarm	20.88	R510 318 969.01	R9 367 107 050.67	3.69 VA 1.00 W 3.34 Wh
Genetic Algorithm	26.47	R474 621 570.91	R9 402 804 448.77	467.00 VA 467.09 W 1 178.00 Wh
Pattern Search Optimisation	9.10	R510 318 981.37	R9 367 107 038.31	3.70 VA 1.00 W 3.34 Wh
Surrogateopt	18.80	R475 060 567.74	R9 402 365 451.95	471.10 VA 668.96 W 1 189.76 Wh
Paretosearch	52.62	R509 688 293.84	R9 367 737 725.84	438.82 VA 1 035.88 W 2 773.90 Wh
Ant Colony Optimisation for Continuous Domains	18.25	R475 134 469.84	R9 402 291 549.84	427.17 VA 427.19 W 1 078.85 Wh
Artificial Bee Colony	80.11	R474 620 333.52	R9 402 805 686.16	465.69 VA 465.75 W 1 175.12 Wh
Bee Algorithm	14.15	R478 846 807.42	R9 398 579 212.26	543.11 VA 748.92 W 1 265.39 Wh
Biogeography Based	22.48	R474 621 610.43	R9 402 804 409.25	464.61 VA 464.62 W 1 172.51 Wh
Matrix Adaptation	30.45	R510 712 680.29	R9 366 713 339.39	1.00 VA 1.00 W 1.00 Wh
Differential Evolution	26.13	R480 324 033.12	R9 397 101 986.26	581.66 VA 731.53 W 1 502.44 Wh

Firefly Algorithm	119.54	R474 637 790.89	R9 402 788 228.79	473.52 VA 474.05 W 1 195.91 Wh
Harmony Search	12.11	R475 451 233.43	R9 401 974 786.25	474.04 VA 534.25 W 1 160.85 Wh
Real-Coded Simulated Annealing	42.15	R476 226 840.20	R9 401 199 179.48	408.21 VA 498.80 W 1 050.49 Wh
Shuffled Complex Evolution	59.61	R474 620 174.89	R9 402 805 844.79	466.03 VA 466.03 W 1 176.22 Wh
Invasive Weed Optimisation	14.05	R478 245 911.02	R9 399 180 108.66	524.21VA 489.12 W 1 401.39 Wh
Teaching-learning based Optimisation	40.64	R474 620 174.72	R9 402 805 844.96	466.01 VA 466.01 W 1 176.18 Wh

5.5.6 Current Method of Calculation

Using the daily average for shopping complex 2factory 1 is 494.96kWh.

Table 56: Results of TCO and related values using the method that is currently used.

shopping complex 2	
PV Size	127.84W
Inverter Size	63.92VA
Battery Capacity	494.96Wh
TCO	R511 404 420.04

5.5.7 Findings of Example 5

The plotted time taken for a solution against the TCO for example 5 is below.

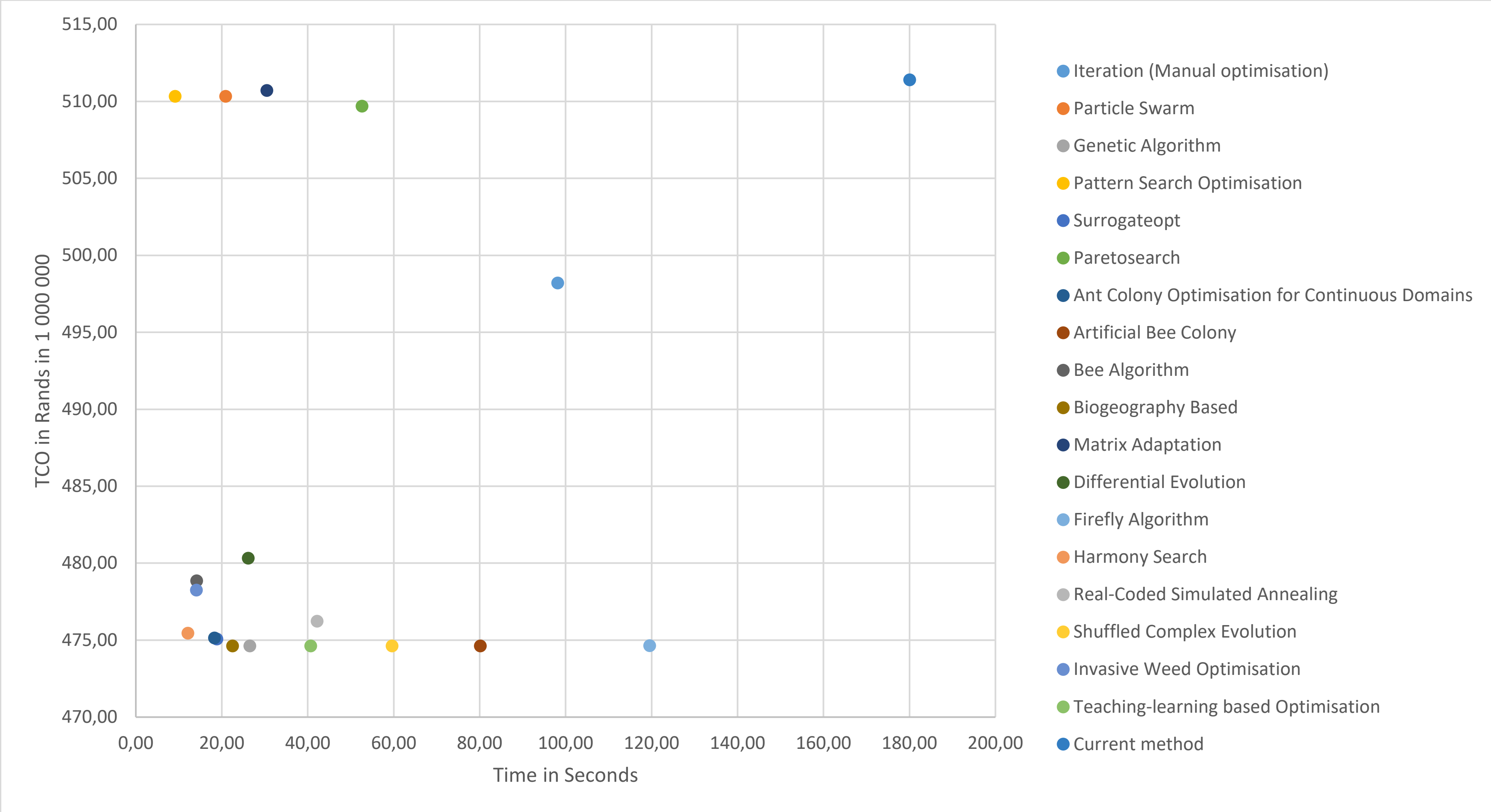

Figure 29: Time vs TCO for Example 5.

The fastest algorithm was Pattern Search at a TCO of R510 318 981.37 and 9.10 seconds. The longest optimisation was Firefly Algorithm at a TCO of R474 637 790.89 and a time of 119.54 seconds. The lowest TCO at R474 620 174.72 was obtained from TLBO at 40.64 seconds. The optimisation algorithm with the next lowest TCO is SCEO at R474 620 174.89 at 59.61 seconds. The difference in TCO between TLBO and SCEO is R0.17.

Comparing the current method used, the TCO is R511 404 420.04, which is the highest TCO. The TLBO TCO resulted in the following values of the inverter, PV, and Battery; 466.01, 466.01, 1 176.18. The most suitable optimisation method is TLBO as has the lowest TCO and was only 0.48 seconds above the average time taken by optimisation algorithms.

Table 57: System Overview Analysis of Example 5Example 1.

Lowest Net Cost System Architecture	**Inverter Size - 466.01VA** PV Size - **466.01VA** **Battery, SC, Capacity - 1 176.18kWh**
Annual Electric Bill	R26 525 471.94
Annual Electricity Cost with PV	R323 304.03
Projected Annual Savings	R470 140 292.25
Annual PV payment	R23 731 008.74
Discount Rate	3.94%
Inflation	Electricity – 2.7% Maintenance – 3.7% Battery – 3.34%
Projected TCO for 20 years	R474 620 174.72
Projected Electric Bill for 20 years	R9 877 426 019.68
Projected Lifetime Total 20 Saving	R9 402 805 844.96

Monthly data for the TLBO solution is shown below. The load can be seen in orange at the top, along with the LA and LI capacity. The SC capacity is on the bottom left, while the available PV is in blue at the bottom. In purple, the grid required kilowatts if using the LI battery option was seen. In yellow, just under the purple is if a LA battery was used, and in green at the bottom in the SC grid required kilowatts. In the June data, Figure 31, as the available PV reduces due to less sunlight in winter, the SC grid requirement, the line in green, increases to stratify the morning load.

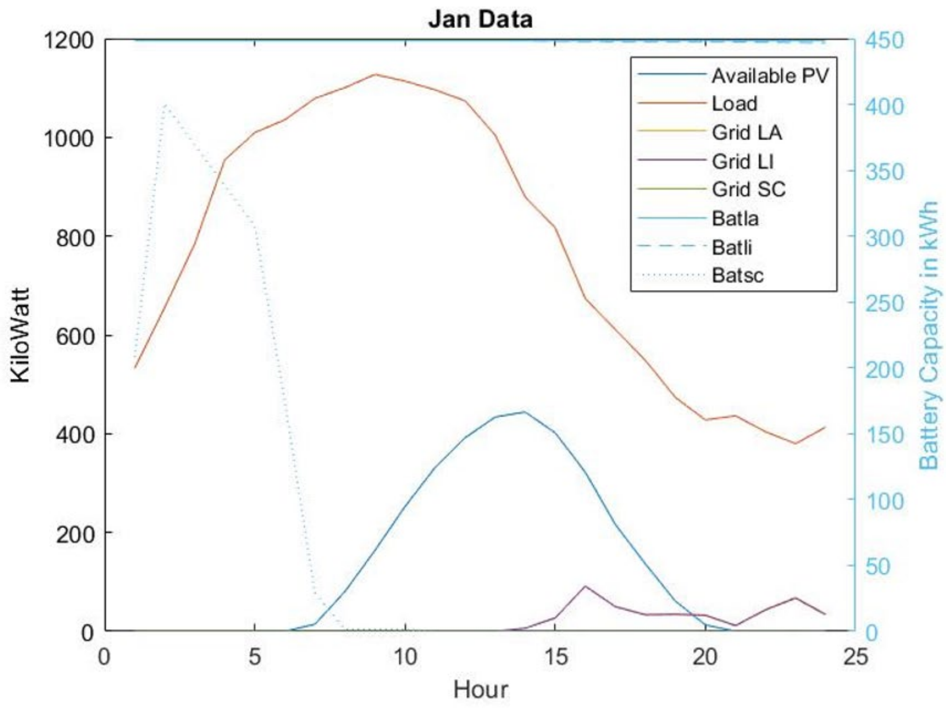

Figure 30: TLBO January Data for Example 5.

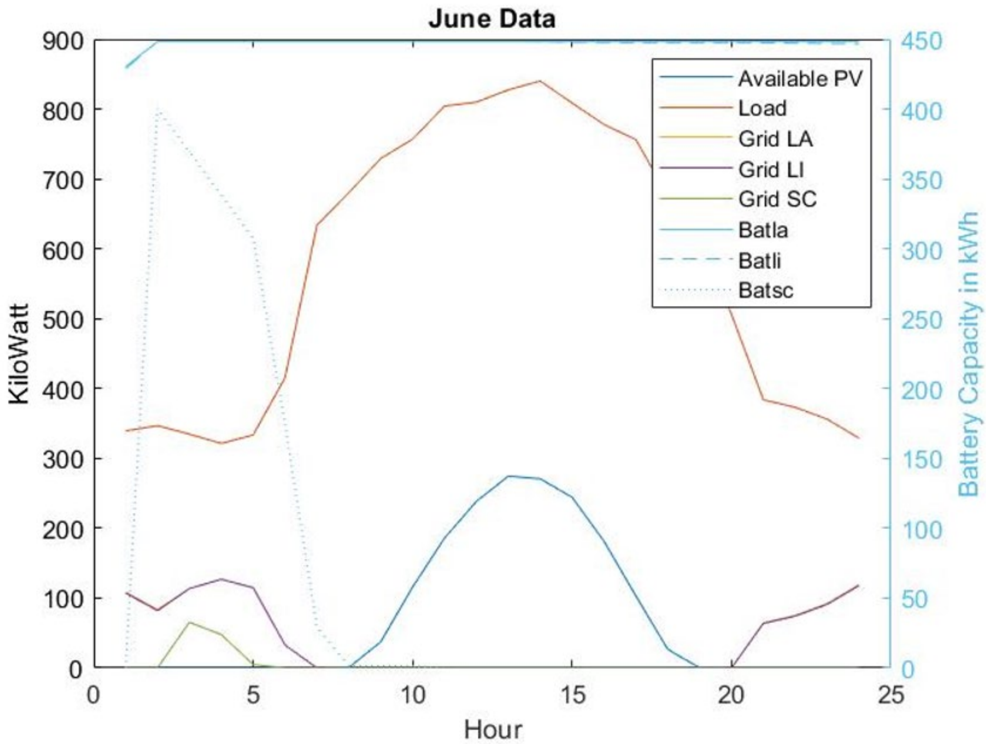

Figure 31: TLBO June Data for Example 5.

