MICROLOAD MANAGEMENT IN GENERATION CONSTRAINED POWER SYSTEMS

Submitted for the Degree of Doctor of Philosophy

at the University of Northampton

2022

JULIUS QUARSHIE AZASOO (MPHIL, BSC (HONS), POS)

"Do everything to get educated BUT do not pay too much for it."

- I saw it somewhere . . . J Azasoo

DECLARATION

I hereby declare that the work described in this thesis is original work undertaken by me for the degree of Doctor of Philosophy, at the Faculty of Arts, Science and Technology (FAST) - University of Northampton, United Kingdom. No part of the material described in this thesis has been submitted for any award of any other degree or qualification in this or any other University or College of advanced education.

Julius Quarshie Azasoo, 2022

RELATED PUBLICATIONS

- ***Azasoo, J.Q.**, Kanakis, T., Al-Sherbaz, A. and Agyeman, M.O., Predictive Approach to Microload Management for Energy Poverty Reduction in Generation Constrained Power Systems [Submitted- First rounds of reviews completed -IEEE Access]*
- ***Azasoo, J.Q.**, Kanakis, T., Al-Sherbaz, A. and Agyeman, M.O., 2020. Heuristic Optimization for Microload Shedding in Generation Constrained Power Systems. IEEE Access, 8, pp.13294-13304*
- ***Azasoo, J.Q.**, Kanakis, T., Al-Sherbaz, A. and Agyeman, M.O., 2019, August. Optimal demand side management in generation constrained power systems. In 2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI) (pp. 29-36). IEEE*
- ***Azasoo, J.Q.**, Kanakis, T., Al-Sherbaz, A. and Agyeman, M.O., 2019, April. Improving electricity network efficiency and customer satisfaction in generation constrained power system. In 2019 6th International Conference on Control, Decision and Information Technologies (CoDIT) (pp. 2010-2015). IEEE*
- *Tweneboah-Koduah S., Tsetse A.K., **Azasoo J.Q.**, Endicott-Popovsky B. (2018) Evaluation of Cybersecurity Threats on Smart Metering System. In: Latifi S. (eds) Information Technology - New Generations. Advances in Intelligent Systems and Computing, vol 558. Springer, Cham. https://doi.org/10.1007/978-3-319-54978-1_28*
- ***Azasoo, J.Q.**, Kuada, E., Boateng, K.O. and Agyeman, M.O., 2017, June. An algorithm for micro-load shedding in generation constrained electricity distribution network. In 2017 IEEE PES PowerAfrica (pp. 396-401). IEEE*

ABSTRACT

The reasons for power systems' outages can be complicated and difficult to pinpoint, but an obvious shortfall in generation compared to electricity demand has been identified as the major cause of load shedding in generation constrained power systems. A sudden rise in demand for electricity on these networks at any time could result in a total collapse of the entire grid. Therefore, in this thesis, algorithms to efficiently allocate the available generation are investigated to prevent the associated hardships and lose experience by the final consumers and the electric utility suppliers, respectively.

Heuristic technique is utilised by developing various dynamic programming-based algorithms to achieve the constraints of uniquely controlling home appliances to reduce the overall demands for electricity by the consumers within the grid in context. These algorithms are focused on the consumers' comfort and the associated benefits to the electricity utility company in the long run. The evaluation of the proposed approach is achieved through microload management by employing three main techniques; General Shedding (GS), Priority Based Shedding (PBS) and Excess Reuse Shedding (ERS). These techniques were evaluated using both Grouped and “UnGrouped” microloads based on how efficient the microload managed the available generation to prevent total blackouts. A progressive reduction in excess microload shedding experienced by GS, PBS, and the ERS shows the proposed algorithms' effectiveness.

Further, predictive algorithms are investigated for microload forecasting towards microload management to prepare both consumers and the electric utility companies for any impending load shedding. Measuring the forecasting accuracy and the root mean square errors of the models evaluated proved the potential for microload demand prediction.

ACKNOWLEDGMENTS

First, this achievement is dedicated to God Almighty for the unending support, good health, strength, sane mind, and the direction to have come thus far. Great is His faithfulness indeed!

I am sincerely grateful to all the loving and caring images of God that He has placed on my path during this PhD journey; May God bless you! My gratitude goes specifically to the following great ones;

My special gratitude goes to my supervisory team Prof. Michael Opoku Agyeman, Dr. Triantafyllos Kanakis (Aldo) and Prof. Ali Al-Sherbaz whose mentorship, continuous guidance and advice has seen me through this special stage of my academic aspirations. Thanks cannot suffice, but thank you! “Ektimó óles tis prospátheiés sas”.

It would not have been possible to complete this journey without the continued financial support and encouragements received from the Ghana Institute of Management and Public Administration (GIMPA), Accra, Ghana, which enabled me to embark on this journey and eventually reach this stage. I would say “akpega de na mi, Mawu na yra mi!” The School of Technology (SOT) staff of GIMPA, you are the family, and many-many thank you.

To the ever-supporting staff of the Faculty of Arts, Science and Technology (FAST) of the University of Northampton, I say, “Thank you so much”. I am also indebted to the following individuals:

- Rev. Mathias Azasoo
- Reuben Nyaledzigbor
- Pastor Theophilus Amoo
- Rev. Dr. Philip Quainoo and Family

DEDICATION

I dedicate this thesis to my wife, Jennifer and children, Martin, Joel and Marie for their understanding and support, enabling me to make this a reality. Of course, the blessed memories of my parents cannot be forgotten when they insisted that knowledge is power. Emmanuel Soetor and Martha Etsa, your efforts and toils have not been in vain. May God Bless you even more!

Table of Contents

List of Figures

List of Tables

LIST OF ABBREVIATIONS

AMI	Automated Metering Infrastructure
AMR	Automated Meter Reading
ANN	Artificial Neural Network
B1E	North Bedroom
B2E	Master/South Bedroom
BME	Basement Plugs & Lights
BPSO	Binary Swarm Optimization
C	Current
CDE	Clothes Dryer
CNN	Convolutional Neural Network
CT	Control Type
CWE	Clothes Washer
D	Demand
DC	Direct Current
Dm	Demand per meter
DNE	Dining Room Plugs
DPS	District Power System
DSM	Demand Side Management
DSR	Design Science Research
DT	Decision Tree
DWE	Dishwasher
EBE	Electronics Workbench
EC	Energy Appliance Controller
ECS	Energy Consumption Scheduler
EM	Energy Modem
EQE	Security/Network
ERGGmL	Excess Reuse General Grouped Microload
ERGmL	Excess Reuse General Microloads
ERGUmL	Excess Reuse General UnGrouped Microloads
ERmL	Excess Reuse Microloads
ERPBGmL	Excess Reuse Priority Based General Microloads
ERPBUmL	Excess Reuse Priority Based UnGrouped Microloads
ERS	Excess Reuse Shedding
ES	Energy Scheduler
EV	Electric Vehicle
FGE	Kitchen Fridge
FRE	HVAC/Furnace
GBM	Gradient Boosting Machines
GCmL	Grouped Controllable Microloads
GGmL	General Grouped Microload
GmL	General Microload Shedding
GMS	GmL Meter Side
GPM/GMM	Gaussian Process Model Regression/Generalized Method of Moments
GRE	Garage

GS	General Shedding
GSM	Global System for Mobile Communications
GSS	GmL Server Side
GUmL	General UnGrouped Microload
HAN	Home Area Networks
HPE	Heat Pump
ICT	Information and communications technology
IPSO	Improved Particle Swarm Optimization
KNNR	K-Nearest Neighbour Regression
L	Microload
LCD	Liquid Crystal Display
Lid	Microload ID
Ln	The nth microload
LP	Load Power
LSSVM	Least Squares Support Vector Machine
MARS	Multivariate Adaptive Regression Splines
MCU	Micro Controller Unit
Mid	Meter ID
MIMO	Multiple Input Multiple Output
mL	Microload
MLR	Multiple Linear Regression
MODE	Multi-Objective Differential Evolution
MOGA	Multi-Objective Genetic Algorithm
MPS	Main Power System
MSE	Mean Square Error
NAN	Neighbourhood Area Networks
NCL	Number of Controllable Loads
NNGA	Neural Network-Genetic Algorithm
NPSO	Niche Particle Swarm Optimization
NSGA	Non-domination Based Sorting Genetic Algorithm
OFE	Home Office
OUE	Outside Plug
P	Power
PAR	Peak-to-Average Ratio
PbGmL/PBGmL	Priority Based Grouped Mircroloads
PBS	Priority Based Shedding
PC	Personal Computer
PGUmL	Priority Based General UnGrouped Mircroloads
PHEV	Plug-in Hybrid Electric Vehicle
PIC	Programmable Integrated Circuit
PLC	Power Line Communication
PS	Power System
Pt	Sum of total Priority of the consumer
PV	Photovoltaics
RF	Random Forest
RFMINO	Radio Frequency Multiple Input Multiple Output

RMSE	Root Mean Square Error
RSE	Rental Home
RT	Random Tree
RTD	Real Time Demand
RTP	Real Time Pricing
SM	Smart Meter
SS	Schedule Status
SVM	Support Vector Machine
SVR	Support Vector Regression
TC	Total Consumption
THE	Instant Hot Water Unit
TOU	Time of Use
TVE	Ent Tv/PVR/AMP
UCmL	UnGrouped Controllable Microloads
UGCmL	UnGrouped General Controllable Microloads
UGmL	UnGrouped General Microloads
UmL	UnGrouped Microloads
UTE	Utility Room Plug
WAN	Wide Area Network
WOE	Wall Oven

Chapter 1

Introduction

1.1 Introduction

The process by which the electricity demand is forced to match the generation is known as electric load management. Electricity demand at any given period is unstable, and this applies to the generation as well. Consumers expect the utility providers to supply them with reliable and uninterrupted electric power supply; electric utility companies are therefore motivated to shed large electrical loads from high-demand peak times to low-demand off-peak time [1-3]. The methods used to achieve this are collectively called load management. There is no problem when generation is far more than the demand (reserve margin), but when the demand, on the other hand, approaches the generation, it may result in an entire grid's total collapse [4]. The uncertainties in demand for electricity from consumers and the availability of modern technologies strengthen utilities to undertake various Demand Side Management (DSM) [5] to achieve optimum electricity availability and use.

