OPTIMAL MEASUREMENT AND VERIFICATION PLAN ON LIGHTING

by

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SUMMARY

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Measurement and Verification (M&V) has become an indispensable process in various incentive energy efficiency and demand side management (EEDSM) programmes to accurately and reliably measure and verify the project performance in terms of energy or cost savings. Due to the uncertain nature of the un-measurable savings, there is an inherent trade-off between the M&V accuracy and M&V cost. Practically, there are three types of quantifiable uncertainties coupled with the M&V process including measurement, modelling and sampling uncertainties. For large-scale lighting retrofit projects that require long-term continuous measurements, the desired sampling effort for savings determination contributes to a significant increase to the M&V cost. On the contrary, the measurement and modelling uncertainties are considered less significant in the lighting M&V process. In order to handle the sampling uncertainties and achieve the required M&V accuracy cost-effectively, three metering cost minimisation (MCM) models are proposed, namely spatial MCM model, longitudinal MCM model, and the combined spatial and longitudinal MCM model to assist the design of optimal M&V metering plans, by which the minimal metering cost is achieved with the satisfaction of the required M&V metering and sampling accuracy. In the proposed MCM models, the objective functions are the M&V metering cost that covers the procurement, installation and maintenance of the M&V metering system whereas the M&V accuracy requirements in terms of confidence and precision levels are formulated as the constraints. Generally, for lighting projects that have multiple

homogeneous lighting groups with different sampling uncertainties, the spatial MCM model is most applicable when the lighting population are properly maintained to avoid lamp population decay. If no project population maintenance activities are carried out, then the lamp population will decay as time goes by. In such a case, the longitudinal MCM model is most suitable to optimise the sample sizes within adjacent reporting years for each lighting group. The combined spatial and longitudinal MCM models exhibits the best performance in terms of metering cost minimisation whilst satisfying the required M&V accuracy, especially for the lighting projects that have multiple lighting groups with different sampling uncertainties and different population decay dynamics. Optimal solutions to the proposed MCM models offer useful information in designing the optimal M&V metering plan, such as the required lighting samples to be measured in each lighting groups, the achieved sampling accuracy in terms of confidence and precision levels as well as the annual and total M&V metering cost for the studied lighting project. The advantages of the proposed MCM models are demonstrated by several lighting retrofit case studies. For the case studies, metering solutions obtained with or without optimisations are calculated and compared. The comparisons highlight the advantageous performance of the proposed MCM models. These MCM models are widely applicable to M&V projects with different technologies, population sizes, and sampling accuracy requirements.

Since the lighting population decays as time goes by, the lighting project performance is not sustainable and vanishes rapidly without proper maintenance activities. The scope of the maintenance activities refers to the replacements of the failed lamps due to the occurrence of non-repairable lamp burnouts. Full replacements of all the failed lamps during every maintenance activity contribute to a tighter project budget due to the expense for the lamp failure identifications as well as the procurement and installation of new lamps. Since neither “no maintenance” nor “full maintenance” is preferable to the lighting project developers, an optimal maintenance planning (OMP) approach is also proposed to decide the optimal number of failed lamps to be replaced, such that the EE lighting project achieves sustainable energy savings whereas the project developers obtain their maximum benefits in the sense of a maximum cost-benefit ratio. The OMP problem is aptly formulated under a control system framework. According to existing studies on the lamp population decay modelling, the lamp population decay dynamics are taken as the plant of the control system. The number of lamps to be replaced is designed as the inputs of the control system. As different lighting technologies have different population decay dynamics, different procurement prices and different rebate tariffs, the control inputs can be optimally decided to satisfy the project budget constraints and project boundary constraints. The optimal maintenance planning problem is then translated into an optimal control problem and solved by a model predictive control (MPC) approach. Since the lighting population has a close relationship with the sample size determination, the optimal maintenance planning approach is also integrated with the proposed MCM models, which further improves the performance and flexibility to the applications of the proposed MCM models for the M&V metering plan designing.

OPSOMMING

TITEL

deur

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Meting en Verifiëring (M&V) het ’n onontbeerlike proses in verskeie energiedoeltreffendheid- en vraagkantbestuurprojekte geword. Dit behels die akkurrate en betroubare meting en verifiëring van projekte in terme van energie of koste besparing. Weens die onsekere aard van onmeetbare besparings is daar ‘n inherente kompromie tussen M&V akkurraatheid en koste. Prakties gesproke is daar drie tipes kwantifiseerbare onsekerhede: meting, monstering, en modellering. Monsteringskoste dra noemenswaardig by tot M&V koste vir grootskaalse retrofit projekte waar langtermyn aaneenlopende metings vereis word. Daarenteen word meting en modelleringskoste as minder noemenswaardig geag vir M&V projekte. Ten einde monsteringskoses te bestuur en steeds aan die akkurraatheidsvereistes vir verslagdoening te voldoen, word drie Metingskoste Minimerings (MKM) modelle voorgestel: ruimtelik, longitudinaal, en gekombineerd. Hierdie modelle behaal ’n minimum koste binne die verslagdoeningsraamwerk. In die voorgestelde modelle is die doelfunksie die M&V metingskoste wat aankoop, installering, en onderhoud van die sisteem insluit. M&V verslagdoeingsvereistes soos vertroue en presiesheid word word as beperkinge geformuleer. In die algemeen, vir beligtingsprojekte wat veelvoudige homogene bevolkings met verskillende onsekerhede het, is die MKM model van toepassing as die bevolkings onderhou word om bevolkingsoorlewing by 100% te hou. As geen onderhoud gedoen word nie, sal bevolkings afneem oor tyd. In hierdie geval sal die longitudinale MKM model gebruik kan word om monstergroottes in opeenvolgende jare te optimeer vir elke homogene bevolkingsgroep. Die gekombineerde ruimtelike en longitudinale MKM model toon die beste prestasie t.o.v. meting en kosteminimering, en bevredig terselfdetyd die M&V akkurraatheidsvereistes, veral vir bevolkingsgroepe met veelvoudige homogene beligtingsgroepe met verskillende monsteronsekerhede en verskillende bevolkingsafname-dinamika. Optimale oplossings vir die voorgestelde MKM modelle bied nuttige inligting vir die ontwerp van optimale M&V metingsplanne. Hierdie sluit in die benodigde monstergroottes vir elke beligtingsbevolking, die monsteringsakkurraatheid in terme van vertroue en presiesheid, en die jaarlikse en algehele metingskoste. Die voordele van MKM modelle word deur verskeie beligtingsretrofitstudies geïllustreer. Vir die gevallestudies word metingsoplossings wat behaal is met en sonder optimering bereken en vergelyk. Die vergelykings beklemtoon die voordelige prestasie van die voorstelde MKM modelle. Hierdie modelle is op ‘n wye reeks tegnologieë, bevolkingsgroottes, en monsteringsvereistes van toepassing.

Omdat die lampbevolking afneem oor tyd, is die projekbesparings nie volhoubaar nie, en verdwyn dit vinnig sonder behoorlike onderhoud. Die omvang van die onderhoudaktiwiteite verwys na die vervanging van gefaalde lampe as gevolg van nie-herstelbare lampuitbranding. Vervanging van alle gefaalde lampe tydens elke onderhoudaktiwiteit dra by tot ’n beter begroting as gevolg van die koste van lampfalingsidentifisering sowel as die aankoop en installering van nuwe lampe. Sedert “geen onderhoud" en “volle onderhoud" beide onaantreklik vir projekontwikkellaars is, word ‘n optimale onderhoud-benadering (OOB) voorgestel om te besluit wat die optimale hoeveelheid gefaalde lampe is wat vervang behoort te word, sodat energiedoeltreffendheidprojekte volhoubare besparings behaal. Die OOB probleem word geformuleer binne ’n beheerstelselraamwerk. Volgens bestaande studies op lamp bevolkingsoorlewing, word die bevolkingsoorlewingdinamika as die fabriek oorweeg. Die aantal lampe wat vervang word, word as die beheersein ontwerp. Omdat verskillende tegnologieë verskillende bevolkingsdinamika, aankooppryse, en kortingstariewe het, word beheerinsette optimaal bepaal om projekbegrotingsbeperkinge te bevredig. Die optimale onderhoudskedule word dan in ’n optimale beheerprobleem vertaal en met model voorspellende beheer opgelos. Omdat beligtingsbevolkings in noue verband met monstergrootte bepalings staan, word die optimale beheerbenadering ook geïntegreer met voorgestelde MKM modelle, wat die perstasie en buigsaamheid van die toepassings in M&V vermeerder.

LIST OF ABBREVIATIONS

AC	Alternative Current
AEG	Authority of Electricity and Gas
AEIC	Association of Edison Illuminating Companies
AR	Autoregressive
ASHRAE	American Society of Heating, Refrigerating and Air Conditioning Engineers
ANN	Artificial Neural Networks
CDD	Cooling Degree Day
CDF	Cumulative Distribution Function
CDM	Clean Development Mechanism
CFL	Compact Fluorescent Lamp
CM	Corrective Maintenance
CMVP	Certified Measurement and Verification Professional
CPUC	California Public Utilities Commission
CSF	Critical Success Factors
CV	Coefficient of Variation
CVRMSE	Coefficient of Variation of Root Mean Square Error
DLC	Direct Load Control
DSF	Double Skin Facade
DSM	Demand Side Management
ECM	Energy Conservation Measure
EE	Energy Efficiency
EEIS	Enterprise Energy Information System
EERS	Energy Efficiency Resource Standards
EMCS	Energy Management and Control Systems
EMV	Evaluation, Measurement and Verification
EPA	Environmental Protection Agency
EPC	Energy Performance Contract
ESC	Energy Savings Certificate
ESCo	Energy Service Company
ESI	Energy-Savings Insurance

EVO	Efficiency Valuation Organization
FEMP	Federal Energy Management Program
4P-CP	Four-Parameter Change-Point
FM	Full Maintenance
GHG	Greenhouse Gas
GP	Gaussian Process
HDD	Heating Degree Day
HDL	Halogen Downlighter
HID	High-Intensity Discharge
IEQ	Indoor Environmental Quality
ICL	Incandescent Lamp
IPCC	Intergovernmental Panel on Climate Change
IPMVP	International Performance Measurement and Verification Protocol
ISM	Integrated Simulation Method
KPI	Key Performance Indicators
LBNL	Lawrence Berkeley National Laboratory
LED	Light-emitting Diode
LFL	Linear Fluorescent Lamp
LFR	Lamp Failure Rate
LMCM	Longitudinal Metering Cost Minimisation
MBE	Mean Bias Error
MCM	Metering Cost Minimisation
MERVC	Monitoring, Evaluation, Reporting, Verification, and Certification
MLR	Multiple Linear Regression
NM	No Maintenance
MPC	Model Predictive Control
MR	Million Rand
M&V	Measurement and Verification
MVR	Measurement, Reporting and Verification
NAPEE	National Action Plan for Energy Efficiency
NZED	Net Zero Energy Building
O&M	Operation and Maintenance
OM	Optimal Maintenance

OMP	Optimal Maintenance Planning
PCA	Principal Component Analysis
PD	Project Developer
PDD	Project Design Document
PDF	Probability Density Function
PI	Post-Implementation
PM	Preventive Maintenance
RMR	Residential Mass Rollout
R^2	Coefficient of Determination
SE	Standard Error
SEER	Sustainable Energy Efficiency Retrofit
SOP	Standard Offer Program
SMCM	Spatial Metering Cost Minimisation
SSC	Small scale
SSD	Sample Size Determination
SVM	Support Vector Machine
THL	Tungsten Halogen Lamp
TWC	Tradable White Certificate
TWh	Tera Watt hour
UK	United Kingdom
USA	United States of America
VSD	Variable Speed Drive

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CHAPTER 1

INTRODUCTION

This chapter introduces concepts of measurement and verification (M&V) from both M&V practice and research aspects. For the M&V practice, fundamental questions about M&V such as "what is M&V", "why M&V", "how to M&V", and "who are involved in M&V" are answered in Section 1.1. Then existing M&V research activities are comprehensively reviewed in Section 1.2 in terms of three broad categories, namely, establishment a scientific and formalised M&V framework, development and improvements of M&V techniques, and compiling and sharing global M&V best practice. In Sections 1.3-1.4, the motivation and contribution of this thesis are summarised together with the layout of this thesis.

1.1 BACKGROUND

1.1.1 M&V concept and benefits

M&V is the process of using measurement to accurately and reliably determine the savings delivered by an Energy Conservation Measure (ECM) [1]. The savings can be claimed from any forms of energy, including electricity, gas, oil, and water, etc., while this thesis will focus on electricity savings that usually refer to the absence of energy use or demand. Indeed, there is no direct way to measure energy or demand savings since the absence of energy use or demand is not measurable. However, the savings can be calculated by comparing measured energy use and/or demand from before and after an ECM implementation. Simple comparison by subtraction of post-implementation energy usage from the baseline quantity is not able to differentiate between the energy impacts of the ECM and those of other factors such as weather or occupancy. In order to quantify the impacts of the ECM alone, the influence of other factors, such as weather and occupancy must be eliminated. Therefore, the M&V process to determine savings with measurements involves measuring post-implementation energy usage and comparing that to the measured baseline usage, adjusted or normalised, to act as a proxy for the conditions that would have prevailed had the ECM not been installed.

Existing M&V practices continuously offer valuable feedbacks to the energy efficiency and demand side management (EEDSM) projects from following perspectives [1, 2]:

- The M&V results contribute to better ECM designs and operations, which will ultimately increase energy savings for future EEDSM projects;
- Transparent and credible M&V process reduces the project risk and enhance financing in terms of both investments and budget managements for EEDSM projects [3];
- The M&V process enhances the value of emission reduction credits and the energy saving certificates [4, 5];
- M&V helps to quantify the performance of ongoing EEDSM projects and the results can be used to predict the performance of future EEDSM programmes.

Given the enormous benefits of M&V, it has gradually become an indispensable process in various incentive EE programmes such as clean development mechanism (CDM), tradable white certificate (TWC) scheme, EEDSM programmes, and performance contracting. For instance, the study [6] examines five possible M&V based approaches for the energy savings evaluation under the international greenhouse gas trading programme. In [5], both the metering approach and the deemed saving approach are introduced for M&V under the TWC scheme. Studies [7, 8, 9] introduce the EEDSM programmes in the European, India and the United States respectively, and they also emphasize that the M&V process offers valuable feedback in improving the programme design. In addition, both studies [10, 11] clearly highlight that M&V is the mechanism to ensure that the energy savings are indeed achievable and thus becomes an important function of performance contracting.

1.1.2 Guidance on M&V principles

The best M&V practices are conducted with the guidance of various M&V guidelines, protocols and standards at state, regional, national and international levels. A number of M&V guidance documents are briefly summarised in [12, 13] in terms of the purpose, scope, and intended audience of the existing M&V guidance. In this section, an in-depth review and analysis of different M&V guidance documents based on [12, 13] are provided in order to add clarifications on "how M&V is performed" under different EEDSM programmes in various countries.

Originating in the USA, the international performance measurement and verification protocol (IPMVP) has evolved into a worldwide standard for M&V and is used in more than forty countries [1]. Clear definitions of terminologies and heavy emphasis on consistent, transparent methods are the core precepts of the IPMVP. It also offers best-practice methods for measuring and verifying the results of ECMs including fuel saving measures, load shifting and energy reductions through installation or retrofit of equipment, and/or modification of operating procedures, water efficiency, and renewable-energy projects in both private and public facilities. Moreover, the IPMVP has established a systematic M&V framework, in which four different M&V methodologies namely, Option A: retrofit isolation (key parameter measurement); Option B: retrofit isolation (all parameter measurement); Option C: whole facility measurement; and Option D: calibrated simulation are presented to accommodate energy conservation projects with different characteristics. The IPMVP's flexible framework of options allows M&V practitioners to craft the appropriate M&V plan for each situation and instill confidence in those hoping to reap the benefits of the project being evaluated. The details may differ from project to project, but the options and methods presented in the IPMVP have been successfully implemented in thousand of projects and programs in dozens of countries. For example, [14] uses the IPMVP guideline to perform a preliminary assessment for the Louisiana Home Energy Rebate Offer project while [15] presents the IPMVP application and the results of four different calculation options applied to an existing building equipped with an innovative HVAC device in France. The four M&V options enable the user flexibility of savings assessment in terms of both cost and methodologies. A particular M&V option is chosen based on the expectations for EE project performance uncertainties and other project specific features. The options are different, but none of the options is necessarily more expensive or more accurate than the others. Each has advantages and disadvantages based on site specific factors, and the customers' needs and expectations. The IPMVP has been proven effective in addressing the baseline establishment and savings verification issues for various energy conservation projects over the past 20 years [16].

In addition to the IPMVP, there has been considerable efforts to define standards and best practices that increase the performance of energy efficiency projects and make the savings realised more predictable and repeatable. Although these M&V guidelines are specifically designed for various programmes in different regions or countries, such guidelines are inherently similar to the IPMVP. For instance, the Federal Energy Management Program (FEMP) has released its own document for measurement and verification [17]. It provides guidelines and methods to measure and verify the savings from federal agency performance contracts. It contains standard procedures to quantify the savings resulting from EE equipment, renewable energy, co-generation, water conservation, and improved operation and maintenance projects. In addition, an extension of the FEMP M&V guideline is also available in [18] to provide detailed guidance of using the IPMVP Option A approach introduced in the FEMP Guidelines. The Option A guideline introduces detailed methods of using stipulations to the ECMs that are covered in the FEMP M&V Guidelines: such as motors, lighting, chillers, and variable-speed drives (VSDs) [18]. The discussions focus on stipulations in projects involving boilers, energy management and control systems (EMCS), water conservation, new construction, operations and maintenance (O&M), and renewable energy. The prescribed procedures in [18] are impartial, reliable, repeatable, and can be applied consistently to other similar projects.

Similarly, American Society of Heating, Refrigerating and Air Conditioning Engineers (ASHRAE) Guideline 14-2002 [19] was developed to assist the measurement and verification of energy and demand savings in pre-retrofit and post-retrofit applications. The ASHRAE M&V guideline provides a specific compliance path for a few M&V approaches, which include information on uncertainty analysis, regression analysis, measurement systems and equipment, and case studies. The NAPEE EM&V [20] describes a structure and several model approaches for calculating energy, demand, and emission savings resulting from facility (non-transportation) EE programmes that are implemented by cities, states, utilities, companies, and similar entities. This guideline categorises the EE evaluation into impact evaluation, process evaluation, and market effects evaluation while the guideline itself focuses on impact evaluation in which concepts and approaches for estimating the gross savings, net savings, avoided emissions and co-benefits are provided.

Besides the above-mentioned national and international level M&V guidelines in the USA, there are also a number of state or regional level M&V guidance documents that provide different performance evaluation protocols and programme regulations. For instance, California's Measurement and Evaluation Protocols [21, 22] provides the rules for impact evaluations to determine the energy savings achievements of programs for which shareholder earnings are awarded. This framework presents provides a structured decision process in which quality and reliability considerations directly influence evaluation designs for evaluating energy savings, metering and monitoring efforts, program implementation process, market effects studies, non-energy effects research, and information-and-education program evaluations. The framework also includes a market-based perspective for calculating and using avoided costs and for conducting cost-effectiveness tests. The Xcel Energy proposes M&V approaches in three distinct categories, namely deemed savings estimates, simplified M&V approach, and full M&V approach to assist the performance evaluation for both retrofit and new constructed projects under the Texas Commercial and Industrial Standard Offer Program (SOP) [23]. Further practical guidance for project sponsors on how to prepare and execute an M&V plan is also provided. The PJM Manual 18B focuses on the M&V of the nominated EE value of EE resources [24]. This guideline follows the general M&V methodologies developed in [1, 17] but specialised in providing guidance to M&V plans and post-installation M&V reports on both the project level and measurement level components. The ISO New England manuals [25, 26] specify required information, details, approaches, methodologies, conditions, calculations, variables, parameters, monitoring, validations, reporting, certifications, responsibilities, and plan format for measurement and verification of performance to be used for various demand response programmes.

Based on IPVMP [1], FEMP M&V guideline [17] and ASHRAE Guideline 14 [19], a number of M&V guidelines have also been established in different countries in order to support the performance evaluation under national EEDSM programmes. In South Africa, the guidelines [2, 27] provide standard approaches to measurement and verification of energy savings and energy efficiency with the assurance that actual savings should always be more than or equal to the reported savings. The Australian M&V guideline [28] provides an overview of current best practices for measuring and verifying savings outcomes of energy efficiency projects in Australia. It offers provides additional conceptual and operational details about the use of M&V for energy performance contract (EPC) projects.

The M&V handbook [29] is designed for base personnel to assist in evaluating the performance of energy projects, whether completed with government funds by EPC or DSM. The reference handbook provides tools for developing and evaluating ECM baselines and validating the performance of the implemented ECMs typically seen at the Air Force installation. The handbook offers practical and cost effective M&V options that provide the greatest benefit to cost ratio for each technology. The AEIC M&V guideline aims to standardise terminology used in association with demand response and M&V as it applies to load research practices [30]. In addition, [30] defines and contrasts the various methodologies used in both the measurement (impact evaluation) and verification process of demand response including the development and application of Baselines. This guideline deals exclusively with the measurement of demand reduction (kW) achieved by demand response programs. The Pacific Northwest National Laboratory has developed a standard M&V framework on lighting retrofit and replacement projects [31], which provides site owners, contractors, and other involved organisations with the essential elements of a robust M&V plan for lighting projects. It includes details on all aspects of effectively measuring light levels of existing and post-retrofit projects, conducting power measurement, and developing cost effectiveness analysis. In addition, EURAC Research Institution proposes a standard M&V process for net zero energy building (NZEB) to assist with the planning, implementation and data evaluation for NZEB monitoring [32]. The document is divided in two main parts focusing on energy balance and indoor environmental quality (IEQ) assessment. The monitoring can be used to compare design versus real performance for building energy label verification or as a tool to further improve building performance.

1.1.3 M&V participants and their relationships

As summarised in the IPMVP, M&V participants are coming from broad areas including energy performance contractors and their clients, new building designers, utility DSM programme designers, emission reduction trading programme designers, and voluntary energy users, etc. In various incentive EEDSM programmes, the aforementioned participant in the M&V process can be classified into four parties namely, project sponsors, ESCo, end users, and M&V body [2]. More precisely, as introduced in [33], “project sponsors” refer to a bank or utility that funds the EEDSM programme,“ESCo” means companies that provide EE or load reduction services to customers that own or operate facilities such as buildings or factories; “end users” are the groups and individuals who purchase electricity for their private use; and “M&V body” is responsible for monitoring and verification of the energy and demand reduction achieved by EEDSM projects.

M&V is a standard process to impartially quantify the savings for all DSM project participants. Figure 1.1 shows an interactive relationship between the principal project participants and the M&V body. It is observed that the M&V body is interactive with different project participants but stands apart from the programme environment in order to ensure its independence and impartiality. The purpose of M&V is thus to facilitate agreement between the project participants on the project outcomes.

In terms of detailed functionality, the utility is obliged to

1) make funds available to implement the EEDSM programme in accordance with the energy management regulatory policies [33];

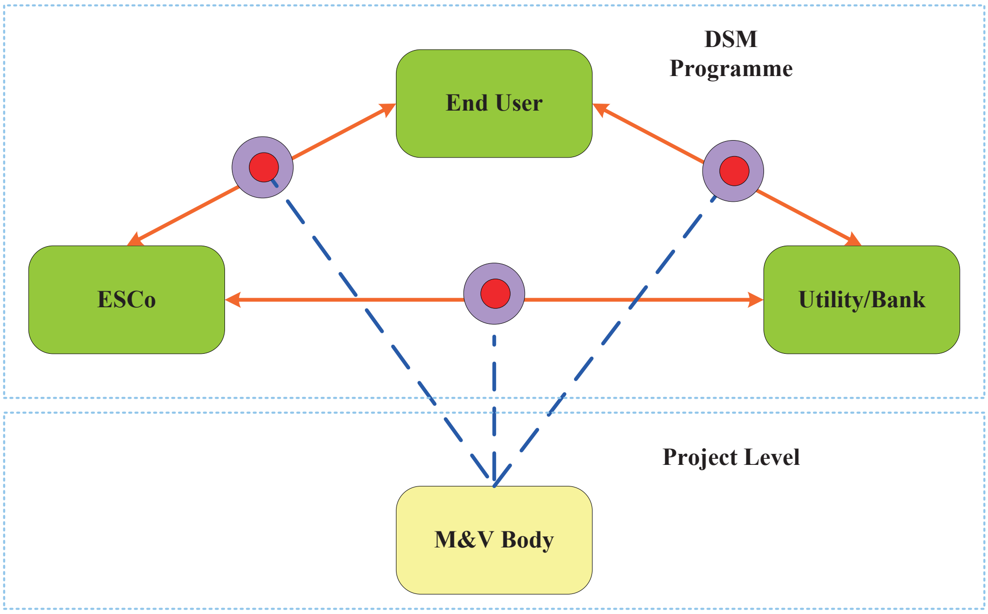

Figure 1.1: M&V process participants.

2) evaluate project proposals submitted by approved ESCos;

3) recruit accredited M&V bodies for all EEDSM projects.

The ESCos are responsible for

1) developing project proposals and submit them to the utility for evaluation and approval;

2) ensuring that a performance and maintenance contract is in place with customers for each EEDSM project;

3) implementing the project and ensuring the sustainability of the ECM measures at least over the useful life of the ECM measure.

The M&V bodies are independent to

1) perform M&V on all projects in accordance with the M&V protocols specified by the utility;

2) develop M&V plans for various EEDSM project with different characteristics;

3) collect M&V data at a central database and make performance reports available in a specified format by the utility.

In most of the EEDSM programmes, there are no obligations on end users although arguments have been raised in [34]. Yet they are encouraged and motivated to implement ECMs or to shift their energy usage from peak to off-peak periods, and collaborate with other project participants during the project implementation and M&V process.

1.2 LITERATURE REVIEW ON MEASUREMENT AND VERIFICATION

Currently, research in the M&V field focus on three broad categories, namely developments of a scientific and formalised M&V framework, improvements on M&V techniques, and examples of M&V best practice.

The needs of the scientific and formalised M&V framework become urgent in reporting reliable energy savings and carbon emission reductions from energy efficiency programmes, especially when critical arguments have been raised in [35, 36] that M&V is widely regarded as an inaccurate science: an engineering practice relying heavily on professional judgement. In order to develop a solid ground for the M&V framework, the studies [35, 36] present a mathematical description of the energy efficiency M&V problem and thus casts into a scientific framework the basic M&V concepts, propositions, techniques and methodologies. The study [37] presents a formalised concept in developing the baseline that is flexible to deal with situation when changes in the energy services level involved. Rich and extensive experience of EM&V in the United States has been summarised in [38] in terms of three aspects, namely technical issues primarily focusing on EM&V methods and protocols, policy issues regarding how EM&V results will be used by energy efficiency program managers and policymakers, and the infrastructure that focusing on the development of EM&V professionals and an EM&V workforce. The study [39] provides a summary of M&V practices in various states in US under the energy efficiency resource standards (EERS) scope. The report [40] presents an overview of guidelines developed for the monitoring, evaluation, reporting, verification, and certification (MERVC) of energy-efficiency projects for climate change mitigation.

Some other M&V studies call for standard M&V processes under various energy efficiency programmes such as EEDSM, EPC, NZEB, and TWC. For example, [41] describes the experiences of California and Korea in addressing the issue of conducting the measurement and evaluation process of EEDSM programmes. The case studies show that the development of an infrastructure and process for conducting rigorous measurement and evaluation takes time and needs the active participation of many stakeholders. A set of critical success factors (CSFs) of EPC have been developed in [42] for sustainable energy efficiency retrofit (SEER) of hotel buildings in China. M&V has been identified as one of the most important parts of EPC procedure, to identify the project result and energy savings. It is commented in [43] that standarised contracts and M&V protocols are one of the applicable strategies to foster the development of the ESCo industry in Europe. It is recommended in [44] that standard procedures for the measurement and verification of savings as well as for standard contract terms will help develop the energy service company (ESCo) industry in Japan. In [3], M&V has been introduced as a technical strategy to reduce the risk in the energy-savings insurance (ESI) mechanism. As argued in [45], it is possible to use actuarial pricing approach to quantify the associated risks for project decision-making. However, this approach requires a large number of actual EPC project data, but the non-standardised project information and poor data quality often hinder the development of a reliable actuarial database. The IPMVP and specific elements of an M&V system that address components of an energy savings certificate (ESC) system are discussed in [16]. In order to encourage energy conservation and emission reduction, [46] calls for a establishment of a set of standard contracts, M&V procedures and rational benefits distribution system for the expansion on EPC mechanism thoroughly in China. In [47, 48, 49], the economic, energy and environmental impact of the Louisiana energy fund has been calculated by the industry M&V protocol under the EPC scheme. The study [50] presents a consistent framework for setting Net ZEB definitions, in which specially designed M&V process are expected for the evaluation of the Net ZEB energy performance.

Fundamental concepts of the TWC schemes is introduced in [5], in which both the M&V theory and practices are reviewed and discussed in different European countries. The experience of the tradable energy efficiency certificates in Italy is summarised in [51], where three M&V methods are proposed namely the deemed savings, engineering methods (partially ex post), and complete monitoring plans approved ex ante by the Authority of Electricity and Gas (AEG). The study [52] briefly discusses the existing M&V problems such as the application and development of deemed savings approach, the trade-offs between the M&V cost and robustness, handling the inconsistencies of energy savings or cost-effectiveness outcomes across different countries in the TWC scheme.

Besides the discussions on the scientific and formalised M&V framework, M&V techniques have attracted considerable research activities. In the literature, the M&V technique studies typically focus on the following topics:

- handling M&V uncertainties cost-effectively;

- baseline setting and modelling;
- best choice of the IPMVP options;
- savings accounting issues on uncertainty and persistence;
- development of information system to support M&V practice.

As the M&V savings are naturally unmeasurable and uncertain, there is an inherent trade-off between the M&V accuracy and M&V cost. “How to handle the M&V uncertainty cost-effectively” is one of the most fundamental and important issues in the M&V framework. However, very limit discussions on this topic are found in the literature. A Gaussian Process (GP) modelling framework is presented in [53] to determine energy savings and uncertainty levels in M&V. The GP models capture complex nonlinear and multi-variable interactions as well as multi-resolution trends of energy behaviour. In addition, the GP M&V models handle the different sources of uncertainty in a systematic way, which leads to significantly less expensive M&V practice. Both the physical parameter uncertainties and user behaviour uncertainties are analysed in [54], together with a sensitivity analysis of the building simulation model to determine the thermal performance and energy consumption. And [55] presents the case for financial and performance risk analysis in energy efficiency projects, and then describe techniques and examples to identify sources of risks of the verified savings. The risks can be quantified by CV or a monte-carlo simulation. In addition, the risks can be managed by technical approaches such as M&V, energy savings insurance or actuarial pricing risk management approach.

The importance of proper baseline setting for M&V has been emphasized in several studies [11, 56]. For instance, [11] gives detailed baseline setting methodologies and examples of baseline setting for EPC. In [56], up to date methods and tools available for energy benchmarking purpose are reviewed to assist the building energy benchmarking approach selection during the commissioning process. The proposed methodologies are also applicable for baseline establishment during the M&V process.

Existing M&V studies have proposed various baseline modelling techniques that can be applied for M&V best practice. These baseline modelling techniques generally include stochastic models, regressions models and calibrated simulation models. For example, [57] has proposed a normative energy model based on Bayesian calibration, which is able to model the energy consumption patterns in large sets of buildings efficiently with quantifiable uncertainties associated with model parameters.

The study [58] documents a general statistical methodology to assess the accuracy of baseline energy models, for the M&V of whole building energy savings.

Regression models have been widely applied to develop baseline models for the M&V purpose with detailed model identification and validation by the uncertainty indicators of coefficient of determination (R^2) and coefficient of variation of root mean square error (CVRMSE). The study [59] evaluates the performance prediction ability and model suitability of 11 empirically-based performance models for centrifugal water chillers. The results of [59] provide important reference values for selecting empirically-based performance models for energy analysis, energy efficiency measurement and verification for in centrifugal water chiller systems. In [60], two different modelling methodologies are applied to the CHP plant: thermodynamic modelling and artificial neural networks (ANN). Satisfactory results are obtained with both modelling techniques, confirming good capability of the models for predicting plant behavior and their suitability for baseline energy consumption determining purposes. The study [61] proposes regression models to statistically identify the building-specific daily energy balance load pattern without prior knowledge of building systems and operations. The mean CVRMSEs of the four-parameter change-point (4P-CP) models, multiple linear regression (MLR) models, and the MLR models incorporating AR(1) error structure ranged from 6.9% to 10.4%. Overall, the MLR models with the outside air temperature and humidity load variables presented the most balanced performance taking account of the availability of variables and the ease of estimation and parameter interpretation. The study [62] presents a method to compute the error associated with estimates of several DR parameters using a regression-based baseline model. A metric has also been developed to determine how much observed DR variability results from baseline model error rather than real variability in response. The support vector machine (SVM), a new neural network algorithm is applied in [63] to forecast building energy consumption in the tropical region.

As alternative solutions to the regression models, energy baselines are determined by computer intelligent simulations of energy usage of the whole facility. Simulation routines are calibrated to predict an energy usage and demand pattern that reasonably matches the actual energy consumption. Caution is warranted, as this option typically requires considerable skill in calibrated simulation and considerable data input; so the process can be quite costly. For example, [64] presents a systematic and automated way to calibrate a building energy model that can be used for M&V of building retrofit projects, predictions of savings from energy conservation measures, and commissioning building systems. In addition, [65] has proposed a consistent, practical approach to enhance the model performance of the IPMVP Option D by using the visual inspection methods, parametric studies, and the optimisation method. The study [66] evaluates the predictive accuracy of lighting energy consumption carried out by the EnergyPlus program [67] and by the integrated simulation method (ISM), using the Daysim program [68]. Results indicate that the lighting energy consumption with ISM is relatively more accurate than the EnergyPlus results without ISM. A building baseline model has been proposed in [69] by eQUEST simulation software. The model is calibrated by surveyed building occupancy rate, lighting power density schedule and equipment power schedules. The calibrated model is validated by the quantification of Mean Bias Error (MBE) and RMSE against the actual electricity billing data. In [70], the calibrated simulation M&V approach is adopted to quantify the annual energy impact of the wall insulation in buildings, the verified results aim to support an innovative argument that insulation increases cooling load at certain cooling temperature set-point. Three building envelope retrofit strategies have been evaluated in [71] through a calibrated simulation approach. The calibrated simulation model is developed with a full year building monitoring data. This model is then used to evaluate the annual energy savings, CO_2 emissions, improvements of indoor thermal environment, and the financial investment and payback analysis for various potential envelope retrofit strategies, in order to obtain an optimal envelope retrofit strategy. Existing case studies and methods are reviewed in [72] for calibrating whole building energy models to measured data. It also describes a systematic, evidence-based methodology that emphasizes the version control and zone-typing (a process of deciding on the various types of thermal zones used in a model based) for the calibration of these models. In [73], the baseline energy consumption model of a building with multi-floor radiant slab cooling system is established by a building simulation model that is calibrated with relevant data obtained from field measurements. The model is further applied to evaluate the energy improvement performance by three different ECMs such as improved building system control, updated building system configuration and better building envelope design. The study [74] proposes a simulation-based method to evaluate the probability of energy saving shortfall taking into account the variations in the influential parameters, including weather conditions, occupancy, operating hours, thermostat set-point, etc., during the contract term with the application of a detailed building energy simulation programme, sensitivity analysis and Monte Carlo simulation techniques. The study [75] has revealed that the factors and parameters, namely previous energy use, project cost, consultant experience and engagement, and implementation of a good operation plan contribute to the successful implementation of energy efficiency measures in buildings. In addition, the persistence of the energy efficiency measures is influenced by the achieved savings in the first year, the guaranty period, and the implementation of the operation measures. The study [76] outlines a procedure to develop and calibrate DRQAT simulation models and applies this procedure to eleven field test buildings.

The study [4] outlines the experience to date with the measurement and evaluation of ESCs. Three savings certification approaches are briefly summarised and compared, namely the deemed savings approach, engineering approach with some field measurement, and energy monitoring approach. Since different energy saving determination approaches are applied in various energy conservation programmes, the reported energy savings by different M&V processes are with different credibility, uncertainty and persistence levels. It is thus important to address the savings accounting issues across various energy saving programmes. Ref. [6] examines five possible approaches namely, the IPMVP options approach, quantitative uncertainty assessment, two different approaches of qualitative uncertainty assessment, and Environmental Protection Agency (EPA)'s conservation verification protocol to deal with the savings discounting issues due to their inherent uncertainties.

The applicability of the four IPMVP options are tested, compared and discussed in the following case studies. The studies [15, 77] dedicate to the testing and the experience feedback of the IPMVP and its application in an existing building equipped with an innovative HVAC system. The applicability of the four IPMVP options are tested and analysed in this case study. In addition, [78] reviews the four IPMVP options for M&V, and argued that the metering approach is more advantageous than the standard savings factors approach (deemed-savings approach) in addressing the rebound effect and savings persistency issues in the savings certificate trading schemes.

In addition to the above-mentioned M&V techniques, information systems that facilitate the measurement and management of energy systems are also developed to support the M&V practice. For instance, [79] outlines a prototype enterprise energy information system (EEIS) that supports strategic energy management by comprehensive energy monitoring and targeting, integrating with energy modelling software and business databases, and supporting M&V. The study [80] has constructed an information system that integrates sensors data, power meter readings and occupancy conditions, in order to quantify energy saved in the whole facility is measured and reported in real-time by an improved version of the IPMVP option C to assist the measurement and verification processes. In addition, [81] invents a system and method for measuring the energy savings in an environment to which one or more energy saving materials has been applied.

In addition to the studies on M&V framework and techniques, examples of best M&V practices can also be found in the literature. For instance, [82] describes an M&V case study on quantifying the energy, demand and cost savings due to the installation of a motor sequencing controller on a coal conveyor belt system. Ref. [83] describes a pilot effort to measure load reductions from a residential electric water heater load control program using low-cost statistically based measurement and verification approaches. In [84], a "deemed savings estimates" M&V approach is proposed by modelling historical data, which are sampled from 288 end users of the regional direct load control (DLC) programmes. Also in [85], annual electricity savings from lighting retrofit in three facilities are verified by short- and long-term monitoring. [86] presents a measurement and verification methodology used to quantify the impacts of load shifting measures that are implemented on large industrial fridge plant system in South Africa. The financial and energy impacts of CFL bulbs in a rural area evaluated in [87] by a simple before-and-after analysis. The study [88] describes a methodology and procedures to measure and verify the impact on the electricity use of lighting load reduction project implemented at a gold mine. The case study [89] measures an actual behavior of a multi-story double skin facade (DSF) in South Korea and the verification of simulation model was made against measured data, and a case study was conducted based on the verified model to identify the energy consumption reduction with the application of DSF and the seasonal operation strategy.

1.3 M&V RESEARCH PROBLEM IDENTIFICATION AND MOTIVATION

1.3.1 M&V research problem identification

Based on the introductions to the M&V guidelines and review of existing M&V research articles in Sections 1.1-1.2, the identified M&V problems are listed as follows.

1) establishment a scientific and formalised M&V framework.

2) developments and improvements of M&V techniques, which includes:

- handling M&V uncertainties cost-effectively;
- baseline development and modelling;
- best choice of the IPMVP options;
- issues on savings determination and accounting;
- developments of information system to support M&V practice.

3) documenting and sharing global M&V best practice.

As commented in [90], standardised protocols for M&V, additionality, and net effects of energy efficiency impact are critical to maintaining confidence in utility- or government-sponsored programmes. Although there are similarities among international M&V standards, regional protocols from European and United States energy efficiency programmes, significant differences in terms of allowed approaches as well as terminologies are used. For instance, five definitions of savings from ECMs are introduced in [91] in terms of projected savings, gross savings, claimed savings, evaluated gross savings and net savings. Harmonising these protocols will facilitate international trade in both energy efficiency industry and development of international agreements for climate change mitigation. As reviewed in Section 1.2, there are several publications trying to address this issue. However, existing case studies show that the development of standardised M&V framework takes time and needs strong supports from many stakeholders, especially from the energy policy makers and EEDSM programme designers.

The improvements of the M&V techniques are also contribute to fast development of a mature M&V framework. For the M&V techniques listed above, the most challenging and important problem is to handle M&V uncertainties, preferably in a cost-effective manner given limited M&V budget. Typical M&V cost from several international M&V guidelines are summarised in Table 1.1. Practically,

Table 1.1: M&V cost.

M&V Guidelines	Costing Rules
IPMVP [1]	Annual M&V costs less than 10% of annual savings
FEMP [17]	Annual M&V costs between 1% to 10% of project cost savings
California Evaluation Framework [22]	Option A: Estimate 1% - 3% of annual cost savings
	Option B: Estimate 3% - 15% of annual cost savings
	Option C: Estimate 1% - 10% of annual cost savings
	Option D: Estimate 3% - 10% of annual cost savings
M&V handbook [29]	M&V cost limits to 5% of annual cost savings with Option A
	M&V cost limits to 10% of annual cost savings with Option B & C

uncertainties that are coupled in the M&V process need to be properly handled to ensure the M&V reporting accuracy. There are unquantifiable uncertainties arise from poor meter placement, inaccurate estimates in the IPMVP Option A or mis-estimation of interactive effects in the IPMVP Option A or B [1], which have not been addressed technically in the M&V field. As summarised in [1, 17, 53, 36], the quantifiable M&V uncertainties includes modelling uncertainty, measurement uncertainty, and sampling uncertainty. Detailed definitions and causing factors of these uncertainties are introduced in

Section 2.3. In the literature, there is a consensus that one of the most challenging aspects of M&V is to reduce M&V uncertainties to an acceptable level with a reasonable M&V cost. Among the three types of M&V uncertainties, intensive research efforts have been conducted to handle the modelling uncertainty during the process of baseline development. For instance, the studies [53, 57] focus on dealing with the M&V modelling uncertainties by a Gaussian process modelling framework. Refs. [64, 92] quantify the modelling uncertainties by the indicators of R^2, CVRMSE, MBE, etc. However these studies seldom perform any cost analysis in dealing with the modelling uncertainties. Very few M&V related articles have paid special attention to address the measurement and sampling uncertainties. Only several studies [54, 6, 92, 10] briefly mention to apply statistical sampling approach for the savings evaluation, and articles [6, 92, 53] provide limited discussions on the measurement uncertainties. Theoretically, there are sufficient technique supports to handle the sampling and measurement uncertainties. For instance, a number of sampling techniques together with the sample size determination approaches have been provided in [93, 94, 95, 96, 97, 98]. In addition, sufficient guidance to fight against the measurement uncertainties can be found in [99, 100, 101, 102]. In addition, practically M&V project stakeholders hold the opinions that measurement and sampling uncertainties can be handled by "use high accuracy meters and sufficient samples sizes".

It is true that the measurement uncertainties can be handled by applying sophisticated measurement instruments while the sampling uncertainties to be reduced by taken sufficient sample sizes. However, M&V practitioners cannot enjoy such a luxury due to the limited budget for the projected savings verification. As commented in [36], an M&V metering plan obtained by the professional judgements of M&V practitioners may be far from optimal especially when there are particular requirements on the M&V accuracy and M&V cost. The study [36] further proposes to develop optimal M&V plans in the sense of achieving acceptable M&V performance accuracy with minimal measurement and sampling cost. The general mathematical description of the optimal M&V metering plan problem, has been proposed in [36]. However, with the aid of the study [36], the optimal M&V metering plans for specific M&V projects still need to be redeveloped with the consideration of project specific budget plans, technologies, measurement complexities and accuracy requirements as well as population sizes.

Currently, four M&V options are developed in the IPMVP, which are widely accepted and applied in the global M&V practices. Advisory suggestions and qualitative analysis are provided in various M&V guidelines [17, 1] and research articles [77, 80, 14, 36] to assist the selection of an appropriate M&V option. However, there are still lack of quantitative calculations and analysis to identify the best IPMVP options for a specific projects by an optimisation approach, as the best IPMVP solution for a typical project should be able to achieve the desired M&V accuracy with minimal measurement and sampling cost, or even with the shortest measurement duration.

As introduced in [4, 90], energy savings certificate can be issued either by ex-post (based on the measurement of actual performance) or ex-ante (based on engineering estimates). Compared to ex-ante certification, ex-post certification increases measurement and verification costs but provides greater accuracy and reliability. Practically, there are three approaches to determine energy savings, i.e., deemed savings approach that does not require field measurement but only decide project savings with default factors for free rider and persistence of energy savings; engineering approach with some field measurement, and energy monitoring approach, which follows the IPMVP framework. Practically, different energy conservation programmes may use different savings certificate approach, which offers different levels of credibility on the energy savings persistence. The study [103] presents a conceptual framework for analysing persistence of energy savings, summarises the limited experience about persistence, provides guidance for conducting retrospective and prospective persistence studies, and suggests strategies for ensuring persistence. In recent years, there are a number of programmes start to address the energy savings persistence issue. For instance, performance tracking activities are conducted in the South African National EEDSM programme to continuously check the sustainability of the reported demand/energy savings [104, 2]. Under the CDM programme, the energy saving performance of lighting projects should be tracked for up to 10 years, whilst other projects may be tracked for up to 21 years [105]. Also in [106], it argues that studies on persistence are critical and highly useful for energy efficiency research. However, currently research on energy savings persistence is still in its infancy although [103] has provided useful guidance for both conducting research in this area and developing policies and mechanisms to help ensure the persistence of energy savings in the 1990s.

