Optimal Sizing of Solar Energy Systems

at SolarAfrica

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Executive Summary

Solar energy providers are experiencing increased opportunity in their market as solar and other renewable energy technologies become more affordable, accessible and socially encouraged. While this means there is opportunity for renewable energy providers, it also lowers the barriers of entry to the market - creating more competition for existing renewable energy companies. This places an emphasis on efficient project turnover time and low cost power supply to customers. To achieve both of these goals, a solar energy provider must perform system sizing quickly (before the customer turns to another provider) and effectively to ensure they offer the customer the lowest price possible, while still making sufficient return on their investment in a solar system.

Systems are often conservatively sized by the energy provider to minimise risk of their minimum return on investment not being met. The study contained herein investigates the hypothesis of oversizing a solar energy system in the South African market to obtain additional revenue that outweighs the costs required to oversize a system. A computer model was designed and developed for SolarAfrica to determine the optimal size system for a given site and consequently, to answer the research hypothesis which was proven correct. Multiple ways of defining the optimal system are explored in this report through the maximisation of differential income, profit and customer savings, respectively. Three heuristic-based optimisation methods (Genetic Algorithm, Particle Swarm Optimisation and Iterative Method) are compared with regards to their timeliness and effectiveness in determining an optimal solution.

The report is concluded by selecting the most appropriate objective function and optimisation method for SolarAfrica's case. The ways in which the developed model is anticipated to create value for SolarAfrica when implemented are also detailed, along with a final recommendation for future research and testing.

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Acronyms

SA	SolarAfrica
HRES	Hybrid Renewable Energy System
PV	Photovoltaic
LP	Linear Programming
GA	Genetic Algorithm
PSO	Particle Swarm Optimisation
IM	Iterative Method
TOU	Time of Use
GUI	Graphical User Interface
MARR	Minimum Acceptable Rate of Return
NPV	Net Present Value
ROI	Return on Investment
CPI	Consumer Price Index

Chapter 1

Introduction

1.1 Problem Background

The global push towards renewable energy sources is becoming ever more pertinent as strain on the world's most essential resources continues to rise with globalisation and exponential population growth. The need to reduce human dependency on traditional fossil fuel energy sources is essential to sustain and protect the earth's natural resources for generations to come. There is in particular, prevalent opportunity to adopt renewable energy sources in Africa.

Known widely as the continent that has been slowest in technological and economic development, some places in Africa have skipped the fossil fuel stage altogether and many Africans' first experience of electricity connection is by means of solar power. This is only made possible through 'The Great Acceleration' - the rapid development of technology in recent decades [4]. As stated by the African Progress Panel in 2015, "No region has more abundant or less utilized renewable energy than Africa" [16]. Solar energy is no exception and the potential for its growth and widespread use in Africa is evident. Encouraging governments and the public to develop such renewable energy infrastructure in places where there is currently no electricity infrastructure, may in some ways prove to be easier than encouraging more first world countries to change their habits and already-existent fossil fuel infrastructure. However, this opportunity for growth does not come without its challenges. One of the greatest being the hefty cost associated with purchasing the equipment for a solar Photovoltaic (PV) system [15].

This is because solar system equipment and components have not yet undergone large-scale commercial production - meaning energy suppliers and consumers have not yet been able to benefit from the economies of scale that usually lead to lower product prices [15]. The use of batteries in particular, to store solar energy is still too expensive for many solar energy suppliers to make use of. Most solar energy systems therefore operate on a use-as-produced basis, causing a problem if consumer energy demand is greater than solar energy produced by the system at a given time. It is therefore essential that solar energy systems are designed to produce the maximum power output possible for the consumer while still remaining feasible enough for solar energy providers to finance, install and maintain.

1.2 Company Overview

SolarAfrica (SA) provides customised solar energy solutions for industrial, commercial and residential customers. SA owns the solar energy systems used by customers in order to eliminate the need for customers to incur the hefty capital outlay usually required to purchase a solar system. Customers pay a variable tariff to SA for each unit of power consumed that is produced by the solar system. SA then bills each customer on a monthly basis as the relevant municipality would.

The company started in Mauritius in 2011 and has since expanded its operations to South Africa and Kenya after identifying the aforementioned opportunity for growth in the African market. SA is responsible for designing, financing and maintaining the solar systems installed for customers. The company's vision is to continuously make a positive impact on society by providing opportunities for business, office-park and home owners to reduce reliance on non-renewable energy sources without having to incur the high initial capital costs to do so.

1.3 Problem Statement

There are a number of constraints and factors that make it challenging for solar energy suppliers across the globe to design and scale the optimal size solar system [7]. In the case of SA in particular, maximum available area, minimum Return on Investment (ROI), seasonal solar yields, solar panel degradation, consumer demand patterns and equipment and maintenance costs all impose limitations. Furthermore, two prevalent factors influence the sizing of a solar energy system for SA and many other energy suppliers - the nature of a Hybrid Renewable Energy System (HRES) and power demand patterns of consumers.

1.3.1 Hybrid Renewable Energy System

All of SA's customers have a HRES set-up with two power sources. The first, a traditional grid connection to Eskom and the second, a connection to the on-site solar system. Both power sources are necessary for two important reasons. Firstly, solar energy's limited capacity to produce energy in different weather and light conditions means it is often incapable of matching consumer demand in low yield times of day (i.e. early morning and late evening). Secondly, on-site battery packs to store excess solar energy produced are not yet a reality for SA, meaning all solar energy must be used as it is produced.

This set-up is best explained by a hypothetical example. Consider a consumer with a power demand of 100 kW at a particular time. If the on-site solar system is only able to produce 30 kW at that particular time for the consumer then the deficit of 70 kW will be supplied by the grid (Eskom). This example is demonstrated with Figure 1.1.

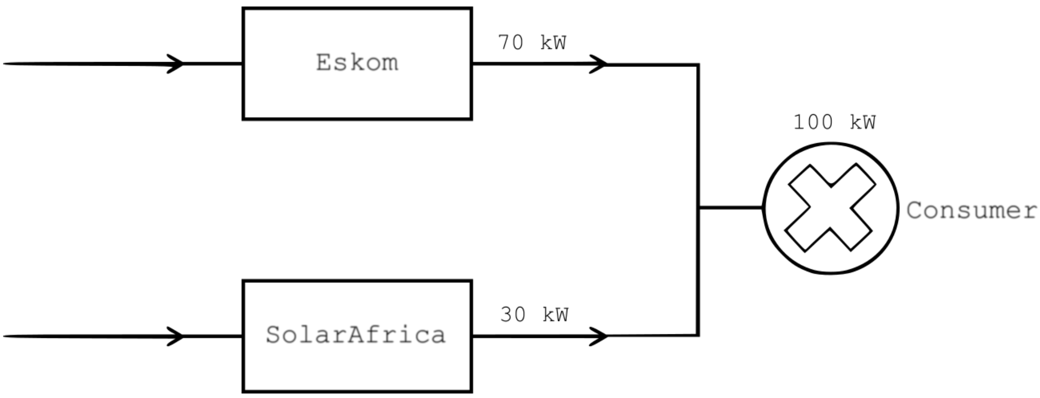

Figure 1.1: Solar-grid hybrid renewable energy system

It should be noted that the higher the proportion of consumer demand fulfilled by solar at any given time, the higher SA's monthly revenue from usage tariffs and the lower the proportion of fossil fuel energy used. For every unit of power Eskom provide to the consumer in place of SA, SA incur the lost opportunity cost of revenue that could have been earned on that unit of power.

1.3.2 Power Demand patterns

SA has three main consumer categories: residential, commercial and industrial. *Residential* refers to housing complexes where a solar system has been installed to power town house units, *commercial* to a business and *industrial* to an office park, mall or any other large site. Due to the inherently unique nature of each consumer's activities, each consumer category has a different power demand pattern. Power demand patterns of existing customers are an important source of information in determining the size of a solar system for a new customer.

A prevalent challenge for SA is reducing the mismatch between consumer demand and solar energy production. This mismatch is evident in Figure 1.2 [1] where the typical power demand of a residential household over the course of a day is plotted with the typical power produced by solar throughout the day.

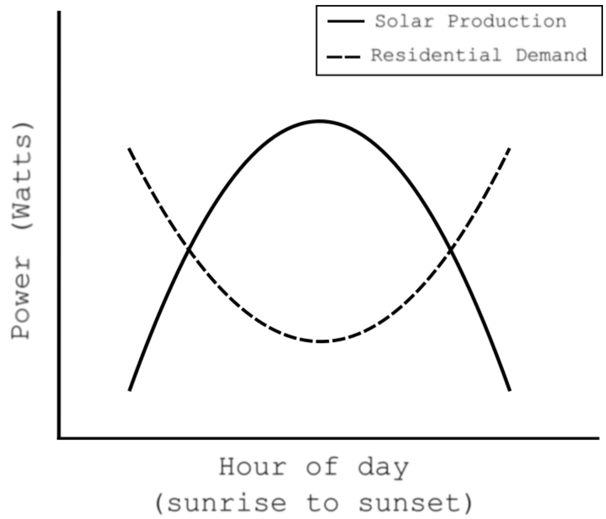

Figure 1.2: Typical residential household power demand vs. solar production

While commercial and industrial customers have energy demand patterns closer to that of solar energy production, there will always be a mismatch at some time of day. The solar energy system will therefore be sized either over-capacity or under-capacity.

1.3.3 Research Question

Because all of SA's systems are subject to the use-as-produced nature of solar energy and different power demand patterns, it is challenging to correctly size a solar system for a new site. At present, all solar systems are sized to be under-capacity by SA in order to ensure unnecessarily high equipment and maintenance costs are not incurred. However, there is an opportunity to investigate and quantify the trade-off between the loss of potential revenue from an under-capacity system and the excess costs of an over-capacity system. The over-capacity vs. under-capacity trade-off is represented by Figure 1.3.

Under-capacity design leads to lost revenue in the form of electricity tariffs that SA could have earned by supplying more of the consumer's power demand. This is because a larger system that produces higher solar yield values, can match more of the consumer's power demand. A smaller system however, means less consumer demand is met with solar and more by Eskom who provide the power to fulfil customer demand that SA's system does not have the capacity to produce.

[1] Figure 1.2 is not constructed with actual data and is only for explanatory purposes

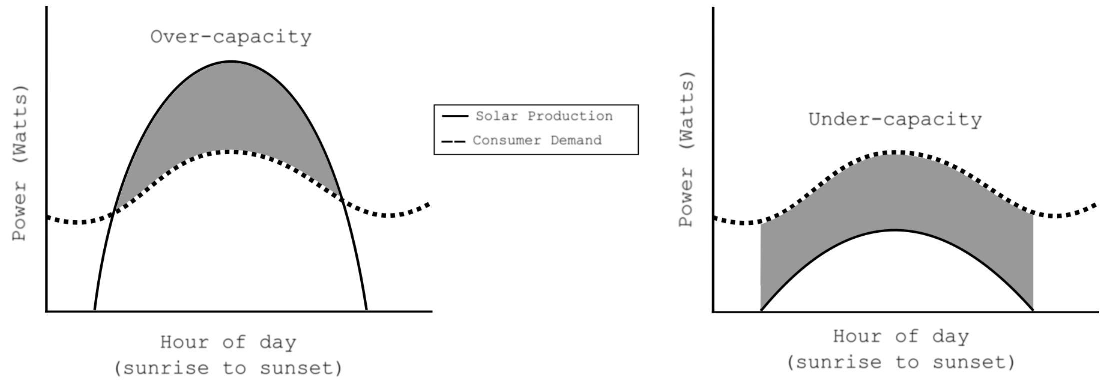

Figure 1.3: Over-capacity vs. under-capacity solar system

Over-capacity design on the other hand, leads to a system that produces more power than required by the customer, causing SA to incur unnecessarily high equipment, installation and maintenance costs. Due to South African regulation, the excess power produced by solar cannot be fed back into the grid for the receipt of revenue in most cases. Any excess solar energy produced by a system is therefore considered as overproduction costs to SA. The trade-off between over and under-capacity design underpins the research question of this study which is to:

"Determine whether the financial benefit obtained from oversizing solar energy systems is greater than the costs incurred to do so."

