OPTIMAL METERING PLAN IN AN ENERGY EFFICIENCY PROJECT FOR A FERROCHROME PLANT

by

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SUMMARY

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An accurate measurement of retrofitted loads is essential for the quantification of energy savings in an energy conservation measure project. This research presents an optimal meter placement approach to an ECM project in a ferrochrome plant. The ECM project is implemented in a selected plant in a ferrochrome production line in which three different types of loads are considered for retrofitting.

The aim of this research is to minimize the metering costs associated with the measurement and verification process while satisfying the precision and accuracy requirements for the sampling and measurement plan. The metering costs are reduced by using two types of metering devices. One meter yields highly accurate data measurements, has superior functionality to the other meter and is consequently highly priced. Different sampling requirements for the ECM project are evaluated and an optimal solution is found by selecting a combination of inexpensive and expensive metering equipment. The proposed optimal meter placement configuration yields a combination of meters with the highest accuracy in the ECM and has the lowest cost.

OPSOMMING

OPTIMALE METINGSPLAN IN 'N ENERGIEDOELTREFFENDHEIDSPROJEK VIR 'N FERROCHROOMAANLEG

deur

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Sleutelwoorde:	Optimale meting-en verifikansieplan, particle swarm optimization, optimale metingsplasing

Akkurate meting van retropassingladings is uiters belangrik vir die kwantifisering van energiebesparings in 'n energiekonservasiemaatstaf (ECM). Hierdie werk bied 'n optimale meterplasingbenadering tot 'n ECM-projek in 'n ferrochroomaanleg. Die ECM word toegepas op 'n aparte aanleg in 'n ferrochroomproduksielyn en drie tipes ladings word oorweeg vir retropassing. Die studie beoog om die metingkoste geassosieer met die meting- en verifikasieproses te minimeer terwyl dit terselfdertyd voldoen aan die presisie- en akkuraatheidvereistes vir die toetsing- en metingplan. Om die metingkoste te verminder, word twee tipes meters gebruik, 'n dure en 'n goedkope. Die verskil tussen die twee meters is hulle funksionaliteit; die duur meter het meer funksionaliteit en meet meer akkuraat, terwyl die goedkoop meter minder funksionaliteit en 'n laer akkuraatheidsvlak het.

Verskillende toetsingvereistes vir die ECM word geévalueer en 'n optimale oplossing word verkry deur die keuse van'nkombinasie van goedkoop en duur metingstoerusting. Die voorgestelde optimale meterplasingkonfigurasie lewer 'n kombinasie van meters met die hoogste akkuraatheid in die ECM en kos die minste.

LIST OF ABBREVIATIONS

AC	Air-conditioning system
CV	Coefficient of Variation
dSM	Demand Side Management
ECM	Energy Conservation Measure
EE	Energy Efficiency
ESCO	Energy Service Companies
ESM	Energy Savings Measure
ESRS	Exogenous Stratified Random Sampling
GA	Genetic Algorithm
IPMVP	International Performance Measurement and Verification Protocol
LED	Light-emitting Diode
M&V	Measurement and Verification
PSO	Particle Swarm Optimization
SA	Simulated Annealing
SD	Standard Deviation
SRS	Simple Random Samples
TOU	Time of Use
VSD	Variable Speed Drive
ZAR	South African Rand

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CHAPTER 1

INTRODUCTION

1.1 PROBLEM STATEMENT

1.1.1 Context of the problem

Most of the energy consumption within the overall industry is attributed by the manufacturing industry. In 2007 the industrial sector consumed 51% of the energy globally [1]. It is estimated that electric motors use up to 60% of all electricity consumed by the South African industry [2]. Therefore, there is an opportunity for increasing savings through energy efficiency (EE) campaigns and initiatives in industry [2]. These opportunities can be achieved by applying demand side management (DSM) strategies to all facets of the industry, ranging from electricity efficiency to building EE and process optimization [1].

Modern-day ferrochrome production faces a number of challenges due to unstable ferrochrome prices and increasing demands to maximize throughput whilst minimizing waste and addressing poor operating conditions. The cost distribution for a South African ferrochrome production plant is made up of three main factors, namely, chromite ore, electricity and reductants. The three main factors account for 30% of the total production cost. The final 10% is made up of maintenance, labour and the disposal of waste [1] - [3].

Energy consumption in ferrochrome production is divided into several processes, each consuming a certain amount of energy. The highest energy consumption is attributed to the smelting processing plant, which accounts for 90% of the energy consumption. The remaining 10% is attributed to all the auxiliary plants that contribute to ferrochrome production

[3].

A survey of the literature study on EE in ferrochrome plants reveals that more work has been done on furnaces in terms of EE ranging from design to operation [3] - [4]. In this research an ECM project is implemented in the auxiliary plant, namely the ore beneficiation plant and the buildings therein.

1.1.2 Research gap

There are several challenges in quantifying the savings achieved for an optimal metering plan in an ECM program. The first challenge in optimal metering plan is identifying key performance indicators of the data before and after retrofitting for baseline modeling. The second challenge arises from identifying locations within an ECM network where measurements of the highest accuracy can be captured with the least cost incurred. The last challenge arises from the shortcoming in the method used in processing insufficient data which affects the actual savings and causes large discrepancies between the measured values and the estimated savings. These challenges are caused by using a heuristic approach to measurement and verification (M&V) metering plan.

1.2 RESEARCH OBJECTIVE AND QUESTIONS

The goal of this research is to present an optimization model for minimizing the metering costs associated with the M&V metering plan. The approach used for minimizing the metering costs is to use a combination of two types of metering equipment with different functionality and costs. The optimal meter placement problem is formulated as a binary integer programming problem that uses the binary decision variables $\{0,1\}$ to optimally place meters on retrofitted equipment. The problem investigated is classified according to the load homogeneity, the sampling criterion, the accuracy requirement and the coefficient of variation. The constraints of the optimization model must be achieved while minimizing the metering costs. The following constraints must be satisfied.

- The total metering cost must not exceed 10% of the total annual energy savings assessed in an ECM program [5];

- For every group under consideration at least one item of metering equipment must be used;
- Both precision and sampling requirements must be satisfied by each group;
- A good overall accuracy requirement must be achieved by the model.

This research must address the following questions:

- How much metering savings can be achieved by using an optimal metering plan?
- Which items of equipment must be monitored in a population?
- What is the influence of the precision and confidence level on the coefficient of variation in an optimal metering plan?
- What is the relationship between the sampling criterion and the coefficient of variation?
- What is the overall optimal metering accuracy?

1.3 HYPOTHESIS AND APPROACH

In order to realize savings from the M&V metering plan, the coefficient of variation and the sampling criteria can be varied to realize an optimal metering plan so that the cost of metering is reduced and the accuracy of the estimated savings is not compromised. The hypothesis is tested using the following method:

- Investigate the literature on optimal meter placement problems in EE and power systems;
- Mathematical modeling: Formulate an optimization model that minimizes the cost of metering in an M&V plan;
- Investigate the relationship between the metering costs and the sampling criteria;
- Investigate the effect of the sampling criteria and the coefficient of variation to the metering costs;

- Case study: Use a selected plant in a ferrochrome production line and evaluate the accuracy, precision, cost and sampling requirements for optimal meter placement and evaluate the sensitivity of the optimization model;
- Software: Use MATLAB to solve the optimization problem.
- Compare the results of the optimization model and heuristic approach used for meter placement.

1.4 RESEARCH GOALS

The goals for this research are as follows:

- Formulate a robust optimal meter placement model for an ECM with a mixture of loads;
- Minimize the metering costs associated with the M&V metering plan whilst satisfying the precision, accuracy and sampling requirements;
- The metering cost must be less than 10% of the annual energy savings assessed in an energy savings project;
- There must be no redundancy on metering.

1.5 RESEARCH CONTRIBUTION

This research presents a robust optimization model that mitigates the heuristic approach used for meter placement. It eliminates the aforementioned challenges by optimally minimizing the M&V metering cost in an ECM project while addressing the accuracy, cost and modeling limitations. An optimal metering plan is formulated for EE projects and the model is formulated as a binary integer programming problem. The optimal solution selects the type of meter that should be installed and place the meter in the ECM network. Furthermore, the optimization model also shows a relationship between the coefficient of variation and the sampling criteria on the metering costs.

1.6 OVERVIEW OF THIS STUDY

In this research an optimal meter placement method is formulated. The sampling, accuracy and precision requirements are set for the optimal meter placement method and a certain budget constraint is placed on the overall metering plan. The optimization method used is particle swarm optimization (PSO), which can only be applied to unconstrained optimization problems. Therefore, the optimization model is transformed from a constrained model to an unconstrained one using the penalty function method. This chapter reviews the context of the optimal metering plan for M&V, the research gap, the research objectives and the research questions. The research is structured as follows: The following chapter presents a comprehensive literature review on the subject of optimal meter placement with relation to the metering plan in EE projects and the optimal meter placement problem. Chapter 3 formulates the optimal metering plan model and chapter 4 presents the results of the model. A full discussion of the results is presented chapter 5. Chapter 6 gives a comprehensive conclusion and a recommendation for a future study.

CHAPTER 2

LITERATURE STUDY

In this chapter a detailed literature study is performed for optimal metering in an M&V plan. A comprehensive literature review is conducted on the algorithm used for optimal meter placement.

2.1 CHAPTER OBJECTIVES

This chapter begins with a literature study presented on demand side management (DSM) strategies that can be applied to demand savings projects. The DSM strategies are further divided into two types, that is, load management and energy efficiency (EE). A literature review of each strategy is presented in this chapter. The chapter continues with a method that is used for verifying the demand savings, that is, the measurement and verification process. A literature review on M&V presents four international performance measurement and verification protocol (IPMVP) options and the three methods used for verifying demand savings. These methods are sampling, modeling and measurement requirements. A literature study on optimal meter placement for demand savings is presented from the M&V perspective. The different optimization methods that are applied to optimal meter placement are reviewed and the chapter concludes with the challenges and contributions of this research.

2.2 DSM OVERVIEW

The most cost effective way of reducing greenhouse gases and meeting the global demands for reducing CO_2 emissions is by using EE techniques. Most of the EE programs focus on commercial and industrial customers to reduce the energy consumption and CO_2 emissions.

In South Africa alone, industry consumes approximately 65% of all electrical energy and it is with that knowledge that Eskom has made DSM a high priority for reducing energy consumption.

In conjunction with Eskom's initiative for energy reduction, the South African Department of Energy has also made a commitment to achieve a 12% energy reduction by 2015 [6]. This must be achieved by applying DSM strategies that are divided into two parts, namely EE and Load Management.

2.2.1 Energy efficiency

The mathematical ratio of the output to the input energy is referred to as energy efficiency. It is measured from a scale of zero to one; with zero indicating poor EE conversion and one indicating an excellent EE conversion. The EE value is a good indicator for energy use of a system and its normally used in energy management programs as a guideline for potential cost savings in an ECM. According to [7], EE encompasses four efficiency classifications. Namely, technology efficiency, performance efficiency, operational efficiency and equipment efficiency.

The measure of efficiency for energy conversion is defined as technology efficiency [7]; the law of energy conservation is the limiting factor to technology efficiency. There are several key indicators for evaluating technology efficiency, which are feasibility, return on investment and the life-cycle cost to mention a few [6].

Equipment efficiency on the other hand is the measure of the energy output of isolated individual items of energy equipment with respect to their input specified energy. In equipment efficiency, the equipment is separated from the entire system. The typical indicators used for evaluating equipment efficiency are maintenance constraints and equipment capacity constraints. The difference between technology efficiency and equipment efficiency is illustrated by considering an EE motor example. The study of the motor efficiency improvement from poor to higher efficiency forms part of the technology efficiency improvement, however, the replacement of a poor efficiency motor with a high energy efficient motor falls within equipment efficiency [6].

In a case where an entire system is evaluated, operational efficiency is a tool that must be used for such cases. It evaluates the system input and output to measure the effectiveness of the operational efficiency. It also considers different system component efficiency and measures the EE of the system as one operational unit. The indicators for operational efficiency are based on the system component such as physical coordination which is size of the physical space and the time coordinaton is based on time control[6]. The last EE measure is the performance measure. Performance efficiency is determined by external indicators such as production of the system, the cost incurred, the type of energy source used and the environmental impacts caused by the system [6].

2.2.2 Load management

The latter part of DSM strategy focuses on maintaining a constant load factor approaching unity. The load management techniques are classified into five techniques, namely valley filling, strategic conservation, load shifting, strategic load growth and peak clipping. Each technique has a unique way of changing the shape of the load profile and thus reducing demand [8].

Peak clipping, also referred to as load shedding, simply switches off the load for a short period when the demand exceeds the supply on the network. Load shifting refers to moving the load from one tariff structure to another. For example, using a time of use (TOU) tariff structure to move the load from peak hours to off peak hours. Load shifting refers to moving loads from peak hours to either standard or off-peak hours in order to have a load factor close to one and reduce energy cost. Valley filling refers to building loads during off-peak periods which results in increasing the utilization of the installed capacity. The strategic load conservation technique uses EE techniques for reducing the load, while the strategic load growth increases energy consumption and sales outside of the valley-filling periods [8] - [9].

2.3 MEASUREMENT AND VERIFICATION

Measurement and verification is a method used to determine the actual savings from measurements of a facility that is undergoing an ECM. The savings from the ECM can be quantified using guidelines from the international performance measurement and verification protocol (IPMVP) and other institutions. In order to quantify the savings, energy data from the pre-implementation and post-implementation phase must be compared to quantify the savings [5] and [10].

When applying the different DSM strategies to an ECM, there must also be an independent party that can measure and verify the energy reduction and savings. This separate entity provides transparency on the savings achieved by the ECM program. There are a number of stakeholders involved in any ECM program. These stakeholders include the utility, the client, the energy service companies (ESCO) and the M&V team. The utility provides rebates on all savings achieved by implementing the ECM and the ESCO or project developer implements the respective DSM strategies. Thus, the M&V team is the independent third party that measures and verifies the energy reduction and savings. Fig. 2.1 shows the process followed for optimal meter placement in an ECM project.

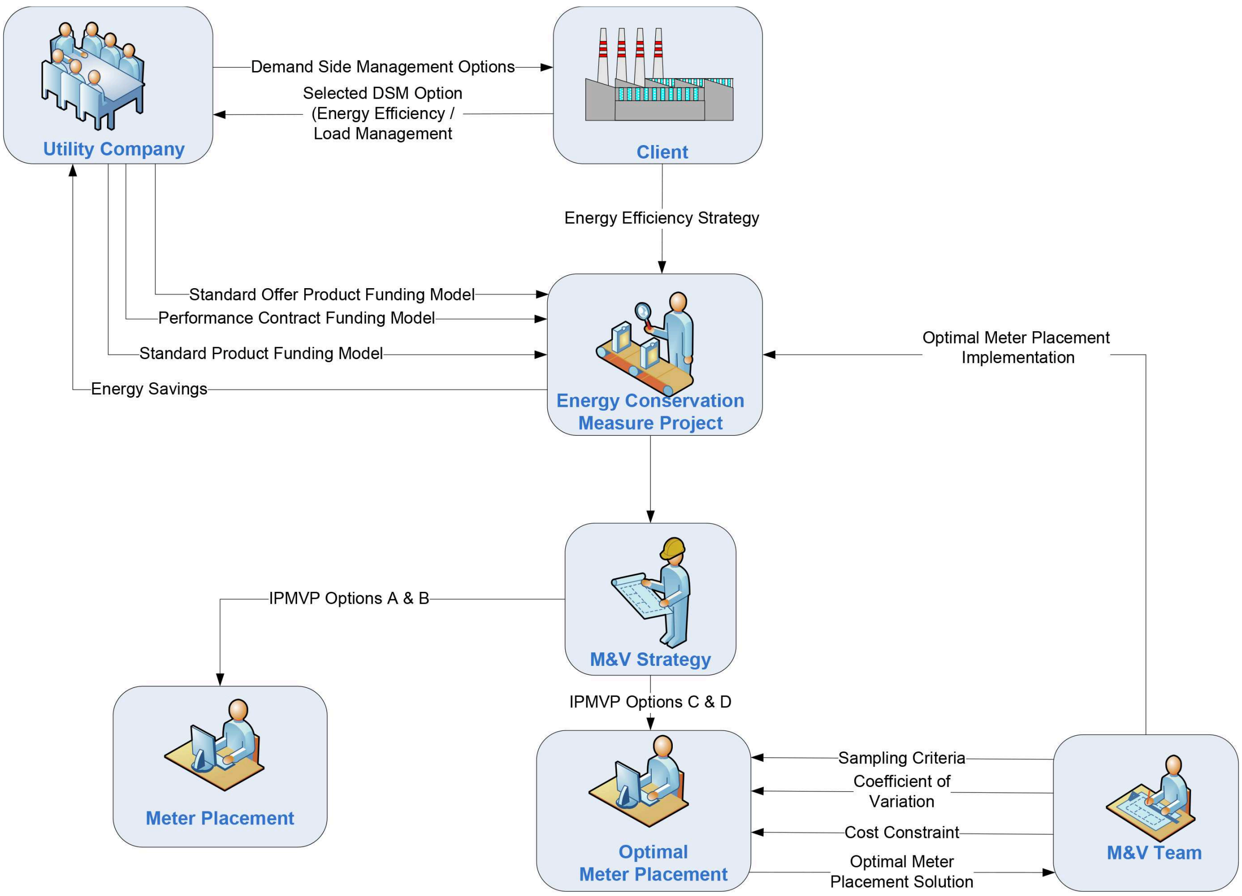

Figure 2.1: Optimal meter placement overview

2.3.1 General principles

The M&V process depends on variety factors; one of the factors that affect the M&V process is the complexity required for the measurement of equipment, the total samples required and the metering equipment thereof, the IPMVP guideline option selected, the total number of EE measures as well as the interaction among them, and the number of independent variables in the model. All these factors are required for quantifying the energy savings with high accuracy for maximum return on savings [6]. These factors increase the M&V costs in the EE programs.

The M&V energy savings activities are guided by the IPMVP [10]. There are other guidelines that are similar to the IPMVP, namely ASHRAE's guideline, the M&V guideline for the Federal Energy Management Program [5], the South African M&V guideline for DSM projects [2] and SANS 50010 to mention a few. The IPMVP recommends four options i.e. Options A to D. Option A is applied to partially measured retrofit with isolation, which means that only parameters that affect the savings are measured. Option B is for isolated retrofits with complete measurement. Option C is applied to measuring the whole facility undergoing retrofitting and does not require full measurement, but rather a sample measurement representing the entire population of the retrofit. The last option in the IPMVP is a comprehensive calibration simulation for which savings are determined through simulations. This is done by modeling the energy use of a facility by measuring only a handful of equipment and estimating the energy usage of other equipment. A typical M&V process is shown in Fig. 2.2.

Fig. 2.2 shows the three stages in estimating the energy savings, that is, the pre-implementation phase, the retrofitting stage and the post-implementation stage [10]. Throughout the process of applying an ECM, as illustrated by the curves in Fig. 2.1, it is apparent that data must be gathered to form a baseline and post-implementation profile, since the adjusted baseline uses information from both the pre-implementation and post-implementation phase. Furthermore, the ASHRAE's guidelines recommend that the baseline model must include variables that may change due to changing conditions and these variables must have a significant influence on the energy usage.