5.6 Example 6

5.6.1 Site Information

This example data is from a shopping complex in Durban, for confidential purposes, this complex was referred to as shopping complex 3.

Table 58: Site information of Example 6Example 5.

Location	Durban, South Africa
Time Zone	Africa/ Johannesburg

5.6.2 Average Electric Energy Consumption

The table that follows is the hourly monthly average consumption of shopping complex 3. factory 3

Table 59: Monthly Consumption of shopping complex 3.

Month	Hourly Monthly Average (in kW)
January	198.38
February	188.93
March	176.65
April	95.40
May	112.29
June	117.99
July	130.77
August	136.62
September	135.26
October	151.89
November	84.22
December	92.40

Table 60: Electric Consumption from the grid for Example 6.

Hourly Monthly Average	Annual Consumption	Annual Peak Demand Month
134.85kW	38 700.84kW	January at 240.38kW

5.6.3 Load Profile of Example 6

Below is an image of the load profile of the factory used in Example 6.

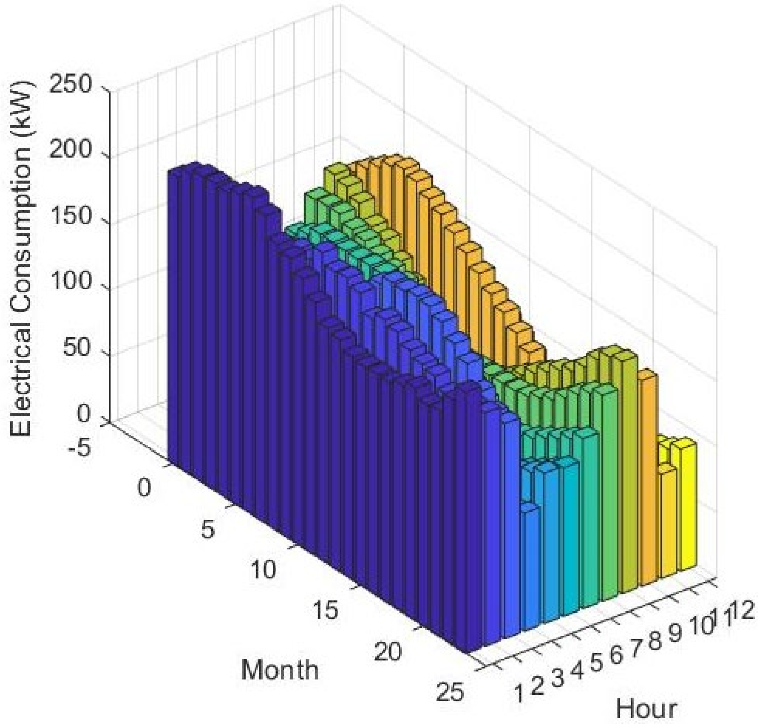

Figure 32: Plotted profile of shopping complex 3 - Hourly Monthly Average Electrical Consumption.

5.6.4 Base System Electric Bill

The following table shows the interpreted electric bill for each month.

Table 61: Electric Bill (Grid supplied only) of Example 6Example 5.

Month	Monthly Electricity Costs (in Rands)
January	670 019.75
February	646 527.12
March	608 020.20
April	323 053.22
May	375 139.92
June	396 495.78
July	438 652.10
August	453 171.31
September	443 352.29
October	505 191.44
November	283 716.77
December	311 279.02
Annual Total	5 454 618.91

5.6.5 Comparison of Optimisation Algorithms Results

Different algorithms have been formulated and the results of each algorithm, for Example 6, is tabulated below. The calculated cost of electricity for twenty years with no PV is R2 031 164 418.15.

Table 62: Results of Example 6 using multiple algorithms. Where an upper bound was required, the value of 500 was used.

Algorithm	Time taken for solution in seconds	TCO	Savings for 20 years (Electricity-TCO)	Inverter, PV, Battery values
Iteration (Manual optimisation)	81.15	R93 090 563.41	R1 938 073 854.74	1 500.00 VA 760.00 W 240.00 Wh
Particle Swarm	24.02	R92 223 334.40	R1 938 941 083.75	85.00 VA 85.00 W 215 Wh
Genetic Algorithm	21.29	R97 876 341.69	R1 933 288 076.45	3.69 VA 1.00 W 3.34 Wh
Pattern Search Optimisation	7.77	R97 876 354.05	R1 933 288 064.10	3.70 VA 1.00 W 3.34 Wh
Surrogateopt	15.04	R98 270 052.97	R1 932 894 365.18	1.00 VA 1.00 W 1.00 Wh
Paretosearch	60.23	R98 270 052.97	R1 932 894 365.18	1.00 VA 1.00 W 1.00 Wh
Ant Colony Optimisation for Continuous Domains	18.38	R92 228 856.69	R1 938 935 561.47	83.49 VA 83.49 W 211.04 Wh
Artificial Bee Colony	80.44	R92 224 783.03	R1 938 939 635.11	86.00 VA 86.71 W 217.67 Wh
Bee Algorithm	12.11	R92 276 699.14	R1 938 887 719.01	92.86 VA 97.39 W 233.68 Wh
Biogeography Based	22.49	R92 229 192.81	R1 938 935 225.33	83.56 VA 85.73 W 211.19 Wh
Matrix Adaptation	31.49	R98 270 052.97	R1 932 894 365.18	1.00 VA 1.00 W 1.00 Wh
Differential Evolution	22.55	R92 722 417.87	R1 938 442 000.27	81.58 VA 274.84 W 229.67 Wh
Firefly Algorithm	117.93	R92 251 806.20	R1 938 912 611.95	86.59 VA 288.51 W

				219.00 Wh
Harmony Search	10.13	R94 505 793.98	R1 936 658 624.17	49.56 VA 51.51 W 112.67 Wh
Real-Coded Simulated Annealing	43.11	R98 162 268.45	R1 933 002 149.70	1.00 VA 1.00 W 1.85 Wh
Shuffled Complex Evolution	63.29	R92 221 203.80	R1 938 943 214.34	85.62 VA 85.62 W 216.40 Wh
Invasive Weed Optimisation	14.62	R92 353 281.05	R1 938 811 137.10	77.95 VA 253.30 W 196.77 Wh
Teaching-learning based Optimisation	38.58	R92 221 184.44	R1 938 943 233.70	85.61 VA 85.62 W 216.40 Wh

5.6.6 Current Method of Calculation

Using the daily average for shopping complex 3factory 1 is 106.03kWh.

Table 63: Results of TCO and related values using the method that is currently used.

shopping complex 3	
PV Size	27.40W
Inverter Size	13.70VA
Battery Capacity	106.03Wh
TCO	R98 521 112.64.

5.6.7 Findings of Example 6

Below is a visual representation of the findings from example 6, the time taken to find a solution against the TCO in Rands.

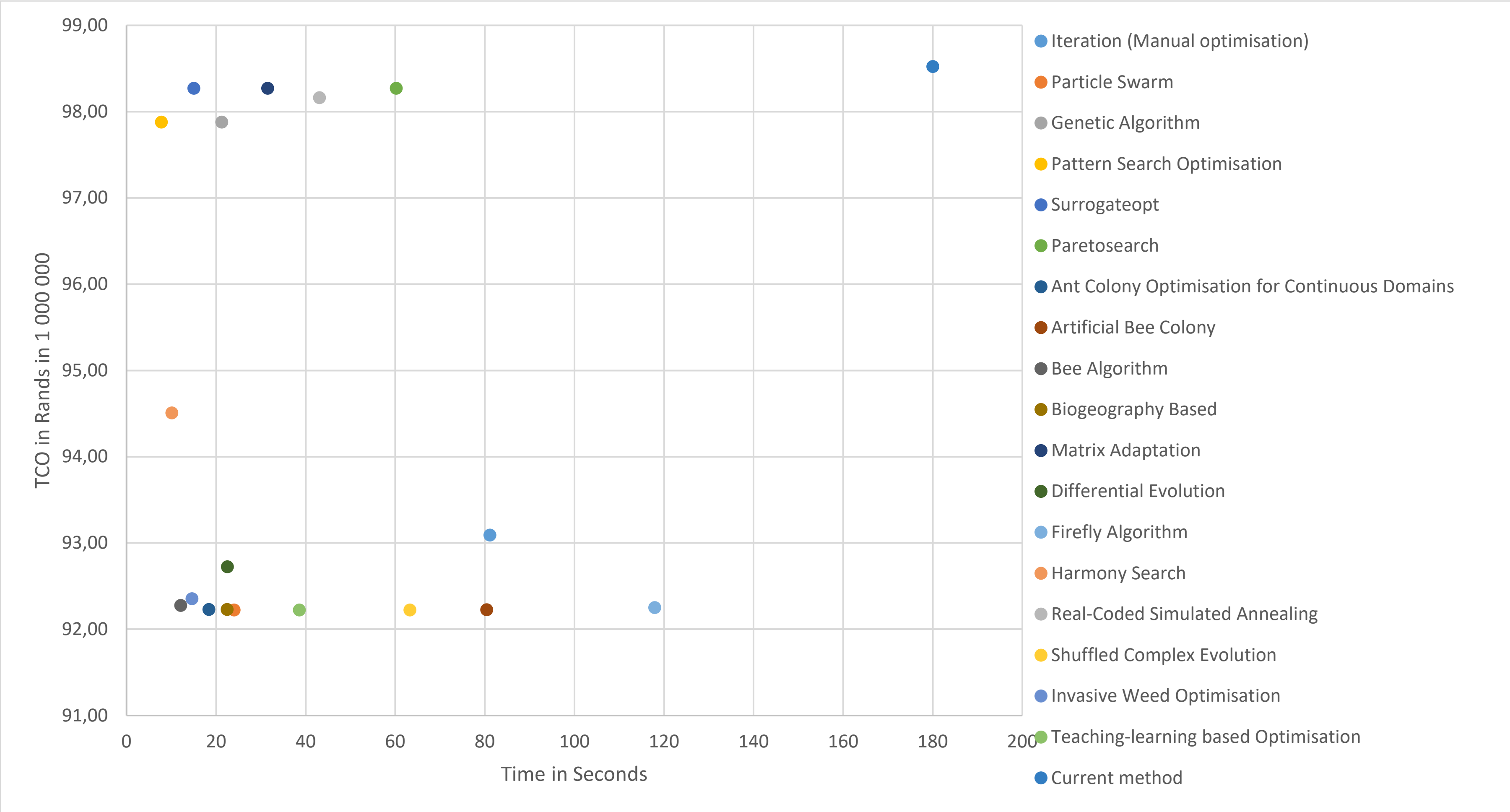

Figure 33: Time vs TCO for Example 6.

Values of the inverter, PV, and battery of 3.70, 1.00, and 3.34 respectively was the fastest solution at 7.77 seconds from the Pattern Search algorithm. With the average optimisation time being 34.59 seconds, the slowest time of 117.93 belonging to FA, is 3.41 times the average. The fastest algorithm resulted in a TCO of R97 876 354.05, which is R5 655 169.61 more than the lowest TCO. TLBO provided the lowest solution at values of 85.61, 85.62, and 216.40, for the inverter, PV, and battery respectively. R92 221 184.44 was the TCO from TLBO, taking 38.58 seconds. The next best TCO at R19.36 higher than TLBO was SCEO at 63.29 seconds and a TCO of R92 221 203.80.