1.4 Research Design

The focus of this project is to develop a computer model that can determine the optimal size of a solar energy system, given the necessary constraints and inputs. The optimal system size will be defined by three different objective functions, namely: maximise differential income [2], maximise profit and maximise customer savings. In addition to sizing a system to maximise SA's profit, the model is also expected to significantly reduce the time-frame to size a project which is currently 2-3 days. The present method used by SA is time consuming due to a lack of information centralisation, reproducibility and excessive human judgement.

It is anticipated that the model will need to be integrated with the on-site computer information system (*Unifii*). The intention is for the model's Graphical User Interface (GUI) to be provided by *Unifii* that will call on the optimal sizing model's script. *Unifii* will allow the user to enter input data in the form of constraints and variables and then select a run option to execute the model's code. The model will compute the results with the user specified inputs and display the relevant output result to the user. While integration of the model with the current information system does not form part of the scope for this project, it is considered throughout the design process to ensure successful implementation is possible.

1.5 Research Methodology

The problem at hand is by nature an Operations Research problem and the importance of using a design research paradigm to approach and solve such a problem is emphasised by Manson [14]. Manson proves the design research approach to be beneficial for Operations Research

[2]Differential income is the expected increase in revenue obtained from a particular business decision less the change in costs to be incurred from choosing that course of action.

work by evaluating three Operations Research articles against the seven guidelines for design research prescribed by Hevner [20]. The five step methodology that Manson summarises will be used.

Step 1: Awareness of the Problem

This step is addressed in Sections 1.3 and 1.4 where a clear understanding of the problem is presented. Chapter 2 that follows also forms a crucial part of this step as it demonstrates awareness of the possible solution approaches, methods within them and specific tools that have been proven to be successful in solving this type of problem. The formal project proposal presented serves as the output for this stage as it explains the research effort and the reason it will be conducted.

Step 2: Suggestion

The proposed design artefact is a computer model to accommodate the problem of optimally sizing a PV solar system. The design artefact will fulfil the required functionality and operate as detailed by the model design in Chapter 4. Three different algorithms will be used to determine the optimal solution: Iterative Method (IM), Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO). Multiple versions of the design artefact will be created to accomodate and compare each of these algorithms. The formulation of an algorithm for the Maximisation Function that each of these three methods will call on, also forms part of the design artefact.

Step 3: Development

R-Studio is selected as the development software for the design artefact. Firstly, for its extensive data handling and statistical analysis functionality, secondly for the compatibility of *R* as a coding language with SA's on-site information system *Unifii* and thirdly because it is known to have numerous optimisation packages. The Maximisation Function and IM will be coded from scratch in *R-Studio* and the GA and PSO algorithms applied by means of freely available packages in *R-Studio*. The development of this artefact is deconstructed into three primary phases, namely: Data Tidying and Analysis (Chapter 3), Model Design (Chapter 4) and Model Solution and Validation (Chapter 5).

Phase A: Data Tidying and Analysis

This phase consists of all tasks required to tidy, analyse and understand the input data for the proposed model. The four primary datasets: *Solar Yield*, *User Consumption*, *Cost* and *Tariff* will be tidied using the *tidyr* and *dplyr* packages in *R-Studio* with reference to the principles of Wickham and Grolemund [22]. Once tidied for analysis, the behaviour of each dataset will be analysed. Any unexpected results or findings are to be addressed before completing this phase. This phase will be considered complete once all data necessary for the model to run is processed and available in an appropriate format to be input into the final model.

Phase B: Model Design

Phase B is expected to overlap with the end of phase A to some extent in that the model design will determine the required format for the input data prepared in phase A. Phase B will also consist of declaring variables for the various factors to be included in the model as well as constraints, necessary formulae and most importantly - the accurate construction of the objective function. Furthermore, the desired outputs of the model will also be determined during this phase by determining the information that is most important to the user. Once all variables, constraints, formulae and the objective function are correctly declared and closely evaluated, this phase will be considered complete.

Phase C: Model Solution and Validation

Phase C consists of translating the model design into computer code in *R-studio* to make the model a 'one-click' script that can be run by an on-site computer. This phase will require research and extensive consideration to determine which optimisation packages available in *R-studio* are most applicable. This phase will be considered complete once the model in *R-studio* effectively processes all the input data and produces the desired result by running the script and determining the optimal system size.

Step 4: Evaluation

The designed artefact (computer model's) success will be evaluated by means of verification and validation. Verification will be completed by means of ensuring the model accurately represents the decision making steps required by SA to size a solar system and that any assumptions made in its construction are valid. Model validation will be done by testing the model's ability to produce realistic results in consultation with SA employees experienced in system sizing.

Step 5: Conclusion

The fifth and final stage requires critical assessment whereby the results of the project and the different algorithms used are recorded. This entails documenting the design artefact's ability to fulfil the functionality required as well as any of its limitations and flaws. The optimisation algorithm that best suits SA's needs must be determined in this step. This is important for future use and integration of the model into the current information system. Essentially, assessment of whether the project successfully answered the design question must crucically be determined to decide whether further research and use of the model is justified or not. If further research is justified, implementation of the model into SA's current operations must be addressed.

Chapter 2

Literature Review

2.1 Solar System Components

At the most basic level, a solar energy system comprises of three main components: PV solar panels, an inverter and a mounting system [21]. PV solar panels function by absorbing particles of light and converting them into useful electrical energy. However, solar panels produce low voltage direct current electricity and the inverter in a solar energy system is used to convert this energy into alternating current to power lights and appliances in a home or business [8]. The third component (a mounting system) is required to fix the solar panels to a building roof or alternatively onto a stand that is fixed into the ground. This component is crucial to the long-term success of the project as solar panels by nature will be subjected to harsh environmental conditions such as rain, wind and hail [21]. While solar energy systems can be particularly important in reducing carbon footprint over the long-term, their components are subject to a number of limiting factors that make them challenging to correctly size.

2.2 System Sizing Challenges

PV panels are available in a number of different sizes with some capable of producing substantially more power than others. All solar panels are susceptible to degradation that causes a reduction in the power they are capable of producing over time [9]. This degradation occurs for reasons such as extreme ultraviolet exposure, heavy wind and other harsh weather conditions that cause the photovoltaic cells within the solar panel to degrade and operate less effectively over time. The National Renewable Energy Laboratory (NREL) [9] found that the improvement in solar panel technologies since 2000 significantly decreased the annual degradation of most PV panels from 1% to less than 0.05%. Solar inverters are not capable of converting 100% of the direct current electricity received into alternating current either and usually operate at efficiencies ranging between 95-97%, meaning 3-5% of the energy produced by solar panels is lost as heat during this conversion [6]. Mounting system selection and installation can also be challenging as there are often a number of constraints. Maximum available roof or ground space, chimneys, other roof fixtures as well as roof angles and orientations all constrain a system's design [3].

Another typical challenge for sizing solar systems is determining the power output the system as a whole needs to produce. Because most solar systems and SA's in particular, are subject to the use-as-produced nature of solar energy (addressed in Section 1.3.1), many form part of a HRES with an additional source to supply the deficit in consumer power demand. In order to displace as much of the additional source's supply as possible, power produced by solar needs to match consumer demand as accurately as possible. This is a significant problem considering a site's power demand pattern is usually unknown before system sizing takes place. Sizing solar systems becomes increasingly complex for solar energy providers because of consumers' unqiue and unknown power demand patterns. The ability of these energy providers to make a profit is dependent on providing a system that supplies power to match consumer demand. This makes it crucial for solar energy providers like SA to size systems in a way that meets as much power demand as possible with as little overproduction cost as possible.

2.3 System Sizing Approaches

To size systems in a way that minimises the discrepancy between power supply and demand, both of these datasets are needed. However, in practice actual data is sometimes only available for one dataset which leads to numerous different approaches being taken towards minimising the supply-demand mismatch. One of which, is to forecast PV solar system yield as accurately as possible. This was done by Pelland et al. [17] who completed day-ahead forecasting of PV solar systems with the use of Numerical Weather Prediction, Geostationary Satellite Imagery and Persistence Whole Sky Imagery. Analysis of the results found Geostationary Satellite Imagery to be the most accurate technique and stochastic learning techniques with exogenous input to be highly competitive in accuracy [17]. Pelland et al. [17] show this yield prediction approach to be effective if the necessary forecasting techniques and data are available. SA use a similar approach to minimise the mismatch between solar power supply and consumer demand, only SA's yield forecasting is performed with the use of an on-site simulation program *PVsyst*. This simulation tool (*PVsyst*) produces expected yield values for a proposed system while accounting for key factors influencing solar yield such as location specific weather data, inverter selection and panel mounting angle [1]. At present, this simulation tool does not account for degradation and only produces a year's worth of solar yield values.

Another approach to minimise the mismatch between supply and demand is to predict consumer power demand as accurately as possible. Electrical power demand can be complex to predict because of a number of influencing weather, socio-economic and demographic variables such as gross domestic product, wind-chill index, temperature and even population [2]. Electrical power demand is also subject to the behaviour of individuals and daily work cycles that create peak and off-peak periods. There are so many influencing variables that it is not justified to attempt to quantify the effect of each individually on power demand for a specific site [2]. Power demand is therefore either forecasted by means of an Autonomous Model or Conditional Model. Autonomous models rely on historical data as they use the past growth of electricity demand to forecast the future growth (and demand). Conditional models also rely on historical data however, they attempt to relate past electricity demand growth to some of the aforementioned influencing variables (gross domestic product, wind-chill index etc.) [2]. SA do not employ either of these models to predict power demand at present. This is because some of SA's customers do not have hourly metering equipment installed before approaching SA to size a system to their needs. Whereas, with a typical municipal power station that supplies power to a large area, the metering infrastructure is already in place and the total power demand of the area need only be monitored and met. The nature of solar energy requires that the infrastructure is suitably sized as the system's capacity to produce cannot be changed once it is installed. On the other hand, fossil fuel energy providers' capacity to produce power is not as limited by the infrastructure that is used to supply power to homes or businesses. Solar energy providers like SA therefore require more focus on sizing the system correctly to generate sufficient energy from the power source and fossil fuel energy providers like Eskom require more focus on managing the energy source by ensuring sufficient coal and other fuel sources are available to meet the power demand.

Another challenge for SA in predicting power demand is that SA do not provide power as a municipal power station does to a single large area, but rather to numerous unique customers.