In the pre-implementation phase of the M&V process, all the energy consumption parameters are identified and monitored over a specified period. This period can range from one month to

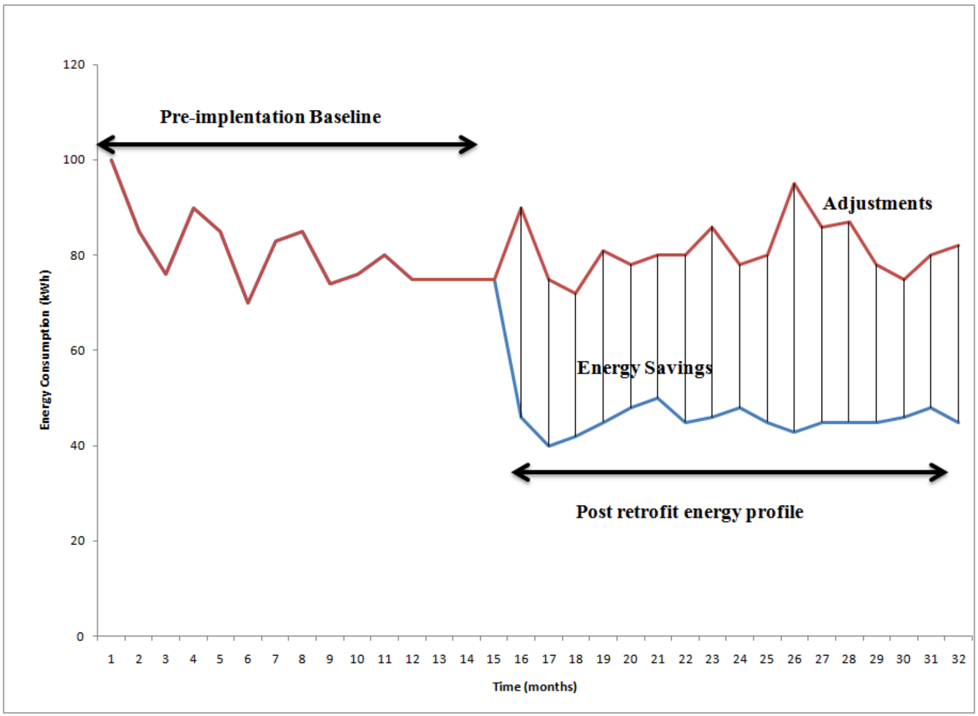

Figure 2.2: M&V process

one year depending on the specified M&V plan. Moreover, in the pre-implementation phase all the metering equipment are placed according to the IPMVP option selected as specified in the M&V plan and the energy profile is captured for future usage in the process as shown in Fig. 2.2.

In the retrofitting or implementation stage, the energy savings strategy is implemented. This strategy can be any one of the DSM strategy. For example, installing variable speed drives (VSD) on a variable load application.

The post-implementation stage of the process assess the estimated saving resulting from implementing the EE strategy. In Fig. 2.2, the energy savings estimation is shown as the difference in the adjusted energy consumption and the new energy consumption after the EE strategy. The adjusted energy consumption is defined as the energy that would have been consumed had no EE strategy been implemented in the second stage.

2.3.2 Selection criteria for different IPMVP options

As already mentioned, there are four IPMVP options from which an ECM can be implemented. Fig. 2.3 illustrates the process of selecting a suitable option that can be applied to different ECM programs.

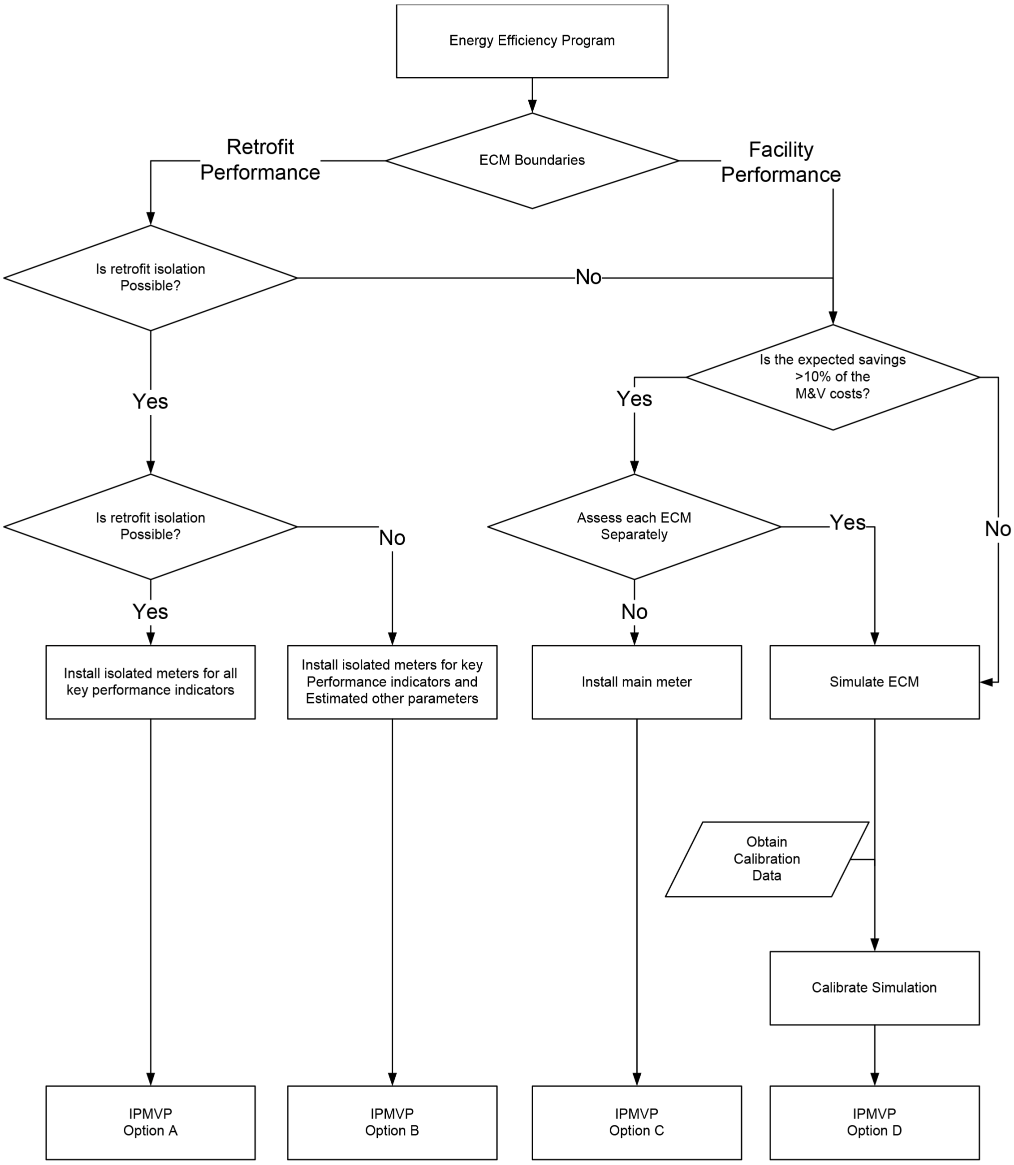

Figure 2.3: IPMVP selection process

As shown in Fig. 2.3, the IPMVP option A and B require retrofit isolation whereas, option C and D does not require a retrofit isolation. The flow sheet provides a clear guideline for selecting the appropriate IPMVP option for an ECM.

2.4 METER PLACEMENT PROBLEM

The meter placement method has previously been applied to the field of power systems. In general it is normally applied to improve the network observability. This is accomplished by installing meters on a distribution system to measure critical parameters of the system such as voltage, reactive power, active power and harmonics etc, all these parameters are referred to as parameter estimations [11]. There are several methods that can be implemented for parameter estimation in a distribution system, all of which uses optimization for meter placement. The most prominent method used in parameter estimation is the heuristic approach [11]. The heuristic approach is normally divided into two steps. The first step places meters heuristically across the distribution network at randomly selected locations. The latter step uses a load estimation and confidence interval to ensure that all randomly placed meters adhere to the required confidence interval. The second step tests if the randomly chosen place satisfies the confidence interval and if satisfied then the location of the meter is approved and the method proceeds to the next branch. This step is repeated until all the meters are placed. The following guidelines are used for meter placement [11], viz.

- Meter failure;
- Space availability;
- Automation switch location;
- Unbalanced property of distribution systems.

In selecting the location for meter placement all four guidelines must be investigated thoroughly. Since there is always a possibility of meter failure, the metering system must be reliably designed so that in an event of one meter failing the meter closest to it will capture the required parameter estimation. In a large distribution network the issue of space availability is concerning and because of that, the meter placement method must always take into account the cost factor. In a large distribution system all meters must be automated and be able to measure the imbalances in the distribution system.

In every meter placement problem, there are four requirements that must be adhered to, namely; [11] and [12].

- Accuracy;
- Cost;
- Reliability;
- Insufficient data processing requirement.

2.4.1 Accuracy requirements

In the accuracy requirements, the proposed metering scheme used must realise the desired accuracy from the parameter estimation. In [12], the total metering cost is minimized subject to the accuracy requirements. The approach uses a performance index to establish a probabilistic consideration of measurement failures. Furthermore, the method uses the measurement sensitivity to evaluate the accuracy requirements and this is accomplished by adding or eliminating redundant measurements via a process of sequential meter elimination. The main objective of the accuracy requirement is to estimate the system parameters.

2.4.2 Reliability requirements

The objective of reliability requirement is to maintain observability on the network even when meters fail or there is loss of measurement on the network. In [11], a method is proposed which maintains observability against loss of network branches by using a process of elimination. A linear programming method is used for choosing the configuration that ensures that the network is fully observable.

2.4.3 Insufficient data requirements

Another requirement that must be adhered to in the meter placement problem is the insufficient data requirement. The metering system must detect and identify insufficient data in measurements. This is achieved by increasing the reliability of the system [13].

2.4.4 Cost requirements

The cost requirements must be kept low for the desired accuracy, reliability and insufficient data processing requirements. In [12], all the important aspects of meter placement problem are addressed. The problem is thus solved in three stages to achieve all the requirements. The first stage minimizes the cost of metering by considering the accuracy requirement and this is achieved by placing a minimum set of meters which achieves the accuracy requirement. The second stage places additional meters to incorporate the reliability requirement, and this is based on the loss or failure of metering equipment. The last stage places meters based on the insufficient data requirement.

2.4.5 Meter placement in EE projects

The optimal sampling approach presented in [14] uses the accuracy and cost requirement for meter placement without selecting equipment to be monitored. In this research the meter placement requires decisions to be made regarding the location and type of meter that must be installed. Therefore this metering plan is formulated as a binary integer programming problem of $\{0,1\}$. The M&V metering plan requirements states that not more than 10% of the annual energy savings costs should be spent on metering while maintaining the accuracy requirements. Hence, this research also focuses on the two requirements for meter placements, that is, cost effective metering plan and the desired accuracy requirements for the parameters observed.

2.5 UNCERTAINTIES IN QUANTIFYING SAVINGS

The aim of the metering plan is to accurately quantify the actual savings in an ECM project. However, a certain level of uncertainty is always introduced by the measuring equipment when quantifying the energy savings. These uncertainties introduced by measuring equipment can be controlled by reducing the random errors and data bias. The factors that affect the random errors are the measuring equipment used as well as the measurement techniques applied and the sampling procedures. Data bias is affected by the quality of measurement data and the assumptions used for data analysis. Thus, there exists a direct correlation between M&V cost and reducing errors because when the errors are reduced, the M&V costs are increased.

By definition, the energy savings computation involves a comparison of measured energy data before and after the retrofit, and an adjustment is required to superimpose the two measurements to a common operating condition [5]. The measurement and adjustments used for quantifying savings also introduce some error and uncertainty. These errors may arise from meter inaccuracy, sampling procedures or adjustment procedures. In quantifying the energy savings from the measurements, the true values are unknown but some of the estimates can be quantified using statistical methods.

The errors in quantifying savings occur in three ways:

- Modeling. Modeling errors are the result of poor mathematical modeling such as including variables that have no impact on the performance of the model; and excluding critical variables that affect the models performance.

- Sampling. The sampling error arises from the fact that a portion of the population is measured to infer the total population. This introduces some level of uncertainty in the measured information.

- Measurement. Measurement error arises from the actual measuring equipment used for capturing data. This can be any physical equipment like a flow meter. The magnitude of such equipment is normally given by the manufacturer. This type of error can be managed by continuously calibrating the instrument at regular intervals.

2.6 MODELING ERRORS

The M&V procedures used from the performance based contracts applies very strict M&V practices for quantifying energy savings and uncertainty from the retrofits [10]. As previously mentioned, the measured data from the retrofit is used to estimate the uncertainty levels using the IPMVP guidelines. The energy savings are quantified by comparing the energy use prior to the ECM and energy use after the ECM. The difference between the pre-implementation energy consumption and the post-implementation energy consumption is the energy savings.

$$E_{savings} = E_{pre-retrofit} - E_{post-retrofit} \pm E_{adjustments}. \tag{2.1}$$

In equation (2.1), the energy savings indicate the savings achieved by an energy-savings program, the $E_{pre-retrofit}$ is the energy consumption prior to the EE program, and the $E_{post-retrofit}$ is the energy consumption after the implementation of the EE program. The $E_{adjustments}$ is the adjustment term, which superimpose the pre-retrofit energy use to post-retrofit conditions. It can be seen from equation (2.1) that the method of quantifying savings relies on baseline modeling.

Energy modeling is the a mathematical formation of the relationship existing between the dependent and independent variables. Different methods have been used to explore uncertainties in baseline modeling. In [15], the IPMVP recommends linear regression models for baseline modeling. A Gaussian process modeling framework is presented in [16]; this method is used to quantify energy savings together with the uncertainty levels arising from the M&V practices. Moreover, methods such as Monte Carlo analysis can be used for determining the risk involved in data management [17]-[18]. Advanced methods have also been developed to quantify uncertainties using Bayesian setting in order to mitigate and quantify uncertainties in building energy models.

All the aforementioned methodologies focus on mitigating errors in quantifying energy savings from modeling. In general there are several errors that are introduced in modeling that must be mitigated. The following factors are critical for mitigating errors in a model.

- Using out-of-range data;
- Omission of relevant variables;
- Inclusion of irrelevant variables;
- Functional form and;
- Data shortage.

2.6.1 Using out-of-range data

When using the out of range data this normally result in the data that does not represent the actual energy consumption of the facility which results in an unreliable model. The out-of-range data may include values that are out of range [19], thus increasing the uncertainty level in the model which also leads to poor savings estimation.

2.6.2 Omission of relevant variables

The majority of the complex energy system have a high correlation with the model independent variables. For example, in a building retrofit, the known variables that affect the energy consumption may include relative humidity, solar radiation temperature and outdoor dry-bulb temperature to mention a few. Omission of relevant independent variables may result in savings error. One of the most important tools that can help mitigate such a problem is the evaluation of the coefficient of determination, commonly referred to as R^2 value; the range of coefficient of determination indicates the correlation between the dependent and independent variables. An R^2 value that is too low indicates poor correlation between independent and dependent variables and this may indicate that some of the relevant variables may have been omitted from the model [20] - [21].

2.6.3 Inclusion of irrelevant variables

While omission of a relevant variable may create problems in quantifying savings, the inclusion of irrelevant variables is negligible to the dependent variable. If the two irrelevant and relevant variables are correlated in the model, the result turns to bias the coefficient of the relevant variables [5] and [22].

2.6.4 Functional form

There are many modeling techniques that are data based that can be used as functional forms for the M&V process. These functional-forms include the time series method [23], neural networks [24], polynomial regression [25] and support vector machine [26]. While there may be many techniques that can be used for modeling, sometimes a relationship is modeled incorrectly by assuming an incorrect functional form. A typical case where such an incorrect functional form is used is in the case of modeling a linear relationship with a non-linear physical relationship. In selecting a functional form, different techniques can be used to find the best fit for the data under consideration such that the overall error in quantifying savings is greatly reduced.

2.6.5 Data shortage

Data shortage results in errors due to insufficient data and this can be classified in terms of quality, that is, not enough data points, or time, which means using an incorrect time frame for exploring another time frame. The data that is used for modeling an energy system must be in the range of operations of the facility. It must also include different time periods as well as different seasons of the year in order to have a clear picture of the consumption through out the year [25].

2.7 SAMPLING ERRORS

The objective of observing a sample in an M&V metering plan as opposed to the entire population is to reduce the monitoring cost. The process of sampling involves selecting any subset of the elements of a population for monitoring and evaluation. This process normally creates errors because the entire population under consideration is not measured and these errors are normally controlled by ensuring that the sample parameters fall within the specified confidence and precision level. In an M&V metering process where savings are quantified from sampling a certain level of confidence and precision is required to give an indication of the savings achieved. In the process of estimating energy savings the different population parameters are inferred. These parameters are the population mean, the standard deviation and the confidence level. The confidence level is then used to infer the probability of the savings estimation [10].

In [27], an alternative sampling approach is used as a reliability based sampling method which is used for simulations and re-sampling. This method uses unit-to-unit variation to determine the sample sizes for reliability cases. This type of method ensures that the reliability of the sample size represents the reliability of the entire army fleet under consideration. The analytical approached used relies on principles of classical statistics such as confidence, precision and hypothesis testing. Precision and confidence are used to determine the sample sizes and the hypothesis is used to determine the acceptable precision. This approach to sampling firstly selects a random sample without replacement from the entire simulated population and computes the first random sample size. Then re-sampling is done to ensure that the simulated finite population is not an aberration from an unusual stream of random numbers and the new finite population is simulated before the next sample size is drawn.

The next sampling strategy considered is simple random sampling (SRS). For SRS, the minimum acceptable sample size, N, is determined by the desired level of accuracy of the estimated probabilities. Another sampling technique used is the exogenous stratified random sampling (ESRS) [14] and [28]. In this sampling technique, the population is first divided into mutually exclusive groups, each representing a proportion of the total population. The basis for creating the groups can be any characteristics common to the population.

The sampling methods mentioned thus far are of great significance in both theoretical and practical applications. However, the disadvantage is that they focus on computing the sample sizes with a fixed precision and confidence level. The method presented in this research uses both the SRS method and ESRS sampling methods, and the precision and confidence levels are varied for each subset of the sample under consideration.

The various methods for calculating sampling size requirements are outlined above and have been derived either from general theory related to the calculation of sampling error, or from a combination of experience and simulation work. The two methods discussed, that is, the SRS and ESRS approaches, are derived from theories relating sample size requirements to issues of sampling error in random samples. Based on the statistical theory, the SRS and ESRS approaches are derived so as to provide the sample size necessary for the construction of confidence intervals around the choice probabilities based on some level of acceptable error.

In the SRS sampling method a sample is randomly selected from a population; and the probability of selecting each sampling unit is the ratio of the sample size to the entire population. [5]. The following issues are critical in optimizing the sample sizes [14].

- Select homogeneous samples from the population.
- Determine the desired precision and confidence level.
- Decide on the level of disaggregation.
- Calculate the initial population size.

- Adjust the sample size; and
- Finalize the new sample size.

2.7.1 Selecting homogeneous samples from population

In the selection of a homogeneous population, samples with common characteristics are grouped together; the selection of homogeneous population for sampling reduces the cost of monitoring. This approach samples different groups according to their common characteristic and they are then grouped together and sampled separately. Even though the units are grouped according to common characteristics, in order to maintain randomness within the sample, a random sample is drawn within each homogeneous group.

2.7.2 Determining the desired precision and confidence level

The confidence level and desired precision are known as point estimation. Point estimation is the process of sampling in order to estimate an average value of an entire population. In sampling, the estimated value from the point estimation is merely an estimate of the actual value[19]. In short, confidence and probability ensures that the point estimate will fall within the precision range. The estimated values from the confidence and precision interval are required for estimating the actual value range. A higher precision and confidence level requires large samples. In this research a 90/10 sampling criterion is used. This implies that 90% of the measured value is within the stated confidence interval with $\pm10\%$ precision.

2.7.3 Deciding on the level of disaggregation

In deciding on the level of disaggregation, there must be clear guidance. When using the disaggregation method, a clear confidence and precision level criteria must be applied to the different homogeneous groups or applied to the measurement of components. In [14], the same level of confidence is used throughout the entire population with different sampling groups in order to minimize the metering cost.

2.7.4 Calculating the initial population size

In sampling, certain confidence and precision criteria must be met. The initial sample size starts with computing the maximum error. This measure is used in estimating the precision of a sample mean [5].

$$E = z\frac{s}{\sqrt{n}}, \tag{2.2}$$

where

z is the z-statistic,

n is the sample size,

s is the standard deviation of the sample and,

E is the maximum error value.

The z-statistic value is found from any statistics handbook such as [19]:

$$z = \frac{x - \mu}{\frac{s}{\sqrt{n}}}, \tag{2.3}$$

where μ is the population mean and x is the sample mean. Since the true mean of in (2.3) is unknown, the only known part is the different values of the z-statistic from confidence levels. Based on the two equations, a sample size is determined using the following equation:

$$n = \frac{z^2 s^2}{E^2}, \tag{2.4}$$

In equation (2.4) n is the sample size for an infinite population. The standard deviation and the maximum error can be represented using the same units of measurement. Moreover, the coefficient of variation given in equation (2.5) is clearly shown to depend on the sample mean and standard deviation.

$$C_v = \frac{s}{x}. \tag{2.5}$$

In a similar manner, equation (2.6) shows the maximum error:

$$\gamma = \frac{E}{x}, \tag{2.6}$$

where γ is the precision. Substituting C_v and γ into equation (2.4), one gets a unit-less expression, as shown in equation (2.6) as given in [5]:

$$n = \frac{z^2 C_v^2}{\gamma^2}. \tag{2.7}$$

Equation (2.7) is used in estimating a group sample size, it is known as the infinite sample size equation.