Comparing the current method used, the TCO is R98 521 112.64, this is the highest TCO obtained. TCO optimisation is not achieved when maximising the PV. The TCO has lower values with smaller differences when different optimisation techniques are used.

While Pattern Search is the fastest optimisation, the difference in TCO is high and was therefore not considered a viable solution. TLBO was 3.06 times faster than the FA, and 24.71 seconds faster than SCEO. However, the SCEO solution takes longer and yields a higher TCO than TLBO. The most suitable optimisation method is TLBO.

Table 64: System Overview Analysis of Example 6.

Lowest Net Cost System Architecture	**Inverter Size - 85.61VA** PV Size - **85.62VA** **Battery, SC, Capacity - 216.40kWh**
Annual Electric Bill	R5 454 618.91
Annual Electricity Cost with PV	R65 824.60
Projected Annual Savings	R96 947 161.69
Annual PV payment	R4 611 059.22
Discount Rate	3.94%
Inflation	Electricity – 2.7% Maintenance – 3.7% Battery – 3.34%
Projected TCO for 20 years	R 92 221 184.44
Projected Electric Bill for 20 years	R2 031 164 418.15
Projected Lifetime Total 20 Saving	R1 938 943 233.70

The TLBO solution figures can be seen below. The load can be seen in orange at the top, along with the LA and LI capacity. The SC capacity is on the bottom left, while the available PV is blue at the bottom, and around the available PV is the required energy from the grid-dependent on each type of storage. These figures show the average hourly data for January and June. In Figure 35: TLBO June Data for Example 6.Figure 35 the increase in the requirement from the grid, if an LI battery is used, which can be seen in purple.

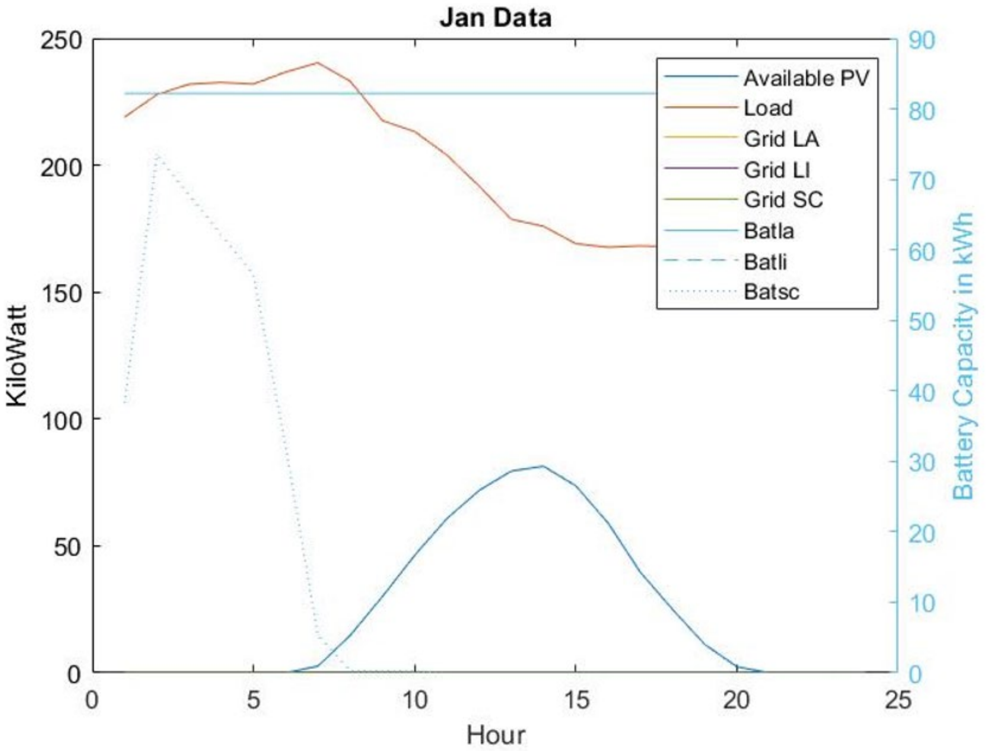

Figure 34: TLBO January Data for Example 6.

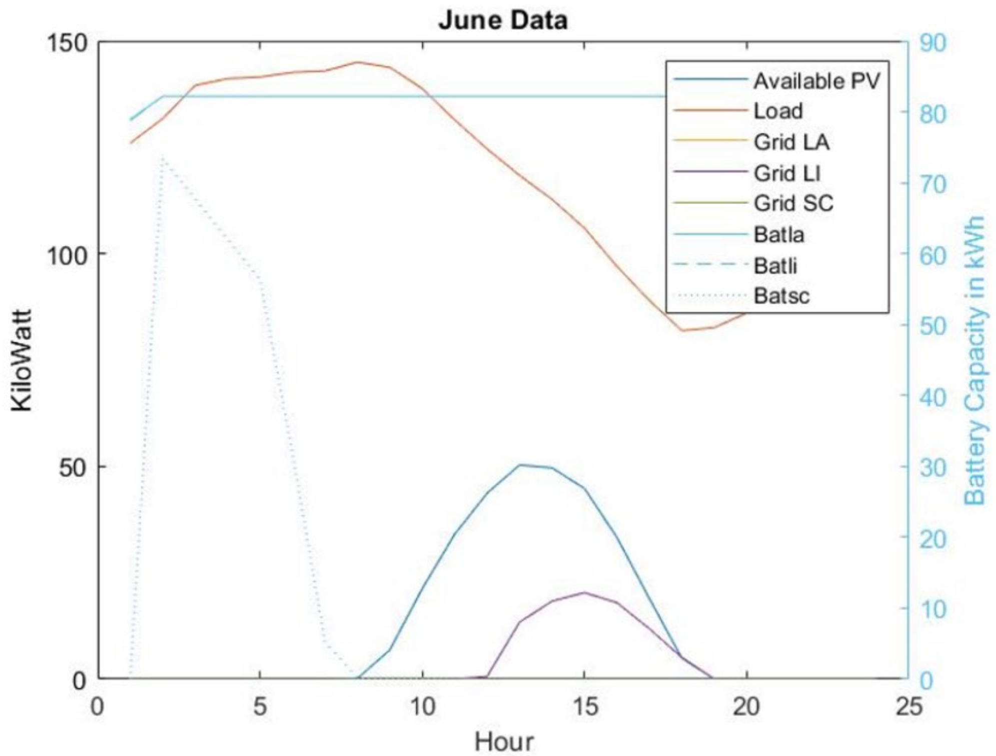

Figure 35: TLBO June Data for Example 6.

5.7 Example 7

5.7.1 Site Information

This example data is from a housing complex in Durban, for confidential purposes, this complex was referred to as housing residence.

Table 65: Site information of Example 7.

Location	Durban, South Africa
Time Zone	Africa/ Johannesburg

5.7.2 Average Electric Energy Consumption

The table that follows is the hourly monthly average consumption of the housing residence.

Table 66: Monthly Consumption of the housing residence.

Month	Hourly Monthly Average (in kW)
January	195.18
February	218.15
March	204.48
April	186.45
May	165.11
June	226.95
July	241.20
August	243.97
September	213.25
October	238.16
November	226.87
December	188.04

Table 67: Electric Consumption from the grid for Example 7.

Hourly Monthly Average	Annual Consumption	Annual Peak Demand Month
212.32kW	61 147.4kW	June at 397.35kW

5.7.3 Load Profile of Example 7Example 5

Below is an image of the load profile of the factory used in Example 7.

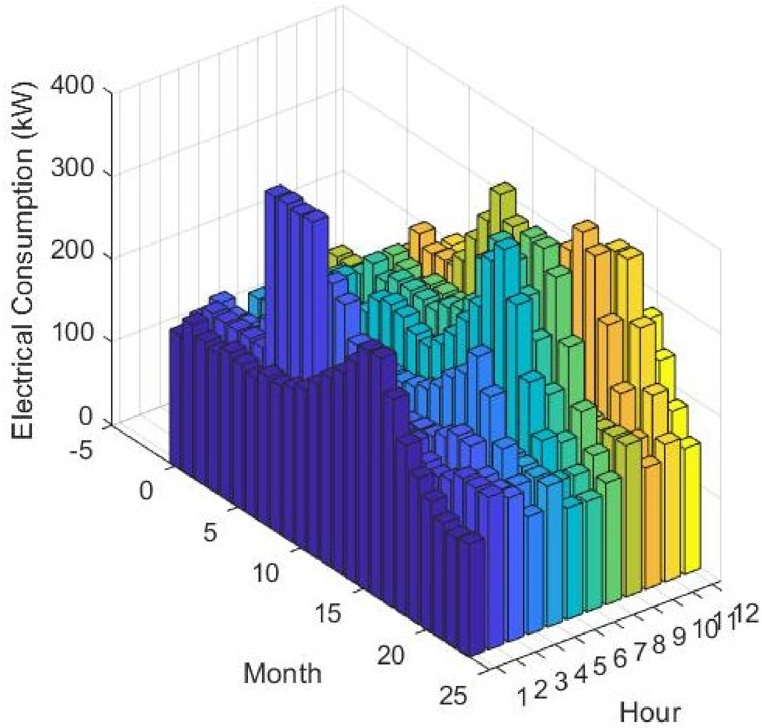

Figure 36: Plotted profile of housing residence - Hourly Monthly Average Electrical Consumption.

5.7.4 Base System Electric Bill

The following table shows the interpreted electric bill for each month.

Table 68: Electric Bill (Grid supplied only) of Example 7.

Month	Monthly Electricity Costs (R)
January	599 500.27
February	731 665.62
March	640 148.32
April	503 168.89
May	472 223.68
June	641 341.97
July	719 214.92
August	694 461.33
September	641 237.42
October	673 565.51
November	608 195.09
December	517 624.07
Annual Total	7 442 347.11

5.7.5 Comparison of Optimisation Algorithms Results

Different algorithms have been formulated and the results of each algorithm, for Example 7, is tabulated below. The calculated cost of electricity for twenty years is R3 327 904 741.67.

Table 69: Results of Example 7 using multiple algorithms. Where an upper bound was required, the value of 500 was used.

Algorithm	Time taken for solution in seconds	TCO	Savings for 20 years (Electricity-TCO)	Inverter, PV, Battery values
Iteration (Manual optimisation)	94.35	R41 345 984.87	R3 286 558 756.80	1 500.00 VA 760.00 W 480.00 Wh
Particle Swarm	20.37	R41 019 115.82	R3 286 885 625.85	3.80 VA 1.00 W 3.37 Wh
Genetic Algorithm	30.55	R30 340 959.60	R3 297 563 782.07	163.00 VA 163.00 W 412.00 Wh
Pattern Search Optimisation	5.23	R41 019 115.82	R3 286 885 625.85	3.80 VA 1.00 W 3.37 Wh
Surrogateopt	15.24	R41 433 126.03	R3 286 471 615.64	1.00 VA 1.00 W 1.00 Wh
Paretosearch	55.08	R41 433 126.03	R3 286 471 615.64	1.00 VA 1.00 W 1.00 Wh
Ant Colony Optimisation for Continuous Domains	17.62	R30 340 353.52	R3 297 564 388.15	163.44 VA 163.44 W 413.07 Wh
Artificial Bee Colony	81.49	R30 340 389.64	R3 297 564 352.03	163.55 VA 163.82 W 413.36 Wh
Bee Algorithm	30.66	R30 380 649.99	R3 297 524 091.68	161.21 VA 219.28 W 404.02 Wh
Biogeography Based	23.12	R30 475 683.22	R3 297 429 058.45	178.18 VA 227.23 W 448.94 Wh
Matrix Adaptation	32.39	R41 433 126.03	R3 286 471 615.64	1.00 VA 1.00 W 1.00 Wh
Differential Evolution	23.77	R39 232 282.38	R3 288 672 459.30	63.28 VA 311.55 W 81.46 Wh
Firefly Algorithm	116.00	R30 346 425.11	R3 297 558 316.56	163.40 VA 200.02 W 413.25 Wh

Harmony Search	12.48	R30 496 808.72	R3 297 407 932.95	173.12 VA 242.70 W 424.95 Wh
Real-Coded Simulated Annealing	47.71	R41 252 019.18	R3 286 652 722.49	1.00 VA 1.00 W 2.89 Wh
Shuffled Complex Evolution	62.38	R30 340 347.07	R3 297 564 394.60	163.33 VA 163.33 W 412.78 Wh
Invasive Weed Optimisation	14.86	R30 952 978.61	R3 296 951 763.06	187.24 VA 169.48 W 473.67 Wh
Teaching-learning based Optimisation	42.12	R30 340 347.05	R3 297 564 394.62	163.33 VA 163.33 W 412.79 Wh

5.7.6 Current Method of Calculation

Using the daily average for housing residence is 167.53kWh.