However, the threshold is mostly exceeded because demand is more than the generation and supply. Such an imbalance can lead to the breakdown of generating units; thus, some of the demand must be blocked to maintain frequency equilibrium [10, 11, 12]. The best load management and frequency monitoring procedures thus become issues of prime importance to nations. They seem to be most important in developing countries whose generating capacities are always yet to catch up with the demand levels (see [9, 14, 15]). In this thesis, we refer to the utility companies in such countries as generation constrained power systems. Such generation constrained power systems thus need peculiar solutions to solve load management challenges.

Moreover, when this monitoring has been done, and there is a need to continually block an amount of load from the system to maintain a safe and economic running of the overall generating, transmitting and distributing systems, and just measuring frequency to block the loads will be insufficient. As a result, many countries have resulted in various means of intentionally sharing the effect of the quest to balance the electric network across their consumers. Some countries must turn OFF certain communities for periods (Ranging from hours to weeks) or even sometimes months and then restoring the power by turning OFF some other communities that were previously ON similarly, to match the demand with the supply [1, 15-20]. The advancement of technology has enabled smart meters to be used to monitor changes in frequency and remotely turn OFF households [21]. By means of a smart meter, some countries could turn OFF specific or group of appliances in a household aiming at levelling the frequency to equilibrium. As the demand for electricity is continually growing along with the increasing dependency on modern technologies that are mostly if not entirely driven by one form of electricity or the other [22-24], there is the need to focus attention on how this load shedding can be optimized in a way that consumers can still use their essential electric power-driven devices during the period of load shedding implementations or in times of supply shortfalls.

Smart metering promises an interim solution to the problem. Smart meters allow the implementation of time-varying billing methods that support the reduction of power system peak demand [25-27]. Energy suppliers send time-varying price information to smart meters through a Wide Area Network (WAN) [28]. Many smart meters have data registers to store energy consumption with different price schemes. For example, in some developed countries, smart meters can store price schemes that vary half-hourly or quarter hourly. Current endeavors in smart grid research have been focusing mostly on optimization techniques modelled to minimize bill payments, PAR and peaking. Recent work by Yaghmaee et al., in [13] focuses on controlling residential loads comprising storage devices in addition to local sources of energy generation to achieve DSM in a two-tier cloud-based implementation.

Considering recent strives made in the design of smart metering technologies; it has become empirical that it finds root in the load management sector. Therefore, there is the need to harness the functionalities of the smart meter into the load management research where load-shedding and its related calculations are performed on the smart metering platform at the microload levels by strategically taken OFF specific microloads to stabilize the power system or to always make electricity available to across the entire electric grid.

1.2 Problem Statement

Another aspect of the demand side management is micro-grids, where consumers can sell their self-generated electricity power back to the utility for effective reductions in their utility bills [32, 33]. In Ghana, for example, water levels in all the dams have dropped drastically and are still dropping as a result of consistent insufficient rainfall over a long period. The drop in the water level can heavily be attributed to the fall in the flow of water from the upstream as a result of dam construction on its path at Burkina Faso [34].

Even if the generating units are running at their full capacities, many countries are still faced with the issue of rising numbers of consumers of electricity, planned maintenances as well as breakdown of generating, transmission and distribution units. Increasing the generation capacities and the provision of a high number of spare units and parts could be one of the ways to handle these issues. This requires huge financial investments, which may not be readily available to most countries facing this situation. This menace is even worse in developing countries.

In the face of falling installed generation capacities coupled with the increasing number of consumers, the power systems must be protected by systematically blocking electricity to various parts of the country [32]. However, in view of these problems, constrained power systems must perform load shedding due to higher demand than generation resulting in completely cutting OFF electricity power to sections of a country or even the entire country [35]. The smart meter is equipped with intelligence to collect granular metering information on household/company and device basis at a precision order as well as remotely connect and disconnect the meter from the electricity supply [25].

The recent hike in electricity management in the world presents an opportunity to investigate how these smart metering systems could be enhanced to ameliorate problems associated with the processes adopted by constrained power systems in order to prevent country-wide power outages. This practice, referred to as load shedding, creates inconvenience for the consumers and at the same time causes the utility to lose huge amounts of revenue [10].

1.3 Aims and Objective

This research work examines and reviews the present methods of load shedding as a guide to the development of microload shedding smart metering system by addressing the shortfalls of the existing approaches and technologies. Hence, this thesis presents a novel microload shedding technique for managing generation constrained power systems. Furthermore, considering the opportunities and challenges introduced by the microload shedding in the smart grid, this thesis provides efficient algorithms and optimization techniques for managing the microloads.

Specifically, the microload management smart metering system should be able to automatically or semi-automatically implement the microload shedding based on schedule or other indicators such as load profile or essential load requirements as well as consumer set priorities. The following objectives are achieved in the light of the above aim.

Objective I: *The existing methods of electricity load management have been reviewed*

Objective II: *Existing load management algorithms and optimisation techniques have been reviewed*

Objective III: *Microload management algorithms and optimisation techniques for microload shedding have been proposed and designed*

Objective IV: *The proposed microload management algorithms have been evaluated*

Objective V: *Efficient forecasting techniques have been implemented and applied to microload shedding*

1.4 Thesis Contributions

Although this research intends to provide a better customer experience, it has the potential to improve revenue generation for the utilities by continually providing services to their consumers even in the severest situations of generation deficiencies and or equipment failures. Through the microload management approach proposed in this thesis, consumers can monitor and control their energy consumptions efficiently in real-time or periodically at a more granular level.

The main contributions have been categorized as primary for those contributions that can be directly measured or seen from the output of the research and secondary for indirect contributions. The next subsections assess these categories of contributions.

1.4.1 Primary contribution

Theoretically, this research surveys theories associated with electricity management, smart metering and information systems and presents different perspectives to current approaches in electricity management and energy metering. The algorithms, optimisation techniques, and methodologies outlined in this research will go a long way to shape future research in these fields of research. By developing such a system, the research contributes practically by introducing a new kind of smart metering system and approach with its tools and methods. The demonstration of the ability to use the smart meter to gather Real-Time Demand (RTD) as a granular demand would constitutes a novel approach in the management of electricity for both consumers and electric utilities. Another primary contribution is the design of a smart metering system with algorithms and optimisation techniques capable of performing load limiting on the meter. As an effort to reduce global warming to some extent, this research provides an opportunity for the generation constrained power systems to share the scares electricity resources among their consumers without the need for excessive peaking.

1.4.2 Secondary contribution

This thesis becomes a point of reference to researchers working not only in the fields of smart metering, embedded systems but also electricity distribution and optimisation as well as information systems research [36, 37]. It will also contribute to the Human-Computer Interaction research domains [38, 39]. Notwithstanding the above, the developed artefact, microload manageable smart metering system will serve as a guide to future smart metering designs and as an exemplar to the Design Science Research (DSR) and its methodology [38].

1.5 Outline of Thesis

The background aims and objectives of the research are presented in Chapter One. The same chapter presents an overview of the problem in the Problem Statement section and outlines some research contributions. The thesis outline is also presented in Chapter One. Chapter Two reviews the literature on modern trends in electricity management and argues that current electricity management methods are good and effective for short-term intervention but pose a great burden on the consumers that negatively affect their livelihood when used as a long-term measure to stabilise the electricity network. It further argues that electricity has become the fabric of any society and must always be made available. This chapter again reviews current research on smart metering, focusing on the adopted communication technologies and the intended benefits. Pieces of the literature review show that the current design methods cannot be used for microload management. This has therefore, forced the need to research into a design that considers the granular load consumptions of all devices and appliances to enable microload management. Algorithms and optimisation techniques being used in most non-constrained power systems were also reviewed along with the potential to predict the future consumer and generation towards informing the stakeholders ahead of such microload shedding is also reviewed.

Chapter Three presents the System Model and the various abstractions involved in the algorithms' design, along with the associated assumptions. The chapter emphasises the positivist philosophy using heuristics. Furthermore, this chapter presents the design consideration of the microload manageable smart metering system. It outlines the requirements through models based on available tools and components required to design the smart microload meter and a simulator to evaluate the concept and the associated algorithms.

Chapter Four presents the first proposed microload shedding algorithm dubbed General Microload Shedding Algorithm while introducing the concept of Grouped Microloads (GmL) and Ungrouped Microloads (UmL). The results and discussions on evaluating the General Microload shedding Algorithm on GmL and UmL are presented in this chapter. Finally, this chapter concludes that there is significant excess load shedding and the intended request values observed and therefore argues for the need for further perspectives to reduce this excess shedding.

Chapter Five looks at the development of the algorithm and optimisation techniques that enable more efficient microload management by eliminating the excess load shed and the intended ones observed in the General Microload Shedding approach; introducing the Priority Based Microload Shedding Algorithm does this. The PBmL Shedding Algorithm was evaluated on both Grouped Microloads (GmL) and the Ungrouped Microloads (UmL); the results show significant reductions in the excess shedding. Further, Excess Reuse Microload (ERmL) Shedding algorithm was proposed and discussed in Chapter Six.

To take advantage of the modern trend being presented by the advancement of ICTs, Chapter Seven discusses the potential for predictive algorithms in electricity generation and demand forecasting for microload management. Finally, the conclusion and future outlooks for this research were discussed in Chapter Eight.

The various chapters are related to each other as follows; chapters are categorised into Relevance, Approach, Output and Evaluation. Chapters One and Two focus on the Relevance of the research. Chapter Three shows the Approach, and Chapters Four, Five, Six and Seven demonstrate the research's Output along with the Testing and Evaluation. Conclusion and Future Directions are presented through Chapter Eight.

1.6 Highlights of Contributions

In order to establish the niche of this research, the thesis presents overview and new perspectives on the smart grid and micro load shedding in Chapters 1 - 3. Following these chapters, novel solutions and algorithms are then proposed and evaluated in Chapters 4 - 6.

Specifically, the concept of microload shedding was introduced in Chapter 1 by giving an overview of the state of art research on electricity grid through which the aims and the objectives of the thesis were derived. Review of related literature is presented in Chapter 2 under the broad headings: smart metering systems; current optimization techniques and algorithms in smart grid, and overview of energy forecasting. The reviewed research works were then categorised as the drivers of smart grid into key objective areas as demand side management (DSM), peak to average ratio (PAR) reduction, cost minimisation (CM), consumer privacy and security (CPS), integration of renewable sources of energy (IRSE), and demand forecasting (DF) showing key research focusing on these thematic areas of smart grid.