2.7.5 Adjust the sample size

If the population size being sampled is less than 20 times of the sample size, the sample can adjusted [5]. In the case where the population is small, a finite population correction factor can be used to adjust the population as shown in (2.8) and given in [5]:

$$n_s = \frac{n \times N}{n + N}, \tag{2.8}$$

where,
n_s is the sample size for small population,
N is the population size.

2.7.6 Finalize the new sample size

Once the actual C_v from the sample is computed, a new C_v must be compared to the assumed C_v of the population. This may result in a different actual sample size not meeting the required precision criterion. This means that if the actual C_v is less than the initial assumed value, then the sample size will meet the desired precision requirements. However, if it is larger than the initial value it will not meet the desired precision requirements unless the sample size is increased beyond the initial infinite and finite sample sizes.

2.8 MEASUREMENT ERRORS

The energy meters are used to measure dependent and independent variables as part of the M&V program. In actual fact, all meters used are not 100% accurate in measurement and this presents an error in measurement, although the latest measuring equipment may have a very high accuracy that is close to 100%. A meter is typically classified in terms of the precision rate. This precision rate can also be classified as the fraction of the current or maximum reading on the meter's scale. It is important to clearly note where the maximum reading of the meter is for the meter's precision.

In a case when a meter is over sized, the precision of the meter is affected since a meter's precision is stated relative to the maximum reading and this reduces the actual metering precision. The wear on the metering system results in mismatch of data and if the meter is not recalibrated to reduce the mismatch, this results in measurement errors. Hence, the meters must be calibrated regularly against known standards. In addition, there are other factors that can also influence the accuracy of the meter and reduce the precision; these factors are not limited to the following

- Data that is lost due to poor telemetry systems;

- Poor meter placement.

In [29] - [30], Eskom has specified three-phase energy metering, that can be used in measurement and verification projects. These specifications can be used as guidelines for metering requirement.

2.9 RATIONALE FOR THIS STUDY

The main challenges in this study is optimizing the metering cost by reducing the total number of samples to be measured. The reduction of samples affects the measured data that must be used for baseline modeling before and after an ECM. Moreover, the challenge is also in identifying samples that must be monitored from the entire population. This presents a difficulty in measuring the pre-implementation and post-implementation energy savings.

The literature reviewed clearly elaborates on the key focus areas for improving energy savings quantification. The areas that are mentioned for improved energy savings quantification are:

- Modeling inaccuracies;
- Sampling inaccuracies; and
- Measurement inaccuracies.

All these areas are addressed in detail in the literature study. For the modeling inaccuracies, different approaches are used for reducing the uncertainty in the model. One of the approaches recommended by the IPMVP guidelines is regression analysis for modeling. This approach to modeling has a limitation in terms of adequately capturing autocorrelations existing at higher time resolutions. This limitation is often mitigated by baseline adjustments. However, this does not entirely eliminate the problem. Other methods used to mitigate such uncertainties are Monte Carlo, Bayesian and most recently the Gaussian process.

Uncertainties due to poor modeling are addressed by the aforementioned modeling techniques and in this research the modeling techniques are not considered further for minimizing the metering costs in the M&V process.

In this research, the focus is on sampling and measuring uncertainties. As far as sampling is concerned, different sampling techniques are used. These techniques range from simple random sampling to systematic sampling and cluster sampling to exogenous stratified random sampling. As clearly elaborated on the sampling literature, sampling uncertainties arise from the use of restricted sample sizes. The advantage of this research is the ability to use a combination of sampling techniques for achieving optimal metering plan. The disadvantage of using the SRS technique only is that the entire sample is assumed to be homogeneous, which is normally not the case in an ECM. On the other hand, using the ESRS techniques requires all homogeneous samples to be grouped together and this may result in sample sizes being too small. This study uses SRS and ESRS for sampling in order to mitigate the aforementioned challenges and improve sampling.

In the measurement uncertainties, the precision level of the metering system is controlled by considering the weighted average of the precision level. This research also focuses on measuring uncertainties.

The existing study on an optimal sampling plan in the M&V process is applied to lighting projects [14] and [22]. There is no evidence of a mixture of loads for optimal sampling and the cases considered only focus on finding the total number of samples. It is essential to minimize the metering costs in order to reduce the M&V costs.

2.10 OPTIMIZATION IN OPTIMAL METERING PROBLEM

There are three approaches for evaluating the meter placement optimization problem. They are classical mathematical optimization, neighborhood search and population search. The classical mathematical techniques are mainly based on branch and bound programming [12], [13] and [31]. In [31], the binary integer linear programming approach is used for state estimation which minimizes the total investment cost that is subject to accuracy requirements. Moreover, in [12], a similar sequential approach is used for addition or elimination of metering equipment. The main challenge with the classical mathematical techniques is that the process is very computational extensive and it increases with the problem complexity. Therefore for a large network the classical mathematical approach is not efficient. Furthermore, the size and the non-linearity of this meter placement problem makes this technique computationally expensive.

The second type of approach used in meter placement problem is the neighborhood search. The simulating annealing SA optimization method is applied to the meter placement problem for parameter estimation in [32]. SA is a meta-heuristic approach to meter placement. Although SA produces near optimal solutions, it has a disadvantage of a long computational time when compared to other optimization techniques.

The last type of approach used is population based. It is divided into two categories, namely evolutionary search and swarm intelligence. These categories are genetic algorithm and particle swarm algorithm. A genetic algorithm based meter placement for parameter estimation of harmonic sources is presented in [33]. Although GA has been applied to meter placement problems there are several limitations arising from its application. The first limitation is that it falls into a local minimum and cannot recover. The latter limitation arises from expensive implementation of GA. PSO is an evolution algorithm developed by Kennedy and Eberhart [34] which is inspired by nature such as a flock of birds feeding. PSO starts with a random population matrix and searches for the optimal cost while mimicking the natural social behavior of birds within a flock. In PSO random population matrix rows represents the particles or agents, which are flown through hyper-dimensional search space in the process of searching for the optimal solution. The particles follows the flock by mimicking the movement of the group thus reaching either a local minimum or global minimum point. Thus each particle closely monitors its neighbor and move according to the overall swarm movement.

PSO has fewer algorithm parameters as compared to its counterpart GA, this feature makes PSO attractive and unlike GA, PSO has no evolution operators such as mutation and crossover. In addition to that, its unique feature that makes it desirable to use in industrial problems is the flying potential through hyperspace, which accelerates towards better solutions.

More research is being done on novel methods of solving discrete variables using PSO. In [35] - [36] binary PSO strategies are used for meter placement problems. Since binary optimization is a specialized form of integer optimization a paper in [37] describes a constrained problem formulation. The algorithm proposed in [37] can be transformed from integer optimization to binary optimization and it is much better for solving, as it still maintains the continuous form of PSO. This is a more effective method compared to original binary PSO that uses a sigmoid probability function to decide on whether the particle is zero or one. This approach in[37] uses the continuous form of PSO to solve the binary optimization problem and thus accelerates convergence of the optimal solution.

2.11 CHALLENGES AND LIMITATIONS OF THE SELECTED APPROACH

The challenges and limitations of this approach are:

- The formulation of the optimization models;
- The formulation of binary PSO with continuous variables;

- Characterizing and grouping different loads.

2.12 CONTRIBUTION OF THIS STUDY

The contribution of this study can be summarized as follows:

- The optimization model uses both SRS and ESRS sampling techniques.
- The optimization model not only gives the total number of samples, but also selects specific equipment to be sampled in a group.
- The study focuses on retrofitting a mixture of loads ranging from simple lighting to motor-related loads.
- Two different energy meters are used for minimizing costs. These meters are categorized as expensive and inexpensive. Both meters can measure power; however, the precision and accuracy of the two meters are different. The expensive meter has a higher precision and accuracy level and inexpensive meter has the least precision and accuracy.
- This study controls the overall measurement precision for the entire sampled population. This limits the measurement uncertainty.
- Since samples must be specially selected, only binary optimization can be used. However, since the model used is nonlinear, the normal MATLAB library cannot solve nonlinear binary optimization problems, PSO is used for solving the optimization model.

CHAPTER 3

OPTIMAL METERING PLAN MODEL

3.1 CHAPTER OVERVIEW

An optimization model for an optimal metering plan in an M&V plan is formulated in this chapter. In addition, the PSO method used for solving the problem is presented.

3.2 OPTIMAL METERING PLAN

In this section the optimal meter placement problem is formulated by an optimization approach. The method used minimizes the performance index or cost function which is subject to several constraints. The cost function is established as the sum of two types of metering devices. The meter placement problem in this research requires knowledge of where a meter must be installed and what type it should be and hence it is formulated as a {0,1} binary integer programming problem. Moreover, the optimization problem must satisfy both the cost and accuracy requirements.

3.2.1 Optimization model

Let x_{1i} and x_{2i} be binary variables representing class A and B metering equipment. The numbers 1 and 2 simply differentiate between class A and class B meters and i is the index of the retrofitted equipment.

$$x_{1i} = \begin{cases} 1 & \text{if class A meter is selected for the } i\text{-th equipment;} \\ 0 & \text{if class A meter is not selected for the } i\text{-th equipment;} \end{cases}$$

and

$$x_{2i} = \begin{cases} 1 & \text{class B meter is selected for the } i\text{-th equipment;} \\ 0 & \text{class B meter is not selected for the } i\text{-th equipment.} \end{cases}$$

It follows that for a total of N retrofitted items of equipment under consideration the cost function can be represented as the sum of the metering equipment as follows:

$$\min J = \sum_{i=1}^{N} (O_1 x_{1i} + O_2 x_{2i}), \tag{3.1}$$

where J is the cost function to be minimized, O_1 and O_2 are the cost of purchasing and installing class A and B meters respectively in Rand (ZAR) per unit. The normal metering cost consists of the data servicing cost, metering cost, and professional fee. However, in this research we only consider the metering cost, since it is the largest portion of costs associated with M&V.

The cost function is subject to the following constraints for all $i = 1, 2, ..., N$.

$$0 \leq x_{1i} + x_{2i} \leq 1, \quad i = 1, 2, ..., N, \tag{3.2}$$

$$\sum_{i=1}^{k_1} (x_{1i} + x_{2i}) \geq 1, \tag{3.3}$$

$$\sum_{i=k_1+1}^{k_2} (x_{1i} + x_{2i}) \geq 1, \tag{3.4}$$

$$\sum_{i=k_2+1}^{N} (x_{1i} + x_{2i}) \geq 1, \tag{3.5}$$

$$\sum_{i=1}^{N} (O_1 x_{1i} + O_2 x_{2i}) \leq C, \tag{3.6}$$

$$\frac{k_1 \sum_{i=1}^{k_1} (x_{1i} + x_{2i})}{k_1 + \sum_{i=1}^{k_1} (x_{1i} + x_{2i})} \leq (\frac{z_{\frac{\alpha}{2}} C_v}{\gamma})^2, \tag{3.7}$$

$$\frac{(k_2 - k_1)\sum_{i=k_1+1}^{k_2}(x_{1i} + x_{2i})}{(k_2 - k_1) + \sum_{i=k_1+1}^{k_2}(x_{1i} + x_{2i})} \leq (\frac{z_{\frac{\alpha}{2}} C_v}{\gamma})^2, \tag{3.8}$$

$$\frac{(N - k_2)\sum_{i=k_2+1}^{N}(x_{1i} + x_{2i})}{(N - k_2) + \sum_{i=k_2+1}^{N}(x_{1i} + x_{2i})} \leq (\frac{z_{\frac{\alpha}{2}} C_v}{\gamma})^2, \tag{3.9}$$

$$\frac{a\sum_{i=1}^{N} P_i x_{1i} + b\sum_{i=1}^{N} P_i x_{2i} + \frac{\sum_{i=1}^{N} a x_{1i} + b x_{2i}}{\sum_{i=1}^{N} x_{1i} + x_{2i}} \sum_{i=1}^{N}(1 - x_{1i})(1 - x_{2i})P_i}{\sum_{i=1}^{N} P_i} \leq \beta, \tag{3.10}$$

where

N is the total number of equipment retrofitted;

k_1 is the total number of items of equipment retrofitted in group 1;

k_2 is the total number of items of equipment retrofitted in group 2;

C is the maximum budget set aside for the metering costs in the M&V plan;

$z_{\frac{\alpha}{2}}$ is the statistically desired confidence interval;

C_v is the coefficient of variation;

γ is the desired precision requirement;

a is the rated accuracy of measurement for the class A meter;

b is the rated accuracy of measurement for the class B meter;

P_i is the power rating of each item of equipment being retrofitted (kW); and

β is the desired measurement accuracy for the system.

As presented in chapter 2, the objective of observing the sample is to identify particular characteristics that can represent a population from the sample. The constraints in equation (3.2) to equations (3.10) use SRS and ESRS methods to characterize the samples.

The first constraint in equation (3.2) ensures that for each item of equipment under consideration for retrofitting, only one class of meter can be installed; either class A or class B. This ensures that there is no redundancy in the metering process and thus no additional costs are incurred, since there are more than 100 items of equipment and the goal is not to measure all items of equipment but a sample from each group. The SRS and ESRS methods are used for grouping the items of equipment. The following criteria is used for grouping items of equipment:

- Equipment homogeneity;
- Operating hours;
- Location of equipment;
- Equipment duty cycle; and
- Equipment voltage.

The loads that are considered are classified as lighting, AC and motor-related loads. Therefore, three homogeneous groups are formed based on the load classification. A further breakdown can also be made to classify equipment based on duty cycle, operating hours and voltage level. However, this is not necessary, as all items of equipment in each group has the same duty cycle, voltage level and operating hours and they are located in the same area. The constraints in equation (3.3) - (3.5) represent three groups under consideration for retrofitting. These constraints imply that for each group in the energy system at least one class of meter must be installed. This ensures that sampling occurs in each group.

Since the objective of this optimization model is to reduce the metering cost, it is also important to impose a cost constraint. Constraint (3.6) is the budget constraint which ensures that the total budget set aside for metering costs in the M&V plan is not surpassed. It also limits the amount of money that can be spent on achieving the precision, accuracy and sampling for the project. The guideline for setting the budget cost is based on the annual M&V cost. This is normally set to be less than 10% of the annual M&V costs.

Constraints (3.7) - (3.9) represent the sampling and precision requirements. These sampling constraints are based on equations (2.7) and (2.8) of section 2. The initial estimate of the sample size is based on an infinite population in equation (2.7). However, since the objective is to minimize the metering cost, a finite sample size must be computed. This is done using equation (2.8). Therefore, the finite sample size must be less than the initial infinite sample in order to reduce the metering costs, which results in constraints (3.7) - (3.9) for the three groups.

The last non-linear constraint (3.10) is the metering accuracy requirement. It is divided into measured equipment and unmeasured equipment. The first part of the equation $a\sum_{i=1}^{N} x_{1i}P_i$

represents the inaccuracy of the measured part due to the meter inaccuracy. The second part is the weighted average inaccuracy of all unmonitored items of equipment, i.e. $\frac{\sum_{i=1}^{N} ax_{1i}+bx_{2i}}{\sum_{i=1}^{N} x_{1i}+x_{2i}}$. The overall inaccuracy is controlled by the accuracy requirement β for the entire metering plan.

3.3 THE PENALTY FUNCTION METHOD

There are several ways of handling constraints in optimization problems [38]-[39]. The penalty function method constitutes a global approach to unconstrained optimization problems; it is motivated by the idea of using unconstrained optimization techniques to solve problems of constraints. The method applied to solve constrained optimization problems is to convert an optimization problem into an unconstrained optimization problem. The penalty function method is used to incorporate the constraints. These constraints are added to the objective function such that any violation can be penalized using the penalty function method. The general penalty function method for optimization problems is obtained by adding a penalty for in-feasibility and forcing the solution to be feasible. The optimal solution achieved by implementing the penalty function approaches that of the original optimization problem [40] and [41].

The exact penalty function is applied to the constrained optimization problem and transformed into an unconstrained optimization problem. There are two other methods that can be used to deal with the penalty function. The first method that can be considered for the penalty function is the death penalty method. In the death penalty method, the constraints are evaluated only within their feasibility region. Although the computation for this method is straight forward and simple, the disadvantage of using this type of penalty function method lies in the manner of searching the optimal solution; that is, if in the initial searching phase no feasible solution is obtained then the search for feasibility is terminated. It is even worse for equality constraints since it is easy for the search to find a feasible solution. Thus even if there exist some feasible solution, this method will not detect it if the initial search result in an infeasible solution [35] and [42].

Another method that can be considered for transforming constrained optimization into an unconstrained one is the Lagrangian method. The Lagrange method is used for constrained optimization problems. This method uses an augmented objective function which combines constraints and the original objective function. The optimization problem to be solved is the augmented function. The result of solving the augmented objective function is saddle point of the Lagrangian problem. Using this method does not always guarantee the saddle point. While this method is also simple to implement and easy to solve, its main disadvantage is that it does not always reach an optimal solution. Moreover the assumption of the convexity of the Lagrangian with respect to the decision variables is vital [35], which is not always the possible in other optimization problems.

The following section describes the exact penalty function method which is applied to the meter placement optimization model.

3.4 BINARY PSO

To address the shortcoming of the other optimization methods used, a PSO based method is used to solve the meter placement problem. The method applied in this research is adapted from [37] which applies PSO to solve mixed integer optimization problems. Since PSO cannot be applied to discrete variables, this methods converts discrete variables into continuous variables using a penalty function with limits set on the variables. Moreover, this method mitigates the limitations of applying PSO to unconstrained optimization problems by transforming the optimization problem from constrained optimization problem to an unconstrained one. The problem is then changed from discrete to continuous unconstrained optimization and the augmented objective function is solved using the PSO algorithm. The following discrete binary penalty function is used for transforming binary variables into continuous variables :

$$\rho(x) = \frac{1}{2}\sum_{i=1}^{n}(\sin(2\pi(x_i - 0.25)) + 1). \tag{3.11}$$

Suppose an optimization problem that is composed of binary variables is formulated as follows:

$$\min y(x), \tag{3.12}$$

$$g_k(x) \leq 0 \quad k\text{=1,2,....}ncon, \tag{3.13}$$

$$x^c_{i,L} \leq x^c_i \leq x^c_{i,U} \quad i\text{=1,2,...,}m. \tag{3.14}$$

Here m is the total number of variables and x^c_i is a continuous variable vectors with $x^c_{i,L}$,

$x^c_{i,U}$ being the lower and upper continuous bounds respectively. Furthermore, the objective function to be optimized is $y(x)$ and $g_k(x)$ is the inequality constraint. The superscript c implies that the variable is continuous and $ncon$ refers to the inequality constraints in the model. By combining the equations and inequalities from (3.11) - (3.14), an augmented objective function can be written as follows [37]:

$$F(x) = y(x) + s\rho(x) + r\sum_{k=1}^{ncon} max[0, g_k(x)]. \tag{3.15}$$

In equation (3.15) the two parameters s and r are the penalty and inequality parameters. The new augmented objective function is $F(x)$; and the severity of the penalty depends on the penalty parameters s and r.