With today's technology, information systems are very supportive for M&V practice. As introduced in Section 1.2, development on the M&V information system include both hardware designs and software designs. Typical examples on hardware designs are introduced in [80, 107]. Useful software that has been widely applied for M&V include, but are not limited to, EnergyPlus [108], eQuest [69], Energy-10 [109], and PRIMES [110], etc.

As the M&V industry develops, it is expected that more and more M&V best practice case studies to be published and documented for representative countries, sectors, and technologies, in order to assist and contribute to the development of M&V capacity and skills; improve the awareness level and inform stakeholders on M&V best practices, and produce referential and citable material on M&V that can be used for further studies, research and performing M&V [111].

1.3.2 Motivation and objectives

As one of the certified measurement and verification professionals (CMVPs), the author of this thesis has been working as an M&V practitioner for the South African national EEDSM projects since September 2010. Over the past several years, a great number of large-scale lighting retrofit projects has been implemented in South Africa, such as national CFL rollout programme [112, 113] and residential mass rollout programme [114]. During the M&V process of these large-scale lighting retrofit projects, M&V practitioners encountered great challenges in dealing with the following two problems: **1)** to design an optimal M&V metering plan that uses minimal number of meters for sampling but achieves the desired sampling accuracy with minimal M&V metering and sampling cost; **2** to maintain the sustainability of the projected savings when the lamp population decays as time goes by. It is interesting to see that both problems are under the research scope of development and improvement of M&V techniques.

Given that existing literature does not provide readily available answers to the above two questions, this thesis aims to address these two problems, in order to provide useful technical supports to the M&V practice. Due to the uncertain nature of the unmeasurable savings, there is an inherent trade-off between the M&V accuracy and M&V cost. In order to achieve the required M&V accuracy cost-effectively, three types of metering cost minimisation (MCM) models will be developed to assist the design of optimal M&V metering plans, which minimise the metering cost whilst satisfying the required metering and sampling accuracy of M&V. On the other hand, the energy savings achieved by implementing EE lighting retrofit projects are sometimes not sustainable and vanish rapidly given that lamp population decays as time goes by, especially when without proper maintenance activities. Scope of maintenance activities refers to replacements of failed lamps due to nonrepairable lamp burnouts. Full replacements of all the failed lamps during each maintenance interval contribute to a tight project budget due to the expense for the lamp failure inspections, as well as the procurement and installation of new lamps. Since neither “no maintenance” nor “full maintenance” is preferable to the EE lighting project developers (PDs), an optimal maintenance plan will also be developed to optimise the number of replacements of the failed lamps, such that the EE lighting project achieves sustainable performance in terms of energy savings whereas the PDs obtain their maximum benefits in the sense of a cost-benefit ratio.

1.4 RESEARCH CONTRIBUTION AND LAYOUT OF THESIS

The major contributions of this thesis have been published by several journal articles as listed in the Publication section. The contributions are briefly summarised below, which also served as a layout description of this thesis.

In Chapter 1, the basic M&V concept is introduced with an overview of international M&V standards, protocols, and guidelines. In order to identify the research scope and directions for this thesis, a comprehensive literature review on M&V is conducted. Based on this, it is proposed to conduct future M&V research in three major areas, namely the establishment a scientific and formalised M&V framework; developments and improvements of M&V techniques; and documenting and sharing global M&V best practice. And the author further clarifies the motivation and objectives of this thesis.

Chapter 2 introduces the M&V framework in terms of definition, measurement boundaries and the core M&V methodologies, the scope and importance of M&V plan and metering plan, with further discussions on different terminologies of M&V savings. M&V uncertainties and reporting protocols are introduced with descriptions on the sampling techniques that are widely used to quantify the M&V sampling uncertainty.

In Chapter 3, international lighting EE and management activities are reviewed, followed by the general M&V process on lighting EE projects with detailed discussions on baseline and savings determination methodologies by the four IPMVP options. New findings on the lighting peak demand diversity factor are also presented in this chapter.

In order to deal with the inherent trade-off between the M&V accuracy and M&V cost, three MCM models are developed in Chapters 4-6, namely a spatial MCM model, a longitudinal MCM model, and a combined spatial and longitudinal MCM model, to assist the design of optimal M&V metering plans, by which the minimal metering cost is achieved with the satisfaction of the required metering and sampling accuracy. The advantages of the proposed MCM models are demonstrated by case studies of lighting retrofit project.

In Chapter 7, an optimal maintenance plan has been developed to optimise the number of replacements of the failed lamps, such that the EE lighting project achieves sustainable performance in terms of energy savings whereas the PDs obtain their maximum benefits in the sense of cost-benefit ratio. This optimal maintenance planning (OMP) problem is aptly formulated as an optimal control problem under the control system framework, and solved by a model predictive control (MPC) approach. A case study is presented to illustrate the effectiveness of the proposed control system approach.

In Chapter 8, an integrated MCM model with optimal maintenance plans for lighting retrofit projects is developed. With the optimal solutions to the integrated model, the project sponsors receive extra profit in terms of a higher cost-benefit ratio, and sustainable energy savings over a 10-years' crediting period. The project performance is accurately measured and verified with desired M&V accuracy. The effectiveness of the proposed integrated model has been illustrated by an case study.

Chapter 9 concludes this thesis with some near future research plans on the topics of "optimal M&V plan" and "optimal lighting maintenance plan".

CHAPTER 2

PRELIMINARIES

2.1 CHAPTER OVERVIEW

This chapter offers necessary preliminary knowledge for the formulation of optimal metering and maintenance problems. To start with, the M&V framework is introduced in terms of definition, measurement boundaries and the four IPMVP options, the scope and importance of M&V plan and metering plan, with further discussions on different concepts of M&V savings. Thereafter, M&V uncertainties and reporting protocols are introduced with descriptions on the sampling techniques that are widely used to quantify the M&V sampling uncertainty.

2.2 MEASUREMENT AND VERIFICATION

2.2.1 What is M&V?

As mentioned in Chapter 1, M&V is defined as a process of using measurement to accurately and reliably determine the savings delivered by an ECM. The internationally recognised M&V protocol for M&V practice is the IPMVP [1], which provides global M&V best practice techniques for verifying the results of energy efficiency projects in residential, commercial and industrial facilities. The general M&V principle introduced in the IPMVP is illustrated in Figure 2.1. The M&V activities can be summarise as "cut once and measure twice" [115]. As shown in Figure 2.1, installation of an ECM cuts the project cycle into two periods, one is the baseline period and the other is the reporting or post-implementation (PI) period. In the baseline period, the energy usage is measured and taken as the M&V baseline. With the effects of the ECM, energy consumption is expected to be reduced at the PI period. The actual energy consumed at the PI period is also measurable for savings determination. Practically, various conditions may affect baseline energy use from one time period to the next, including weather, building occupancy, and production volume. From an M&V point of view, the electrical energy savings must be calculated under the same set of conditions. In practice, savings are most frequently reported under the PI conditions. In such cases, the M&V baseline needs to be adjusted under the PI conditions, which represents the energy that would have been consumed had the ECM not been installed, known as adjusted baseline. Determination of the savings is thus not straightforward as the adjusted baseline under the PI conditions does not physically exist and therefore cannot be measured. Thus the IPMVP defines energy savings as

Energy savings = Baseline energy use - Actual energy use $\pm$ Adjustments,

or straightforwardly written as

Energy savings = Adjusted baseline energy use - Actual energy use.

In addition to the above explanation of general M&V principles, detailed mathematical descriptions of the M&V process are also available in [36, 53] for readers' interests.

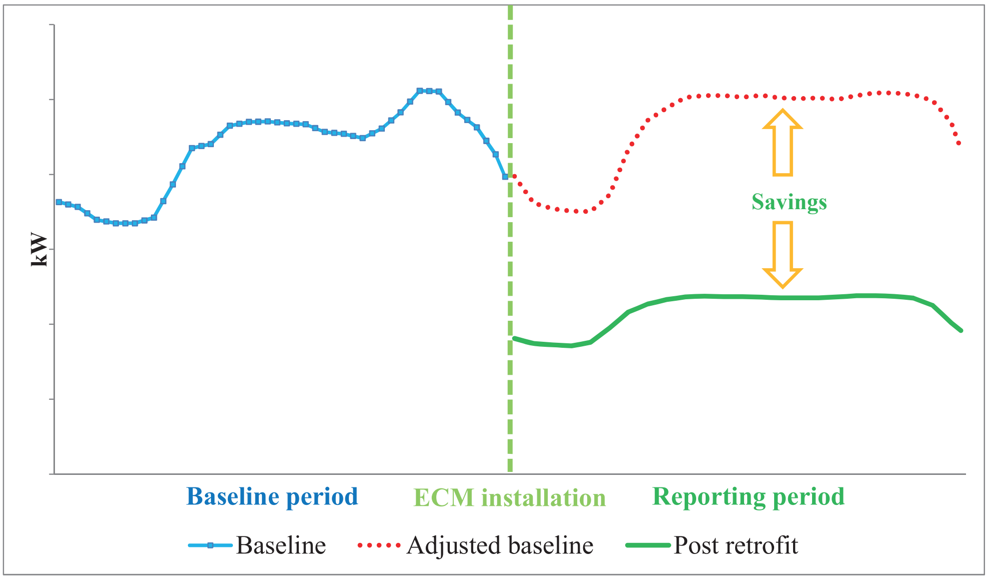

Figure 2.1: M&V of energy savings.

Internationally, there are other two similar terminologies contain the elements of "measurement" and "verification", i.e., measurement, reporting and verification (MRV) and evaluation, measurement and verification (EM&V) In order to avoid confusions among these three terminologies, brief introductions on MRV and EM&V are also provided as follows.

MRV is the process to ensure transparent, comparable, coherent, complete and accurate accounting of international greenhouse gas (GHG) inventories. Robust MRV is fundamental to track progress on emissions reduction efforts, finance and other commitments, and to build trust among parties and ensure environmental integrity. Internationally accepted quality criteria for the MRV of GHG gas emission and reduction are laid out in IPCC 2006 Guidelines for National Greenhouse Gas Inventories [116].

The primary purposes for the EM&V framework are to reliably document energy efficiency programme effects and to improve programme design and operations to be more cost-effective at obtaining energy resources [117, 22]. The three major components of the EM&V framework are impact evaluation, process evaluation and market effect evaluation [39]. Impact evaluations focus on estimating the gross and net effects from implementation of one or more EE programmes. The impact evaluation often employs metering and verification tools to help accurately determine the post-implementation programme savings. The process is a systematic assessment of an EE programme to document programme operations at the time of examination and improve the programme's efficiency or effectiveness for acquiring energy resources. The market effect evaluation assesses how energy efficiency programmes influence markets for energy and energy-efficient products.

In this thesis, the terminology M&V always refers to measurement and verification of the impact of EEDSM projects.

2.2.2 Measurement boundary and IPMVP options

As briefly introduced in Chapter 1, the IPMVP offers four measurement options for savings determination, namely Options A, B, C, and D [1]. For different project scopes, savings may need to be reported either for an entire facility or simply appliances in it. Therefore, boundary of the savings to be claimed must be clearly determined. This boundary is called measurement boundary in the IPMVP, which is defined as an imaginary boundary that is drawn around appliances and/or facilities to segregate those which are relevant for savings reporting from those which are not. The energy governing factors that affects the energy use within the boundary must either be measured or estimated. Any energy effects occurring beyond the measurement boundary are called "interactive effects". The energy effects of the ECMs need to be carefully addressed, where significant energy effects should be determined from measurements with the rest being estimated or ignored.

If only a piece of equipment is affected by an ECM, a measurement boundary can be drawn around the equipment. Then all energy governing factors of the equipment within the boundary can be measured. This approach is the Retrofit Isolation Options, both Options A and B. If an ECM affects the facility energy usage, the meters should be place to measure the energy supply to the entire facility for performance and savings assessment. The measurement boundary is the whole facility in this case. Sometimes multiple ECMs are installed within one facility, then retrofit isolation options are applicable only when there are no interactions among these ECMs and clear isolated measurement boundaries can be drawn to segregate the effects of each ECM. Otherwise, the whole facility needs to be taken as the measurement boundary. Where baseline or reporting period data are unreliable or unavailable, energy data generated by a calibrated simulation model can be applied to recover the missing data, for either part or all of the facility. The measurement boundary is drawn accordingly.

The importance of the measurement boundary in the M&V option selection is illustrated by the following case study: "if 200 inefficient computers in Room C are replaced by 300 energy efficient ones, then how do you draw the measurement boundaries for the savings determination? Assume that the interactive energy effects between the computers and other electrical devices are not significant." Two possible solutions are:

Solution 1: Given the assumption in the case study, no interactive effects are considered and retrofit isolation approach is applicable. At the baseline stage, sub-boundaries can be drawn around individual inefficient computers. The project measurement boundary is the summation of the 200 sub-boundaries, see Boundary A as shown in Figure 2.2. After retrofitting, there are 200 efficient computers within Boundary A but the rest 100 units are out of the measurement boundary. The savings of the 200 computers can be determined by the measurement data before and after the retrofits. A new measurement boundary B is drawn around the 100 new computers. In lacking of baseline of Boundary B, savings in Boundary B need to be determined by a calibrated simulation approach. The project savings are the total of savings from both Boundaries A and B.

Solution 2: The measurement boundary can also be drawn around the Room C as shown in Figure 2.2. A whole facility approach is used to measure the energy usage of Room C before and after the retrofitting actions. At the post-implementation stage, necessary baseline adjustments have to be performed for the savings calculation due to the unit number change within the measurement boundary.

In this case study, savings obtained from the two solutions should be very close to each other but the M&V cost might be different due to different M&V approaches are used.

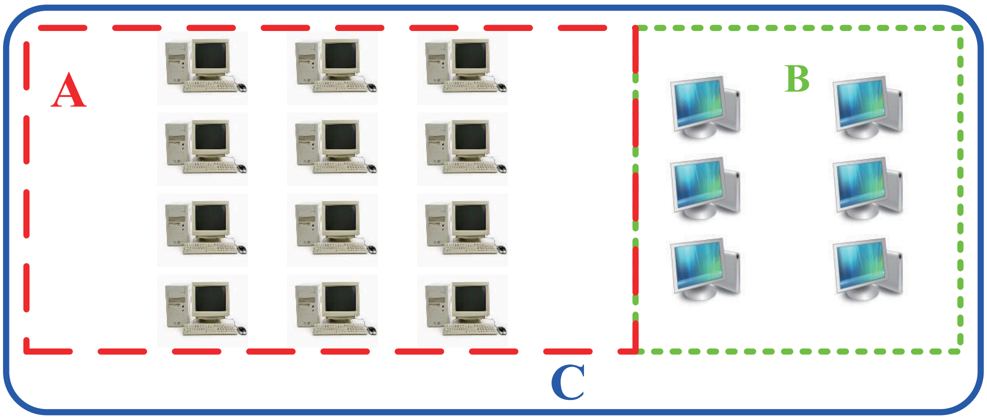

Figure 2.2: Case study of M&V boundary.

For the savings calculation on various ECM-affected facilities or systems, one of the most adequate option can be suitably chosen in terms of measurement boundary, accuracy, and cost considerations.

Option A - Retrofit Isolation: Key Parameter Measurement. Savings under Option A are determined by partial field measurement of the energy usage that can be isolated from the energy use of the rest of the facility. Measurements may be either short-term or continuous. Partial measurement means that only part of the key parameters that affects the system energy use to be measured with some other parameters stipulated in case total impact of possible stipulation errors is not significant to the final savings. Better understanding of the operation philosophy of the ECM will ensure that stipulated values fairly represent the real value. Stipulation details need to be provided in the M&V plan, along with necessary uncertainty analysis. Savings are estimated from both engineering calculations using measurements and stipulations. However the Option A does not allow a direct stipulation of savings [18]. Since stipulation of values are usually easier and less expensive, the Option A approach is widely applied in lighting retrofit, constant load motor efficiency, VSDs, chiller/boiler replacement projects. For instance, a typical application of Option A is a lighting retrofit, where pre/post fixture watts are stipulated from a standard fixture wattage table, and operating hours are derived from measurements of fixture run-time. For any applications of Option A, stipulations must be performed based on reliable, traceable, and documented source of information.

Option B - Retrofit Isolation: All Parameter Measurement. Savings under Option B are determined by full field measurements of the energy use that can be isolated from the energy use of the rest of the facility. Short-term or continuous measurements are taken over the measurement periods. Savings are determined by engineering calculations using measurements. Comparing to Option A, Option B is usually more costly but brings higher accuracy on the determined savings.

Option C - Whole Facility. Savings are determined by measuring energy use at the whole facility level. This approach is usually chosen when impact of a single ECM cannot be isolated on component level or multiple ECMs are installed with interactive effects on each other. However, Option C is limited to projects whose expected savings are greater than 10% of the metered energy baseline. Short-term or continuous measurements are usually taken over both the baseline and PI periods. Savings are estimated from an analysis of whole facility metering data, either by simple comparisons or regression analysis. This approach usually contains facility specific baseline adjustment factors.

Option D - Calibrated Simulation. Option D is a comprehensive calibrated simulation, whereby computer simulations for the system performance is conducted to calculate energy savings. Savings are determined through simulation of the energy use of components or the whole facility. Simulation routines should be demonstrated to adequately model actual energy performance measured in the facility. This option usually requires considerable skills in calibrated simulation, which is usually believed to be the most costly approach for M&V practice, especially when simulation models are not available.

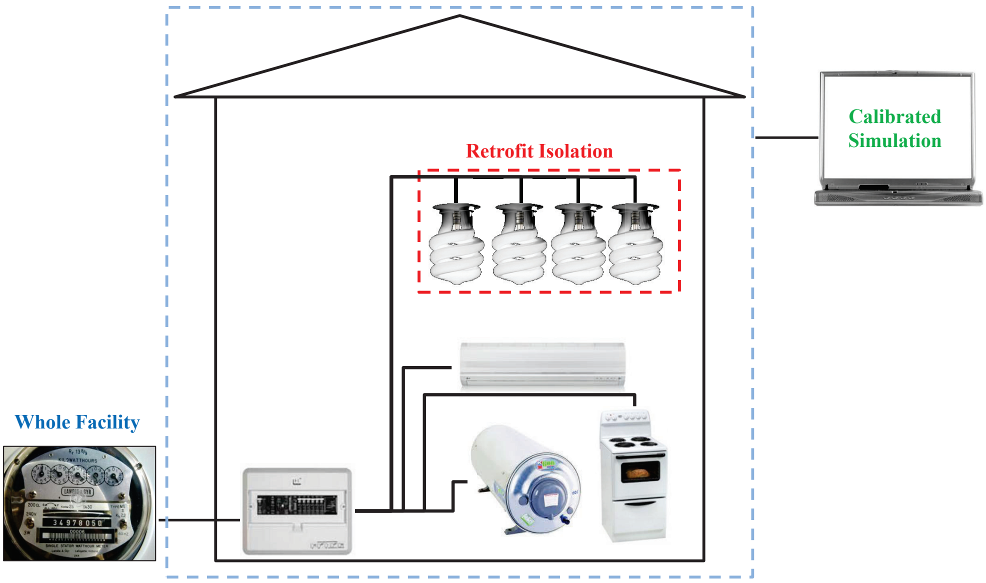

Figure 2.3: M&V boundary and IPMVP options.

As illustrated in Figure 2.3, Options A and B focus on the performance of specific ECMs and involve measuring the energy use of systems affected by each ECM, separately from that of the rest of the facility. Before and after measurements are compared to determine savings. Options C and D assess the energy savings at the facility level, when the ECM cannot not easily measured in isolation from the rest of the building. Option C assesses savings by analysing utility bills before and after the implementation of an ECM. Option D uses simulations of equipment or facilities, when baseline or PI data are unreliable or unavailable. Generally, Option D requires more time and skill and is more costly than the other three options A, B and C. Although the four M&V methods are discussed in detail in [1], it is still difficult to find a proper M&V method or plan for a complex energy project so that the reported performance is accurate enough. Selection of a best M&V option represents a balance between accuracy and cost. Improvements to the M&V approach are introduced iteratively, with the incremental M&V costs compared to a reduction in savings uncertainty.

2.2.3 M&V plan and metering plan

This subsection introduces the contents of the M&V plan and metering plan with brief discussions on how to develop prioritised M&V plan and metering plan.

An essential part of the entire M&V process is the development of an M&V plan, which gives a complete procedure that needs to be followed for the savings evaluation before an ECM is implemented. A successful M&V plan enables verification by requiring transparent reports of actual project performance. As summaries in [1], the key contents of an M&V plan includes: description of the ECM, selection of the IPMVP option and measurement boundary, energy usage data and conditions of both the baseline and reporting period, baseline adjustment algorithm, metering plan, and quality assurance procedures. The metering plan forms a key part of the M&V plan, which includes the meter specifications, number of samples to be measured, expected accuracy, monitoring variables and periods, and budget analysis and management. However it is extremely difficult to develop a uniformed M&V plan for all M&V processes due to the different nature and characteristics of projects with different ECM installations.

The ECM installation cuts the M&V process into baseline period and reporting period. The baseline period should be established to represent all operating modes and conditions of a facility, spanning a full operating cycle from minimum energy use to maximum. All fixed and variable energy driving factors need to be identified from representative baseline data. In addition, the baseline period is best to coincide with the period immediately before the ECM installation. The reporting period should encompass at least one normal operating cycle of the equipment or facility, in order to fully characterise the savings effectiveness in all normal operating modes. When an ECM can be turned on and off easily, baseline and reporting periods may be selected that are adjacent to each other in time.

The M&V savings are always uncertain since they are not directly measurable. There is an inherent trade-off between the M&V uncertainties and M&V cost on individual M&V projects. The prioritisation of the M&V plan and metering plan can be formulated to minimise the M&V cost but achieving the designated M&V accuracy. The cost spent on M&V is a complex functions with the considerations of the IPMVP option and measurement boundary selected, the number of ECMs and the complexity and amount of interaction among them, level of detail and effort associated with establishing baseline, amount and complexity of the measurement equipment (design, installation, maintenance, calibration, data reading, and/or removal), sample sizes used for metering representative EE devices, number and complexity of independent variables that are accounted for in mathematical models, duration of the reporting period, accuracy requirements, and experience and professional qualifications of the people conducting the savings determination.

2.2.4 Concepts of M&V savings

Energy savings can either be generated from small scale energy efficiency projects with one or several ECM installations or by implementations of large-scale energy efficiency programmes. Usually an EE programme includes a number of EE projects.

At the project level, the IPMVP framework savings are defined as the reductions in energy use. The savings can be expressed as avoided energy use or normalised savings. Avoided energy use are reported under the conditions of the reporting period, which related to what energy would have been used without the ECM. Baseline period energy needs to be adjusted to reporting period conditions for the determination of the avoided energy use. Sometimes, the reporting conditions may be chosen to be the baseline period, some other arbitrary period, or a typical, average or “normal” set of conditions. In this case, energy uses of both the reporting period and baseline period are adjusted from their actual conditions to the selected common fixed set of conditions. Savings calculated under a common fixed set of conditions are called normalized savings.

At the programme level, there are two types of savings normally desired from impact evaluation: gross savings and net savings. Gross savings are calculated for programme participants relative to their prior participation usage. Net savings are the savings that would have occurred for these participants over the same time period had the programme were not implemented.

For the impact evaluation of a typical EE programme, the net savings are derivable from the gross savings as follows:

Net savings = Gross savings $\times$ (1 + spillover rate - free ridership rate).

Free riders are programme participants who would have installed the same energy efficiency measures if there had been no programme. The spillover effects includes both the participant spillover effects and the non-participant spillover effects. Participant spillover occurs when end users who have participated in a programme purchase and install measures that are supported by the programme without using programme incentives or services. Nonparticipant spillover occurs when end users who have not participated in a particular programme adopt the energy efficiency measures that the programme supports as a result of the programme due to their exposure to programme-related public relations, vendor promotions, or word-of-mouth about the programme and the benefits of efficiency measures [118, 119].

The persistence of energy savings are discussed in research articles [16, 3, 103], and M&V guidelines [1, 106]. Fundamental philosophies to deal with the savings persistence problems are either to report savings more accurately by periodic routine and non-routine baseline adjustments or to ensure sustainable performance of the installed ECMs. For instance, the study [16] argues that savings are inherently dependent on behaviour which is driven by many factors beyond energy usage. Any ECMs may then be subject to a re-evaluation caused by non-routine adjustments. The IPMVP [1] also comments that energy savings are more at risk from adverse shifts in performance because its ECMs may fail, fade or be bypassed. Persistence of energy savings can be achieved beyond the M&V reporting period by completing the follow on efforts. For instance, if Options B and C have been used for verifying savings, the project will have metering in place for the routine measurement of consumption. More importantly, models will also have been developed that correlate energy use with driving factors such as weather. These same models can be re-tuned to estimate energy consumption that accounts for ECM installation. On the other hand, the study [103] provides guidance for conducting retrospective and prospective persistence studies, and suggests strategies for ensuring persistence. It is suggested in [3] that good wear-and-tear policy requires replacement of non-durable items during the contract term of energy savings, which ensure the persistence of savings via a responsible maintenance programme.

2.3 M&V UNCERTAINTIES AND M&V REPORTING

The concept of uncertainty is different from error though the two are sometimes used interchangeably. According to [19], an error is the deviation of measurements from the true value, while uncertainty is defined as the range or interval of doubt surrounding a measured or calculated value within which the true value is expected to fall within some degree of confidence. Thus the main difference between error and uncertainty depends on whether the true value is known.

Uncertainties of reported energy savings by M&V always exist and this fact has been widely acknowledged in popular M&V guidelines [17, 1, 19, 27]. In the guidelines [19, 1], M&V uncertainties are summarised to come mainly from modelling, sampling and measurement. Modelling uncertainty is caused by inaccuracy in mathematical modelling due to inappropriate functional form, inclusion of irrelevant variables, exclusion of relevant variables, etc. The skill level of the M&V practitioners who build the model also may affect the modelling accuracy. Sampling uncertainty appears when only part of the energy system is measured and used to represent the overall systems. A typical example can be the measurement of 100 residential houses' energy consumption patterns out of a residential region which consists of 1000 houses. Measurement uncertainty arises from the inaccuracy of sensors, data tracking errors, drift since calibration, imprecise measurements, etc., which can often be estimated from manufacturer's specifications and managed by calibration [1]. Meter selection has a direct impact on the measurement uncertainty, and this can be influenced by the process dynamics under measurement. For instance, the longitudinal data of a highly varied underlying process may only be captured by a higher class meter with a rapid sampling frequency and sufficient storage, while a lower class meter may only be used for capturing a slow-varying variable or quantity. The guideline [17] further subdivides these three sources of uncertainties as: modelling, sampling, measurement, and estimates, where estimated errors refer to those cases where direct measurement is either not available or too expensive, then estimated values are used during the savings calculation. Such an estimation indeed can be treated as modelling errors since the estimation of system parameters can be regarded as part of the energy system modelling. It is therefore reasonable to consider the modelling, sampling and measurement as the most important sources of M&V uncertainty. The guideline [19] calls such uncertainties as quantifiable uncertainties, while referring to other types of uncertainties as unquantifiable, which include uncertainties arising from systematic errors (human or technique errors), random or accidental errors (e.g. errors of judgement), mistakes, etc.

2.3.1 M&V uncertainties

The quantifiable M&V uncertainties are modelling, sampling and measurement uncertainties.

Mathematical models are often built for routine baseline adjustment, and linear regression is the most often mathematical models built in M&V practices. Modelling errors of these mathematical models are the source of modelling uncertainty. For instance, [1] has an example in the modelling of monthly energy consumption E_m in a building:

$$E_m = 342000 + 63 \times H_d + 103 \times C_d + 222 \times O_{cu},$$

where H_d and C_d represent heating degree days (HDDs) and cooling degree days (CDDs), respectively; and occupancy O_{cu} refers to the percentage of occupancy of the building. This formula is obtained from linear regression, and there are always deviations from the actual measured data. This kind of deviations is the modelling uncertainty. If the occupancy level is unknown, then an even rougher model between E_m and $\{H_d, C_d\}$ can be built. Its uncertainty will usually be larger than the model with occupancy due to the exclusion of relevant variables.

As discussed in [1], modelling uncertainty can also be caused by using values outside the probable range of independent variables; insufficient number of independent variables in the model; inclusion of irrelevant variables; inappropriate functional form; insufficient or unrepresentative data; etc. The R^2, Standard Error, t-statistics, etc., are advised to be used to evaluate the accuracy of the model.

Meters are installed at sampled places to monitor energy systems. However, there is no meter that will be 100% accurate, this is the so-called measurement uncertainty. Fortunately, specifications on the relative precisions of meters can often be found in the data sheets. Accredited laboratories can also indicate meter accuracies in their meter calibration reports. For example, a report says that the uncertainty of measurement of a type of meter is $\pm 0.06\%$.

Sampling uncertainty is caused by the fact that in many projects, particularly large-scale programmes, not all the appliances are measured, and usually the mean value of the measured energy data is calculated and extrapolated to the entire population. However, this sampling uncertainty can be minimised with the aid of the relevant statistical theory. The number of samples to be chosen can be properly managed by statistical formulae so that the M&V metering cost can be minimised while the confidence/precision of the reported savings can be maintained at an acceptable level.

The measurement uncertainty is most of the time carefully dealt with by selecting the most suitable meters and sensors. For instance, the selection of the above mentioned meter with relative precision $\pm$ 0.06% can lead to extremely high confidence/precision in certain applications. Modelling uncertainty is often controllable by properly selecting the model structure, high level of data fitting, etc. The sampling uncertainty, of both spatial and longitudinal data sets, nevertheless, is the most dominant factor in determining the eventual overall reporting uncertainty, technically and cost-effectively. In the literature and most of the popular guidelines and protocols, the focus of the discussion is sampling uncertainty. It is also noted that it may affect each other when dealing with these three types of uncertainties. For instance, when dealing with sampling uncertainty, one may decide on sampling methodology of stratified random sampling where different strata have different uncertainty characteristics. Thus, the different strata require different level of accuracy in meter selection, and this in turn affects the way models should be built for different strata.

2.3.2 M&V reporting

As noted in [1], it is feasible to quantify many uncertainty factors but not all of them, and an M&V saving report should include both the quantifiable uncertainty factors and the qualitative elements of uncertainty such that uncertainty factors can be recognised and reported either quantitatively or qualitatively. The reported savings, as suggested in [19, 1], should be accompanied by the corresponding confidence and precision, and as explained in [19], “a statistical precision statement without a confidence level defined is, in fact, meaningless”. Therefore, an acceptable format of reported savings would be something like: the energy saving is 20 GWh $\pm$ 10% precision with 85% confidence. Guidelines [17, 1] provide also a reliable way to calculate standard errors of reported energy savings for uncertainties coming from modelling, sampling, and measurement; thus the confidence or precision of the reported savings can be determined from calculated standard errors. An example of saving uncertainty is illustrated in Figure 2.4.

In Figure 2.4, the probability of each observed value is given. From this figure, it can be calculated that the probability for the true mean value to fall between 1800 to 2200 is 90%. One can also state

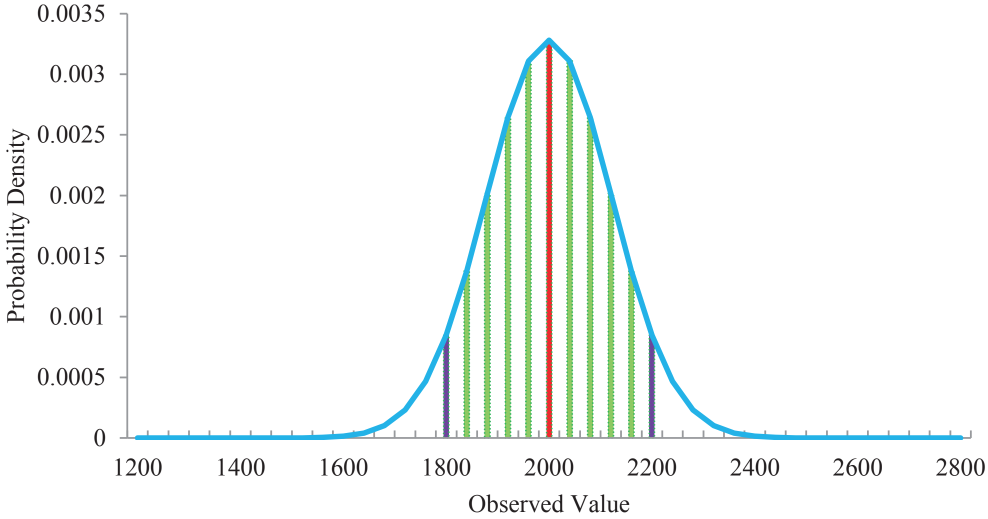

Figure 2.4: Confidence and precision.

that the reported value of 2000 has 90% confidence and 10% precision, which is widely known as the 90/10 criterion[1].

2.3.2.1 Statistical understanding of savings report

The reported savings can be demand savings and/or energy savings. For simplicity, consider the case to report a single energy saving figure. Following [1, 19], the value is reported in the format: α kWh savings with β% confidence and γ% precision. The saving α is often equal to the mean M_n of certain sample data series X_i, which can be the measured energy consumption, etc. However, this α can also be chosen as a different value from the mean M_n while the confidence and precision still satisfy relevant requirements, and this diversity of reported saving values within acceptable confidence/precision requirement is overlooked in all the existing M&V guidelines. This concept is going to be discussed and illustrated in this section. A general assumption for these sampled data series X_i is that they are independent random variables, identically distributed (i.i.d.) with common mean m and common variance σ^2. The Strong Law of Large Numbers implies that when n tends to infinity, then M_n is sufficiently close to m, and S_n^2 is sufficiently close to σ^2 [120]. An important result from probability theory is the Central Limit Theorem [121] which shows that if X_i's are i.i.d. with finite mean m and common variance σ^2, then the mean M_n converges in the normal distribution $\mathcal{N}(m,\sigma^2)$. This implies

[1]Following the notation of the 90/10 criterion, in this thesis, x/y is used to denote x% confidence and y% precision where x and y are both numerical numbers.

that for sufficiently large n, the probability density function of $\frac{M_n-m}{\sigma\sqrt{n}}$ is approximately

$$f(x) = \frac{1}{\sqrt{2\pi}}exp(-\frac{1}{2}x^2).$$

However, in many cases n may not be big enough, and the so-called t-statistics has to be used. That is, let $T = \frac{M_n-m}{S_n\sqrt{n}}$, then it will satisfy the Student's t density with (n-1) degree of freedom. Recall that a general Students' t probability density function (PDF) with k degree of freedom has the form:

$$f_k(x) = \frac{((1+x^2/k)^{-(k+1)/2}}{\sqrt{k}B(\frac{1}{2},\frac{k}{2})},$$

where B is the Beta function. Denote the cumulative distribution function (CDF) $F(y)$ to be the probability for $T \leq y$, then its value can be calculated for any given y in various software programmes, e.g., Matlab function $tcdf(y,k)$ and Excel *TDIST* function.

The savings report (α,β%,γ%) implies that the probability of the actual saving lying in the interval [(1-γ%)α, (1+γ%)α] is β%. Let $P(\cdot)$ be the CDF. Note that although α may possibly be different from the mean m, the reported saving is still assumed to satisfy the same Student t-distribution. Therefore, the following relations hold:

$$\begin{aligned}
\beta\% &= P((1-\gamma\%)\alpha \leq Reported\ Savings \leq (1+\gamma\%)\alpha) \\
&= P(Reported\ Savings \leq (1+\gamma\%)\alpha) - P(Reported\ Savings \leq (1-\gamma\%)\alpha) \\
&= P(M_n \leq (1+\gamma\%)\alpha) - P(M_n \leq (1-\gamma\%)\alpha) \qquad (2.1) \\
&= P\left(\tfrac{M_n-m}{S_n\sqrt{n}} \leq \tfrac{(1+\gamma\%)\alpha-m}{S_n\sqrt{n}}\right) - P\left(\tfrac{M_n-m}{S_n\sqrt{n}} \leq \tfrac{(1-\gamma\%)\alpha-m}{S_n\sqrt{n}}\right) \\
&\approx F\left(\tfrac{(1+\gamma\%)\alpha-m}{S_n\sqrt{n}}\right) - F\left(\tfrac{(1-\gamma\%)\alpha-m}{S_n\sqrt{n}}\right),
\end{aligned}$$

That is,

$$\beta\% \approx F\left(\frac{(1+\gamma\%)\alpha-m}{S_n\sqrt{n}}\right) - F\left(\frac{(1-\gamma\%)\alpha-m}{S_n\sqrt{n}}\right), \qquad (2.2)$$

which implies that the mean m, the standard error SE=$S_n/\sqrt{n}$, reported saving α, confidence β%, and the precision γ% are not independent; given any four of them, one can solve the approximated Equation (2.2) to find the remaining one. The IPMVP gives the calculation of the standard error SE in details, with this SE and an expected precision $\gamma\%$, mean value m, one can find out the corresponding confidence for any proposed reported saving α. This is to say, once all metered data are available, the M&V plan will determine the t-distribution such that m and SE are calculable, and Equation (2.2) can be used to determine the confidence whenever the precision and the expected reporting saving are given.

2.3.2.2 M&V reporting regarding uncertainties

This subsection discusses acceptable and unacceptable M&V savings reported regarding uncertainties, and also conservative and optimistic reported saving values.

An acceptable M&V report gives the savings with the clear confidence and precision levels required by the energy efficiency programme regulations. The reported savings are often written in the following format:

Savings $\pm$ Precision% with Confidence%.

For example, if the 90/10 criterion is employed to identify whether a report is acceptable, then an acceptable M&V report will report savings with a confidence greater than 90% (i.e., 90%-100%) and a precision less than 10% (i.e., 0%-10%). The following reported saving is therefore deemed acceptable:

Saving = 10 kWh $\pm$ 1 kWh with 90% confidence, or
Saving = 10 kWh $\pm$ 10% precision with 90% confidence.

The unacceptable M&V reports are summarised as follows:

- report savings either without stating confidence or precision levels;
- report savings with confidence or precision levels out of acceptable bounds; For example, if the reported confidence is less than 90% and the precision is poor than 10%, then the report is unacceptable under the 90/10 criterion;
- report savings in the format "Savings $\leq$ or $\geq$ x with y% confidence"; although some of the statements are statistically correct, they are unacceptable for M&V purposes.

In certain circumstances, the confidence and/or precision levels may exceed the required benchmark values agreed by the project participants. For example, assume the benchmark uncertainty requirement is 80/20. Due to an improved sampling regime, i.e., increased sample size or longer measurement period, the savings may be reported as 100 kWh with 90% confidence and 10% precision. Further assume the probability distribution is normal distribution, then the M&V professional may perform the calculation by Equation (2.2) and report savings optimistically as:

Savings = 118.6 kWh $\pm$ 23.72 kWh=118.6 kWh $\pm$ 20% precision with 80% confidence.

The M&V professional may also report the savings conservatively as:

Savings = 87.06 kWh $\pm$ 17.52 kWh = 87.06 kWh $\pm$ 20% precision with 80% confidence.

Obviously, both the optimistic and conservative reporting figures are statistically valid and meet the benchmark criterion of 80/20. Any such savings report satisfies the confidence/precision requirement and thus acceptable. These acceptable reports have the associated potential to increase or decrease the reported savings. However, these reported savings must not be checked and understood alone without considering the corresponding confidence and precision under a certain probability distribution.

Note that SANS 50010 [27] requires that: "Uncertainty shall be managed to ensure that reported savings are likely to be conservative. Exact quantification of uncertainty is not required, however; uncertainty shall be taken into account such that more accurate measurement or a more rigorous M&V process cannot invalidate the result. In this context, invalidating a result means that lower savings are reported."

2.3.2.3 M&V report uncertainty benchmark

International M&V uncertainty reporting requirements vary widely. The most prominent work in the field has been done in the United States, where reporting confidence and precision requirements vary by states or electricity utilities. Most standards and protocols require that confidence and precision levels be reported. It is noted that some protocol, standards or guidelines do not specify benchmark confidence and precision levels, but stipulate that these levels should be agreed upon between the stakeholders at the M&V planning phase. Organisations have different approaches to benchmark uncertainty values. In certain cases, different confidence and precision levels are required for different kinds of projects. For example, ASHRAE distinguishes different uncertainty levels for different M&V options such as Calibrated Simulation or Whole Facility Measurement [19]. In California, different confidence and precision requirements are set according to the purpose of the performance tracking conducted (retention, degradation, effective useful life studies) [22]. Table 2.1 provides a summary of international confidence and precision requirements for M&V reporting.

Table 2.1: International M&V accuracy requirements.

Region/ Organisation	Project Type	Confidence (%)	Precision (%)
IPVMP [1]	All	90%	10%
FEMP [17]	All	80%, 90%	10%, 20%
ISO New England [25]	All	80%	20%
Minnesota [122]	All	90%	10%
PJM Interconnect [24]	All	90%	10%
CDM [123, 124]	Large scale	95%	5%
	Small scale	90%	10%
California [119]	Basic rigour	90%	30%
	Enhanced rigour	90%	10%
Ontario, Canada [125]	Large projects	90%	20%
	Retrofit projects	90%	10%
	DSM	90%	5%

2.4 SAMPLING TECHNIQUES

2.4.1 Basic statistics

This subsection provides some terminologies that are used frequently in this thesis.

Let X_i, $i = 1,2,\ldots,n$, be n sample data points, then the following concepts are defined for the X_i's:

Sample mean (M_n):

$$M_n = \sum_{i=1}^{n} \frac{X_i}{n};$$

Sample variance (S_n^2): The variance of the above samples X_i $(i = 1,2,,n)$ is:

$$S_n^2 = \frac{\sum_{i=1}^{n}(X_i - M_n)^2}{n-1};$$

Sample standard deviation (S_n):

$$S_n = \sqrt{S_n^2};$$

Sample standard error (SE):

$$SE = S_n/\sqrt{n};$$

Coefficient of variation (CV):

$$CV = S_n/M_n;$$

Absolute precision is computed from sample standard error using a "t" value from the "t-distribution" which can be found from existing tables [93] or calculated from statistical software, i.e., Excel or Matlab:

Absolute precision = $t \times SE$.

Relative precision of the mean M_n is:

$$t \times \frac{SE}{M_n}.$$

In this thesis, the accuracy requirement of the savings is defined as a combination of confidence and precision levels.

Precision Level: Precision level is the measure of the absolute or relative range within which the true value is expected to occur with some specified level of confidence.

Confidence level: Confidence level refers to the probability that the quoted range contains the estimated parameter.

2.4.2 Sampling strategies

This section reviews a number of sampling approaches and typical situations for application. The sampling information mainly relates to determine point estimates of a parameter mean value.

Simple Random Sampling—Simple random sampling, or random sampling without replacement, is a sampling design in which n distinct units are selected from the N units in the population in such a way that every possible combination of n units is equally likely to be the sample selected [126, 94]. Simple random sampling is suited to homogeneous populations. The cost under simple random sampling could be higher than other sampling approaches when the population is large and geographically dispersed.

Stratified Random Sampling—For the stratified random sampling, when the studied population is not homogeneous but instead consists of several subgroups which are known/thought to vary, then it is more representative to take a simple random sample from each subgroups separately. The subgroups are called strata. When stratifying the population, no population element can be excluded and every element must be assigned to only one stratum. Stratified random sampling is most applicable to situations where there are obvious groups of population elements whose characteristics are more similar within groups than across groups.

Systematic sampling—Systematic sampling is a statistical method to randomly select elements from an ordered sampling frame. One typical systematic sampling strategy is the equal-probability method, in which every lth element in the ordered sampling frame is selected, where sampling interval l is calculated as:

$$l = population\ size\ (N)/sample\ size\ (n)$$

Using this approach, each element in the population has a known and equal probability to be selected. The M&V practitioners shall ensure that the chosen sampling interval does not hide a pattern to ensure the randomness. The starting point must also be randomly selected. Systematic sampling is only applicable when the targeting population is logically homogeneous, since the systematic sample units are uniformly distributed over the population.

Clustered sampling—Clustered sampling refers to a sampling technique where the population is divided into sub-groups (clusters), and the sub-groups are randomly sampled, rather than sampling the individual elements. The data are collected on all the individual elements in the selected sub-groups. In contrast to stratified sampling, where the element of interest is grouped into a relatively small number of homogeneous segments, cluster sampling is used when “hierarchical” groups are evident in a population, such as villages and households within villages, or buildings and appliances within buildings.