The grid architecture adopted for the research was introduced in Chapter 3 where the research problem was formulated. In Chapter 4, the first algorithm addressing the shortfall of the traditional load shedding was developed and evaluated using microload demands, this is referred to as General Microload Shedding Algorithms comprising meter-side and server-side sub-algorithms which are then applied to grouped and ungrouped microloads. The evaluation results show that average of 0.63% and 6.98% excess microload shedding for the grouped and ungrouped microloads representing excess shedding of 4.33kW and 47.03kW respectively.

Priority based microload shedding algorithms were further proposed in Chapter 5 and evaluated on the grouped and the ungrouped microloads with the aim of given the end-users the ability to choose priority for the microloads and at the same time reducing the excess shedding observed from the general microload shedding algorithm. The results obtained by using this algorithm show an improvement in the previous approach but still recorded some excess microload shedding. A significant reduction in the excess curtailment was achieved which will ultimately help the utility companies to reduce wastage and losses resulting from over shedding. There was a reduction of the over-shedding from 74.01kW to 4.16kW after employing the Priority-based microload shedding techniques using the Ungrouped Priority Loads (UPL) consumption profiles. Additionally, the actual percentage shedding was also improved from 11% to 0.6% when subjected to a 10% microload shedding using the UPL load profiles for example.

The Chapter 6 considers the reuse of the excesses in the implementation of the various algorithms discussed previously. These set of algorithms were referred to as excess reuse algorithms. A progressive reduction in the excess shedding has been observed from the Excess Reuse General Microloads (ERGmL) to the Excess Reuse General Ungrouped Microload (ERPBUmL), producing the lowest excess shedding recorded. For example, ERPBUmL shedding resulting in 0.33kW, 0.20kW, 0.21kW, 0.09kW and 0.05kW as the average of the excess shedding for 2%, 5%, 10%, 15%, 20% and 30% request for shedding respectively compared to the 4.33Kw and 47.03kW recorded excesses during the general grouped and ungrouped microload shedding. The level of excess load shedding produced under the ERPBUmL makes it ideal for implementation in live grid infrastructure.

Finally, the impact of predicting the demand to prepare both consumers and the electric utility companies for potential load shedding is discussed in Chapter 7. The accuracy of the forecast conducted indicates an average accuracy of 58.87% and 56.78% when using SVR and KNNR respectively, while previous research reported 41.01%, 26.57%, 47.02% and 41.37% for RF and other forecasting models.

1.7 Chapter Summary

In this chapter, the problem domain is broadly introduced where insufficient generation of electricity energy to meet the increasing demand is shown to be having severe impact on the distribution of electricity to the end users and the safe running of the electricity network. DSM has been observed to be applied to maintain the stability of the electric network, yet there is a major gap in how the DSM is implemented in some countries with noticeable generation shortfalls.

The aims and the objectives of the research are also discussed in this chapter along with the contributions of the research which are categorised into primary and secondary contributions. Finally, the highlights of contributions and outline of the thesis is discussed, and the chapter concluded.

Chapter 2

Literature Review

2.1 Introduction

This chapter addresses the first objective of this research (To review the existing electricity load management methods) by discussing the prime concepts and current issues in smart metering systems. The costs of energy have been increasing over the years due to the growth in the population [41]. As a result, the energy demand is now more than its supply resulting in an increased in the peaking cost of an extra generation of electric power. Consequently, it is therefore, critical to find alternative energy generating sources. The smart grid or power distribution system can generate, transmit and distribute power [40]. Because of existing technologies, the smart grid gradually becomes a full reality in many countries [42]. However, the smart grid must have an accepted communication standard to communicate across various platforms effectively. The research work in [42] suggest that the security and the reliability of the smart grid are also important areas of concern and must be adequately dealt with to aid the development and acceptance of smart meters.

Kamble and Bodkhe in [43] also argue that energy saving has become very important and an urgent step to be taken because of the day-to-day increase in the populace. Therefore, there is a need to monitor and manage the energy that consumers use. The importance of the security issues in smart grid to costumers also led to the evaluation of cybersecurity threats on the smart grid by Tweneboah-Koduah et al. in [44], where various cyber-attacks were tested on a smart metering infrastructure. It revealed that the smart grid's vulnerabilities are multifaceted and required further research to assure consumers of the security of their metering data.

To further understand the state of the art of the current research activities in smart metering, focusing on the electricity grid, this chapter attempts to review research activities on smart grid, focusing on smart metering design, communication technologies, and their utility. The chapter also examines those smart grid research focusing on algorithms for PAR and optimization techniques to reduce the cost to the consumer and the utility, along with articles aiming at efficiently integrating renewable sources of electricity and storage devices. In addition, some privacy and security issues have been considered along with energy forecasting to prepare both consumers and the utilities towards any possible load shedding. The chapter concludes by highlighting research and practical implications of the reviewed articles and proposes some further research areas in smart grid aiming at reducing the impact of the load shedding practices in generation constrained power systems.

2.2 Smart metering Systems

This subsection reviews literature on smart metering systems, their intended aims and the communication technologies employed. A smart meter is designed to communicate its status, readings, and tamper states to a centralized system on a network. Configuration information such as billing rates, meter types, remote shutdown and other information relating to metering is sent back to the meter bi-directionally between it and a central server system [45]. Smart meters include water and gas metering and sometimes a combination of these three, but we refer to the electricity in this thesis.

2.2.1 Smart Metering for Electricity Management

Exploring Automated Meter Reading (AMR) design as an advantage over traditional meters, Popa in [46] claimed that AMR is better than the conventional meter reading because the latter is error-prone and time-wasting. On the other hand, AMR solves the conventional meter reading problems, but it also needs a system that can communicate the data read to the central computer system, where all the meters have been connected. The ZigBee technology can connect the meters to the central computer if the system will be wireless and if it will not cover a long distance and GSM if the distance to be covered is more than 100 meters. It is also mentioned that there are already power lines in almost all buildings; therefore, it is financially efficient because no cost will be incurred to fix these lines. AMR based on Power Line Communication (PLC) technology is thus proposed in [47]. The research, however, failed to acknowledge the challenges of PLC, such as interference and signal attenuation.

Aiming at the reduction of the energy consumed by smart meters and plug-in hybrid electric vehicles, the researchers in [48] proposed a coalition game approach to smart meter data communication were a group of smart meter and Plug-in hybrid electric vehicles (PHEVs) communicate to the WAN through one of them as a cluster head. Whiles the work was based on a simulation of the algorithm, it presents a whole new perspective of smart metering. However, in terms of security, it presents an opportunity for other researchers to investigate how neighbouring smart meters may learn of the data to be communicated to the central system and the data received from the central system.

Owen and Ward, in [49] proposing a pathway to facilitate quick response to smart metering adoption, argued that, unlike other technologies that have seen much change and evolution over the years, smart meters had not seen much change. The research identified some pathways that could lead to the quick facilitation of smart metering adoption. These are: regulatory barriers should be removed to aid the installation of the smart meters and try out smart meters immediately to motivate the implementation of smart meters. But smart meters offer opportunities for both households and energy suppliers. For households, they can conserve energy since they get feedback on how much energy they are consuming. On the other hand, it helps them generate more income for the energy suppliers because energy conserved can be used to serve other households, which improves their efficiency and availability.

To enable consumers' presentation with their energy consumptions and the ability to control their loads, Apperley and Kalyan in [50] show an electricity dashboard. They argue that the dashboard provides instant overview and consumption information and the availability of power and control appliance, which will go a long way to minimize energy consumption and enhance energy efficiency. Timely consumption information is critical to the consumer as post-hoc energy consumption information presented to the user may only serve for bill payment or records, but real-time or near real-time information could be more effectual for electricity [51]. To solve the increasing demand for electricity in Malaysia [52], [53] and Ahmad et al. in [54] suggested and designed a monitoring system that monitors the increasing rise in the consumption of energy across the country. This automated monitoring system is connected to a central hub using the GSM network, providing feedback to the consumers and the utilities. The feedback generated helps users to form energy conservation habits. GSM was used as the communication technology for the design of the metering infrastructure. The opportunity presented in this research using GSM technology can be replicated so that consumers can set priorities for their essential appliances for the proposed microload management approach.

Utility companies in Ghana are losing so much revenue as a result of energy theft. NUNOO and Attachie in [55], showed that they lose over a billion US dollars annually. Most of the energy theft is as a result of illegal connections where the culprits do not pay for the energy they use. Others tamper with their meters and therefore pay lesser than they are supposed to pay. Electricity theft has increased over the years in Ghana. As a result, a system to monitor the theft of electricity at a remote location and using a back tracking algorithm to achieve this was proposed.

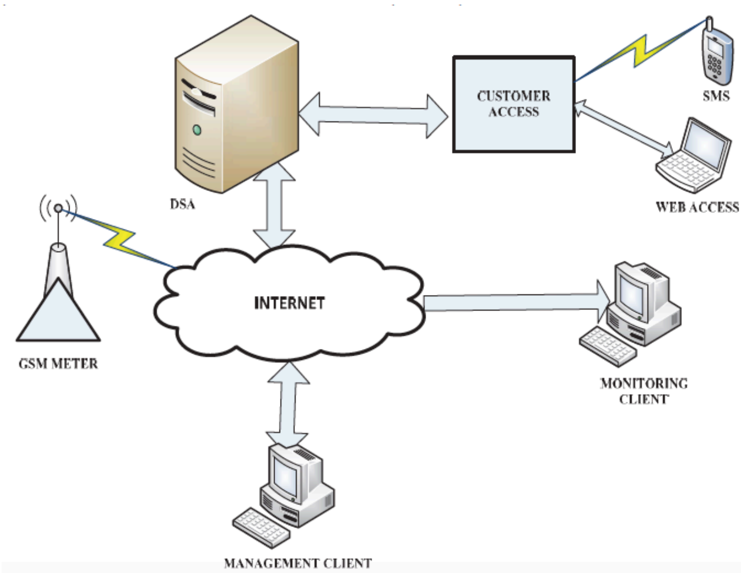


Figure 1 Smart Metering Architecture

Using the prevailing nationwide coverage of GSM infrastructure in Ghana and most developing countries, Azasoo and Boateng [45, 56] proposed and designed a GSM-based smart metering system to harness smart meters' potential for deployment in Ghana. Their proposed systems were tested and proven to help solve the problem of timely billing information and tamper notification being one of the prevailing menaces among the electricity utilities. The proposed smart meter could be configured as prepayment or post-payment meters. Another case for adopting smart meters was the savings that it could make when the meters communicate granular consumption details to the utilities for billing and planning purposes. The architecture of their proposed system is presented in Figure 1.