The initial value for s is given in [37]. If the penalty is either too large or too small, the problem becomes too hard for PSO to solve. Therefore a penalty parameter must be chosen such that the problem does not converge too soon or become infeasible[37]. The initial value of s in (3.16) is given in [37] as follows:

$$s_d = 1 + \rho(x_d). \tag{3.16}$$

In equation (3.16) s_d is the initial value which is taken as the minimum value in a group as shown in (3.17).

$$s^1 = min\{s_1, s_2, ..., s_m\}. \tag{3.17}$$

In (3.18) s^k is the k-th iteration parameter.

$$s^{k+1} = s^k \times exp(1 + \rho(p^k_g)). \tag{3.18}$$

From (3.18) p^k_g is the best solution in the swarm for the entire group at k-th iteration. The position x^k_d and velocity v^k_d of particle are updated as follows:

$$x^{k+1}_d = x^k_d + v^{k+1}_d, \tag{3.19}$$

$$v_d^{k+1} = wv_d^k + c_1r_1(p_d^k - x_d^k) + c_2r_2(p_g^k - x_d^k). \tag{3.20}$$

In (3.20), parameters r_1 and r_2 represents random numbers in the range of [0,1], and c_1 and c_2 are the acceleration constants normally chosen as 2. The parameter w represents the inertia of the swarm and p_d^k and p_g^k are the best solution achieved by the swarm, with p_g^k as the model's optimal solution. The inertia term is given as follows in equation (3.21) [37]:

$$w = e_{max} - \frac{e_{max} - e_{min}}{k_{max}} \times k. \tag{3.21}$$

Here e_{max} and e_{min} are the minimum and maximum values of the inertia terms, which are 0.9 and 0.4, and the maximum iteration is given by k_{max}. The following convergence criterion is used from equation (3.22):

$$\frac{|F(p_g^k) - f(p_g^k)|}{|F(p_g^k)|} \leq \epsilon. \tag{3.22}$$

In (23) ϵ is a very small positive number that must be chosen to improve convergence and in this research a value of 0.01 is used. The binary particle swarm optimization algorithm is executed according to the following steps:

Step 0: The initial parameters are set, i.e. the iteration counter k is set from $k = 1, 2, 3, ..., k_{max}$, the initial parameter of the particle d is set from $d = 1, 2, 3, ..., D$. Both the position x_d and velocity v_d for the PSO are also set at random.

Step 1: Compute the penalty function (3.11) for all binary variables as well as the initial value of the penalty function (3.17).

Step 2: Evaluate the augmented objective function in (3.15).

Step 3: Determine p_d^k andp_g^k.

Step 4: Evaluate the convergence from (3.22). If (3.22) is less than ϵ then there exists a discrete value near p_g^k and the penalty parameter is reset to (3.17) else the penalty parameter is updated (3.18).

Step 5: Update the position and velocity for every particle (3.19) and (3.20) and the iteration counter is increased $k = k + 1$

Step 6: The iteration counter is compared to the maximum iteration k_{max} and if the iteration counter is less than the maximum iteration then the algorithm returns to step 2 else it outputs P_g as the optimal solution.

The method presented has an advantage of using continuous variables to represent the discrete nature of the optimization problem; it also takes advantage of the PSO algorithm to handle continuous variables in order to solve a discrete variable problem. This simplifies the search process. Fig. 3.1 shows the process flow diagram of implementing the PSO algorithm.

3.5 ENERGY MODEL

The proposed optimal metering plan is applied to a plant that consists of different energy groups. The energy groups are classified according to equipment homogeneity. An ECM for the ore beneficiation plant is considered in which 110 items of equipment are retrofitted. The plant consists of office space and a processing plant. The processing plant is composed of several motor-related loads such as pumps, conveyor belts, fans and milling circuits; all the motor related loads have different motor sizes with varying and constant loads. The office-related loads are composed of resistive loads and inductive loads from office lighting to air conditioning (AC) systems. In total the energy system consist of three groups of equipment for energy retrofitting. The opportunity for EE lies in the inefficient lighting used in the plant and offices, as well as inefficient usage of the office AC system. The opportunity for the processing plant lies in the utilization of the motors in relation to their respective application. Fig 3.2 shows the energy model.

The objective of this research is to design an optimal metering plan for the M&V plan. This metering plan uses two types of metering devices. Both meters can be used to measure active power (kW), reactive power (kVar), apparent power (KVA), the power factor and the total energy consumption (kWh). The proposed ECM for the groups ranges from the installation of VSD, motion sensors to energy-efficient lighting.

3.5.1 Lighting loads

The lighting is also considered for retrofitting. All the inefficient lights are replaced with EE lights. In the process of replacing the lights, the lighting luminosity is not compromised for the sake of EE.

3.5.2 AC system

The other group considered for EE is the air conditioning system. The EE initiative for the air conditioning system is to install motion sensors that are interlocked with the AC. This

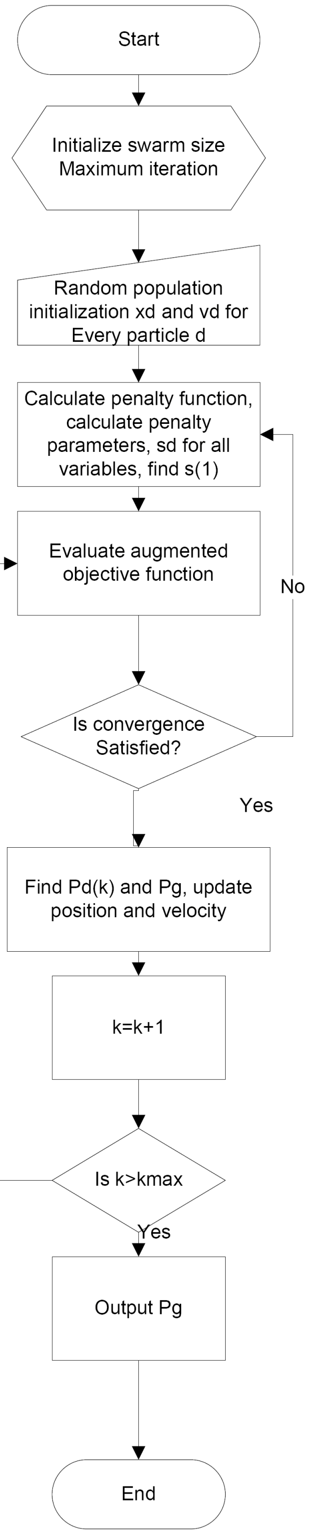

Figure 3.1: PSO algorithm [37]

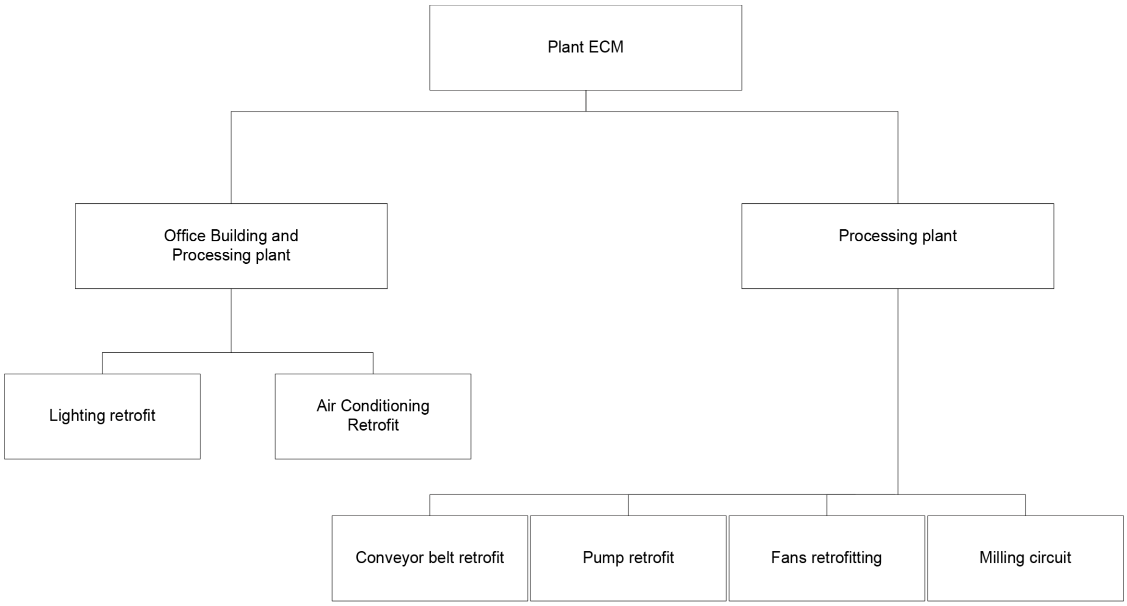

Figure 3.2: Energy system model for the ore beneficiation plant

will ensure that no AC system is on when the room or office is unoccupied for more than five minutes.

3.6 SOFTWARE USED TO IMPLEMENT THE MODEL

The optimal metering plan in the research project is implemented and solved using MATLAB. In this case MATLAB does not have a built-in function for PSO and as such, the algorithm is programmed into the MATLAB environment for the optimal metering plan problem. Since PSO is a meta-heuristic technique, it cannot necessarily guarantee that the solution is optimal, but it gives a very good approximation of the true optimal solution.

CHAPTER 4

CASE STUDY

4.1 CHAPTER OVERVIEW

In order to investigate the model's effectiveness, a PSO based algorithm is implemented on a plant undergoing EE program. The plant considered is the ore beneficiation plant and buildings across the plant. It consists of 110 equipment that are retrofitted. The cost of sampling is investigated with and without using the optimization model. Different precision and confidence levels are investigated to find the best sampling criterion that can realize the highest accuracy with the least cost incurred. Table 4.1 gives the equipment, quantity, proposed EE alternatives and the operating hours per day. The equipment is classified and grouped together, i.e. group 1, 2 and 3. Group 1 is all the motor-related retrofits, group 2 is the AC system and the last group is the lighting system. Moreover, the simulation studies presented are based on different sampling requirements which must achieve the proposed cost requirements. The total ECM project cost is R 5,000,000, of which a maximum of 10% is allocated to the M&V metering plan.

4.2 SAMPLING PLAN FOR THE GROUPS

In order for sampling to be meaningful, the points mentioned in section 2 must be adhered to. That is:

- Sample homogeneity;
- Determine the desired precision and confidence level;

Table 4.1: Proposed alternatives to be implemented for the three energy groups

Description	Number	Power(kW)	Proposed Action	Operating hours
Fans	2	160	VSD	00:00 - 23:00
Pump 1	1	110	VSD	00:00 - 23:00
Pump 2	1	160	VSD	00:00 - 23:00
Conveyor 1	1	11	VSD	00:00 - 23:00
Conveyor 2	1	22	VSD	00:00 - 23:00
Conveyor 3	1	22	VSD	00:00 - 23:00
Conveyor 4	1	45	VSD	00:00 - 23:00
Mill motors	2	500	VSD	00:00 - 23:00
AC type 1	25	10	Motion sensor	07:00 - 20:00
AC type 2	10	2	Motion sensor	07:00 - 20:00
AC type 3	15	5	Motion sensor	07:00 - 20:00
MAG44/125	25	0.125	50 W LED	00:00 - 23:00
HP10 400HPS	10	0.400	200 W LED	00:00 - 23:00
HP15 1000HPS	15	1.00	340 W Induction	00:00 - 23:00

- Calculate initial population size without the optimization model;
- Adjust initial sampling size and;
- Finalize sampling size.

In order to minimize the cost of metering for the energy system, the sampling plan requires all homogeneous equipment in the energy system to be grouped together. This implies that the lighting group must be sampled separately from the AC group since they are not homogeneous equipment; and likewise the motors must also sampled separately from the other two groups. In this research different sampling approaching are investigated [14] and [43]. The common sampling criteria of 90/10 is used for all groups. A very good precision is required for sampling as the new energy after retrofitting is subtracted from the old energy before retrofitting, this precision reduces the uncertainty level in the quantification of savings. The uncertainties in the three energy groups are characterized by the coefficient of variation C_v.

4.2.1 Estimating coefficient of variation C_v for the three groups

The C_v is defined in equation (2.4) as the fraction of standard deviation to the sample mean for point estimation [5]. The C_v values are between zero and one; with zero indicating minimal uncertainty in measurement and one indicating a large uncertainty in the monitored parameter [44].

The estimated C_v values for the three groups are obtained as follows. For the lighting group, an on-site energy audit reveals that the total utilization is 24 hours for samples that were monitored in the group. The estimated mean value of baseline daily energy consumption is 531 kWh with a standard deviation of 106. By definition of C_v, the C_v value of lighting is 0.198; this is similar to a lighting retrofit project implemented for CDM [14]. The unknown C_v is computed using equation (2.4) which resulted to 0.199 and therefore a C_v value of 0.2 is selected for the lighting group. The same logic can be followed for estimating the C_v of the AC system and motor-related loads. However, for group 1 and 2 the C_v must be estimated. According to [45] - [46] a C_v of 0.5 is proposed for retrofits where a coefficient of variation C_v is estimated. Table 4.2 shows the estimated C_v for the three groups.

Table 4.2: C_v estimates for the three groups

Sample	Description	SD	Mean	Estimated C_v
Group # 1	Motor loads	-	-	0.5
Group #2	AC loads	-	-	0.5
Group #3	Lighting load	106	531	0.2

4.2.2 Metering specification

Since the energy consumption in the groups changes more rapidly, the metering devices to be installed must be able to handle a high sampling frequency. The metering device specifications for the two recommended meters are shown in Table 4.3. In the metering cost, the monthly hosting cost is the same for both meters and it will therefore not form part of the costing.

Table 4.3: Metering costs for class A and B

Category	Class A	Class B
Voltage range	110 - 380 V	110 - 380 V
Current range	50 mA - 500 A	50 mA - 500 A
Accuracy	±2%	±5%
Time resolution	0.25 s	300 s
Memory capacity	8 MB	6 MB
Cost	R21,730	R19,840
Monthly hosting cost	R150	R150

4.2.3 Initial population estimation

In order to estimate the initial population of the three groups, the samples for each group must be known. In total there are 110 items of equipment undergoing retrofitting. The population size is further divided into three groups, which are divided as follows: Group 1, which consists of all motor-related loads, has a total of 10 items of equipment. The second group, which is the AC system group has a total of 50 items of equipment. The lighting group also has 50 items of equipment undergoing retrofitting. Furthermore, both the AC and lighting groups are further classified into subgroups which are referred to as type 1, type 2 and type 3. In group 2, there are 25 type 1 AC systems, 15 type 2 and 10 type 3 AC systems. Similar to the AC system, the lighting system is further divided into three subgroups based on the characteristics of the lighting system.

In the first case study a 90/10 criterion is used for estimating the population which is similar to [14], [47] - [48]. In order to estimate initial population, both the infinite population size and the adjusted finite population size must be computed using equations (2.7) and (2.8). Table 4.4 shows the infinite and finite population size of each group using the 90/10 sampling criterion.

The initial population is computed without using the population size. It uses the sampling criterion, the normalized statistical value for the criterion, the C_v value and the precision. This method is used when the population size is unknown and the population estimated is

Table 4.4: Initial population n_s for the three groups

Description	N	C_v	$Z_{\frac{\alpha}{2}}$	n	n_s
Group # 1	10	0.5	90/10	68	9
Group # 2	50	0.5	90/10	68	29
Group # 3	50	0.2	90/10	10	9

too large. However, the finite population estimate uses equation (2.8). In the estimate both the infinite population estimate and the group's population size are taken into consideration for computing the sample size. This method is preferred, as it reduces the number of samples required and the total metering cost.

The equipment list that is used in the optimization model is given in Table 4.5.

Table 4.5: Proposed alternatives to be implemented for the three energy groups

Description	**Optimization index (i)**	P_i **(kW)**	**Group no**
Conveyor 1	1	11	Group 1
Conveyor 2	2	22	Group 1
Conveyor 3	3	22	Group 1
Conveyor 4	4	45	Group 1
Pump 1	5	110	Group 1
Pump 2	6	160	Group 1
Fan 1	7	160	Group 1
Fan 2	8	160	Group 1
Ball Mill 1	9	500	Group 1
Ball Mill 2	10	500	Group 1
HP15 lights	01 - 15	1.000	Group 3
HP 10 lights	01 -10	0.400	Group 3
MAG44 lights	01 - 25	0.125	Group 3
Type 1 Aircon	01 -25	10	Group 2
Type 2 Aircon	01 -10	2	Group 2
Type 3 Aircon	01 -15	5	Group 2

4.3 PARAMETERS USED

In this section, the PSO parameters and the optimization model parameters are given. Firstly the optimization model parameters are considered and then followed by the PSO parameters for solving the meter placement problem.

4.3.1 Optimization parameters

The cost function in (3.1) is represented by O_1 and O_2. As mentioned in chapter 3, the cost of metering refers to purchasing and installation of both class A and B metering. Therefore, equation (3.1) can be rewritten as follows:

$$J = \sum_{i=1}^{110} (21730x_{1i} + 19840x_{2i}), \tag{4.1}$$

where the cost of O_1 and O_2 is given in Table 4.3 and the total population size for each group is given in Table 4.4. The first constraint in (3.2), is divided into two constraints. The first part is given in equation (4.2)

$$x_{1i} + x_{2i} \geq 0, \quad i = 1, 2, ..., 110, \tag{4.2}$$

and the second part follows in equation (4.3):

$$x_{1i} + x_{2i} \leq 1, \quad i = 1, 2, ..., 110. \tag{4.3}$$

The constraints (3.3) - (3.5) are for the three groups as shown in Table 4.4; the values for k_1 and k_2 are also given in Table 4.4. The first group has a population of 10. Therefore, $k_1 = 10$ and the second group has a population size of 50 which makes $k_2 = 50$. The last group has a population size of 50 and the group ranges from 61 to 110. This is shown by constraints (4.4) - (4.6) as follows:

$$\sum_{i=1}^{10}(x_{1i}+x_{2i})\geq 1, \tag{4.4}$$

$$\sum_{i=11}^{60}(x_{1i}+x_{2i})\geq 1, \tag{4.5}$$

$$\sum_{i=61}^{110}(x_{1i}+x_{2i})\geq 1. \tag{4.6}$$

The next constraint is the cost constraint. Since the budget for the project is R5,000,000 and the M&V metering budget is limited to 10% of the overall project cost [5]. The metering costs is limited to R500,000. Equation (4.7) shows the budget constraint.

$$\sum_{i=1}^{110}(21730x_{1i}+19840x_{2i})\leq 500000. \tag{4.7}$$

The confidence and precision constraints are defined as the 90/10 criterion for the first case and varies for different cases. Table 4.6 has all the parameters for the constraints.

$$\frac{10\sum_{i=1}^{10}(x_{1i}+x_{2i})}{10+\sum_{i=1}^{10}(x_{1i}+x_{2i})}\leq 68, \tag{4.8}$$

$$\frac{50\sum_{i=11}^{60}(x_{1i}+x_{2i})}{50+\sum_{i=11}^{60}(x_{1i}+x_{2i})}\leq 68, \tag{4.9}$$

$$\frac{50\sum_{i=61}^{110}(x_{1i}+x_{2i})}{50+\sum_{i=61}^{110}(x_{1i}+x_{2i})}\leq 10. \tag{4.10}$$

The last constraint is the accuracy requirement constraint. It considers the measurement of samples and accuracy. The overall accuracy of 10% is selected for this study. The accuracy for each class of meter is given in Table 4.3 and the power rating of each equipment is given in Table 4.5.

$$\frac{0.02\sum_{i=1}^{110} P_i x_{1i} + 0.05\sum_{i=1}^{110} P_i x_{2i} + \frac{\sum_{i=1}^{110} 0.02x_{1i}+0.05x_{2i}}{\sum_{i=1}^{110} x_{1i}+x_{2i}} \sum_{i=1}^{110}(1-x_{1i})(1-x_{2i})P_i}{\sum_{i=1}^{110} P_i} \leq 0.1, \tag{4.11}$$

Table 4.6 gives a summary of all the optimization parameters used in the case studies.

Table 4.6: Proposed alternatives to be implemented for the three energy groups

Description	Optimization parameter
O_1	R21,730
O_2	R19,840
k_1	10
k_2	50
N	110
Project budget	R5,000,000
C	R500,000
β	10%

The table shows all the parameters used in the optimization model.

4.3.2 PSO parameters

The position acceleration constants c_1 and c_2 must maintain the following relationship:

$$c_1 + c_2 \leq 4. \tag{4.12}$$

In this research the acceleration constants are set to 2. The population size and number of iterations are chosen to be 220 and 500. The optimization model has 220 variables to be solved, i.e. $x_{1,1}, x_{1,2}, ..., x_{1,110}$ and $x_{2,1}, x_{2,2}, ..., x_{2,110}$. Table 4.7 shows all the optimization parameters used in this study.

As the search for optimal solution proceeds the PSO inertia term decreases gradually according to equation (3.22). The e_{max} and e_{min} are the maximum and minimum values of the

Table 4.7: Proposed alternatives to be implemented for the three energy groups

Description	PSO parameters
c_1	2
c_2	2
e_{min}	0.4
e_{max}	0.9
r	100
k_{max}	500
ϵ	0.1
Particle$d$	220
Swarm m	10

inertia term as explained in chapter 3. The penalty parameter r is chosen to be 100 in this research.