Table 70: Results of TCO and related values using the method that is currently used.

housing residence	
PV Size	43.29W
Inverter Size	21.65VA
Battery Capacity	167.53Wh
TCO	R41 892 720.89

5.7.7 Findings of Example 7

The figure below is the time taken for a solution plotted against TCO in Rands.

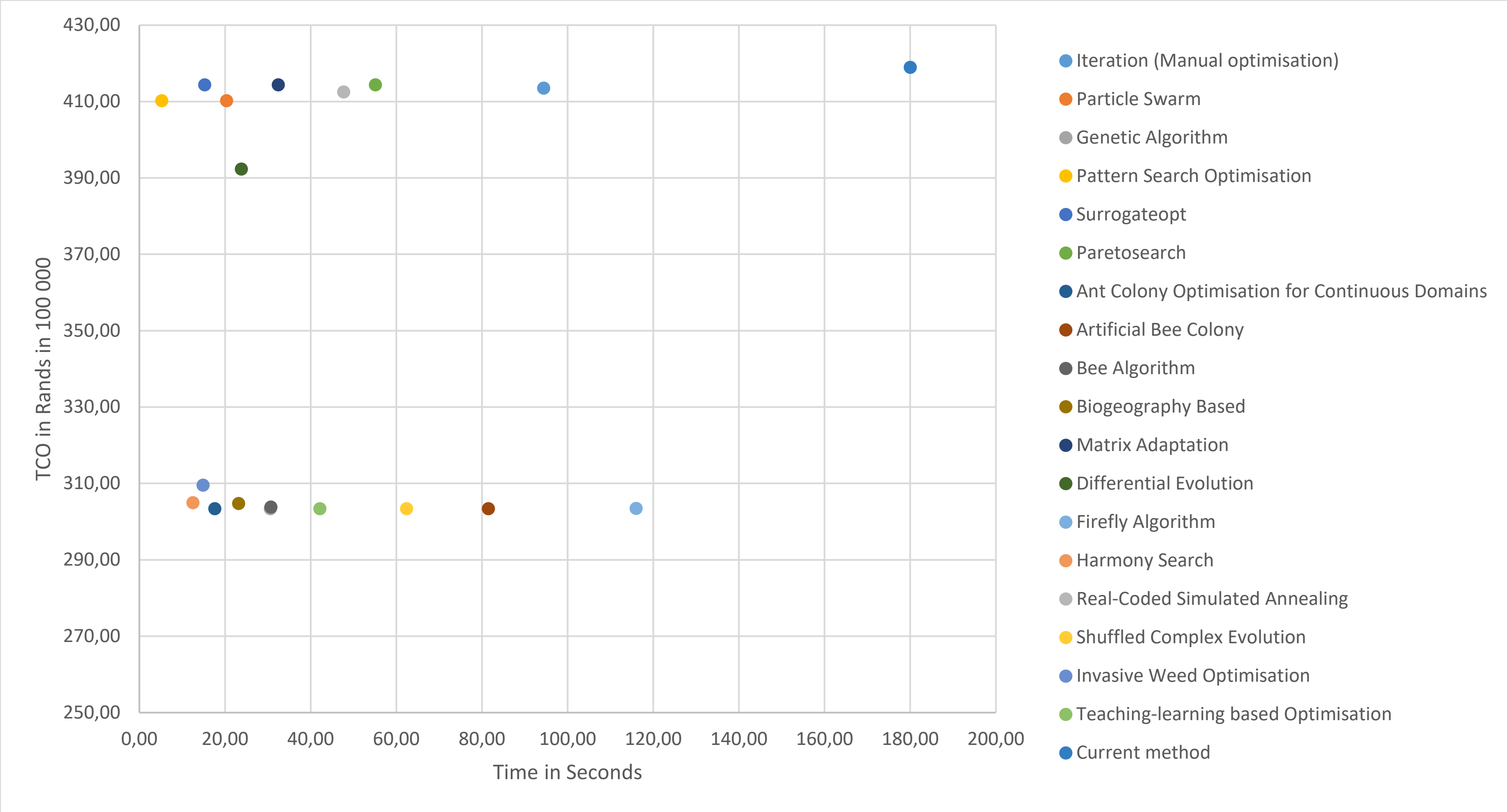

Figure 37: Time vs TCO for Example 7.

The lowest TCO of R30 340 347.05 was the solution of TLBO at 42.12 seconds. The second-lowest TCO was SCEO at R30 340 347.07, only R0.02 higher than TLBO, and 20.26 seconds slower at 62.38 seconds. The average time taken by optimisation algorithms was 39.83 seconds. TLBO had values of 163.33, 163.33, and 412.79 for the inverter, PV, and battery respectively. The fastest algorithm was Pattern Search at 5.23 seconds, while the slowest at 116.00 seconds was Firefly Algorithm.

Comparing the current method used, the TCO is R41 892 720.89. This is a difference of R11 551 773.84. The TCO has lower values with smaller differences when different optimisation techniques are used.

The most suitable optimisation method is TLBO, it has the solution of the lowest TCO, and is faster than the solutions close to it.

Table 71: System Overview Analysis of Example 7.

Lowest Net Cost System Architecture	**Inverter Size - 163.33VA** PV Size - **163.33VA** **Battery, SC, Capacity - 412.79kWh**
Annual Electric Bill	R8 936 968.36
Annual Electricity Cost with PV	R83 920.30
Projected Annual Savings	R164 878 219.73
Annual PV payment	R1 517 017.35
Discount Rate	3.94%
Inflation	Electricity – 2.7%. Maintenance – 3.7%. Battery – 3.34%
Projected TCO for 20 years	R30 340 347.05
Projected Electric Bill for 20 years	R3 327 904 741.67
Projected Lifetime Total 20 Saving	R3 297 564 394.62

The figures below show monthly data for the SCEO solution. The load can be seen in orange at the top, along with the LA and LI capacity. The SC capacity is on the bottom left, while the available PV is blue at the bottom, and around the available PV is the required energy from the grid-dependent on each type of storage. The change in PV available from January to June can be seen, along with the change of the grid requirement seen in both purple and green (LI and SC) respectively.

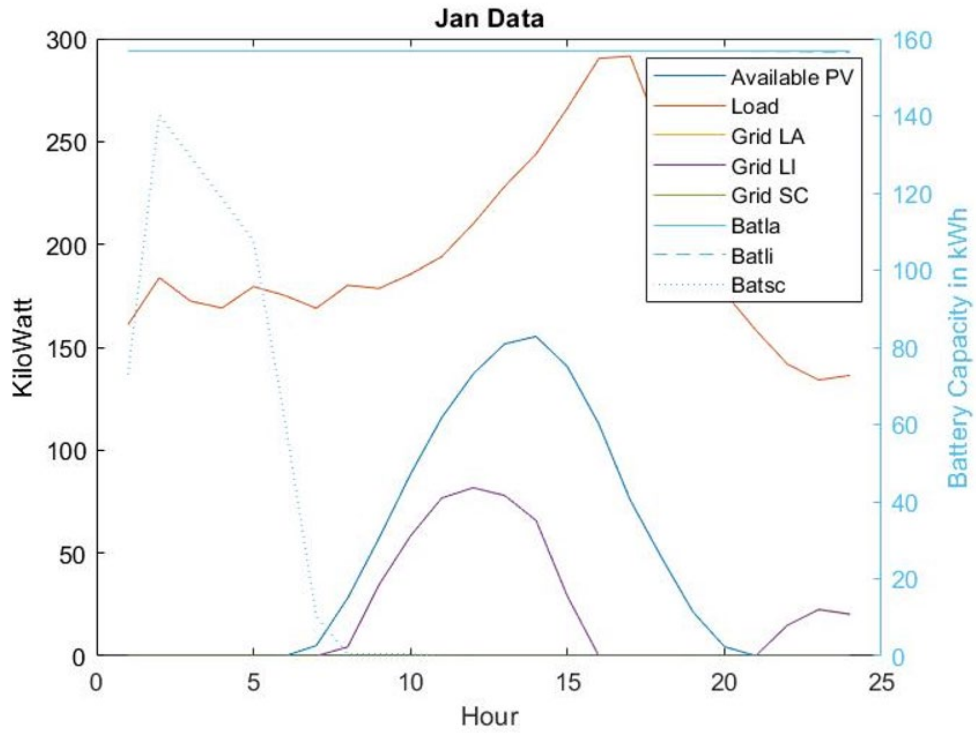

Figure 38: TLBO January Data for Example 7.

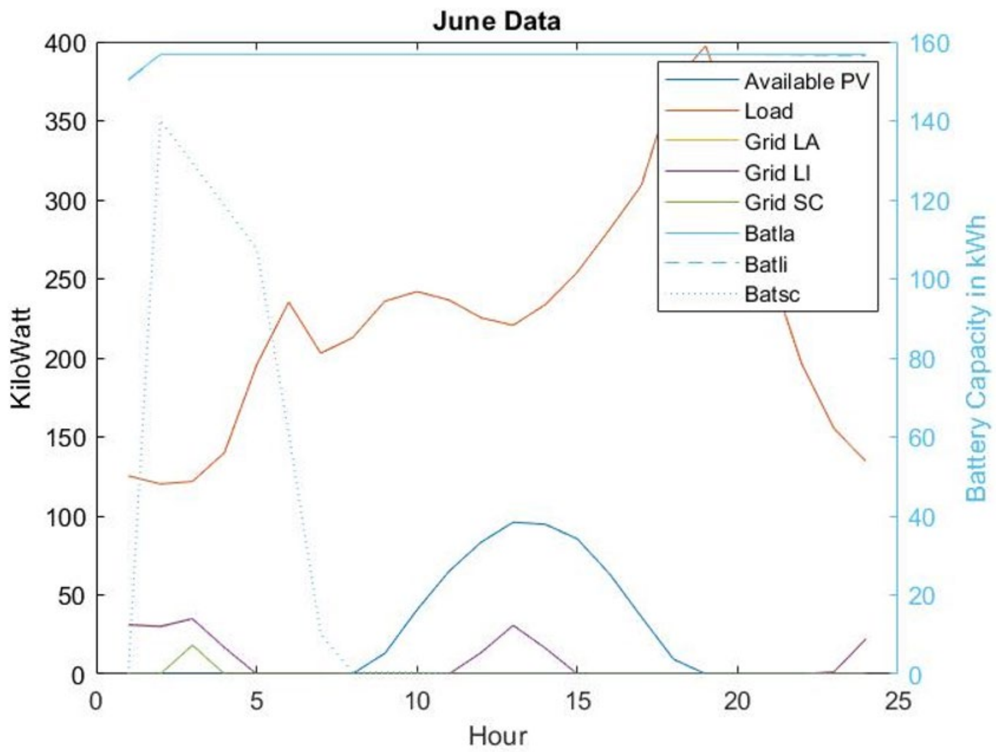

Figure 39: TLBO June Data for Example 7.

5.8 Summary of findings

Each of the examples showed that the integration of solar energy into a building would reduce the total value paid after twenty years. The savings of a building depend on the type of building, the load, choices of the inverter, solar panels, storage device, and the optimisation used.

The table below is a more detailed summary of the results of each example, and which optimization provided the fastest solution, and the lowest TCO.

Table 72: Summary of findings of examples.