However, domestic energy can be managed using simple and cost-effective technologies like PLC and Bluetooth [57, 58], while emphasizing that energy management is very important. Domestic energy usage also accounts for a greater percentage of energy usage in a country due to inefficient use and lack of energy conservation and practice. Smart metering can automatically read the meters to know the usage of energy in an apartment. The electricity consumers will also be aware of the amount of energy they are consuming, which will help them develop means to conserve their energy [45]. Nguyen et al. in [59] designed and tested a device that consists of Energy Modem (EM) and Energy Appliance Controller (EC) to be used in place of smart meters or can be used with the smart meters. The EC can control power switches whilst the EM is responsible for line communication. The authors argue that the most significant aspect of their work is that the EC and EM are inexpensive technologies and is also available in the general market without showing the total cost of such proprietary implementations and other related interoperability issues. The PIC 16F877A is the main component of the Microcontroller Unit (MCU). The Power Line Communication (PLC) module is another key element of their proposed system.

The general frequency across the electricity network and/or the Peak Average Ratio (PAR) is a key determinant for the efficiency of the network. Commercial or residential DSM aims at reducing PAR by the provision of Time of Use (ToU) billing and other incentives through an ultimate minimization of customers' bills when loads shifted to a cheaper price period representing a win-win for both the utility companies and the customers [60]. The PAR load demand of a power network is computed as the ratio of the daily peak to the average load levels. Fractional programing was utilized in [62] aiming at maximizing the benefits of the domestic consumer by improving the energy utilization efficiency.

2.2.2 Smart Metering Communication Technologies and Security issues

One of the issues facing the current smart metering deployment is the communication between the smart meter and the central system (i.e. server). Radio Frequency multiple-input and multiple-output (RFMIMO) based communication network for smart metering is proposed by Koschel et al., in [63] where the smart meter was placed in a basement of a building. They achieved about 150 meters distance between two points located at two different buildings at a frequency less than 1 GHz through the provision of RF-MIMO extension for small-scale-fading compensation. They did not consider the amount of energy consumed by the proposed communication system, the cost of deploying a MIMO technology in a vast smart metering implementation, and the advantage of the MIMO compared with the technologies included in the communication standards for smart metering [64].

To conserve the energy needed for the smart meter home area network, the application interface approach was adopted based on fixed and adaptive duty cycling, transmitter energy consumption control, and data reduction techniques used in the research work, thereby proposing a novel technique known as adaptive sleep time [65]. The research employed an off-the-shelf ZigBee shield with both having LCD screens that could significantly draw a great amount of energy within the research framework; however, the novelty of the adaptive sleep time reduces the overall energy consumed by the smart meters themselves.

Cybersecurity threats are dangerous attacks on a computer system that has useful data by malicious people to destroy the system or gain information that should not be in their possession [44,66]. The above is a key concern for smart metering and its acceptance; thus, measures are being put in place to avert these malicious acts. To enhance security in a short and long-range, Zigbee technology or Bluetooth wireless communication was proposed in [67], [68] for monitoring the energy consumption of an apartment, including the appliances. A simulation model for the smart metering attack was proposed, designs and tested in [69]. A survey of attacks and vulnerabilities in computer systems was conducted by [70], revealing several vulnerabilities in computer systems that could be extended to smart metering infrastructure requiring further research in smart metering and security. Some of these attacks include but not limited to the following: Human error, User abuse of authority, Direct probing, Probing with malicious software, Direct penetration and Subversion of security mechanism.

Privacy problems of smart metering are highlighted by Rial and Danezisin in [71]. They described the problem as being of great concern to scientists, politicians and all stakeholders within the smart grid, and as a result, they are finding ways to reduce these threats. The smart meter reading can provide vital information about a household as a result of load monitoring. Consumption data could also enable one to know the profile of inhabitants of a house and their lifestyle. To preserve the privacy of smart meters, there is the need to establish a system that will ensure as well as guarantee this. A solution is then proposed to enable electricity meters to communicate securely to the energy user where the users merge the secured readings from the meter with an authenticated tariff policy to get their bill. The bill is then taken to the energy providers to ensure correctness and ensure personal information security. The proposed system's importance is in its flexibility since the calculation can be done on any device.

Le et al., proposed a remote power monitoring system that measures and controls the abnormal energy usage by public building residents [72]. This is to enable the effective and efficient provision of electrical energy. When the remote power monitoring system records any abnormal electrical power usage, the data is sent to a gateway through a wireless network made up of a power-sampling chip, Wireless Radio Frequency (RF), Micro Controller Unit (MCU), relay gateway and a Personal Computer (PC). The researchers hope that when governments penalise residents who overuse energy, they will have energy conservation in mind.

The need to put in place infrastructure and low-cost tools using existing technologies to make the smart meters more efficient and smarter is emphasised [73]. An AMI meter consists of a meter, a home portal, an access point that collects data in a neighbourhood with a central hub is proposed. The research focused on the meter, access point and the central hub arguing that it forms a central part of the smart metering system’s demand responsiveness. They considered Home and Neighbourhood Area Networks, using the Zigbee technology. Also, the network depends on a mesh topology; it presents security implication for the neighbourhood, which could be solved in this context by transmitting all metering data directly to a NAN access point.

In smart grid technology, review was conducted on different security issues related to the communication network. On distribution, smart grid technology is vital in minimizing the energy cost by utilizing an energy management mechanism. From a consumer perspective, the reduction of the energy cost also reduces the electricity bills paid. On the other side, the supplier minimizes the consumers' peak demands in order not to operate the peak power plants.

2.3 Current Optimization Techniques and Algorithms in Smart Grid

In [74], the research aimed at reducing peak load by introducing an Energy Consumption Scheduler (ECS) into a smart meter. Residential type user was considered with an ECS incorporated with functionality to communicate with both the user and the provider. Every appliance was given a pre-emption state; an appliance with a higher priority is given a lower pre-emption state, meaning that they are less likely to be pre-empted. The cost of per unit power generation was greatly reduced due to an over 30% reduction in peak demand levels, as shown from their analysis.

The paper [75] explores the opportunity in demand-side management by proposing a DSM energy consumption-scheduling scheme for domestic appliances and reducing both peak-average-ratio and the resultant inconvenience posed to consumers. The researchers considered three categories of appliances: shiftable, throttle-able and essential appliances. To reduce the total cost associated with energy consumption under the Peak-Average-Ratio, their scheduling scheme aims to achieve an optimized response strategy. A multi-objective optimization problem was developed to consider user preferences, thereby reducing the inconvenience caused to the user. Their study shows that the scheduling scheme was effective within a peak-average-ratio constraint and considers different consumer preference levels.

An attempt has been made by Tsagarakis et al. in [76] to reshape the demand pattern of low voltage domestic loads in so doing reducing the cost and the greenhouse gas emission levels. The shifting of the non-critical domestic wet load category was considered in their work. The research shows that financial factors have a greater impact on the total cost of reduction on both production and consumption of power than those in greenhouse carbon, thereby showing that any future attempt should consider the financial aspects. The smart building's cyber-physical management was also proposed in [77] to reduce peak demand and efficiently allocate solar power. In order to form an agent-based energy profile, energy profile classification was used. The home agent considered the uncertainties of load profiles.

Ru et al., in [78], attempted to solve the problem associated with the determination of battery storage size used in photovoltaic systems connected to the grid to reduce the net cost of power and the capacity loss of the battery. Additionally, customer load requirements are satisfied with a reduction in peak power purchase. Excess electricity from PV is sold back to the grid or stored on the battery. With Time of Use pricing, the electricity can be purchased at a low-price period and sold back to the grid during a higher price period. A method for evaluating the battery's economic value compared to buying power from the grid is also proposed.

Similarly, Yang et al. in [60] proposed a cost minimization to the utility and benefit to the consumer while increasing the flexibility of how often a user could use a device during a particular pricing period. They considered user satisfaction and cost due as a result of demand fluctuations. Their numerical formulations considered residential, commercial and industrial users. An optimal game-theoretic Time of Use pricing strategy was proposed. However, the research considered only one source of electricity generation as opposed to modern smart grid trends. The results of their proposed system showed a reduction in peak demand, improved utility profit, and reduced the cost of electricity consumed by the user while ensuring their benefit. A different approach may be required in a generation constrained power system where a typical normal demand cannot be met. From the consumer perspective, the cost minimization is the most important parameter of the DSM objectives. In peak hours, the generation cost is very high due to the demand as well as the consumers' bills. In [31], various approaches have been utilized to develop efficient algorithms in order to minimize the electricity cost.

A Distributed Sub-gradient algorithm is proposed to achieve a convergence between the electricity generation and consumption within a smart grid infrastructure relying on the utility's ability to exchange information with the users [79]. It was noted that even when there is a loss of data between the two communicating parties, convergence was still achieved. Fixed consumption over an adjustable specified time frame and elastic loads were considered in their setup. The elastic load consumptions represented satisfaction to the user.

The authors in [80] proposed a Home Energy Management System to reduce electricity utility clients' energy cost. The results of the work demonstrated over 16 percent savings to the consumers. Comfort and discomfort levels were considered in their work. Also, aiming at demand reduction to reduce the demand-supply mismatch, a multi-agent framework for implementing demand-side management in the smart grid is proposed by Nunna and Doolla in [81].

In response to the increasing demand for electricity emanating from Electric Vehicles (EV), Cao et al. proposed and tested an automated EV charging system that responds to using pricing information from the utility company. Test results from their heuristics implementations showed a lower cost to the consumer, and a significant reduction in peak loads [82]. Their approach considers only EV loads with no reference to the other loads that exist alongside the EVs.