4.4 CASE STUDY SIMULATIONS

In this section detailed case studies are presented. A plant that is undergoing an EE measure is considered for the case study.

4.4.1 Cases study

Table 4.8 shows five cases considered for sampling an EE retrofitting project.

Table 4.8: Case study specifications for Cases A to E

Description	Case A	Case B	Case C	Case D	Case E
Group # 1	90/10	90/10	90/10	90/10	90/10
Group # 2	90/10	70/30	80/20	90/5	97/3
Group # 3	90/10	70/30	80/20	90/5	97/3

Case A

In Case A, the confidence level and precision are set to the 90/10 criterion. Table 4.9 shows the different C_v values for the three groups used in Case A. Moreover, Table 4.9 shows the optimization results which are compared to the computed expected samples.

Table 4.9: Case A optimization results

Description	Z	C_v	Expected	Actual
Group # 1	90/10	0.5	9	4
Group # 2	90/10	0.5	29	13
Group # 3	90/10	0.2	9	7

The optimization results for Case A are shown in Table 4.10.

Table 4.10: Case A meter allocation

Description	Class A	Class B	Actual	Cost
Group # 1	3	1	4	R85,030
Group # 2	6	7	13	R269,260
Group # 3	3	4	7	R144,550

The difference in the costs of applying the optimization model verses using the conventional statistical approach is shown in Table 4.11.

Table 4.11: Case A cost comparison when using optimization and without optimization

Description	Class A	Class B	Total	Budget	Variance
Optimal results	R260,760	R238,080	R498,840	R500,000	R1,160
No optimization	R1,021,310	-	R1,021,310	R500,000	-R521,310
No optimization	-	R932,480	R932,480	R500,000	-R432,480

Figure 4.1 shows the number of items of equipment selected per group and the meter type selected.

Figure 4.2 shows a comparison of the statistical approach and the optimization model results which are based on the number of meters selected and the type of metering equipment used.

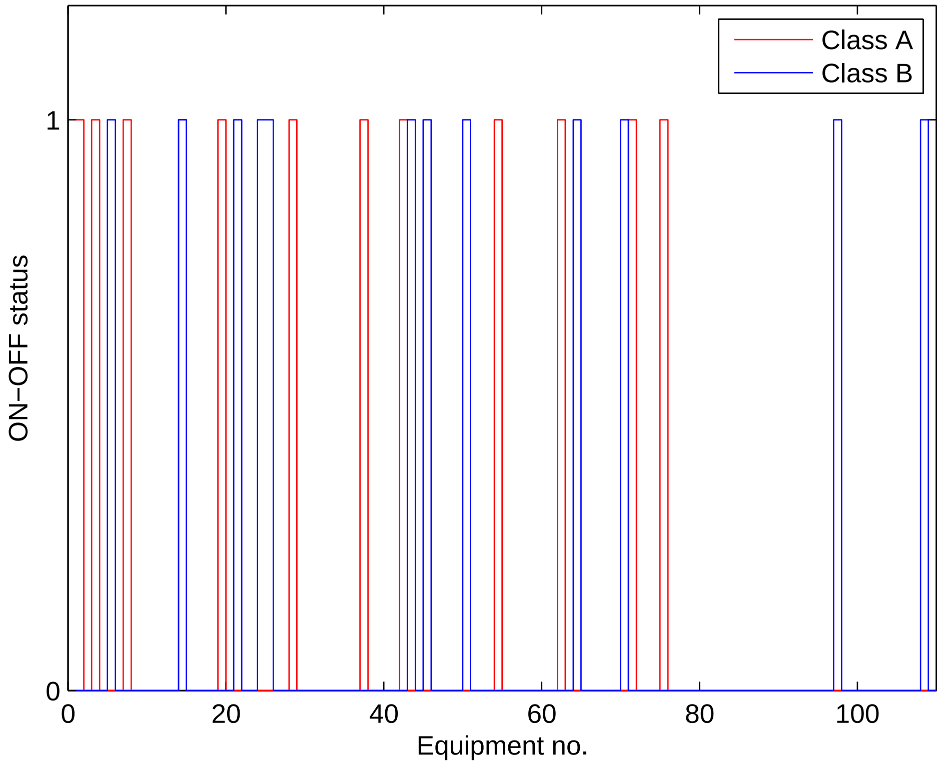

Figure 4.1: Case A meter allocation per equipment

Case B

In Case B, the confidence level and precision level for group 1 is maintained at the 90/10 criterion and while group 2 and 3 are set to the 70/30 criterion. Table 4.12 shows the different C_v values for the three groups used in Case B and the optimization results.

Table 4.12: Case B optimization results

Description	Z	C_v	**Expected**	**Actual**
Group # 1	90/10	0.5	9	-
Group # 2	70/30	0.5	3	-
Group # 3	70/30	0.2	0	-

Case C

In Case C, the confidence level and precision level for group 1 is set to the 90/10 criterion

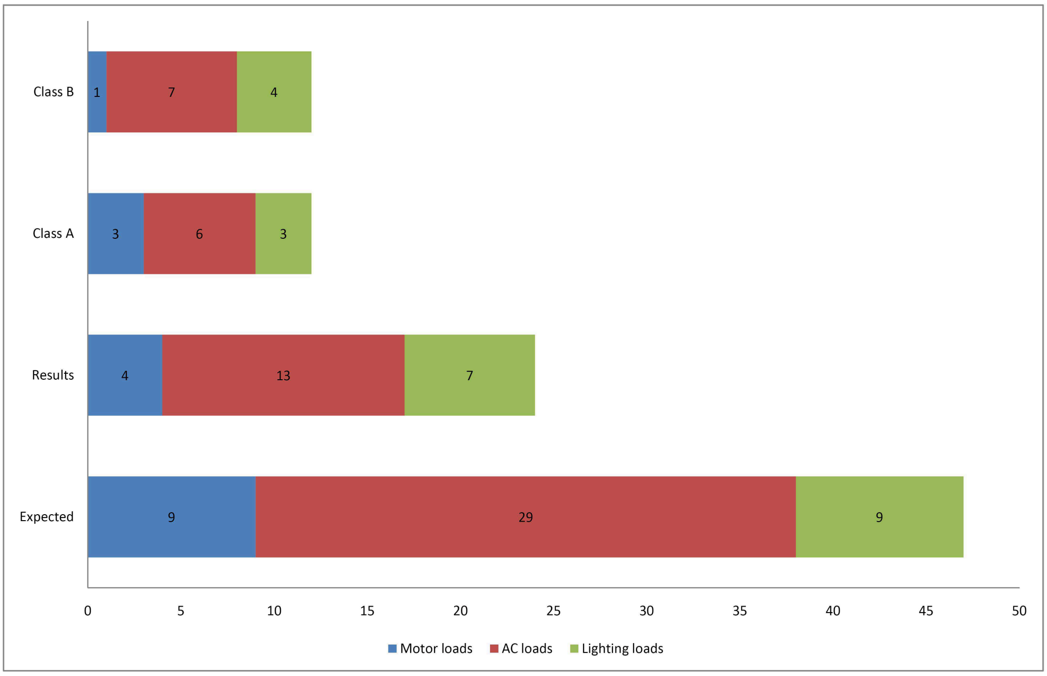

Figure 4.2: Case A meter allocation per class

and group 2 and 3 are set to the 80/20 criterion. Table 4.13 shows the different C_v values for the three groups and the optimization results.

Table 4.13: Case C optimization results

Description	Z	C_v	**Expected**	**Actual**
Group # 1	90/10	0.5	9	1
Group # 2	80/20	0.5	9	4
Group # 3	80/20	0.2	2	2

The optimization results for Case C metering allocation is given in Table 4.14.

Table 4.14: Case C meter allocation

Description	**Class A**	**Class B**	**Actual**	**Cost**
Group # 1	1	0	1	R21,730
Group # 2	2	2	4	R83,140
Group # 3	1	1	2	R41,570

Table 4.15 shows the total cost of applying the optimization model and using the statistical approach. The results are compared to the budget cost.

Table 4.15: Case C cost comparison when using optimization and without optimization

Description	Class A	Class B	Total	Budget	Variance
Optimal results	R86,920	R59,520	R146,440	R500,000	R353,560
No optimization	R434,600	-	R434,600	R500,000	R65,400
No optimization	-	R396,800	R396,800	R500,000	R103,200

Figure 4.3 shows the metering unit selected per equipment and the type of meter selected.

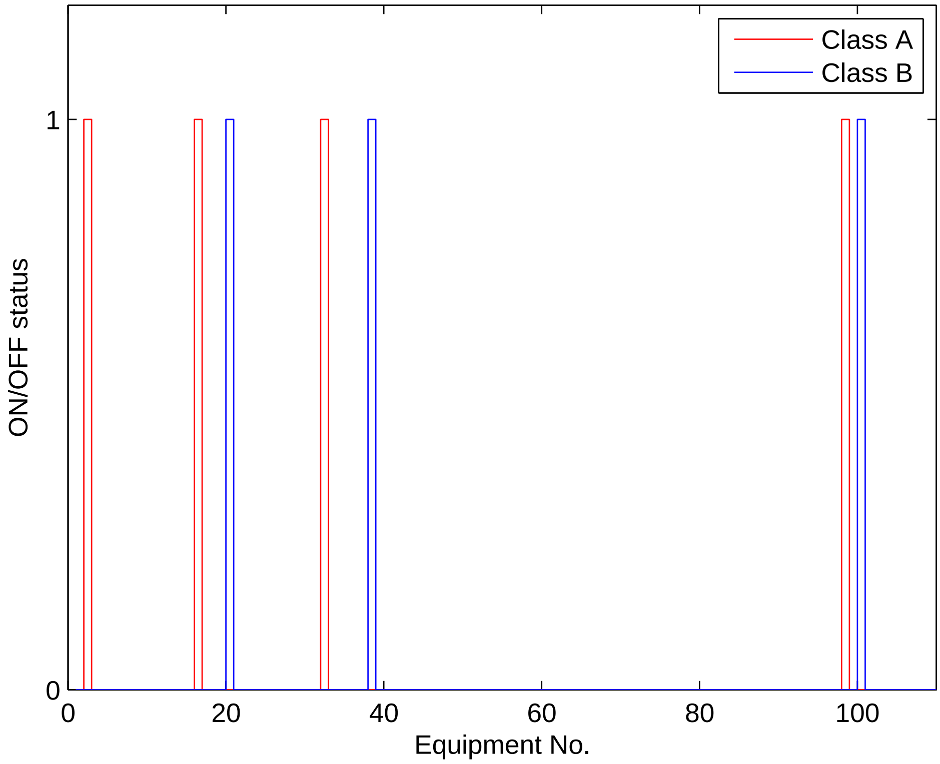

Figure 4.3: Case C meter allocation per equipment

Figure 4.4 shows the meter allocation per class and this is compared to the number of meters allocated without using the optimization model.

Case D

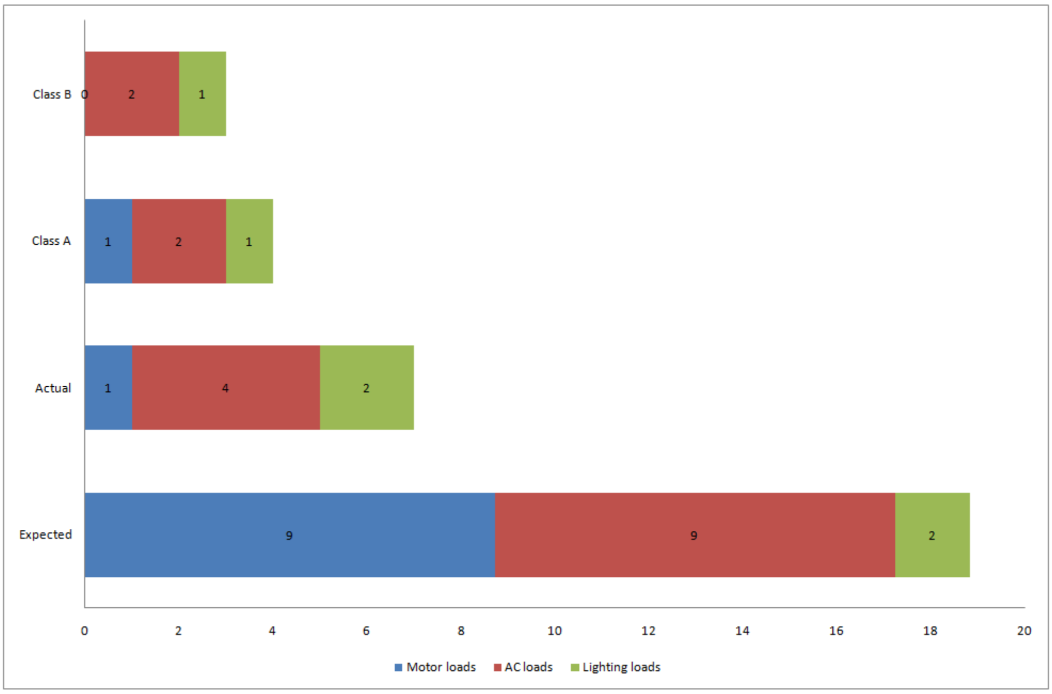

Figure 4.4: Case C meter allocation per class

In Case D, the confidence level and precision level for group 1 is maintained at the 90/10 criterion and group 2 and 3 are improved to the 90/5 criterion. Table 4.16 shows the different C_v values for the three groups used in Case D and the optimization results.

Table 4.16: Case D optimization results

Description	Z	C_v	Expected	Actual
Group # 1	90/10	0.5	9	4
Group # 2	90/5	0.5	42	11
Group # 3	90/5	0.2	23	7

The optimization results for Case D metering allocation per class are given in Table 4.17.

Table 4.18 shows the total cost of applying optimization and the cost without using the statistical approach to sampling. The cost of metering is compared to the budget cost.

Figure 4.5 shows the meter allocation per equipment when the optimization model is applied to the case study.

Table 4.17: Case D meter allocation

Description	Class A	Class B	Actual	Cost
Group # 1	3	1	4	R85,030
Group # 2	8	3	11	R233,360
Group # 3	1	6	7	R140,770

Table 4.18: Case D cost comparison when using optimization and without optimization

Description	Class A	Class B	Total	Budget	Variance
Optimal results	R260,760	R198,400	R459,160	R500,000	R40,840
No optimization	R1,610,585.10	-	1,610,585.10	R500,000	-R1,110,585.10
No optimization	-	R1,470,502.00	R1,470,502.00	R500,000	-R970,502.00

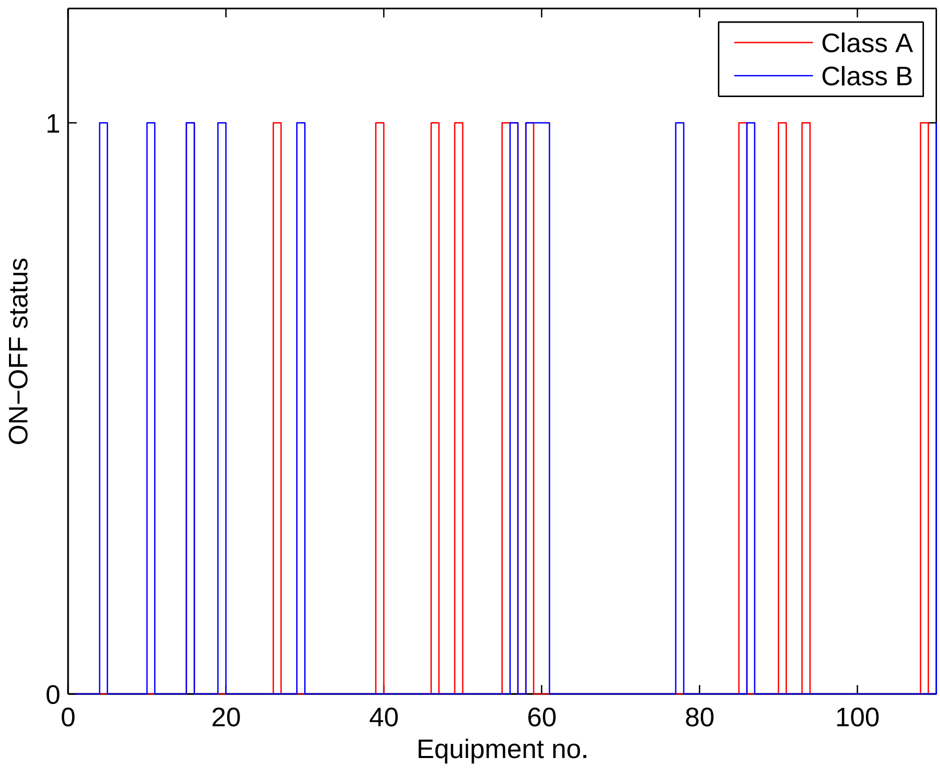

Figure 4.5: Case D meter allocation per equipment

Figure 4.6 shows the meter allocation per type and this is compared to the number of meters allocated using the optimization model.

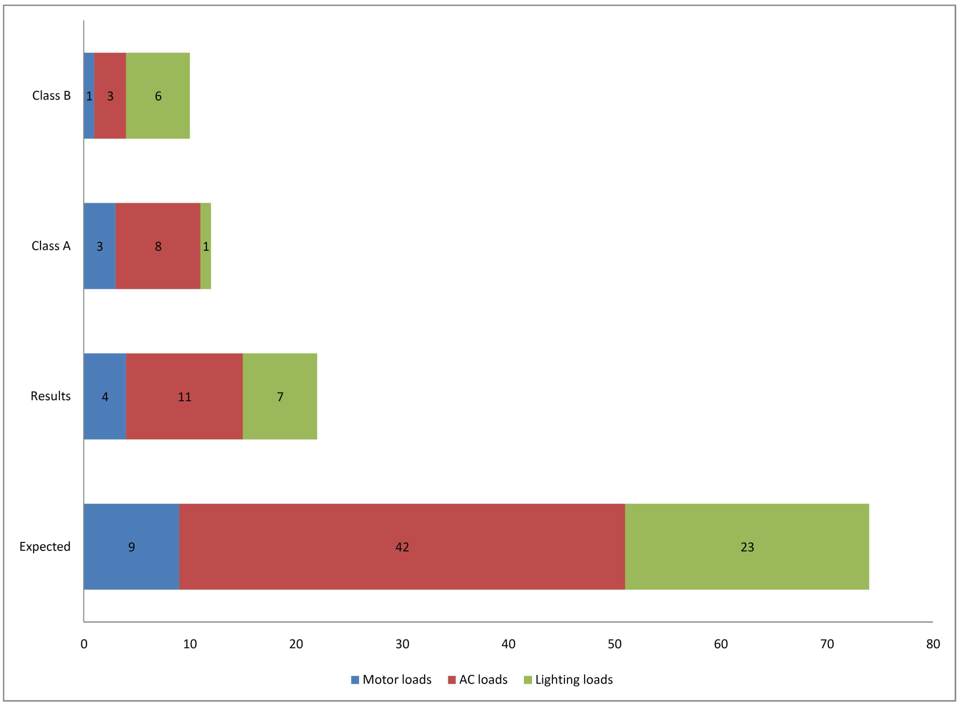

Figure 4.6: Case D meter allocation per class

Case E

In Case E, the confidence level and precision level for group 1 is set to the 90/10 criterion and group 2 and 3 are set to the 97/3 criterion. Table 4.19 shows the different C_v values for the three groups used in Case and the optimization results.

Table 4.19: Case E optimization results

Description	Z	C_v	Expected	Actual
Group # 1	90/10	0.5	9	3
Group # 2	97/3	0.5	48	12
Group # 3	97/3	0.2	40	7

The optimization results for Case E metering allocation per type is given in Table 4.20.

Table 4.21 shows the total cost of applying optimization and the cost without using optim-

Table 4.20: Case E meter allocation

Description	Class A	Class B	Actual	Cost
Group # 1	1	2	3	R61,410
Group # 2	3	9	12	R243,750
Group # 3	6	1	7	R150,220

ization.

Table 4.21: Case E cost comparison when using optimization and without optimization

Description	Class A	Class B	Total	Budget	Variance
Optimal results	R217,300	R238,080	R455,380	R500,000	R44,620
No optimization	R2,303,380	-	R2,303,380	R500,000	-R18,803,380
No optimization	-	R2,103,040	R2,103,040	R500,000	-R1,603,040

Figure 4.7 shows the meter allocation per equipment when the optimization model is applied to the case study.