Multi-stage sampling—Multi-stage sampling is a more advanced form of cluster sampling. Measuring all the elements in the selected clusters may be prohibitively expensive, or not even necessary. With multi-stage sampling, the cluster units are often referred to as primary sampling units and the elements within the clusters as secondary sampling units. In contrast to cluster sampling where all of the secondary units are measured, in multi-stage sampling data are collected for only a sample of the secondary units. Multi-stage sampling can be further extended to three or more stages. For example, one might group the population into complexes, then buildings, and finally lighting fixtures.

Detectability—The probability that an object in a selected unit is observed: whether seen, heard, caught, or detected by some other means, it termed its detectability. In the basic sampling framework, it is assumed that the variable of interest is detectable without error for each unit in the sample. In many actual situations, this is hardly the case. For instance, a sampled or monitored lighting device may be burnt out, which results in a failed measurement of the energy use. However, in this study, it is assumed all targeted lighting samples are detectable.

2.4.3 Sample size determinations

Different kinds of sample size determination (SSD) methodologies have been proposed in literature. These SSD methodologies can be classified into two broad groups, the frequentist methods and the Bayesian methods [95]. The frequentist methods have been applied to determine sample size for the evaluation of the reliability performance of the United States fleet [96], and the control of both size and power in clinic trials [98]. For the Bayesian methods, [97] summaries the theory and practice of Bayesian statistics while [127] describes a Bayesian approach in choosing the sample size by optimising utility functions.

As provided in standard statistics text books [128], the initial sample size n_0 to achieve certain confidence and precision level of homogeneous population is calculated by

$$n_0 = \frac{z^2 CV^2}{p^2}, \tag{2.3}$$

where z denotes the abscissas of the normal distribution curve that cut off an area at the tails to give desired confidence level, also known as the z-score, and p is the relative precision. For the 90/10 criterion, z=1.645 for 90% confidence and p=10% as the allowed margin of error. The values of z at various confidence levels are tabulated in many statistics books [129]. z can be calculated by the Z-transformation formula

$$z = \frac{\bar{x} - \mu}{\sigma / \sqrt{n}}. \tag{2.4}$$

CV is defined as the standard deviation of the metering records divided by the mean. CV is a positive value and a larger CV value corresponds to a higher sampling uncertainty.CV can be estimated from spot measurements or derived from previous metering experience. If CV is unknown, 0.5 is historically recommended by [17] as the initial CV. Usually more samples are required to achieve a higher confidence level and a better precision level for a given CV value. The initial sample size n_0 can be adjusted by Eqation (2.5) [128] when the population N is a finite number. As can be observed in Equation (2.5)

$$n = \frac{n_0 N}{n_0 + N} = \frac{CV^2 z^2 N}{CV^2 z^2 + N p^2}, \tag{2.5}$$

when N reduces from $+\infty$ to 0, the sample size will become smaller.

Figure 2.5 plots the sample sizes against different CV values with some popular confidence/precision levels. Figure 2.5 shows that more sample sizes are required to achieve a higher confidence level and a better precision level for a given CV value.

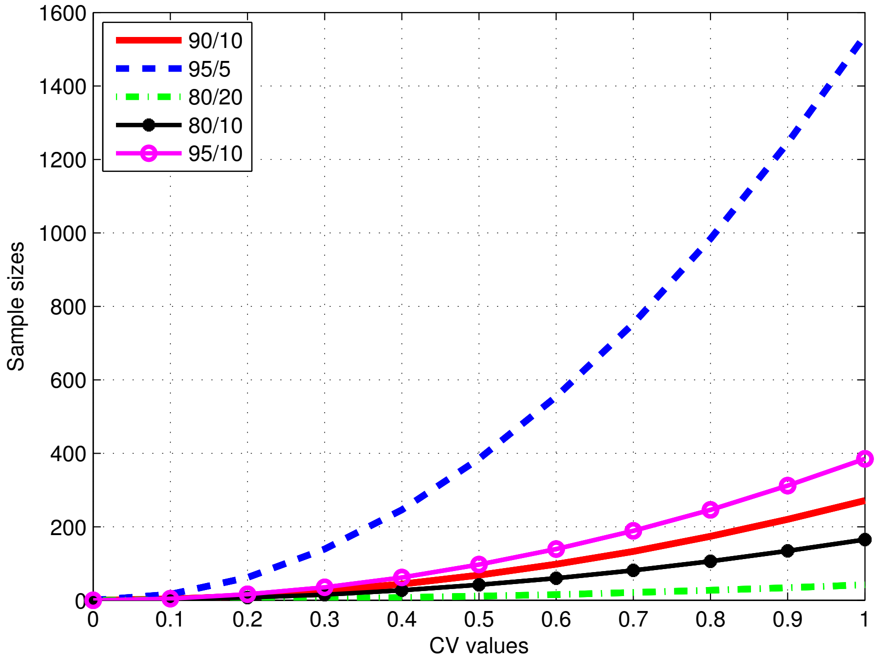

Figure 2.5: Sample sizes versus CV values.

CHAPTER 3

MEASUREMENT AND VERIFICATION PRACTICE ON LIGHTING

3.1 CHAPTER OVERVIEW

Lighting energy use E is calculated as the product of two independent variables, power P and usage time t [130]:

$$E = P \times t.$$

In practice, lighting energy conservation solutions either contribute to a reduction of the input wattages or the operating hours of the lighting systems. The input wattage of lighting systems can be reduced by using high energy efficiency lamps or dimmable lighting sensors. In addition, the applications of lighting control that automatically switch off the lighting systems when not use contribute to the reduction of lighting operating hours.

In this chapter, the energy efficiency and management solutions to reduce the lighting energy usage are reviewed. Thereafter general M&V process to quantify the impact of lighting energy efficiency projects/programmes are introduced together with detailed lighting baseline and savings determination methodologies with the four IPMVP options. Findings on lighting peak demand diversity factor is also described, which is essential for developing lighting demand usage model. The scope of M&V metering plan on lighting projects is also introduced at the end of this chapter.

3.2 ENERGY EFFICIENCY AND MANAGEMENT ON LIGHTING

Lighting is the first service offered by electric utilities and continues to be one of the largest electrical end-uses. For 2005 it is estimated that grid-based electric lighting consumed 2 651 Tera Watt hour (TWh) of electricity, which is 19% of global electricity consumption [131]. Past research has shown that a great potential of energy savings can be generated with the lighting EE solutions [132, 133, 131, 134, 135]. For instance, [132, 133] indicate that the global cost of lighting energy is approximately $230 billion per year, of which $100 to $135 billion can be saved with today's technologies. The study [134] has performed a cost-benefit analysis and emission reduction assessment of lighting retrofits in residential sector. In addition, [135] reveals that a significant reduction in energy intensity of at least 50% compared to the actual average electricity use for lighting in the North European. As described in [131], the technical components of a lighting system includes naked lamp, control gear, and fixtures. The types of naked lamps include incandescent lamps (ICLs), tungsten halogen lamps (THLs), linear fluorescent lamps (LFL), Compact fluorescent lamps (CFL), cold-cathode fluorescent lamps, low-pressure sodium lamps, high-intensity discharge (HID) lamps, such as mercury vapour lamps, high-pressure sodium lamps, metal halide lamps, ceramic metal halide lamps, induction lamps, and light-emitting diodes (LEDs). More detailed lighting performance characteristics in terms of efficacy, lumen maintenance and temperature, colour, and rated life span, etc. can be found in [131].

As suggested in [131], the most effective lighting energy efficiency lighting solutions are lighting retrofit and lighting control. The lighting retrofit is to replace inefficient lamps with efficient ones. Currently, CFLs and LEDs are widely used in the lighting retrofit projects. For instance, solar powered LED lighting technology is introduced in [136] and CFL technology is applied in [134]. The lighting control systems that automatically regulate lighting in response to need can have a positive effect on energy consumption given that human behaviour is a major factor in lighting energy use as people often forget to switch lighting off when they leave a space. Lighting control technologies range from manual switching and dimming to occupancy sensors, photosensors, centralised controls and timers. Typical lighting energy efficiency solutions are summarised as follows [131]:

- Phasing-out of inefficient incandescent lamps;
- Higher-efficiency lamps and fixtures;
- Higher-efficiency and more versatile ballasts;

- Routine use of efficient lighting controls;
- Greater use of daylighting technologies;
- Greater use of sophisticated lighting design;
- Stimulation of new, higher-efficacy lighting technologies.

Also as commented in [137], the above-mentioned lighting EE solutions either contribute to a reduction of the input wattages or the operating hours of the lighting systems, and these measures are widely taken in residential [138], commercial [139] and industrial sectors [140] around the world. The impact evaluation by an M&V process of lighting projects with the above-mentioned lighting EE solutions is discussed in this chapter.

3.3 GENERAL M&V PROCESS FOR ENERGY EFFICIENCY LIGHTING PROJECTS

Given an EE lighting retrofit project with an initial lamp population of N, the lamp population can be classified into I homogeneous lighting groups when the same technical specifications, similar energy consumption uncertainties and population decay dynamics of the lamps are identified in the ith lighting group, where i is the counter of lighting groups. For lighting retrofit projects, EE lighting technologies, i.e., CFLs, LEDs, or solar-powered lamps are employed to replace existing less efficient lamps such as halogen downlighters (HDLs) and ICLs. The retrofit interventions do not change the existing lighting control configurations and illumination levels.

Let a lighting retrofit project has a three-months' baseline measurement period and K years' reporting period during which the project performance is measured, verified and reported. Notation $k = 1, 2, \ldots, K$ denotes the counter of the project reporting years, where k=0 denotes the baseline year. $F(\Psi)$ and $G(\hat{\Psi})$ denote energy models, where notations Ψ and $\hat{\Psi}$ represent a set of energy governing factors in the baseline and post-retrofit periods, respectively. To ensure a fair comparison, the projected energy savings S under the post-retrofit condition are calculated by Equation (3.1)

$$S = F(\hat{\Psi}) - G(\hat{\Psi}), \tag{3.1}$$

where $F(\hat{\Psi})$ is the adjusted baseline in the post-retrofit period. For the lighting technology, energy models $F(\cdot)$ and $G(\cdot)$ should at least include the energy governing factors, such as the lamp population

$N_i(k)$, rated power $P_i(k)$ and daily operating hours $O_i(k)$. For simplicity $P_i(k)$ and $O_i(k)$ can be determined in combination as the daily energy consumption $E_i(k)$.

3.4 LIGHTING BASELINE AND SAVINGS DETERMINATION METHODOLOGIES

As baseline is crucial for savings determination over the entire M&V process of EE lighting projects, the lighting baseline methodologies have been discussed in various technical reports such as the CDM lighting project guidelines [124, 123, 141, 142, 143], M&V guidelines [1, 17, 18, 19], M&V case studies [144, 145, 146], and research articles [130, 147, 148, 149, 150, 151, 152]. In this sections, the lighting baseline and savings methodologies from the above-mentioned documents are reviewed and summarised.

3.4.1 Baseline and savings determination by Options A & B

The IPMVP Options A & B: retrofit isolations are widely recommended for the baseline and savings determination for lighting energy efficiency projects. For instance, M&V methods to the common lighting ECMs, including both lighting retrofit and lighting control are given in [17, 18]. The savings in EE lighting projects come from the applications of more efficiency lighting equipment. In the FEMP document [17, 18], key information related to M&V of EE lighting projects include:

- Developing existing equipment inventory: equipment inventories should include counts of lighting fixtures, lamps, and ballasts, together with additional details such as usage area description, counts of malfunctioning lighting fixtures, control style, lumen levels, and space heating/cooling conditions.

- Determining burning hours and a peak demand diversity factor: in lighting retrofit projects without control modifications, the operating hours are assumed to be the same over the baseline and reporting period. For projects aim to claim peak demand savings, a diversity factor must be determined and applied to avoid double-counted demand reductions. At any facility, only a portion of lamps will be on during the peak demand schedule. Sometimes, time-stamped operating data are collected to determine the percent of lamps in operation during the peak period.

- Accounting for interactive effects: for areas that are heated and cooled, interactions may be identified between the lighting equipment and HVAC systems. A lighting retrofit will reduce the cooling loads in summer but increase heating loads in winter. These effects are usually ignored as the cooling bonus and the heating penalty cancel each other over a year.

- Savings calculations: when the interactive effects are ignorable, the energy/demand savings for EE lighting projects can be calculated as follows:

$$kWh\ Savings = kW_{Baseline} \times Hours_{Baseline} - kW_{Post} \times Hours_{Post},$$

$$kW\ Savings = (kW_{Baseline} - kW_{Post}) \times Diversity\ Factor,$$

  where *Diversity Factor* is defined as the percentage of lighting load on during the utility's peak demand for the usage group or individual piece of device of a lighting project.

- Ongoing verification: it is important to regularly verify the retrofits' potential to perform. Practically, equipment types, quantities, and condition need to be verified in order to ensure overall performance, some sites may even specify a maximum allowable number of burn-outs in the reporting period.

For the lighting control projects, the savings are the reduced energy use due to decreased run-times (or reduced load factor if auto-switching or dimming is employed) of the lighting equipment due to daylight or occupancy controls. Most of the issues pertaining to lighting controls are similar to lighting retrofits. During the ongoing verification, performance of the controls must be verified by field testing. For occupancy controllers, sensitivity and delay time should be checked. For daylight sensors, illumination threshold set points need to be verified to ensure proper operation.

There are three M&V case studies given in [1]. The Option A is adopted for both the lighting retrofit and lighting operational control projects. But Option B is used for the street lighting project with both lighting retrofit and dimming control. In addition, the IPMVP also summarises the applicable measurement and estimation strategies under various ECM situations, as shown in Table 3.1.

In the ASHRAE M&V guideline, six methods for calculating savings from lighting ECMs have been proposed, such as:

1. Baseline and PI measured lighting wattage and stipulated diversity profiles;

2. Baseline and PI measured lighting wattage and sampled diversity profiles;

Table 3.1: Option A for lighting M&V.

Situations	**Measurement vs. Estimation Strategy**		**Adherent to Option A**
	Operating Hours (t)	**Power** (P)	
ECM reduces t	Measure	Estimate	Yes
	Estimate	Measure	No
ECM reduces P	Estimate	Measure	Yes
	Measure	Estimate	No
ECM reduces both P & t			
P uncertain	Estimate	Measure	Yes
	Measure	Estimate	No
t uncertain	Measure	Estimate	Yes
	Estimate	Measure	No
P & t unknown	Measure	Estimate	No-Use Option B
	Estimate	Measure	

3. Baseline measured lighting wattage with sampled diversity profiles, and PI wattage with continuous diversity profile measurements;

4. Baseline measured lighting wattage with sampled diversity profiles and PI continuous metered lighting;

5. Methods #1, #2, or #3 with measured thermal effect (heating and cooling);

6. Baseline and PI metered lighting measurements and thermal measurements.

Of the proposed six methods, the thermal interactions are ignored in the first 4 methods but considered in Methods #5-6. The six methods are applicable to calculate the both the energy savings and peak demand reductions in various lighting retrofit or lighting control projects.

In both the case studies of the PELP study [146] and the South Africa CFL door-to-door rollout programme [113, 112], the energy savings are determined as the wattage reduction resulting from the replacement of an incandescent bulb with a CFL, multiplied by the hours of use for each subsidized CFL installed. The energy savings are calculated by considering the following adjustment factors: persistence, free-ridership, snapback, usage adjustment, and losses.

The CDM lighting project guideline AMS-II.C [123] offers indicative simplified baseline and monitoring methodologies for the demand-side energy efficiency activities for specific technologies such as installing new energy efficiency lamps, ballasts, refrigerators, motors and fans. The AM0046 [124] focuses on large scale CDM lighting projects and the monitoring requirements of this methodology are very cumbersome according to [153]. The AMS-II.J [141] is actually a deemed savings methodology that has relaxed the heavy monitoring requirements of AM0046. But the AMS-II.J generates significantly less CERs than the AMS-II.C due to a very conservative assumption on average daily utilisation of CFLs. The AMS-II.L [142] offers guidance to the activities that lead to the adoption of EE lamps to replace inefficient lamps in outdoor or street lights. And the AMS-II.N [143] is a guideline to the demand side CDM EE projects for the installation of EE lamps and/or controls in buildings.

For CDM lighting projects with different characteristics, different guidelines may be adopted for the CER quantification. However, the lighting baseline energy calculation approaches are found to be quite similar in all the aforementioned lighting guidelines [123, 141, 124, 142, 143] as given in Equation (3.2)

$$E_B = \sum_{i=1}^{I} (N_i \cdot P_i \cdot O_i), \tag{3.2}$$

where N_i, P_i and O_i are the number, power and the average daily operating hours of devices in the ith lighting group, I is the total number of lighting groups for a certain CDM project. P_i and O_i may be determined separately or in combination, i.e., as energy consumption in order to simplify the uncertainty analysis of the measurements. Thus, Equation (3.2) could be simplified into

$$E_B = \sum_{i=1}^{I} (N_i \cdot E_j), \tag{3.3}$$

where E_i is the daily energy consumption per lamp in the ith group.

3.4.2 Savings determination by Option D

In the literature, the IPMVP Option D: calibrated simulation approach is also widely applied for the baseline and savings determination on lighting EE projects, especially in the residential sectors where highly uncertain lighting usage behaviours are often observed. Understanding detailed consumption characteristics of the lighting systems will not only assist the evaluation of utility's baseline and peak demand but also improve the reliability of energy savings verification of EE lighting projects. Direct representative measurements of the lighting energy use can provide such data and information. However, detailed sub-metering of the entire lighting population has prohibitive cost. In lacking of measurements, modelling of lighting load shape is a cost-effective option for electricity utilities. In the literature, sound research has been done in order to develop accurate and representative lighting load consumption models. In addition, existing research works have revealed that occupants' behavior, building characteristics, and the available daylight levels are the key factors of residential lighting consumptions [130, 147, 148, 149, 150, 151, 152]. For instance, [130] compares the differences and similarities of residential lighting demand in different countries in terms of occupant behaviours and dwelling characteristics. Reference [147] has generated monthly CFL load curves by incorporating the daily usage patterns and the dwelling characteristic from household surveys. Both [149] and [150] have developed residential lighting demand models by considering the domestic occupancy patterns and the daylight availability. However, the two studies are different in modelling the residents occupancy since [149] generates the occupancy with three-state non-homogeneous Markov Chain and [150] develops residents' activity profile based on surveyed time-use data describing what people do and when at a 10-minute resolution [151]. By analysing the high-resolved measurements on actual lighting demand in 100 United Kingdom (UK) homes, [152] has built a model that is capable of capturing residential lighting load variations due to the interaction of available daylight and the behaviour of occupants down to 1 minute intervals. In order to apply these lighting load shape more flexibly in various practical lighting projects, the studies [147, 152] have normalised the lighting load shape by the peak demand and then multiplied a calibration scalar to adjust the load shape under different occupancy, dwelling and natural lighting levels.

Based on studies [147, 152], a typical calibrated simulation model for the demand savings of lighting energy conservation measures is given as follows:

$$S(t) = \sum_{i=1}^{I} (P_i - \hat{P}_i) \times N_i \times LP(t) \times D_f, \tag{3.4}$$

where $S(t)$ is the demand savings profiles at time t during a day; P_i and $\hat{P}_i$ are the lighting wattage before and after the lighting ECM installation, respectively; N_i is the number of lighting units in ith lighting group; $LP(t)$ denotes the percentage load profile at time t that is normalised against the total capacity, and the peak value of $LP(t)$ is 100%. D_f is the peak demand diversity factor, which is defined as the fraction of lights that are operating during the facility's peak demand period [17, 18]. In Equation (3.4), the parameters P_i, $\hat{P}_i$, i and N_i are usually identified by walk through energy audits.

$LP(t)$ can be measured and sampled by interval power meters while D_f can be accurately determined by taking time-of-use measurements. The D_f can also be estimated from walk-through observations by noting the percentage of fixtures operating during the time when the building peak demand is most likely to be set.

3.5 FINDINGS ON LIGHTING PEAK DEMAND DIVERSITY FACTOR

As discussed in Section 3.4, the lighting peak demand diversity factor plays an important role in the determination of peak demand reduction of EE lighting projects. For some of the implemented large-scale lighting projects [146, 113], the peak demand diversity factors D_f have been verified. For instance, the PELP report provides a summary of D_f for typical days in each of the four seasons. Also in [113], it is found that 95.1% of the lamps are burning in low income households and 85% lamps are burning in middle income households during 18:00-20:00 in South Africa. In this section, results of a survey study that has been performed under the South African National Residential Mass Rollout (RMR) programme are given. The RMR Programme is an Eskom[1] approved energy efficiency initiative for homeowners and people who live in residential facilities such as hostels, flats, etc. It enables residents to have certain energy saving technologies installed in their home free of charge on a standard installation. RMR includes bulk replacements of inefficient lighting, implementation of energy saving technologies and load control devices in the residential sector. By end of 2012, Eskom approved technologies include CFLs, LED downlighters, flow restricted showerheads, pool pump and geyser timer control. According to the installation databases, more than 4.3 million CFLs are installed in a great number of residential households in South Africa. Representative measurement for D_f implies prohibitive cost for such a large-scale lighting mass rollout programme. Therefore, telephone survey is considered less expensive for the lighting peak demand diversity factor characterisation. Detailed process of the telephone survey are listed as follows:

Step 1: Questionnaire design for the telephone survey. In the questionnaire, the following three questions are asked and answers are gathered from the registered household representatives listed in the installation databases.

- Q1: Our database shows that a number of *** CFLs/LEDs are installed by the RMR programme, is that correct? Please answer Yes or No. If No, how many CFLs/LEDs are installed?

[1]Eskom is a South African electricity public utility and is the largest electricity producer in Africa.

- Q2: On average, how many of these CFLs/LEDs are burning between 6 to 8 o'clock in the weekday evenings?

- Q3: Do all the above-mentioned lighting devices work properly? Please answer Yes or No. If No, how many CFLs/LEDs are malfunctioning?

Step 2: Grouping, sample size determination and allocation. The lighting population for the peak demand diversity factor investigation is counted in the RMR installation databases, in which the number of CFLs installed per household in different geographic locations are well documented. After comprehensive inspections of databases, it is found that a few entries in the database contain extremely large number of CFL installations, i.e., more than 1000 lamps per location. These abnormal entries are excluded in the survey. After screening of the RMR installation database, it is found that majority of the households has no more than 50 lamps installed. Before the telephone survey, a hypothesis has been raised that the lighting diversity factor may be different in households with different number of installed CFLs. And most likely D_f will decrease as the number of available CFLs in household increases. Follow this hypothesis, the involved households are classified into 51 groups, denoted by G_j, where j=1, ..., 51. In the jth ($j \leq 51$) group, there are j CFLs installed per household and the 51th group contains all the rest of the households that have more than 50 CFLs installed. Then in each of the jth group, 50 households are planned to be sampled and interviewed. And these samples are randomly selected and evenly distributed in different geographical locations.

Step 3: Select effect survey outputs for analysis. The selection criteria are as follows:

- When abnormal outcomes are found in the survey outputs, reasons for the abnormal outcome must be found out and new samples are taken to replace the samples with abnormal outcomes. For instance, one of the sampled households gives an answer that 492 lamps were installed but none of the lamps were burning during weekday evening peak. The auditor eventually found out that the area was for a group of blind people. Therefore, this sample is abandoned for the diversity factor calculation and a new sample is taken to replace this sample.

- In case conflicts are found in the survey outputs, the samples will also be replaced by new samples. For instance, there is one household with only 2 lamps installed but recorded as 3 lamps were burning during the weekday evening peak. Although this might be a typo of the auditor, this sample is removed and a new sample is taken to ensure the sample size is sufficient to be representative.

Step 4: Summarise and analysis the surveyed outputs. The results are given in the next subsection.

The lighting peak demand diversity factor is analysed and characterised when all the survey outputs are available. For each household, D_f is calculated by its definition. For instance, one household is dispatched with 4 CFLs in total. The survey finds that on average 2 out of the 4 are burning during evening peak, then $D_f = 2/4 = 50\%$ for this household. The survey has successfully reached 915 households by the telephone interviews. A number of 13 449 CFL units has been installed in these sampled households. Among these lamps, 5900 lamps are burning during evening peak, where $5900/13449 = 43.87\%$. The conclusion could be that the average lighting D_f of the RMR programme is 43.87%. However, more interesting characteristics of the lighting peak demand diversity factor has been found and provided below. Within the sampled 915 households, 858 of them are with at least 1 lamp installed. The other 57 households only get showerheads and/or geyser timers installed. More detailed lighting diversity factor survey results are given in Table 3.2 and it is observed that higher D_f is observed in the households with fewer CFLs dispatched.

Table 3.2: Detailed D_f survey results

Number of CFLs	Sample size	Total CFL installed	Number of CFLs “on"	CFL D_f
1	69	69	68	99%
2	71	142	118	83%
3	61	183	138	75%
4	74	296	232	78%
5	46	230	176	77%
6	46	276	201	73%
7	26	182	125	69%
8	33	264	166	63%
9	22	198	103	52%
10	29	290	162	56%
11	23	253	131	52%
12	17	204	102	50%

Figure 3.1 plots the D_f from the sampled households against the number of CFLs. As shown in Figure 3.1, the D_f cannot be easily represented by a constant figure. Indeed, D_f varies when the number of CFLs per househod changes. More precisely, D_f decreases when the number of CFLs in

households increases in a certain range, particularly when the CFLs are less than 35 per household as shown in Figure 3.3. In Figure 3.1, it is found that the D_f curve is relatively smooth. In addition, the curve can be divided into three segments. Segment 1 represents the D_f of the households with 1-3 CFLs; Segment 2 represents the D_f of the households with 4-9 CFLs and Segment 3 represents the D_f of the households with 10-12 CFLs. Moreover, Segments 1-3 can be fitted by the linear trend lines excellently given that each fitting holds a very high R^2 as shown in Figure 3.2 (R^2 closer to 1 indicates better goodness-of-fit.). The fitted trend lines are the mathematic models to describe the properties of the D_f.

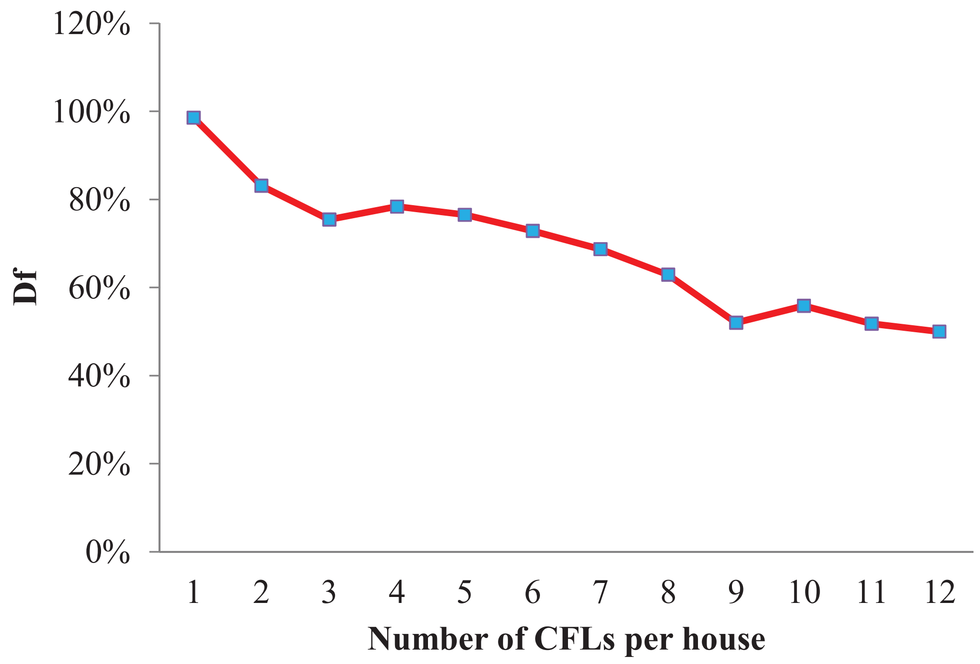

Figure 3.1: CFL D_f plot (up to 12 CFLs per house)

When looking at a wider range of the D_f outputs in Figure 3.3, it is found that the identified D_f in households with more than 13 lamps are with a considerably high variability. This may be caused by three reasons. Firstly, the effective sample sizes to investigate the households with larger number of CFLs are relatively smaller. The unbalanced distribution of sample sizes is due to database discrepancies. During the survey, when the auditor called a household with 18 CFLs installed as shown in the database, sometimes the homeowner told that only 15 or even fewer CFLs are installed. Eventually more samples for the households with fewer CFLs retrofits are interviewed. Secondly, the D_f might be naturally of high variability and cannot be represented by a simple trend line or a regular shape of function. This can only be verified when more sampled results are obtained. Thirdly, high variabil-

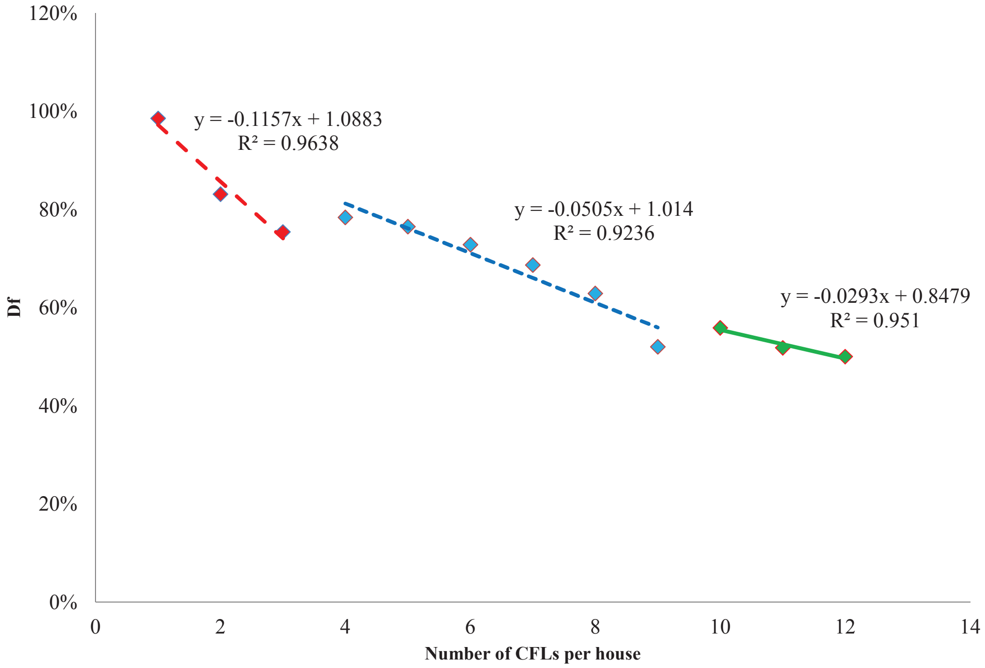

Figure 3.2: CFL diversity factor fitting

ity is naturally associated with the high uncertainty of the answers from the surveyed homeowners: people in a household with 4 CFLs can easily identify the number of CFLs in use during the evening peak, while the homeowner with 50 or more CFLs installed in a house might not be so easy to give a definite answer, or might not be willing to provide such an answer. However, the diversity factor for the households with 13-35 CFLs is also given in Figure 3.3. In addition, this diversity factor curve can also roughly divide into another two segments. In Figure 3.3, Segment 4 represents the D_f of the households with 13-35 CFLs; Segment 5 represents the D_f of the households with more than 35 CFLs. It is also interesting to find that households with more than 35 CFLs tend to have a higher D_f than the households with 13-35 CFLs. Particulary, the D_f for Segment 4 is 38% in average while the diversity factor for Segment 5 is 46%. This may be in accordance with the truth that the economically better off people, denoted by Segment 5, are more likely to install a large number of CFLs and careless about how many CFLs are burning in the household in terms of financial savings. Even though more interesting connections of the lighting diversity factor results shown in Figure 3.3 with the social and economic status of a household can be made, this thesis does not indulge in such speculations.

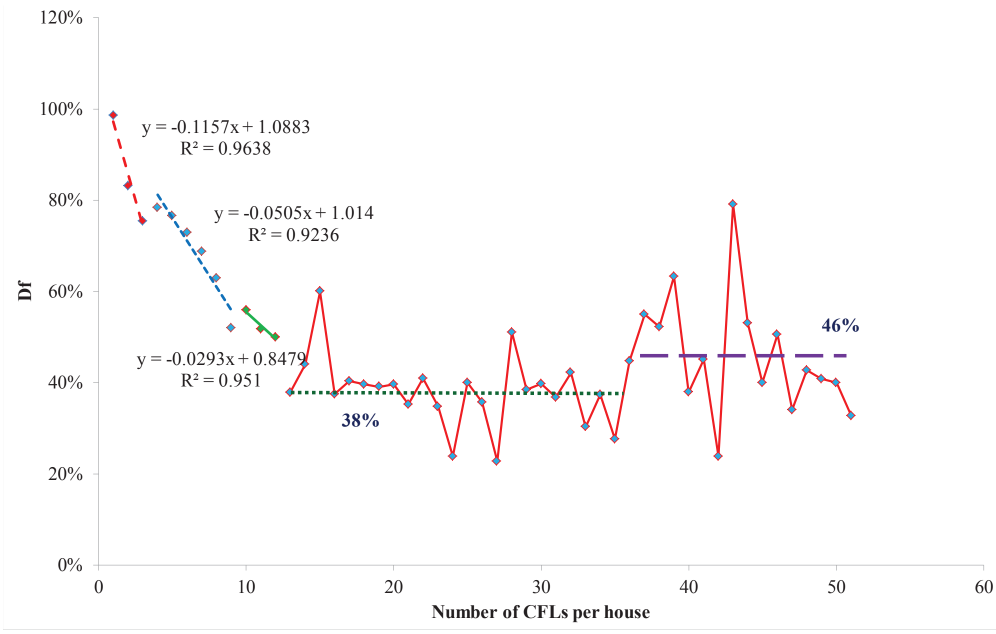

Figure 3.3: CFL diversity factor plot and fitting (up to 50 CFLs per house)

In conclusion, the D_f can approximately be denoted by the following function.

$$f(x) = \begin{cases} -0.1157x + 1.0883, x \in [1,3], \\ -0.0505x + 1.0140, x \in [4,9], \\ -0.0293x + 0.8479, x \in [10,12], \\ 0.38, x \in [13,35], \\ 0.46, x \in [36,+\infty). \end{cases} \tag{3.5}$$

where $f(x)$ denotes the fitting curves of the D_f, x is the number of CFLs in a certain household. $f(x)$ can be flexibly applied to identify the average lighting diversity factor for different lighting projects.

3.6 SCOPE OF M&V METERING PLAN

During the M&V process, metering plan will be designed to support the baseline and savings determination methodologies, in order to obtain high quality and reliable data for the baseline and savings calculation. According to the previous discussions, general scope of the metering plans for the EE lighting retrofit projects that are applicable to the case studied in the thesis are summarised as follows:

1) Two energy governing variables namely the survived lamp population $N_i(k)$ and daily energy consumption per lamp $E_i(k)$ in the ith lighting group need to be continuously sampled and metered. More precisely, $N_i(t)$ needs to be sampled and $E_i(t)$ will be monitored by long-term metering over the projects' baseline and reporting period. Each monitored and sampled variable must satisfy the desired accuracy, i.e., the 90/10 criterion.

2) The meters will be purchased and installed during the baseline period. The baseline lighting system will be measured for 3 calendar months.

3) The lamp population decay dynamics of $N_i(t)$ will be discussed later in this thesis. The required sample sizes for metering $E_i(t)$ will be decided by the proposed metering cost minimisation models.

4) Meters will be installed to monitor the sampled lamp appliance individually. Meters with different functionality and prices will be applied in different lighting groups. Calibration and maintenance of the metering systems will be performed regularly.

CHAPTER 4

SPATIAL METERING COST MINIMISATION

4.1 CHAPTER OVERVIEW

In this chapter, a spatial metering cost minimisation (SMCM) model is developed with the spatial stratified sampling approach. The SMCM model helps to design optimal M&V metering plans for EE lighting projects. To formulate the SMCM model, the lighting population is classified into different groups according to different lighting energy consumption uncertainties, which are characterised by CV. The SMCM model takes considerations of the population size, CV, meter prices, and required sampling accuracy level of each lighting group. And the SMCM model minimises the project metering cost with the optimal sample size in each group. The optimal number of samples from each group is randomly selected and measured by power meters. The meters with different prices and different functionalities are selected according to the CV values of different lighting groups. The optimal solutions to the minimisation problem minimise the metering cost whilst satisfying the required M&V accuracy. The effectiveness of the SMCM is illustrated by a case study. Relationships between the optimal metering cost and the population sizes, CV values, and the meter equipment cost are further explored by simulations. The metering cost minimisation model proposed for lighting systems is applicable to other similar lighting projects as well.

4.2 INTRODUCTION

In M&V practice, sampling uncertainty is usually unavoidable for lighting projects with large and dispersed population. Based on the available information on the UNFCCC's website[1], a number of energy efficiency lighting projects have been registered as SSC CDM projects. Most of these

[1] http://cdm.unfccc.int/methodologies/index.html

projects applies the simple random sampling approach to determine the number of lighting samples to be measured based on the assumption that the project lighting population is homogeneous [105, 154].

However, homogeneity is not always observed over the entire lighting population of EE lighting projects. Sometimes, energy usage pattern of lighting elements are more similar within small lighting groups instead of population. In these cases, the lighting population can be divided into different groups according to different lighting energy consumption uncertainties. To take sampling on the energy usage of lighting elements across different lighting groups, the stratified random sampling approach is recommended. The idea to minimise the M&V metering cost under the stratified sampling approach is illustrated by Figure 4.1.

Figure 4.1 shows a simple case of an EE lighting project with only two types of lamps involved. To design the optimal M&V metering plan for this project, energy consumption uncertainties of the lighting population can be estimated to check the homogeneity of the lighting population. Usually, small percent but representative lighting samples will be taken and their energy consumptions, working powers, and operating hours will be measured for a short period. With the measured data, CV values of the lighting energy usage can be calculated. If the obtained CV values of each sample lamps are very close, then the lighting population can be assumed as homogeneous and the simple random sampling approach is applicable. In case the obtained CV values are obviously separative by a clear threshold, then the lighting population can be stratified into different stratum. For instance, one group of lamps are with energy usage $CV \leq 20\%$ while the other group of lamps are with energy usage $CV > 20\%$. Then the lighting population can be classified into two groups. For some other projects, lighting population may also be divided into multiple lighting groups according to the tested CV values. In some of the EE lighting programmes[155, 94], the sampling accuracy on the project level is to satisfy the 90/10 criterion. When applying the stratified sampling approach, it is wise to let the group with lower uncertainty to have a very good confidence/precision such as 95/5 by applying large number of less expensive meters that are adequate for the measurements of low uncertain energy usage patters, and let the group with higher uncertainty to have a relative poor confidence/precision such as 85/15 by reducing the number of very expensive meters that have to be used to measure the highly uncertain energy consumption uncertainties. By doing so, the project level sampling accuracy satisfies the 90/10 criterion. Following the above idea, an MCM model is proposed to determine the optimal confidence/precision levels in each lighting group, such that the metering cost can be minimised while the overall 90/10 criterion is maintained. This model is formulated to cater for lighting

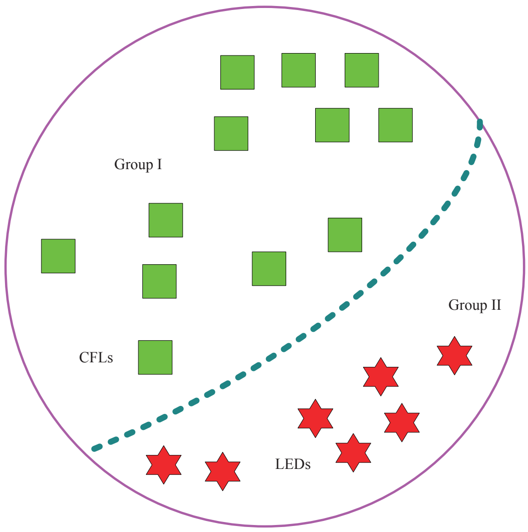

Figure 4.1: Spatial stratified random sampling.

projects with multiple lighting groups as well.

4.3 MODEL FORMULATION

In this chapter, an optimal M&V metering plan is designed as follows.

1) The crediting period of the EE lighting project is 10 years. Project performance reports will be compiled on annually basis after project implementation.

2) Meters will be randomly distributed and installed during baseline period to measure the daily energy consumption of each sampled lamp in the ith group for 3 calendar months. The sample sizes are decided by the proposed SMCM model. Each sampled lamp is monitored by one meter.

3) Once decided in the baseline period, the same sample sizes are applied at the post-implementation stage. The daily energy consumption of the sampled lamps will be continuously measured over the crediting period.

4) Calibration and maintenance of the metering systems will be performed on monthly basis to ensure that the metering devices are working in good condition over the crediting period.

4.3.1 Modelling assumptions

The SMCM model is developed under the following assumptions.

1) Inflation is not considered for the lighting project.

2) Let X_i, i=1, 2, ..., I be the random variables that denote the daily energy consumption data sets in the ith lighting group. Recalling the well-known Central Limit Theorem [121], it is assumed that X_i's follow normal distributions, that is, $X_i \sim \mathcal{N}(\mu_i, \sigma_i^2)$, where μ_i is the true mean and σ_i is the true standard deviation. Then for any n_i samples drawn in the ith lighting group, the sample mean distribution satisfies a normal distribution $\bar{X}_i \sim \mathcal{N}(\mu_i, \sigma_i^2/n_i)$ [93].

3) Assume that X_i's are independent, then the sample mean $\bar{X}$ for the lighting population will follow a normal distribution $\bar{X} \sim \mathcal{N}(\mu, \sigma^2)$, where

$$\mu = \frac{\sum_{i=1}^{I} N_i \mu_i}{\sum_{i=1}^{I} N_i},$$

and

$$\sigma^2 = \sum_{i=1}^{I} \frac{\sigma_i^2}{n_i} \cdot \frac{N_i^2}{(\sum_{i=1}^{I} N_i)^2}.$$

4.3.2 Spatial metering cost minimisation model

The objective is to find the optimal solution $\lambda = (z_1, \ldots, z_I, p_1, \ldots, p_I)$ that minimises

$$f(\lambda) = \sum_{i=1}^{I} (a_i + b_i + kc_i) \times n_i, \tag{4.1}$$

where k is the number of months in the crediting period, and $k = 123$ including the baseline monitoring period (3 months) and the crediting period (10 years, 120 months); z_i and p_i denote the z values and precision levels in the ith group, respectively; a_i, b_i, and c_i represent the metering device procurement, installation, and monthly maintenance cost per unit in the ith group, respectively; and n_i is the optimal sample sizes in the ith group, which is calculated by Equation (2.5).

The required 90/10 criterion can be formulated as the constraints, in which z can be calculated by the Z-transformation formula

$$z = \frac{\bar{x} - \mu}{\sigma/\sqrt{n}}, \tag{4.2}$$

and the constraints based on the 90/10 criterion are expressed as follows:

$$\begin{aligned} z &= \frac{\frac{\sum_{i=1}^{I} N_i \bar{x}_i}{\sum_{i=1}^{I} N_i} - \frac{\sum_{i=1}^{I} N_i \mu_i}{\sum_{i=1}^{I} N_i}}{\sqrt{\sum_{i=1}^{I} \frac{\sigma_i^2}{n_i} \cdot \frac{N_i^2}{(\sum_{i=1}^{I} N_i)^2}}} \\ &= \frac{\sum_{i=1}^{I} N_i (\bar{x}_i - \mu_i)}{\sqrt{\sum_{i=1}^{I} \frac{\sigma_i^2}{n_i} \cdot N_i^2}} \\ &= \frac{\sum_{i=1}^{I} N_i z_i \cdot \frac{\sigma_i}{\sqrt{n_i}}}{\sqrt{\sum_{i=1}^{I} \frac{\sigma_i^2}{n_i} \cdot N_i^2}} \\ &\geq 1.6450, \end{aligned} \tag{4.3}$$

and

$$\begin{aligned} p &= \frac{\frac{\sum_{i=1}^{I} N_i \bar{x}_i}{\sum_{i=1}^{I} N_i} - \frac{\sum_{i=1}^{I} N_i \mu_i}{\sum_{i=1}^{I} N_i}}{\frac{\sum_{i=1}^{I} N_i \bar{x}_i}{\sum_{i=1}^{I} N_i}} \\ &= \frac{\sum_{i=1}^{I} N_i \bar{x}_i - \sum_{i=1}^{I} N_i \mu_i}{\sum_{i=1}^{I} N_i \bar{x}_i} \\ &= \frac{\sum_{i=1}^{I} N_i z_i \cdot \frac{\sigma_i}{\sqrt{n_i}}}{\sum_{i=1}^{I} N_i \bar{x}_i} \\ &\leq 10\%. \end{aligned} \tag{4.4}$$

In summary, the problem is to find $\lambda = (z_1, \dots, z_I, p_1, \dots, p_I)$ that minimises the objective function

$$f(\lambda) = \sum_{i=1}^{I} (a_i + b_i + kc_i) \times ceil\left(\frac{CV_i^2 z_i^2 N_i}{CV_i^2 z_i^2 + N_i p_i^2}\right), \tag{4.5}$$

subject to the constraints

$$\begin{cases} z \geq 1.6450, \\ p \leq 10\%, \end{cases} \tag{4.6}$$

where the ceil function $ceil(\cdot)$ rounds a real number to the nearest integer which is greater than or equal to this real number.