	Findings
Example 1	The fastest algorithm was PS but this did not have the lowest TCO. The lowest TCO at R403 736 956 284.15 is obtained from PSO and SCEO. PSO took 74.00 seconds and SCEO took 68.25 seconds, a difference of 5.75. Comparing the current method used, the highest TCO. The most suitable optimisation method is SCEO.
Example 2	The fastest algorithm was Pattern Search at 9.03 seconds, while the slowest at 182.69 seconds was Firefly Algorithm. The lowest TCO was obtained from PSO, while Differential Evolution had the highest TCO. The most suitable optimisation method is PSO.
Example 3	The fastest algorithm was Pattern Search at 6.16 while the slowest algorithm was FA at 138.97 seconds. The lowest was obtained from PSO and Differential Evolution had the highest TCO. The TCO has lower values with smaller differences when different optimisation techniques are used. The difference in time between PSO and Pattern Search is 37.96, however, this does not justify the TCO difference, the most suitable optimisation method is PSO.
Example 4	The lowest TCO came from the SCEO, at 6.97 seconds, pattern search was the fastest yet third-highest TCO after GA and DE. It should also be noted there is a small difference between PSO and SCEO, the time taken for the optimisation algorithms PSO and SCEO to run to completion, is 44.33 and 64.98, a difference of 20.65 seconds. The most suitable optimisation method is PSO.
Example 5	The fastest algorithm was Pattern Search and the longest optimisation was FA. The lowest TCO was from TLBO the optimisation algorithm with the next lowest TCO being SCEO. The difference in TCO between TLBO and SCEO is R0.17.The most suitable optimisation method is TLBO as has the lowest TCO and was only 0.48 seconds above the average time taken by optimisation algorithms.
Example 6	Pattern Search algorithm was the fastest solution at 7.77. With the average optimisation time being 34.59 seconds, the slowest time of 117.93 belonging to FA, is 3.41 times the average. TLBO provided the lowest solution taking 38.58 seconds. The next best TCO at R19.36 higher than TLBO was SCEO at 63.29 seconds. While Pattern Search is the fastest optimisation, the difference in TCO is high and was therefore not considered a viable solution. TLBO was 3.06 times faster than the FA, and 24.71 seconds faster than SCEO.

Example 7	The lowest TCO was the solution of TLBO at 42.12 seconds. The average time taken by optimisation algorithms was 39.83 seconds. The fastest algorithm was Pattern Search at 5.23 seconds, while the slowest at 116.00 seconds was Firefly Algorithm.

Each of the different optimization algorithms has its benefits. The table below is a concise tabulation of the different methods of optimization used and the benefits and drawbacks of each of them. This information comes from the examples, and/ or from [110] to [111].

Table 73: A summary of the advantages and disadvantages of each optimisation algorithm used.

Algorithm	Advantages	Disadvantages
Iteration (Manual optimisation)	• Values chosen for inverter, PV, and battery are real.	• Increased room for error. • Time taken for a solution is long.
Particle Swarm	• Relatively fast to solution. • Simple algorithm. • High efficiency. • Robust, few parameters to adjust, and information interaction.	• Possible to find a local optimum. • Rate at which it converges to a solution is low.
Genetic Algorithm	• Relatively fast to solution. • Versatile – searches different options at the same time and thus reducing the chance of local optimum being found and minimises computations. • Self-learning, answer improves over time	• Possibility that an early optimisation is given. • Local optimum is possible. • Many parameters.
Pattern Search Optimisation	• Time to the solution is the fastest as compared to all other methods. • Accurate as mesh size is changed around the optimum point as iterations occur.	• A local minimum is possible if the incorrect initial points are chosen.
Surrogateopt	• Simple and flexible. • Efficient.	• Higher value TCO when compared to other optimisation techniques.
Paretosearch	• Optimisation that is a compromise of all values.	• Local optimum is possible.
Ant Colony Optimisation for Continuous Domains	• Robust. • Information interaction. • Group collaboration	• Randomisation of decisions. • Local optimum is possible.

Artificial Bee Colony	• High possibility of a global optimum.	• Possible to find a local optimum. • As the algorithm progresses, with each iteration it becomes slower.
Bee Algorithm	• High possibility of a global optimum.	• Local optimum is possible.
Biogeography Based	• Relatively fast. • Adaptive learning. • High accuracy.	• As the algorithm progresses, with each iteration it becomes slower.
Matrix Adaptation	• Effective in large-scale problems. • Simple implementation.	• Strongly dependent on the parameters chosen.
Differential Evolution	• Relatively fast. • Simple implementation. • Handles complex optimisation.	• Local optimum is possible.
Firefly Algorithm	• Easy to implement.	• Slowest time to solution compared to different optimisation methods used.
Harmony Search	• Second fastest algorithm after Pattern Search. • Effective for data clustering.	• May result in a lack of change in the optimum solution as the number of iterations approaches zero.
Real-Coded Simulated Annealing	• Effective in large-scale distribution problems. • An optimal solution is reached more easily as it avoids a local optimum. • Straightforward implementation.	• Slow to the solution. • Possible local optimum. • Low adaptability.
Shuffled Complex Evolution	• Use of different evolutionary algorithms. • Adaptation during optimisation.	• Relatively slow.
Invasive Weed Optimisation	• Fast to the solution. • Solutions come from previous solutions, weeds can come from other weeds.	• Early convergence to a solution.
Teaching-learning based Optimisation	• Provided the lowest TCO for smaller loads.	• Relatively slow.

The findings above provide answers to the research question, how to achieve financial optimization of a building's energy consumption. To achieve an optimised solar energy integration system optimisation before selecting PV panels and a battery should be done. The lowest TCO from algorithms differs based on the load, while the fastest algorithm to a solution was consistent, the Pattern Search algorithm. The optimised TCO does not size for peak power from solar panels.

How the companies and governments advise users to size a PV system to cater for the maximum load, referred to the current method, resulted in a higher TCO for all examples. Each case showed Firefly Algorithm to take the longest to find a solution, above the average time taken by other optimisation techniques. The fastest algorithm for all examples was Pattern Search. There was a variation of the lowest TCO solution, the lowest solution for industrial buildings derived from Particle Swarm Optimisation, while the lowest solution for commercial and residential buildings was the outcome of Teach-Learning Based Optimisation.

6 Chapter 6 – Conclusion & Recommendations

6.1 Conclusion

The content included in previous chapters displays the need for renewable integration, the benefits of storage of the energy produced, and how to optimise the energy usage using the total cost ownership equation. The TCO considers the cost of equipment, replacement after the end of life, and the cost of electricity. The code developed is similar to previous work as it includes integration of a renewable system with the current electricity grid. However, it adds value to the South African context as the code uses the latest tariffs available from eThekwini Municipality, considers various optimisation techniques, and incorporates the cost of electricity into the TCO. Definitive information to support the hypothesis was put forward below, along with recommendations of improvements for further studies below.

With the effects of climate change becoming more apparent, and with the necessity to work from home, the sustainability of buildings must be re-analysed. Due to COVID-19, many businesses, institutions, and governments have called for employees to work from their place of residence, or home. These extra hours, on average eight, contribute to higher electricity consumption, and in turn a higher cost of electricity.

The TCO information chapter details the TCO for each component: the PV panels, the inverter, the cables, the tariffs, the battery, and the SC. Each item has a separate TCO when considering an initial purchase, maintenance, and possible replacement. The TCO is comprehensive as the inflation rate and discount factor, interest rate, are both from December 2021. The growth annuity equation allowed for the successive annual maintenance cost to be calculated by the most correct rate as provided by STATS SA. The replacement calculations found in Objective Function section are specific to each storage system used and each year that each replacement would take place.

The examples showed that each building type uses a different optimisation method to return the lowest TCO. Particle Swarm Optimisation, when used for industrial buildings produced the lowest TCO. When smaller loads were considered, commercial buildings and residential housing, the lowest TCO came from Teaching-Learning Based Optimisation. In each case, the fastest and slowest optimisation technique was Pattern Search and Firefly Optimisation respectively.

The technicalities of the system where the battery charges, discharges and remains idle at times matching the appropriate tariff, proved to assist in the cost-saving. The maximisation of the available PV as a method of integration was proved to result in the highest TCO, answering one of the research questions. The answer to which algorithm provides the lowest TCO changed according to the size of the load, a larger load resulted in the PSO algorithm while a smaller load achieved the lowest TCO from TLBO. The fastest algorithm was PS and the slowest was FA.

The research question of how to achieve financial optimization of a building's energy consumption was answered. The lowest TCO algorithm and the fastest results algorithm were found. The optimised TCO does not size for peak power from the solar panels but rather used the storage when the price of electricity was high.

6.2 Recommendations

A few recommendations that would provide an advanced TCO are adjustments to the model itself. Further insight into the following areas can assist in producing a more accurate TCO: the installation cost, the possibility of a dual hybrid system, a battery cycle count, and a performance management report.

The installation of a PV system requires knowledge that includes the placement of panels to absorb the most light, the percentage loss of power from DC to AC, (generally 25%) and the maximum demand should be roughly 25% of the breaker size. These are general rules of thumb in the solar industry. However, research into the accuracy of this along with the additional cost of erection can be considered. The possibility of the inclusion of a second renewable source such as wind can be added to the model. This would prove interesting as the cost before wind installation, including maintenance – which is much higher for wind turbines, can be compared to the saving on electricity and the possibility of storing this energy can be analysed.

Further research may focus on the number of cycles for the changing of batteries over some time, as batteries currently require to be changed every five or ten years. A more precise method would be to count the number of cycles of charging and discharging the battery has gone through in its life span. A battery charge test could be done to confirm if the battery requires replacement or if it can continue in operation.

To effectively evaluate the performance of a building, benchmarks of performance must be compared against a building performance [112]. Performance techniques include monthly and annual comparisons, while hourly consumption comparisons also is an option. Design intent, comparison with other buildings, economic analysis of energy-efficient strategies, and long-term performance records, all assist in the measurement of a building's energy performance [112]. Additional benefits include the ability the detect performance trends, scheduling maintenance at the most appropriate time, building relevant, and the capacity to allow for increasing the use of renewable energy [112].

7 References

[1] GreenMatch, "How to Choose a Solar Panel," 2021. [Online]. Available: https://www.greenmatch.co.uk/blog/2014/08/how-to-choose-a-solar-panel. [Accessed 20 December 2021].

[2] Energy Matters, "HOW MANY SOLAR PANELS NEEDED TO POWER A HOME?," [Online]. Available: https://www.energymatters.com.au/residential-solar/home-solar-sizing/. [Accessed 20 December 2021].

[3] U.S. Department of Energy, "Planning a Home Solar Electric System," [Online]. Available: https://www.energy.gov/energysaver/planning-home-solar-electric-system.. [Accessed 20 December 2021].

[4] Unbound Solar, "How to Size a Solar System: Step-by-Step," Unbound Solar, 14 July 2020. [Online]. Available: https://unboundsolar.com/blog/how-to-size-solar-system#:~:text=To%20figure%20out%20how%20to,ll%20need%20for%20your%20system.. [Accessed 20 December 2021].

[5] The Sun Pays, "Solar System Sizing Tool & Calculator," [Online]. Available: https://shop.thesunpays.co.za/pages/solar-system-sizing-calculator. [Accessed 20 December 2021].

[6] SINETECH, "How to size a Professional PV Solar System," SINETECH, [Online]. Available: https://sinetechstore.co.za/knowledge-centre/how-to-size-a-professional-pv-solar-system/#. [Accessed 21 December 2021].

[7] Alternate Energy Tutorials , "How to Size a Solar Power System," Alternate Energy Tutorials , 2021. [Online]. Available: https://www.alternative-energy-tutorials.com/solar-power/how-to-size-a-solar-power-system.html. [Accessed 21 December 2021].

[8] Energy Maxx Solar, "How to determine the solar system size needed for a commercial building.," Energy Maxx Solar, 14 November 2019. [Online]. Available: https://maxx-solar-energy.co.za/6748/how-to-determine-the-solar-system-size-needed-for-a-commercial-building/. [Accessed 21 December 2021].

[9] P.Kanakasabapathy and B.Shyam, "Renewable Energy Utilization in India –Policies, opportunities and challenges," in *2017 IEEE International Conference on Technological Advancements in Power and Energy (TAP Energy)*, 2017.

[10] B. Kroposki and D. Mooney, "Electricity, Resources, and Building Systems Integration at the National Renewable Energy Laboratory," in *2009 IEEE Power & Energy Society General Meeting*, Calgary, AB, Canada, 2009.