Figure 4.8 shows the meter allocation per type and this is compared to the number of meters allocated without using the optimization model.

4.4.2 Sensitivity analysis

The sensitivity analysis is a measuring technique used to monitor the sensitivity of the model parameters as well as changes in the model structure. In this research, the sensitivity analysis is performed on the parameters in which different C_v, precision and confidence level are set to different parameters. This sensitivity analysis is performed to monitor the robustness of the model due to changes in the parameters.

Sensitivity analysis is performed to study the model uncertainties due to changes in the model parameters. Table 4.22 shows different cases to be considered when the confidence and precision levels are kept constant and C_v is varied from 0.1 to 0.7.

One of the objectives of the sensitivity analysis is to investigate the model's stability and

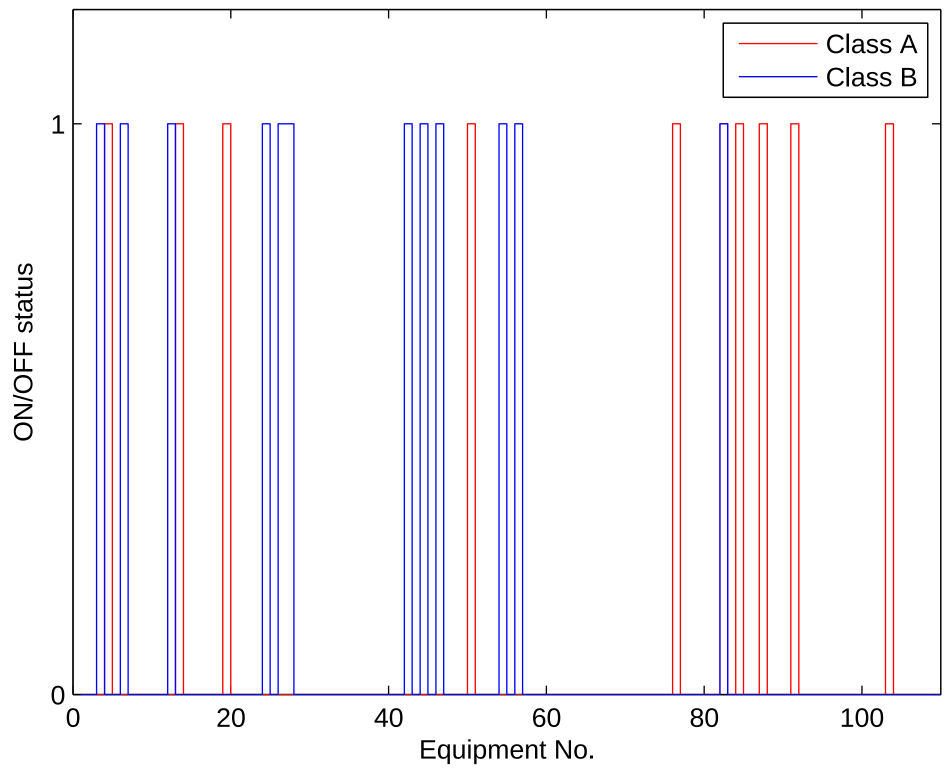

Figure 4.7: Case E meter allocation per equipment

Table 4.22: Sensitivity analysis of the model

Description	Case A	Case B	Case C
Confidence level	90/10	90/5	90/20
C_v	0.1 - 0.7	0.1 - 0.7	0.1 - 0.7

robustness to changes in the parameters. The following parameters are changed and the cost of metering is investigated:

- Confidence level and precision - this is affecting constraints (3.7) - (3.9). If the desired confidence is increased or decreased the metering costs must also change accordingly. The higher the precision requirements, the higher the number of samples required to meet that confidence level and vice versa. As such this parameter must be monitored to see its influence on the optimal metering plan.

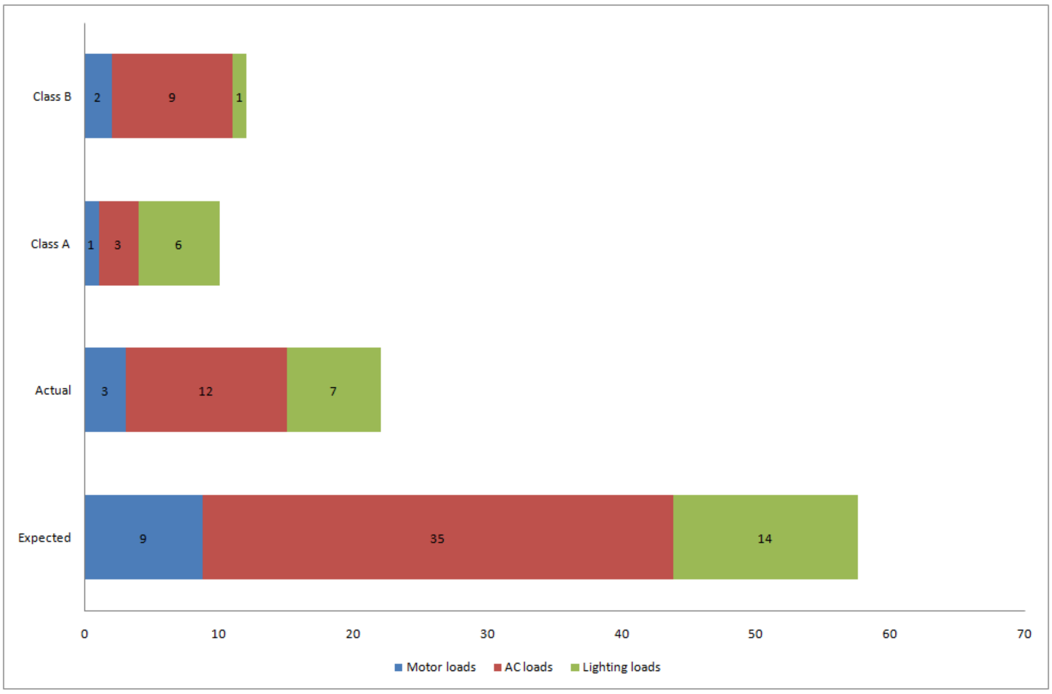

Figure 4.8: Case E meter allocation per class

- Coefficient of variation C_v - the C_v value has an influence on the number of meters that are required to measure the energy profile or lighting hours and it is very important to estimate it so that it represents the population under study. If the estimated C_v is close to the measured C_v, this means that the data collected meets the desired confidence and precision; however, if the estimated C_v is far from the measured one then the precision and confidence is affected and more samples are required to achieve the initial requirements on confidence and precision level. This parameter affects the metering costs and must be investigated thoroughly to minimize its effect on the metering costs.

The scaling of parameters does not affect the optimum point and as such no scaling of parameters will be considered for the sensitivity analysis.

Case A

As shown in Table 4.23, the desired confidence and precision level is the 90/10 criterion and the C_v value is varied. The objective is to monitor the sensitivity of the model to the constraints as stated in Table 4.23. Table 4.24 shows the influence of varying the C_v value for a constant 90/10 criterion. The sensitivity analysis also shows the best C_v value for the

90/10 criterion.

Table 4.23: Case A group 1 sensitivity analysis for the 90/10 criterion

C_v	**Expected**	**Actual**	**Class A**	**Class B**	**Cost**
0.1	2	1	1	0	R21,730
0.2	5	2	1	1	R41,570
0.3	7	2	2	0	R43,460
0.4	8	4	0	4	R81,250
0.5	9	2	1	1	R41,570
0.6	9	1	0	1	R19,840
0.7	9	1	0	1	R19,840

Table 4.24 shows the sensitivity analysis for group 2 equipment for the 90/10 criterion.

Table 4.24: Case A group 2 sensitivity analysis for the 90/10 criterion

C_v	**Expected**	**Actual**	**Class A**	**Class B**	**Cost**
0.1	3	6	3	3	R124,710
0.2	9	6	4	2	R126,600
0.3	16	4	2	0	R126,600
0.4	23	7	5	2	R148,330
0.5	29	9	5	4	R188,010
0.6	33	12	7	5	R251,310
0.7	36	9	4	5	R186,120

Table 4.25 shows the sensitivity analysis for group 3 equipment for the 90/10 criterion

Sensitivity analysis is shown in Figures 4.9 - 4.11.

Case B

As shown in Table 4.22, the desired confidence and precision levels are the 90/5 criterion and the C_v value is varied. The objective is to monitor the sensitivity of the model to the constraints as stated in Table 4.22. Table 4.26 shows the influence of varying the C_v value for a constant 90/5 criterion used for all the motor-related loads. The sensitivity analysis

Table 4.25: Case A group 3 sensitivity analysis for the 90/10 criterion

C_v	Expected	Actual	Class A	Class B	Cost
0.1	3	7	3	4	R144,550
0.2	9	4	1	3	R81,250
0.3	16	6	2	4	R122,820
0.4	23	6	2	4	R122,820
0.5	29	7	1	6	R140,770
0.6	33	6	3	3	R124,710
0.7	36	7	2	5	R146,660

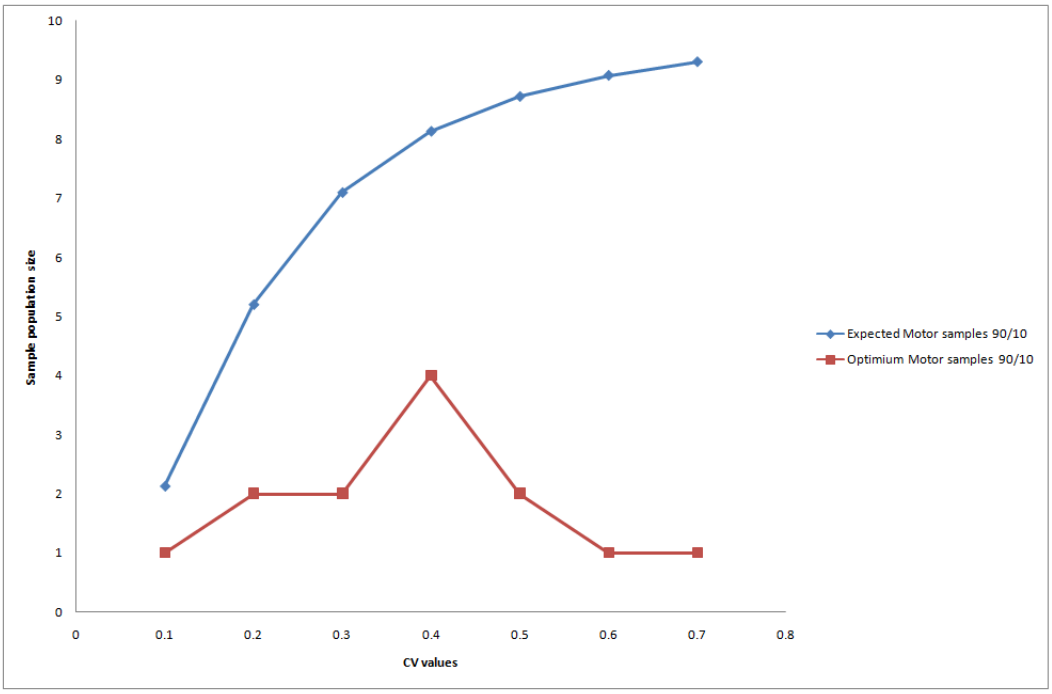

Figure 4.9: Case A sensitivity analysis for motor loads with 90/10 criterion

also shows the best C_v value for the 90/5 criterion.

Table 4.27 shows the sensitivity analysis for group 2 equipment for the 90/10 criterion.

Table 4.28 shows the sensitivity analysis for group 3 equipment for the 90/10 criterion.

Sensitivity analysis is shown in Figures 4.13 - 4.16.

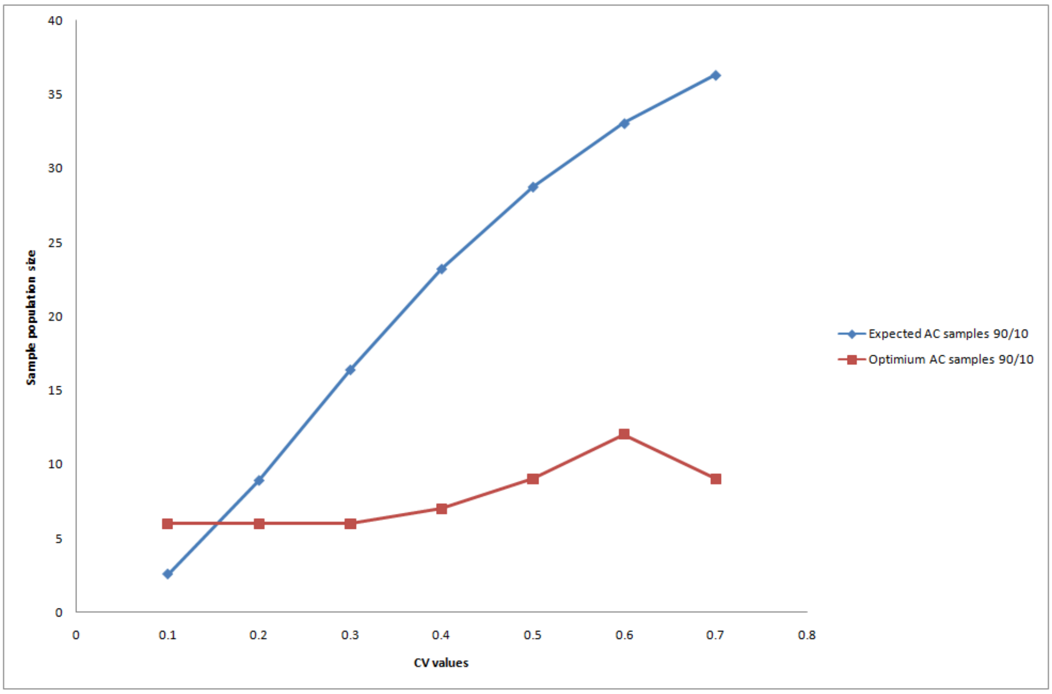

Figure 4.10: Case A sensitivity analysis for air conditioning loads with 90/10 criterion

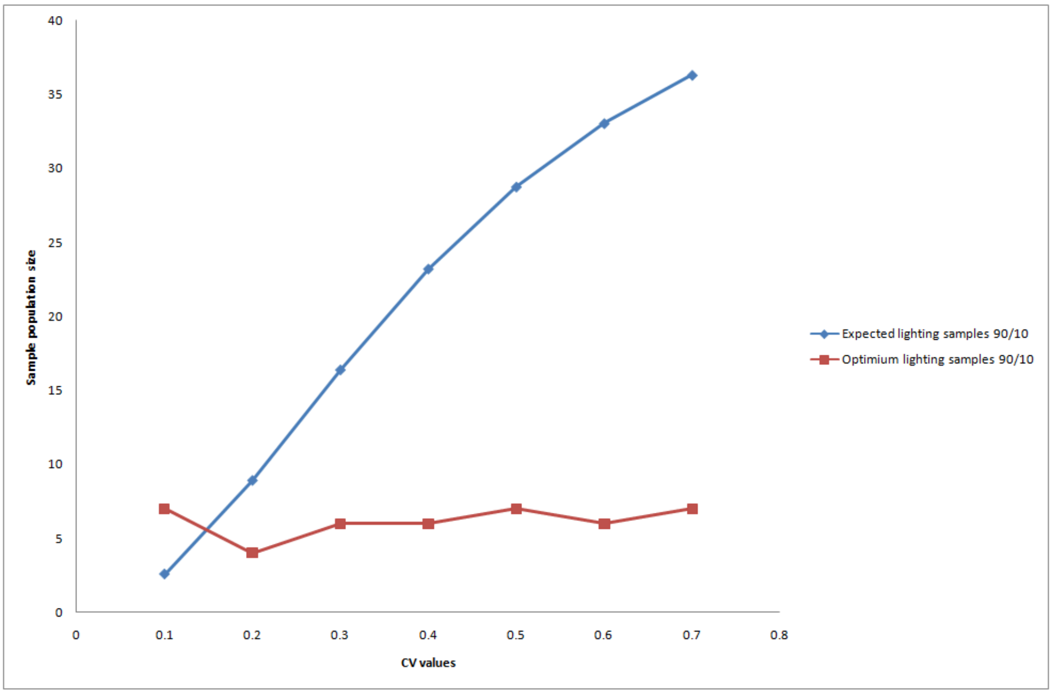

Figure 4.11: Case A sensitivity analysis for lighting loads with 90/10 criterion

Case C

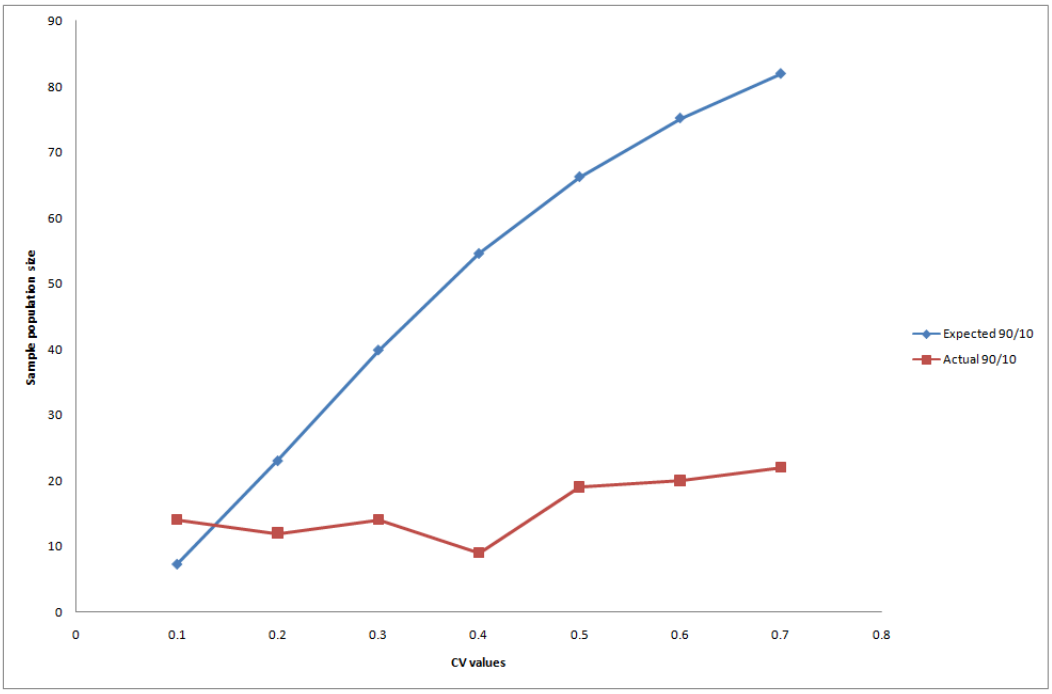

Figure 4.12: Case A sensitivity analysis for all loads with 90/10 criterion

Table 4.26: Case B group 1 sensitivity analysis for the 90/5 criterion

C_v	**Expected**	**Actual**	**Class A**	**Class B**	**Cost**
0.1	6	1	1	0	R21,730
0.2	9	2	2	0	R43,460
0.3	9	1	0	1	R19,840
0.4	10	1	0	1	R19,840
0.5	10	1	1	0	R21,730
0.6	10	1	1	0	R21,730
0.7	10	3	0	3	R59,520

The desired confidence and precision levels are the 90/20 criterion and the C_v value is varied. The objective is to monitor the sensitivity of the model to the constraints as stated in Table 4.22. Table 4.29 shows the influence of varying the C_v value for a constant 90/20 criterion used for all the motor-related loads. The sensitivity analysis also shows the best C_v value for the 90/20 criterion.

Table 4.30 shows the sensitivity analysis for group 2 equipment for the 90/10 criterion.