4.3.3 Case study

In this section, an optimal M&V metering plan designed for a lighting retrofit project is taken as a case study to illustrate the effectiveness of the proposed SMCM model in reducing the M&V cost while achieving the required M&V accuracy.

A lighting retrofit project that aims to reduce lighting load in 44 government hospitals in South Africa is in the process of being registered as a CDM energy efficiency lighting project. A number of 404 296 CFLs will be installed to replace less energy efficient HDLs and ICLs that are currently in use. The 14 W and 20 W CFLs will be installed in exchange of equal number of normal luminous flux 60 W ICLs and 100 W HDLs, respectively. Motion sensors are currently in use for the 100 W HDL lighting systems. The CFLs will be directly installed to replace the HDLs with no modification to the existing lighting control systems. The exchanged HDLs and ICLs will be counted, stored, and destroyed, by an authorised disposal company. The CFLs with a rated lifetime of 10 000 hours, manufactured by Philips, have the equivalent or higher lumen to the replaced HDLs and the ICLs. An energy audit is conducted to gather all relevant information of this project to help with M&V plan design. Detailed information of this project is listed in Table 4.1.

Table 4.1: Details of the lighting project.

Technology	**Wattage**	**Operating Schedule**	**Quantity**
ICL→ CFL	60 W → 14 W	8:00-16:00	263 519
HDL→ CFL	100 W → 20 W	Motion sensor control	140 777

Project participants conduct a cost analysis for the discussion of investment barrier. The average unit price of CFLs used in this project is R 27[2], other financial details associated with this project can be found in Table 4.2.

Table 4.2: Lighting project cost analysis.

Total number of CFLs to be installed	404 296	**Units**
Costs		
Average price of CFL	27	Rand per unit
CFL distribution	5	Rand per unit
Subtotal	12.94	Million Rand
HDL, ICL, CFL collection, transportation, and disposal	1.03	Million Rand
CDM process cost (PDD writing, validation, monitoring and verification, etc)	1.72	Million Rand
Total project cost	15.69	Million Rand

[2]The annual average USD to Rand exchange rate in 2012 is 1 USD= R 8.209.

For this lighting retrofit project, daily energy consumption patterns of the lighting population are not homogeneous due to application of motion sensors. Therefore, the involved HDL and ICL lamps can be stratified into different strata according to CV of the lighting daily energy consumption. To estimate the CV values, daily operating hours of a small sample of lamps without control devices are recorded. The sampled lamps are burning 8 hours a day on average with a standard deviation of 1.5 hours. The rated power of an ICL lamp is 60 W. Thus the estimated daily energy consumption per ICL is 0.48 kWh with a standard deviation of 0.09 kWh. The daily energy consumption CV of the ICLs is 0.19. For the HDLs, although the lighting operating schedule is unknown, a rough but confident estimation is that on average the HDLs are burning 6 hours per day. In this case, a CV value as high as 0.5 is historically recommended by [17]. Thus, the estimated daily energy consumption of the HDLs is 0.6 kWh with a standard deviation of 0.3 kWh. If drawn a CV threshold 0.2, then the lighting population can be classified into two groups, where Group I is the 263 519 ICLs with daily energy consumption CV less than 0.2, and Group II is the 140 777 HDLs with daily energy consumption CV values between 0.2 and 0.5.

Since the energy consumption in Group II changes more frequently than that in Group I , the metering devices to be installed in Group II need to have a very high sampling frequency based on Shannon' sampling theorem [156]. In addition, the meters to be installed in Group II need to have advanced control chips with high clock frequency and large memory capacity for the data storage. The metering device specifications of the two recommended meters (Type T_1 and Type T_2) are provided in Table 4.3. The specifications indicate that the Type T_2 meters are capable of capturing the uncertainties in Group I. However, the Type T_1 meters are not applicable for the measurement in Group II.

Table 4.3: Metering device specifications.

Categories	**Type T_1**	**Type T_2**
Voltage range (AC)	150-270 V	100-380 V
Current range	50 mA-50 A	10 mA-100 A
Accuracy	$\pm$ 0.01%	$\pm$ 0.002 %
Time resolution	300 s	0.5 s
Memory capacity	32 kB	8 MB

Group I will be installed with less expensive meters to check its energy consumption variations, and Group II will be installed with expensive meters to monitor its real time energy consumption. According to [99], the key components of the metering cost include meter procurement cost, installation cost and maintenance cost. The costs of Type T_1 and Type T_2 meters are listed in Table 4.4 as given by the meter suppliers.

Table 4.4: Metering equipment cost (per unit).

Categories	**Type T_1**	**Type T_2**
Meter purchase (once-off)	R 876	R 3 146
Meter installation (once-off)	R 195	R 320
Meter maintenance (monthly)	R 45	R 98

The overall 90/10 criterion for this project can be maintained by letting Group I have a very better confidence/precision while letting Group II have a relatively poorer confidence/precision. This results in a greater number of less expensive meters being installed in Group I, and a smaller number of expensive meters being installed in group II in order to minimise the metering cost.

4.3.4 Base case

Before solving the optimisation problem, the metering cost to achieve the 90/10 criterion without optimisation is calculated as a benchmark for comparison purposes. According to the energy audit and metering equipment cost in Table 4.4, the initial values to solve the model in Equations (4.5)-(4.6) are summarised in Table 4.5.

Table 4.5: Initial values.

Parameters	**Group I**	**Group II**
Meter unit price	a_1=R 876	a_2=R 3 146
Installation per meter	b_1=R 195	b_2=R 320
Monthly maintenance	c_1=R 45	c_2=R 98
Monitored months	k=123	k=123
CV values	$CV_1 = 0.20$	$CV_2 = 0.50$
Estimated $\bar{x}_i$	$\bar{x}_1 = 0.48$ kWh	$\bar{x}_2 = 0.60$ kWh
Population sizes	N_1=263 519	N_2=140 777

For the government hospital lighting project, if the simple random sampling approach is applied to the entire lighting population, a worst possible CV value of 0.5 can be used for the sample size calculation by Equation (2.5), the obtained sample size is 68 with a metering cost of R 1 055 360 given that expensive meters should be used when CV is high. For this solution, the 90/10 criterion is achieved without spending unnecessary money on metering. In this scenario, the metering cost shares 6.76% of the total project cost. Without considering optimisation, another possible solution might be that the 90/10 criterion is applied to Group I and II, where $\lambda = (1.6450, 1.6450, 0.1, 0.1)$ for sample size determination. The corresponding sample sizes and metering cost are calculated as shown in Table 4.6. It shows that the overall confidence and precision are 97.76% and 9.94%, respectively, at the total metering cost of R 1 128 206, which occupies 7.19% of the total project cost. In this scenario, the expected sampling accuracy is much better than the required 90/10 criterion, which is unnecessary.

Table 4.6: Sample size and metering cost without optimisation.

Parameters	**Group I**	**Group II**	**Overall**
Confidence	90%	90%	97.76%
Precision	10%	10%	9.94%
Meter numbers	11	68	79
Number of samples	11	68	79
Total cost	R 72 666	R 1 055 360	R 1 128 026

4.3.5 Optimal solution

Now consider the metering cost minimisation model given in Equations (4.5)-(4.6) which is a non-linear programming problem. To find the solution to this case study, the computations are carried out by the Matlab program. In particular, the optimal solutions are computed by the "fmincon" code of the Matlab Optimisation Toolbox. The optimisation settings of the "fmincon" function are shown in Table 4.7, where the interior-point algorithm is chosen as the optimisation algorithm; the three termination tolerances on the function value, the constraint violation, and the design variables are also given. In addition, "fmincon" calculates the Hessian by a limited-memory, large-scale quasi-Newton approximation, where 20 past iterations are remembered. Besides these settings, a search starting point λ_0 and the boundaries of the design variable are also assigned.

Besides these settings, a search starting point λ_0 as well as the boundaries of the design variable are also required for "fmincon" to work. Table 4.8 gives the optimal solution with $\lambda_0 = (0.21, 0.86, 0.85, 0.26)$, lower bound $lb = (0, 0, 0, 0)$ and upper bound $ub = (+\infty, +\infty, 1, 1)$.

From a mathematical perspective, the sample sizes, which are integer numbers, must be solved through integer programming algorithms. Since this study arises from the practical issues of minim-

Table 4.7: Optimisation settings.

Categories	**Options**
Algorithm	interior-point
TolFun	10^{-45}
TolCon	10^{-45}
TolX	10^{-45}
Hessian	‘lbfgs’, 20

ising the metering cost, real-valued sample sizes are used during the optimisation. After the optimal solution λ^* is found, the ceil function is applied to obtain the integer sample sizes. Mathematically, the rounded sample sizes by the ceil function are only sub-optimal solutions. Henceforth, the terminologies “optimal/optimise” and “minimal/minimise” may only refer to the rounded sub-optimal solutions.

Table 4.8: Optimal results 1.

Parameters	**Group I**	**Group II**	**Overall**
Confidence	93.09%	57.84%	90.25%
Precision	9.77%	10.35%	9.85%
Meter numbers	14	16	30
Number of samples	14	16	30
Total cost	R 92 484	R 248 320	R 340 804

It is found that with the constraints of the 90/10 criterion for the overall project, the obtained confidence/precision 93.09/9.77 for Group I and 57.84/10.35 for Group II contribute to an overall 90.25/9.85 accuracy. With these optimal solution, the optimal metering cost is R 340 804, occupies 2.17% of the total project cost, which is significantly reduced than the overall metering cost without the optimisation as given in Table 4.6. Comparing with the results in Table 4.6, the metering cost for Group I increases. However, the metering cost of Group II reduces sharply. The overall metering cost is reduced whilst the 90/10 criterion is satisfied.

Due to the nonlinear nature of the minimisation problem, the optimal solutions may not be unique although the minimal objective function value is unique. Table 4.9 gives another set of optimal solutions with the initial search point $\lambda_0 = (2.1, 2.4, 0.62, 0.22)$. It is clear that although the confidence and precision of the two groups are different from the values in Table 4.8, the 90/10 criterion is still

Table 4.9: Optimal results 2.

Parameters	Group I	Group II	Overall
Confidence	84.87%	70.30%	90.15%
Precision	7.71%	13.43%	9.82%
Meter numbers	14	16	30
Number of samples	14	16	30
Total cost	R 92 484	R 248 320	R 340 804

achieved and the optimal sample sizes and the metering cost remain unchanged.

According to the discussions and analysis in this section, the metering costs with or without the optimisation are summarised in Tabel 4.10. Note that the figures in the "Metering cost (%)" column are calculation against the total project cost of 15.69 million Rand. Comparing to the metering plan without the optimiation, the metering cost savings of 0.71 million Rand, which is 4.52% of the total project cost, are achieved without sacrificing the overall sampling accuracy.

Table 4.10: Metering cost analysis.

Solutions	Accuracy	Samples	Metering cost (R)	Metering cost (%)
No optimisation 1	90/10	68	R 1 055 360	6.76%
No optimisation 2	97.76/9.94	79	R 1 128 026	7.19%
Optimal solution 1	90.25/9.85	30	R 340 804	2.17%
Optimal solution 2	90.15/9.82	30	R 340 804	2.17%

4.4 MODEL ANALYSIS AND DISCUSSION

The metering cost minimisation model in Section 4.3 is built for the M&V plan of a particular CDM lighting retrofit project. When analysing model in Equations (4.5)-(4.6), it is found that three key components, M_i, CV_i and N_i will affect the overall metering cost for a given accuracy requirement. Actually, for different lighting projects, the population sizes N_i, the initial CV values CV_i, and the individual metering system cost M_i may vary. In order to investigate the metering cost reduction opportunity for other similar lighting projects, three simulations are run to characterise the impacts of the parameters N_i, CV_i, and M_i to the optimal metering cost for similar lighting projects. In each simulation, only one of the above three parameters will change. More precisely, N_2 is changed in the first simulation to investigate the relationship between the population size and the optimal metering cost;

CV_1 is changed in the second simulation to identify the relationship between initial CV values and the optimal metering cost; M_1 is changed in the third simulation to analyse the relationship between the individual metering system cost and the optimal metering cost. The optimal settings remain the same as the settings provided in Section 4.3. The search starting point is $\lambda_0 = (0.21, 0.86, 0.85, 0.26)$ for the three simulations. As mentioned in Section 4.3, due to the nonlinear nature of the minimisation problem, the optimal confidence/precision levels are not unique since there exist different combinations of optimal confidence/precision levels that satisfy the 90/10 criterion constraints. Different valid combinations of optimal confidence/precision levels are obtained by applying a different search starting point λ_0. Some artificial initial values are applied to the three simulations.

Results of the simulations are shown in Figures 4.2-4.13. For the legends in Figures 4.2, 4.3, 4.6, 4.7, 4.10, and 4.11, the confidence/precision levels of Group I and Group II are denoted by the dotted line (in red) and the dashed line (in blue), respectively. The confidence/precision levels for the overall project that are calculated by the real-valued sample sizes are denoted by the solid line (in green) while the overall project confidence/precision levels calculated by the rounded sample sizes are denoted by the dash-dotted line (in black).

4.4.1 Optimal metering cost versus population sizes

In this simulation, let N_2 increase from 10 000 to N_1 =1 000 000 by an increment of 10 000. Initial values for this simulation are listed in Table 4.11. The corresponding optimal results are presented in Figures 4.2-4.5.

Table 4.11: Initial values for the Simulation 1.

Parameters	Group I	Group II
M_i	M_1=R 5 000	M_2=R 50 000
CV_i	$CV_1 = 0.2$	$CV_2 = 0.5$
$\bar{x}_i$	$\bar{x}_1 = 0.56$ kWh	$\bar{x}_2 = 0.36$ kWh

In Figure 4.2, the confidence levels of Group I are always higher than those of Group II. The green solid line shows that the desired 90% confidence of the overall project is satisfied. It can also be observed that the confidence levels calculated by the rounded sample sizes are greater than or equal to the project confidence calculated by the real-valued sample sizes.

In Figure 4.3, as N_2 increases, the precision levels of both Group I and Group II increase. The precision levels of Group II increase more quickly than those of Group I in order to balance the overall project precision within 10%. In addition, the project precision levels that are calculated by the real-valued and rounded sample sizes are within the desired 10% precision.

Figures 4.4 and 4.5 show that the sample sizes and the metering cost increase as N_2 increases.

According to the results shown in Figures 4.2-4.5, the influence of Group II to the overall accuracy is small when N_2 is small, i.e., when N_2 <10 000, only one meter is needed to maintain the overall 90/10 criterion. However, as N_2 increases, the uncertainties of Group II increase rapidly because CV_2 is high. Therefore, the required sample size of Group II increases quickly.

4.4.2 Optimal metering cost versus CV values

In this simulation, let CV_1 increase from 0.005 to CV_2=0.5 by an increment of 0.005. Initial values for this simulation are listed in Table 4.12. The optimal solutions are presented in Figures 4.6-4.9.

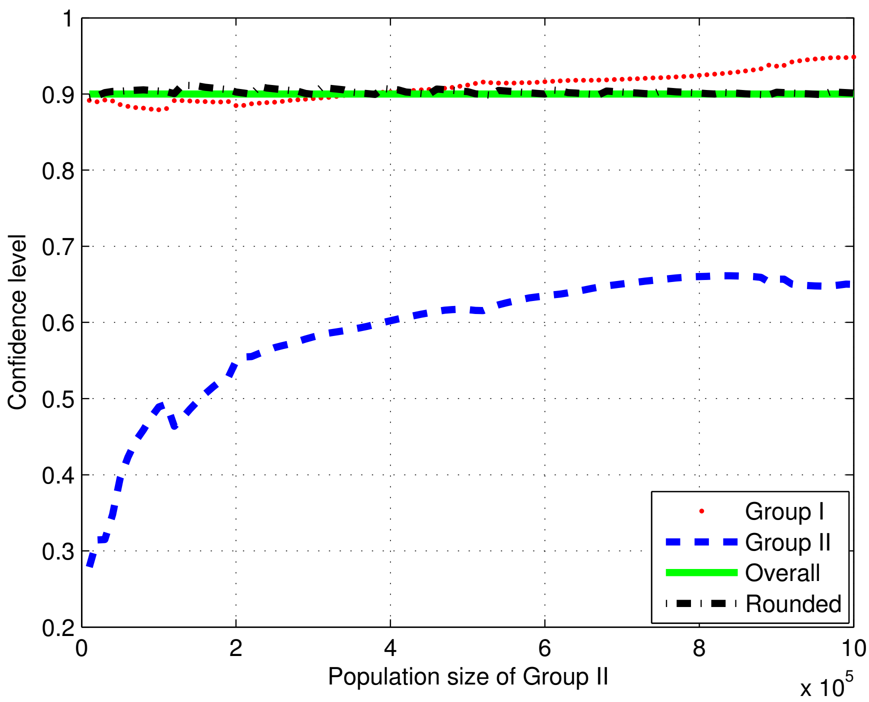

Figure 4.2: Confidence levels when N_2 changes.

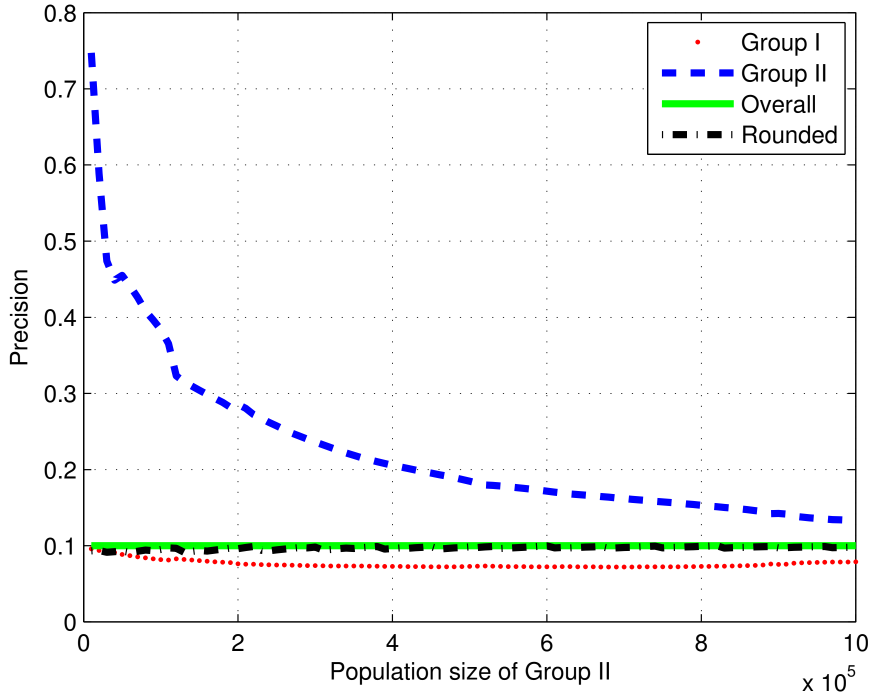

Figure 4.3: Precision levels when N_2 changes.

Table 4.12: Initial values for the Simulation 2.

Parameters	**Group I**	**Group II**
M_i	M_1=R 5 000	M_2=R 50 000
$\bar{x}_i$	$\bar{x}_1 = 0.56$ kWh	$\bar{x}_2 = 0.36$ kWh
N_i	N_1 =1 000 000	N_2=300 000

Figure 4.6 shows that the confidence levels of both Group I and Group II decrease when CV_1 increases. The confidence levels of Group I are higher than Group II. The overall confidence as shown in the solid line (in green) satisfies the 90% confidence. However, it is noted that the rounded overall confidence level is a little lower than the 90% confidence when CV_1 is between 0 and 0.1. The reason is that real-valued sample sizes are allowed during the optimisation in this study. The optimal solutions for real-valued sample sizes may sometimes become suboptimal when ceil function is applied to these optimal solutions. In the worst case, the real-valued sample sizes satisfy the 90% confidence while the rounded sample sizes obtained by the ceil function do not satisfy the 90% confidence as shown in Figure 4.6. In this case, it is suggested to increase necessary sample size to achieve the desired accuracy. To illustrate, consider the lowest confidence level 86.87% of the rounded overall confidence as shown by the first point in the dash-dotted line (in black) in Figure 4.6. Detailed information for this point is listed in Table 4.13. From Table 4.13 it is clear that the confidence level in Group I is very close to 100%. Calculation shows that even the confidence level in Group I increases to 99.99%, the overall confidence can only achieve 89.36%. Therefore, the only solution is to increase the number of meters in Group II. When 3 meters are installed in Group II, the rounded overall confidence becomes 90.99% which meets the 90% confidence requirement. Since the installation of only 2 meters in

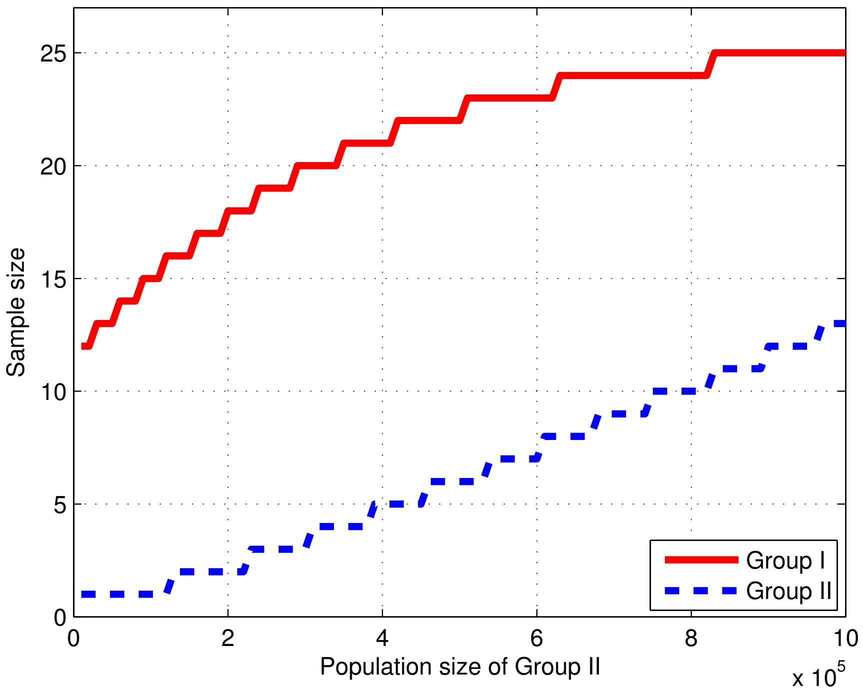

Figure 4.4: Number of meters when N_2 changes.

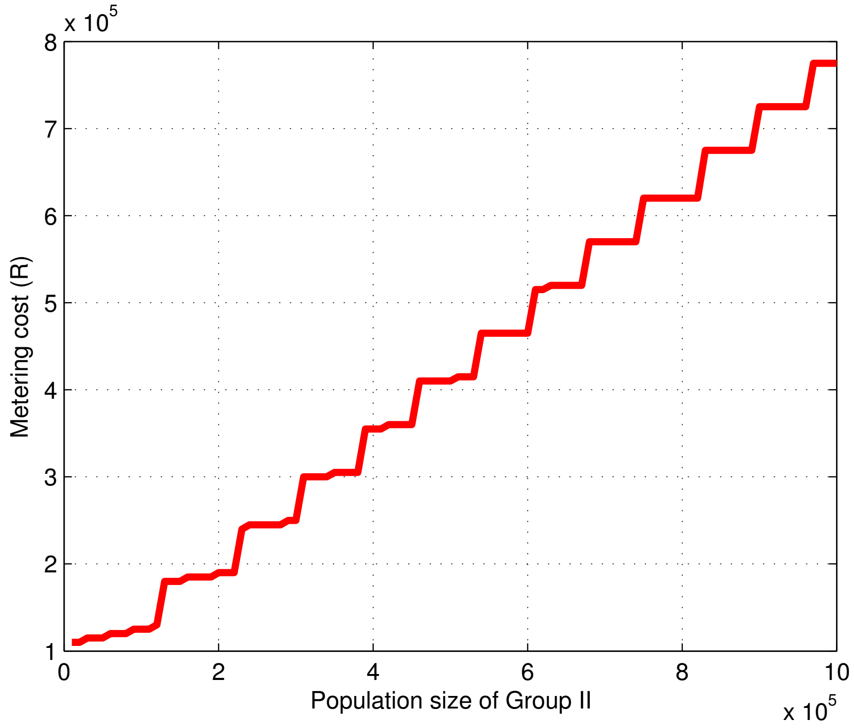

Figure 4.5: Metering cost when N_2 changes.

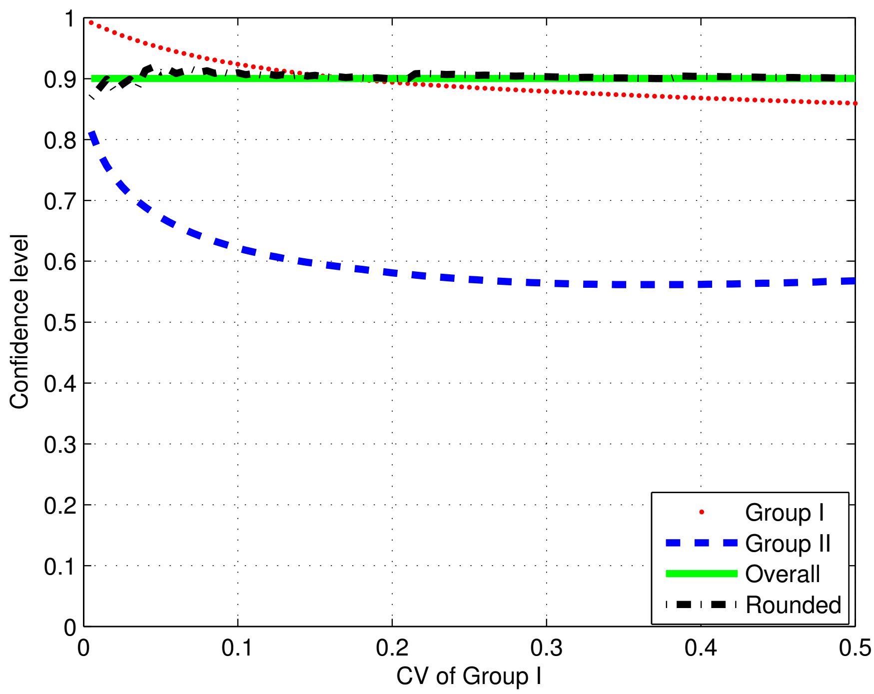

Figure 4.6: Confidence levels when CV_1 changes.

Table 4.13: Solution analysis.

Parameters	Group I	Group II	Overall
Confidence	99.19%	81.29%	86.88%
Precision	2.44%	49.20%	8.65%
Meter numbers	1	2	3
Total cost	R 5 000	R 100 000	R 105 000

Group II will never meet the 90/10 criterion, while the installation of 3 meters in Group II will meet the 90/10 criterion, this solution must be optimal.

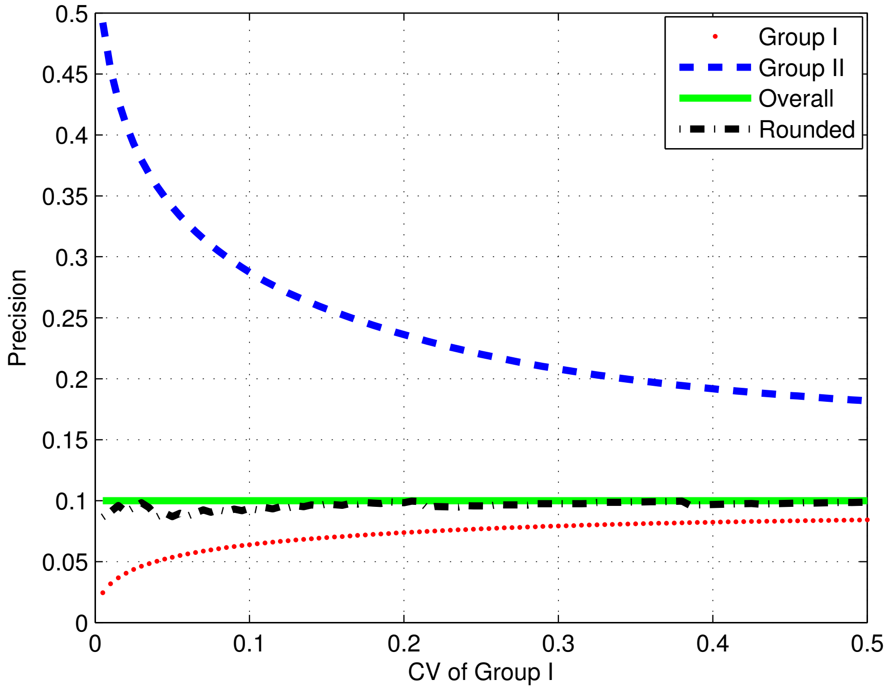

Figure 4.7: Precision levels when CV_1 changes.

In Figure 4.7, it is noted that as CV_1 increases, the precision of Group I becomes worse but remains within 10%. The precision of Group II improves but the precision is always worse than that of Group I. The overall precision maintains within the 10% margin of error.

As shown in Figure 4.8, more samples are needed to maintain the 90/10 criterion as CV_1 increases. Figure 4.9 shows the overall metering cost keeps going up since the sample sizes of both Group I and Group II increase.

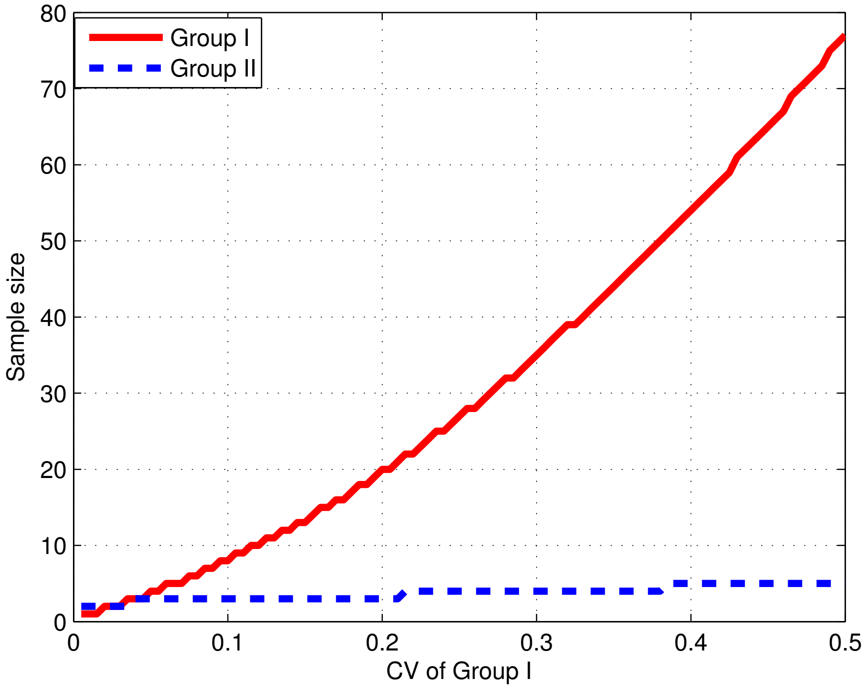

Figure 4.8: Number of meters when CV_1 changes.

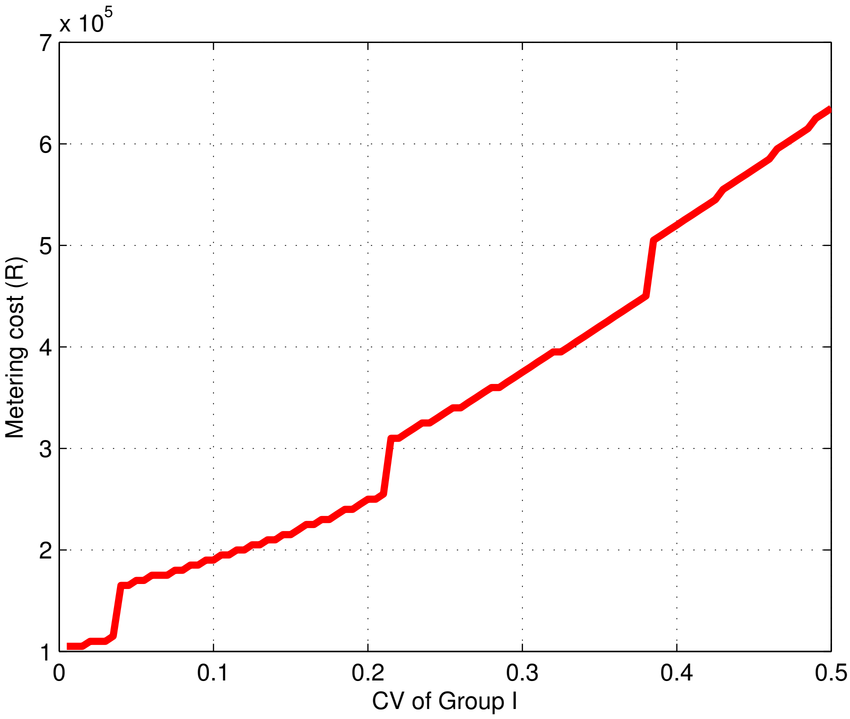

Figure 4.9: Metering cost when CV_1 changes.

The results provided in Figures 4.6-4.9 show that, when $CV_1 < 0.1$, less than 10 samples can maintain the confidence of Group I over 90% and the precision within 10%. However, as CV_1 becomes greater, the uncertainties of Group I increase rapidly since the population size of Group I is dominant.

4.4.3 Optimal metering cost versus individual meter cost

In this simulation, assume that the individual meter cost M_1 increases from 500 to M_2=50 000 by an increment of 500. The initial values for this simulation are listed in Table 4.14. The optimal solutions are presented in Figures 4.10-4.13.

Table 4.14: Initial values for the Simulation 3.

Parameters	Group I	Group II
CV_i	$CV_1 = 0.2$	$CV_2 = 0.5$
$\bar{x}_i$	$\bar{x}_1 = 0.56$ kWh	$\bar{x}_2 = 0.36$ kWh
N_i	N_1 =1 000 000	N_2=300 000

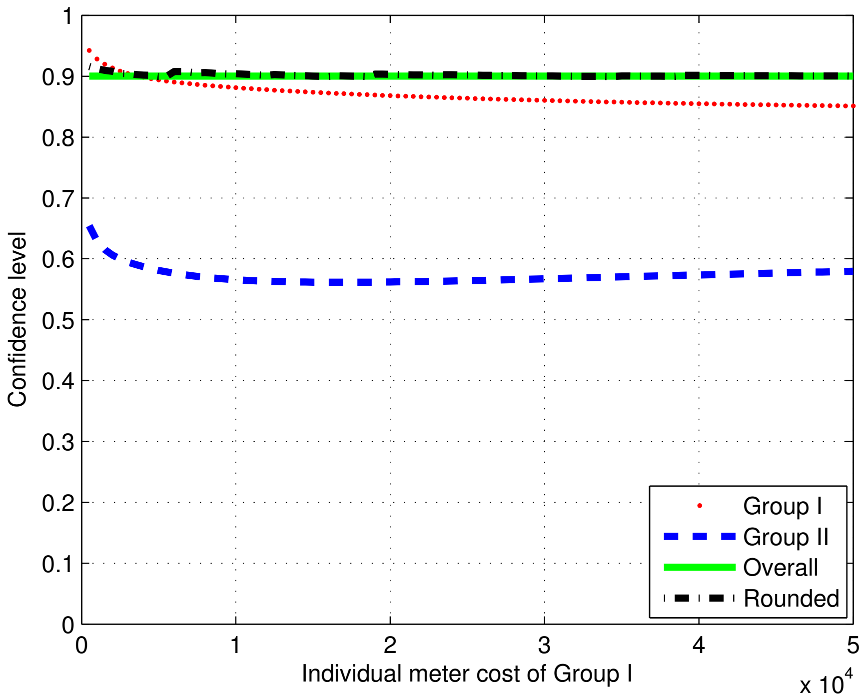

Figure 4.10: Confidence levels when M_1 changes.

In Figure 4.10, as M_1 increases, the confidence levels of both Group I and Group II go down slowly. The confidence levels of Group I are higher than those of Group II. The project confidence levels calculated both by the real-valued and rounded sample sizes satisfy the desired 90% confidence.

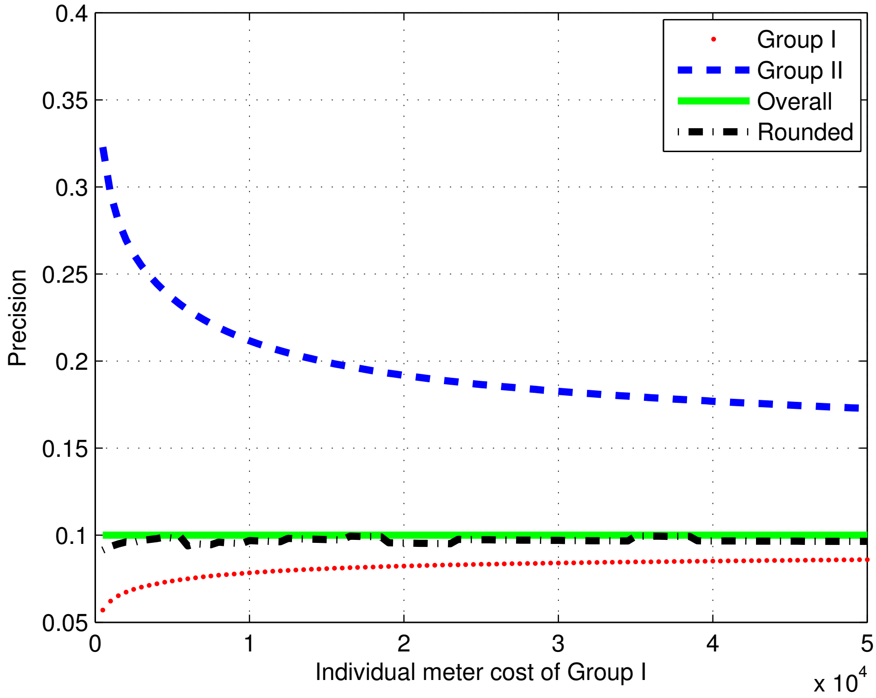

Figure 4.11: Precision levels when M_1 changes.

In Figure 4.11, it is clear that the precision levels of Group II increase continually as M_1 goes up. However, the precision of Group I becomes worse since less meters are installed in Group I when M_1 increases.

In Figure 4.12, the sample size of Group I decreases but the sample size of Group II increases as M_1 goes up.

Figure 4.13 clearly shows that the general trend of the metering cost is going up when M_1 increases. Sometimes, the metering cost decreases a little because the sample size of Group I decreases while the sample size of Group II does not change.

Based on the results shown in Figures 4.10-4.13, when M_1 is small, more samples are drawn from Group I to achieve certain confidence and precision levels. However, as M_1 increases, the sample size of Group I tends to decrease in order to reduce the metering cost of the project.

4.4.4 Remarks on the simulations

The three simulations indicate that the proposed SMCM model is applicable to reduce the metering cost for lighting retrofit projects with different population sizes, CV values, and metering devices. The simulation results also reveal possibilities of further reducing the M&V metering cost. For instance, fewer sample sizes may be required to achieve the 90/10 criterion once a smaller CV value is obtained by short-term measurements, instead of using the worst case CV of 0.5. In addition, the simulation results can also be taken as an example of simplifying the proposed metering cost minimisation methodology. It is suggested to pre-calculate and tabulate optimal metering cost and samples for typical lighting projects with different population sizes, CV values or metering device costs.

4.5 CONCLUSION

In this chapter, an SMCM model is proposed to assist the M&V metering plan of lighting retrofit project. The minimal metering cost is achieved by optimising the confidence and precision levels of each lighting group under the constraint of the desired 90/10 criterion for the overall project. In order

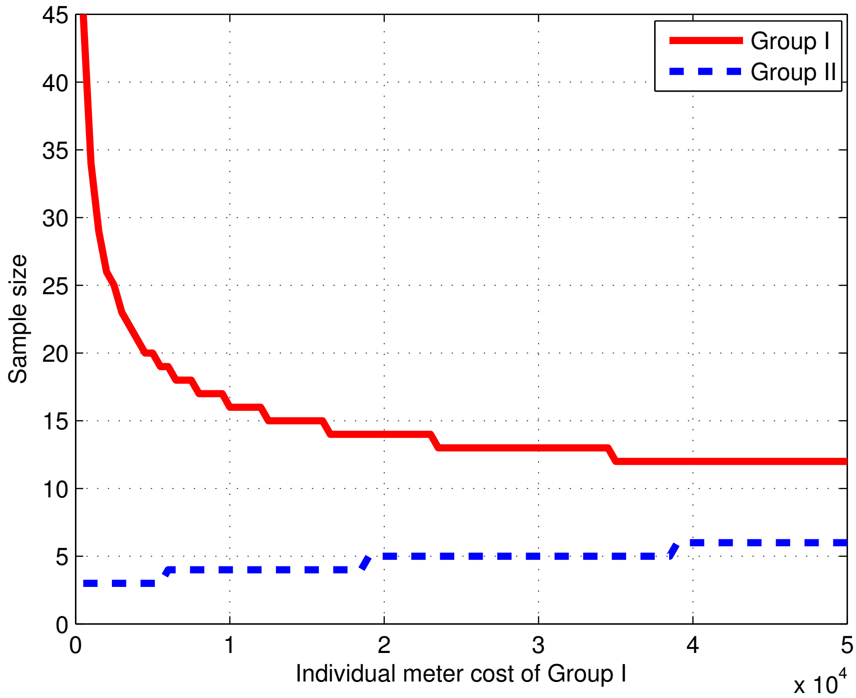

Figure 4.12: Number of meters when M_1 changes.

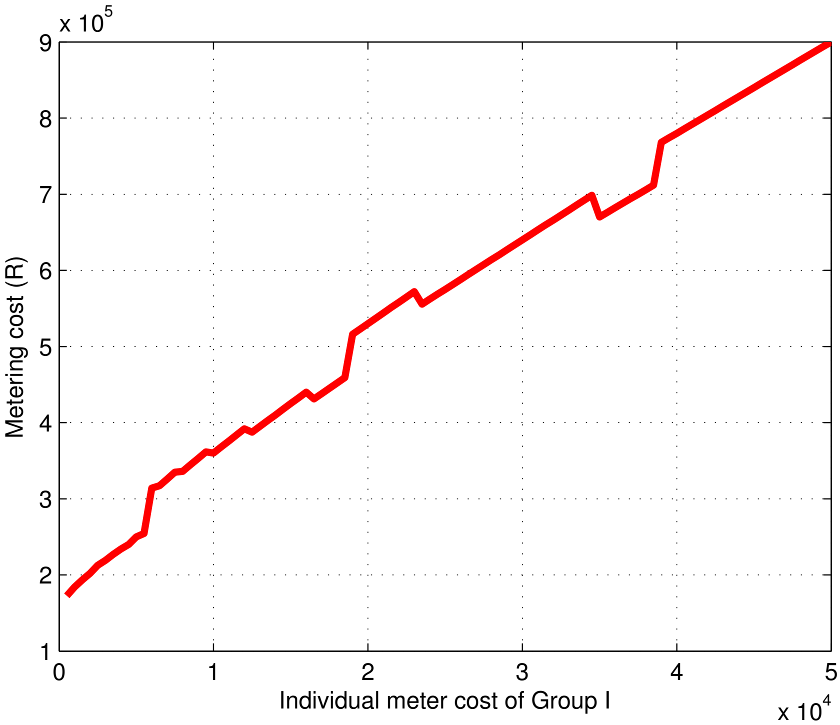

Figure 4.13: Metering cost when M_1 changes.

to further analyse the metering cost reduction performance for other similar lighting energy efficiency projects, three simulations are conducted to investigate the relationships between the optimal metering cost and population sizes, CV values, and meter equipment cost of different lighting groups. The simulation results indicate that the proposed metering cost minimisation model can be applied to different lighting projects. In addition, the proposed model is also applicable to minimise the metering cost for projects with sampling accuracy requirements other than the 90/10 criterion.

CHAPTER 5

LONGITUDINAL METERING COST MINIMISATION

5.1 CHAPTER OVERVIEW

The SMCM model is introduced in Chapter 4 to optimise the M&V metering plan without considering the lighting population decay dynamics over the long term. Practically, the project lamp population will decay due to lamp breakage, theft or other unpredicted damages. Sampling theory [128] indicates that sample size can be reduced when sampled population size becomes smaller. In this chapter, a longitudinal metering cost minimisation (LMCM) model is proposed to reduce the M&V metering cost by balancing the sampling uncertainties across adjacent reporting years over the lighting projects' life cycle when lighting population decays. The idea is to optimally decide the required annual confidence and precision levels over the projects' crediting period. The LMCM model takes considerations of different lamp population decay characteristics, CV of the lighting daily energy usage, meter prices, and required sampling accuracy level for each project reporting period. The optimal solution to the LMCM problem minimises the metering cost whilst satisfying the required M&V accuracy. The effectiveness of the LMCM is illustrated by a lighting retrofit case study. The LMCM model is applicable for homogeneous lighting population with similar energy usage patterns and lamp population decay dynamics.