A demand-side management implementation to ease the quest for the reduction in the average price of power and the total consumption of industrial consumer is proposed in [83]. A deregulated market scenario was considered for the simulation with a sample case study. A stochastic model was proposed with real-time and day-ahead pricing schemes based on a set of historic data. The proposed implementation also achieved a lower total procurement cost. An optimal residential demand response scheme based on a multi-agent system to evaluate the network's optimality was also proposed in [84]. The simulation results from the algorithm show a reduced electricity payment and PAR ratio. The main stakeholders are modelled as a Home Agent and Retail Agent. The home agent performs three main functions; predict load, predict price and control load.

A load shedding algorithm for industrial loads by using genetic algorithms based on mixed-integer nonlinear programming solver is proposed in [85]. Their proposed system uses DC micro-grid incorporated with DC storage system to shift AC controllable devices per Time of Day (TOD) tariff. Their results were compared with load shifting strategy that employs AC distribution Grid with no DC Micro Grid. Results of the work shows a peak load reduction of about 19 percent signifying that the amount of power drawn from AC has reduced drastically.

A technique to match power outage patterns with demand side management schemes is proposed with a graphical user interface for consumers to be able to get at forehand the savings they will make if they adopt certain strategies in the consumption patterns for the next day. The research is aimed at encouraging consumers to use renewable sources of power [86]. Another group of researchers considered a situation where users are equipped with devices that can store electrical energy, by adopting game theory for the formulation of the energy consumption and the energy storage [87]. The players in the game are the users with the energy consumption schedules being the strategies. Two distributed demand side management algorithms were then proposed where the goal of the player is to minimize the cost of energy with privacy preservation and a reduced signaling from their central controller. The researcher concludes that the simulation result of the proposed algorithms was a mutual benefit for both consumers and the utility providers.

A demand side management approach was proposed in [88] where an assumption is made of an aggregator that communicates with a particular household through a meter by imposing a restriction or limit on the total power that could be consumed by a house within a specified time frame. The consumers are then required to adjust the consumptions of the individual household appliances to reflect the restrictions imposed by the meters. The proposed approach was then compared with a real-time market price to demonstrate how their approach can provide a series of guide for consumers when they are to select a load curtailment service contract.

Architecture for home energy management was presented with an automated demand response framework for appliances scheduling in a smart home [89]. An optimization problem was formulated and solved using a Genetic algorithm based on Real Time Price model and Inclining Block Rate. The simulation result shows a significant reduction in peak-average-ratios and energy cost representing a positive outcome of the research.

A fairness approach to demand side management is explored, where the cost of energy is fairly distributed across users with a given smart grid. An algorithm to protect the consumer's privacy was also proposed and tested in [90]. Neighbouring grids trade with each other with power being routed from surplus locations to deficit locations through coordination with a distributed energy resource. Two categories of load were considered, namely shiftable and curtailable loads. A priority-based incentive mechanisms was also adopted to encourage customer participation as suggested in [91].

A Cooperative Game and Stackelberg Game approach to demand side management is proposed in [92]. The players in the Stackelberg game are the utility as the leader with the consumer as the followers. The utility leads by setting the price per kilowatt energy consumed by the followers (consumers). In the cooperative game algorithm, the consumers share their instantaneous total energy consumption cooperatively, thereby optimizing their prices per unit watt by scheduling various loads within their individual controls. The performance of the proposed system was the measure of peak-average-ratio and the total energy consumed by the individual consumers.

A game theoretical framework-based algorithm was used to propose a model predictive control algorithm, which combines photovoltaic generation and energy storage capability in [93]. The proposed algorithm uses real-time-updated forecasts to reduce errors and enhance realistic benefits while allowing competition among the subscribers. The results show that there was a slight increase in the cost of power using the proposed algorithm and have a reported improved accuracy of forecasting instead. Aiming at preventing user from cheating in an Auction energy sale market, a smart meter that record users power consumption and provides information to the energy provider is proposed in [94]. A utility function was used to model the users' preferences and usage patterns that are then utilized in proposing an enhanced Arrow-d' Aspremont Gerard-Varet mechanism to enforce truthfulness. As an incentive, users found to have declared less consumption than they consumed were made to pay more for their unit power. The results of their simulations show that the proposed system ensures truth telling and benefit both the consumers and the providers.

A cloud based smart energy hub is proposed for implementing demand side management for gas and electricity in [95]. There is a coordinated interconnection among the smart energy hubs representing each domestic house. In [95], the integrated demand side management is modelled as a non-cooperative game. To achieve equilibrium, a distributed algorithm is then proposed. The cloud computing framework was compared with a typical processing technique to determine its effectiveness. Results from the proposed infrastructure shows a more cost-effective energy of each hub and peak-average-ratio of the demand was also reduced drastically.

Guo et al. investigated how to reduce the corresponding energy cost with real time electricity pricing. They proposed a system that has a good trade-off between cost saved and the capacity of the storage device in addition to PV-utility grid system. The Lyapunov Optimization Technique was used to solve the stochastically formulated mathematical problem aimed at optimizing the cost along with the capacity of the storage devices. Practical Data set was used to evaluate the performance of the proposed algorithm [96].

In a related work, the ability of smart meter to respond efficiently to time of use price signals from the utility within smart grid architecture was also explored where a linear programming algorithm in a rolling window manner was used to formulate and solved the problem in [97]. It aims at maximizing the utility of the consumer subject to a minimum daily consumption level. The method was evaluated against a similar scenario without smart grid, and it was reported that the proposed technique was more efficient in terms of cost savings than the other. The cost structure of purchasing electricity from a generator and users device specific scheduling flexibility was used to compute electricity cost minimization problem with which the willingness for the users to shift their electricity consumption was also probabilistically modelled. An algorithm was developed to compute the day-ahead-pricing and another for estimating and refining the reactions of the users to the prices. Evaluation was done with data from Ontario Electricity. The proposed algorithm proved a significant reduction in the cost of providing electricity to the users [98].

In order to take full advantage of the smart grid, Wang et al. in [99] developed a power network model comprising of electricity suppliers, utility companies, consumers who are made up of appliances and storage systems. The consumptions of the various loads and their work patterns were also considered representing a key novelty in the proposed model. A distributed load-scheduling algorithm based on convex optimization with social welfare improvement as a constraint was developed and tested. Simulation results of the proposed model show the efficacy of the model.

The communication overhead and computational burden imposed by a large-scale centralized optimization algorithm was shown to greatly reduce with a proposed hierarchical, iterative distributed optimization algorithm by Braun et al. in [100]. Simulation results of the proposed algorithm show substantial reduction in the number of iterations required to achieve convergence of the algorithm implying a reduction in computational and communication burden.

An ergodic framework for energy management was developed to enhance the existing frameworks where active power shedding and reactive support was stochastically [101-103] tested through the engagement of smart inverters in [104]. The test setup comprised of a 56-bus grid and 123-bus feeder. The result was compared with deterministic energy management [105] and the proposed framework was found to be more efficient in terms of cost savings. It shows that the decentralization and localized implementations are important in the achievement of a better efficiency.

A model for predicting the effect of applying variable tariff structure on electricity load profile is proposed in [106]. The paper alludes to the fact that there was significant domestic load shifting of about 8% amounting to a financial gain of 35 Euros per year. Dominant among these savings was the one derived from wet appliance and only 5 Euros per year is reported for consumer appliances and television.

A related work argues that relying on the future autonomous users to cooperate in relaying packets so that other users can optimize their energy will not be realistic as in so doing; they may lose energy and opportunity cost by helping to share other nodes packets. Hence a pricing-based joint user-and-network centred incentive approach is proposed. The method compels selfish nodes to forward data. This was achieved by compensating the forwarders in terms of their real and opportunity cost captured as a net utility expression, thus becoming the Pareto Optimality of the nodes [107]. The approach could be used in a smart grid where the utility and the meters represent the nodes, and their gain will be the reduction of energy consumption from the perspective of the utility and the reduction in energy cost from the point of view.

Also, PAR and consumer preferences as a constraint are multi-objectively explored by Liu et al. [108]. The system model considers shiftable and throttleable loads using a scheduling algorithm-based demand side management approach. A key finding of the proposed mechanism was that consumers' acceptance of the scheduling mechanism was key to the successful implementation. The system's objective was to minimize energy cost and the associated inconvenience and, by so doing reducing the overall PAR of the electricity network. The proposed system's effectiveness was evaluated in a simulation environment.

A single source smart grid was also considered by Manaseh et al. in [109], where the main aim was to reduce the overall load on the grid. Consumer self-generated and energy storage devices were used to formulate a PAR reduction strategy. Simulation results from the proposed system suggest a cost-benefit for the end-users and PAR reduction across the entire grid. A Generalized Tot for Tat (GTFT) dominant game-based energy scheduling algorithm centred on game theory was proposed for scheduling demand as a response mechanism [110]. A multi tariff methodology to avoid rising demand was adopted based on individual and community usage. The shiftability of loads was based on PAR. The proposed system was subject to a simulation-based evaluation and was reported as very effective.

Similarly, energy production and storage were formulated as an optimization problem to reduce PAR using energy scheduling (ES) in [109]. The renewable energy source was also used, with the storage devices being activated during low demand and released during peak demand periods. As a result, peak hour consumption is minimized, demonstrating a cost-saving for both the utility and the end-users. Also, in research by Nguyen et al. [111], distributed user profile was used in the adoption of game theory aimed at reducing PAR of the utility.

Hajj and Awad used the demand and utility pricing vector-based game-theoretical approach in [112] to show the effectiveness of demand-side management in the simulation environment with a single source smart grid. The end-user’s objective was to reduce the cost of energy and the utility, on the other hand, to improve their power profile by reducing the PAR. A converged Nash Solution was obtained based on the dual constrained optimization problem. Experimental results from the evaluation of their systems show that the proposed method effectively reduced both PAR and the effective cost of energy bore by the consumer.

Another key area of the smart grid is energy forecasting. In terms of generation constrained power systems, forecasting the demand and the supply of electricity can go a long way to prepare both consumers and the utility companies to take necessary actions towards prompt responses to any possible load shedding and in this case microload shedding. A motivation of energy forecasting in general is presented in subsection 2.4 where some key terminologies and background are illustrated. While subsection 2.5 gives review of related works on energy forecasting in smart grid.

2.4 Overview of Energy Forecasting

There are different regression models identified from literature in [144,156,159] including but not limited to K-Nearest Neighbour Regression (KNNR), Multivariate Adaptive Regression Splines (MARS), Support Vector Regression (SVR), Random Forest (RF), Artificial Neural Network (ANN), and Decision Tree (DT). However, in this research, it is worth noting that summaries of prediction experiments based on KNNR, SVR, RF, ANN and DT are presented.