Each of these unique customers have different power needs and are dispersed across South Africa and other countries. This means some degree of consumer profiling is required to categorise similar customers according to site characteristics such as size and primary function (home, business or industrial). Ideally, new customer sites could be categorised according to the consumer profiles created from existing demand data. However, this is still not an exact science as there is no way of easily determining a new consumer's future behaviour. For example: if a site were to undergo expansion, downsizing or a change in function, the power demand would be expected to change significantly.

2.4 Optimal Sizing Methods

In spite of the challenges discussed in Sections 2.2 and 2.3, the increasing popularity of renewable energy source utilisation in recent years has led to many studies on the optimisation and sizing of not just solar, but many types of HRESs. Optimal sizing of a HRES's components is essential to ensure consumer power requirements are met with minimum investment in equipment and maintenance costs for the energy supplier [7]. Meeting consumer's energy demands with minimum costs enables suppliers to provide renewable energy at a lower price, therefore encouraging more consumers to reduce their carbon footprint.

GA and PSO are two commonly used metaheuristic methods to optimally size a HRES. Because GA and PSO are both metaheuristic methods, neither is guaranteed to determine the global optimum when searching for an optimal solution. Instead these methods determine a local optimum, which can be the same as the global optimum, but is often weaker, [23].

2.4.1 Genetic Algorithm

GA mirrors the process of natural selection where the fittest individuals in a given population are selected for reproduction to produce offspring for the next generation who inherit the characteristics of the parents, [23]. In this scenario, individuals are solutions to the problem to be solved (i.e. a value to be maximised). An initial population of possible solutions is generated and a fitness function is then used to assess the possible solutions and grade each according to its value. In the application of this algorithm to system sizing, different system sizes (within a minimum and maximum constraint) would be the possible solutions and the value - the value of the objective function to be maximised. The possible solutions with the highest gradings from evaluation are then selected and used to create new possible solutions using a method called crossover. Mutation is then applied with low random probability to alter the characteristics (system size) of some of the new possible solutions to maintain diversity and prevent premature convergence to a less favourable solution (local optima). The process then repeats itself until an optimum is reached or new solutions are produced that do not differ significantly from the previous (parent) solutions. Once this happens, the process terminates and the remaining solution with the best grading is selected as the optimal solution.

2.4.2 Particle Swarm Optimisation

PSO mimics a tightening pattern concept demonstrated by flocking animals, in particular birds that circle over an area where there is a target (food source). Each time a bird gets closer to the target it tweets as a signal for the rest of the flock to follow. When another bird gets closer, it tweets louder and this continues until one of the flock find food.

This is applied as an optimisation method with multiple iterations and a group of variables. The group of variables have their values adjusted each iteration by the algorithm to be nearer to particle's value that is presently closest to the target. The algorithm makes use of three variables: target value, current best solution and a stopping value to terminate the algorithm if the target is not found. Particles are sent around a solution space to simulate the flock of birds, with each having a velocity value and a personal best value that represents how close the particle has come to reaching the target. The velocity value of each particle is assigned based on its distance from the target. Particles that are further away, therefore have a higher velocity and those that are closer a lower velocity to decrease their chance of veering off course and missing the nearby target. When a particle comes closer to the target than any other particle has before, the current best solution value is updated with this particle's personal best value. As the algorithm runs through iterations, the current best solution value therefore approaches the target and comes nearer until one of the particles reaches the target or the algorithm terminates.

2.4.3 Method Application

Erdinc and Uzunoglu [7] evaluate numerous methods that have been used in recent years to determine the optimal configuration and sizing of HRESs. Of these tools, there is significant literature on GA and PSO which are claimed to be the most advantageous to solving problems of this nature, however numerous methods are considered.

Shen [19] optimally sizes a standalone PV system and solar array battery in Malaysia. The optimal system (that with minimum cost) is determined with the use of available data on power demand, local weather and loss of power supply probability. The problem is formulated by variables, sets and an objective function as in Linear Programming (LP), but is solved graphically with the use of a three-dimensional plot. Both predicted solar yield values and power demand data are used to determine the optimal solution in this study.

Khatib et al. [10] also point out consumer power demand and meteorological data as two crucial datasets to determine the optimal solution of a PV solar system. More than 15 optimal sizing studies are summarised where the use of these datasets have enabled an optimal solution to be determined, whether it be to minimise system cost, levelized cost of energy or electricity production cost [10]. Although most of the studies addressed by Khatib et al. are for standalone PV systems (i.e. those with battery storage), they make use of hourly power consumption and meteorological data. These datasets are both available for all SA sites that the final model will size. Maximum available area that is converted to maximum system size is also a factor considered by most studies that note it to be an important constraint on the solution space [10]. Khatib et al. [10] furthermore address the use of Neural Networks as an Artificial Intelligence method used by some to optimally size systems with synthetic hourly power demand.

Makhloufi [13] compares the use of classical optimisation methods against GA use to size PV systems. Variable power demand and the non-linear characteristics of some components make the use of classical optimisation methods such as 'worst month method' and 'loss of power supply probability' particularly challenging. Makhloufi [13] points out that a lack of meteorological or power consumption data in PV sizing problems is well suited to techniques such as GA and PSO. Furthermore, GA's accuracy in determining such solutions is proven to be signficantly greater than either of the aforementioned classical optimisation methods.

Further studies where GA has been successfully applied to problems of this nature are demonstrated by Koutroulis et al. [11] who apply them to optimally size a stand-alone photovoltaic/wind-generator system and by Lagorse et al.[12] who economically design a HRES composed of PV, wind and a fuel cell as sources. Similarly, the methods used in a PSO solution approach are explained by Erdinc and Uzunoglu [7] and successful applications demonstrated by Sanchez et al. [18] and Denghan et al. [5] who use it to determine the optimal size of a HRES and hydrogen-based wind/photovoltaic plant, respectively. However, it should be noted that although GA and PSO may be successfully used to optimally size PV systems, they are metaheuristics methods that do not yield exactly optimal solutions [23].

LP, a tool evaluated by Erdinc and Uzunoglu [7], is capable of determining exactly optimal solutions when sufficient input data is available [23]. LP is also proven to be substantially easier to code than GA or PSO and is effective to use when data is available to remove the need for a heuristics approach to be taken [7]. The reduction of a complex model to a mathematical set of constraints and objective function make LP formulation more accessible and easily understood by a wider audience, when compared to GA that is particularly difficult to create a conceptual design for but not to use. LP is however, known to have greater computational time inefficiency when compared to GA and PSO. This is partly because of its ability to yield an exactly optimal solution that heuristic algorithms do not guarantee [23].

2.5 Method Selection

Although LP appears to be an appropriate approach for its aforementioned abilities, the problem at hand cannot be solved with LP because of its non-linear nature (i.e. panel degradation, multiple tariff escalations and different time value of money cash flows). The non-linear nature of SA's optimal sizing problem makes it best suited to be solved with a metaheuristics technique. It is also evident from Section 2.4 that both GA and PSO have been successfully used to solve system sizing problems of a similar nature. Solar yield data is always available to SA through means of their *PVsyst* simulation program and for the purpose of this study it is assumed that one year of client load data is always available. Because the two primary datasets are available for this calculation, no forecasting needs to be done by the final computer model. Neural Networks, although investigated will not be considered for use in this particular project because of their need for a training procedure and shear complexity. Use of a COTS (Commercial off the shelf system) is also not considered due to the limited functionality of most and their inability to represent all source characteristics unique to the situation [7]. SA's preference is also to have an in-house developed solution that can be easily integrated into their current information system (*Unifii*).

Once the optimal system size has been determined there are a number of factors that must be considered by SA in the design of the system to meet that size. Inverter sizes, number of inverters, panel configuration and minimum and maximum panel size all influence the final (kWp) power output of the system and it is therefore not always possible to achieve the optimal system size exactly. This is the case for SA in practice, meaning that the resolution of accuracy required by the design team is (kWp) integers. Therefore any further accuracy in the form of decimal points is not of significant importance as it is not likely, for example that a system could be designed and built to be 35.64 kWp. An IM that tests system sizes at each possible kWp value is consequently another way to determine the optimal system size. All three methods: IM, GA and PSO are used to determine the optimal system size and the pros and cons of each of these selected methods assessed.

Chapter 3

Data Tidying and Analysis

3.1 Data Tidying

In SA's case, four primary datasets are required to determine the best possible system size for a site. Techniques detailed by Wickham and Grolemund [22] are used to tidy each dataset into an easily workable format to perform operations on. Three conventions are used: each variable in a dataset is placed in its own column, each observation placed in its own row and each value placed in its own cell.

Each dataset is contained in its own file format (*.csv* or *.xlsm*) and both formats are accommodated with conversion of the dataset into more general matrix formats to apply calculations and other operations on. The four primary datasets read, cleaned and operated on by the sizing calculator are:

Solar Yield Data - The power produced by a specific size solar system at a particular location. This data is obtained from the on-site simulation tool *PVSyst* that uses historic weather data of the specified location to produce a prediction of solar yield for the specified system size. *PVSyst* generates the prediction in the format of a *.csv* file and consists of hourly (kW) yield values for the duration of a single year.

Power Consumption Data - Power consumption data for a particular site is either retrieved from an on-site data logger that reads consumer power demand (kW) in 30 minute intervals or from the customer themselves when approaching SA to size a system to their needs. Logged data is stored in a Microsoft Excel *.xlsm* file, while data from customers is usually in the format of a *.csv* file.

Cost Data - This consists of the equipment and installation costs (R/Wh) for SA's three primary suppliers. The costs differ depending on the interval in which the proposed system size (kWp) falls. These costs are charged by suppliers on a (R/Wh) basis and decrease as the size of the system to be purchased increases. This data is stored in a *.csv* file.

Electricity Tariff Data - Time of Use (TOU) data consisting of the rate charged (R/kWh) for electricity by the site's relevant municipality. Each hour's TOU rate is dependent on the season (high/low) and period of day (standard, peak or off-peak) in which power is consumed by the client. These seasons and periods are determined by the National Energy Regulator of South Africa (NERSA) who specify rates for each municipality across the country. This data can be retrieved from NERSA's website in the form of a *.pdf* file and is converted into a *.csv* file for easy use in the sizing process.

3.2 Data Analysis

The objective function and algorithm comparison detailed in this study are completed with a single site for consistency in comparison. SA sized a system for this commercial site in Kwaggafontein (Bloemfontein, South Africa) at the beginning of 2018. This site is an ideal case study choice for two reasons. Firstly, this site has already been sized with present methods, making data available to validate a sizing model and preventing any possible bias in the values calculated with present sizing methods. Secondly, data on a site's actual power demand is not always available to SA before sizing a system however, a year's worth of power consumption data is available for the site in Kwaggafontein. Expected solar yield values at this location were produced by SA's *PVsyst* simulation program that accounts for weather, panel-tilt and other conditions. To orientate the reader on this site and the nature of the problem addressed in Chapter 1, some preliminary data analysis on the site is provided.

3.2.1 Solar Yield vs. Power Consumption

The actual demand and expected solar yield values for this site size are plotted in Figure 3.1. Although, the nature of solar energy makes it incapable of perfectly matching consumer demand patterns (for reasons addressed in Section 1.3.2), it is evident that under-capacity system sizing is the present approach used by SA. It is precisely this undersizing and the opportunity to incur some degree of overproduction cost in order to earn more revenue in the long run, that prompted development of an optimal sizing calculator.