5.2 INTRODUCTION

The LMCM model optimally determines the annual sample sizes over the projects' crediting period by considering the required confidence and precision levels and the lighting population decay dynamics.

The model is expected to be applicable to lighting projects with different characteristics such as different population sizes, different energy consumption uncertainties, different sampling accuracy requirements, different crediting periods, and different reporting intervals. The optimisation idea is illustrated by the following example. Given a lighting retrofit project whose savings performance is required to be reported every two years with an expected sampling accuracy of 90/10 criterion, then it may require 50 samples in the first year but only 30 samples in the second year to satisfy the 90/10 criterion when lighting population decays. In this case, 50 meters must be commissioned in the first crediting year with 20 surplus and unnecessary samples in the second year. Alternatively, let 40 samples be installed in the first year to achieve a poor accuracy as 80/20, these 40 samples may be sufficient to achieve a better accuracy such as 95/5 when the lighting population decreases in the second year. The combined accuracy over the two-year reporting period may still meet the 90/10 criterion. When comparing the two metering plans, the latter requires only 40 samples to initialise the metering system instead of 50 meters, which contributes to a reduction of the project metering cost.

To implement the optimisation idea, an LMCM model needs to be developed to calculate the required annual confidence and precision levels, and the optimal sample sizes that satisfy the desired 90/10 criterion over each reporting period. To establish this model, a cost function that covers the meter procurement, installation and maintenance costs of the metering system over the crediting period is formulated as the objective function. The required sampling accuracy of each performance report, which is given in terms of cumulative confidence and precision is formulated as the constraints of the LMCM model. Without loss of generality, the 90/10 criterion is applied as the constraint for this model. A lamp population decay model proposed in the CDM guideline AMS-II.J [141] is adopted and incorporated in both the objective function and the constraints. With the LMCM model, the required annual sample sizes are optimised without violating the 90/10 criterion constraints whilst the metering cost for the overall project is minimised. The advantages of the proposed model are illustrated by a case study of a lighting retrofit project.

5.3 LAMP POPULATION DECAY MODELLING

A linear lamp population decay model is proposed in the AMS-II.J [141] as given in Equation (5.1)

$$f(k) = \begin{cases} k \times H \times \frac{100-Y}{100 \times L}, & \text{if} \quad k \times H < L, \\ 100\%, & \text{if} \quad k \times H \geq L, \end{cases} \tag{5.1}$$

where k denotes the kth crediting year, Y is the percentage of lamps that are operating at the rated lifetime, whose recommended value is 50. H is the annual average operating hours of the lamps and L is the rated lifespan of a kind of lamp, which can be obtained from the lamp specification. $f(k)$ denotes the percentage of lamps that fails to work in the kth year after installation and when $k \times H \geq L$, $f(k) = 100\%$, all lamps are deemed to be failed and no more incentive will be issued for the lighting project.

5.4 ASSUMPTIONS AND MODELLING

The following assumptions apply to the LMCM model.

(1) The sampled lamps can be isolated and measured.

(2) The lamp population do not decay during the baseline period and the duration for project implementation is negligible.

(3) During the reporting period, maintenance will be performed to the meters in use but not to the backup meters. In addition, inflation is not considered in this model.

(4) The lamp population decay model uncertainties are not considered.

(5) The random variable $X(k)$ denotes the daily lamp energy consumption in the kth year. Recalling the well-known Central Limit Theorem [121], the random variable $X(k)$ is assumed to be subject to normal distribution, specifically, $X(k) \sim \mathscr{N}(\mu(k), \sigma(k)^2)$, where $\mu(k)$ and $\sigma(k)$ denote the true mean and true standard deviation in the kth year. If $n(k)$ samples are drawn in the kth year, the sample mean $\bar{X}(k)$ also follows a normal distribution $\bar{X}(k) \sim \mathscr{N}(\mu(k), \sigma(k)^2/n(k))$ [93].

(6) The $\bar{X}(k)$'s are independent and a series of the $\bar{X}(k)$'s over the crediting period will follow a normal distribution $\bar{\chi}(K) \sim \mathscr{N}(\theta(K), \Gamma(K)^2)$, where $\bar{\chi}(K)$ is the cumulative sample mean up to the Kth crediting year,

$$\bar{\chi}(K) = \frac{\sum_{k=1}^{K} N(k)\bar{x}(k)}{\sum_{k=1}^{K} N(k)};$$

$\theta(K)$ is the cumulative true mean up to the Kth crediting year,

$$\theta(K) = \frac{\sum_{k=1}^{K} N(k)\mu(k)}{\sum_{k=1}^{K} N(k)};$$

and $\Gamma(K)$ is the cumulative standard deviation up to the Kth crediting year,

$$\Gamma(K) = \sqrt{\sum_{k=1}^{K} \frac{\sigma(k)^2}{n(k)} \cdot \frac{N(k)^2}{\left(\sum_{k=1}^{K} N(k)\right)^2}},$$

where $\bar{x}(k)$ is the value of the sample mean $\bar{X}(k)$ in the kth year. Applying the Z-transformation formula

$$z = \frac{\bar{x} - \mu}{\sigma/\sqrt{n}},$$

one has

$$Z(\delta) = \frac{\bar{\chi}(\delta) - \theta(\delta)}{\Gamma(\delta)}, \tag{5.2}$$

and

$$P(\delta) = \frac{\bar{\chi}(\delta) - \theta(\delta)}{\bar{\chi}(\delta)}, \tag{5.3}$$

where δ ($1 \leq \delta \leq K$) is the year to develop the project performance report. $Z(\delta)$ and $P(\delta)$ are the cumulative z-score and precision level up to the δth crediting year.

The LMCM problem is translated into an optimisation problem, which minimises the metering cost whilst satisfying the desired 90/10 criterion constraints. The design variables are the confidence and precision levels in the kth year. The annual metering costs over the crediting period are listed in Table 5.1 and the metering cost function is summarised in Equation (5.8). The metering cost for the baseline period includes the meter procurement, installation and 3 months' maintenance cost of $n(0)$ meters. During the crediting period, maintenance cost is only required for the meters in use. As the lamp population decays, the number of required meters may also decease. If fewer meters are required in the $(k+1)$th year than the installed meters in the kth year, then the surplus meters remain onsite for backup use. The backup meters are denoted by $B(k)$ and

$$B(k) = max(B(k-1), 0) + n(k-1) - n(k).$$

On the other hand, if more meters are required in the $(k+1)$th year than the available meters in the kth year, then some extra meters will be purchased and installed. In Table 5.1, $S(k)$ is defined as follows,

$$S(k) = \frac{1}{2} sgn(B(k)) - \frac{1}{2} = \begin{cases} 0, & \text{if} \quad B(k) > 0, \\ -\frac{1}{2}, & \text{if} \quad B(k) = 0, \\ -1, & \text{if} \quad B(k) < 0, \end{cases} \tag{5.4}$$

where the sign function

$$\text{sgn}(t) = \begin{cases} 1, & \text{if} \quad t > 0, \\ 0, & \text{if} \quad t = 0, \\ -1, & \text{if} \quad t < 0. \end{cases} \tag{5.5}$$

Table 5.1: List of annual metering cost and backup meters.

Year	Meters	Metering cost	Backup meters
0	$n(0)$	$(a+b+3c)*n(0)$	$B(0)=0$
1	$n(1)$	$12c*n(1)+B(1)S(1)*(a+b)$	$B(1)=max(B(0),0)+n(0)-n(1)$
2	$n(2)$	$12c*n(2)+B(2)S(2)*(a+b)$	$B(2)=max(B(1),0)+n(1)-n(2)$
...	...	...	...
k	$n(k)$	$12c*n(k)+B(k)S(k)*(a+b)$	$B(k)=max(B(k-1),0)+n(k-1)-n(k)$

Let $z(k)$ and $p(k)$ represent the z-score and the relative precision, then the sample size $n(k)$ is calculated by

$$n(k) = ceil\left(\frac{z(k)^2CV(k)^2N(k)}{z(k)^2CV(k)^2+N(k)p(k)^2}\right), \tag{5.6}$$

in which

$$N(k) = N(0)*(1-f(k)), \tag{5.7}$$

where $N(0)$ is the lighting population in the baseline period, which is the same as the number of energy efficient lamp installations. The function $f(k)$ is the lamp population decay model as defined in the Subsection 5.3.

In summary, the metering cost minimisation model is to find

$$\lambda = (z(1), p(1), \ldots, z(K), p(K))$$

that minimises

$$f(\lambda) = (a+b+3c)\times n(0) + \sum_{k=1}^{K}(12c\times n(k) + B(k)S(k)(a+b)), \tag{5.8}$$

subject to the constraints

$$\begin{cases} Z(\delta) \geq 1.645, \\ P(\delta) \leq 10\%. \end{cases} \tag{5.9}$$

where $\delta = \{2,4,...,K\}$ if it is planned to report the performance every the other year; [1] a, b, and c are the meter procurement, installation, and maintenance prices per unit, respectively.

[1] Obviously, one can also let $\delta = \{1,4,7,...,K\}$ when other reporting intervals are agreed by the project stakeholders.

5.5 CASE STUDY: MODEL APPLICATION TO A CDM LIGHTING PROJECT

5.5.1 Backgrounds of a CDM lighting project

As given in one of the CDM PDDs [157], the project activity is to boost the energy efficiency of South Africa's residential lighting stock by distributing CFLs free of charge to households in the provinces of Gauteng, Free State, Limpopo, Mpumalanga and Northern Cape. There are approximately 607,559 CFLs to be distributed to replace the in use inefficient ICLs. The 20 W CFLs will be directly installed to replace the same number of 100 W ICLs. The CFLs with a special designed long rated life of 20,000 h provide equivalent lumen to the replaced ICLs. The walk through energy audit results show that the daily operating schedules of the ICLs are quite uncertain. However, the old lighting systems roughly burn 4.5 h per day on average. The removed ICLs will be stored and destroyed while counting and crushing certificates for the ICLs will be provided by a disposal company.

5.5.2 M&V plan

Daily energy consumptions of the lamps will be monitored and sampled in both baseline and crediting period. There is only one kind of lamps involved in both the baseline and crediting period, it is assumed that the lighting systems are homogeneous either before or after the retrofitting, and simple random sampling approach can be adopted for the sampling [94].

The proposed LMCM model will be applied to design an optimal sampling plan for this project. The model determines the optimal sample size and these samples will be randomly selected and monitored where the baseline lamps are in use. A detailed metering and sampling plan is designed as follows.

(1) The crediting period of this project is 10 years. The monitoring reports will be compiled every 2 years post implementation. The sampled parameters must satisfy the 90/10 criterion in each performance report.

(2) The meters will be purchased and installed during the baseline period. The daily energy consumption of the baseline lamps will be measured for 3 months.

(3) The daily energy consumption of the sampled lamps will be continuously measured during the crediting period. The sampled lamps are under good maintenance condition to ensure detectability.

(4) Meters will be installed to monitor the sampled lamp appliance individually. The metering devices are installed without reallocation. Necessary calibration and maintenance of the metering systems will be performed regularly on a monthly basis.

Since the sampling targets exhibit high uncertainties, high accuracy meters with the specifications listed in Table 5.2 are recommended. According to [99], the key components of the metering cost include meter procurement cost, installation cost and maintenance cost. The cost implications are also given in Table 5.2 as provided by a local meter supplier.

Table 5.2: Metering device specifications.

Categories	**Values**
Voltage range (AC)	100-380 V
Current range (AC)	10 mA-100 A
Accuracy	$\pm$ 0.2 %
Time resolution	0.5 s
Memory capacity	8 MB
Procurement cost (per unit)	R 4,032
Installation cost (per unit)	R 420
Monthly maintenance (per unit)	R 122

5.6 OPTIMAL SOLUTION TO THE CASE STUDY

5.6.1 Initial values for the model

Now consider solving the metering cost minimisation model given in model (5.8)-(5.9) for the case study. Due to the nonlinear nature of the model, there are no closed form solutions to be directly applied. In this study, only numerical solutions to this model are discussed with practical initial values that are identified from the walk through energy audit.

In the objective function (5.8), the metering equipment cost including procurement, installation and maintenance is obtained from meter suppliers. The annual optimal sample sizes are determined by $z(k)$, $p(k)$, $N(k)$ and $CV(k)$, where $z(k)$ and $p(k)$ are the design variables, $N(k)$ is calculated by Equation (5.7). Since metering data are not available at the planning stage, $CV(k)$=0.5 is assumed to be applicable in the crediting period. Since the metering system monitors the same target, it is also assumed that the value of annual sample mean $\bar{x}(k)$ remains constant. Thus the annual standard deviation $\sigma(k)$ is also constant, and $\sigma(k) = CV(k)\bar{x}(k)$.

The energy audit results indicate L=20,000 h, H=1,460 h and $Y = 50$. The lamp failure rates are calculated by Equation (5.1) and listed in Table 5.3.

Table 5.3: CFL failure rate.

Year	**1**	**2**	**3**	**4**	**5**
LFR	4.56%	9.13%	13.69%	18.25%	22.81%
Year	**6**	**7**	**8**	**9**	**10**
LFR	27.38%	31.94%	36.50%	41.06%	45.63%

In summary, the initial values to solve model (5.8)-(5.9) are provided in Table 5.4.

Table 5.4: Initial values.

Parameters	**Values**
Meter unit price	a=4,032
Installation per meter	b=420
Monthly maintenance	c=122
CV	$CV(k)$= 0.5
Initial population	$N(0)$=607,559
Reporting years	δ=2, 4, 6, 8, 10

5.6.2 Benchmark

In order to demonstrate the advantages of the proposed LMCM model, the metering costs for the case study without optimisation are calculated as a benchmark for comparison purpose. Without optimisation, the 90/10 criterion will probably be directly applied to decide the sample sizes for each crediting year.

The metering costs for this project without optimisation are summarised in Table 5.5. The CFL population decay dynamics are also considered for the solutions without optimisation. The CDM programme applies a linear CFL population decay model and the survived lamp population also follows a linear function as shown in Figure 5.1. It shows that around half of the lamps are survived at the end of the 10th year. This suggests a great potential of metering cost reduction.

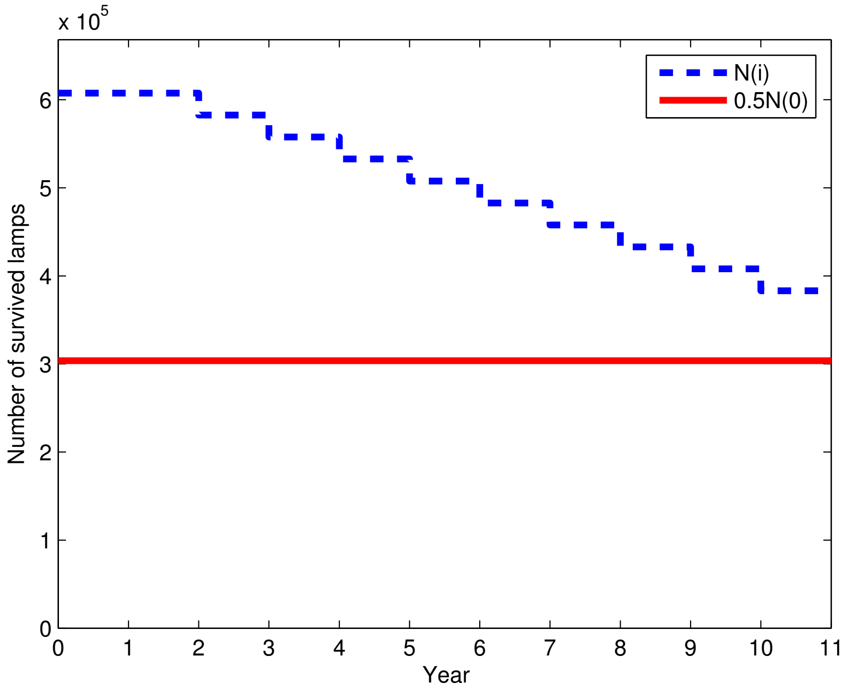

Figure 5.1: Survived lamps over crediting period.

As shown in Table 5.5, an overall metering cost of R 1,323,144 needs to be invested. It is also found that as the 90/10 criterion is satisfied during each year, the cumulative confidence and precision levels for the monitoring reports that are developed in the Years 2, 4, 6, 8 and 10, are much better than the 90/10 criterion, which are unnecessary.

5.6.3 Optimal solution

The Matlab function “fmincon” is applied to find the optimal solution to model (5.8)-(5.9). The optimisation settings of the “fmincon” function are shown in Table 5.6, where the interior-point algorithm is chosen as the optimisation algorithm; the three termination tolerances on the function value, the constraint violation, and the design variables are also given. In addition, “fmincon” calculates the Hessian by a limited-memory, large-scale quasi-Newton approximation, where 20 past iterations are remembered. Besides these settings, a search starting point λ_0 and the boundaries of the design variable are also assigned.

Table 5.5: Metering plan without optimisation.

Year	$z(k)$	$p(k)$	$Z(k)$	$P(k)$	$n(k)$	Cost (R)
0	90%	10%	90.00%	9.97%	68	367,264
1	90%	10%	90.00%	9.97%	68	99,552
2	90%	10%	**98.00%**	**9.97%**	68	99,552
3	90%	10%	99.56%	9.97%	68	99,552
4	90%	10%	**99.90%**	**9.97%**	68	99,552
5	90%	10%	99.98%	9.97%	68	99,552
6	90%	10%	**99.99%**	**9.97%**	68	99,552
7	90%	10%	100%	9.97%	68	99,552
8	90%	10%	**100%**	**9.97%**	68	99,552
9	90%	10%	100%	9.97%	68	99,552
10	90%	10%	**100%**	**9.97%**	68	99,552
Total	n/a	n/a	n/a	n/a	**68**	**1,323,144**

Table 5.6: Optimisation settings.

Categories	**Options**
Algorithm	interior-point
TolFun	10^{-45}
TolCon	10^{-45}
TolX	10^{-45}
Hessian	'lbfgs', 20
lb: $(z(1), p(1), \ldots, z(10), p(10))$	$(0, 0, \ldots, 0, 0)$
ub: $(z(1), p(1), \ldots, z(10), p(10))$	$(+\infty, 1, \ldots, +\infty, 1)$
λ_0: $(z(1), p(1), \ldots, z(10), p(10))$	$(1, 0, \ldots, 1, 0)$

From a mathematical perspective, the sample sizes, which are integer numbers, must be solved through integer programming algorithms. Since this study focuses on the practical issues of minimising the metering cost, real-valued sample sizes are used during the optimisation. After the optimal solution λ^*=$(z(1), p(1), \ldots, z(10), p(10))$ is found, the ceil function is applied to obtain the integer sample sizes. Mathematically, the rounded sample sizes by the ceil function are only sub-optimal solutions. Henceforth, the terminologies "optimal/optimise" and "minimal/minimise" only refer to the rounded sub-optimal solutions.

Table 5.7: Optimal metering plan.

Year	$z(k)$	$p(k)$	$Z(k)$	$P(k)$	$n(k)$	Cost (R)
0	60.91%	7.38%	59.84%	7.19%	34	163,812
1	60.91%	7.38%	59.84%	7.19%	34	49,776
2	86.16%	12.74%	**90.00%**	**9.98%**	34	49,776
3	53.81%	11.17%	89.40%	10.25%	11	16,104
4	42.88%	8.78%	**90.14%**	**9.91%**	11	16,104
5	35.78%	9.34%	88.53%	9.46%	7	10,248
6	39.61%	10.70%	**90.31%**	**9.85%**	6	8,784
7	28.74%	9.03%	89.98%	9.67%	5	7,320
8	33.86%	11.03%	**90.39%**	**9.78%**	4	5,856
9	25.39%	9.30%	90.49%	9.68%	4	5,856
10	28.28%	10.74%	**90.53%**	**9.69%**	3	4,392
Total	n/a	n/a	n/a	n/a	**34**	**338,028**

Table 5.7 gives the optimal solutions such as $z(k)$, $p(k)$, $Z(k)$, $P(k)$, $n(k)$ and the annual metering cost. Comparing to Table 5.5, it is found in Table 5.7 that the cumulative confidence and precision levels for each performance report satisfy the 90/10 criterion. In addition, the sample size is minimised and the overall metering cost is reduced considerably. Specifically, the overall metering cost without optimisation is around 1.323 million Rand. With the optimisation model, the overall metering cost is around 0.338 million Rand. The metering cost has been reduced 74.45% with the application of the proposed LMCM model.

Besides the optimal results listed in Table 5.7, Figures 5.2-5.4 show the annual and cumulative confidence/precision levels, and annual adopted meters and backup meters, respectively. In these figures, Year [0,1) denotes the baseline period and Years [1, 11) denote the reporting period.

In Figure 5.2, the dashed line (in blue) represents the optimal annual confidence levels while the solid line (in red) represents the cumulative confidence levels. Although the optimised annual confidence levels are poorer than 90%, the cumulative confidence levels satisfy the required 90% confidence during the reporting years, particularly in the Years 2, 4, 6, 8 and 10.

In Figure 5.3, the annual optimal precision levels are denoted by the dashed line (in blue) and the

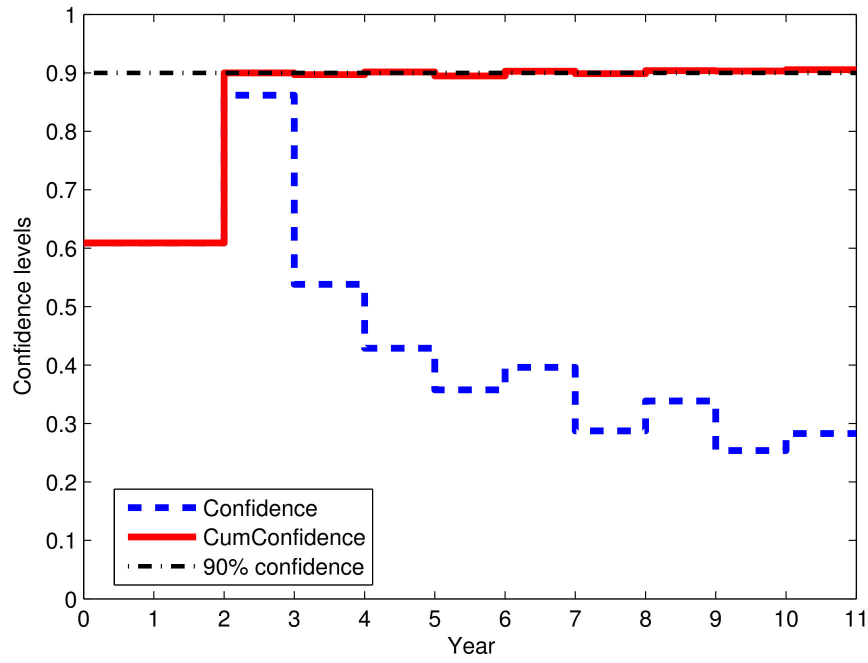

Figure 5.2: Annual and cumulative confidence levels.

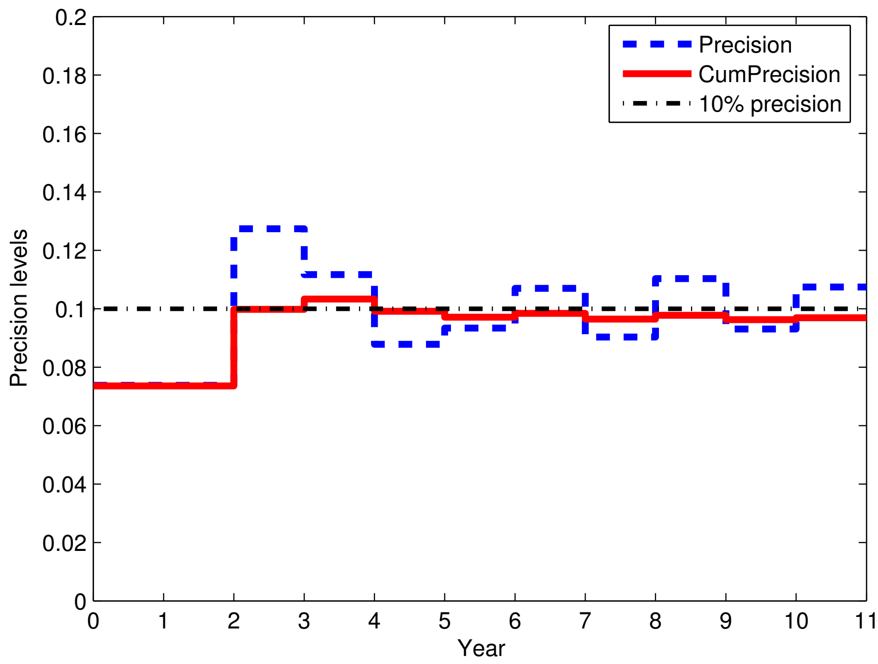

Figure 5.3: Annual and cumulative precision levels.

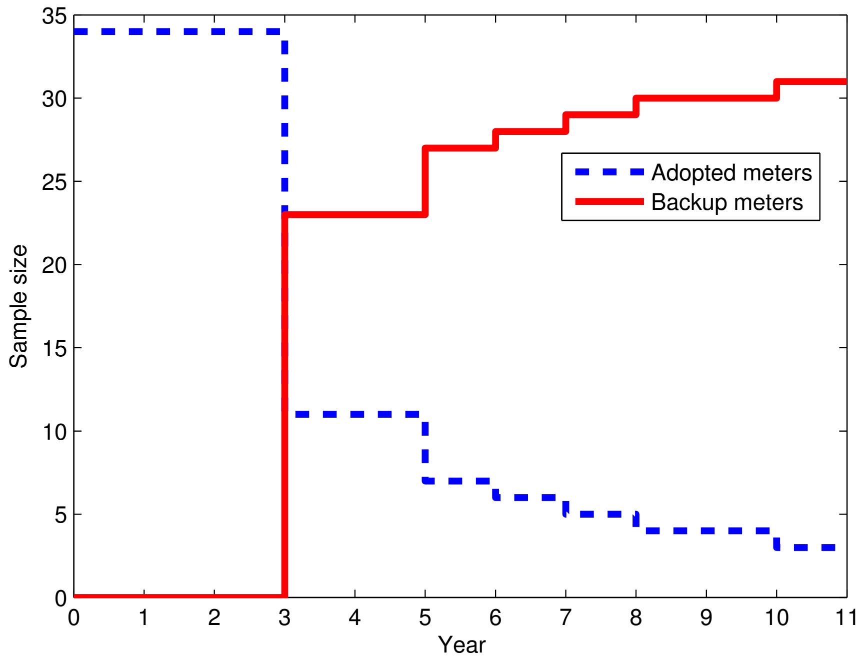

Figure 5.4: Annual adopted meters and backup meters.

cumulative precision levels are represented by the solid line (in red). It is observed that the cumulative precision levels in the Years 2, 4, 6, 8 and 10 are always within the boundaries of 10% error band. It confirms that all the constraints in model (5.8)-(5.9) are satisfied.

In Figure 5.4, the optimised sample size is denoted by the dashed line (in blue) and the backup meters is represented by the solid line (in red). It is found that the sample sizes generally decrease as the lamp population decays. It is also observed that for each 2-year reporting period, i.e. Years 1-2, Years 3-4, the samples do not change too much. However, the sample sizes change significantly across reporting periods, i.e., across Years 2-3, Years 4-5. It indicates that the proposed model tries to balance the samples within the reporting periods in order to minimise the metering cost. It is also observed that there are backup meters at the end of the project. These meters can be removed and sold out at a lower price or be reused in other similar lighting retrofit projects.

5.6.4 Model application and discussion

The case study illustrates that the proposed LMCM model is useful in designing the optimal M&V metering plan for lighting projects. However, different lighting projects have different initial lamp population, different lamp population decay dynamics, and different reporting intervals. In order to apply the proposed model flexibly to different lighting projects, necessary modifications of the initial lamp population, the lamp population decay model, and the reporting intervals must be considered. For instance, the lifespan and usage patterns of the lamps in different projects may be different, which will result in different lamp population decay characteristics. Over the crediting period, the survived lamp population influences the determination of sample sizes. The proposed model will also be applicable if incorporating an alternative lamp population decay model. More CFL lamp population decay models are investigated in [158] and case studies of the sampling plan design with the application of a nonlinear CFL lamp population decay model can be found in [104]. In other cases, the reporting intervals for the project performance may be designed to be every 3 years [159]. The model is still applicable while the constraints in model (5.8)-(5.9) are updated according to the specified reporting intervals.

5.7 CONCLUSION

In this study, an LMCM model is proposed to assist the optimal M&V metering plan designs of EE lighting projects. The metering cost is minimised by optimising the annual confidence and precision levels during the crediting period under the constraint of the 90/10 criterion for each performance report. The proposed LMCM model can be flexibly applied to other similar lighting projects. For instance, the model can be applied to LED retrofitting projects by adopting LED population decay models. And the proposed model is applicable to lighting projects with different monitoring report intervals. In addition, this model can also be applied to projects with an accuracy requirement other than the 90/10 criterion.

CHAPTER 6

OPTIMAL METERING PLAN FOR MEASUREMENT AND VERIFICATION

6.1 CHAPTER OVERVIEW AND INTRODUCTION

Chapter 4 has proposed an SMCM model to balance the sampling uncertainties across lighting groups. The SMCM model is applicable and useful in optimising the M&V metering plan, but without considering the lighting population decay dynamics over the projects' life cycle. Then Chapter 5 introduces an LMCM model to balance the sampling uncertainties across adjacent reporting years. The LMCM model is applicable for homogeneous lighting population with similar energy usage patterns and population decay dynamics.

The SMCM model is insufficient to deal with the lamp population decay dynamics, while the LMCM model cannot be directly applied to the lighting projects with inhomogeneous population. In order to accommodate lighting projects with multiple lighting groups but different energy consumption patterns and population decay dynamics across groups, an improved MCM model is proposed to further reduce the lighting project M&V metering cost by balancing the sampling uncertainties both spatially across homogeneous lighting groups and longitudinally over adjacent reporting years in this chapter. The proposed model is formulated as a combined spatial and longitudinal MCM model. In this model, the design variables are the required annual confidence and precision levels for each lighting group. The objective function is a cost function that covers the procurement, installation and maintenance of the M&V metering system. The sampling accuracy requirements are formulated as the constraints. In order to demonstrate the advantages of the proposed MCM model, an optimal metering plan is designed for a lighting retrofit project with two lighting groups as a case study.

Optimal solutions for the case study are obtained by the proposed combined spatial and longitudinal MCM model with the consideration of the project specific characteristics. The optimal solutions provide useful and sufficient M&V metering plan information such as the required lighting samples to be measured in each lighting groups, the achieved sampling accuracy in terms of confidence and precision levels as well as the annual and total M&V metering cost for the studied lighting project. The case study demonstrates the advantageous performance of the proposed spatial and longitudinal MCM model in designing cost-effective M&V metering plan whilst satisfying the M&V accuracy requirements. This model will be widely applicable to design the optimal metering plan for various M&V lighting projects with different population sizes and sampling accuracy requirements.

6.2 FORMULATION OF THE OPTIMAL M&V METERING PLAN PROBLEM

In this section, the optimal M&V metering plan problem is formulated as a combined spatial and longitudinal MCM model under necessary modelling assumptions, with the considerations of lamp population decay dynamics.

6.2.1 Lamp population decay modelling

As discussed in Equations (3.1) and (2.5), the survived lamp population is crucial for the M&V baseline adjustment, savings calculation, and sample size determination. Without an accurate model to characterise the lamp population decay dynamics, the survived lamp population needs to be frequently sampled and counted. The inspections on the survived lamp population at different time intervals over the projects' crediting period are helpful for the project performance evaluation, M&V metering plan design, and necessary maintenance planning. But the regular inspection approach is usually very costly and time-consuming as such inspections have to be conducted repeatedly for various lighting projects with different characteristics. In order to alleviate the lamp population inspection burdens, the lamp population decay dynamics are characterised by various models that have been established from biological population dynamics study or from reliability engineering experiments. For instance, the studies [158, 104] have performed an informative review on the existing lamp population decay dynamics and proposed a reliable lamp population decay model that is improved from existing models as given in [146, 113]. The general form of the model is provided in Equation (6.1)

$$s(\tau) = \frac{1}{\gamma + \alpha e^{\beta \tau}}, \tag{6.1}$$

where $s(\tau)$ is the percentage of survived devices at time τ for a lighting project, τ is counted from the beginning of lamp installations. $\alpha = e^{-L}$ and L is the rated average life span of a certain model of the EE devices. Following CDM guidelines [141], the rated average life span is declared by the manufacturer or responsible vendor as being the expected time at which 50% of any large number of EE devices reach the end of their individual lives. β is the slope of decay and γ is initial percentage lamp survival at $\tau = 0$. Thus, values for β and γ can be obtained by solving the following system of equations:

$$\begin{cases} s(0) = 1, \\ s(L) = 0.5. \end{cases} \tag{6.2}$$

The discrete and dynamical form of model (6.1) is also given in [158, 104] as follows

$$s(k+1) = \tilde{\beta}\tilde{\gamma}s(k)^2 - \tilde{\beta}s(k) + s(k), \tag{6.3}$$

where $s(k)$ is the survived percentage of the lighting project population at the kth sampling interval. Note that for different lighting groups, the parameters $\tilde{\beta}$ and $\tilde{\gamma}$ are different and they can be obtained by the system identification approach proposed in [158, 104].

6.2.2 Modelling and assumptions

According to the metering plan given in Subsection 3.6, the daily energy consumption $E_i(t)$ needs to be monitored by long-term measurement over the baseline and post-retrofit periods. Thus the measurement uncertainties and sampling uncertainties must be properly handled to ensure the satisfaction of the required 90/10 criterion. In order to reduce the measurement uncertainties, the metering devices need to be carefully selected with full considerations of their accuracy levels and cost implications. According to [99], the key components of the metering cost include meter procurement cost, installation cost and maintenance cost. In order to design a cost-effective metering plan, it is suggested to use different metering devices with different memory capacities, data transmission functions and accuracy levels for lighting groups with different uncertainties. Hence the meters will be selected according to the estimated CV values in various lighting groups. Particularly, if $CV < 0.25$, the less expensive metering with acceptable accuracy will be chosen. Otherwise if $CV \geq 0.25$, then expensive and sophisticated meters will be applied. In general, measurement uncertainties are ignorable when the accuracy levels of the selected M&V meters are much better than the 90/10 criterion.

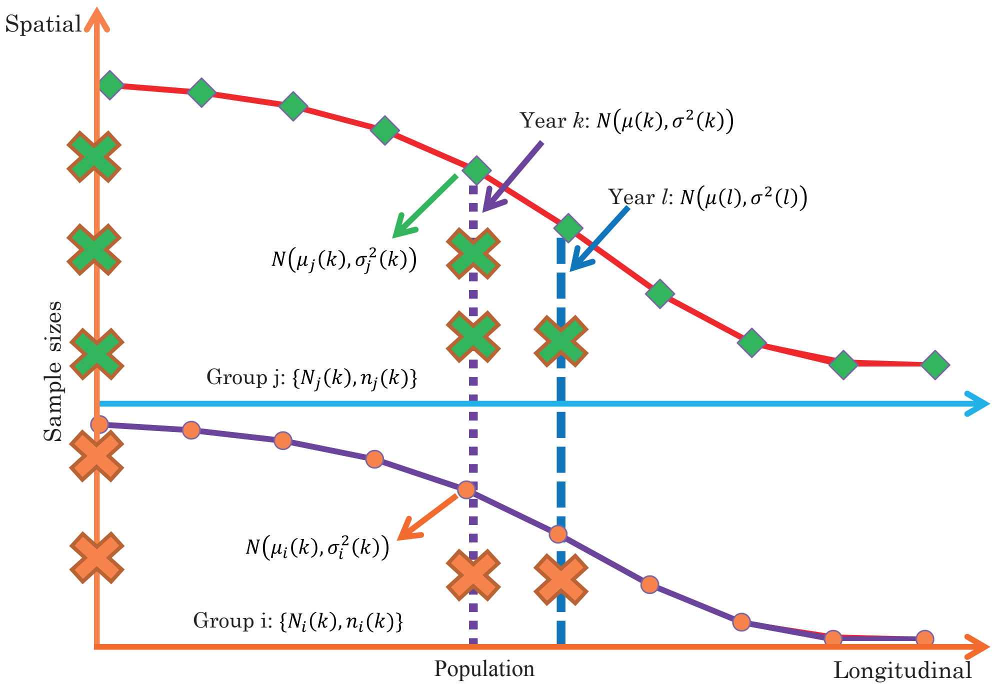

Figure 6.1: Illustration for modelling.

The sampling uncertainties can be handled by suitable choice of the sampling approach and proper determination of sample sizes. In this chapter, the stratified random sampling approach is applied and the required samples to be metered are determined by the combined spatial and longitudinal MCM model in order to achieve the 90/10 criterion for the sampled and metered variables cost-effectively. The optimisation ideas of the combined spatial and longitudinal MCM model are illustrated by Figure 6.1. On the spatial domain at the kth year, the lighting project population is classified into I homogeneous strata according to different uncertainty levels of the daily energy consumption for individual lamps. In the kth year, let $z_i(k)$ and $p_i(k)$ denote the z score and the precision levels in the ith group, $z(k)$ and $p(k)$ denote the combined z score and precision levels across all subgroups, respectively; $N_i(k)$ and $n_i(k)$ denote the survived lamp population and the required sample size in the ith group of the kth year, respectively. $N(k)$ denote the total survived lamp population in the kth year, and

$$N(k) = \sum_{i=1}^{I} N_i(k).$$

The spatial sampling uncertainties across all lighting groups in the kth year can be analyzed as follows. Let $X_i(k)$ be the random variable that denote the daily energy consumption for individual lamps of the ith lighting group in the kth year. From the well-known Central Limit Theorem [121], it is assumed that $X_i(k)$ follows normal distribution $X_i(k) \sim \mathcal{N}(\mu_i(k), \sigma_i(k)^2)$ given the large lamp population in the

ith group, where $\mu_i(k)$ is the true mean value, $\sigma_i(k)$ is the true standard deviation. If any $n_i(k)$ samples are drawn from the ith lighting group, the sample mean distribution satisfies a normal distribution $\bar{X}_i(k) \sim \mathscr{N}(\mu_i(k), \sigma_i(k)^2/n_i(k))$ [93]. Assume the sampled lamps are measured independently, then the $\bar{X}_i(k)$'s are independent and the combined distribution for the $\bar{X}_i(k)$'s in all lighting groups in the kth year is denoted by $X(k) \sim \mathscr{N}(\mu(k), \sigma(k)^2)$, where the combined sampled mean value $\bar{x}(k)$ for the total lighting population is calculated by

$$\bar{x}(k) = \frac{\sum_{i=1}^{I} N_i(k)\bar{x}_i(k)}{N(k)}, \tag{6.4}$$

the true mean value $\mu(k)$ for the total lighting population is calculated by

$$\mu(k) = \frac{\sum_{i=1}^{I} N_i(k)\mu_i(k)}{N(k)}, \tag{6.5}$$

and the true standard deviation $\sigma(k)$ for the total lighting population is calculated by

$$\sigma(k)^2 = \sum_{i=1}^{I} \frac{(\sigma_i(k)N_i(k))^2}{n_i(k)N(k)^2}. \tag{6.6}$$

The z transformation function in the ith lighting group of the kth year is given by

$$\bar{x}_i(k) - \mu_i(k) = z_i(k) \cdot \frac{\sigma_i(k)}{\sqrt{n_i(k)}}. \tag{6.7}$$

where $\bar{x}_i(k)$ is the sample mean in the ith group of the kth year and $\sigma_i(k) = \bar{x}_i(k)CV_i(k)$. Assume that the estimated daily energy consumptions and CV values in the ith group will not change over the credit period, then the standard deviation $\sigma_i(k)$ in the ith group of the kth year will remain unchanged.

The combined annual z score $z(k)$ and relative precision level $p(k)$ are calculated by

$$z(k) = \frac{\bar{x}(k) - \mu(k)}{\sigma(k)}, \tag{6.8}$$

and

$$p(k) = \frac{\bar{x}(k) - \mu(k)}{\bar{x}(k)}. \tag{6.9}$$

On the longitudinal domain over the crediting period, the project performance may need to be reported regularly at fixed reporting intervals, i.e., in the years of $\delta = \{2, 4, ..., K\}$, to the project developers and related stakeholders by M&V practitioners. In both the baseline year and the reporting years, the measured parameters need to satisfy a required accuracy level, i.e., the 90/10 criterion. It is clear that less samples are required to achieve the 90/10 criterion when the project population decays. For a performance report covers the years k and l, the possible sample size for the years k and l might be 30 and 10, respectively to achieve the 90/10 criterion. Then the initial investment must be made available for 30 meters in the kth year while the surplus 20 meters become unnecessary in the lth year. An optimal metering plan may be designed to install 20 meters for both the years k and l, such that a lower accuracy level, i.e., 85/15 is reached in the year k but a higher accuracy level, i.e., 95/5 is obtained in the year l. However, the combined accuracy level across the years k and l satisfies the 90/10 criterion.

In order to quantify the sampling uncertainties on the longitudinal domain, it is assumed that the installed metering system will not be relocated over the K years and the same sampled lighting units will be continuously measured. Thus the metered data from the Years 1 to $(k-1)$ will also be analyzed together with the metered data in the kth year. Further assume that $\bar{X}(k)$'s are independent, then the combined distribution for the $\bar{X}(k)$'s over the K years will follow a normal distribution $\bar{\chi}(k) \sim \mathcal{N}(\theta(k), \Gamma(k)^2)$, where

$$\bar{\chi}(K) = \frac{\sum_{k=1}^{K} N(k)\bar{x}(k)}{\sum_{k=1}^{K} N(k)}, \tag{6.10}$$

$$\theta(K) = \frac{\sum_{k=1}^{K} N(k)\mu(k)}{\sum_{k=1}^{K} N(k)}, \tag{6.11}$$

$$\Gamma(K)^2 = \sum_{k=1}^{K} \left(\frac{\sigma(k)N(k)}{\sum_{k=1}^{K} N(k)} \right)^2. \tag{6.12}$$

Let $Z(\delta)$ and $P(\delta)$ denote cumulative z score and cumulative precision levels by end of the δth year, respectively, then

$$Z(\delta) = \frac{\bar{\chi}(\delta) - \theta(\delta)}{\Gamma(\delta)}, \tag{6.13}$$

$$P(\delta) = \frac{\bar{\chi}(\delta) - \theta(\delta)}{\bar{\chi}(\delta)}. \tag{6.14}$$

As the lamp population decays, the number of required meters may also decease. Thus, if less meters are required in the kth year than the available meters installed in the $(k-1)$th year, then the surplus meters remain onsite for backup use. Let $B_i(k)$ denote the surplus meters in the kth year; a_i, b_i and c_i denote the meter procurement, installation and maintenance cost for each metering device in the ith group, respectively. Then the combined spatial and longitudinal MCM model is formulated under follow assumptions: **1)** The lighting population will not decay during the baseline period. The time for the project implementation can be ignored; **2)** During the credit period, maintenance will only be performed to the effective meters; **3)** The inflation/deflation of the metering cost will not be considered; **4)** The uncertainty of the lamp population decay model is ignorable.

Let the design variable be $\lambda = (\lambda(0),\ldots,\lambda(k),\ldots,\lambda(K))$, where $\lambda(k) = (z_1(k),\ldots,z_I(k),p_1(k),\ldots,p_I(k))$. The objective functions can be denoted by

$$\begin{aligned} f(\lambda) &= \textstyle\sum_{i=1}^{I}(a_i+b_i+3c_i)n_i(0) \\ &+\textstyle\sum_{k=1}^{K}\sum_{i=1}^{I}[12c_i n_i(k)+B_i(k)S_i(k)(a_i+b_i)]. \end{aligned} \tag{6.15}$$

$B_i(k)$ is calculated by

$$B_i(k) = max(B_i(k-1),0)+n_i(k-1)-n_i(k),$$

where $B_i(0)=0$, and $S_i(k)$ is defined as

$$S_i(k) = \mathrm{sgn}(B_i(k)) = \begin{cases} 0, & \text{if} \quad B_i(k)>0, \\ -\frac{1}{2}, & \text{if} \quad B_i(k)=0, \\ -1, & \text{if} \quad B_i(k)<0, \end{cases}$$

where $sgn(.)$ is the sign function. The constraints are are summarised as

$$\begin{cases} z(0) \geq 1.645, \\ p(0) \leq 10\%, \\ Z(\delta) \geq 1.645, \\ P(\delta) \leq 10\%. \end{cases} \tag{6.16}$$

where $\delta = \{2,4,...,K\}$. [1] The combined spatial and longitudinal MCM model is denoted by $C((6.15),(6.16))$.

6.3 CASE STUDY

In this section, an optimal metering plan is designed for a lighting retrofit project as a case study to illustrate the advantages of the proposed combined spatial and longitudinal MCM model.