Table 4.27: Case B group 2 sensitivity analysis for the 90/5 criterion

C_v	**Expected**	**Actual**	**Class A**	**Class B**	**Cost**
0.1	12	6	2	4	R122,820
0.2	28	6	4	2	R126,600
0.3	37	4	2	2	R83,140
0.4	42	6	2	4	R122,820
0.5	44	8	4	4	R166,280
0.6	46	6	5	1	R128,490
0.7	47	7	5	2	R148,330

Table 4.28: Case B group 3 sensitivity analysis for the 90/5 criterion

C_v	**Expected**	**Actual**	**Class A**	**Class B**	**Cost**
0.1	12	8	2	6	R162,500
0.2	28	6	2	4	R122,820
0.3	37	5	2	3	R102,980
0.4	42	12	7	5	R251,310
0.5	44	11	6	5	R229,580
0.6	46	10	4	6	R205,960
0.7	47	10	4	6	R205,960

Table 4.29: Case C group 1 sensitivity analysis for the 90/20 criterion

C_v	**Expected**	**Actual**	**Class A**	**Class B**	**Cost**
0.1	0	-	-	-	-
0.2	1	1	1	0	R21,730
0.3	3	2	0	2	R39,680
0.4	4	1	0	1	R19,8400
0.5	5	1	1	0	R21,730
0.6	6	1	1	0	R21,730
0.7	7	2	2	0	R43,460

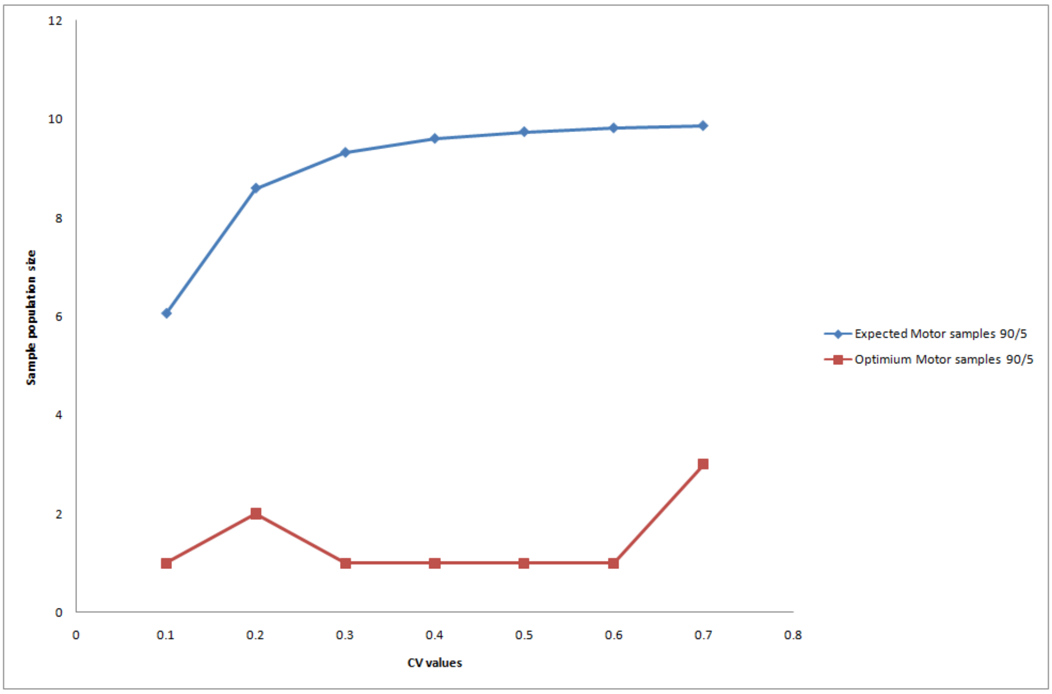

Figure 4.13: Case B sensitivity analysis for motor loads with 90/5 criterion

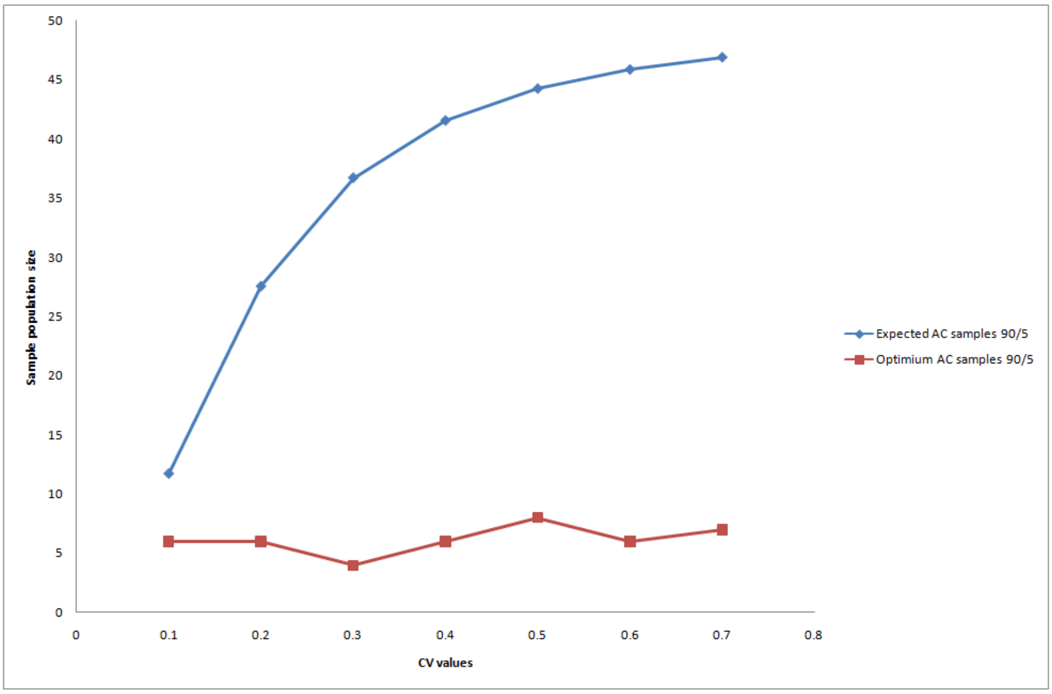

Figure 4.14: Case B sensitivity analysis for air-conditioning loads with 90/5 criterion

Table 4.31 shows the sensitivity analysis for group 3 equipment for the 90/10 criterion

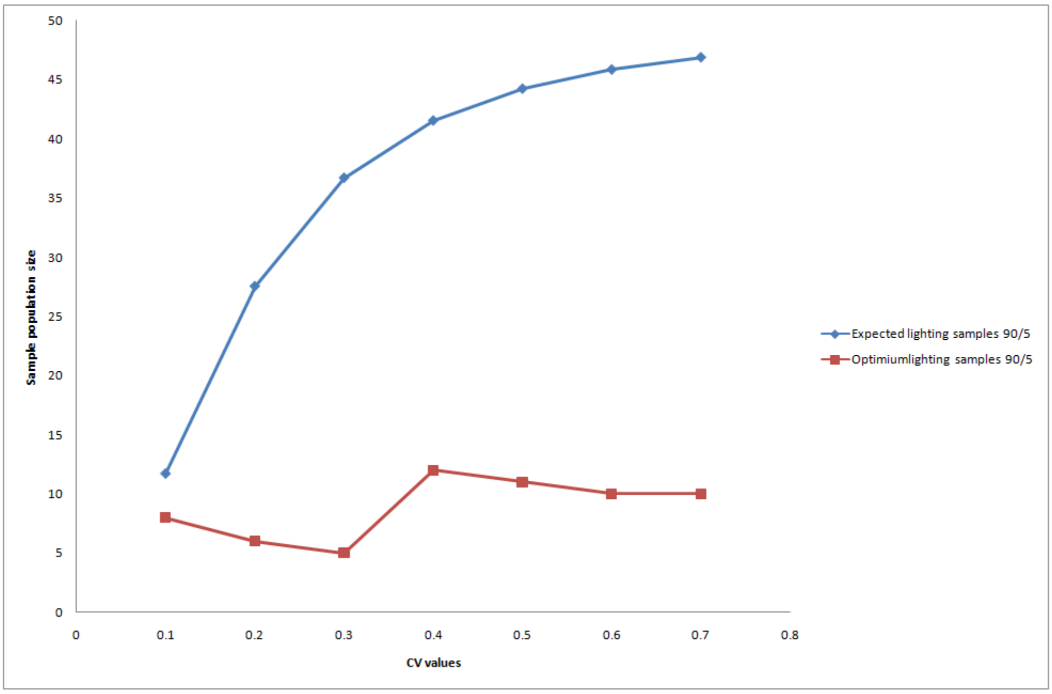

Figure 4.15: Case B sensitivity analysis for lighting loads with 90/5 criterion

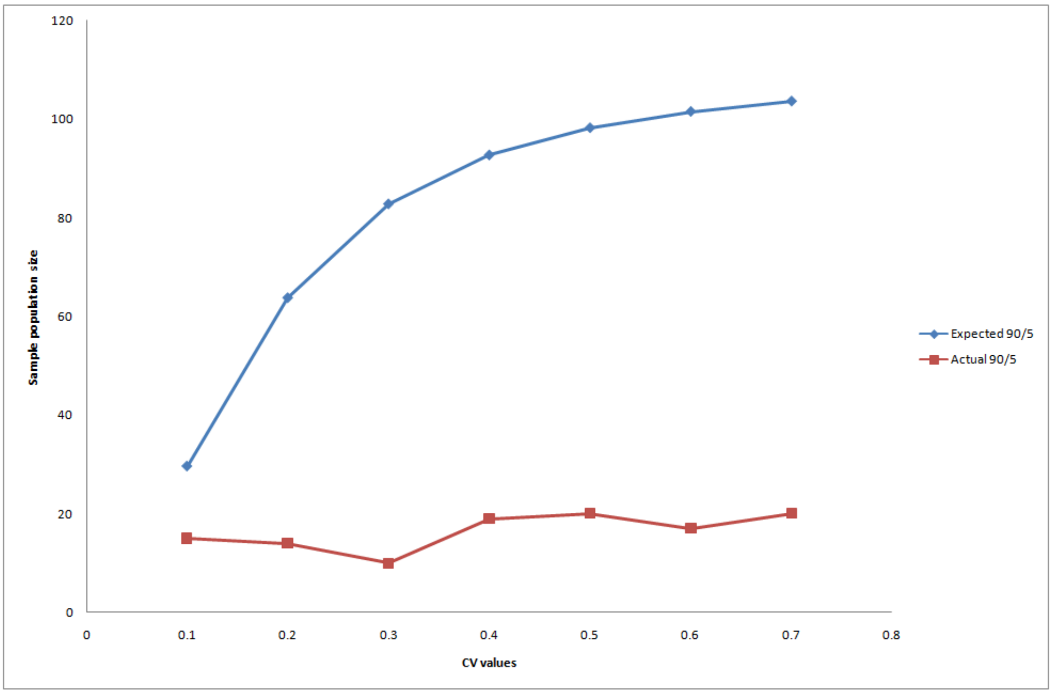

Figure 4.16: Case B sensitivity analysis for all loads with 90/5 criterion

Sensitivity analysis is shown in figures 4.17- 4.20.

Table 4.30: Case C group 2 sensitivity analysis for the 90/20 criterion

C_v	**Expected**	**Actual**	**Class A**	**Class B**	**Cost**
0.1	0	-	-	-	-
0.2	2	1	1	0	R21,730
0.3	3	10	6	4	R209,740
0.4	6	14	9	5	R294,770
0.5	9	9	7	2	R191,790
0.6	11	16	8	8	R332,560
0.7	14	10	3	7	R204,070

Table 4.31: Case C group 3 sensitivity analysis for the 90/20 criterion

C_v	**Expected**	**Actual**	**Class A**	**Class B**	**Cost**
0.1	0	-	-	-	-
0.2	2	3	2	1	R63,300
0.3	3	10	6	4	R209,740
0.4	6	6	3	3	R124,710
0.5	9	10	7	3	R211,630
0.6	11	4	0	4	R79,360
0.7	14	7	6	1	R150,220

Figures 4.21 - 4.23 show the samples size of each group against the C_v values.

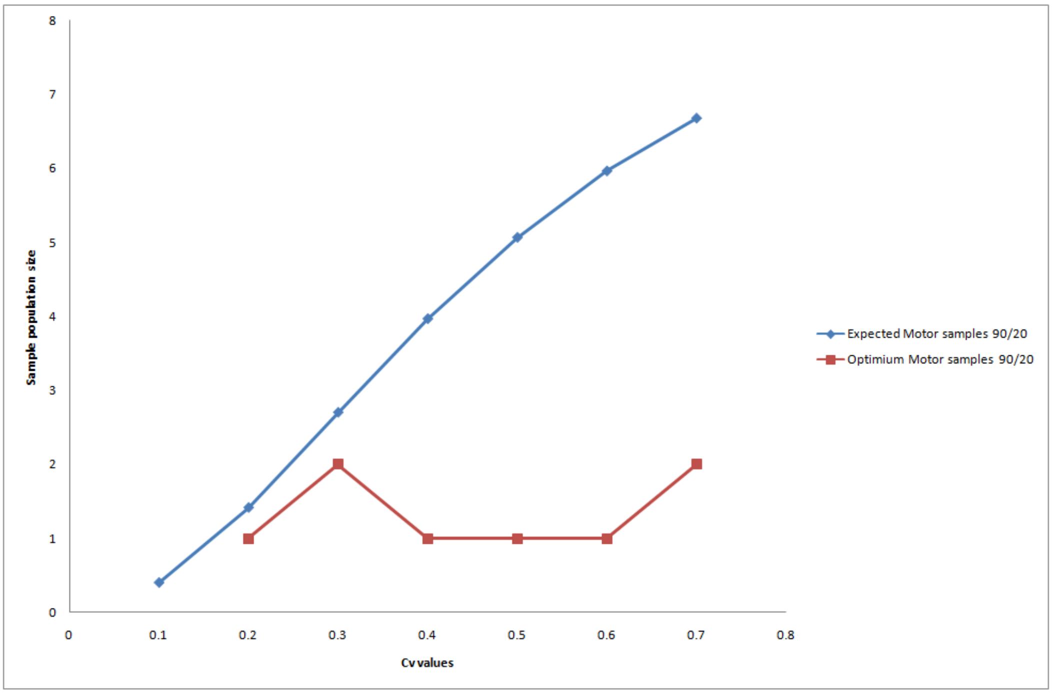

Figure 4.17: Case C sensitivity analysis for motor loads with 90/20 criterion

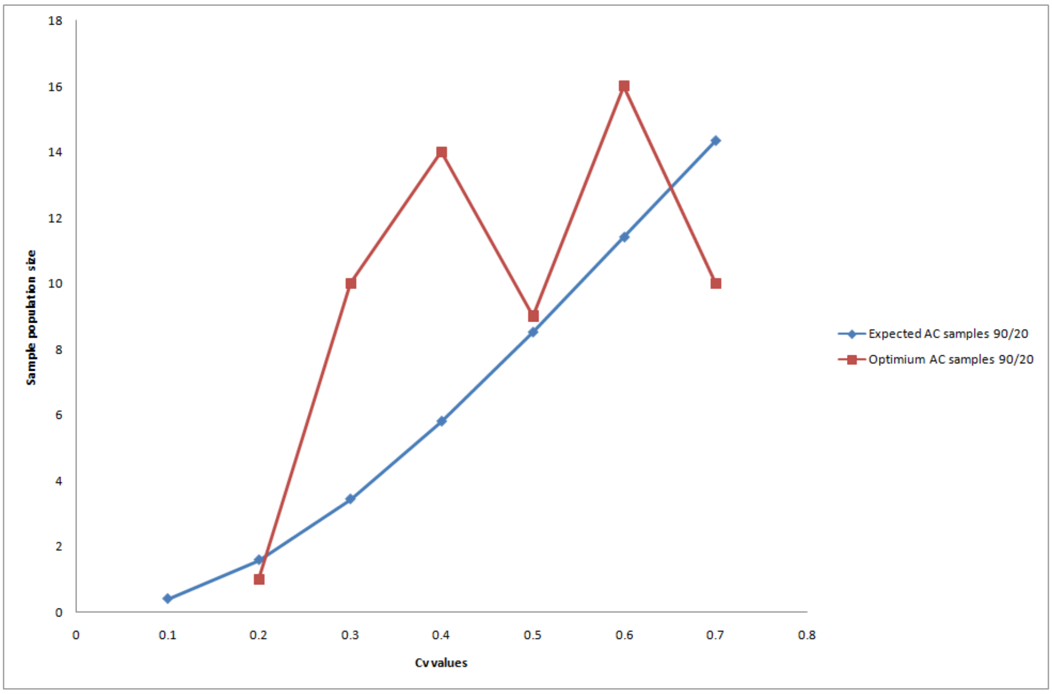

Figure 4.18: Case C sensitivity analysis for air-conditioning loads with 90/20 criterion