2.4.1 K-Nearest Neighbour Regression (KNNR)

The KNNR is a non-parametric classification approach developed in 1951 and further expanded in the 1970s mainly for classifying data sets, but it can also be used for regression problems. It falls under the supervised machine learning techniques. The KNNR is simple yet very powerful for prediction. It stores all the dataset marked for the training in memory and does nothing until a prediction is needed; that is why it is often referred to as a lazy learning algorithm [187].

The number of nearest neighbours (k) is critical in the performance of the KNNR model. AS a result, correctly computing the value of k becomes essential as a low value of k means the high influence of noise, and a higher value implies higher computational expenses. One way of estimating k value is:

$$k = \sqrt(n) \qquad \text{(Equation 2.1)}$$

where, ***n*** is the number of entries.

Another approach is the use of the Elbow Technique and computing the accuracy of various K values, which was eventually used for this research.

2.4.2 Multivariate Adaptive Regression Splines (MARS)

Introduced in 1991 by Jerome Friedman, MARS is also a non-parametric regression model. The nonlinear interactions between the variables are automatically modelled as extensions of linear models. The model determines the core functions and the associated variable from the dataset [186]. Most open-source implementation of it uses the name; "Earth", because the trademark and license of MARS is own by Salford Systems.

MARS models are built in the form shown in the Equation 2.2 below in which the weighted sum of the basic function $\beta_j(x)$ has one being multiplied by the related coefficient $\aleph_j$;

$$F(x) = \sum_{j=0}^{k} \aleph_j \, \beta_j(x) \qquad \text{(Equation 2.2)}$$

where, the constant coefficient is represented as $\aleph_j$ and the basic function is represented as $\beta_j(x)$ taken one the following forms;

1. $\beta_j(x) == a\ constant\ 1$
2. $\beta_j(x) == hinge\ function$
3. $\beta_j(x) == product\ of\ two\ or\ more\ hinge\ functions$

2.4.3 Support Vector Regression (SVR)

When Support Vector Machine (SVM), which is focused on binary classification, is used for real-world prediction problems, it is called SVR. It is used for non-linear data sets [188]. The advantage of the SVR is the flexibility it provides such that an acceptable error margin can be selected for a given experimental setup.

The entire training dataset can be represented as $[(X_{iPredict}, X_{iActual})_i = 1,2,3, \ldots \breve{\mathcal{M}})]$ where, the actual dataset is $X_{iActual}$, the expected predicted value is represented as $X_{iPredict}$ and the number of elements in the dataset is given as $\breve{\mathcal{M}}$. SVR works by mapping the $X_{iActual}$ into n-dimensional space containing features formulated as the non-linear relationship between the independent variables and the dependent variables. This is represented as an optimized hyperplane with the function shown in equation 2.3 below.

$$f(x) = U^t \times \mathcal{V}(x) + b \qquad \text{(Equation 2.3)}$$

where, $f(x)$ represents the $X_{iPredict}$ values, the n-dimensional weight factor is represented as the U, the mapping of the $X_{iActual}$ is represented by the $\mathcal{V}(x)$ and adjustable factor is the b.

2.4.5 Random Forest (RF)

RF was proposed by L. Breiman a decade ago and has remained very successful as a regression and classification model; it employs averaging of predictions from multiple randomised decision trees. A high level of importance is placed on the input features. It has been known to be quite flexible in terms of regression and classification applications. On the other hand, it is computationally very expensive [189].

2.4.6 Artificial Neural Network (ANN)

Developed in the 1950s, ANN is a prediction algorithm that mimics the brain's biological structure. It operates like a black box and does not bother so much about the box's elements (i.e. the individual inputs). ANN can manage very large and complex datasets with multiple interrelated parameters. Relationships between the parameters and the independent/dependent variables are learnt by observing previous patterns in the dataset [190].

2.4.7 Decision Tree (DT)

DT has been widely used for energy forecasting because household energy consumptions involve various patterns. It is used for classification and regression. The approach falls under the non-parametric supervised learning techniques. Simple decision gathered from the data is used to develop models that predict the dependent variables. DT uses the white box approach where the details of a given explanation can be represented as Boolean logic.

Mathematically, given an actual dataset containing the independent variable $X_{iActual}$, represented as the vector $X_i \in \eta^n$; where, i =1, 2, 3, …, n and a label vector $\mu \in \eta^l$, samples with similar target values are grouped together when the feature space is split. Further information about the DT can be found at [191].

2.5 Related Works on Energy Forecasting

Mahmood et al. proposed a classification method based on time of use and other constraints. Cost efficiency and the utility of the appliances were determined by applying binary swarm optimization (BSO) [133]. To reduce the impact of higher consuming appliances on the overall demand of a home, Pipattanasomporn et al. [134] proposed a home management algorithm that keeps the total energy consumed from a household at predetermined levels based on certain priorities. Similarly, Liu et al. applied particle swarm optimization to determine the support vector machine's parameters and feature selection [135].

Rodrigues et al. [136] proposed an Artificial Neural Network (ANN) method for predicting the home demand and confirmed the efficacy of the proposed approach through simulation. Consequently, the technique further revealed that the artificial neural network represents a reliable technique in predicting household energy consumption. They concluded that their approach was more effective for hourly and daily demand predictions. An optimization method was proposed by Li et al. [195] and compared with multi-objective differential evolution (MODE), non-dominated sorting genetic algorithm (NSGA), multi-objective genetic algorithm (MOGA) and multi-objective particle swarm optimization (MOPSO). Among these multi-objective algorithms, MODE yielded the best performance.

To increase the forecasting accuracy, Butt et al. in [137] proposed long short-term memory to ascertain the local trend and extract similar short and medium time series fore-casting patterns and, further, for learning the relationships in the data set, convolutional neural network along with multi-layer perceptron was utilized. The utility of the proposed prediction technique was validated through a real-world experimental setup.

Juan et al. also proposed a hybrid decision support system based on the Zero-One Goal Programming model and Genetic Algorithm to improve sustainable performance [138]. The effect of weather on energy usage and energy efficiency and various forecasting methods were reviewed by Lazos et al. [139].

The Recurring Neural Network technique for demand prediction of a single home was also proposed and investigated by Kong et al., [140] to overcome usage uncertainty and high volatility in electric demand. Their proposed approach outperformed the previous methods they compared their results to. A single household energy consumption and weather information were collected by Makonin et al., in [141] and [142]. Further, Shin et al., in [143], also collected data with higher precision and 22 separate houses.

Machine learning based on regression analysis was used to predict household consumption in [144], where dimensionality reduction was performed using principal component analysis to find the hidden patterns to cluster the data. Visibility, temperature and humidity were among the climate variables integrated to forecast the consumption. The researcher in [145] developed a two-stage learning method; representational learning and regression technique to reduce the computational complexity involved in relearning existing data for prediction. Where learning of pattern in aggregate data was used to regress on individual appliance groupings. Computational simplicity and flexibility of handling changes in metering data were observed to be key benefits of the proposed architecture. Recognized user activities were extracted using information theory to optimized home appliances' demands.

To optimize the demand from households, a knapsack optimization problem was formulated by Cottone et al. [146]. Short-term load forecasting model improvement based on daylight information was investigated by Lopez et al. in [147]. The proposed approach uses both neural network and autoregressive components for the prediction. Improvement was recorded as compared to previous techniques. Domestic demand of Urban area was investigated by Tian et al. using spatial regression and ordinary least square methods. The LaGrange statistical test methods and regression analysis were performed on gas and electricity usage using household energy consumption profiles and council tax. The method was evaluated on a simulation setup that proves the regression analysis's performance [148].

The impact of using smart home appliances on electricity bill and variable electricity pricing along with a method to predict the demand based on time of use of these devices was investigated by Gottwalt et al. [149], in which homes equipped with smart meters were simulated to generate load profiles with flat tariffs. They concluded that when the load is shifted, the utility may experience a new peak at a different time. To preserve the comfort of the user and at the same time reduce the electric bills, Rasheed et al. proposed a technique that uses a multiple-binary knapsack optimization method. Weather conditions, electric prices and behavioural responses of 3 types of appliances were optimized. The efficacy of the proposed approach was shown through simulation [150].

The flexibility of wet appliances was forecasted using a stochastic agent-based approach in [151]. The proposed approach was validated using empirically obtained data. They concluded that the share of energy consumed at night hours could be increased based on the existing flexibility, leading to an effective reduction in the consumption recorded at night hours. Genetic Algorithm, ANN, and SVM were used to predict buildings' energy requirement based on weather data by Zhu et al. [152]. Appliance demand forecasting for peak demand reduction using machine learning was also investigated by Haq et al. [153]. They concluded that their approach outperforms previously reported techniques using smart meter consumption data based on clustering, neural network and support vector machine.

The ensemble method was used by Wang et al. based on a bagging tree model. The evaluation metrics of the proposed model demonstrated comparatively better compared to other techniques [154]. Appliance demand patterns were mathematically extracted as state duration probabilities and their usage periods to predict the future demand by Dinesh et al. [155]. Calendar and seasons were considered the improvement of the performance. The result was compared with various machine-learning algorithms, after which their approach performed better than all of them.

Short-term demand was predicted by Torabi et al. using a hybrid model made up of ANN and SVM representing. Further, using 3 clusters reduces the error rate when evaluated against the ANN and the SVM individually [156]. Khakimova et al., 2017 proposed a model predictive control system based on the optimization technique [157] to reduce execution time and associated complexities. The cost, power, complexities of various machine learning techniques were analysed by Kaur and Bala, based on household energy prediction towards energy consumption reductions [158].

The ensemble method was utilized by Divina et al., 2018 to predict the short-term energy demand using RF, GBM and ANN as base models [159]. Muralitharan et al. used CNN and then NNPSO and NNGA for the optimization of energy usage. It was observed that NNPSO was good for long-term prediction, and NNGA performed better for short-term prediction [160]. Active data driven methods; LSSVM, SVM, ANN, GPMGMM and Physics-based models were used to examine a hybrid model approach to energy prediction by Dong et al. in [161].