6.3.1 Background of the lighting projects

A lighting retrofit project is going to be implemented in order to reduce the lighting load in 45 provincial hospitals in South Africa. It is planned to install 263 519 CFLs to replace existing inefficient

[1] Obviously, one can also let $\delta = \{1,4,7,...,K\}$ when other reporting intervals are agreed by the project stakeholders.

ICLs. In addition, 140 777 units of LEDs will be installed to replace the less energy efficient HDLs. The 12 W CFLs and 6 W LEDs will be adopted to replace the 60 W ICLs and 50 W HDLs, respectively. The ICLs are mainly installed in office rooms and burning during 8:00-16:00 everyday. The HDLs are installed in the corridors and hallways where motion sensors are currently in use to control the HDL lighting systems. The CFLs and LEDs will be directly installed to replace the ICLs and HDLs without changing the existing lighting control systems. The EE lamps have the equivalent lumen to the replaced old lamps. The CFLs have a rated life of 3 years while the LEDs have a rated life of 6 years. According to the agreements between the project sponsors and PDs, the energy saving performance of this project must be verified and reported in every 2 years' intervals over 10 years crediting period. PDs are responsible for the M&V cost that at least covers the metering system procurement, installation and maintenance. The energy consumption of the lighting system will be sampled and measured over the 3 months baseline period and the entire crediting period.

The involved lamps are naturally classified into two subgroups according to their different daily energy consumption uncertainties. Group I is the 263 519 ICLs and Group II is the 140 777 HDLs. The lighting classification remains unchanged after project implementation. The energy consumption uncertainties can be estimated by spot measurement during the on site project survey. For instance, the estimated daily energy consumption per lamp in Group I is 0.48 ± 0.09 kWh in the baseline period and 0.096 ± 0.018 kWh in the crediting period. CV value of the daily energy consumption per lamp in Group I is around 0.19. The energy consumption uncertainties in Group II are larger than those in Group I as the lamps are controlled by motion sensors. In this case, a CV value as high as 0.5 is recommended by [17] for Group II over both the baseline and crediting periods. The estimated daily energy consumption per lamp in Group II is 0.20 ± 0.10 kWh in the baseline period and 0.024 ± 0.012 kWh in the crediting period based on an assumption that on average the lamps are burning 4 hours per day with a low confidence. Since the energy consumption behaviours in Group II changes more frequently than those in Group I, the metering devices to be installed in Group II should be more advanced, i.e., with higher intelligent control units, faster sampling frequency and larger memory capacity. The Group II meters are capable of capturing the real time energy consumption in both groups but Group I meters are not applicable for the measurements in Group II. More detailed project information is summarised in Table 6.1 from the on site project survey.

Once the coefficients $\tilde{\beta}$ and $\tilde{\gamma}$ in (6.3) are identified, the lamp population decay dynamics are determined for this case study. In Figure 6.2, the horizontal axis denotes the count of years where Year k corresponds to the duration [k, k+1). For instance, Year 0 corresponds to the duration [0,1), denotes the baseline period and Years 1 to 10 correspond to the duration [1,11), denote the crediting period. The vertical axis denotes the survived population of the CFLs in Group I and that of the LEDs in Group II. It is observed that Group I has a higher initial lamp population. However, as the CFLs have shorter life span than the LEDs, the lamp population in the LED group becomes larger than that in the CFL group from the 5th year to the 10th year of the lighting project. In the following subsections,

Table 6.1: Lighting project details.

Parameters	**Group I**	**Group II**
Meter unit price	a_1=R 876	a_2=R 3 146
Installation per meter	b_1=R 195	b_2=R 320
Monthly maintenance	c_1=R 45	c_2=R 98
CV values	$CV_1(k) = 0.19$	$CV_2(k) = 0.50$
Baseline estimates	$\bar{x}_1(0) = 0.48$ kWh	$\bar{x}_2(0) = 0.20$ kWh
Post-retrofit estimates	$\bar{x}_1(k) = 0.096$ kWh	$\bar{x}_2(k) = 0.024$ kWh
Coefficient $\tilde{\beta}$ in (6.3)	$\tilde{\beta}_1 = 1.1438$	$\tilde{\beta}_2 = 1.0297$
Coefficient $\tilde{\gamma}$ in (6.3)	$\tilde{\gamma}_1 = 0.8553$	$\tilde{\gamma}_2 = 0.9201$

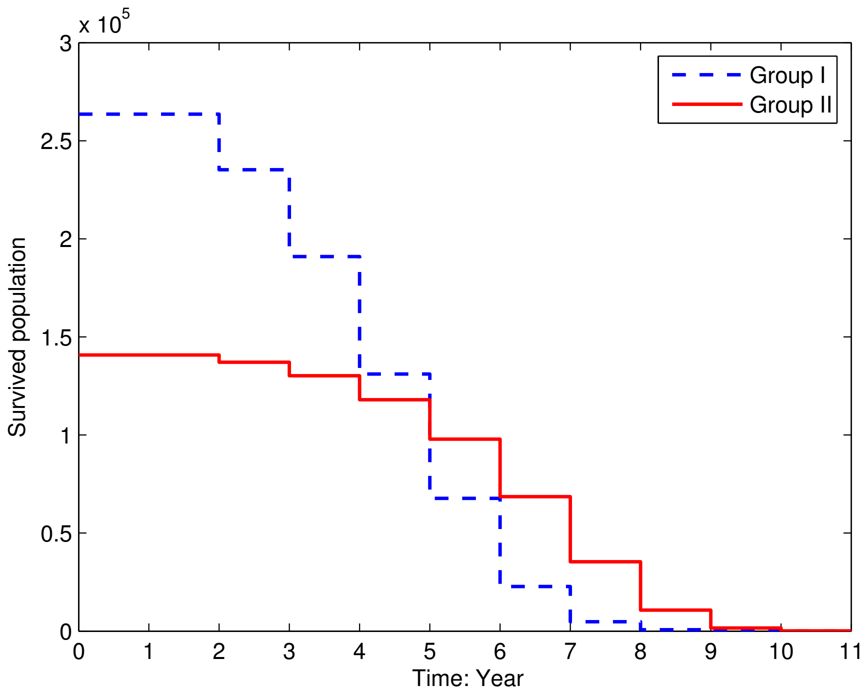

Figure 6.2: Survived lamp populations.

the required sample sizes in the ith lighting group are determined with the consideration of the lamp population decay dynamics as shown in Figure 6.2.

6.3.2 Benchmark

In order to maximise the PDs' profits, the proposed MCM model $C((6.15),(6.16))$ will be applied to find the most suitable metering plan for the M&V of the hospital lighting retrofit project. As to demonstrate the advantages of the proposed combined spatial and longitudinal MCM model, the metering plan without optimisation is calculated as a benchmark for comparison purpose.

For the hospital lighting retrofit project, a possible solution without optimisation might be that the 90/10 criterion is applied to the sampling target in both Groups I and II, where $\lambda_i(k) = (1.645_1(k), 1.645_2(k), 0.1_1(k), 0.1_2(k))$. The corresponding z-scores, precisions, sample sizes and metering costs are calculated as shown in Table 6.2. It shows that the precision levels are better than 10% while the worst z-score is higher than 1.645 for each monitoring report. The total metering cost over the baseline and crediting period is R 1 115 732. In this scenario, the expected sampling accuracy is better than the required 90/10 criterion, which is not necessary.

Table 6.2: Metering cost without optimisation.

Year	$Z(k)$	$C(k)$	$P(k)$	$n_1(k)$	$n_2(k)$	Cost (R)
0	**1.9665**	**95.06%**	**9.90%**	**10**	**68**	**267 740**
1	1.8500	93.57%	9.89%	10	68	85 368
2	**2.6234**	**99.13%**	**9.89%**	**10**	**68**	**85 368**
3	3.2122	99.87%	9.90%	10	68	85 368
4	**3.6682**	**99.98%**	**9.90%**	**10**	**68**	**85 368**
5	3.9677	99.99%	9.90%	10	68	85 368
6	**4.1110**	**100%**	**9.90%**	**10**	**68**	**85 368**
7	4.1617	100%	9.90%	10	68	85 368
8	**4.1747**	**100%**	**9.90%**	**10**	**68**	**85 368**
9	4.1767	100%	9.90%	9	68	85 368
10	**4.1769**	**100%**	**9.90%**	**7**	**65**	**85 368**
Total	**n/a**	**n/a**	**n/a**	**10**	**68**	**1 115 732**

6.3.3 Optimal solutions

For the hospital lighting retrofit project, the optimal metering plan can be obtained by solving the model $C((6.15),(6.16))$ with the application of the project specific information as given in Table 6.1. To find the solution for this case study, the computations are carried out by the Matlab program. In particular, the optimal solutions are computed by the "fmincon" code of the Matlab Optimisation Toolbox. The optimisation settings of the "fmincon" function are shown in Table 6.3, where the interior-point algorithm is chosen as the optimisation algorithm; the three termination tolerances on the function value, the constraint violation, and the design variables are also given. In addition, "fmincon" calculates the Hessian by a limited-memory, large-scale quasi-Newton approximation, where 20 past iterations are remembered. Besides these settings, a search starting point λ_0 and the boundaries of the design variable are also assigned.

Table 6.3: Optimisation settings.

Categories	**Options**
Algorithm	interior-point
TolFun	10^{-45}
TolCon	10^{-45}
TolX	10^{-45}
Hessian	'lbfgs', 20
lb: $(z_i(k),\ p_i(k))$	(0, 0)
ub: $(z_i(k),\ p_i(k))$	$(+\infty$, 1)
λ_0: $(z_i(k),\ p_i(k))$	(0.2, 0.2)

From a mathematical perspective, the sample sizes, which are integer numbers, must be solved through integer programming algorithms. Since this study arises from the practical issues of minimising the metering cost, real-valued sample sizes are used during the optimisation. After the optimal solution λ^* is found, the ceil function is applied to obtain the integer sample sizes. Mathematically, the rounded sample sizes by the ceil function are only sub-optimal solutions. Henceforth, the terminologies "optimal/optimise" and "minimal/minimise" may only refer to the rounded sub-optimal solutions.

The studied hospital lighting retrofit project includes different lighting groups with different daily energy consumption uncertainties. In addition, these lighting groups exhibit different lamp life spans and population decay dynamics. These project characteristics strongly indicate the applicability of the combined spatial and longitudinal MCM model as discussed in Section 6.2. In order to full reveal the superiority of the proposed model $C((6.15),(6.16))$, the optimal solutions obtained solely by the SMCM model in [160] and the LMCM model in [161] are also given in the following subsections for comparison.

6.3.3.1 Spatial optimisation

The SMCM model in [160] aims to balance the sampling uncertainties across lighting groups by assigning optimal confidence and precision levels to the lighting groups with different energy consumption uncertainties. For this case study, the spatial optimisation model is formulated as follows. The design variable is $\lambda = (\lambda(0),\ldots,\lambda(k),\ldots,\lambda(K))$, where $\lambda(k) = (z_1(k),z_2(k),p_1(k),p_2(k))$, $k = 0,1,\ldots,K$. The objective function is given in (6.15) that subject to the constraints

$$\begin{cases} z(k) \geq 1.645, \\ p(k) \leq 10\%. \end{cases} \tag{6.17}$$

The spatial optimisation model is denoted by $S((6.15),(6.17))$. The model $S((6.15),(6.17))$ is solved with the initial values given in Table 6.1 and the optimisation settings in Table 6.3. The obtained confidence levels, precision levels and optimal sample sizes are shown in Figures 6.3-6.5. In addition, the numerical optimal solutions and metering cost are summarised in Table 6.4.

In Figures 6.3-6.5, the horizontal axes denote the count of years and the vertical axes represent the confidence levels, precision levels and sample sizes, respectively. In Figures 6.3-6.4, optimal confidence and precision levels are presented, where the dashed line (in blue) and the solid line (in red) denote the confidence and precision levels for Group I and II, respectively; the dash-dotted line (in green) denotes the combined confidence and precision levels across lighting groups over the kth year while the starred line (in black) denotes the cumulative confidence and precision levels up to the kth year. As shown by the dash-dotted lines (in green) in both Figure 6.3 and Figure 6.4, the constraints in (6.17) are satisfied.

In Figure 6.5, the sample sizes in Group I and Group II are denoted by the dashed line (in blue) and the solid line (in red), respectively. The total sample sizes are denoted by the starred solid line (in black). It is observed that the sample sizes in Group I is greater than those in Group II during the years [0, 5) but becomes smaller than those in Group II during the years [6, 11). As discussed

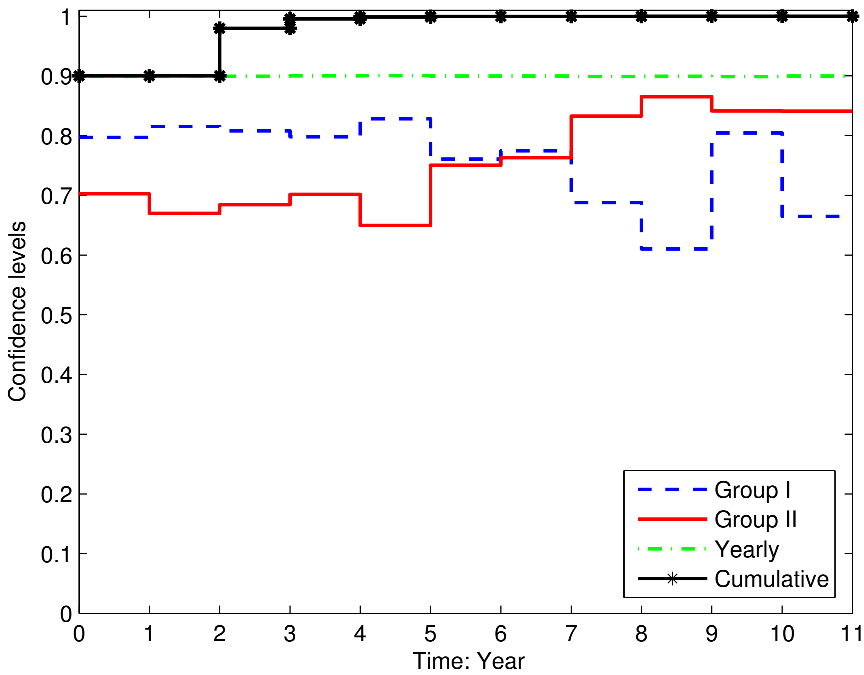

Figure 6.3: Confidence levels (spatial optimal only).

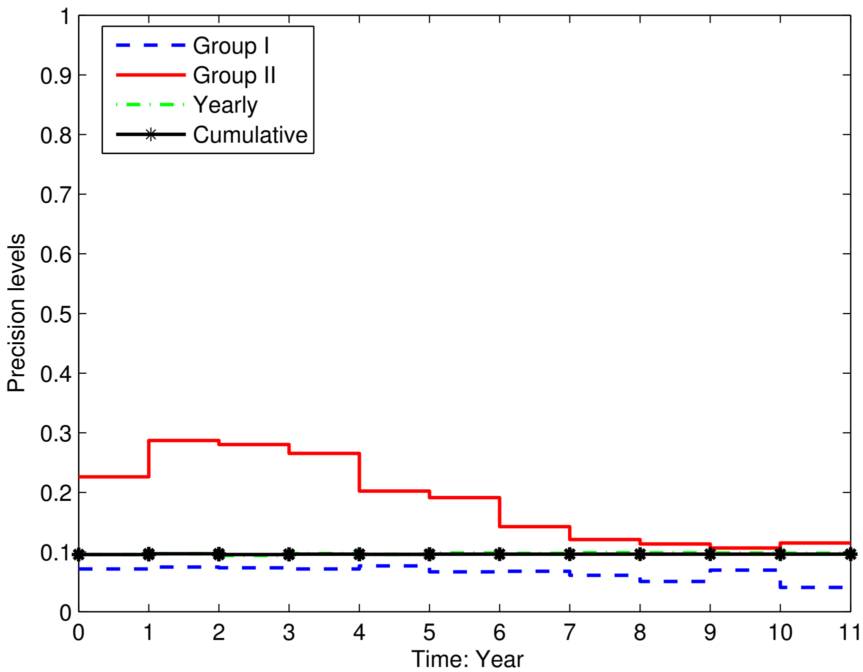

Figure 6.4: Precision levels (spatial optimal only).

in [160], the sample sizes change when population changes. To achieve a certain level of sampling accuracy, greater number of samples are usually taken for a larger population. However, it is worthy mentioning that in Year 5, $N_1(5) < N_2(5)$ but $n_1(5) > n_2(5)$ as shown in Figure 6.5. The reason is that the model $S((6.15),(6.17))$ attempts to use as many as less expensive meters used in Group I in order to minimise the total metering cost.

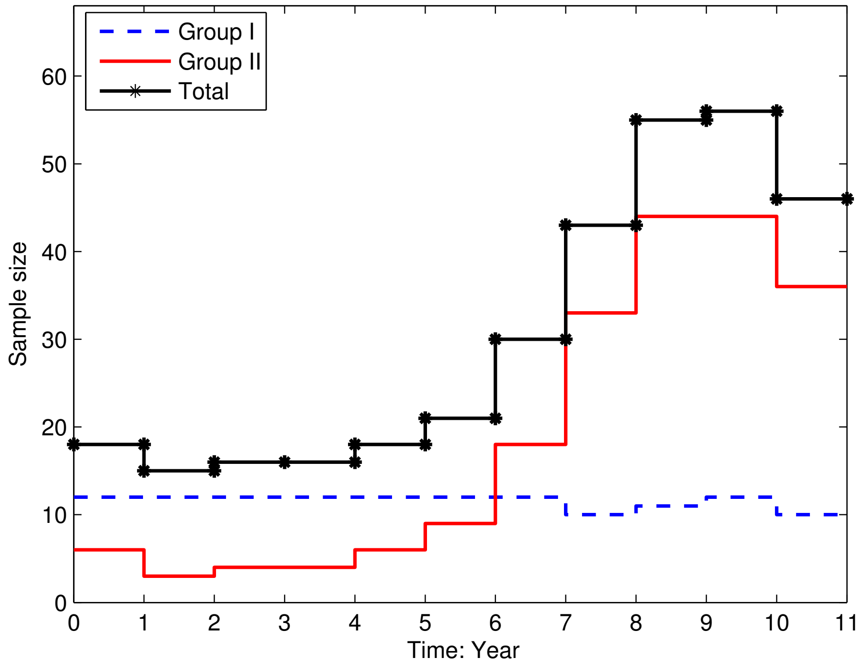

Figure 6.5: Number of meters (spatial optimal only).

In Table 6.4, $Z(k)$ is translated into the confidence levels $C(k)$. One may be very surprised to see that more samples are required when population decays in Group II. This is because that Group II has a relatively larger population and a higher CV as well than those in Group I in the years [6, 10), which result in a greater number of sample sizes to satisfy the required sampling accuracy. This is the major disadvantage of the SMCM model.

6.3.3.2 Longitudinal optimisation

The LMCM model in [162] and [161] aims to balance the sampling uncertainties across adjacent reporting years by designing optimal confidence and precision levels in each reporting years. For this case study, the longitudinal optimisation model is formulated as follows. The design variable is $\lambda = (\lambda(0),\ldots,\lambda(k),\ldots,\lambda(K))$, where $\lambda(k) = (z_1(k), z_2(k), p_1(k), p_2(k))$, $k = 1,\ldots,K$. The objective

Table 6.4: Metering cost with spatial optimisation.

Year	$Z(k)$	$C(k)$	$P(k)$	$n_1(k)$	$n_2(k)$	Cost (R)
0	**1.6452**	**90.01%**	**9.58%**	**12**	**6**	**37 032**
1	1.6448	90.00%	9.73%	12	3	10 008
2	**2.3185**	**97.96%**	**9.59%**	**12**	**4**	**11 184**
3	2.8278	99.53%	9.64%	12	4	11 184
4	**3.2124**	**99.87%**	**9.64%**	**12**	**6**	**13 536**
5	3.4659	99.95%	9.65%	12	9	27 462
6	**3.5883**	**99.97%**	**9.66%**	**12**	**18**	**58 842**
7	3.6331	99.97%	9.66%	10	33	96 198
8	**3.6447**	**99.97%**	**9.66%**	**11**	**44**	**95 810**
9	3.6464	99.97%	9.66%	12	44	58 224
10	**3.6466**	**99.97%**	**9.66%**	**10**	**36**	**47 736**
Total	**n/a**	**n/a**	**n/a**	**12**	**44**	**467 216**

function is given in (6.15) that subject to the constraints

$$\begin{cases} z_i(0) \geq 1.645, \\ p_i(0) \leq 10\%, \\ Z_i(\delta) \geq 1.645, \\ P_i(\delta) \leq 10\%. \end{cases} \tag{6.18}$$

Assume the $\bar{X}_i(k)$'s are independent over the years [0, K), then the combined distribution for $\bar{X}_i(k)$'s over the K years in the ith group will follow a normal distribution $\bar{\chi}_i(k) \sim \mathcal{N}(\theta_i(k), \Gamma_i(k)^2)$, where

$$\bar{\chi}_i(K) = \frac{\sum_{k=1}^{K} N_i(k)\bar{x}_i(k)}{\sum_{k=1}^{K} N_i(k)}, \tag{6.19}$$

$$\theta_i(K) = \frac{\sum_{k=1}^{K} N_i(k)\mu_i(k)}{\sum_{k=1}^{K} N_i(k)}, \tag{6.20}$$

$$\Gamma_i(K)^2 = \sum_{k=1}^{K} \left(\frac{\sigma_i(k) N_i(k)}{\sum_{k=1}^{K} N_i(k)} \right)^2. \tag{6.21}$$

Let $Z_i(\delta)$ and $P_i(\delta)$ denote cumulative z score and the cumulative precision levels by end of the δth year in the ith group, respectively, then

$$Z_i(\delta) = \frac{\bar{\chi}_i(\delta) - \theta_i(\delta)}{\Gamma_i(\delta)},$$

and

$$P_i(\delta) = \frac{\bar{\chi}_i(\delta) - \theta_i(\delta)}{\bar{\chi}_i(\delta)}.$$

The longitudinal optimisation model is denoted by $L((6.15),(6.18))$. The model $L((6.15),(6.18))$ is solved with the initial values given in Table 6.1 and the optimisation settings in Table 6.3. The obtained confidence levels, precision levels and optimal sample sizes are shown in Figures 6.6-6.8. In addition, the numerical optimal solutions and metering cost are summarised in Table 6.5.

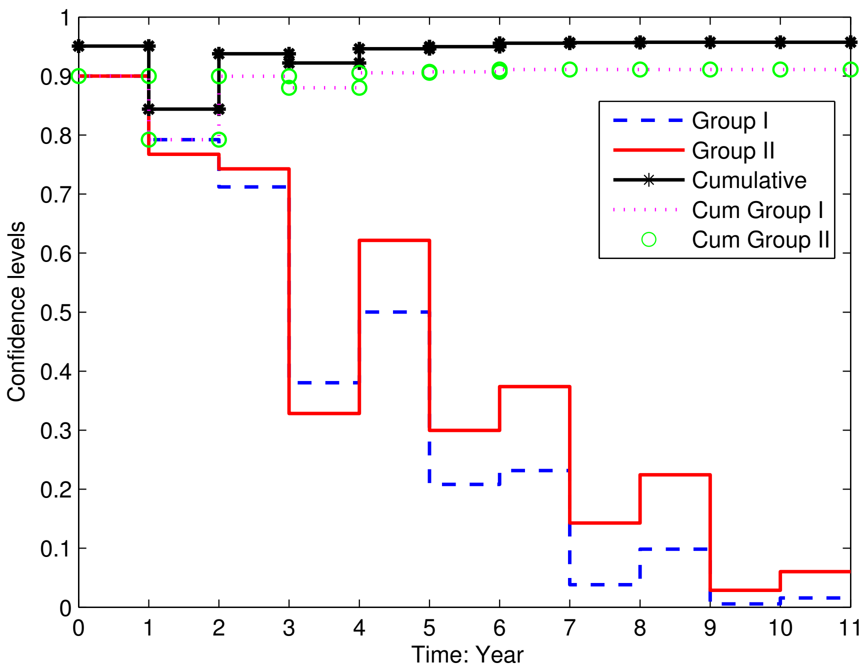

Figure 6.6: Confidence levels (longitudinal optimal only).

Figures 6.6-6.8 share the same presentation style as Figures 6.3-6.5 in terms of the horizontal and vertical axes. In Figures 6.6-6.7, optimal confidence and precision levels are presented, where the dashed line (in blue) and the solid line (in red) denote the confidence and precision levels for Group I and II, respectively; the starred line (in black) denotes the cumulative confidence and precision levels up to the kth year; in addition, the dotted line (in purple) and the circle line (in green) denote the cumulative confidence and precision levels up to the kth year in the ith group. As shown by the dotted lines (in purple) and the circle lines (in green) in both Figure 6.6 and Figure 6.7, the constraints in (6.18) are satisfied.

In Figure 6.8, the sample sizes in Group I and Group II are denoted by the dashed line (in blue) and the solid line (in red), respectively. The total sample sizes are denoted by the starred solid line (in black). As can be seen in Figure 6.8, the samples required during the baseline period are determined without optimisation. During the reporting period, the required sample sizes within every two years' reporting interval are very close in Group II, i.e., 35 and 34 samples are required in Years 1-2 while 11 and 10 samples are required in Years 3-4 in order to minimise the metering cost by balancing the sampling uncertainties within each reporting interval. The same sample size commitment pattern is also observed in Group I. Obviously the samples are optimally decided over the reporting period within lighting groups with the application of the model $L((6.15),(6.18))$. However, it is expected that the metering cost can be further minimised when spatial optimisation ideas can also be incorporated during both the baseline and reporting periods.

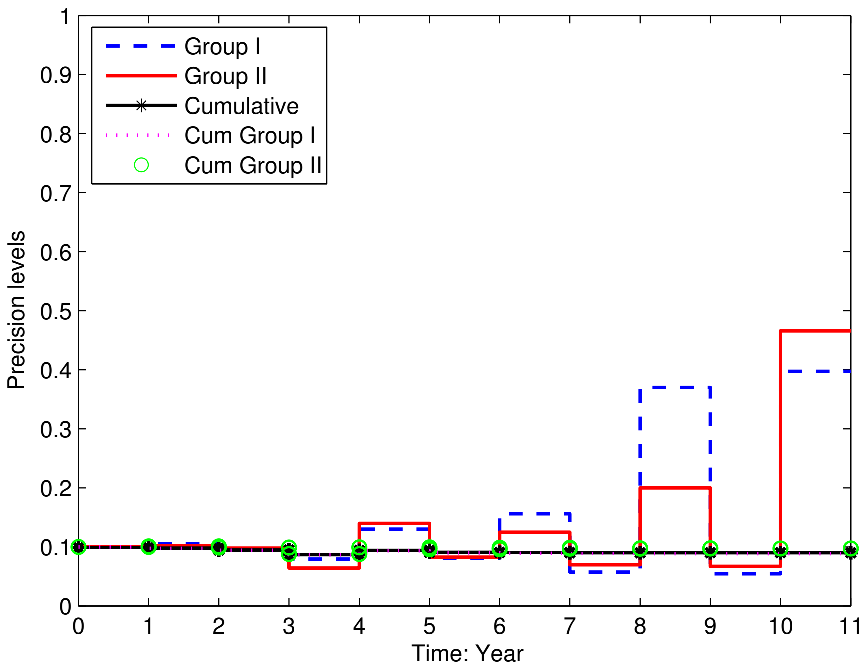

Figure 6.7: Precision levels (longitudinal optimal only).

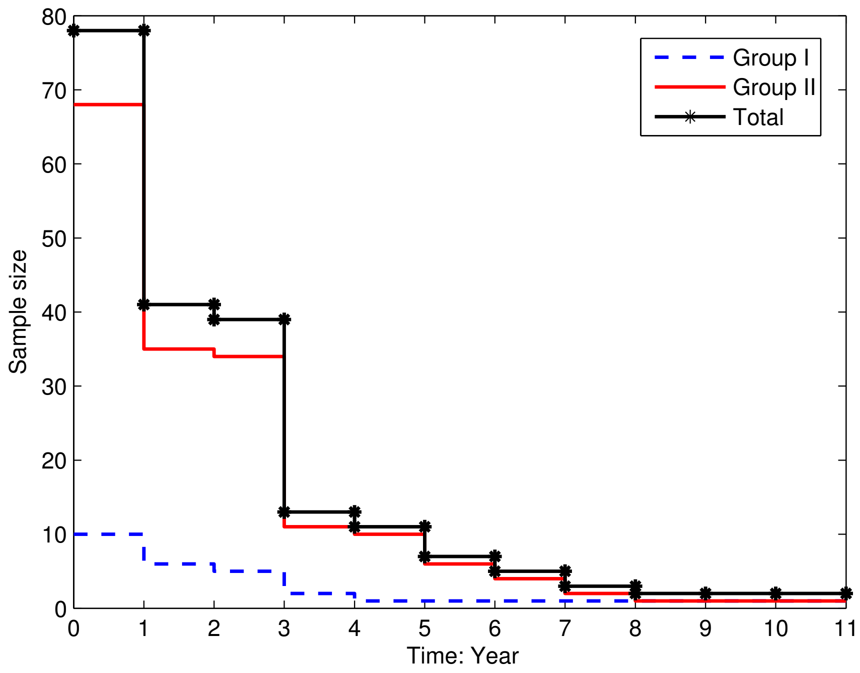

Figure 6.8: Number of meters (longitudinal optimal only).

Table 6.5: Metering cost with longitudinal optimisation.

Year	$Z(k)$	$C(k)$	$P(k)$	$n_1(k)$	$n_2(k)$	Cost (R)
0	**1.9655**	**95.06%**	**9.90%**	**10**	**68**	**267 740**
1	1.4179	84.38%	9.80%	6	35	44 400
2	**1.8639**	**93.77%**	**9.48%**	**5**	**34**	**42 684**
3	1.7629	92.21%	8.67%	2	11	14 016
4	**1.9278**	**94.61%**	**9.41%**	**1**	**10**	**12 300**
5	1.9577	94.97%	9.09%	1	6	7 596
6	**2.0113**	**95.57%**	**9.06%**	**1**	**4**	**5 244**
7	2.0192	95.65%	9.00%	1	2	2 892
8	**2.0267**	**95.73%**	**9.01%**	**1**	**1**	**1 716**
9	2.0268	95.73%	9.01%	1	1	1 716
10	**2.0268**	**95.73%**	**9.01%**	**1**	**1**	**1 716**
Total	**n/a**	**n/a**	**n/a**	**10**	**68**	**402 020**

6.3.3.3 Combined spatial and longitudinal optimisation

In this section, the combined spatial and longitudinal MCM model $C((6.15),(6.16))$ is solved with the initial values given in Table 6.1 and the optimisation settings in Table 6.3. The obtained confidence levels, precision levels and optimal sample sizes are shown in Figures 6.9-6.11. In addition, the numerical optimal solutions and metering cost are summarised in Table 6.6.

Table 6.6: Metering cost with combined spatial and longitudinal optimisation.

Year	$Z(k)$	$C(k)$	$P(k)$	$n_1(k)$	$n_2(k)$	Cost (R)
0	**1.6585**	**90.28%**	**9.65%**	**14**	**5**	**35 684**
1	1.2148	77.55%	9.21%	7	2	6 132
2	**1.6727**	**90.56%**	**9.28%**	**6**	**2**	**5 592**
3	1.6680	90.47%	9.22%	2	1	2 256
4	**1.7252**	**91.55%**	**8.96%**	**2**	**1**	**2 256**
5	1.7276	91.59%	8.69%	1	1	1 716
6	**1.7540**	**92.06%**	**8.64%**	**1**	**1**	**1 716**
7	1.7529	92.04%	8.55%	1	1	1 716
8	**1.7549**	**92.07%**	**8.54%**	**1**	**1**	**1 716**
9	1.7550	92.07%	8.54%	1	1	1 716
10	**1.7550**	**92.07%**	**8.54%**	**1**	**1**	**1 716**
Total	**n/a**	**n/a**	**n/a**	**14**	**5**	**62 216**

Figures 6.9-6.11 share the same presentation style as Figures 6.3-6.5 in terms of the horizontal and vertical axes. In Figures 6.9-6.10, optimal confidence and precision levels are presented, where the dashed line (in blue) and the solid line (in red) denote the confidence and precision levels for Group I and II, respectively; the starred line (in black) denotes the cumulative confidence and precision levels up to the kth year. As shown by the starred lines (in black) in both Figure 6.9 and Figure 6.10, the constraints in (6.16) are satisfied.

In Figure 6.11, the sample sizes in Group I and Group II are denoted by the dashed line (in blue) and the solid line (in red), respectively. The total sample sizes are denoted by the starred solid line (in black). As can be seen in Figure 6.11, the samples required during the baseline period are determined solely by spatial optimisation. In addition, as both the spatial and longitudinal MCM ideas are applied

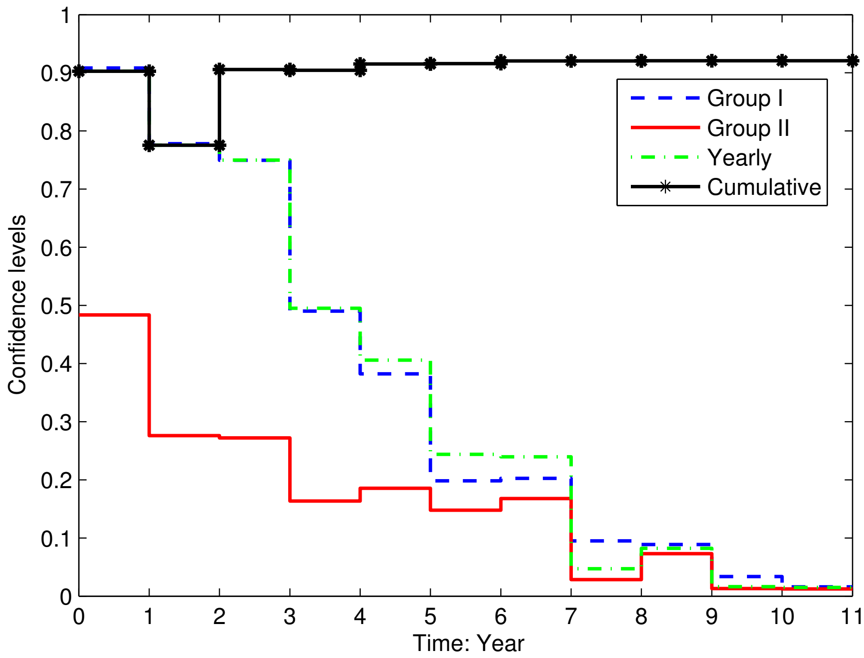

Figure 6.9: Confidence level (spatial & longitudinal optimal).

during the reporting period, the required sample sizes are optimised whereas the metering cost is significantly reduced.

When comparing the solutions listed in Table 6.2 and Tables 6.4-6.6, it is observed that all the $Z(\delta)$'s and $P(\delta)$'s are satisfying the 90/10 criterion in the scenarios of no optimisation, spatial optimisation only, longitudinal optimsation only and combined spatial and longitudinal optimisation. Obviously, the model $C((6.15),(6.16))$ offers the minimal metering cost in terms of total metering cost of the hospital lighting project without violating the sampling accuracy requirements.

6.4 MODEL APPLICATION AND DISCUSSION

The case study suggests that MCM models $S((6.15),(6.17))$, $L((6.15),(6.18))$ and $C((6.15),(6.16))$ are all useful in designing the optimal metering plan for the M&V of lighting retrofit projects. For lighting projects that have multiple lighting groups with different uncertainties, the spatial MCM model $S((6.15),(6.17))$ is most applicable when the lighting population during the projects' life cycle are properly maintained to avoid lamp population decay. If the lamp population decays as time goes by, then the longitudinal MCM model $L((6.15),(6.18))$ is most suitably applied to optimise the sample sizes within reporting intervals for each lighting group. Also learnt from the case study, the model $C((6.15),(6.16))$ exhibits the best performance in terms of metering cost minimisation whilst satisfying the required 90/10 criterion for each reporting interval. In order to apply the model $C((6.15),(6.16))$ more flexibly, the lamp population decay dynamics for different homogeneous lighting groups need to be specifically identified by addressing the lamps' life spans, usage patterns and technological specifications. More over, if the lighting retrofit projects are sponsored under different EEDSM programmes, then project performance reporting schedule δ in the model $C((6.15),(6.16))$ may be altered, which will result in different optimal sample size regimes.

Moreover, it is likely that M&V practitioners may need to design optimal M&V metering plan under different sampling accuracy requirements other than the 90/10 criterion such as 85/5, 95/5, and 99/1. The optimal sample size regimes and the relative metering cost are also calculated and provided in Table 6.7. It can be expected that better sampling accuracy requirement implies higher M&V metering cost over the entire project crediting period. For instance, the 99/1 criterion indicates much higher metering cost than the 90/10, 85/5, and 95/5 accuracy criteria.

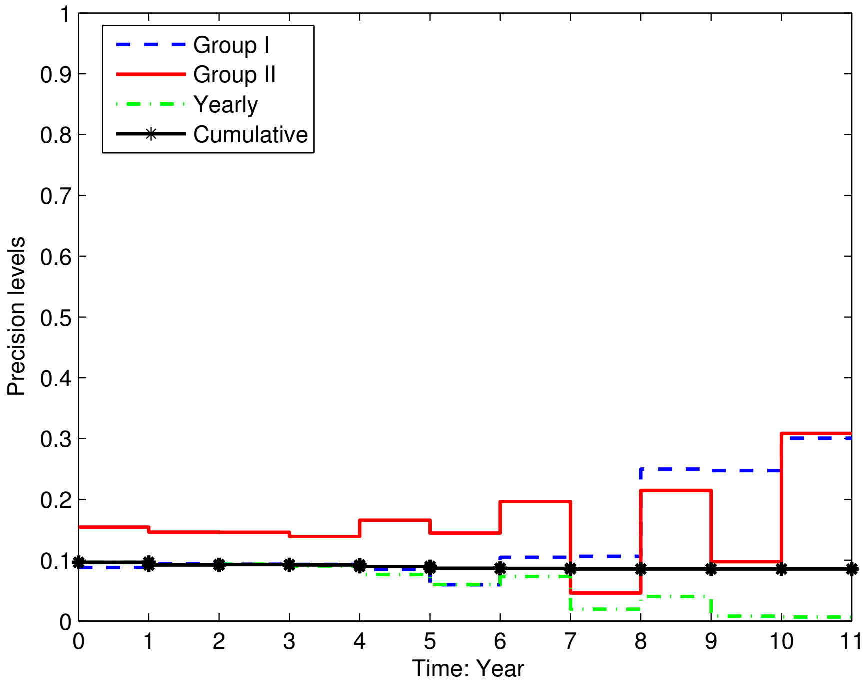

Figure 6.10: Precision levels (spatial & longitudinal optimal).

Table 6.7: Metering costs for different accuracy criteria.

Criteria	**85/5**			**95/5**			**99/1**		
Year	$n_1(k)$	$n_2(k)$	Cost (R)	$n_1(k)$	$n_2(k)$	Cost (R)	$n_1(k)$	$n_2(k)$	Cost (R)
0	41	14	102 086	76	26	189 416	3 268	1 080	8 002 008
1	19	5	16 140	35	9	29 484	1 488	362	1 229 232
2	17	5	15 060	31	9	27 324	1 348	349	1 138 344
3	7	2	6 132	11	4	10 644	454	138	407 448
4	5	2	5 052	8	3	7 848	313	125	316 020
5	2	2	3 432	4	3	5 688	160	106	211 056
6	1	1	1 716	2	2	3 432	55	73	115 548
7	1	1	1 716	1	1	1 716	14	33	46 368
8	1	1	1 716	1	1	1 716	1	12	14 652
9	1	1	1 716	1	1	1 716	1	5	6 420
10	1	1	1 716	1	1	1 716	1	2	2 892
Total	**41**	**14**	**156 482**	**76**	**26**	**280 700**	**3 268**	**1 080**	**11 489 988**

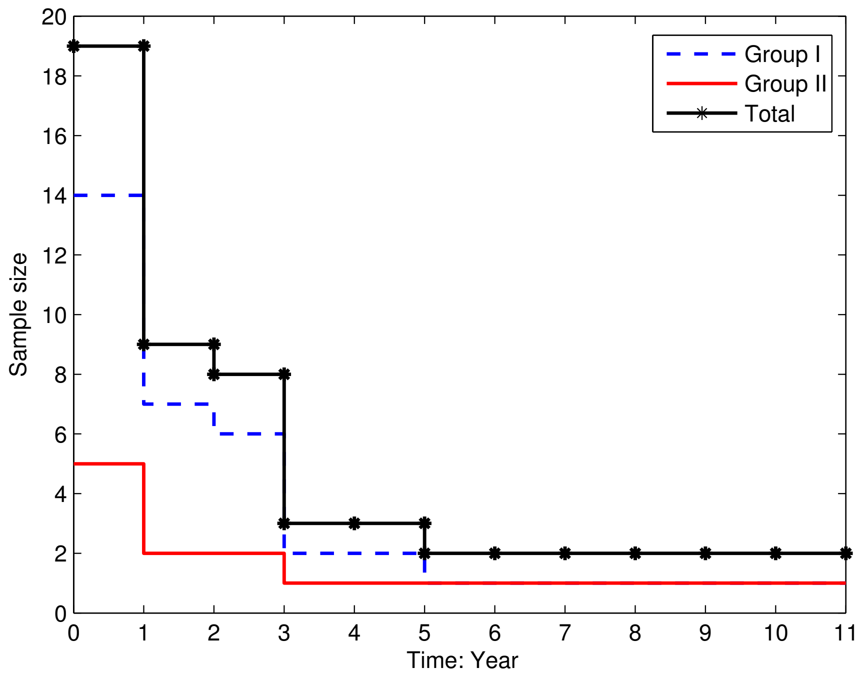

Figure 6.11: Number of meters (spatial & longitudinal optimal).

6.5 CONCLUSION

In this chapter, a combined spatial and longitudinal MCM model is proposed to assist the optimal M&V metering plan designs for the EE lighting retrofit projects. With the application of this model, the M&V metering cost is minimised by optimising the confidence and precision levels in different lighting groups over the projects' crediting period. As illustrated by the case study, the proposed MCM model is able to determine the optimal sample sizes for each lighting group over the projects' life cycle. These sample sizes are found adequate to satisfy the constraint of the required 90/10 criterion in both the baseline period and the project crediting period. The proposed combined spatial and longitudinal MCM model can be flexibly applied to other similar lighting retrofit projects with different technologies, different project population variations, different reporting intervals or different sampling accuracy requirements.

CHAPTER 7

OPTIMAL LIGHTING PROJECT MAINTENANCE PLANNING

7.1 CHAPTER OVERVIEW AND INTRODUCTION

Due to the great savings potential of lighting energy usage, a large number of lighting retrofit projects have been implemented under various incentive EE programmes such as CDM [163], TWC scheme [164, 5], DSM programmes [2], and performance contracting [10]. However, maintenance has not been suitably addressed in most of the existing lighting projects, such as the Polish energy efficiency lighting project [146] and some CDM energy efficiency lighting projects in [157, 159]. And no maintenance activities are required for the implemented lighting projects in the CDM lighting guidelines [124, 141]. For these "no maintenance" lighting projects, the service level of the installed EE lighting devices will be deteriorated due to the following lighting failure factors, i.e., flickering, lumen depreciation caused by age or dirt, lamp burnouts or ballast failures as time goes by. These lighting failure factors will consequently cause deceases of both the lighting project population and performance. To deal with the lamp population decay of these EE lighting projects, the guidelines [124, 141] apply a penalise factor, which is called lamp failure rate (LFR) to the energy savings calculation and further restrict that no credits will be issued to the implemented projects when 50% of the initial population is failed during the project crediting period. Under these rules, although lighting projects are allowed a crediting period of 10 years, most of these projects only obtain rebates for the first couple of years due to the lamp failures [157, 159]. The EE lighting projects are only considered sustainable when the survived lighting population is equal to or greater than 50% of their initial population by proper maintenance. To this end, some latest designed lighting project guidelines [142, 143] request to perform continuous replacements of all the failed lamps. Practically, the following barriers hold the PDs back from performing such full maintenance policy. Firstly, the maintenance activities can only be carried out when the project device failures are observed during the project inspections. However, continuously monitoring and sampling the lighting devices' working conditions are very costly and time-consuming when large decentralised lamp population is involved. Secondly, the maintenance activities also require additional investments for the procurement and installation of the new lighting devices. The extra investments sometimes contribute to a tighter project budget.

Since neither the "no maintenance" nor the "full maintenance" policy is preferable to the PDs, it is thus interesting to find an "optimal maintenance" policy that contributes to a sustainable energy/cost savings whilst the PDs obtain their maximum financial benefits in the sense of the cost-benefit ratio by optimising the maintenance actions and schedules. The OMP problem can be aptly formulated under the control system framework and solved by a control system approach. In the literature, the control system approach has been adopted to deal with similar OMP problems for various commercial and industrial systems. For instance, scheduling of periodic maintenance for transportation equipments is accomplished by a fuzzy control system approach in [165]. Ref. [166] outlines six types of decisions to design the optimal maintenance strategy as part of the entire control system optimisation. The principal component analysis (PCA) approach has been used in [167] that helps the prediction of the type and time of future device failures, which also contributes to the optimal scheduling of maintenance work. In [168], it designs optimal maintenance policies based on impulse control models in which the optimal actions and schedules are optimised for a compound Poisson shock model. In addition, the optimal control and stochastic control approaches are applied respectively in [169] and [170] to assist the planning of production and maintenance in a flexible manufacturing system.