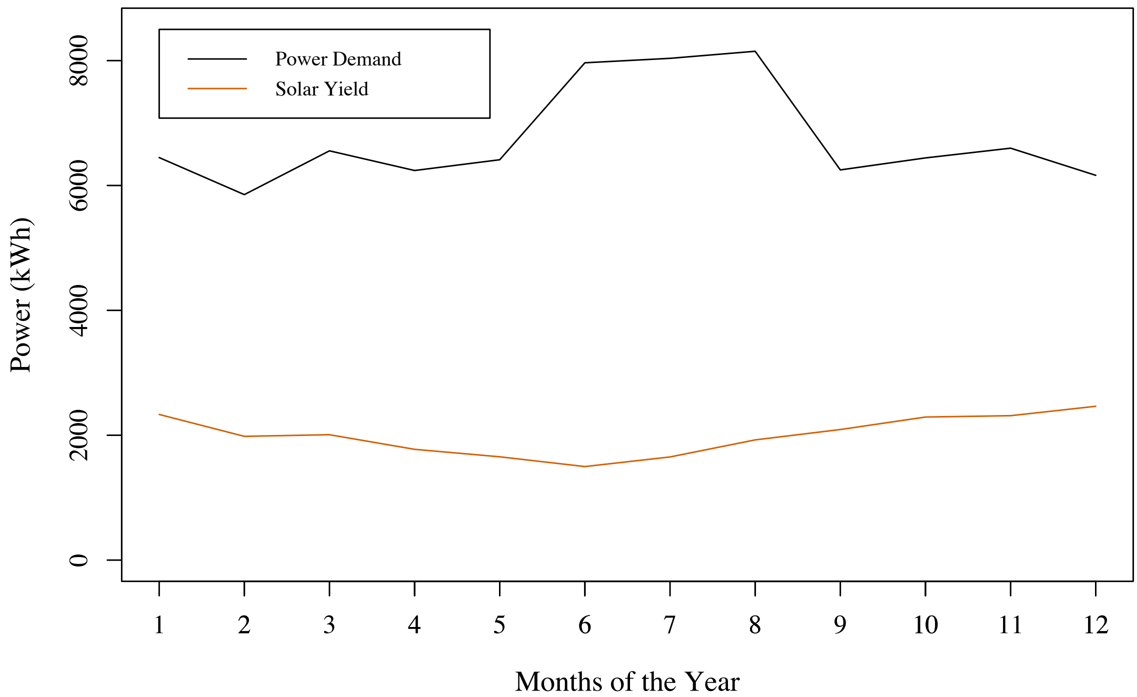

Figure 3.1: Solar yield vs. power demand

3.2.2 Eskom Tariff

This site uses and pays for electricity supplied by Eskom on a TOU basis - meaning the rate a consumer is charged for consuming a (kWh) of power supplied by Eskom, is specific to the season (high or low), and period (peak, standard or off-peak) that hour falls under. Figure 3.2 shows this TOU structure defined by Eskom.

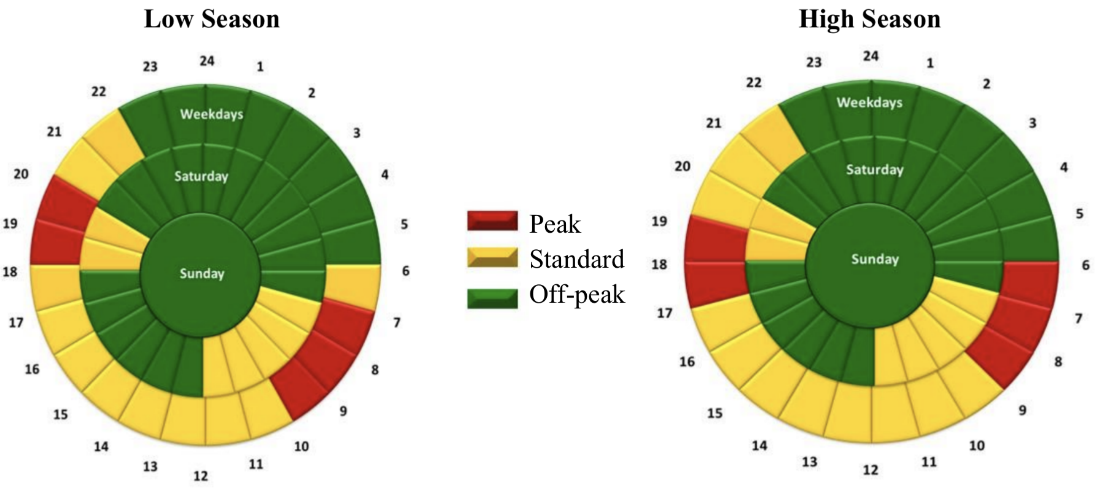

Figure 3.2: Eskom's low and high season time of use tariff structure

Each municipality supplied by Eskom has a unique set of rates that are charged for the different periods defined. The site of interest falls under the Manguang Municipality and the TOU tariffs specified by NERSA for this particular site are given in Table 3.1.

Table 3.1: Manguang Municipality TOU Tariffs

Season	Period	Rate (R/kWh)
Low	Standard	1.3438
Low	Peak	1.7917
Low	Off-peak	1.1341
High	Standard	1.8136
High	Peak	3.2994
High	Off-peak	1.7480

3.2.3 Equipment and Installation

The cost of equipment and installation is different for each of SA's suppliers but is specified on a (R/Wh) scale by each that is underpinned by 'bulk discount' pricing. Figure 3.3 demonstrates a supplier's costs for different system size intervals.

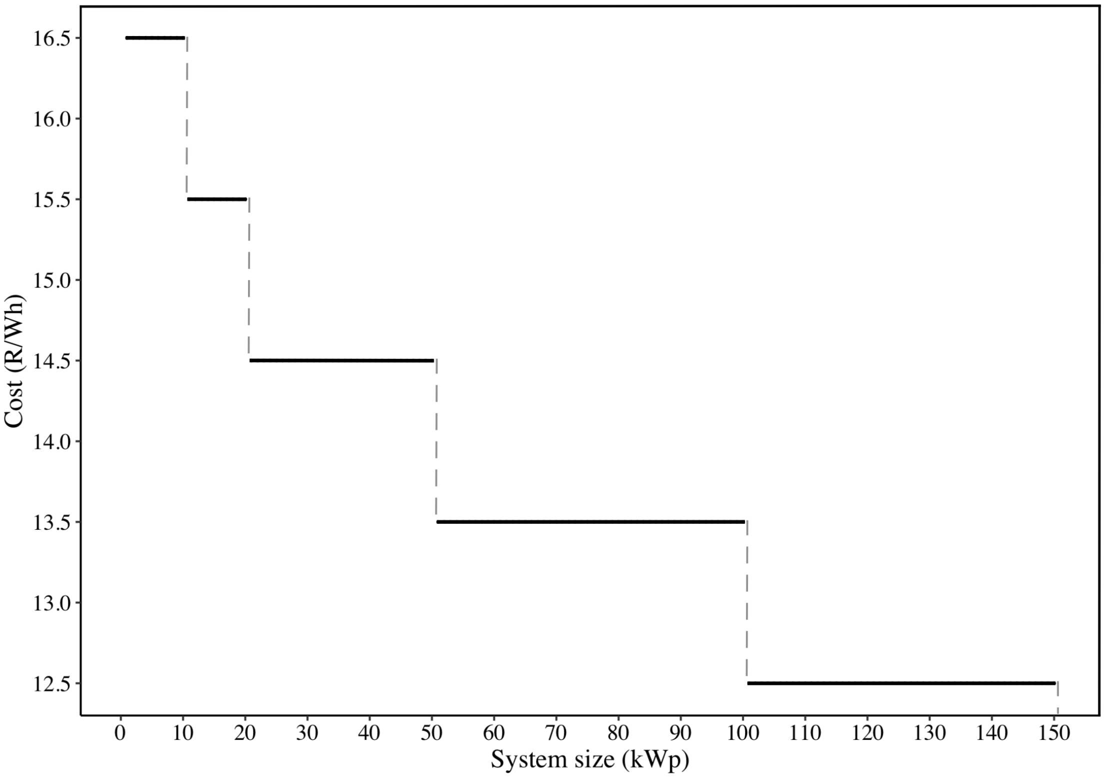

Figure 3.3: Supplier equipment and installation cost for different system sizes

Chapter 4

Model Design

The design of the model is constructed of five principal steps that in sequence perform the necessary tasks to determine the optimal system size from the four primary datasets (Section 3.1) and user specified inputs. Figure 4.1 summarises the five primary operations of the model, the sequence of execution and the manner in which the fifth operation calls a Maximisation Function.

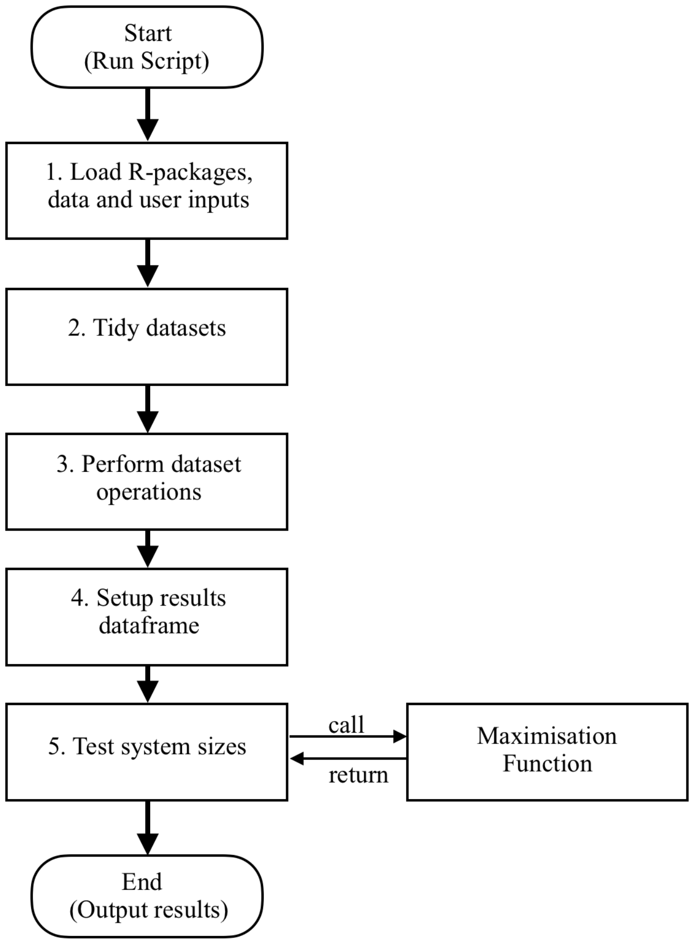

Figure 4.1: Flowchart of model operations

Each step is a section of code that performs a specific function. Firstly, the necessary R-packages to run the model are loaded, along with the four primary datasets and the input values specified by the user. The model then tidies the *Solar Yield* and *User Consumption* datasets into the desired format for calculations and operations. After which, data operations are performed in step three where conditions are tested and datasets populated with the necessary TOU tariff rates and other variables. A dataset to store the results of the algorithm while it is run is constructed and setup in step four before system sizes are tested in step five by calling on the Maximisation Function that returns the objective function value each time. After all possible system sizes have been tested, the model ends its run process by displaying an output of results to the user specifying: optimal system size, the maximised objective function value, a dataset of results (profit, revenue, overproduction etc.) for all system sizes tested as well as a graphic showing the relationship between system size and the objective function.