[11] Z. Chen, Q. Liu, X. Xiao, N. Liu and X.Yan, "Integrated Mode And Key Issues Of Renewable Energy Sources And Electric Vehicles' Charging And Discharging Facilities In Microgrid," in *2nd IET Renewable Power Generation Conference (RPG 2013)*, Beijing, 2013.

[12] M. Taplamacıoğlu and H. Gözde, "Integration of Renewable Energy Sources into Turkey Electric Energy Network," in *2018 5th International Conference on Electrical and Electronics Engineering*, 2018.

[13] Z. Cabrane, M. Ouassid and M. Maaroufi, "Performance Analysis of Supercapacitor Integration in Photovoltaic Energy Storage System," in *2015 3rd International Renewable and Sustainable Energy Conference (IRSEC)*, Morocco, 2015.

[14] O. Ciftci, M. Mehrtash, F. Safdarian and A. Kargarian, "Chance-Constrained Microgrid Energy Management with Flexibility Constraints Provided by Battery Storage.," in *2019 IEEE Texas Power and Energy Conference (TPEC)*, USA, 2019.

[15] O. M. Longe, K. Ouahada, H. C. Ferreira and S. Chinnappen, "Renewable Energy Sources Microgrid Design for Rural Area in South Africa," in *ISGT 2014*, USA, 2014.

[16] I. Berry and J. Heinzmann, "Economics of Energy Storage for Dispatchable Solar," in *2016 IEEE Power and Energy Society General Meeting (PESGM)*, Boston, MA, USA, 2016.

[17] T.A.Main and K.A.Folly, "Effects of Tariffs and Energy Saving Schemes on Domestic Households Energy Consumption," in *2013 Africon*, Pointe aux Piments, Mauritius, 2013.

[18] F. Kadda, S. Zougar, M. E. Hafyani and A. Rabhi, "Contribution to the optimization of the electrical energy production from a Hybrid Renewable Energy system," in *2014 5th International Renewable Energy Congress (IREC)*, Hammamet, Tunisia, 2014.

[19] C. Keles, B. B. Alagos and A. Kaygusuz, "Multi-source energy mixing for renewable energy microgrids by particle swarm optimization," in *2017 International Artificial Intelligence and Data Processing Symposium (IDAP)*, Malatya, Turkey, 2017.

[20] N. K. Paliwal, R. Mohanani, N. K. Singh and A. K. Singh, "Demand side energy management in hybrid microgrid system using heuristic techniques," in *2016 IEEE International Conference on Industrial Technology (ICIT)*, Taipei, Taiwan, 2016.

[21] B. A. Thango, J. A. Jordaan and A. F. nnachi, "Total Ownership Cost Evaluation for Transformers within Solar Power Plants," in *2020 6th IEEE International Energy Conference (ENERGYCon)*, Gammarth, Tunisia, 2020.

[22] W. Commerell, R. Müller and V. Shanmuganandam, "Life time costs in solar home systems," in *2014 3rd International Conference on the Developments in Renewable Energy Technology (ICDRET)*, Dhaka, Bangladesh, 2014.

[23] J. S. Goud, S. Tunga, Q. Sultana and S. Bindu, "Li-ion based optimally sized grid interfaced roof top PV system," in *2016 3rd International Conference on Electrical Energy Systems (ICEES)*, Chennai, India, 2016.

[24] J. Venkatesh, S. Chen, P. Tinnakornsrisuphap and T. S. Rosing, "Lifetime-dependent battery usage optimization for grid-connected residential systems," in *2015 Workshop on Modeling and Simulation of Cyber-Physical Energy Systems (MSCPES)*, Seattle, WA, USA, 2015.

[25] R. Jean-Luc, F. Gonon, L. Favre and E.-L. Niederhäuser, "Convergence of Multi-Criteria Optimization of a Building Energetic Resources by Genetic Algorithm," in *2018 International Conference on Smart Grid and Clean Energy Technologies (ICSGCE)*, Kajang, Malyasia, 2018.

[26] E. Tsioumas, D. Papagiannis, M. Koseoglou, N. Jabbour and C. Mademlis, "An Effective Methodology for the Optimal Sizing of the Renewable Energy Sources and Energy Storage System in a Nearly Zero Energy Building," in *2020 International Conference on Smart Grid and Clean Energy Technologies (ICSGCE)*, Kuching, Malaysia, 2020.

[27] D. Madathil, V. R. Pandi, K. Ilango and M. G. Nair, "Differential evolution based energy management system for zero net energy building," in *2017 International Conference on Technological Advancements in Power and Energy (TAP Energy)*, Kallam, India, 2017.

[28] V. Ten, D. Sharipova and V. Nikulin, "Approach to control of hybrid renewable power system on the basis of adaptive control with local parametric optimization," in *2014 International Conference on Renewable Energy Research and Application (ICRERA)*, Milwaukee, WI, USA, 2014.

[29] M. Fiorelli, E. R. Sanseverino, F. Massaro, S. Favuzza, M. Ippolito and G.Zizzo, "The energy market impact of climate change on electricity generation in Europe," in *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, Palermo, Italy, 2018.

[30] S. Ramirez-Sandi and J. Quiros-Tortos, "Evaluating the Effects of Climate Change on the Electricity Demand of Distribution Networks," in *2018 IEEE PES Transmission & Distribution Conference and Exhibition - Latin America (T&D-LA)*, Lima, Peru, 2018.

[31] "NASA - Global Climate Change," 3 May 2019. [Online]. Available: https://climate.nasa.gov/. [Accessed 4 MAy 2019].

[32] "Union of Concerned Scientists," 17 November 2016. [Online]. Available: https://www.ucsusa.org/global-warming/science-and-impacts/science/temperature-is-rising. [Accessed 05 May 2019].

[33] C. Media, "Engineering News," 09 January 2019. [Online]. Available: https://www.engineeringnews.co.za/article/africas-increasing-demand-for-energy-2019-01-09/rep_id:4136. [Accessed 05 May 2019].

[34] P.Kanakasabapathy and B.Shyam, "Renewable Energy Utilization in India –Policies, opportunities and challenges," in *2017 IEEE International Conference on Technological Advancements in Power and Energy (TAP Energy)*, 2017.

[35] B.Kroposki and D. Mooney, "Electricity, Resources, and Building Systems Integration at the National Renewable Energy Laboratory," in *2009 IEEE Power & Energy Society General Meeting*, Calgary, AB, Canada, 2009.

[36] M. Attia, N. Haidar, S. M. Senouci and E. Aglzim, "Towards an Efficient Energy Management to Reduce CO2 Emissions and Billing Cost in Smart Buildings," in *15th IEEE Annual Consumer Communication & Networking Conferencing (CCNC)*, 2015.

[37] Arena, "Arenawire," 15 March 2018. [Online]. Available: https://arena.gov.au/blog/distributed-energy-resources/. [Accessed 27 April 2019].

[38] Irena, "IRENA - International Renewable Energy Agency," October 2017. [Online]. Available: https://www.irena.org/publications/2017/Oct/Electricity-storage-and-renewables-costs-and-markets. [Accessed 05 July 2020].

[39] A. Shahid, "Smart Grid Integration of Renewable Energy Systems," in *7th International Conference on Renewable Energy Research and Applications*, Paris, 2018.

[40] P. S. Sauter, B. V. Solanki, C. A. Cañizares, K. Bhattacharya and S. Hohmann, "Electric Thermal Storage System Impact on Northern Communities' Microgrids," *IEEE TRANSACTIONS ON SMART GRID,* vol. 10, no. 1, pp. 852-863, 2019.

[41] A. Nakaruk, C. Sorrell, T. Palmer and L. Bowen, "Solar-Thermal Energy Conversion and Storage: Conductive Heat Transfer Using Bulk Graphite," in *2009 IEEE International Conference on Applied Superconductivity and Electromagnetic Devices*, Chengdu, China, 2009.

[42] Y. Fang, S. Zhao and Z. Li, "Concentrating Solar Power Station Optimal Operation Model," in *2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2)*, Beijing, China, 2018.

[43] M. Brain, C. W. Bryant and C. Pumphrey, "HowStuffWorks," [Online]. Available: https://electronics.howstuffworks.com/everyday-tech/battery3.htm. [Accessed 2019 July 06].

[44] Battery University, "Battery University," 28 March 2019. [Online]. Available: https://batteryuniversity.com/learn/article/comparing_the_battery_with_other_power_sources. [Accessed 15 November 2020].

[45] J. Marsh, "Energy Sage," 10 January 2019. [Online]. Available: https://news.energysage.com/lithium-ion-vs-lead-acid-batteries/. [Accessed 06 January 2020].

[46] J. Svarc, "Clean Energy Reviews," 28 November 2019. [Online]. Available: https://www.cleanenergyreviews.info/blog/simpliphi-pylontech-narada-bae-lead-acid-battery. [Accessed 06 January 2021].

[47] M. B. &. C. W.Bryant, "How Capacitors Work," HowStuffWorks, [Online]. Available: https://electronics.howstuffworks.com/capacitor.htm. [Accessed 2019 July 06].

[48] P. Svasta, R. Negroiu and A. Vasile, "Supercapacitors - an Alternative Electrical Energy Storage device," in *2017 5th International Symposium on Electrical and Electronics Engineering (ISEEE)*, Romania, 2017.

[49] A. Perera, J.-L. Scartezzini and N.A.Iliadis, "Multi-Stage Integration of Renewable Energy Technologies into Standalone Energy Systems," in *2018 5th International Symposium on Environment-Friendly Energies and Applications (EFEA)*, Rome, Italy, 2018.

[50] A. Lombard and S. L. Ferreira, "The spatial distribution of renewable energy infrastructure in three particular provinces of South Africa," *BULLETIN OF GEOGRAPHY. SOCIO–ECONOMIC SERIES,* vol. 1, no. 30, pp. 71-85, 2015.

[51] A. E. &. T. Kåberger, "Renewable energy auctions in South Africa outshine feed-in," *Energy Science & Engineering,* vol. 4, no. 3, pp. 190-193, 2016.

[52] A. Arif, Z. Wang, J. Wang, B. Mather, H. Bashualdo and D. Zhao, "Load Modeling - A Review," *IEEE,* vol. 9, no. 6, 2018.

[53] S. Lande, Prof.S.P.Ghanegaonkar and D. N. G. &. Dr.V.N.Pande, "Dynamic load model and its incorporation in MATLAB based Voltage Stability Toolbox," in *17th Power Systems Computation Conference* , Stockholm, 2001.

[54] M. Rosen, "SA businesses are on the back foot thanks to load shedding. Is there a way out?," 31 January 2020. [Online]. Available: news24.com/citypress/voices/sa-businesses-are-on-the-back-foot-thanks-to-load-shedding-is-there-a-way-out-20200131. [Accessed 01 June 2021].

[55] A. Thackrah, "Exxaro seeks NUM wage resolution," 13 October 2020. [Online]. Available: https://www.argusmedia.com/en/news/2149627-exxaro-seeks-num-wage-resolution. [Accessed 01 June 2019].

[56] P. Bremen, J. Oehmen and R. Alard, "Cost-transparent Sourcing in China Applying Total Cost of Ownership," in *2007 IEEE International Conference on Industrial Engineering and Engineering Management*, Singapore, 2007.

[57] R. Ritsma, A. Tuyl and B. Snijders, "Buying The Lowest Total Cost of Ownership (TCO).," in *2009 Conference Record PCIC Europe*, Barcelona, Spain, 2009.

[58] W. Commerell, R. Müller and V. Shanmuganandam, "Life Time Costs in Solar Home Systems," in *IEEE*, 2014.

[59] Circuit Globe, "Circuit Globe," [Online]. Available: https://circuitglobe.com/electricity-tariffs.html. [Accessed 03 October 2020].

[60] S. Jiang, "Total Cost of Ownership Analysis between D.G, Hybrid and Solar Energy Power Supply Systems for BTS," in *Intelec 2013; 35th International Telecommunications Energy Conference, SMART POWER AND EFFICIENCY*, Berlin, 2013.

[61] D. C. Jordan and S. R. Kurtz, "Photovoltaic Degradation Rates — An Analytical Review," *Progress in Photovoltaics Research and Applications,* vol. 21, no. 1, 2012.

[62] B. Nehme, N. K. M'Sirdi and T. Akiki, "Investigating a New Operating Point For PV Panels Seeking Maximum Life Span," in *2017 IEEE 44th Photovoltaic Specialist Conference (PVSC)*, Washington, DC, USA, 2017.