The control system framework is also applicable in this study since the population dynamics of the EE lighting projects are characterised and modelled as state space equations. The lamp population decay dynamics of the project are taken as the plant of the control system. Practically, the failure dynamics of the EE lamps vary from different individuals due to different technical specifications, working conditions and operating schedules. In order to simplify the modelling complexities but without loss of generality, it is assumed that the lighting project population be classified into several homogeneous groups, where devices in the same group are of the same technical specification (i.e., model, make, rated power, life span, etc.), the same operating schedule and working condition. Consequently, lighting devices from the same group are deemed to have the same energy saving and economic performance, and the same population decay dynamics. In this case, the state variables can be chosen as the survived lighting population in each homogeneous group instead of the working/fail status of individual lighting devices. In order to achieve sustainable energy savings and maximum project profits, it is recommended to optimally control/replace a number of failed lighting devices during each maintenance interval. The number of failed lamps to be replaced is taken as the control variable of the control system. As different lighting technologies have different population decay dynamics and different rebate tariffs, the control inputs can be optimally decided based on the PDs' budget availability.

Bringing the OMP problem of the EE lighting projects into the control system framework exhibits the following advantages. Firstly, the OMP problem can be formulated as an optimal control problem. Optimal solutions to this problem determine the optimal maintenance policy, with which sustainable energy savings are maintained whilst the maximum project profit is achieved in terms of the cost-benefit ratio. Secondly, classic control theories and methodologies can be applied to further improve the designed maintenance strategy. In this study, MPC approach is introduced to solve the OMP problem as it converges to the optimal solution fast and is advantageous in dealing with the control system uncertainties and disturbances with the establishment of a closed-loop control system [171, 172]. An optimal maintenance plan for an EE lighting retrofit project is designed as a case study to illustrate the effectiveness of the proposed control system approach. In addition, multiple simulations are carried out to test the applicability of the proposed model to other similar lighting projects with different rebate tariffs, different lighting device life spans, and different unit retrofit prices. The case study and the simulation results suggest that the proposed optimal control model is widely applicable to other similar projects.

7.2 PROBLEM FORMULATION

In this section, the OMP problem is mathematically formulated, followed by discussions on the maintenance policy and lamp population decay dynamics.

7.2.1 Maintenance policy for lighting projects

In order to design optimal maintenance plans for EE lighting projects, the most suitable maintenance policy that covers both the maintenance actions and schedules needs to be properly selected. As defined in MIL-STD-721C [173], maintenance actions refer to retain an item in or restore it to a specified condition. Maintenance actions can be classified by two major categories: preventive maintenance (PM) and corrective maintenance (CM), where PM means all actions performed in an attempt to retain an item in specified condition by providing systematic inspection, detection, and prevention of incipient failures and CM refers to all actions performed as a result of failure, to restore an item to a specified condition [174, 175, 173]. PM is commonly carried out at fixed time intervals to improve the availability or to extend the life of the system while CM is performed at unpredictable intervals as the occurrence of failure cannot be known a priori [168]. In the literature, massive maintenance policies have been proposed with cost-effectively maintenance actions and schedules. These policies are well summarised in [174, 175] in terms of single-unit system maintenance policies and multi-unit system maintenance polices. Particularly, the age-dependent PM policy, periodic PM policy, failure limit policy, sequential PM policy and repair limit policy are specilised for the single-unit systems while the group maintenance policy and opportunistic maintenance policy are most applicable to the multi-unit systems.

As commented in [174], the aforementioned maintenance policies are sometimes applied in combination in order to obtain "global" optimal cost savings. However, the maintenance policy should not be designed too complicated to cause inconvenience in implementation in practice. For the EE lighting projects with large population, the periodic PM policy is most practical since it neither leads to unequal maintenance intervals, nor requires records on the unit usage and age. From the PDs' point of view, the principal maintenance objective of running the EE lighting project is no longer for longevity of individual lighting device but for sustainable project performance and rebates. Thus on the device level, the CM that refers to direct replacements of the failed lamps is considered on occurrence of lamp failures. On the project level, it is more feasible to perform PM by replacing part of failed lamps at certain maintenance intervals, in order to maintain the lighting project population between 50% and 100%. The CM to the entire project refers to the "full maintenance" policy that is sometimes not applicable due to the budget and/or time constraints.

In summary, the most applicable maintenance philosophy for the EE lighting projects is the periodic group preventive maintenance. The periodic PM will be performed at fixed intervals in terms of different countable time intervals such as hourly, daily, weekly, monthly or yearly, depending on the importance of the studied lighting systems. For instance, for the general lighting services in residential sectors, PDs may be allowed to perform the maintenance actions on annual basis. One may argue that negative impacts of not replacing failed lamps may be incurred since users no longer have adequate lighting to perform necessary tasks. In practice, this valid concern is suitably addressed by allowing the users to replace the failed lamps themselves but excluding the rebate for such replacements from the PDs' benefits. However, for lighting projects with critical lighting systems, such as traffic lights, surgery lighting systems, the maintenance actions must be performed more frequently to ensure the required lighting service level. Based on the selected maintenance philosophy for the EE lighting projects, the rest of this chapter will focus on the optimisation of the number of failed lamps to be replaced at fixed maintenance intervals.

7.2.2 OMP problem formulation under control system framework

The OMP problem is formulated under the control system framework in this subsection. Given a lighting retrofit project with I kinds of EE devices involved, then each kind of EE devices can be classified into the same lighting group when the ith lighting group exhibits the same lighting technology, same operating schedule and working condition. Let t_0 and t_f denote the beginning and end of the project crediting period, respectively. Once the project crediting period $[t_0,\, t_f]$ and the maintenance schedules are determined, $t_k = t_0 + kT$, $k = 0, 1, \ldots, K-1$ is used to denote the time intervals for the maintenance, where T is a constant to represent the fixed maintenance interval. When time sequence $\{t_k\}$ and T are both determined, t_k can be simply denoted by k and the time period $[t_k,\, t_{k+1})$ is simplified as $[k,\, k+1)$. $x_i(0)$ denotes the quantity of the initial installation of the EE lighting devices in the ith group. Generally, the lighting project OMP problem is to find the optimal control sequences $\mathbf{u}(k)$=$[u_1(k), u_2(k), \ldots, u_I(k)]^T$ within the time period $[0, K)$. Here $u_i(k)$ is the control system input, which is the number of replacements of the failed lamps during the interval $[k,\, k+1)$ in the ith group. Then the OMP problem under the control system framework is formulated in the following general form:

$$\begin{cases} \mathbf{x}(k+1) = \mathbf{f}(\mathbf{x}(k)) + \mathbf{u}(k) + \mathbf{w}(k), \\ \mathbf{y}(k) = \mathbf{x}(k) + \mathbf{v}(k), \end{cases} \tag{7.1}$$

where $\mathbf{x}(k)$=$[x_1(k), x_2(k), \ldots, x_I(k)]^T$, denotes the state variable that corresponds to the number of survival EE devices for the time interval $[k,\, k+1)$ in the ith group. The system output $\mathbf{y}(k)$ is the measurements of $\mathbf{x}(k)$, more precisely, $y_i(k)$ is the sampling result of $x_i(k)$ at time k in the ith group. $\mathbf{f}(\mathbf{x}(k))$ denotes the function to characterise the project population decay dynamics. In addition, $\mathbf{w}(k)$=$[w_1(k),\, w_2(k),\, \ldots,\, w_I(k)]^T$ and $\mathbf{v}(k)$=$[v_1(k),\, v_2(k),\, \ldots,\, v_I(k)]^T$ denote the modelling uncertainties and measurement disturbances, respectively.

7.2.3 Lighting population decay dynamics modelling

In order to solve the OMP problem, the lighting population decay dynamics model $\mathbf{f}(\mathbf{x}(k))$ needs to be characterised. The CDM guideline [141] has proposed a linear lamp population decay model, which is widely used for CDM projects. However, this model is not good enough to characterise the lamp population decay dynamics as it assumes a constant hazard rate of the EE lighting devices [158, 104]. The studies [158, 104] offer an informative review on the existing lamp population decay dynamics models as can be found in [146, 113]. In addition, [158, 104] also proposed a general form of the population decay dynamics model by re-calibrating existing models established from biological population dynamics study or from reliability engineering experiments. The general form of the model is provided in Eqation (7.2).

$$s(t) = \frac{1}{c + ae^{bt}}, \tag{7.2}$$

where $s(t)$ is the percentage of survived devices at time t for a lighting project, t is counted from the completion of the EE lighting project implementation. $a = e^{-L}$ and L is the rated average life span of a certain model of the EE devices. The rated average life span is declared by the manufacturer or responsible vendor as being the expected time at which 50% of any large number of EE devices reach the end of their individual lives [141]. b is the slope of decay and c is the initial percentage lamp survival at $t = 0$. Thus, with a given L, b and c can be obtained by solving the following equations:

$$\begin{cases} s(0) = 1, \\ s(L) = 0.5. \end{cases} \tag{7.3}$$

The discrete and dynamic form of model (7.2) is also given in [158, 104] as follows

$$s(k+1) = \tilde{b}\tilde{c}s(k)^2 - \tilde{b}s(k) + s(k), \tag{7.4}$$

where $s(k)$ is the survived percentage of the lighting project population at the kth sampling interval. Note that for different EE lighting devices, the parameters $\tilde{b}$ and $\tilde{c}$ are different and they can be obtained by the system identification approach proposed in [158, 104].

Given that $s(k)$ in model (7.4) is a percentage against the total population, this model can be easily converted into

$$x_i(k+1) = \tilde{b}_i\tilde{c}_i x_i(k)^2 / x_i(0) - \tilde{b}_i x_i(k) + x_i(k). \tag{7.5}$$

Note that the Equation (7.5) is only applicable when the following assumptions hold.

1) The lighting project involves a large number of lighting devices such that Equation (7.5) is statistically representative for the lighting population decay dynamics.

2) The lighting devices in the ith category are homogeneous and follow the same failure dynamics.

3) The time delay for the individual lighting device installation and commissioning can be ignored.

4) The replacements of the failed lighting devices will not change the lamp population decay dynamics.

7.2.4 Control objective and constraints

For the lighting projects mentioned in Subsection 7.2.2, PDs will receive different rebate values for installing different types of EE lighting devices, denoted by R_i (R[1]/kWh) on annual basis after the project implementation if the projects are maintained sustainable over the crediting period. However, PDs have to pay for the project transaction cost including the project design, implementation, performance evaluation and maintenance at their own budget. The initial investment Θ_1 of the project is estimated by

$$\Theta_1 = \sum_{i=1}^{I} \alpha_i x_i(0) + \beta, \tag{7.6}$$

where α_i denote the cost related to individual EE lighting device, including the procurement, delivery, removal of an old device and installation of a new device in the ith lighting group; β denotes the project transaction cost, usually β occupies 10% of Θ_1 and it is a once-off expense per project.

The performance of an energy conservation project is usually quantified by a M&V approach [1, 36]. The lighting project performance is calculated by the product of the number of survived lighting population and the average savings of individual EE lighting unit. As time goes by, the total project rebate will become less and less given that the lighting population decays if the failed EE lighting devices are not replaced. In case no maintenance is carried out, the PDs' benefit is calculated by

$$\Pi_1 = \sum_{i=1}^{I} \sum_{k=0}^{K-1} r_i \bar{x}_i(k) - \Theta_1, \tag{7.7}$$

where r_i is the rebate per EE device in the ith group, $r_i = R_i ES_i$. ES_i is the energy saving (in kWh) per EE device that is determined by the M&V approach. For simplicity, it is assumed that both r_i and ES_i are constant during each sampling interval. $\bar{x}_i(k)$ represents the number of survived EE lighting

[1] R is short for the South African Currency: Rand. The annual average USD to Rand exchange rate in 2013 is 1 USD = R 9.65.

devices in the ith group during the time period $[k, k+1)$. $\bar{x}_i(k+1)$ is calculated by Equation (7.5) and

$$\bar{x}_i(k+1) = f_i(\bar{x}_i(k)).$$

As discussed previously, proper replacements of failed lamps contribute to a sustainable project performance, which will consequently increase the PDs' benefit. From PDs' point of view, although the project maintenance brings additional benefits, it requires extra investments. If a number of $u_i(k)$ failed EE devices will be replaced during the time interval $[k, k+1)$, then the PDs' benefit is calculated by

$$\Pi_2 = \sum_{i=1}^{I} \sum_{k=0}^{K-1} [r_i x_i(k) - \alpha_i u_i(k)] - \Theta_1, \tag{7.8}$$

where $x_i(k)$ represents the number of survived EE lamps in the ith group during the time period $[k, k+1)$ and $x_i(k)$ is calculated by the state equation in Equation (7.1). When replacing the failed EE devices, the additional investment needs to cover the expenses for each replacement, which is calculated by $\alpha_i u_i(k)$.

With additional investments for a proper project maintenance, the PDs' absolute benefit Π_2 might be greater than Π_1. However, a greater Π_2 does not imply that the project with maintenance is more beneficial than the project without maintenance since this is not a fair-comparison. To ensure a fair-comparison, the total project benefit needs to be normalised against the total project investment. This normalised value is called cost-benefit ratio between the total project profit and the total project investment. The cost-benefit ratio J_1 for the project without maintenance is calculated by Π_1/Θ_1. The cost-benefit ratio J_2 for the project with maintenance is calculated by Π_2/Θ_2 where

$$\Theta_2 = \Theta_1 + \sum_{i=1}^{I} \sum_{k=0}^{K-1} [\alpha_i u_i(k)].$$

Therefore, to maximise PDs' benefits, the objective function is to

$$\min \quad J_2 = -\frac{\Pi_2}{\Theta_2}. \tag{7.9}$$

The inequality constraints of the OMP problem are given as

$$\begin{cases} x_i(k) \leq x_i(0), \\ x_i(k) \geq 0.5 x_i(0), \\ \sum_{i=1}^{I} \sum_{j=0}^{k-1} [\alpha_i u_i(j) - r_i x_i(j)] \leq 0, \end{cases} \tag{7.10}$$

where the first two constraints indicate that the project population shall be within the boundary of $[0.5x_i(0),\ x_i(0)]$. The lower bound is designed to guarantee the projects' sustainable performance.

The upper bound is a hard constraint since $x_i(0)$ is decided by the project scope boundary. The third constraint is the limit of the available budget for the maintenance. In other words, the expense for the maintenance at time k must not exceed the cumulative available profits of the project at the end of the time period $[0, k-1)$. Apparently, the requirements of the "full maintenance" may sometimes violate the third constraints.

The OMP problem is then translated into an optimal control problem as follows:

Given the control system dynamics (7.1), the objective function (7.9) and the inequality constraints (7.10), the OMP problem is to find an optimal control sequence $u_i(k)$ that minimises J_2 subject to the equality constraints (7.1) and inequality constraints (7.10).

The formulated OMP problem can be directly solved by open loop optimal control techniques when random measurement errors and model uncertainties are negligible. However, due to the unavoidable uncertainties and disturbances coupled in the OMP problem, it is more appropriate to adopt a closed-loop control approach that is robust against the system uncertainties and disturbances to solve the problem.

7.3 MPC ALGORITHM TO THE OMP PROBLEM

This section proposes an closed-loop MPC approach to solve the OMP problem due to its superiority in handling the possible modelling uncertainties and measurement disturbances in the control systems.

The OMP problem in Section 7.2 is defined over the time interval [0, K) to optimise the control variables $[u_i(0), u_i(1), \ldots, u_i(K-1)]$. It is obvious that when the same OMP problem is considered over the time interval $[m,\ m+N)$, $m \in [0, K)$, then the control variables are changed into $[u_i|_m(m), u_i|_m(m+1), \ldots, u_i|_m(m+N-1)]$. In an MPC approach, a finite-horizon optimal control problem is repeatedly solved and only the first control input is applied to the system. Consider an optimisation horizon with length N, the OMP problem over the time interval $[m, m+N)$ can be defined as the following optimisation problem:

$$\min\ \tilde{J}_2 = -\tilde{\Pi}_2/\tilde{\Theta}_2, \qquad (7.11)$$

subject to state and input constraints

$$\begin{cases} x_i|_m(m+h) \leq x_i(0), \\ x_i|_m(m+h) \geq 0.5x_i(0), \\ \pi(m) + \sum_{i=1}^{I} \sum_{q=m}^{m+h-1} [\alpha_i u_i|_m(q) - r_i x_i|_m(q)] \leq 0, \\ x_i|_m(m+h) = f_i(x_i|_m(m+h-1)) + u_i|_m(m+h-1), \end{cases} \tag{7.12}$$

and the terminal constraint

$$\sum_{i=1}^{I} [\alpha_i u_i|_m(m+N-1) - r_i x_i|_m(m+N-1)] \leq 0, \tag{7.13}$$

where $h \in [1,2,\ldots,N)$ and the notation $|_m$ means that the value is obtained based on the information available at time m; and

$$\pi(m) = \sum_{i=1}^{I} \sum_{q=0}^{m-1} [\alpha_i \bar{u}_i(q) - r_i x_i(q)] \tag{7.14}$$

denotes the cumulative available profits at the end of the time period $[0, m-1)$, and $\bar{u}_i(q)$'s are the control inputs obtained at time q.

$$\tilde{\Pi}_2 = \sum_{i=1}^{I} \sum_{h=m}^{m+N-1} [r_i x_i|_m(h) - \alpha_i u_i|_m(h)] - \Theta_1, \tag{7.15}$$

$$\tilde{\Theta}_2 = \Theta_1 + \sum_{i=1}^{I} \sum_{h=m}^{m+N-1} [\alpha_i u_i|_m(h)]. \tag{7.16}$$

Both the objective functions (7.11) and constraints (7.12) are nonlinear as the population decay dynamics model in Equation (7.5) is nonlinear. The interior-point algorithm is chosen to to find the optimal solutions [176]. The MPC formulation of the OMP problem in (7.11)-(7.16) can be solved over the prediction horizon $[m, m+N)$ given the initial condition $x_i(m)$. Let the obtained optimal control inputs be denoted by $\{\mathbf{u}_i^*|_m, i = 1,2,\ldots,I\}$, then only the optimal solution in the first sampling period $[m, m+1)$ is applied, denoted by $\bar{\mathbf{u}}_i|_m$=$\mathbf{u}_i^*|_m(1)$. According to Equation (7.12), the obtained optimal $\bar{\mathbf{u}}_i|_m$ is applied to calculate $\mathbf{x}(m+1)$ and $\mathbf{y}(m+1)$. $\mathbf{y}(m+1)$ then becomes the initial condition of the MPC formulation over the next prediction horizon $[m+1, m+N+1)$. Thus a closed-loop feedback is obtained. In case of applying the MPC approach on a finite time interval with length K, then the optimisation horizon (or control horizon, which is equivalent to prediction horizon in this study) is reduced to $N = K-m$ when $N > K-m$. This process will be repeated until all the optimal control inputs $\bar{\mathbf{u}}$ are obtained over the period $[0, K)$.

For an undisturbed control system model, where the modelling uncertainties $\mathbf{w}(k)$ and measurement disturbances $\mathbf{v}(k)$ are not considered, the system output $\mathbf{y}(k)$ equals the predicted state variable $\mathbf{x}(k)$ and is taken as the initial state for the optimal control problem over the next finite horizon. The above ideas can be formulated as **Algorithm 1**.

Algorithm 1: MPC algorithm to the OMP problem.

Initialisation: Given K, N and input $\mathbf{x}_i(0)$ and let m=0.

1. Compute the optimal solution $\{\mathbf{u}_i^*|_m\}$ of the problem formulated in (7.11)-(7.16).
2. Apply the MPC control $\bar{\mathbf{u}}_i|_m$ to the OMP problem. The rest of the solutions $\{\mathbf{u}_i^*|_m(h)\}$ are discarded. $x_i(m+1)$ is calculated by

$$x_i(m+1) = f_i(x_i(m)) + \bar{\mathbf{u}}_i|_m.$$

3. Let $m := m+1$ and go back to Step (1).

The above MPC algorithm is executed over the entire control period $[0,K)$ to solve the OMP problem.

Assumption 1. *Parameters α_i, r_i and decay function $f_i(x)$ satisfy:*

$$0.5x_i(0) - f_i(0.5x_i(0)) \leq \frac{0.5r_ix_i(0)}{\alpha_i}. \tag{7.17}$$

Remark 1. *Assumption 1 indicates that, if $x_i(j)$ happens to reach its lower bound, there always exists a beneficial control $u_i = \frac{0.5r_ix_i(0)}{\alpha_i}$ to guarantee that $x_i(j+1)$ is within constraints.*

Proposition 1. *Suppose that all parameters satisfy the condition given in **Assumption 1**. With the MPC **Algorithm 1**, the closed-loop system possesses the following properties:*

1. *the optimisation is always feasible, if it is feasible at $k=0$;*
2. *there are benefits after retrofitting in every step, or namely $\pi(m) \leq 0$.*

Proof.

1. At $k=0$, the optimisation problem (7.11) is feasible. It will be proved as following that feasibility at $k=j$ implies feasibility at $k=j+1$.

   Suppose that, at $k=j$, the optimisation problem (7.11) is feasible, and its solution can be obtained by

$$\mathbf{u}_i^*|_j = [u_i^*|_j(j), \cdots, u_i^*|_j(j+N-1)]^T.$$

The corresponding states are

$$\mathbf{x}_i^*|_j = [x_i^*|_j(j), \cdots, x_i^*|_j(j+N-1)]^T,$$

where $x_i^*|_j(j) = x_i(j)$. The above optimal solution and the corresponding states satisfy all constraints given in (7.12) and (7.13).

According to **Algorithm 1**, the first element of $\mathbf{u}_i^*|_j$ is implemented; consequently, $x(j+1) = x^*|_j(j+1)$.

Then, at $k = j+1$, select

$$\begin{aligned} u_i|_{j+1}(j+1) =& u_i^*|_j(j+1), \\ u_i|_{j+1}(j+2) =& u_i^*|_j(j+2), \\ &\vdots \\ u_i|_{j+1}(j+N-1) =& u_i^*|_j(j+N-1). \end{aligned}$$

It follows that

$$\begin{aligned} x_i|_{j+1}(j+1) =& x_i^*|_j(j+1), \\ x_i|_{j+1}(j+2) =& x_i^*|_j(j+2), \\ &\vdots \\ x_i|_{j+1}(j+N-1) =& x_i^*|_j(j+N-1). \end{aligned}$$

It is obvious that the above predicted controls and states satisfy constraints (7.12). Select

$$\begin{aligned} & u_i|_{j+1}(j+N) = \\ & \min\left[\frac{r_i x_i|_{j+1}(j+N)}{\alpha_i}, \; x_i(0) - f(x_i|_{j+1}(j+N))\right]. \end{aligned} \tag{7.18}$$

At $k = j+1$ the terminal constraint (7.13) is satisfied, indicating that the third line of constraints (7.12) is satisfied.

If $\frac{r_i x_i|_{j+1}(j+N)}{\alpha_i} \leq x_i(0) - f(x_i|_{j+1}(j+N))$, then

$$u_i|_{j+1}(j+N) = \frac{r_i x_i|_{j+1}(j+N)}{\alpha_i} \geq \frac{0.5 r_i x_i(0)}{\alpha_i} \tag{7.19}$$

assuring that the first two lines of (7.12) are satisfied.

If $\frac{r_i x_i|_{j+1}(j+N)}{\alpha_i} \geq x_i(0) - f(x_i|_{j+1}(j+N))$, then

$$u_i|_{j+1}(j+N) = x_i(0) - f(x_i|_{j+1}(j+N)), \tag{7.20}$$

indicating a full maintenance terminal control that satisfies all constraints.

As a result, at $k = j+1$, it can be found at least one feasible solution

$$\begin{aligned}\mathbf{u}_i|_{j+1} \triangleq & [u_i|_{j+1}(j+1), \cdots, u_i|_{j+1}(j+N-1), u_i|_{j+1}(j+N)]^T \\ = & [u_i^*|_j(j+1), \cdots, u_i*|_j(j+N-1), u_i^*|_j(j+N-1)]^T\end{aligned} \tag{7.21}$$

that satisfies all constraints in (7.12) and (7.13), indicating that the optimisation problem (7.11) is feasible at $k = j+1$.

According to mathematical induction, the optimisation problem is feasible at all future times, if it is feasible at $k = 0$.

2. Given that the optimisation is feasible, the fact that $\pi(m) \leq 0$ follows directly from the third line of constraint (7.12).

$\square$

Remark 2. *In this study, the proposed MPC is actually employed to solve an optimisation problem (instead of a control problem). Stability of the closed-loop system is trivial, since system states are always bounded due to constraints* (7.12)*. Consequently, proofs of feasibility and benefits are sufficient to the optimisation problem.*

Remark 3. *Robustness is an inherent property of MPC, and it is the very beginning motivation when MPC is firstly invented. MPC is able to detect the effects of disturbances when measuring the current states, and make corresponding compensations. To guarantee better robustness, some variations are introduced to* ***Algorithm 1*** *as follows.*

In practice, the modelling uncertainties and measurement disturbances are unavoidable. For the lighting projects, the predicted system states that refer to the survived lamp population may not be the same as the actual ones. Also, measurement of the survived lamps is done on sampling basis, usually by M&V inspection bodies, due to the large number of lamps involved. Therefore, the MPC approach developed is applied to a disturbed system with sampled measurement feedback and deals with the uncertainties and disturbances in a closed-loop way. That is, the sampled measurements that are not equal to the actual number of lamps survived are used as feedback information by the controller in optimisation. To demonstrate influences of the uncertainties and disturbances and to verify the MPC method's effectiveness in coping with them, the **Algorithm 1** is modified accordingly: In Step (2), the actual state is obtained by

$$x_i(m+1) = f_i(x_i(m)) + \bar{\mathbf{u}}_i|_m + w_i(m), \tag{7.22}$$

and the measurement of the system output

$$y_i(m) = x_i(m) + v_i(m) \tag{7.23}$$

is taken as the true plant state by the MPC controller in the next optimisation horizon to improve the plant performance. The terms $w_i(m)$ and $v_i(m)$ are simulated by $-\varepsilon_i + 2\varepsilon_i\delta(m)$, where $\delta(m)$'s are independent and identically distributed random numbers in [0,1] and ε_i's are the error bounds. Thus an evenly distributed error from $-\varepsilon_i$ to ε_i is added on the system states $x_i(m)$ during each sampling interval.

7.4 CASE STUDY

In this section, an optimal maintenance plan designed for a lighting retrofit project is taken as a case study to illustrate the effectiveness of the proposed optimal control system approach in solving the OMP problem.

A lighting retrofit project is going to be implemented to reduce the lighting load in various residential households in the Northern areas of South Africa. This lighting project is sponsored by a local utility under the national DSM programme. A large number of energy efficient CFLs and LEDs will be installed to replace existing inefficient ICLs and HDLs, respectively. According to the project regulation policies, the removed HDLs and ICLs will be counted, stored and destroyed by a contracted disposal company. The CFLs to be installed have a rated life of 3 years while the LEDs have a rated life of 6 years. The energy efficiency lamps have the equivalent lumen to the replaced old lamps. The adopted CFLs and LEDs are naturally classified into two homogeneous lighting groups as lamps in each group share the same technical specification, same working condition and operating schedule. Therefore, the same lamp population decay dynamics can also be observed and modelled in each lighting group.

PDs are encouraged to implement the project at their own cost and different rebate rates will be offered by the project sponsor to different lighting technologies. Since the unit retrofit price of an LED is more expensive than that of a CFL, the PDs will receive a higher rebate rate from the installations of LEDs. The project qualifies a crediting period of 10 years, during which PDs can receive their rebates on annual basis if the population of the newly installed EE lighting devices are properly maintained. If more than 50% of one kind of lamps is malfunctioned, then the project rebate will be ceased. The project performance in terms of energy savings will be reported at the end of each crediting year by a third-party M&V inspection company. The number of survived lamps will also be inspected by sampling and surveys at each reporting interval. Once lamp failures are observed, PDs' are allowed to replace some (or all) of the failed EE devices at the end of each crediting year to avoid the cease of project rebates. More project details that obtained from the project participants are listed in Table 7.1.

Table 7.1: Information of the lighting project.

Parameters	**CFL group**	**LED group**
Initial population	$x_1(0)$=404876	$x_2(0)$=207693
Unit retrofit price	α_1=R 32	α_2=R 260
Daily burning hours	O_1=5 h	O_2=10 h
Power of old lamps	P_1=60 W	P_2=35 W
Power of EE lamps	$\hat{P}_1$=14 W	$\hat{P}_2$=4 W
Rebate per kWh	R_1=R 0.42	R_2=R 0.55
Coefficient 1	$\tilde{b}_1\tilde{c}_1 = 0.7478$	$\tilde{b}_2\tilde{c}_2 = 0.8936$
Coefficient 2	$\tilde{c}_1 = 0.8553$	$\tilde{c}_2 = 0.9201$

In order to obtain an optimal maintenance plan for the above-mentioned lighting project, the optimal control sequences $u_i(k)$ need to be identified by the MPC algorithms that are introduced in Section 7.3 with the application of the initial conditions of the parameters appear in Equations (7.11)-(7.16). The relevant initial values are listed in Table 7.1. As discussed, the periodic PM maintenance policy is applied to this lighting project. For this study, the maintenance intervals are decided to be one year in order to align with the annual project performance reporting by the M&V practitioners. The advantage is that the latest sampled and surveyed lamp survival/failure rate of the lighting project population is available as the feedback signals of the control system.

The coefficients in the population decay dynamics model (7.5) are identified by the system identification approach proposed in [158, 104] and also provided in Table 7.1. The annually sampled lamp population decay patterns are presented in Figure 7.1, where the horizontal axis indicates the project crediting years and the vertical axis shows the survived lamp population. Obviously, without proper maintenance, the lamp population decreases very fast to zero as time goes by, which will cause a cease of project rebate.

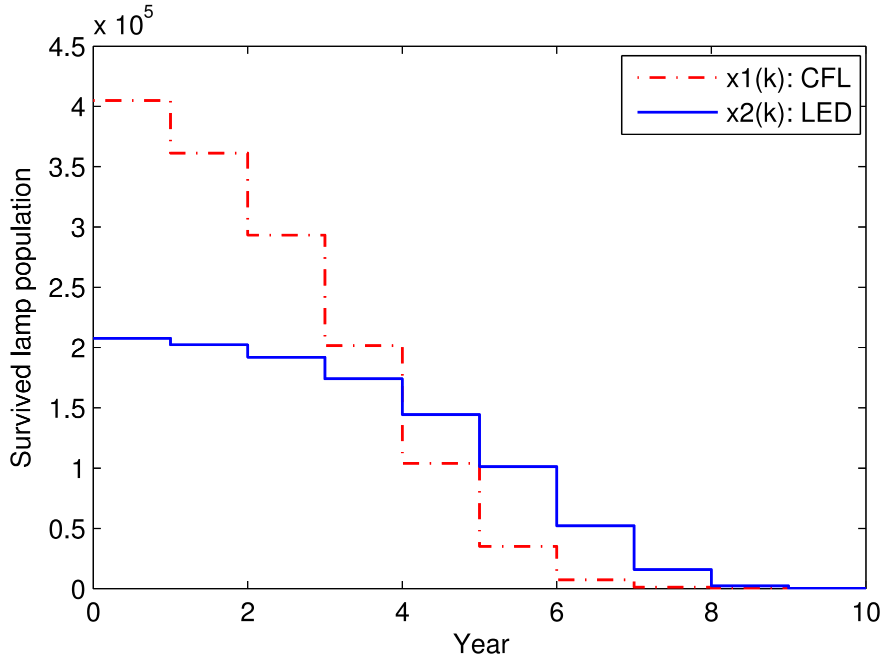

Figure 7.1: Survived lamp population without maintenance.

For this case study, all computations are carried out by the Matlab program. In particular, the optimal control inputs are computed by the "fmincon" code of the Matlab Optimisation Toolbox [171]. The optimisation settings of the "fmincon" function are shown in Table 7.2, where the interior-point algorithm is chosen as the optimisation algorithm; the three termination tolerances on the function value, the constraint violation, and the design variables are also given. In addition, "fmincon" calculates the Hessian by a limited-memory, large-scale quasi-Newton approximation, where 20 past iterations are remembered. Besides these settings, a search starting point and the boundaries of the control variable are also assigned. For the MPC approach, the optimisation horizon N is chosen as 5 years.

The computation results are presented in Figures 7.2-7.3 and Table 7.3. In the Figures 7.2-7.3, the horizontal axes indicate the project crediting years and the vertical axes show the survived lamp population. The solid lines (in blue) denote the system states of the annual survived lamps over the crediting period. The dash-dotted line (in black) denotes the survived lamp population without control/maintenance. The stem lines with a circle (in red) denote the number of failed lamps to be replaced over the 10-year crediting period. As shown by the solid lines (in blue), lamp failures are

Table 7.2: Optimisation settings.

Categories	**Options**
Algorithm	interior-point
TolFun	10^{-45}
TolCon	10^{-45}
TolX	10^{-45}
Hessian	‘lbfgs’, 20
lb:	0
ub:	$x_1(0)+x_2(0)$
$u_i(0)$:	1000

identified at the end of each year, then a number of these failed devices will be replaced as denoted by the stem lines. The optimal control strategy in the CFL group tends to maintain the lamp population to the full population over the entire crediting period. However, no failed LEDs are going to be replaced between the 7th and 10th years.

The key performance indicators (KPI), such as the total investments (in million Rand (MR)) , total profits (in MR), the cost-benefit ratio, and the total energy savings (in MWh) for the lighting retrofit project under the scenarios with no maintenance (NM), full maintenance (FM), and optimal main-

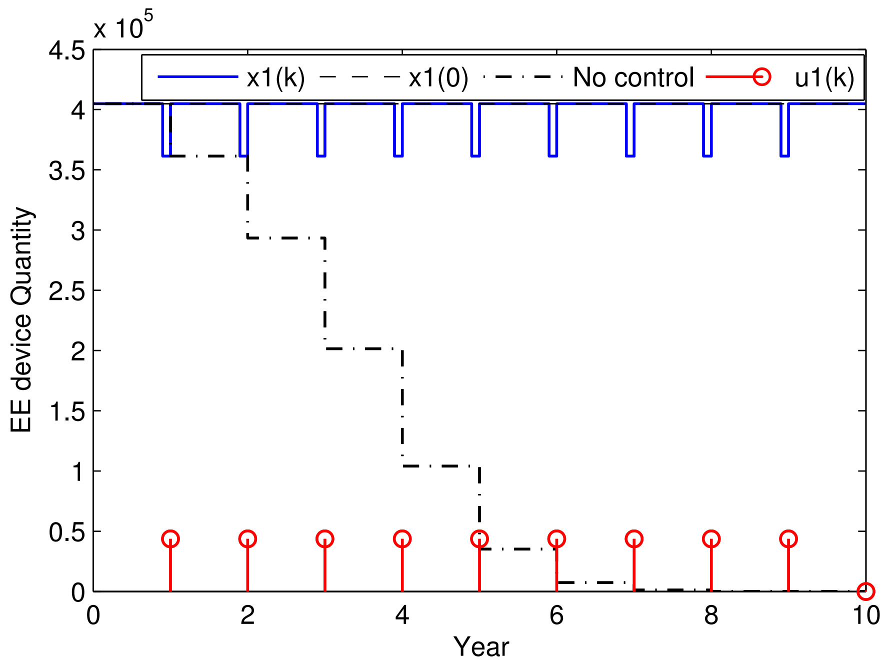

Figure 7.2: Optimal control strategy for the CFL group.

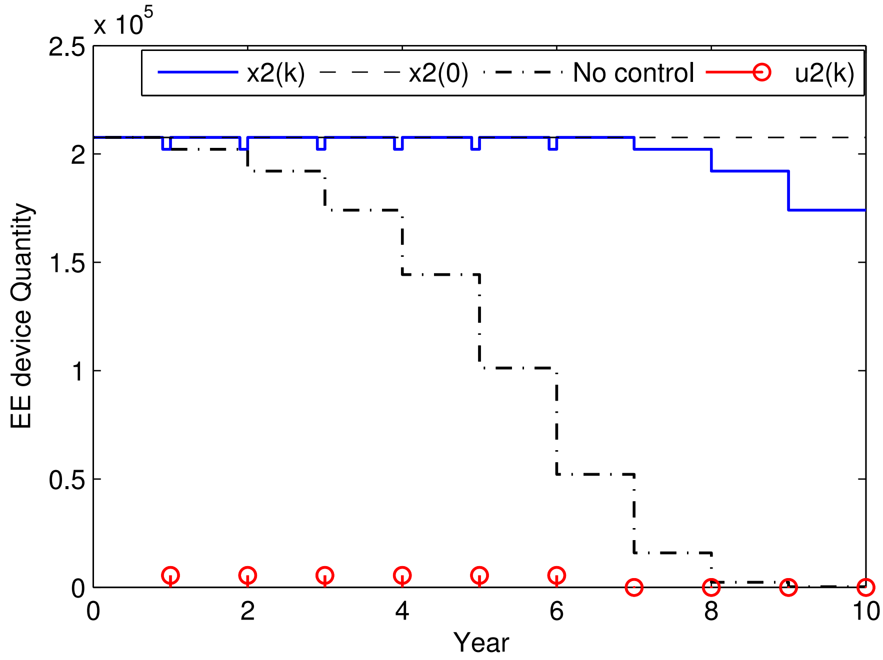

Figure 7.3: Optimal control strategy for the LED group.

Table 7.3: Project key performance indicator analysis.

Key performance indicators	NM	FM	OM	OM v.s. NM	OM v.s. FM
Total investment (MR)	74.396	102.61	95.507	28%	-7%
Total profit (MR)	53.180	197.95	201.650	279%	2%
Cost-benefit Ratio	0.7148	1.9293	2.1113	195%	9%
Energy saving (MWh)	265500	642880	636690	140%	-1%

NM: no maintenance; FM: full maintenance; OM: optimal maintenance; v.s.: versus.

tenance strategies are calculated and summarised in Table 7.3. These key performance indicators in Table 7.3 are calculated without considering the control system disturbances and uncertainties. The comparison of the performance between no maintenance and optimal maintenance strategies indicates that the energy savings increase by 140% with the optimal maintenance strategy. In addition, PDs receive 279% more profits with an extra 28% investment for the project maintenance. As commented in [177], a cost-benefit ratio above one indicates a beneficial programme and a higher cost-benefit ratio implies better financial benefits to the PDs. Thus the lighting project without maintenance is not beneficial to the PDs as the cost-benefit ratio 0.7148 is below one. When comparing the performance between the full maintenance and optimal maintenance strategies, it is observed that with the optimal maintenance strategy, the total project investment is 7% less while the total project profit is 2% more than the same performance indicators under the full maintenance strategy. It is also found the cost-benefit ratio of the optimal maintenance strategy is 9% greater than that of the full maintenance strategy. Although the project energy savings with the full maintenance strategy is 1% higher than that of the optimal maintenance strategy, there are potential risks that the full maintenance strategy cannot be physically implemented due to the PDs' budget constraints.

As discussed in [171], the MPC algorithm is robust against the control system uncertainties and disturbances, which exhibits better performance than the open loop optimisation approach. In practice, the modelled or measured control system states may not be exactly the same as the actual system states due to the unavoidable modelling and measurement uncertainties. In order to test the performance of the MPC algorithm in dealing with the uncertainties and disturbances, an evenly distributed error is added on the measured system states and a system output feedback is also employed in the MPC approach. The error bands of the random noises are $\pm 1\% x_i(k)$ in each lighting group given the large scale of the lighting project population.

Table 7.4: MPC v.s. open loop optimal solutions.

Key performance indicators	MPC	Open loop
Total investment (MR)	95.868	95.504
Total profit (MR)	201.280	198.030
Cost-benefit Ratio	2.0995	2.0735
Energy saving (MWh)	636580	629970

The project key performance indicators calculated with uncertainties by both the MPC approach and the open loop approach are given in Table 7.4. If the uncertainties were not revealed and handled by the MPC approach, then the project key performance indicators would have been calculated by applying the open loop optimal solutions directly to the scenario. Comparing the performance indicators in Table 7.4, the results from MPC approach exhibits better economic benefits and energy savings. This demonstrates the advantageous performance of the MPC approach for the OMP problem against other open loop optimisation approaches. It also reveals that the MPC approach with the system output feedback is able to handle the control system uncertainties.

7.5 SIMULATIONS ON MODEL APPLICATIONS

The case study in Section 7.4 successfully demonstrates the advantageous performance of the proposed approach. In order to test applicability of the proposed model for the OMP design of similar lighting projects, the model performances in terms of the project cost-benefit ratios are calculated and compared under three scenarios:

1) Model performance v.s. rebate tariff;

2) Model performance v.s. lighting life span;

3) Model performance v.s. lighting unit retrofit price.

The simulation results are presented in three subsections as follows.

7.5.1 Model performance versus rebate tariff

For lighting retrofit projects registered under different energy conservation programmes, the rebate tariffs may be different. In the case study, the rebate tariff is R_e=$\{0.42, 0.55\}$, which represents R 0.42/kWh savings for CFL retrofits and R 0.55/kWh savings for LED retrofits. In order to investigate the model performance against different rebate tariffs, a simulation is carried out as follows. The maximum project cost-benefit ratio is calculated by the introduced MPC approach with R_e=$\{0.42, 0.55\}$ as a reference. In the simulation, R_e is changed by $\pm10\%$, $\pm20\%$, and $\pm50\%$. The model performance indicators are calculated each time when R_e changes. The simulation results are shown and compared in Figure 7.4. It is observed that the project performance drops when the rebate tariff decreases. Moreover, for a given rebate tariff, the project cost-benefit ratios calculated by the optimal maintenance, full maintenance, and no maintenance strategies are in the first, second, and third places, respectively. This observation is consistent with the conclusions draw from the case study. It is also noted that when the rebate tariff drops by 50%, the project cost-benefit ratio becomes negative. The control inputs of the optimal maintenance strategies are exactly the same as presented in Figures 7.2-7.3.

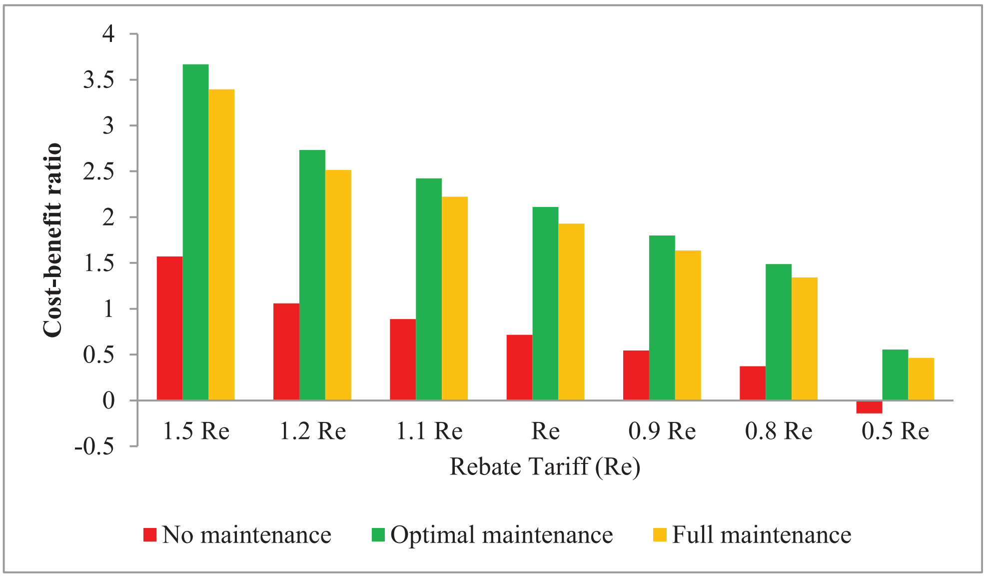

Figure 7.4: Model performance versus rebate tariff.

7.5.2 Model performance versus unit retrofit price

The unit retrofit prices may be different for different lighting retrofit projects. In the case study, the unit retrofit price is denoted by P_r={32, 260}, which represents R 32 per CFL retrofit and R 260 per LED retrofit. In order to investigate the model performance against different unit retrofit prices, a simulation is carried out as follows. The maximum project cost-benefit ratio with P_r={32, 260} is calculated by the introduced MPC approach as a reference. In the simulation, P_r is changed by $\pm$10%, $\pm$20%, and $\pm$50%. The model performance indicators are calculated each time when P_r changes. The simulation results are shown and compared in Figure 7.5. It is observed that the project performance drops when the unit retrofit price increases. Moreover, for a given rebate tariff, the project cost-benefit ratios calculated by the optimal maintenance, full maintenance, and no maintenance strategies are in the first, second, and third places, respectively. This observation is consistent with the conclusions draw from the case study. The control inputs of the optimal maintenance strategies are exactly the same as presented in Figures 7.2-7.3.