4.1 Objective Function

The objective function of the *Maximisation Function* (Figure 4.1) was initially to maximise differential income over the life of the project by testing different system sizes. However, SA's management later decided to investigate two alternative objective functions. All three are detailed below:

The initial objective funciton seeked only to weigh the opportunity revenue that could be earned from a larger system against the overproduction costs of that system over the project life. It therefore, did not not include tariff increases or Net Present Value (NPV) assessement. It simply compared the revenue to be earned from a larger system against the cost of overproduction for that larger system. The objective function (maximise differential income) is defined as follows:

$$\mathbf{max\ z} = \text{Annual opportunity revenue} - \text{Annual overproduction costs} \tag{4.1}$$

The second objective function is that which maximises profit over the life of the project by using relevant time value of money principles. It does not require the value SA would have sized the system to with current methods in its calculation. Profit is maximised by determining the system size that produces the largest NPV. Three important variables are used to perform this NPV calculation: *SAincrease* and *EskomIncrease* - the (%) amount by which SA and Eskom escalate their tariffs annually and *ROI* - SA's Minimum Acceptable Rate of Return (MARR) by which cash flows are brought back to a present value. Instead of quantifying only differential revenues and costs (as with the previous objective function) the full annual revenue, equipment and maintenance costs are accounted for in this objective funciton.

$$\mathbf{max\ z} = \text{Annual revenue} - \text{Equipment and installation cost} - \text{Annual maintenance costs} \tag{4.2}$$

SA's management later decided to investigate a third alternative, which is to maximise customer savings over the life of the project while ensuring a minimum return on investment of 13.5%. This is done by calculating customer savings in each hour of the project life.

$$\mathbf{max\ z} = \min(\text{Consumption, Solar yield}) \times (\text{Eskom tariff} - \text{SolarAfrica tariff}) \tag{4.3}$$

The customer savings in each hour of the project life are then summated to obtain the total customer savings over the project life.

Three different versions of the model exist, each catering for one of the objective functions. The formulated Maximisation Function is the same for each objective function, differing only in the value that is calculated by and returned from the function - which is specific to the value that is being maximised, for example: customer savings.

4.2 Assumptions and Limitations

Certain assumptions are made in the model design regarding solar yield data, SA's, supplier selection process, equipment and maintenance costs, electricity tariff increases and the specified MARR. Variables are used to account for variation in these assumptions by providing the opportunity for senstivity analysis on any of them. The following assumptions are therefore made in the design of model in order to mirror SA's company policies:

4.2.1 Solar Yield

Solar yield values produced by *PVsyst* during a simulation run are assumed to be scalable. The expected solar yield values produced by the simulation are worked back to expected yield values for a 1 kWp size system with the system size specified by the user when running the simulation (y).

$$\text{One kWp yield} = \frac{\text{Simulation values}}{y} \tag{4.4}$$

The yield values for the proposed system size (p) are then calculated by multiplying the yield values for a 1 kWp system with the value of the proposed system size.

$$\text{System yield proposed size} = \text{One kWp yield} \times p \tag{4.5}$$

Solar equipment degradation is accounted for with SA's worst case yearly degradation factor of 0.07%. This is done by extending hourly solar yield values of the proposed system size over the length of the user specified project life and then applying the degradation factor to each year's yield values. Inclusion of this degradation is particularly important because the magnitude of each hour's yield relative to the consumer's power demand in that hour, determines the amount of revenue that can be earned and whether or not there will be overproduction.

4.2.2 Supplier Selection

The model mirrors SA's supplier selection policy by analysing a data sheet of supplier costs for system equipment and installation given in ($Rands/W$). It identifies all possible suppliers for the interval in which the proposed system size falls and selects the supplier that provides equipment and installation at the lowest ($Rands/W$) cost to SA.

4.2.3 Equipment and Maintenance Costs

Annual operations and maintenance costs are applied over the duration of the project life according to SA's current policy - 1.5% of initial equipment and installation cost. This percentage is assumed to be the same, regardless of which supplier is selected.

4.2.4 Tariff Increases

SA's policy for annual tariff increase is Consumer Price Index (CPI) + 1.5%. South African inflation data for the last 20 years has therefore been analysed and assessed with the use of a *Chi-Squared Distribution Test*. The results concluded that the data cannot be found to not follow a normal distribution and the mean value is therefore approximated to be a good representation of the annual inflation rate (5.48%). Eskom's most recent annual TOU tariff increase of 7.32% is applied each year for the duration of the project life.

4.2.5 Minimum Acceptable Rate of Return

SA's specified MARR of 13.5% is applied in order to ensure the project is economically feasible. Furthermore, any system installed by SA is assumed to have no salvage value (as specified by SA' management).

4.2.6 Power Consumption

There is one predominant limitation of the model in that it does not predict user power consumption and requires actual power consumption data to be run. For the scope of this project, it is assumed that a years worth of power consumption data is available to SA to size each new site even though in practice, this is not always the case. In practice, some consumers have a years worth of power consumption data that they can provide to SA to better size a system to their needs, while some consumers do not. At present, SA do not have sufficient data on existing installations for customers to be profiled robustly and it is therefore not possible to forecast a new site's demand with reasonable accuracy. Consequently, the assumption is made that the client's power usage remains constant over the duration of the project life (i.e. same usage every year for 15 years).

SA have however, expressed interest in constructing a load forecasting model that uses a large database of power consumption data (that is presently being collected) in conjunction with customer profiling to predict a new consumer's power consumption. Furthermore, SA are working on installing a datalogger on each new consumer's site in order to monitor power demand for a period of two weeks. This actual data can then be used to help scale any forecast made. Although, this forecasting model falls outside the scope of this study, it should be noted that the optimal sizing model is designed in a way that client power usage is simply a *.csv* file used as an input to the model. This means that any prediction made by a future load forecasting model, need only be output into a *.csv* format to run in the model.

4.3 Algorithm Formulation

The *Maximisation Function* that step five calls on to maximise the selected objective function (Figure 4.1), is a customised programming function developed for SA's case. This function was developed because of the complex nature of the problem at hand and the many data operations that need to be performed to evaluate calculations on an hourly basis over a number of years.

In order for the model to make calculations on an hourly basis over the duration of the project life, there are a number of hour by year matrices that store the relevant solar yield and power consumption data. The general form of this matrix is given below:

$$\text{Project Life} = \begin{array}{c} \begin{array}{ccccc} \mathrm{i}=1 & 2 & 3 & \dots & \mathrm{n} \end{array} \\ \begin{pmatrix} . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \end{pmatrix} \end{array} \begin{array}{l} \\ \mathrm{j}=1 \\ 2 \\ 3 \\ . \\ . \\ 8760 \end{array}$$

where:

$i \triangleq$ The set of years of the user specified project life {1, 2, 3, ...,n}
$j \triangleq$ The set of hours in a year {1, 2, 3, ...,8760}

The following user inputs to the model are important to take note of before visiting the algorithm formulation of the Maximisation Function.

User Inputs

n	$\triangleq$ Duration of project life ($years$)
p	$\triangleq$ Proposed system size being tested (kWp)
min	$\triangleq$ Minimum system size (kWp)
max	$\triangleq$ Maximum system size possible (kWp)
$SAincrease$	$\triangleq$ SolarAfrica annual tariff increase (%)
ROI	$\triangleq$ SolarAfrica's required return on investment (%)
$degradation$	$\triangleq$ Annual Panel degradation (%)

The Maximisation Function is deconstructed into six steps for explanatory purposes. The first of these six steps is Supplier selection (Algorithm 1). Line 1 identifies all possible suppliers for the interval in which the proposed system size falls, line 2 sorts the possible suppliers by lowest to highest cost ($Rands/Wp$) in that interval, line 3 calcuates the cost of equipment and installation for the system and line 4 calculates the annual maintenance cost.

Algorithm 1: Supplier Selection

```
1 CostData ← subset(CostData, Upper Size Interval <= p  Lower Size interval >= p)
2 EquipmentAndInstall ← sort(CostData, Price, increasing)
3 EquipmentAndInstall ← EquipmentAndInstall[1] × 1000 × p
4 maintenanceAnnual ← 0.015× EquipmentAndInstall
```

Algorithm 2 calculates the tariff SA charge the consumer for power in each hour over the duration of the project life. Line 1[1] calculates the tariff (based on company policy) that SA will charge the customer in the first year of the agreement and line 2 defines a matrix to store the tariff value for each hour of the project life. Lines 3 to 7 with line 5 are used to extend this tariff over each hour in the user specified project life and simultaneously apply SA's annual tariff escalation rate.

Algorithm 2: SolarAfrica Rate Calculation

```
1 SAtariff ← ((EquipmentAndInstall × 1000 × ROI) + 100)÷ sum(OnekWpYield)
2 SArateProjectLife ← matrix(rows = 8760, columns = n)
3 for j to n do
4 |   for i to 8760 do
5 |   |   SArateProjectLife [i, j] ← (SAtariff)×(1+SAincrease)^(j−1)
6 |   end
7 end
```

The hourly yield values for the proposed system size over the project life are calculated by Algorithm 3. Line 1 calculates the yield values for every hour in the first year by multiplying the yield values for a 1 kWp system by the proposed system size. Line 2 defines a matrix to store all the values. Lines 3 to 7 with line 5 inside, both apply SA's annual solar panel degradation factor and extend the solar yield values over the duration of the project life.

[1] OnekWpYield is a one year set of solar yield values for a 1 kWp equivalent system as calculated in Section 4.2.1

Algorithm 3: System Yield Calculation

```
systemYieldProposedSize ← OnekWpYield × p
YieldProjectLife ← matrix(rows = 8760, columns = n)
for j to n do
    for i to 8760 do
        YieldProjectLife [i, j] ← systemYieldProposedSize[i] × (1−degradation)^(j−1)
    end
end
```

Algorithm 4 compares the yield value in every hour of the project life against the power consumption value, in order to determine revenue, customer savings and overproduction over the project life. Lines 1 to 3 define matrices for the three aforementioned variables. Line 6 tests whether the power produced by the solar system is greater than the site's power demand in a given hour. The revenue, customer saving and overproduction values are then assigned accordingly in lines 7 to 9 if power supply is greater than user demand or in lines 12 to 14 if user demand is greater than or equal to power supply. These lines enforce a constraint that ensures SA can only earn revenue for supplying the power demanded by the user and not for providing power in excess of demand.

Algorithm 4: Compare Supply and Demand

```
1  RevenueProjectLife ← matrix(rows = 8760, columns = n)
2  SavingProjectLife ← matrix(row = 8760, columns = n)
3  OverProductionProjectLife ← matrix(rows = 8760, columns = n)
4  for j to n do
5      for i to 8760 do
6          if YieldProjectLife [i, j] >= UsageProjectLife [i, j] then
7              RevenueProjectLife [i, j] ← (SArateProjectLife [i, j])×(UsageProjectLife [i, j])
8              SavingProjectLife [i, j] ← (EskomRateProjectLife [i, j]- SArateProjectLife
                 [i, j])×(UsageProjectLife [i, j])
9              OverProductionProjectLife [i, j] ← (YieldProjectLife [i, j]) - (UsageProjectLife [i, j])
10         end
11         else
12         RevenueProjectLife [i, j] ← (SArateProjectLife [i, j])×(YieldProjectLife [i, j])
13         SavingProjectLife [i, j] ← (EskomRateProjectLife [i, j]- SArateProjectLife
             [i, j])×(YieldProjectLife [i, j])
14         OverProductionProjectLife [i, j] ← 0
15
16     end
17 end
```

Algorithm 5 completes two NPV calculations, firstly for project costs (lines 1 to 4) and secondly for revenue (lines 5 to 9). Annual maintenance is a geometric series annuity that increases by SA's escalation rate each year and revenue consists of 15 unique future values that are brought back to a present value.