[63] Ilumen, "Ilumen - What is the lifetime of an inverter?," 2019. [Online]. Available: https://www.ilumen.be/en/what-is-the-lifetime-of-an-inverter/. [Accessed 09 November 2019].

[64] G. Notton, V. Lazarov and L. Stoyanov, "Optimal sizing of a grid-connected PV system for various PV module technologies and inclinations, inverter efficiency characteristics and locations," *Reneable Energy,* vol. 35, no. 2, pp. 541-554, 2009.

[65] M. Fedkin and J. A. Dutton, "Utility Solar Power and Concentration," Penn State, [Online]. Available: https://www.e-education.psu.edu/eme812/node/738. [Accessed 28 October 2021].

[66] J. M. Serrano, "University of Cantabria - ENERGY AND TELECOMMUNICATIONS," 2018. [Online]. Available: https://ocw.unican.es/pluginfile.php/193/course/section/97/EyT-LectureNotes-1718-C2-Solar.pdf. [Accessed 28 October 2021].

[67] Ethekwini Municipality, "Ethekwini Municipality," [Online]. Available: http://www.durban.gov.za/City_Services/electricity/Tariffs/Pages/default.aspx. [Accessed 01 December 2021].

[68] I. Chotia and S. Chowdhury, "Battery Storage and Hybrid Battery Supercapacitor," in *2015 IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA)*, Bangkok, Thailand, 2015.

[69] K. Stenhouse, J. Jenden, B. Afework and J. Donev, "Energy density vs power density," Energy Education, 04 January 2019. [Online]. Available: https://energyeducation.ca/encyclopedia/Energy_density_vs_power_density#:~:text=Energy%20density%20is%20the%20amount,power%20in%20a%20given%20mass.&text=This%20difference%20comes%20from%20batteries,give%20off%20energy%20more%20quickly.. [Accessed 23 June 2020].

[70] P. Wang, L. Zhang and D. Xu, "Optimal Sizing of Distributed Generations in DC Microgrids with Lifespan Estimated Model of Bateries," in *KIEE Electrical Machinery and Energy Conversion Systems*, Jeju, Korea, 2018.

[71] M. Lam, "Medium.com," medium, [Online]. Available: https://medium.com/battery-lab/what-is-dod-for-lifepo4-batteries-335f1dbc9d3d. [Accessed 23 July 2020].

[72] Weibull.com, "Weibull.com - Reliability Engineering Resources, Miner's Rule and Cumulative Damage Models," [Online]. Available: https://www.weibull.com/hotwire/issue116/hottopics116.htm. [Accessed 11 November 2019].

[73] A. Feinberg and A. Widom, "Thermodynamic Extensions of Miner's Rule to Chemical Cells," in *Annual Reliability and Maintainability Symposium. 2000 Proceedings.*

International Symposium on Product Quality and Integrity (Cat. No.00CH37055), Los Angeles, CA, USA, 2000.

[74] Solar Choice, "Solar Choice," 23 May 2017. [Online]. Available: https://www.solarchoice.net.au/blog/levelised-cost-of-storage-compare-battery-value. [Accessed 23 July 2020].

[75] M. Fahmi, R. Rajkumar, R. Arelhi, R. Rajkumar and D. Isa, "The Performance of a Solar PV System Using Supercapacitor and Varying Loads," in *2014 IEEE Student Conference on Research and Development*, Penang, Malaysia, 2014.

[76] A. Pareek, P. Singh and P. Rao, "Analysis and Comparison of Charging Time between Battery and Supercapacitor for 300W Stand-Alone PV System," in *2018 International Conference on Current Trends towards Converging Technologies (ICCTCT)*, Coimbatore, India, 2017.

[77] Trading Economics, "Trading Economics," 2020. [Online]. Available: https://tradingeconomics.com/south-africa/deposit-interest-rate. [Accessed 26 January 2021].

[78] D. Hillier, M. Grinblatt and S. Titman, Financial Markets and Coporate Strategy, Berkshire: McGraw-Hill, 2008.

[79] Stats SA, "Stats SA," 20 January 2021. [Online]. Available: http://www.statssa.gov.za/?page_id=1854&PPN=P0141. [Accessed 26 January 2021].

[80] RJO Futures, "RJO Futures," 2017. [Online]. Available: https://rjofutures.rjobrien.com/learning-center/general-trading/durable-vs-non-durable-goods-whats-the-difference. [Accessed 26 01 2021].

[81] Power From Sunlight, "Power From Sunlight," 21 June 201. [Online]. Available: https://www.powerfromsunlight.com/operational-costs-solar-panel-system/. [Accessed 26 January 2021].

[82] Sustainable.co.za, "sustainable.co.za," January 2021. [Online]. Available: https://www.sustainable.co.za/solar-power/inverters/grid-tied-inverters.html?p=1. [Accessed 09 January 2021].

[83] Digi-Key, "Digi-Key," January 2021. [Online]. Available: https://www.digikey.co.za/products/en/capacitors/electric-double-layer-capacitors-edlc-supercapacitors/61?k=&pkeyword=&sv=0&pv2079=u12V&sf=0&FV=-8%7C61&quantity=&ColumnSort=0&page=1&pageSize=25. [Accessed 09 January 2021].

[84] GWstore, "GWstore: Renewable Energy Solutions," 2021. [Online]. Available: https://gwstore.co.za/product-category/solar-batteries-general-purpose-batteries/supercapacitor-batteries/. [Accessed 22 July 2021].

[85] SOLA, "SOLA," [Online]. Available: https://solagroup.co.za/news/south-africas-solar-resource-compared-to-the-rest-of-the-world/. [Accessed 04 January 2022].

[86] F. A. Khan, N. Pal and S. H. Saeed, "Review of solar photovoltaic and wind hybrid energy systems for sizing strategies optimization techniques and cost analysis methodologies," *Renewables and Sustainable Energy Reviews,* vol. 92, pp. 937-947, 2018.

[87] W. Kellogg, M. Nehrir, G. Venkataramanan and V. Gerez, "Generation unit sizing and cost analysis for stand-alone wind, photovoltaic, and hybrid wind/pv systems," *IEEE Transactions on Energy Conversion,* vol. 13, no. 1, pp. 70 - 75, 1998.

[88] Airbrake, "Airbrake," 15 December 2016. [Online]. Available: https://airbrake.io/blog/sdlc/iterative-model. [Accessed 11 November 2020].

[89] EDUCBA, "EDUCBA," [Online]. Available: https://www.educba.com/iterative-methodology/. [Accessed 01 November 2020].

[90] B. Seixas, G. d. Almeida and V. C. Leite, "Particle Swarm Optimization: A Powerful Technique for Solving Engineering Problems," in *Swarm Intelligence - Recent Advances, New Perspectives and Applications*, London, United Kingdom, IntechOpen, 2019, p. Chapter 2.

[91] R. Hassan, B. Cohanim, O. d. Weck and G. Venter, "A comparison of particle swarm optimization and the genetic algorithm," in *46th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics & Materials Conference* , Austin, Texas, 2004.

[92] S. Shabir and D. R. Singla, "A Comparative Study of Genetic Algorithm and the Particle Swarm Optimization," *International Journal of Electrical Engineering,* vol. 9, pp. 215-223, 2016.

[93] Mathworks, "Global Optimization Toolbox," [Online]. Available: https://uk.mathworks.com/help/gads/index.html?s_tid=CRUX_lftnav. [Accessed 31 December 2021].

[94] X.-S. Yang and M. Karamanoglu, "Chapter 1 - Nature-inspired computation and swarm intelligence: a state-of-the-art overview," in *Nature-Inspired Computation and Swarm Intelligence: Algorithms, Theory and Applications*, London, Academic Press, 2020, pp. 3-18.

[95] B. S. Chaudhari and M. Zennaro, LPWAN Technologies for IoT and M2M Applications, Elsevier, 2020.

[96] P. Kumar, Y. Kumar and M. A.Tawhid, Machine Learning, Big Data, and IoT for Medical Informatics, Elsevier, 2021.

[97] B. Yuce, M. S. Packianather, E. Mastrocinque, D. T. Pham and A. Lambiase, "Honey Bees Inspired Optimization Method: The Bees Algorithm," *Insects,* vol. 4, no. 4, pp. 646-662, 2013.

[98] D. Simon, "Biogeography-Based Optimization," *IEEE Transactions on Evolutionary Computation,* vol. 12, no. 6, pp. 702-713, 2008.

[99] N. Hansen and A. Ostermeier, "Completely Derandomized Self-Adaptation in Evolution Strategies," *Evolutionary Computation,* vol. 9, no. 2, pp. 159-195, 2001.

[100] M. K. Heris, "Yarpiz," 2015. [Online]. Available: https://yarpiz.com/category/metaheuristics/page/2. [Accessed 31 December 2021].

[101] X.-S. Yang, "Multiobjective Firefly Algorithm for Continuous Optimization. Engineering with Computers," *Engineering with Computers volume,* vol. 29, no. 2, pp. 175-184, 2013.

[102] N. F. Johari, A. M. Zain, N. Mustaffa and A. Udin, "Firefly Algorithm for Optimization Problem," *Applied Mechanics and Materials,* vol. 421, pp. 512-517, 2013.

[103] X. Z. Gao, V. Govindasamy, H. Xu, X. Wang and K. Zenger, "Harmony Search Method: Theory and Applications," *Computational Intelligence and Neuroscience,* vol. 2015, 2015.

[104] Q. Y. Duan, V. K. Gupta and S. Sorooshian, "Shuffled complex evolution approach for effective and efficient global minimization," *Journal of Optimization Theory and Applications,* vol. 76, no. 3, pp. 501-521, 1993.

[105] O. B. Nezhad, M. Najarchi, M. M. NajafiZadeh and S. M. M. Hezaveh, "Developing a shuffled complex evolution algorithm using a differential evolution algorithm for

optimizing hydropower reservoir systems," *Water Supply,* vol. 18, no. 3, pp. 1081-1092, 2018.

[106] A.R.Mehrabian and C.Lucas, "A novel numerical optimization algorithm inspired from weed colonization," *Ecological Informatics,* vol. 1, no. 4, pp. 355-366, 2006.

[107] M. Misaghi and M. Yaghoobi, "Improved invasive weed optimization algorithm (IWO) based on chaos theory for optimal design of PID controller," *Journal of Computational Design and Engineering,* vol. 6, no. 3, pp. 284-295, 2019.

[108] R.V.Rao, V.J.Savsani and D.P.Vakharia, "Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems," *Computer-Aided Design,* vol. 43, no. 3, pp. 303-315, 2011.

[109] GeeksforGeeks, "Teaching Learning based Optimization (TLBO)," 12 April 2021. [Online]. Available: https://www.geeksforgeeks.org/teaching-learning-based-optimization-tlbo/. [Accessed 31 December 2021].

[110] K. Y. Lee and M. A. El-Sharkaw, "Preface," in *Modern Heuristic Optimization Techniques*, New Jersey, Institute of Electrical and Electronics Engineers, 2008.

[111] M. Ahangaran and P. Ramezani, "Harmony Search Algorithm: Strengths and Weaknesses," *Journal of Computer Engineering & Information Technology,* vol. 1, no. 2, 2013.

[112] D. Barley, M. Deru, S. Pless and P. Torcellini, "Procedure for Measuring and Reporting Commercial Building Energy Performance," NREL - operated by Midwest Research Institute , Kansas, 2005.

[113] E. Drury, T. Jenkin, D. Jordan and R. Margolis, "Photovoltaic Investment Risk and Uncertainty for Residential Customers," *IEEE JOURNAL OF PHOTOVOLTAICS,* vol. 4, no. 1, pp. 278 - 284, 2014.

[114] GreenMatch, "Green Match - Cleaning and Maintenance Tips for Solar Panels," 01 April 2019. [Online]. Available: https://www.greenmatch.co.uk/blog/2016/04/cleaning-and-maintenance-tips-for-solar-panels. [Accessed 09 November 2019].

[115] S. Fezai and J. Belhadj, "Sizing optimization of a stand-alone photovoltaic system using genetic algorithm," in *18th international conference on Sciences and Techniques of Automatic control & computer engineering - STA'2017*, Monastir, Tunisia, 2017.