A multi-predictor method was proposed by Yin and Chao, for energy demand forecasting with cyber swarm for individual optimal parameter selection for the predictor. MAPE and MSE parameters were used to compare the results. Various predictive models for demand forecasting such as SVM, Bayesian network, ANN and genetic programming were used to evaluate energy and non-energy data sets [162]. The gradient Boosting method was observed to have performed better when appliance-based energy prediction using predictive models such as SVM, MLR, RF and GBM were performed by Candanedo et al. where R-Square, accuracy and RMSE were selected for the evaluation parameters [163].

RF was used by Wang et al. to forecast the energy needed using hourly data. The results were compared with SVR and RT. They further investigated the same model in academic environments and concluded that semester-based forecasting would be better for such an environment instead of an all-year approach, as was mostly the case [164].

A comprehensive analysis of energy classification techniques and prediction models was done by Wei et al. Various clustering models such as K-means and predictive models such as decision tree, statistical regression, GA, ANN and SVM were discussed [165].

Kaur and Bala predicted household energy consumption using ANN, SVR, KNN and Random Forest. Their models were evaluated based on their accuracy for choosing the best model concerning other models [144]. Activity performed, usage duration, rating of appliances was used as constraints to develop an energy demand model by Subbiah et al.

Individual modelling technique and various data sets proved the efficacy of the proposed approach [166]. Gupta et al. utilized several machine learning algorithms to forecast and then compared the results using multiple evaluation parameters for predicting the emergence of heart diseases within a cloud infrastructure [167].

Weather information was considered in predicting solar power generation by Sharma et al. using machine learning algorithms. Accuracy parameter was the evaluation source after employing various regression algorithms, and the SVM prediction algorithm achieved the best accuracy [168]. The dynamic predictive control system was deployed by Ha et al., to research the energy management issues within households. They eventually suggested that a heuristic optimization could be adopted for further refining the results [169].

An optimized artificial neural network was used to predict energy consumption. Ardakani and Ardelhali used Multivariable predictive models in this investigation where the result indicated that IPSO-ANN outperformed all the rest of the prediction algorithms. Hybrid models were compared with SVM and ANN models to predict the energy demand of buildings. The results obtained were evaluated using correlation coefficient and RMSE [170].

Weather, Solar, wind, tidal and other forms of energy sources is the focus of smart grid research nowadays for energy efficiency and demand management [171], [172]. Energy demand prediction is also being researched in commercial, domestic, agricultural, transportation, education and others. Using various machine-learning algorithms [173], [174], [175]. These algorithms are applied to regression and classification techniques on consumption and generation data sets [176], [177].

Household energy consumption plays a significant role in the overall electricity demand, and as such, they are mostly more affected by the continuous blackouts associated with energy-poor countries [178], [179]. This is worsened by the lack of infrastructure to support electricity's continuous growing demand from all sectors. As a result of insufficient generating capacities coupled with mostly dilapidated transmission and distribution networks, most of these electric utility providers are forced to perform load shedding, which has negative effects on both the consumers and the utility companies involved [180], [128], [181].

The purpose of domestic consumption forecasting includes the supply of the minimum required energy, inform the households of the possibility of rolling out blackout, thereby reducing the environmental impact of peaking and the reductions in associated cost to both utility companies and the end-users. A crucial aspect is the effect this has on the already high global warming level and the associated climate change [182], [183]. The evidence of the climate change is becoming more alarming than ever before [184].

A multi-year minutely consumption dataset in [142] was utilized to evaluate the possibilities to enhance energy management through future forecasting of the demands. The influence of weather information on demand is investigated. The evaluation metrics recorded show that prediction and microload management can benefit electric utilities and their end-users and ultimately impact climate change.

Table 1 below, categorises the drivers of smart grid into key objective areas of demand side management (DSM), Peak to Average Ratio (PAR) reduction, Cost minimisation (CM), consumer privacy and security (CPS) and integration of renewable sources of energy (IRSE) and demand forecasting (DF) showing key research focusing on these thematic areas of smart grid from the related works reviewed in this section.

Table 1 Drivers of Smart Grid

References	DSM	PAR	CM	CPS	IRSE	DF
[5, 7, 8, 10, 13, 28, 60, 78, 81-88, 91, 94, 95, 109, 111-114, 118, 123, 124, 127]	**X**					
[113, 114, 123]		**X**				
[31, 60,98, 113,115]			**X**			

[42,44, 66, 71, 90,113]				**X**		
[53,101, 114, 171, 172, 174, 176, 177]					**X**	
[102, 136, 137, 139, 1140, 41, 144, 147, 152-156, 158-161, 165, 174-176, 187,192]						**X**

2.6 Chapter Summary

In summary, it had been deduced that current endeavors in smart grid research had focused mostly on optimisation techniques modelled to minimize bill payments, PAR and peaking, and maintaining consumers preferences. Very recent work by Yaghmaee et al., in [113] focuses on controlling residential loads comprising storage devices in addition to local sources of energy generation sources to achieve DSM in a two-tier cloud-based implementation. An optimisation algorithm with a linear multilevel cost function is then proposed to reduce the cost of energy to the consumer and ultimately reducing the PAR.

Also, Latifi et al., in [114], develop a diffusion strategy-based algorithm to overcome real-time adaptability and additive noise channels or link failures in a smart grid where consumers share only estimated optimal energy consumption trends with their neighbours. By modelling the smart grid as an adaptive network with lower communication overhead, the consumer can sell their excess energy from renewable sources at a more competitive price while achieving minimum PAR and their consumption costs.

In a similar manner, Yang et al., in [60] also proposed ToU based DSM in a smart grid where Game-Theoretic is used to optimise the pricing strategy of ToU billing for increasing and minimising user benefit and cost to the utility companies, respectively. In addition, an aggregated energy hub approach was used to model residential energy consumption in a smart grid. Mix Integer Linear Programing was used to solve the objective function of reducing energy cost and peak demand while considering the preferences of the consumers. However, a key constraint with Mix Integer Linear Programing optimisation approaches is the time and memory resources used to arrive at a solution can be huge when the integer variables are increased. The results obtained from testing the proposed model shows a 20% and 50% reduction in total energy cost and peak power demand, respectively. The model considered gas and electricity as the energy and referred to peak power, which applies only to electricity [115].

The models and those by Uturbey et al. in [116] and Chiş and Koivunen in [117] assume adequate generation with instantaneous cost of peaking as a key constraint on the overall network as well as the preservation of consumers' set priority of use [118], [119]. However, not all electricity networks are able to generate the required electricity to meet the demand of their consumers due to continuous increase in electricity demand with constant or inadequate generation sources. As a result, generation constrained power systems from time to time implement blackouts across sections of their networks [120-122]. This practice, referred to as load shedding, creates inconvenience for the consumers and at the same time causes the utility to lose huge amounts of revenue.

Also, a closely related strand of literature examines the DSM approach based on Home Energy Management System aimed at minimizing the electricity cost to the consumer along with associated discomfort and the reduction in PAR of the entire grid where an energy shifting based home management strategy was proposed by Khalid et al., in [123] to minimize energy consumption and PAR in DSM. The consumer loads were scheduled in a real-time and day-ahead manner. The load then balanced during on-peak and off-peak periods through coordination of home appliances as a knapsack problem for the real-time scheduling. The proposed system considered three pricing schemes Time of Use (TOU), Critical Peak Pricing (CPP), Real-Time Pricing (RTP), where granular microloads are automated for the consumer to make savings on the electricity bill alongside PAR reduction across the grid without considering the situation where the utility is unable to meet even the off-peak demand of the consumers.

The work in [123] was an extension of [124], where Bacterial Foraging and Genetic Algorithms were used to formulate and solve the optimization problem. Therefore, this research seeks to explore ways of deploying the smart metering system to ameliorate the situations.

Chapter 3

The System Model and Problem Formulation

3.1 Introduction

In this chapter, the system model is introduced along with the problem formulations referred to throughout the rest of the thesis. Even though the system model assumes a hierarchical approach, it could be readjusted to meet any modern grid requirements. The problem formulations could also be changed to match any adopted power system grid structure.

3.2 System Model

The System Model comprises a typical power system structure of generation constrained power systems like that of Nigeria and Ghana comprising four (4) key networks, namely: Generation Network, Transmission Network, Distribution Network and the Consumer Network. These networks are categorized into five key Layers, with Layer 1 and Layer 2 being the focus of this research. The electricity grid's pictorial structure is depicted in Figure 2, where the Microload Smart Meters are represented MSM representing households equipped with controllable microloads (mL). The mL(s) are shown in the architecture as Entertainment, Washer/Dryer, Water Heater, and other emerging metering systems. Additionally, the Wide Area Network (WAN), Neighbourhood Area Network (NAN) and Metering Information System Server (MISS) are clearly shown.