Algorithm 5: NPV Calculations

```
termOne ← (1 + SAincrease)^n
termTwo ← (1 + ROI)^−n
termThree ← ROI − SAincrease
EquipmentandMaintenance ← EquipmentAndInstall + ((maintenanceAnnual)× (1 - (termOne
    *termTwo))÷(termThree))
LifetimeRevenue ← 0
for t = 1 to n do
    YearRevenue ← sum(RevenueProjectLife [, t])×(1 ÷ (1+ROI)^t)
    LifetimeRevenue ← LifetimeRevenue + YearRevenue
end
```

Finally, Algorithm 6 differs depending on which of the three objective functions is being maximised. To demonstrate each objective function in the algorithm, the calculation for each is given - differential income to maximise differential income, NPV to maximise profit and customer saving to maximise customer savings. The production cost ($Rands/kWh$) is calculated in line 1 in order for the total cost of overproduction over the project life to be calculated in line 2. Line 5 returns the value to be maximised, which in this case is the NPV value (profit).

Algorithm 6: Final Calculations

```
1 ProductionCostPerkWh ← EquipmentandMaintenance ÷ sum(YieldProjectLife)
2 Differentialincome ← sum(RevenueProjectLife) -
    (sum(OverProductionProjectLife)×ProductionCostPerkWh)
3 NPV ← LifetimeRevenue- EquipmentandMaintenance
4 CustomerSaving ← sum(SavingProjectLife)
5 return NPV
```

4.4 Iterative Algorithm

The Maximisation Function consisting of the algorithms detailed previously, is used by the IM to determine the optimal system size. Step five (Figure 4.1) is performed by the IM that calls the Maximisation Function which calculates and returns the objective function value. The IM tests all possible system sizes (minimum to maximum) in $1kWp$ increments by sending the system size as a parameter to the Maximisation Function and retrieving the corresponding objective function value for that system size. It then asseses whether the returned objective function value is greater than the current maximim (line 4). Line 5 replaces the current maximum with the returned objective function value. Line 6 updates the optimal system size, if the value returned by the Maximisation Function is greater than the current maximum.

Algorithm 7: Test All System Sizes

```
1 CurrentMaximum ← 0;
2 OptimalSize ← 0;
3 for p = min to max do
4     if MaximisationFunction(p) > CurrentMaximum then
5         CurrentMaximum ← MaximisationFunction(p);
6         OptimalSize ← p
7     end
8 end
```

4.5 Genetic Algorithm

The customised Maximisation Function is also used as an input to a GA function called *rgenoud* in *R-studio*. *genoud* is a function in an *R-studio* package called *rgenoud* that uses GA to test different system sizes by changing the function's input value (system size) and receiving the result (objective function value) each time until it has determined the optimal system size - that which produces the greatest differential income, profit or customer saving.

4.6 Particle Swarm Optimisation

PSO is also used to determine the optimal solution. As with GA, the returned value from the Maximisation Function is used as an input to an optimisation function. This optimisation function used is called *PSO* which is contained within an *R-Studio* package called *metaheuristicOpt*. The *PSO* function uses PSO to determine the system size that maximises the objective function value.

A comparison of the results obtained from use of the three different algorithms is detailed in Section 5.2.

Chapter 5

Model Solution

An *R-studio* model was developed based on the model design in Chapter 4. The model contains script that when run, performs the necessary functions to determine the optimal size system (as defined by the selected objective function). The code in *R-studio* runs as a 'one-click' script and produces a graphic of the model results, a dataset summarising these results as well as an output message informing the user of the optimal system size.

Multiple runs of the model were completed to test the results of the different objective functions for the site addressed in Section 3, as well as to test the performance of the different methods (IM, GA and PSO) used to determine the solution.

5.1 Iterative Method Results

5.1.1 Maximise Differential Income

To compare the results of the different objective functions, all three were run with the IM and the same user inputs. The simulation file produced by *PVsyst* produced yield values for a 17.16 kWp system, SA sized the system at 14 kWp with current methods and the maximum possible system size for the site in Kwaggafontein is 33 kWp. SA's MARR of 13.5% is used and worst case panel degradaton of 0.07% is used. Eskom's most recent TOU tariff increase (7.32%) is used as their annual rate increase and SA's annual tariff escalation set to CPI + 1% (6.98%).

When maximising differential income, the optimal system size is determined to be 31 kWp (shown in Figure 5.1), which is more than double the size the system was sized at with present methods (14 kWp). Sizing the system at 31 kWp instead of 14 kWp is expected to yield an additional R 232 959 in differential income for SA over the duration of the project life. System sizes greater than 31 kWp in size, indicate lower potential profit values than 31 kWp because potential revenue to be earned is not justified by the overproduction costs incurred to install and maintain such a large system.

5.1.2 Maximise Profit

When maximising profit (i.e. the NPV value) the optimal system size is in fact determined to be the value the system was sized at with present methods (14 kWp). This system size will ensure that SA's 13.5% ROI is met with an excess of R 17 323. All system sizes with a negative NPV (those 20 kWp and bigger) are in fact not feasible as they do not meet SA's MARR. The value the system was sized at with present methods is not needed to maximise this objective function and this is the reason why Figure 5.2 plots system sizes from 1 through 33 kWp, instead of 14 through 33 kWp.

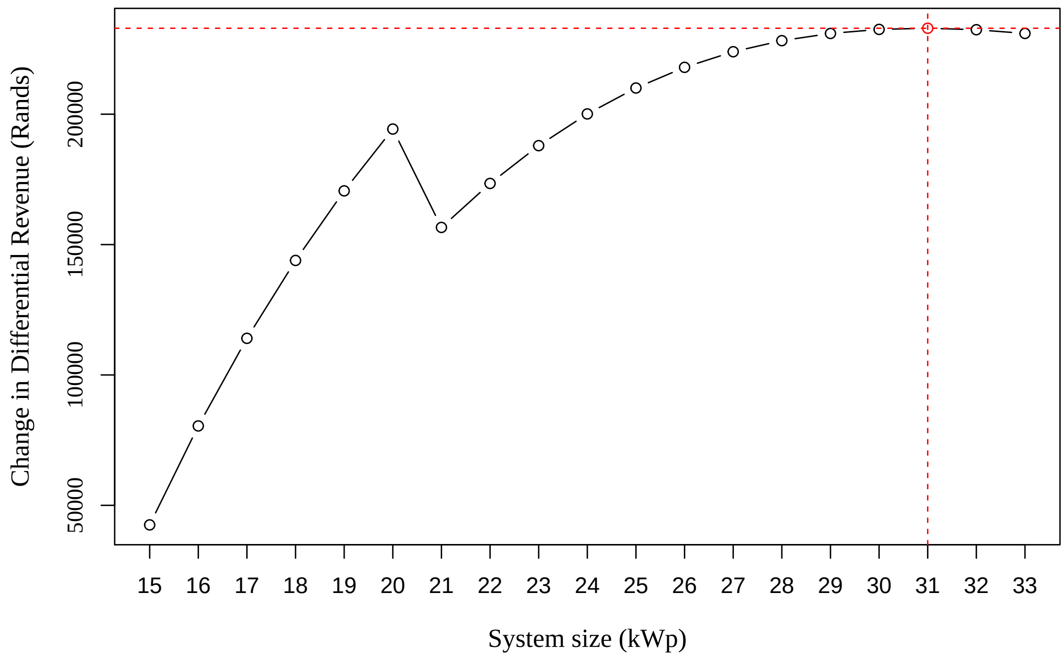

Figure 5.1: Change in differential income for proposed system sizes

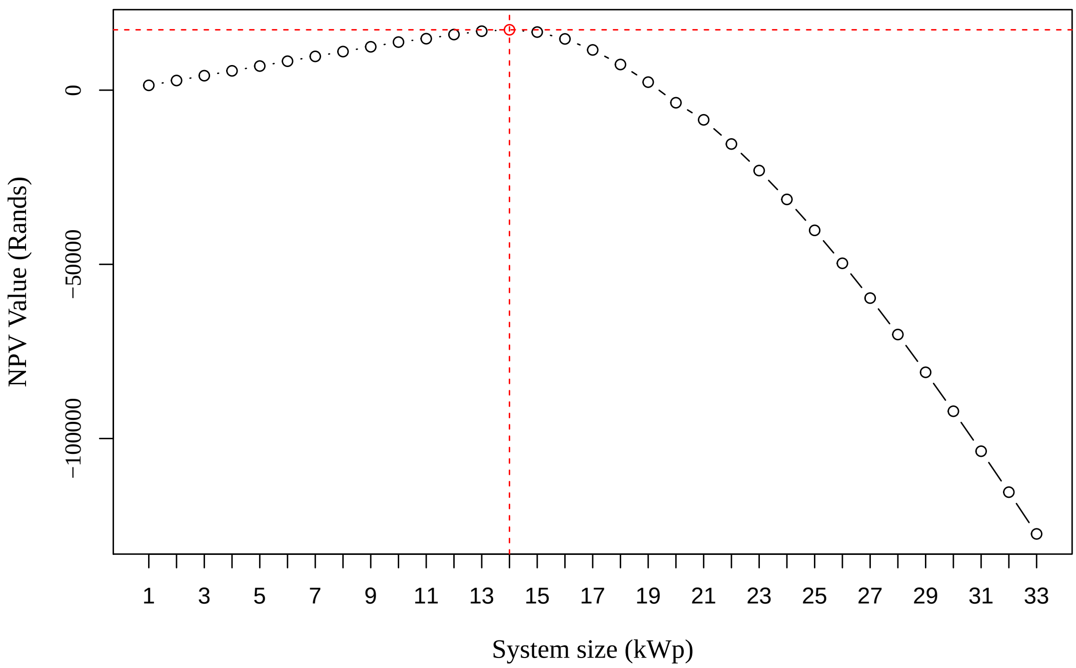

Figure 5.2: Expected NPV values for proposed system sizes

5.1.3 Maximise Customer Savings

To maximise customer savings, the model selects the largest system size possible (to displace as much of Eskom's more expensive power as possible). The model therefore selects the largest system size possible and is only constrained by the maximum system size for this site, which is 33 kWp. This is shown in Figure 5.3.