[116] S. Ramirez-Sandi and J. Quiros-Tortos, "Evaluating the Effects of Climate Change on the Electricity Demand of Distribution Networks," 2018.

[117] M. Brain and C. W. &. C. Pumphrey, "HowStuffWorks," [Online]. Available: https://electronics.howstuffworks.com/everyday-tech/battery3.htm. [Accessed 2019 July 06].

[118] J. Byrne, D. Johnson, L. Spencer, B. Brown, P. Hazendonk and J. Scott, "Multi-criteria PSO-based optimal design of grid-connected hybrid renewable energy systems," *International Journal of Green Energy,* vol. 17, no. 11, pp. 617-631, 2020.

[119] A. Arya, M. Ahmad and S. Anand, "Online Monitoring of Power Extraction Efficiency for Minimizing Payback Period of Solar PV System," in *2015 IEEE International Conference on Industrial Technology (ICIT)*, India, 2015.

[120] V.-H. Dang, N. A. Vien and T. CHung, "A covariance matrix adaptation evolution strategy in reproducing kernel Hilbert space," *Genetic Programming and Evolvable Machines volume ,* pp. 479-501, 2019.

[121] H. Tsai and T. Chen, "Enhancing the Sustainability of a Location-Aware Service through Optimization," *Sustainability,* vol. 12, no. 6, pp. 9441-9455, 2014.

[122] D. Zhang, X. You, S. Liu and H. Pan, "Dynamic Multi-Role Adaptive Collaborative Ant Colony Optimization for Robot Path Planning," *IEEE Access,* vol. 8, pp. 1299558-129974, 2016.

8 Appendix A

This is a part of the MATLAB code developed.

Below is charging and discharging loop for the batteries and SC.

```
C_bat = x(3) * 100;             % Total Capacity Wh from kWh
   h_peak = zeros(24, 1);
   h_peak(6:10)=1;
   h_peak(17:20)=1;
   h_off = zeros(24, 1);
   h_off(1:5)=1;
   h_off(11:16)=1;               %This accounts for solar charging
   h_off(21:24)=1;
   n_ac = 0.85;                 % Inverter efficiency
   n_chla = 0.8;                % Charge efficiency for LA
   n_disla = 0.8;               % Discharge efficiency for LA
   n_chli = 0.95;               % Charge efficiency for Li-ion
   n_disli = 0.95;              % Discharge efficiency for Li-ion
   n_chsc = 0.9;                % Charge efficiency for SC
   n_dissc = 0.9;               % Discharge efficiency for SC
   SOCminla = 0.55;                % State of charge min for LA
   SOCminli = 0.20;                % SOC min for Li-ion
   SOCminsc = 0.015;
   SOCmax = 1.00;                  % State of charge max
   V = 12;                     % Nominal battery voltage
   P_inv = x(1);                  % Inverter size (kVA) (max discharge power)
   P_con = 0.33*P_inv;               % Charge power (kVA)
   selfdisla = 0.0017;            % Self discharge of 5% permonth, lead acid (5/100/30)
   selfdisli = 0.0033;            % Self discharge of 10% permonth, li-ion (10/100/30)
   selfdissc = 0.0167;            % Self discharge of 50% permonth, li-ion (50/100/30)
   P_bat = 0;
   Q_bat = 0;
   SOC_batla = [];
   SOC_batli = [];
   SOC_batsc = [];
   SOC_sc = [];
   SOC_bat = 0.8*SOCmax;             % 20%, 50% or 80%
   loadpvdiff = sum(sum(load)) - sum(sum(solarpv));


   %Battery loop
   %Discharge loop fo LA
   for h = 1:size(h_peak)
      h_peak1 = h_peak(h);
      if h_peak1 == 1   %SOC_bat = 0.5 - SOC_bat; %initial SOC
         if SOC_bat > SOCminla %discharging
            P_bat = min(P_inv,(SOC_bat-SOCminla)*C_bat);
            P_bat = (SOC_bat-SOCminla)*C_bat;
            Q_bat = 0;
```

```
            P_dc = n_ac*P_bat;
            SOC_bat = SOC_bat - selfdisla- P_dc*n_disla/C_bat;
            if SOC_bat < loadpvdiff
               SOC_bat = SOC_bat;
            else
               SOC_bat = 0;
            end
            SOC_batla = [SOC_bat, SOC_batla];
         else
            SOC_bat = SOC_bat;
            SOC_batla = [SOC_bat, SOC_batla];
         end
      else
         if SOC_bat < SOCmax   %charging
            P_bat = -min(P_inv,(SOCmax-SOC_bat)*C_bat);
            P_dc = -n_ac*P_bat;
            SOC_bat = SOC_bat - selfdisla + n_chla*P_dc/C_bat;
            SOC_batla = [SOC_bat, SOC_batla];
         else
            SOC_bat = SOC_bat
            SOC_batla = [SOC_bat, SOC_batla];
         end
      end
   end

   %Discharge loop fo Li-ion
   for h = 1:size(h_peak)
      h_peak1 = h_peak(h);
      if h_peak1 == 1  %SOC_bat = 0.5 - SOC_bat; %initial SOC
         if SOC_bat > SOCminli
            P_bat = min(P_inv,(SOC_bat-SOCminli)*C_bat);
            P_bat = (SOC_bat-SOCminli)*C_bat;
            Q_bat = 0;
            P_dc = n_ac*P_bat;
            SOC_bat = SOC_bat - selfdisli- P_dc*n_disli/C_bat;
            if SOC_bat < loadpvdiff
               SOC_bat = SOC_bat;
            else
               SOC_bat = 0;
            end
            SOC_batli = [SOC_bat, SOC_batli];
         else
            SOC_bat = SOC_bat;
            SOC_batli = [SOC_bat, SOC_batli];
         end
      else
         if SOC_bat < SOCmax
            P_bat = -min(P_inv,(SOCmax-SOC_bat)*C_bat);
            P_dc = -n_ac*P_bat;
            SOC_bat = SOC_bat- selfdisli + n_chli*P_dc/C_bat;
```

```
            SOC_batli = [SOC_bat, SOC_batli];
        else
            SOC_bat = SOC_bat;
            SOC_batli = [SOC_bat, SOC_batli];
        end
    end
end

%Discharge Loop for SC
for h = 1:size(h_peak)
    h_peak1 = h_peak(h);
    if h_peak1 == 1  %SOC_bat = 0.5 - SOC_bat; %initial SOC
        if SOC_bat > SOCminsc
            P_bat = min(P_inv,(SOC_bat-SOCminsc)*C_bat);
            P_bat = (SOC_bat-SOCminsc)*C_bat;
            Q_bat = 0;
            P_dc = n_ac*P_bat;
            SOC_bat = SOC_bat - selfdissc- P_dc*n_dissc/C_bat;
            if SOC_bat < loadpvdiff
                SOC_bat = SOC_bat;
            else
                SOC_bat = 0;
            end
            SOC_batsc = [SOC_bat, SOC_batsc];
        else
            SOC_bat = SOC_bat;
            SOC_batsc = [SOC_bat, SOC_batsc];
        end
    else
        if SOC_bat < SOCmax
            P_bat = -min(P_inv,(SOCmax-SOC_bat)*C_bat);
            P_dc = -n_ac*P_bat;
            SOC_bat = SOC_bat- selfdissc + n_chsc*P_dc/C_bat;
            SOC_batsc = [SOC_bat, SOC_batsc];
        else
            SOC_bat = SOC_bat;
            SOC_batsc = [SOC_bat, SOC_batsc];
        end
    end
end
```

9 Appendix B

Below is another part of the code developed that determines the tariffs and tariff associated costs.

```
for n = 1:12
    if buildingtype == 1
        hours=
        [00.00,opres;01.00,opres;02.00,opres;03.00,opres;04.00,opres;05.00,opres;06.00,stres;
        07.00,pkres;08.00,pkres;09.00,pkres;10.00,stres;11.00,stres;12.00,stres;13.00,stres;14.
        00,stres;15.00,stres;16.00,stres;17.00,stres;18.00,pkres;19.00,pkres;20.00,stres;21.00,s
        tres;22.00,opres;23.00,opres];
        cost = (hours(:,2));
        costlow = (hours(:,2));
    elseif buildingtype == 2
        hours=
        [00.00,opcomhi;01.00,opcomhi;02.00,opcomhi;03.00,opcomhi;04.00,opcomhi;05.00,
        opcomhi;06.00,stcomhi;07.00,pkcomhi;08.00,pkcomhi;09.00,pkcomhi;10.00,stcomhi;
        11.00,stcomhi;12.00,stcomhi;13.00,stcomhi;14.00,stcomhi;15.00,stcomhi;16.00,stco
        mhi;17.00,stcomhi;18.00,pkcomhi;19.00,pkcomhi;20.00,stcomhi;21.00,stcomhi;22.00
        ,opcomhi;23.00,opcomhi];
        hourslow=
        [00.00,opcomlow;01.00,opcomlow;02.00,opcomlow;03.00,opcomlow;04.00,opcomlo
        w;05.00,opcomlow;06.00,stcomlow;07.00,pkcomlow;08.00,pkcomlow;09.00,pkcoml
        ow;10.00,stcomlow;11.00,stcomlow;12.00,stcomlow;13.00,stcomlow;14.00,stcomlow
        ;15.00,stcomlow;16.00,stcomlow;17.00,stcomlow;18.00,pkcomlow;19.00,pkcomlow;
        20.00,stcomlow;21.00,stcomlow;22.00,opcomlow;23.00,opcomlow];
        cost = (hours(:,2));
        costlow = (hourslow(:,2));
    else
        hours=
        [00.00,opinhi;01.00,opinhi;02.00,opinhi;03.00,opinhi;04.00,opinhi;05.00,opinhi;06.00
        ,stinhi;07.00,pkinhi;08.00,pkinhi;09.00,pkinhi;10.00,stinhi;11.00,stinhi;12.00,stinhi;1
        3.00,stinhi;14.00,stinhi;15.00,stinhi;16.00,stinhi;17.00,stinhi;18.00,pkinhi;19.00,pkin
        hi;20.00,stinhi;21.00,stinhi;22.00,opinhi;23.00,opinhi];
        hourslow=
        [00.00,opinlow;01.00,opinlow;02.00,opinlow;03.00,opinlow;04.00,opinlow;05.00,opi
        nlow;06.00,stinlow;07.00,pkinlow;08.00,pkinlow;09.00,pkinlow;10.00,stinlow;11.00,
        stinlow;12.00,stinlow;13.00,stinlow;14.00,stinlow;15.00,stinlow;16.00,stinlow;17.00,
        stinlow;18.00,pkinlow;19.00,pkinlow;20.00,stinlow;21.00,stinlow;22.00,opinlow;23.0
        0,opinlow];
        cost = (hours(:,2));
        costlow = (hourslow(:,2));
    end
  end

  Servicecharge = 0;
  NAC = 0;
  NDC = 0;
  VoltageSurcharge = 0;
  ANAC = 0;
```

```
if buildingtype == 1
   Servicecharge = 164.67 * 12; %per month
      NAC = x(1) * 17.83 * 12; %Network Access Charge,based on all seasons,monthly, this
      is a debt %FeedIn = 100.92/100 * kW generated
elseif buildingtype == 2
   Servicecharge = 432.67 * 12;
            NDC1 = 87.20 * max(load(:,1:12));%Network Demand Charge, calculated based
      on the highest kVA consumed for the month
   NDC = sum(NDC1);
            %NetworkSurcharge = 0.25 * totalcharges %Not including service charge, only
      applicable if demand >= 110kW
   NAC = x(1) * 28.98 * 12;
   %FeedIn = 77.06/100 * kW generated
else
   Servicecharge = 5105 * 12;
   NDC1 = 109.64 * sum(load(:,1:12));
   NDC = sum(NDC1); %
   NAC1 = 36.01 * max(load(:,1:12));
   NAC = sum(NAC1);
   %FeedIn = 70/100 %Different for seasons and times, like TOU
   ANAC = x(1) * 20.67 * 12; %Ancillary Network Access Charge
            VoltageSurcharge = 0.225 * (NDC + NAC + ANAC); %Not including service
      charge, at 400V
end

TariffCharge = Servicecharge + NAC + NDC + VoltageSurcharge + ANAC;
```