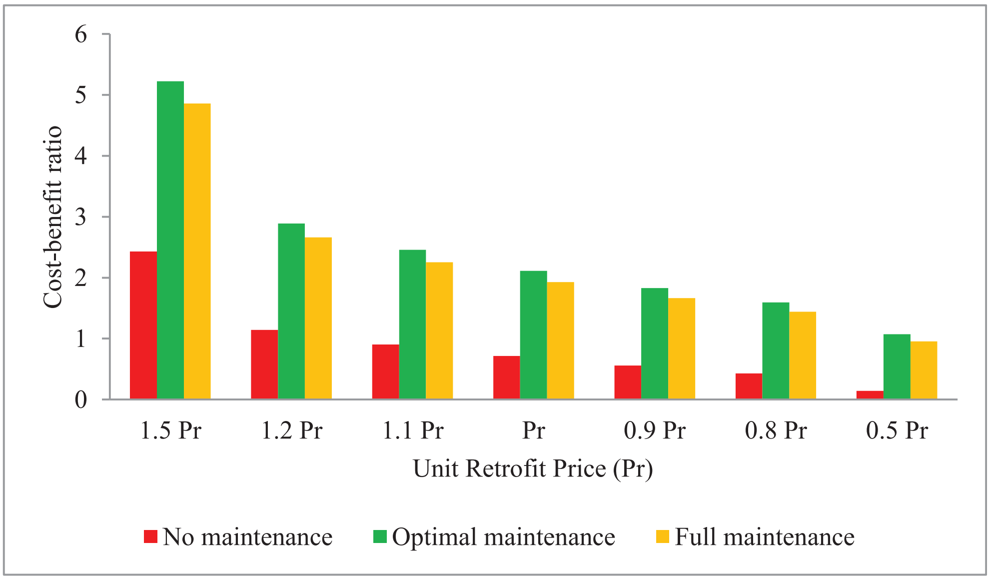

Figure 7.5: Model performance versus unit retrofit price.

7.5.3 Model performance versus lighting life span

As discussed in Subsection 7.2.3, life span determines the lighting population decay dynamics. Lighting devices with various life spans may be involved in different lighting retrofit projects. In the case study, the average lighting device life span is denoted by L_i={3, 6}, which represents an average life span of 3 years for CFLs and 6 years for LEDs. In order to investigate the model performance against different lighting life spans, a simulation is carried out as follows. The maximum project cost-benefit ratio is calculated by the introduced MPC approach with L_i={3, 6} as a reference. In the simulation, L_i is changed by $\pm 10\%$, $\pm 20\%$, and $\pm 50\%$. The model performance is calculated each time when L_i changes. The simulation results are shown and compared in Figure 7.6. It is observed that the project performance drops when the device life span decreases. Moreover, for a given rebate tariff, the project cost-benefit ratios calculated by the optimal maintenance, full maintenance, and no maintenance strategies are in the first, second, and third places, respectively. This observation is consistent with the conclusions draw from the case study.

The control inputs of the optimal maintenance strategies for lighting projects with various life spans are presented in Figures 7.7-7.8. In both figures, it is observed that fewer lamps need to be replaced for lighting projects with longer lighting life spans. For the CFL group, the optimal solutions tend to apply the "full maintenance" strategy. But for the LED group, specific optimal strategies are recommend for lighting projects with different lighting life spans.

7.6 REMARKS AND FUTURE WORK

The major contributions of this chapter can be summarised as follows: **1)** to formulate the optimal maintenance planning problem into the control system framework, whereby the classic control theories such as optimal control and MPC can be applied to solve the maintenance planning problems for the energy efficiency lighting projects. **2)** the maximised lighting project performance and PDs' profits in the case study clearly illustrates the advantageous performance of the optimal maintenance strategies to the lighting projects. **3)** The proposed control system approach in solving the OMP problem will be widely applicable to other similar projects. The results presented in this study will surely contribute to improvements of the energy efficiency project plans and programme regulations.

This work is also worth of further improvements from the following aspects: **1)** The optimal maintenance strategy is determined under the periodic group PM maintenance policies. Obviously, the optimal maintenance plans can also be designed under other applicable maintenance policies, such as the age-dependent PM policy, periodic PM policy, failure limit policy, sequential PM policy, repair limit policy, opportunistic maintenance policy, or any policies established as combinations of the aforementioned maintenance policies. **2)** The optimal maintenance strategy can be expanded to be more general and applicable for EE projects with more than two lighting groups or with other techno-

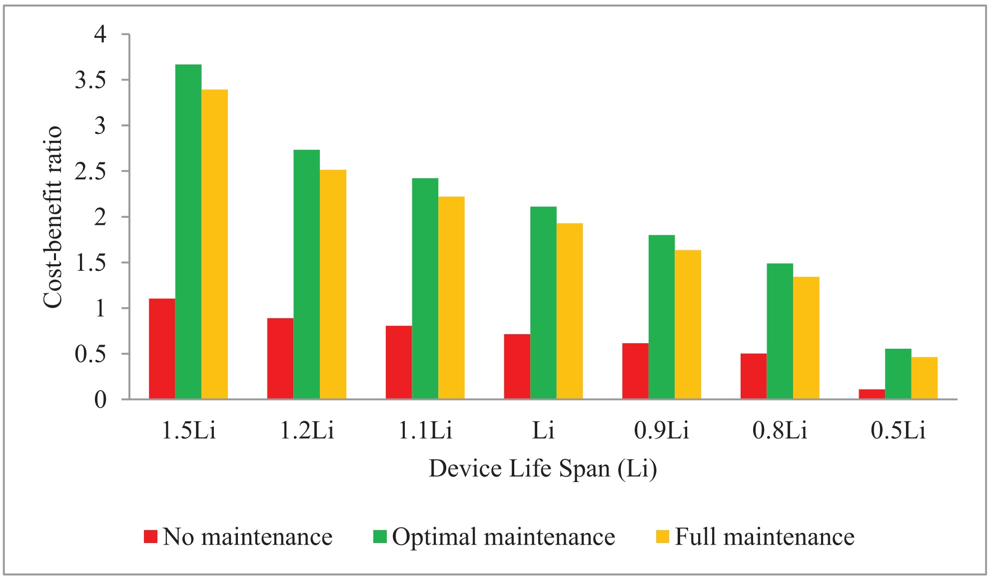

Figure 7.6: Model performance versus device life span.

logies such as air-conditioning systems or water heating systems once the population decay dynamics are identified. **3)** It is also interesting to explore the optimal maintenance policy design over longer project crediting periods or infinite project crediting periods.

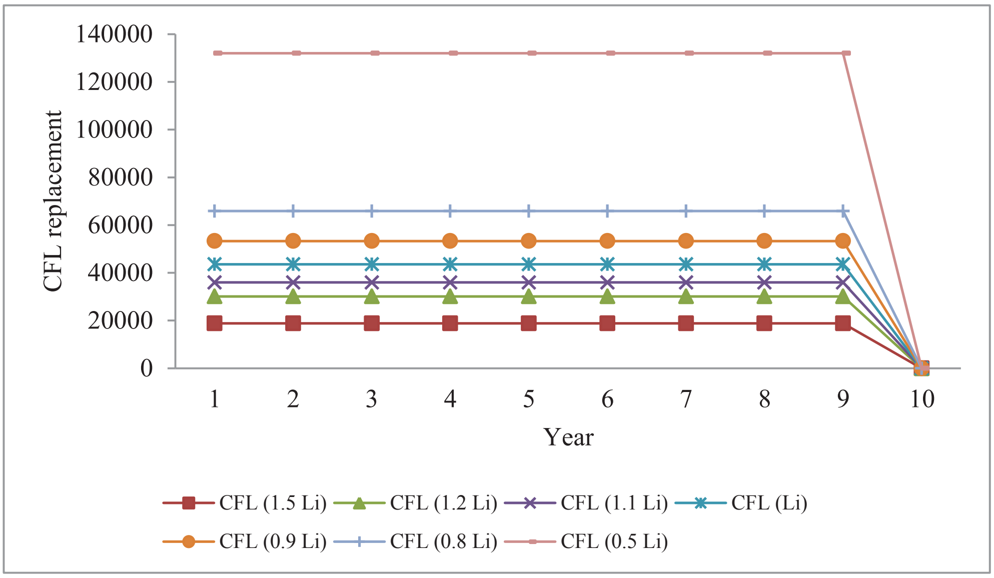

Figure 7.7: CFL replacements versus device life span.

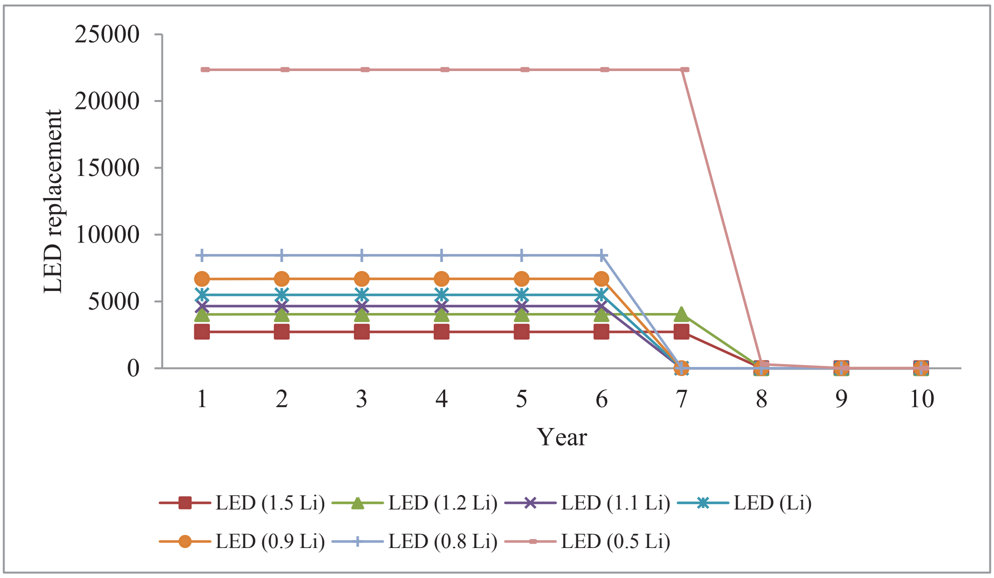

Figure 7.8: LED replacements versus device life span.

CHAPTER 8

INTEGRATED OPTIMAL M&V METERING AND MAINTENANCE PLANS

8.1 CHAPTER OVERVIEW

In this thesis, Chapters 4-6 introduce three types of MCM models, namely SMCM, LMCM, and combined S&LMCM to design optimal M&V metering plans that satisfy M&V accuracy with minimal M&V metering cost. Chapter 7 introduces a control system approach to develop optimal maintenance plans for lighting retrofit projects, which maximise lighting PDs' profit and generate sustainable energy savings. For any large-scale energy conservation lighting programmes, both the M&V functions and maintenance activities are essential during the lighting project's life cycle, especially when lighting project population varies due to lamp failures or replacements. Specifically, the M&V process assesses and tracks the project performance while maintenance activities ensure sustainable energy savings from lighting projects.

In Chapters 4-7, the optimal M&V metering and maintenance plans are introduced and designed independently. Particularly, the optimal M&V metering plans designed by the MCM models are only applicable to lighting projects whose population naturally decreases due to lack of maintenance. For lighting project with optimal maintenance activities, there is no available solution to design the optimal M&V metering plans. In this chapter, it is planned to address this problem by developing an integrated MCM model with optimal maintenance plans for lighting retrofit projects. With the optimal solutions to the integrated model, the project sponsors receive extra profit in terms of a higher cost-benefit ratio, and sustainable energy savings over a 10-years' crediting period. The project performance is accurately measured and verified with desired M&V accuracy. A case study of designing the optimal M&V metering and maintenance plans for an EE lighting retrofit project is presented to illustrate the effectiveness of the proposed model.

8.2 INTRODUCTION

A great energy saving potential can be generated with the implementation of EE lighting retrofit projects [132]. The lighting retrofit solution is to replace inefficient lamps with efficient ones. In the literature, a large number of lighting retrofit projects has been implemented by adopting the CFL and LED technologies [134]. The implementation of large-scale lighting retrofit projects is an effective approach to improve energy efficiency and mitigate the climate change pressure. Practically, the transaction costs of energy efficiency projects are substantial in terms of project maintenance and performance quantification, which hold the lighting PDs back from obtaining their maximum benefits. Practically, the energy saving performance from the implemented lighting project is not sustainable and vanishes rapidly due to lack of maintenance. The scope of the maintenance refers to the replacement of the nonrepairable lamp burnouts. Furthermore, accurate quantification of the lighting project performance is very costly when continuously metering and sampling efforts are required for large dispersed lighting population. In order to maximise the PDs' profits and encourage expanded implementations of EE lighting projects, Chapter 7 has proposed a control system approach to design an optimal maintenance plan at a fixed schedule, by which both the PDs' benefits and the project energy savings performance are maximised. In addition, Chapters 4-6 have developed both spatial and longitudinal metering cost minimisation models to design the optimal metering and sampling plans as to evaluate lighting project performance accurately and cost-effectively. To further improve the PDs' benefits in implementing EE lighting retrofit projects, this study aims to incorporate the advantages of both the optimal maintenance and metering plan for typical lighting EE retrofit projects.

8.3 PROBLEM FORMULATION

In this section, the integration of an optimal maintenance plan and a prioritised M&V metering plan is formulated under the background of large-scale lighting retrofit projects.

Given a lighting retrofit project with I kinds of EE devices involved, each kind of EE devices can be naturally classified into the ith lighting group when the lighting technology, operating schedules and working conditions are observed similar. Let t_0 and t_f denote the beginning and end of the project crediting period, respectively. Once the project crediting period $[t_0, t_f]$ and the maintenance schedules are determined, $t_k = t_0 + kT$, $k = 0, 1, \ldots, K-1$ is used to denote the time intervals for the maintenance, where T is a constant to represent the fixed performance reporting and maintenance interval. When time sequence $\{t_k\}$ and T are both determined, t_k can be simply denoted by k and the time period $[t_k, t_{k+1})$ is simplified as $[k, k+1)$. $x_i(0)$ denotes the quantity of the initial installation of the EE lighting devices in the ith group. Generally, the lighting project OMP problem is to find the optimal control sequences $\mathbf{u}(k)$=$[u_1(k), u_2(k), \ldots, u_I(k)]^T$ within the time period $[0, K)$. Here $u_i(k)$ is the control system input, which is the number of replacements of the failed lamps during the interval $[k, k+1)$ in the ith group. Then the OMP problem under the control system framework is formulated in the following general form:

$$\begin{cases} \mathbf{x}(k+1) = \mathbf{f}(\mathbf{x}(k)) + \mathbf{u}(k) + \mathbf{w}(k), \\ \mathbf{y}(k) = \mathbf{x}(k) + \mathbf{v}(k), \end{cases} \tag{8.1}$$

where $\mathbf{x}(k)$=$[x_1(k), x_2(k), \ldots, x_I(k)]^T$, denotes the state variable that corresponds to the number of survival EE devices for the time interval $[k, k+1)$ in the ith group. The system output $\mathbf{y}(k)$ is the measurements of $\mathbf{x}(k)$, more precisely, $y_i(k)$ is the sampling result of $x_i(k)$ at time k in the ith group. $\mathbf{f}(\mathbf{x}(k))$ denotes the function to characterise the project population decay dynamics. In addition, $\mathbf{w}(k)$=$[w_1(k)$, $w_2(k)$, …, $w_I(k)]^T$ and $\mathbf{v}(k)$=$[v_1(k)$, $v_2(k)$, …, $v_I(k)]^T$ denote the modelling uncertainties and measurement disturbances, respectively. The lighting population decay dynamics model $\mathbf{f}(\mathbf{x}(k))$ has been introduced in Chapter 7.

As discussed in previous chapters, the optimal M&V metering plan aims to provide optimal sample sizes to satisfy the required sampling accuracy for each reporting interval. Mathematically, required sample size is decided by four determinants namely population size, desired z-score, and relative precision, and estimated CV values. Once the optimal maintenance policy is decided, the project population is also determined. The optimal M&V metering plan for lighting projects with optimal maintenance policy is formulated as follows:

During each interval $[k, k+1)$, let $z_i(k)$ and $p_i(k)$ denote the z-score and the precision levels in the ith group, $z(k)$ and $p(k)$ denote the combined z-score and precision levels across all subgroups, respectively; $N_i(k)$ and $n_i(k)$ denote the survived lamp population and the required sample size in the ith group, respectively. $N(k)$ denote the total survived lamp population, and

$$N(k) = \sum_{i=1}^{I} N_i(k).$$

Let $Q_i(k)$ be the random variable that denote the sampled parameter in the ith lighting group during the period $[k, k+1)$ and assume that $Q_i(k)$ follows normal distribution $Q_i(k) \sim \mathcal{N}(\mu_i(k), \sigma_i(k)^2)$ given the large lamp population in the ith group, where $\mu_i(k)$ is the true mean value, $\sigma_i(k)$ is the true standard deviation. If any $n_i(k)$ samples are drawn from the ith lighting group, the sampling distribution of the mean satisfies a normal distribution $\bar{Q}_i(k) \sim \mathcal{N}(\mu_i(k), \sigma_i(k)^2/n_i(k))$. Assume the $\bar{Q}_i(k)$'s are independent and the combined distribution for the $\bar{Q}_i(k)$'s across the I lighting groups is denoted by $Q(k) \sim \mathcal{N}(\mu(k), \sigma(k)^2)$, where the combined sampled mean value $\bar{q}(k)$ for the total lighting population is calculated by

$$\bar{q}(k) = \frac{\sum_{i=1}^{I} N_i(k)\bar{q}_i(k)}{N(k)}, \tag{8.2}$$

the true mean value $\mu(k)$ for the total lighting population is calculated by

$$\mu(k) = \frac{\sum_{i=1}^{I} N_i(k)\mu_i(k)}{N(k)}, \tag{8.3}$$

and the true standard deviation $\sigma(k)$ for the total lighting population is calculated by

$$\sigma(k)^2 = \sum_{i=1}^{I} \frac{(\sigma_i(k)N_i(k))^2}{n_i(k)N(k)^2}. \tag{8.4}$$

According to the z transformation function,

$$\bar{q}_i(k) - \mu_i(k) = z_i(k) \cdot \frac{\sigma_i(k)}{\sqrt{n_i(k)}}. \tag{8.5}$$

where $\bar{q}_i(k)$ is the sample mean in the ith group $\sigma_i(k) = \bar{q}_i(k)CV_i(k)$. Assume that the estimated daily energy consumptions and CV values in the ith group will not change over the credit period, then the standard deviation $\sigma_i(k)$ in the ith group will also remain unchanged.

The combined annual z-score $z(k)$ and relative precision level $p(k)$ are calculated by

$$z(k) = \frac{\bar{q}(k) - \mu(k)}{\sigma(k)}, \tag{8.6}$$

and

$$p(k) = \frac{\bar{q}(k) - \mu(k)}{\bar{q}(k)}. \tag{8.7}$$

Further assume that $\bar{Q}(k)$'s are independent, then the combined distribution for the $\bar{Q}(k)$'s over the K intervals will follow a normal distribution $\bar{\chi}(k) \sim \mathcal{N}(\theta(k), \Gamma(k)^2)$, where

$$\bar{\chi}(K) = \frac{\sum_{k=1}^{K} N(k)\bar{q}(k)}{\sum_{k=1}^{K} N(k)}, \tag{8.8}$$

$$\theta(K) = \frac{\sum_{k=1}^{K} N(k)\mu(k)}{\sum_{k=1}^{K} N(k)}, \tag{8.9}$$

$$\Gamma(K)^2 = \sum_{k=1}^{K} \left(\frac{\sigma(k)N(k)}{\sum_{k=1}^{K} N(k)} \right)^2. \tag{8.10}$$

Let $Z(\delta)$ and $P(\delta)$ denote cumulative z-score and cumulative precision levels by end of the δth year, respectively, then

$$Z(\delta) = \frac{\bar{\chi}(\delta) - \theta(\delta)}{\Gamma(\delta)}, \tag{8.11}$$

$$P(\delta) = \frac{\bar{\chi}(\delta) - \theta(\delta)}{\bar{\chi}(\delta)}. \tag{8.12}$$

As both the optimal maintenance plan and the metering plan contribute to the maximum profit of PDs, they can be considered together in the project cost function. Under typical EE lighting programme, PDs will receive different rebate values for installing different types of EE lighting devices, denoted by R_i, on annual basis after the project implementation if the projects are maintained sustainable over the crediting period. However, PDs have to pay for the project transaction cost including the project design, implementation, performance evaluation and maintenance at their own budget. The initial investment Θ_1 of the project is estimated by

$$\Theta_1 = \alpha_i x_i(0) + (a_i + b_i)n_i(0) + \beta, \tag{8.13}$$

where α_i denote the implementation per lamp retrofit, including the procurement, delivery, removal of an old device and installation of a new device in the ith lighting group; a_i and b_i are the procurement and installation cost per meter device; $x_i(0)$ denotes the new lamp installations and $n_i(0)$ denotes the initial meter installations in the ith lighting group; β denotes the project transaction cost, usually β occupies 5% of Θ_1 and it is a once-off expense per project.

The performance of an energy conservation project is usually quantified by an M&V approach [1, 36]. By the M&V approach, the lighting project performance is proportional to the survived lighting population. As time goes by, the energy savings will decrease due to lighting population decay if the failed EE lighting devices are not replaced. As discussed previously, proper replacements of failed lamps contribute to a sustainable project performance, which will consequently increase the PDs' benefit. From PDs' point of view, although the project maintenance brings additional benefits, it requires extra investments. With additional investments for a proper project maintenance, the PDs' absolute benefit Π_2 might be greater than the profit obtained without maintenance. However, a greater Π_2 does not imply that the project with maintenance is more beneficial than the project without maintenance since this is not a fair-comparison. To ensure a fair-comparison, the total project benefit needs to be normalised against the total project investment. This normalised value is called cost-benefit ratio between the total project profit and the total project investment. The cost-benefit ratio J_2 for the project with maintenance is calculated by Π_2/Θ_2, and

$$\Theta_2 = \Theta_1 + \sum_{i=1}^{I}\sum_{k=0}^{K-1}[\alpha_i u_i(k) + c_i n_i(k) + B_i(k)S_i(k)(a_i+b_i) + \gamma_i \hat{n}_i(k)], \tag{8.14}$$

where c_i is the annual meter maintenance cost, and $B_i(k)$ is calculated by

$$B_i(k) = max(B_i(k-1),0) + n_i(k-1) - n_i(k),$$

where $B_i(0) = 0$, and $S_i(k)$ is defined as

$$S_i(k) = \text{sgn}(B_i(k)) = \begin{cases} 0, & \text{if} \quad B_i(k) > 0, \\ -\frac{1}{2}, & \text{if} \quad B_i(k) = 0, \\ -1, & \text{if} \quad B_i(k) < 0, \end{cases}$$

and $\hat{n}_i(k)$ is the sample size to determine the survived lamp population and γ is the sampling cost per lamp for counting of lamp population, in addition,

$$\Pi_2 = \sum_{i=1}^{I}\sum_{k=0}^{K-1} r_i x_i(k) - \Theta_2, \tag{8.15}$$

where $x_i(k)$ represents the number of survived EE lamps in the ith group during the time period $[k, k+1)$ and $x_i(k)$ is calculated by the state equation in Equation (8.1); r_i is the rebate per EE device in the ith group, $r_i = R_i ES_i$. ES_i is the energy saving (in kWh) per EE device that is determined by the M&V approach. For simplicity, it is assumed that both r_i and ES_i are constant during each sampling interval.

In order to maximise PDs' benefits, the metering cost must be minimised and the maintenance cost must also be optimally allocated to

$$\min \quad J_2 = -\frac{\Pi_2}{\Theta_2}, \tag{8.16}$$

with the design various $\mathbf{z}_i(k)$, $\mathbf{p}_i(k)$, and $\mathbf{u}_i(k)$, which is subject to the following constraints

$$\begin{cases} x_i(k) \leq x_i(0), \\ x_i(k) \geq 0.5x_i(0), \\ \sum_{i=1}^{I}\sum_{j=0}^{k-1}[\alpha_i u_i(j) + c_i n_i(k) + B_i(k)S_i(k)(a_i+b_i) + \gamma_i \hat{n}_i(k) - r_i x_i(j)] \leq 0, \\ Z(\delta) \geq 1.645, \\ P(\delta) \leq 10\%, \end{cases} \tag{8.17}$$

where the first two constraints indicate that the project population shall be within the boundary of $[0.5x_i(0), x_i(0)]$. The lower bound is designed to guarantee the projects' sustainable performance. The upper bound is a hard constraint since $x_i(0)$ is decided by the project scope boundary. The third constraint is the limit of the available budget for the maintenance. In other words, the expense for the maintenance at time k must not exceed the cumulative available profits of the project at the end of the time period $[0, k-1)$. The last two constraints are the M&V sampling accuracy requirements.

8.4 CASE STUDY

In this section, an integrated optimal metering and maintenance plan is designed for a lighting retrofit project as a case study to illustrate the effectiveness of the proposed model. This case study investigates project with a single lighting group.

A lighting retrofit project is going to be implemented to reduce the lighting load in various residential households in the Northern areas of South Africa. This lighting project is sponsored by a local utility under the National DSM programme. There are 404 876 units of 12 W CFLs to be installed to replace existing 60 W ICLs. According to the project regulation policies, the removed ICLs will be counted, stored and destroyed by a contracted disposal company. The CFLs to be installed have a rated life of 4 years and these lamps are burning 6 hours per day on average. The energy efficiency lamps have the equivalent lumen to the replaced old lamps.

The PDs of this project will receive a rebate rated at R 0.42 per kWh savings realised annually from the project sponsors. PDs are encouraged to implement the project at their own cost. The project qualifies a crediting period of 10 years, during which PDs can receive rebates on annual basis if the population of the newly installed EE lighting devices are properly maintained. If more than 50% of the newly installed lamps is malfunctioned, then the project rebate will be ceased. The project performance in terms of energy savings will be reported at the end of each crediting year by a third-party M&V inspection company. The number of survived lamps will also be inspected by sampling and surveys during each maintenance interval. Once lamp failures are observed, PDs' are allowed to replace some (or all) of the failed EE devices at the end of each crediting year to avoid the cease of project rebates. More project details that obtained from the project participants are listed in Table 8.1. The coefficients in the population decay dynamics model (7.5) are identified by the system identification approach proposed in [158, 104] and also provided in Table 8.1.

Table 8.1: Information of the lighting project.

Parameters	**CFL group**
Initial population	404 876
Unit retrofit price	R 32
Daily burning hours	5 h
Rated power of ICLs	60 W
Rated power of CFLs	12 W
Rebate per kWh	R 0.42
Meter unit price	R 4,032
Installation per meter	R 420
Annual maintenance per meter	R 1464
CV	0.5
$\tilde{b}_1\tilde{c}_1$	0.8286
$\tilde{c}_1$	0.8863

In order to obtain the optimal metering and maintenance plan for the above-mentioned lighting project, the optimal replacements $u_i(k)$, z-score $z_i(k)$ and precision $p_i(k)$ need to be identified with the application of the initial conditions of the parameters appear in the model (8.16)-(8.17). The relevant initial values are listed in Table 8.1. For this case study, the maintenance intervals are decided to be one year, while the performance reporting schedule δ=2, 4, 6, 8, ..., 10.

For this case study, all computations are carried out by the Matlab program. In particular, the optimal control inputs are computed by the "fmincon" code of the Matlab Optimisation Toolbox [171]. The optimisation settings of the "fmincon" function are shown in Table 8.2, where the "sqp" algorithm is chosen as the optimisation algorithm; the three termination tolerances on the function value, the constraint violation, and the design variables are also given. In addition, "fmincon" calculates the Hessian by a limited-memory, large-scale quasi-Newton approximation, where 20 past iterations are remembered. Besides these settings, a search starting point and the boundaries of the design variable are also assigned.

The computation results are provided in Tables 8.3-8.4, and also presented graphically in Figures 8.1-8.4. In Table 8.3, $c(k)$ and $C(k)$ denote the annual confidence levels and the cumulative confidence levels, respectively. Year k corresponds to the period of $[k, k+1)$. As shown in Table 8.3, the cumu-

Table 8.2: Optimisation settings.

Categories	**Options**
Algorithm	sqp
TolFun	10^{-30}
TolCon	10^{-6}
TolX	10^{-6}
Hessian	'lbfgs', 20
lb: $(u_i(k),z_i(k),p_i(k))$	(0, 0, 0)
ub: $(u_i(k),z_i(k),p_i(k))$	($x_1(0)$, 5, 1)
Start point: $(u_i(0),z_i(0),p_i(0))$	(1000, 1.5, 0.1)

lative confidence and precision levels satisfy the required 90/10 criterion. The required sample sizes and metering cost are also presented on annual basis.

Table 8.3: Optimal M&V metering plan.

Year (k)	$z(k)$	$c(k)$	$Z(k)$	$C(k)$	$P(k)$	$n(k)$	Cost (R)	$\hat{n}(k)$
0	0.8811	62.17%	0.8811	62.17%	7.55%	34	151 368	15 935
1	1.4453	85.16%	**1.6450**	**90.00%**	**9.97%**	34	49 776	15 935
2	0.2979	23.42%	1.2878	80.22%	8.08%	12	17 568	15 933
3	1.0463	70.45%	**1.6582**	**90.27%**	**9.82%**	12	17 568	15 924
4	0.7840	56.69%	1.7930	92.70%	10.78%	7	10 248	15 906
5	0.2242	17.74%	**1.6634**	**90.37%**	**9.76%**	7	10 248	15 875
6	0.0643	5.12%	1.4759	86.00%	8.67%	5	7 320	15 848
7	0.7763	56.24%	**1.6674**	**90.45%**	**9.69%**	5	7 320	15 861
8	0.7335	53.67%	1.8169	93.07%	10.64%	4	5 856	15 893
9	0.0578	4.61%	**1.6518**	**90.14%**	**9.68%**	4	5 856	15 935
Total	n/a	n/a	n/a	n/a	**34**	**283 128**	n/a	

In the Figures 8.1-8.3, the horizontal axes indicate the project crediting years. In the Figures 8.1-8.2, the the vertical axes display the confidence and precision levels, respectively. It is clearly observed that the required confidence and precision levels are satisfied during the reporting years.

The vertical axes in Figure 8.3 show the survived lamp population. The solid lines (in blue) denote the system states of the annual survived lamps over the crediting period. The dash-dotted line (in black) denotes the survived lamp population without control/maintenance. The stem lines with a circle (in red) denote the number of failed lamps to be replaced over the 10-year crediting period. As shown by

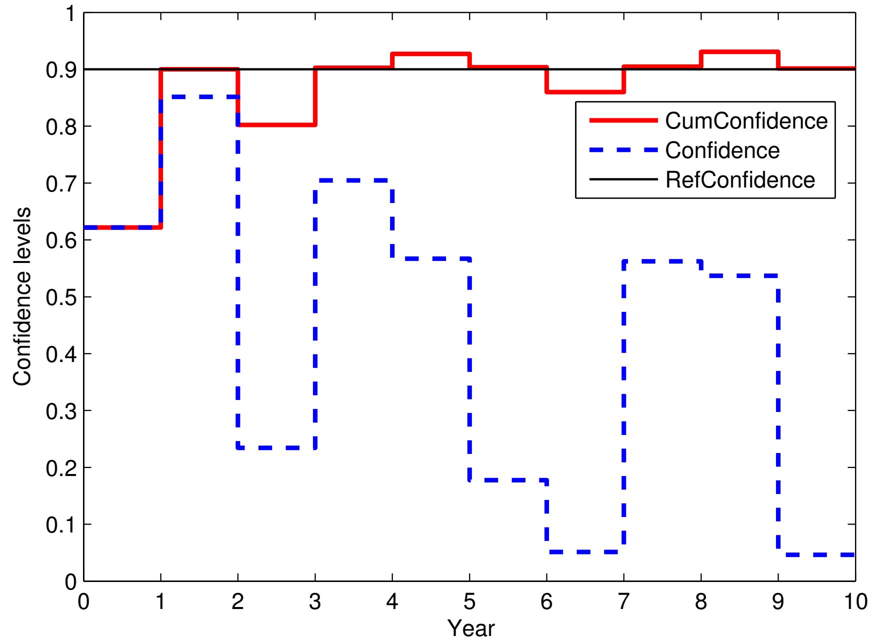

Figure 8.1: Confidence levels.

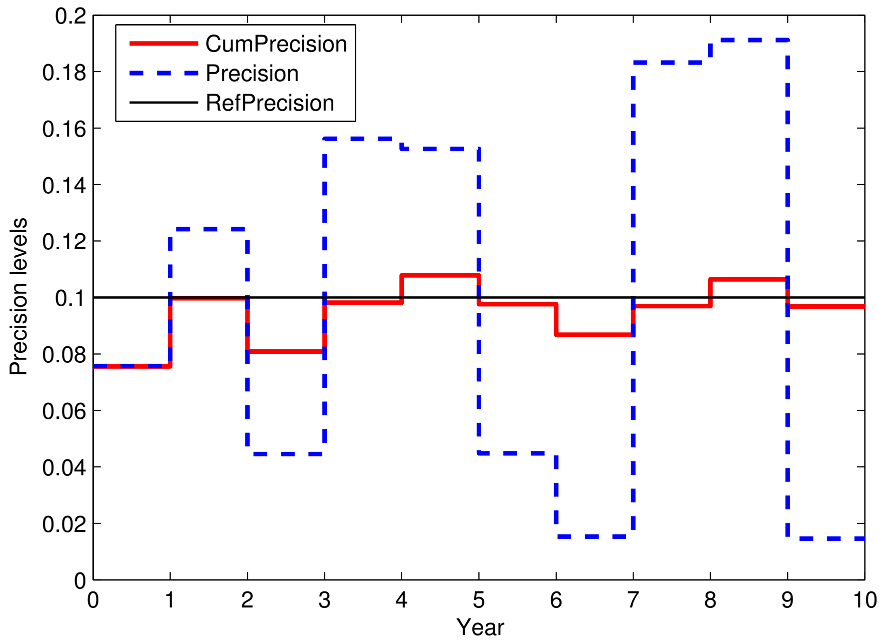

Figure 8.2: Precision levels.

the solid lines (in blue), lamp failures are identified at the end of each year, then a number of these failed devices will be replaced as denoted by the stem lines. Generally, it tends to replace more failed lamps at a later stage of this project when more lamp failures occur.

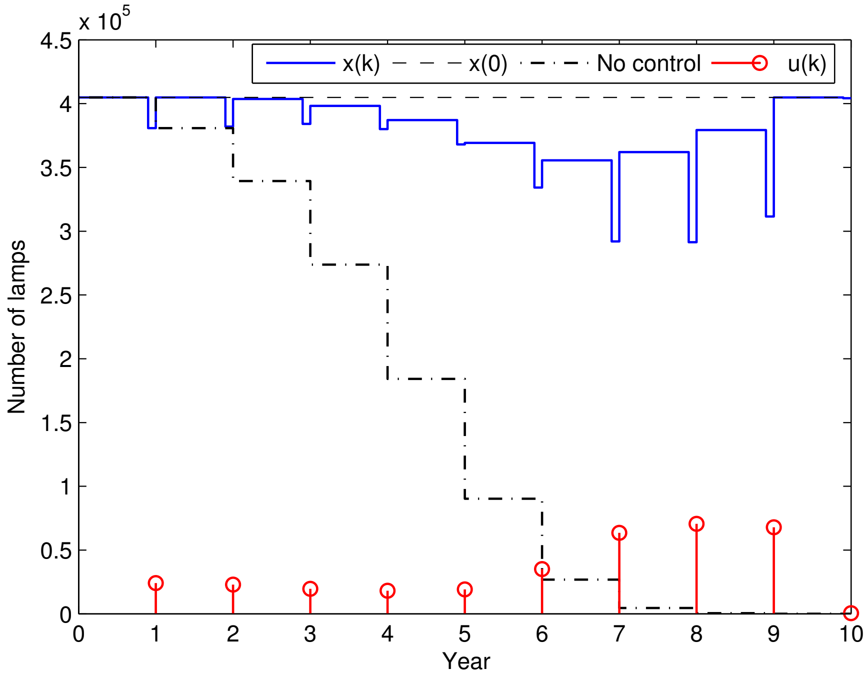

Figure 8.3: Optimal maintenance plan.

In Figure 8.4, the optimised sample size is denoted by the solid line (in red) and the backup meters is represented by the dashed line (in blue). It is found that the sample sizes are influenced by the survived lamp population. It is also observed that for each 2-year reporting period, i.e. Years [0, 2), Years [2, 4), the samples do not change too much. However, the sample sizes change significantly across reporting periods, i.e., across Years [1, 3), Years [3, 5). It indicates that the proposed model tries to balance the samples within the reporting periods in order to minimise the metering cost. It is also observed that there are backup meters at the end of the project. These meters can be removed and sold out at a lower price or be reused in other similar lighting retrofit projects.

The KPI, such as the total investments (in MR) , total profits (in MR), the cost-benefit ratio, and the total energy savings (in MWh) for the lighting retrofit project under the scenarios with no optimisation (NO), MCM only, optimal maintenance (OM) only, and optimal metering and maintenance strategies are calculated and summarised in Table 8.4. The comparison of the performance between no optimisation and the integrated optimal metering and maintenance strategies indicates that the energy savings increase by 127% with the integrated optimal strategy. In addition, PDs receive 144% more profits with an extra 65% investment for the project maintenance. When comparing the performance indicators among the MCM only scenario, the OM only scenario, and the integrated optimal metering and maintenance strategy, it is observed that with the integrated optimal strategy, both the cost-benefit ratio and total energy savings are the highest, which provides the best beneficial solution to PDs.

Table 8.4: Project key performance indicator analysis.

Key performance indicators	NO	MCM	OM	MCM & OM	NO v.s. MCM & OM
Total investment (MR)	16.495	15.548	27.962	27.290	65%
Total profit (MR)	58.795	59.741	121.520	143.550	144%
Cost-benefit Ratio	3.5644	3.8424	4.3460	5.2604	47%
Energy saving (MWh)	179263	179263	355910	406770	127%

NM: no optimisation; MCM: metering cost minimisation; OM: optimal maintenance; v.s.: versus.

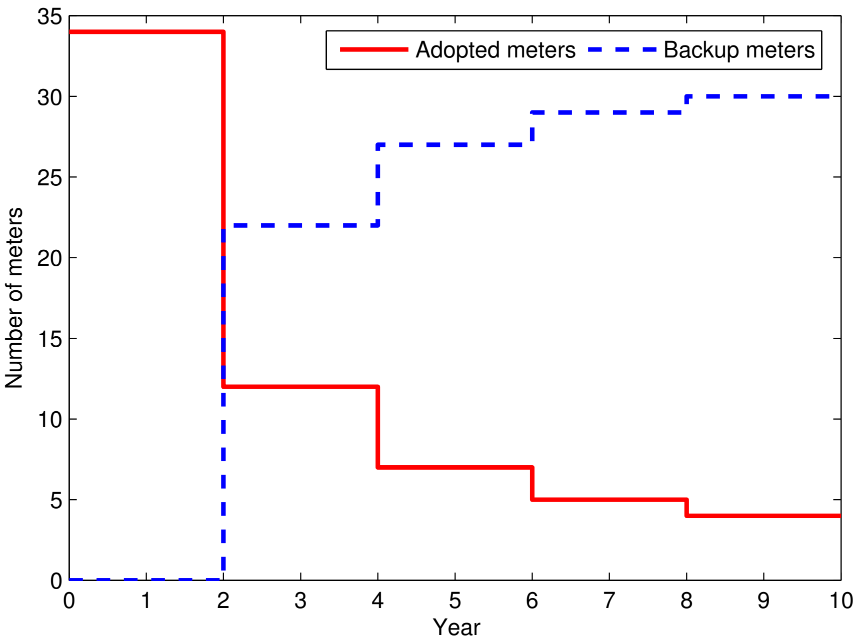

Figure 8.4: Sample size.

8.5 MODEL APPLICATION AND DISCUSSION

The case study suggests that proposed integrated optimal M&V metering and maintenance plans are very useful in maximising PDs' profit from implementation of lighting retrofit projects. The proposed model has incorporated a number of adjustable factors in a practical lighting retrofit project, i.e., the project population, population decay dynamics, CV of energy consumption, desired M&V accuracy, maintenance and reporting frequencies, prices for the lamp retrofitting, sampling, and metering systems. Therefore, this model can be flexibly applied other lighting retrofit projects to assist the project design in terms of optimal M&V plan and maintenance planing.

8.6 CONCLUSION

In this chapter, the optimal M&V metering plan and lighting maintenance plan are integrally designed for lighting retrofit projects. With the adoption of the optimal metering and maintenance plans, the project sponsors receive additional energy savings. The reported project performance is accurate enough to satisfy the M&V accuracy requirements. In addition, the PDs' profit is maximised with proper reinvestment for the lighting project maintenance.

CHAPTER 9

CONCLUSION AND FUTURE WORK

This thesis focuses on the design of optimal M&V plans for the energy/demand savings calculation of energy efficiency lighting projects. Given the inherent trade-off between M&V cost and uncertainty in the M&V practice, the following two critical problems have been fully addressed and solved. **1)** to design an M&V metering plan that uses optimal number of meters for sampling while achieving the desired sampling accuracy with the minimal M&V metering and sampling cost; **2)** to maintain the sustainability of the project savings when the lamp population decays as time goes by.

In this section, the major contributions of this thesis will be summarised together with an outlook of future research activities in the M&V field.

9.1 CONCLUSION

The major contributions of this thesis are summarised as follows.

In Chapter 1, an comprehensive review on the international M&V standards, protocols, and guidelines, together with the M&V related research articles are performed. Based on the summary of existing M&V literature, the author proposes to conduct the M&V research in three major areas, **1)** to establish a scientific and formalised M&V framework; **2)** to develop and improve M&V techniques; and **3)** to summarise and share global M&V best practice.

Chapter 2 aims to offer necessary preliminary knowledge for the formulation of the optimal metering and maintenance problems. Therefore, the M&V framework is introduced in terms of definition, measurement boundaries and the four IPMVP options, the scope and importance of M&V plan and metering plan, with further discussions on different terminologies of M&V savings. Thereafter, M&V

uncertainties and reporting protocols are introduced with descriptions on the sampling techniques that are widely used to quantify the M&V sampling uncertainty.

In Chapter 3, international lighting energy efficiency and management activities are reviewed, followed by the general M&V process on lighting retrofit projects with detailed discussions on baseline and savings determination methodologies by the four IPMVP options. New findings on the lighting peak demand diversity factor is also presented in this chapter.

In order to deal with the inherent trade-off between the M&V accuracy and M&V cost, three MCM models are developed in Chapters 4-6, namely the spatial MCM model, the longitudinal MCM model, and the combined spatial and longitudinal MCM model, to assist the design of optimal M&V metering plans, by which the minimal metering cost is achieved with the satisfaction of the required metering and sampling accuracy. The advantages of the proposed MCM models are demonstrated by several case studies of lighting retrofit projects.

In Chapter 7, an optimal maintenance plan has been developed to optimise the number of replacements of the failed lamps, such that the EE lighting project achieves sustainable performance in terms of energy savings whereas the PDs obtain their maximum benefits in the sense of cost-benefit ratio. This OMP problem is aptly formulated as an optimal control problem under control system framework, and solved by a MPC approach. A case study is presented to illustrate the effectiveness of the proposed control system approach.

In Chapter 8, the MCM models are integrated with optimal maintenance plans for lighting retrofit projects. With the optimal solutions to the integrated model, the project sponsors receive extra profit in terms of a higher cost-benefit ratio, and sustainable energy savings over a 10-years' crediting period. The project performance is accurately measured and verified with desired M&V accuracy. The effectiveness of the proposed integrated model has been illustrated by a case study.

9.2 FUTURE WORK

From author's own perspective, the ongoing and near future M&V research plans are given as follows.

1) to develop an review article by summarising the M&V related policies, standards, protocols, and guidelines, together with the M&V related research articles under the scope of establishing a scientific and formalised M&V framework; developing and improving M&V techniques; and summarising and sharing global M&V best practice.

2) to expand the MCM models for the purpose of handling the measurement, modelling and sampling uncertainties together.

3) improve the optimal maintenance plan on lighting with considerations of the optimal maintenance schedules.

4) further investigations on the peak demand diversity factors on other technologies such as air-conditioners, water heating devices, etc.

5) to decide the optimal boundary for an M&V process, especially when project boundary changes after implementation.

6) to further improve the MCM models by taking considerations of the optimal geographical locations for meter installation.

The author would like to advise the following research topics/areas on M&V to be developed or further explored by other researchers.

1) establishment a scientific and formalised M&V framework.

2) developments and improvements of M&V techniques, which includes:

- handling M&V uncertainties cost-effectively;
- baseline development and modelling;
- best choice of the IPMVP options;
- issues on savings determination and accounting;
- development of information system to support M&V practice.

3) documenting and sharing of global M&V best practice.

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