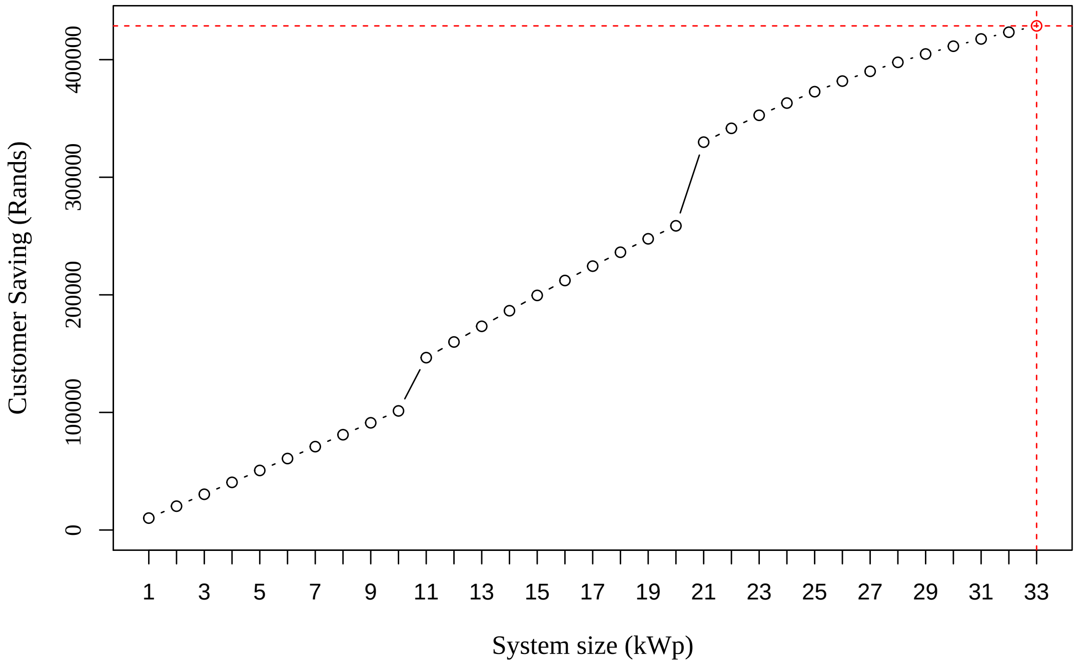

Figure 5.3: Expected customer saving over specified project life

Therfore, it is essential that the 13.5% ROI constraint imposed by management, is used to remove system sizes from the solution space that are infeasible for SA. Once this constraint is applied to the model, the graphical solution is as shown in Figure 5.3. After applying this constraint and eliminating infeasible solutions, the system size that maximises customer savings over the life of the project is determined to be 19 kWp rather than 33 kWp.

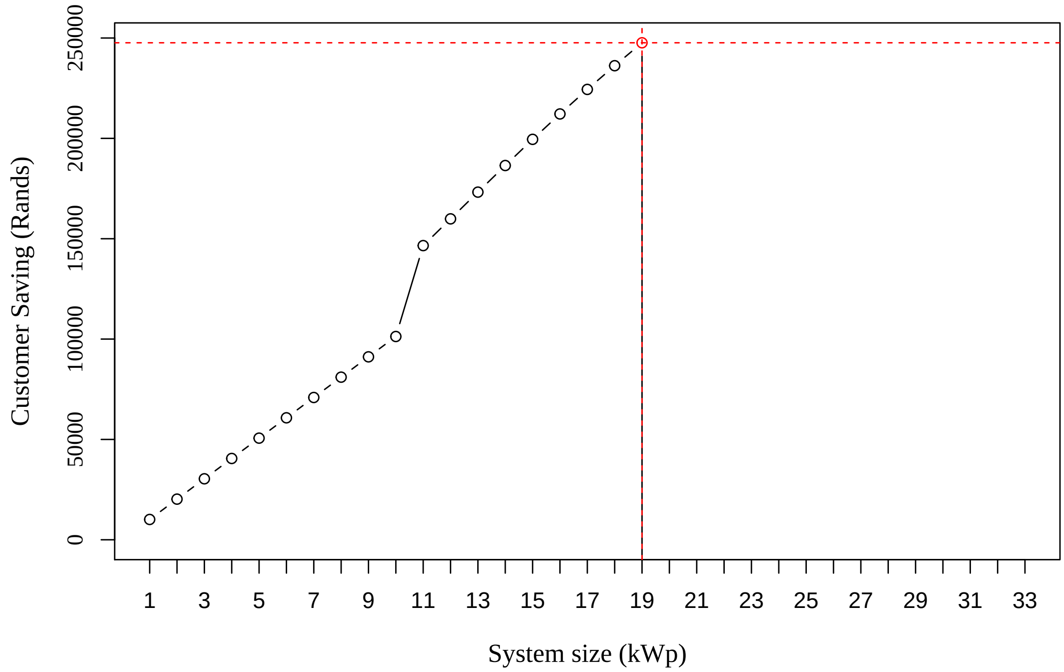

Figure 5.4: Expected customer saving over specified project life with ROI constraint

5.2 Algorithm Comparison

Three different algorithms have been used to maximise profit namely; IM, GA and PSO. Although all three methods call the Maximisation Function, the customised IM provides the following important functionality for the user when determining the optimal solution.

Comprehensive Output - The developed Maximisation Function is contained within a programming function in *R-studio*, enabling it to be called as many times as necessary. This importantly, allows the function to be called multiple times within the IM's for-loop that builds a dataset of variables with each result returned by the function. This dataset can then be displayed to the user after the optimal solution has been reached, giving them a comprehensive output of the profit, revenue, overproduction and other values for each system size tested by the algorithm.

Useful Graphics - The results dataset enables the plotting of graphs for the user to view the relationship between system size and any of the other variables in the dataset (profit, revenue, overproduction etc.) This function is particularly useful for the user to interpret the relationship between system size and other relevant variables for the specific site. If it is not possible in practice to meet the optimal system size for any reason, this functionality provides the user with an opportunity to assess the relationship between system size and the objective function. The user can then make an informed decision on what system size should instead be selected.

The *genoud* (GA) and *PSO* (PSO) functions in *R-Studio* unfortunately, do not provide this same functionality. This is because the inner workings of these functions are not accessible while they are running. The options to view run results in both of these packages are somewhat limited and neither allows for comprehensive output or useful graphics to be produced as with the customised IM.

5.3 Algorithm Results

The three different algorithms were each run with the objective of maximising customer savings in order to compare the performance of each. Thirty runs of each model were completed and the optimal size, maximised customer savings value and solution time of each run recorded.

Table 5.1: Algorithm Results Summary

Algorithm	**Average Run Time (s)**	**Average optimal system size (kWp)**	**Average Customer Saving (R)**
Iterative Method	4.20	19	247 626
Genetic Algorithm	30.13	18.01	236 316
Particle Swarm Optimisation	9.69	17.98	235 967

Table 5.1 shows that IM gets the closest to the global optimum, by achieving the highest customer saving on average. PSO rivals GA in this criterion, with GA achieving only R 350 more in customer savings on average over the project life. In terms of average system size determined, there is a difference between PSO and GA of 0.03 kWp. This difference is insignificant, considering it is not practically possible for SA to design a system to further resolution than a single (kWp) in most cases anyway. GA produced only marginally better results than PSO, which on average is more than 20 seconds quicker at reaching a near identical local optimum. Figure 5.5 shows the run time results of the three algorithms.

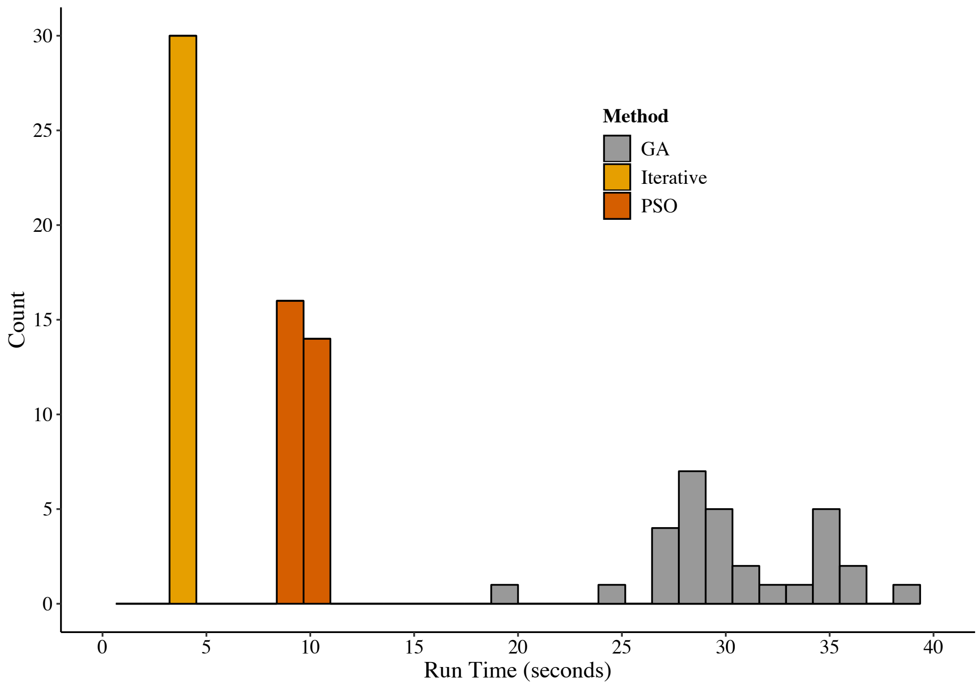

Figure 5.5: Algorithm run time results

IM is substantially quicker than both GA and PSO in its run time. However, it is expected that IM may not determine a solution quicker than the two metaheuristics methods when substantially more system sizes need to be tested (i.e. if the maximum system size for a site was 100 kWp instead of 33 kWp). Use of IM instead of the other algorithms in this scenario would have also resulted in R 10 000 more customer savings over the duration of the project.

5.4 Model Verification and Validation

The model has been verified and validated against the criteria defined by Manson [14] and explained in Step 4 of the Design Methodology (Section 1.5). Both verification and validation were completed through consultation with SA employees experienced in system sizing.

5.4.1 Verification

The model is verified by its ability in a number of ways to accurately reflect the decision making process SA desire system sizing to follow. The four primary datasets (Solar Yield, Power Consumption, Cost and Electricity Tariff) currently used by SA to determine system size are all used by the model to determine the optimal system size. Secondly, the model allows the user to select from multiple objectives when sizing a system. This provides the same flexibility as the current sizing process by enabling the user to decide whether to maximise differential income, profit over project life or customer savings. Finally, the model is also verified in its ability to support sensitivity analysis.

The present system sizing process allows SA employees to perform sensitivity analysis if necessary and functionality to support this part of the decision making process has therefore been included in the model. Numerous user inputs to the model allow the user to explore additional 'what if' scenarios when sizing a system. For example: the Eskom annual tariff increase variable can be set to 15% to explore the possibility of the state owned enterprise increasing electricity costs significantly in the coming years or the project life variable can be changed should SA want to determine the optimal system size for a 10-year Purchase Power Agreement rather than a 15-year agreement.

5.4.2 Validation

Assumptions made when developing the model have been proven reasonable and valid. SA consider solar yield data provided by the on-site simulation program *PVsyst* to be accurate enough for use in system sizing. Supplier selection reflects the policy of cheapest supplier selection which is often the case for SA apart from some instances where a specific supplier is selected for a project for strategic reasons or equipment and installation availability in a specific location. This assumption made in the model design is valid because SA can at any stage change the *Microsoft Excel Cost* datasheet provided as an input to the model, should the company only wish to consider one supplier for a particular site. The model accounts for annual maintenance costs at 1.5% of the initial equipment and installation cost which is deemed to be valid because this is the actual policy used in practice by SA.