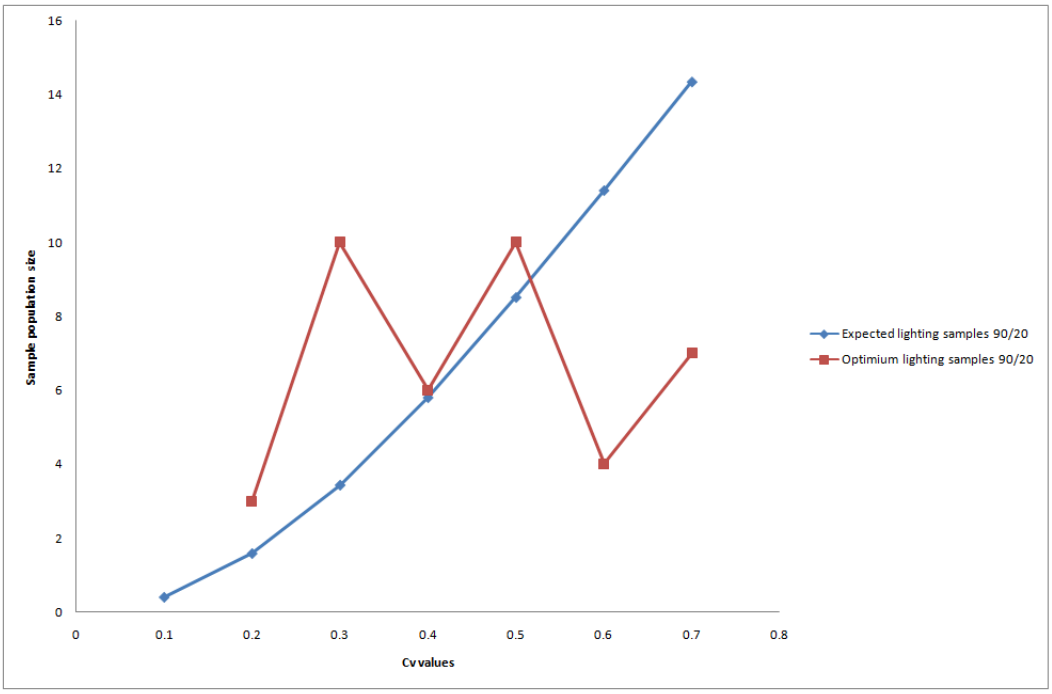

Figure 4.19: Case C sensitivity analysis for lighting loads with 90/20 criterion

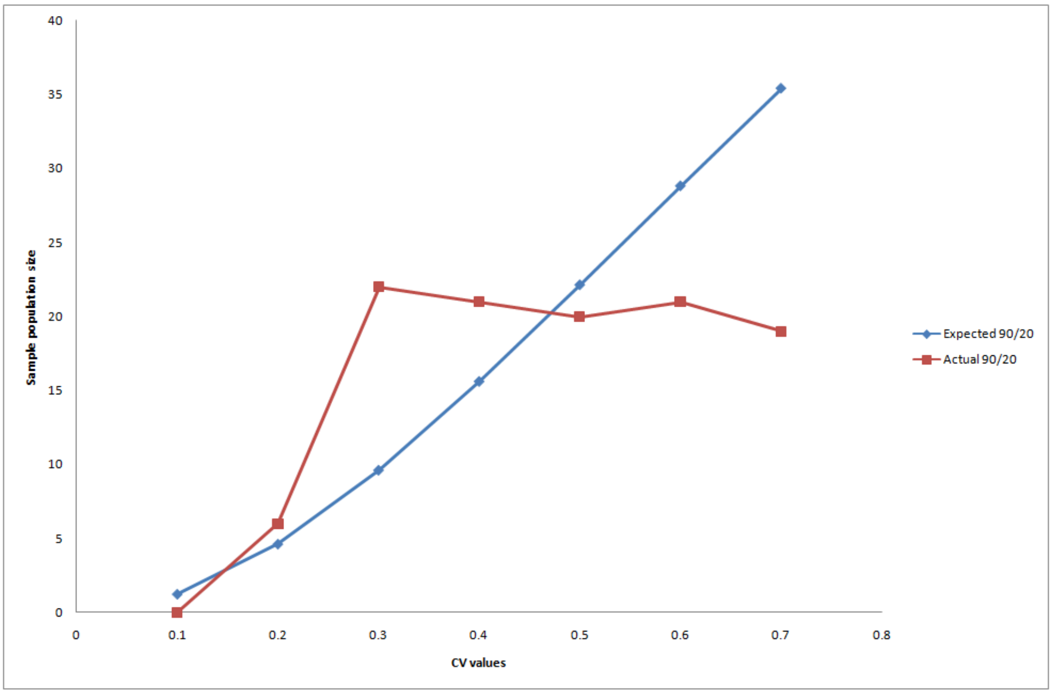

Figure 4.20: Case C sensitivity analysis for all loads with 90/20 criterion

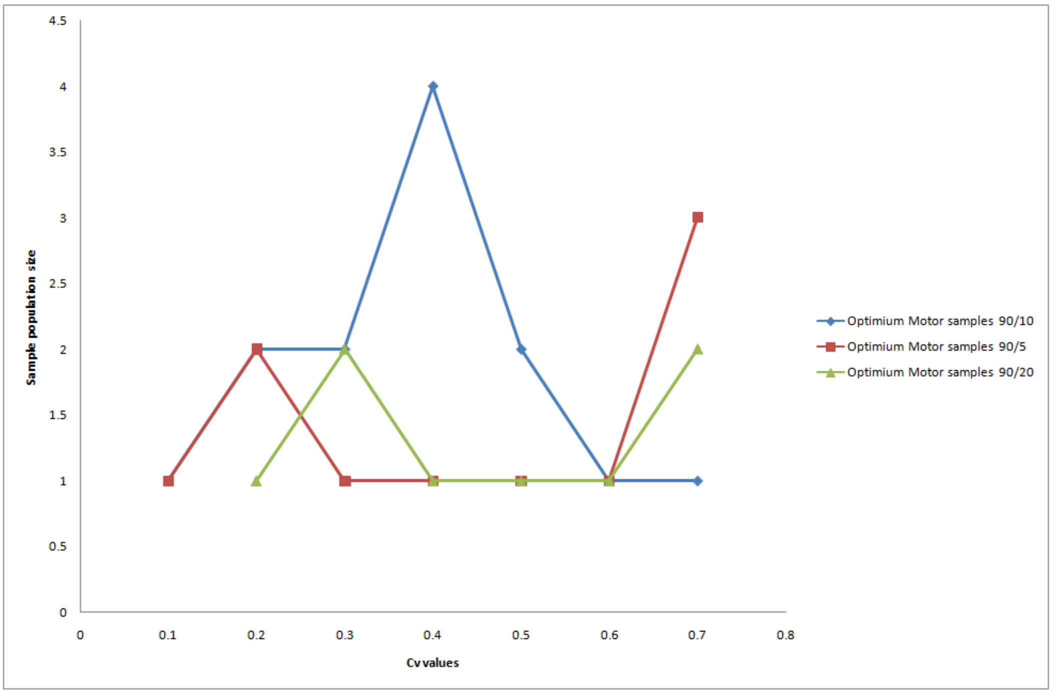

Figure 4.21: Sensitivity analysis for group 1 equipment

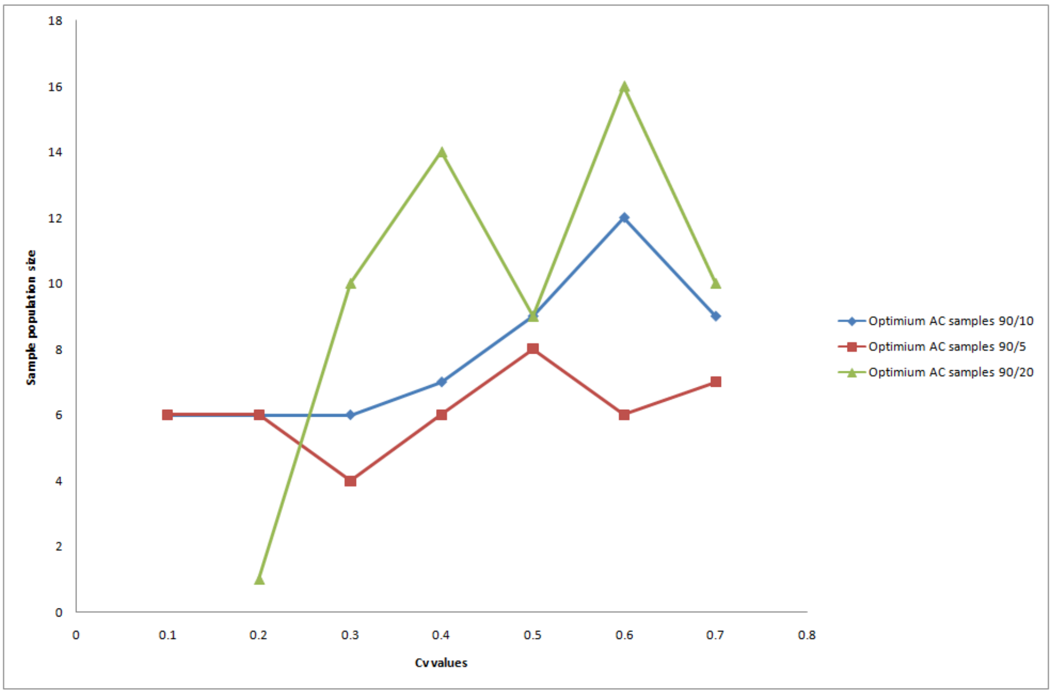

Figure 4.22: Sensitivity analysis for group 2 equipment

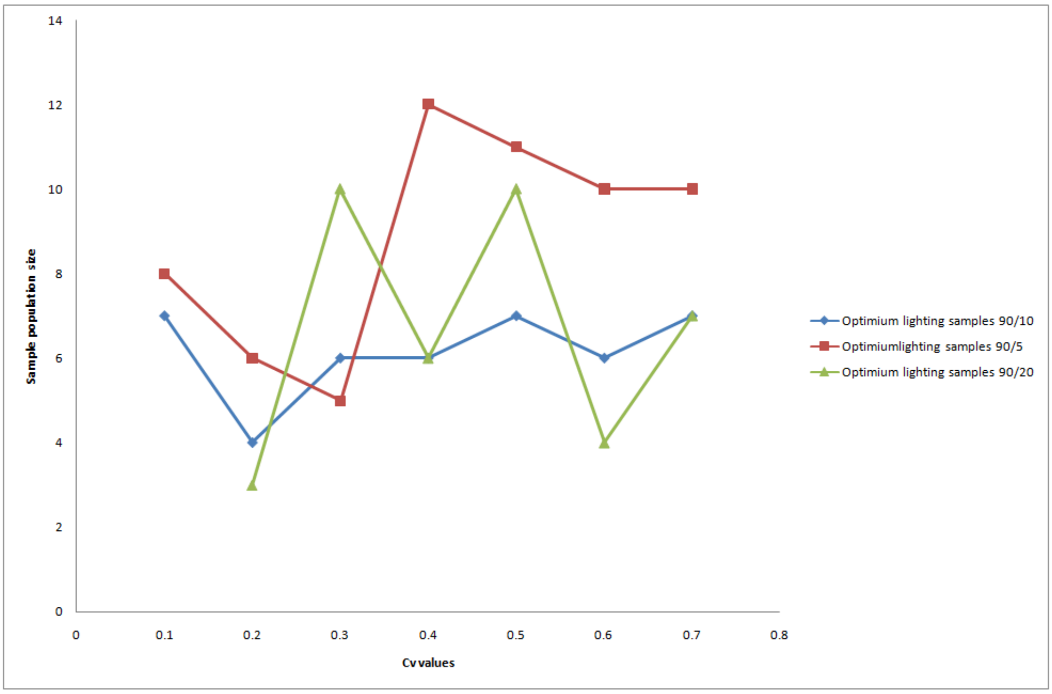

Figure 4.23: Sensitivity analysis for group 3 equipment

CHAPTER 5

DISCUSSION

5.1 CHAPTER OVERVIEW

The case study presented in chapter 4 varies the confidence and precision level while the project cost, accuracy level and specified C_v value are maintained constant. Moreover, a sensitivity analysis is performed to investigate the robustness of the model. In the sensitivity analysis, the right-hand side parameters of constraints (3.7) - (3.9) are varied together with the C_v value. This is used to investigates the model's sensitivity.

5.2 CASE STUDY RESULTS

There is a relationship between the metering cost, confidence and precision level, coefficient of variation C_v and the overall accuracy requirement. Cases A, D and E show the influence of increasing the precision level while maintaining the confidence interval; thus increasing the sample size. Moreover, a clear influence of C_v is noticeable on the sample size and metering costs in these cases. Cases B and C show the influence of relaxing the precision level which results in poor sampling. The result of poor sampling is clearly illustrated by Case B where an optimal solution is not possible since the accuracy requirement is not satisfied and the precision level is reduced.

5.2.1 Case A

In this case a total of 24 samples is achieved by using the optimization model against an expected sample size of 47 samples without using the optimization model. A confidence and precision level of 90/10 is used to solve the optimization model. Since each group has a different C_v value, the number of samples required per group is not the same for all groups. In group 1, there are 10 items of equipment undergoing energy retrofit, while the required number of samples for a C_v of 0.5 is 9. For group 2 and 3 there are 50 items of equipment undergoing EE retrofitting. Group 2 has a C_v of 0.5 while group 3 has a measured C_v of 0.2 and this result in the samples required for each group as 29 and 9. Table 4.4 shows that the C_v value has an influence on the number of samples required in any group.

The difference between the expected number of metering units and the actual number of metering units is the savings achieved. The total metering units found using the optimization model is 24. Twenty-three items of metering equipment are saved by using the optimization model. Table 4.10 shows the cost incurred per group and Table 4.11 shows the cost incurred for acquiring 24 items of metering devices for sampling.

Table 4.11 also shows a comparison of using the optimization model to compute the metering devices required and the effect of not using optimization but using equations (2.7) - (2.8) to compute the sample size. It can also be seen that a saving of R1,160 is realized by utilizing the optimization model, whereas if the optimization model is not used there is over-expenditure as given in Table 4.11. Fig 4.1 shows the allocation of metering devices to the equipment, class A and class B metering devices are chosen optimally. A total of 12 equipment per class is selected to achieve the accuracy required and the sampling criterion. Fig 4.2 shows a detailed classification of metering devices per group and it is compared with the expected metering devices.

5.2.2 Case B

In case B, the confidence and precision requirement for group 1 is kept constant at the 90/10 criterion. While the confidence and precision levels for group 2 and 3 are changed from the 90/10 to the 70/30 criterion. The effect of changing the precision level affects the samples required. In this case the precision is reduced from 10% to 30% at a confidence level of 70%. This implies that fewer samples are required to meet the required precision. The correlation between the C_v value and the precision is clear in this case. Group 2 equipment has a C_v value of 0.5 while group 3 equipment has a C_v value of 0.2. Both groups have the same population size of 50; however, since group 3 has a low C_v value, this means that fewer samples are required. For group 2, the expected number of metering equipment is 3, while for group 3 the expected number of metering equipment is zero. This shows a poor combination of precision and confidence level to the C_v value. For the same precision level of 30%, a C_v value must be greater than 0.5 in order to achieve some level of precision, confidence level and accuracy.

5.2.3 Case C

In this case a total of 7 samples is achieved using the optimization model compared to a total of 20 required without using the optimization model. The confidence and precision levels for group 2 and 3 equipment are set to the 80/20 criterion. Table 4.13 shows the precision and confidence level per group and Table 4.14 shows the expected number of metering devices for groups 1, 2 and 3. It can be seen from both tables that when the precision is relaxed, the number of samples required is also reduced. Therefore, a direct correlation exists between the precision level and sample size. That is, if the precision level is low, fewer samples are required to meet the specification and as a result Fig 4.3 shows the total number of items of metering equipment monitored.This case shows the effect of relaxing the precision level on the sample size. The precision level also affects the overall accuracy of the model. This illustrates a trade off between the metering cost and precision because even though the metering cost requirement is achieved, the precision of the sample is compromised.

5.2.4 Case D

In case D, the precision and confidence level for groups 2 and 3 are set to the 90/5 criterion. That is, a precision of 5% is required for the measured samples. As already established, the higher the precision, the larger the sample size required. A total of 22 samples is achieved by using the optimization model compared to 74 samples without using the optimization model. Table 4.16 shows the metering specification for the three groups. The expected number of metering devices in group 1 is nine, which is close to the population size of 10. For group 2, the expected number of metering devices is 42, which is 88% of the population size; and the expected number of metering devices for group 3 is 23, which is less because of the C_v value of group 3, as shown Table 4.17. In total a 5% precision requires at least 67% of the population to be samples across all three groups. However, by using the optimization model, a different sampling plan is established that meets the precision and confidence level and the budget constraint. Table 4.18 shows the total cost incurred when using the optimization model. A total of 22 metering units is optimally selected for the aforementioned precision requirement. That translates to 12 meters in class A and 10 meters in class B, as illustrated by Figures 4.5 and 4.6.

5.2.5 Case E

This case illustrates the influence of a high precision and the C_v value to the sample size. In this case, a 97/3 criterion is used for group 2 and 3 equipment. Table 4.19 shows the confidence and precision requirements for the three groups. A total of 22 samples is achieved using the optimization model compared to 97 samples required without using the optimization model. Moreover, the sample sizes for group 2 and 3 is restricted by the C_v value. This case illustrates the relationship between the precision level and the C_v value. It can be seen that even though the precision is increased the total samples size is similar to that in Case D. The other factors limiting the samples size is the overall accuracy requirement and the budget constraints. Table 4.20 shows meters allocated per class against the expected meters. A saving of 84 metering units is realized using the optimization model.

In addition, Figures 4.7 and 4.8 show the meter allocation on the equipment undergoing retrofitting and the total number of meters per class allocated in each group. It is clear that the sample size is not only dependent on the precision level but also on the coefficient of variation C_v.

5.3 SENSITIVITY ANALYSIS RESULTS

The sensitivity analysis considers three cases that are investigated in chapter 4. Tables 4.22 - 4.31 shows the sensitivity analysis, while the graphical representation of the sensitivity analysis is due to changes in the coefficient of variation, confidence level and precision as shown in Figures 4.9 - 4.20. The sensitivity analysis performed on the cases A to C in chapter 4 illustrates a clear correlation between the chosen C_v value, the confidence and precision level. The three cases presented show the influence of the variation of the precision level while maintaining a constant confidence interval. The increasing and decreasing of the precision level is monitored while the C_v value is varied between 0.1 to 0.7. It is clearly shown in cases A and B that an increase in the precision level results in an increase in samples and the opposite is true for case C. The following conditions must be satisfied to declare the optimization model robust:

- The model must be efficient and unbiased.
- A Small deviation from the model assumption must not substantially impair the performance of the model.
- The model must ensure that large deviations do not invalidate the model completely.

5.3.1 Case A

The sensitivity analysis is performed on constraints (3.7) - (3.9). In case A a confidence and precision level of 90/10 is used and kept constant, while the C_v is varied from 0.1 - 0.7. The variation of the C_v is based on energy retrofitting projects [10] and [49] for acceptable ranges. For each group, the C_v is varied and the expected metering devices are computed accordingly and compared to the actual results from applying the optimization model.

Table 4.22 and fig 4.9 show the results of varying the C_v value from 0.1 - 0.7. It is clear from the table that the deviation in the actual metering cost is minimal when the highest number of metering devices chosen is four when the C_v is 0.4. The mean for the actual samples required is two.

Table 4.24 and Fig 4.10 show the results of varying the C_v value for the group 2 equipment. The highest number of items of metering equipment expected is 36, when C_v is 0.7 and the actual optimization solution with the highest number of metering devices is 12. A mean of eight meters is required to ensure that a 90/10 criterion is satisfied.

For the group 3 equipment, the sensitivity analysis is shown in Table 4.25 for varying the C_v value. Fig. 4.11 shows a stable sample size with a mean of six metering devices. Therefore, referring to Fig. 4.12, it is clear that the optimization model is robust, as it is insensitive to a small deviation in the parameters of confidence level, precision and coefficient of variation for the 90/10 criterion.

5.3.2 Case B

The sensitivity analysis is performed for the 90/5 criterion and the results are shown in Table 4.26 - 4.28 for all three groups under consideration. It can be seen that for group 1 equipment there is a variance between what is expected and what the optimization model proposes. Furthermore, it can also be noticed that the highest samples expected starts at a C_v value of 0.4 until 0.7 while the highest number of metering equipment exist at a C_v value of 0.7. A mean sample size for the group 1 equipment is 2.

For group 2 equipment, the maximum sample size required is 47 metering devices; this exists at a C_v value of 0.7. The mean average sample size for group 2 equipment is six metering devices with the highest optimal sample size of eight meters when the C_v value is 0.5. Fig 4.13 shows a stable sample size for different C_v values.

The last group considered is the lighting group. In this group the maximum number of required samples is the same as group 2, which is 47. The mean average sample size for this group is nine, with the highest optimal sample occurring when the C_v value is 0.4. Similar to group 2 equipment, Fig 4.14 shows a stable sample size for a varying coefficient of variation.

Fig. 4.16 shows a more stable sample size obtained from the model. It is clear that the model is robust and insensitive to small changes in the parameters of confidence, precision and the coefficient of variation.

5.3.3 Case C

In case C, a confidence and precision level of 90/20 is used to evaluate the sensitivity of the optimization model. For the three energy groups under consideration, the model seems to be robust, as shown in Figures 4.17 - 4.20. The C_v of 0.1 does not give satisfactory results, as it requires no metering devices to achieve the aforementioned criterion. Therefore, a C_v of 0.1 is not be considered for the sensitivity analysis, as constraints (3.7) - (3.9) contradict constraints (3.3) - (3.5) of the optimization model.

The three groups have a stable sample size, as shown in Figures 4.17 - 4.20. This implies that the model is robust and can be applied to a variety of sampling criteria.

5.3.4 Comparison of case A to C

Figures 4.21 - 4.23 show the samples sizes per group for different sampling criteria. In group 1, a 90/10 sampling criterion overshoots at a C_v of 0.4 while for the 90/5 criterion an overshoot is at 0.7. Figure 4.21 shows that an average of 0.4 can be chosen if the C_v is not specified.

Fig 4.22 shows the comparison of group 2 equipment. In this case the overshoot occurs at 0.4 and 0.6 ; this is where a high number of samples are required to achieve the respective precision and confidence level. Fig 4.23 shows group 3 optimal solutions for varying the C_v value. Similar to the other two groups, an overshoot occurs at 0.5 and the 90/10 criterion is more stable than the other two criteria for group 3 equipment.

The sensitivity analysis can also be used as a guideline for selecting a C_v value when it is not specified. From all three cases, it is clear that the C_v value ranges between 0.4 to 0.6 is preferable if no C_v value is specified. The optimization model for an optimal metering plan proves to be robust for varying the parameters in all groups.

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

6.1 CONCLUSION

The optimal M&V metering plan for an EE project is formulated with constraints and PSO is used to solve the model. The model results are optimal and a savings is achieved by implementing the model. The sensitivity analysis is performed to evaluate the parameter sensitivity and the results show that the model is robust. That is, changes in the model constraints results in a different optimal solution. Three different case studies are applied to evaluate the model sensitivity and this model proves to be robust and efficient. Moreover, from the results it is shown that not all objectives are achievable such as the objective of achieving minimal sampling as the precision level is too low and the required confidence interval is high. It can be seen from the results that the number of meters are increased in order to achieve the overall accuracy requirements for such cases. Thus, there exists a direct correlation between M&V cost and reducing errors because when the errors are reduced, the M&V metering costs are increased. The sensitivity analysis also shows that the changes in the precision and confidence interval affect the sampling requirements. Moreover, the sensitivity of the optimization model shows that the model is robust. This can be proved by the robustness of the model under poor sampling requirements as the optimization model still converges to an optimal solution.

6.2 RECOMMENDATIONS

The model presented in this research is not limited to the case study presented, it can also be applied to building EE projects where additional metering requirements can be added.

It is proposed that a multi-objective function method be used for future study. This will consider the metering cost and the precision and confidence level as objective functions. The objective will focus on reducing the metering costs while increasing the confidence and precision level. The research could also use other evolution algorithm for solving the multi-objective function problem. This will increase the complexity of the model. Algorithms such as genetic algorithm and the Pareto algorithm could be used to solve the optimization model, as such a problem will be a mixed integer programming problem, as it will include binary and integer variables.

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