The model has been validated by testing its ability to produce consistent and realistic results. Solar yield and power consumption datasets were first validated to ensure data tidying completed by the model does not incorrectly alter any values. Values produced by the model (equipment cost, cost of power production (R/kWh), revenue and SA's tariff rate) have also been validated. Validation of these values was completed by ensuring each calculation performed by the model produced values closely comparable to the actual values calculated by SA with present sizing methods for the specific site.

5.5 Concluding Remarks

The results from the maximisation of profit objective function show SA's present sizing methods to be accurate in maximising profit for the site in this study. Management have however, decided to pursue maximised customer savings as the objective function with a minimum 13.5% ROI as a constraint.

IM is selected as the solution algorithm to be used for its efficient run time performance, ability to reach the same or better result than the other algorithms, its suitability to practical 1 kWp system sizing and the useful graphics and comprehensive output the user is provided with by using this method.

Chapter 6

Conclusion

In order for a solar energy system to be optimally sized as part of a HRES, the unqiue nature of such a system must be appreciated. Each company often has a different business model and way of defining the optimal size system (evident by the three different objective functions in SA's case). This, in combination with the fact that commercial and residential use of solar technologies is relatively new to most markets, means there is a lack of commercialy available software for renewable energy companies to optimally size systems to their unique needs.

It is important for renewable energy providers to develop optimal sizing systems in order to improve their profits, displace as much fossil fuel energy as possible and ultimately to reduce the cost of solar technologies by growing the industry. Sufficient and reliable data in the form of the four primary datasets (Solar Yield, Power Consumption, Cost and Electricity Tariff) are essential to determine an optimal system size and develop any optimal sizing model. The collection and handling of this data is therefore crucial to solar energy providers and in particular, to SA.

6.1 Research Question

With regards to the research question initially posed, the study reveals that it is in fact beneficial to oversize a system as the additional revenue gained over the project life exceeds the higher installation and maintenance costs that must initially be incurred. Results obtained from maximising *Differential Income* and *Customer Savings* prove the reaearch hypothesis to be correct as both determine the optimal system size to be larger than the value the system was sized at with current methods - 19 kWp and 31 kWp respectively, compared to 14 kWp.

However, results from the *Maximise Profit* objective function show current sizing methods to be accurate in maximising profit and therefore suggest the hypothesis of the research question may not be correct for all sites (i.e. systems should continue to be undersized). Nevertheless, SA have decided to pursue customer savings as the objective function for future use and the research question is therefore deemed to be correct for the site sized in this study.

6.2 Method Selection

Although this study shows IM to be the most timely and effective, it is recommended that SA test the model with larger sites that have more system sizes to be tested by the IM. This is because it is anticipated that the IM will take longer to reach an optimal size in this scenario and PSO's run time may therefore be similar or possibly shorter than that of the IM. IM and PSO will therefore be further pursued for their suitability to SA's case but GA will not for its slow run time performance.

6.3 Value Creation

Implementation of the model is expected to create value for SA in the form of time savings, risk elimination, improved reproducibility and increased personnel availability.

The present method used by SA to size systems is time consuming, vulnerable to human error and not reproducible. SA employees experienced in system sizing use a number of *Microsoft Excel* documents to perform calculations and manipulate data. Analysis of a new site's background is conducted to determine the site's characteristics and determine its operating hours, size, maximum roof space and whether it is a business or household. Employees then search SA's installations database for existing sites with similar characteristics to the new site to be sized. Power consumption data on these existing sites is then used to determine a predicted power demand pattern for the new site. In order to make this prediction, a combination of experience, judgement and calculations is required to identify different patterns in the power consumption data. For example: one must determine whether a site is a 5, 6 or 7-day operation based on its power consumption data. In practice, actual power consumption data for a new site is sometimes available and helps to better size a system for a new site. However, even when this data is available, the current sizing process still does not follow a prescribed method and therefore lacks reproducibility.

Perhaps the most significant value that can be created by implementation of the optimal sizing model, is that it would significantly reduce the time taken to size a system for a given site. At present it takes SA 2-3 days to size a system for a given site, whereas the model can determine the optimal system size in a matter of seconds. It should however be noted that use of the model will not eliminate the need for the required datasets to be generated or retrieved. Power consumption data will need to be received from the potential customer and the solar yield data generated in-house by *PVsyst*. The cost and electricity tariff datasets will not need to be generated each time a site is sized but will need to be updated periodically when supplier costs and Eskom's rates change. Time savings gained from use of the model will be realised in terms of a reduction in the time taken to size a system for a new customer. The sizing model performs many of the calculation, judgement and comparison tasks SA employees involved in system sizing, are currently required to perform manually. The most significant time saving is therefore anticipated to be realised by freeing up time for SA employees involved in system sizing, which will increase personnel availability to SA. SA employees involved in system sizing can then use this additional time to focus their efforts on more taxing system design activities.

Successful implementation of the model will importantly improve reproducibility in the sizing process by providing a consistently reliable result for a given site, regardless of who runs the model, meaning any variation in the form of 'operator-bias' will be removed from the system sizing process. The risk of human error in calculations and data manipulation present in the current process will be eliminated with use of the model. However, the risk of human error in the form of erroneous data entry into the model will still be present and exception handling techniques will need to be applied during implementation to mitigate this risk.

The potential benefits to be realised from use of the model are significant and the cost of further research and testing of the model is relatively low for SA, requiring only resources from employed staff to test and implement. Further research and testing of the model for future use is therefore justified.

6.4 Implementation

The design of the model in *R-Studio* with script in *R* programming language, means the model code can therefore be executed by SA's on-site information system (*Unifii*) without any conversion of code before implementation. *Unifii* will ultimately provide the GUI for the model script and some work will therefore be required to connect the sizing model with *Unifii* to retrieve the user inputs from the GUI and assign them to the corresponding variables inside the model.

SA also plan to develop a power demand forecasting model in future for scenarios where actual load data for the site being sized is not available on an hourly basis. This forecasting model will produce a prediction of consumer power consumption on an hourly basis from monthly power consumption totals (bills). This prediction will then be used as an input to the optimal sizing model (as the Power Consumption Data). In practice the optimal sizing model will operate with the proposed demand forecasting model and *Unifii* as in Figure 6.1.

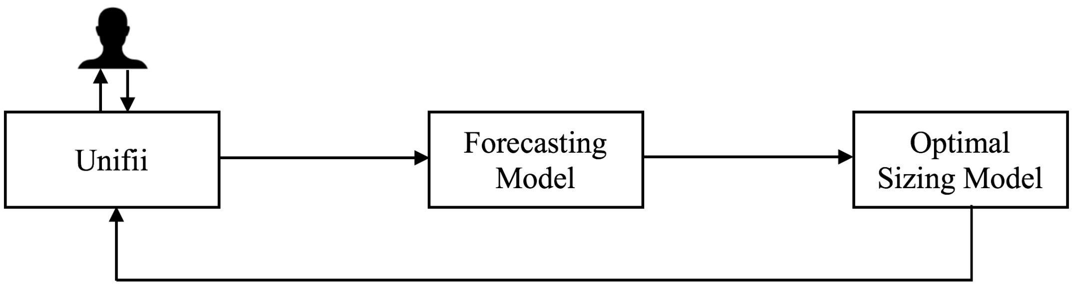

Figure 6.1: Model implementation

The user will run the sizing model which will call on the forecasting model to predict consumer power consumption. This power consumption prediction will then be used as an input to the optimal sizing model which will determine the optimal system size, transfer this information to Unifii and ultimately display the optimal system size and relevant results to the end user.

Unifii's GUI will appear as in Figure 6.2 where the user will be able to enter the user inputs for the optimal sizing model and monthly power consumption totals for the forecasting model.

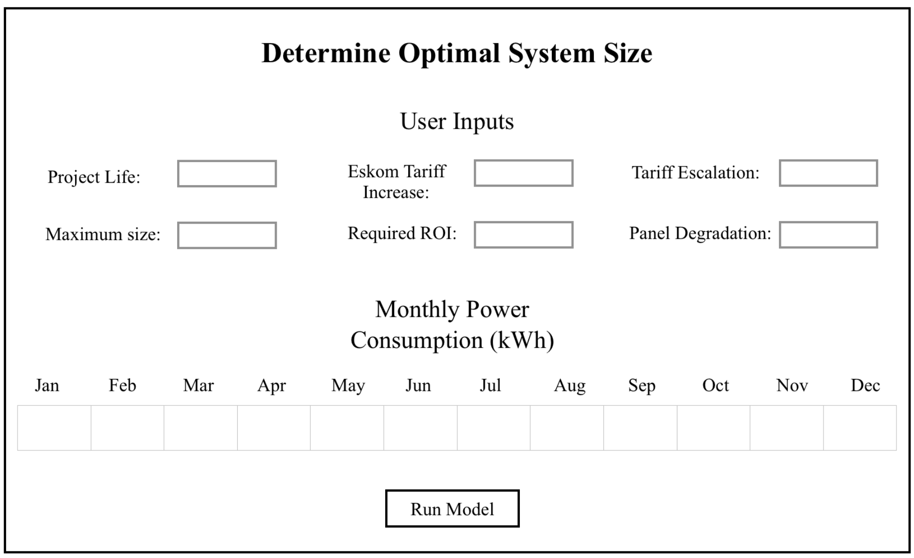

Figure 6.2: Unifii graphical user interface

6.5 Final Recommendations

It is advised that the model be tested with an array of different sites before implementation. This is important to discern whether different or unexpected results are yielded for larger sites and whether IM or PSO should be used in the final model. Once this additional testing is complete and final decisions are made by SA regarding method use, the model can be integrated with *Unifii*.

Furthermore, it is recommended that any power demand forecasting model developed in future be rigorously tested to ensure its results are accurate and reliable before using its output as an input to the optimal sizing model. The use of less accurate forecasted power demand in place of actual power demand will weaken the accuracy and reliability of the final result (optimal system size).

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Appendix A

Plagiarism Declaration

1. I understand what plagiarism is and I am aware of the University of Pretoria's policy in this regard.

2. I declare that this report is my own original work. Where other people's work has been used (from the internet or any other source), this has been acknowledged and referenced in accordance with departmental requirements.

3. I have not used work previously produced by another student or any other person to hand in as my own.

4. I have not allowed, and will not allow, anyone to copy my work with the intention of passing it off as his or her own work..

SIGNATURE ……………………….

Appendix B

Industry Mentorship Form

Department of Industrial & Systems Engineering
University of Pretoria

Final Year Project Mentorship Form
2018

Introduction
An industry mentor is the key contact person within a company for a final year project student. The mentor should be the person that could provide the best guidance on the project to the student and is most likely to gain from the success of the project.

The project mentor has the following important responsibilities:

1. To select a suitable student/candidate to conduct the project.
2. To confirm his/her role as project mentor, duly authorised by the company by signing this **Project Mentor Form**. Multiple mentors can be appointed, but is not advised.
3. To ensure that the **Project Definition** adequately describes the project.
4. To review and approve the **Project Proposal**, ensuring that it clearly defines the problem to be investigated by the student and that the project aim, scope, deliverables and approach is acceptable.
5. To review and approve all subsequent project reports, particularly the **Final Project Report** at the end of the second semester, thereby ensuring that information is accurate and the solution addresses the problems and/or design requirements of the defined project.
6. Ensure that sensitive confidential information or intellectual property of the company is not disclosed in the document and/or that the necessary arrangements are made with the Department regarding the handling of the reports.

Project Mentor Details

Company:	SolarAfrica
Project Description:	Optimal Sizing Calculator
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