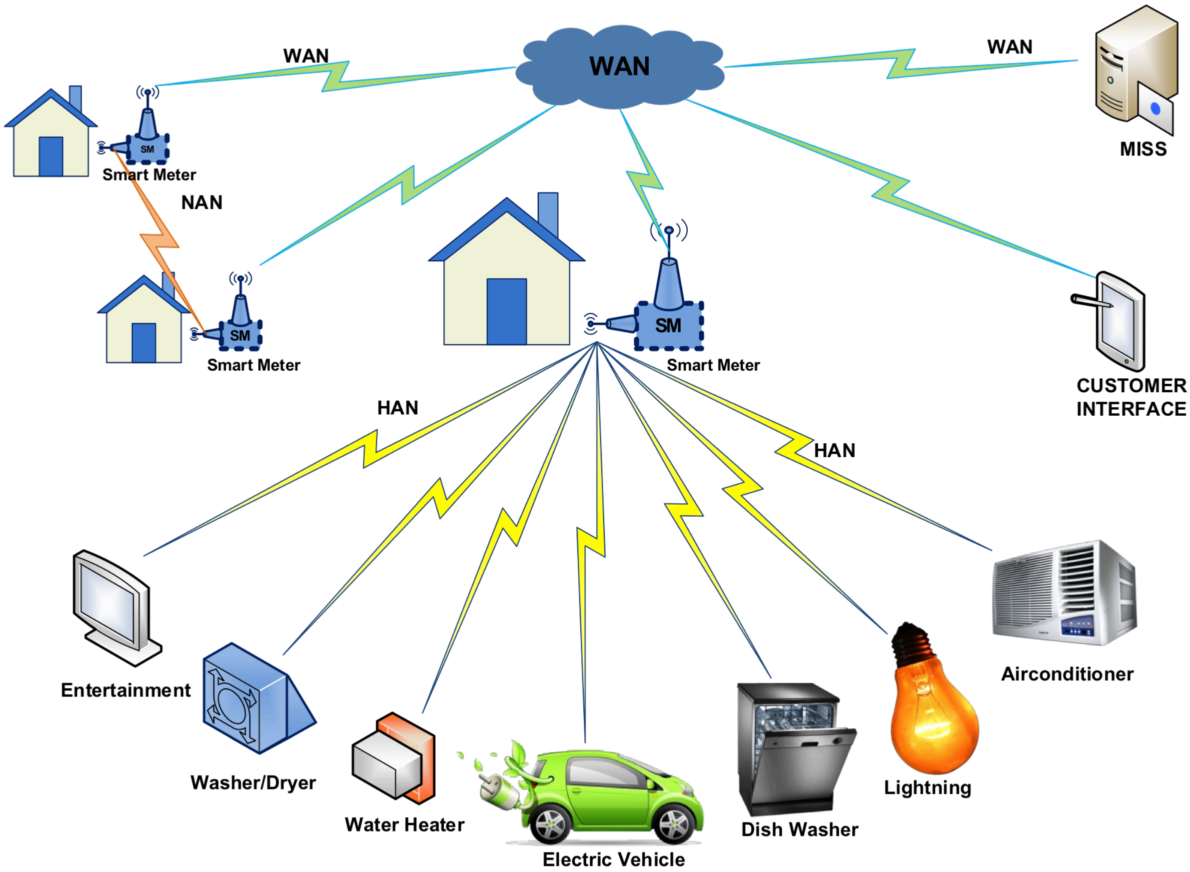


Figure 2 Microload Architecture

The assumption is that the electricity grid is a traditional grid where electricity is generated at a single point source and distributed. The consumers of the electricity make use of it when they need it. The mL is the last level of control and accounts for almost all the total electric energy utilised by the whole Main Power System (MPS), representing the Demand (D) on the overall Power System (PS). Another assumption is that there is no internally self-generated electricity at Layer 2 and Layer 1. The parameters of each Load are; Current (C), Voltage (V), Load Power (LP), Priority (Pr), Status (S = ON =1 or OFF = 0), Load ID (Lid), Control Type (CT), Schedule Status (SS), and could be configured to add more parameters. All these parameters are attached to a particular Load. The Smart Meter (SM) is the main connection to the mL (L = L1, L2, L3, . . Ln) directly connected to it. The parameters considered for this research are; Total Consumption (TC, which is the sum of all LPs), Voltage (V), Current (C), Number of

Controllable Loads (NCL), Meter ID (MId). The list of home appliances considered for the evaluation of the algorithms is shown in Table 2 in the Simulation Setup sub-section of Chapter 4 with their categorisation for six and thirty-five priority levels and their currents (C). The power system structure is also shown in Figure 3.

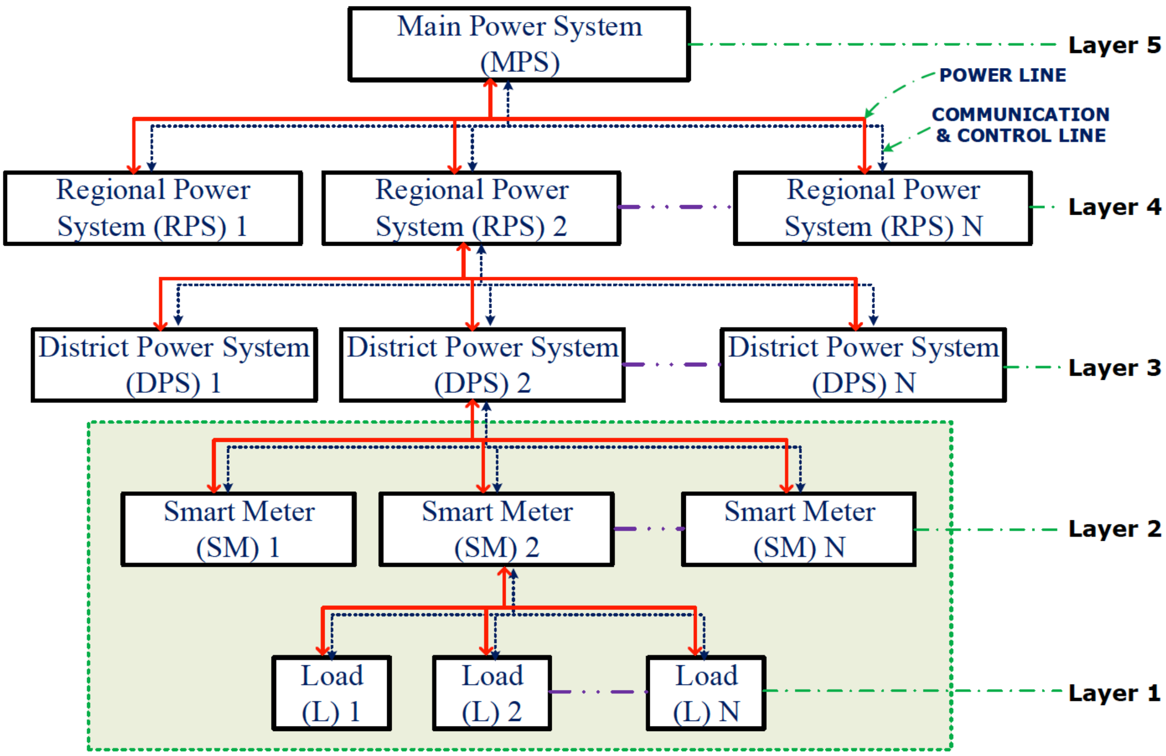


Figure 3 The Power System Structure

3.3 Problem formulation

The research assumes an electric grid made up of residential loads served by a single source of generation. Six controllable grouped loads per household were considered and evaluated and then extended to thirty-five microloads. For the six controllable loads, it is assumed that a group of similar or closely related electric devices are lumped together as a single controllable group to reduce the overall number of identifiable mLs in a house. Four algorithms were proposed and evaluated: GS, PBS, ERGS, and ERPBS. This is aimed at reducing the impact of the traditional approach to load shedding in generation constrained power systems while reducing the PAR within the part of the grid in context.

Additionally, optimisation of the priority of the mLs is proposed to maximise adherence to consumers' set priorities. The optimisation of the available power is intended to reduce the peak to average ratio of the overall electric grid, thereby increasing the network's efficiency. Simultaneously, the priority optimisation will help increase customer satisfaction by making sure that their salient loads are not cut-off by the proposed mechanism. The rated current of an appliance or grouped mL with Priority = p belonging to SM = m∈M, where M represents the total number of Smart Meters (SM) in a particular District Power System (DPS) as shown in Layer 3 in figure 3 as:

Rated Current = I_p^m

The voltage (v) of an SM is given as I_p^m where $m \in M$ whith user priority (P) such that $p \in P$ all belonging to a particular PDS is given as:

$$V_P^m$$

The known consumption of an mL given as $l \in L$ having priority $p \in (SM = m)$ is given as:

$$l_p^m$$

Therefore, we compute the known consumption (l_p^m) as shown in Equation 3.1.

$$l_p^m = I_p^m V_P^m \qquad \textit{(Equation 3.1)}$$

The total load of an SM = $(m \in M)$ at anytime τ, is given as: L_m^τ

The L_m^τ is computed as follows:

$$L_m^\tau = \sum_{p=1}^{n} L_p^m \qquad \textit{(Equation 3.2)}$$

Hence, the total demand TC being D of all SMs $(M \ni m)$ in a particular DPS is computed as:

$$D = \sum_{m \in M}^{k} L_m^\tau \qquad \textit{(Equation 3.3)}$$

where k {k ∈ K| τ = 1}

δ is denoted as the expected demand from a particular DPS. Ideally, D = δ but that has not always been the case resulting in financial losses to the electricity utility companies along with the associated inconvenience caused to the final consumer. The total δ of an SM = $m \in M$ at any time τ, is given as: d_m^τ

δ is computed as follows:

$$\delta = \sum_{p=1}^{n} d_m^\tau \qquad \textit{(Equation 3.3)}$$

A key objective of the proposed algorithms is to distribute the Expected Demand δ such that:

Algorithm Objective 1

$$\delta = \sum_{m \in M}^{k} \sum_{p=1}^{n} L_p^m \qquad \textit{(Equation 3.4)}$$

Another objective is the maximisation of the priority of the users to meet essential energy needs. Let the microload or grouped microload that are not affected by the microload shedding as P* and those affected as P' so that;

$$P = P^* + P' \qquad \textit{(Equation 3.5)}$$

Algorithm Objective 2

$$maximise(P^*) \qquad \textit{(Equation 3.6)}$$

The user priority is denoted as P_r or P_i which is inversely proportional to the total sum of the priority of the consumer given as P_T . Where the constant of this proportionality is P_{rc}. Hence;

$$P_r \propto {}^{1}/_{P_T} \qquad \textit{(Equation 3.7)}$$

Therefore,

$$P_r = {}^{P_{rc}}/_{P_T} \qquad \textit{(Equation 3.9)}$$

Another objective is to reduce the PAR of the entire grid in context and thereby enhancing network efficiency.

Algorithm Objective 3

$$manimise(PAR) \qquad \textit{(Equation 3.8)}$$

The computation for PAR at time τ is given as:

$$PAR_{\tau} = \frac{Max\ Peak\ of\ D\ at\ time\ \tau}{Average\ Max\ Peaks\ of\ D} \qquad (Equation\ 3.9)$$

Therefore, we compute the PAR at τ (PAR_{τ}) as:

$$PAR_{\tau} = \frac{Max\ Peak\ of\ (\sum_{m\in M}^{k}\sum_{p=1}^{n} L_p^m)\tau}{Average\ Max\ Peaks\ of\ (\sum_{m\in M}^{k}\sum_{p=1}^{n} L_p^m)} \qquad (Equation\ 3.10)$$

Microloads with specific user-set priorities from Layer 1 of the power system structure shown in figure 12 is computed in Equation 3.1. The total demand per household shown in Layer 2 is also obtained through Equation 3.2. The Layer 3 of the DPS in Figure 3 observes the total demand from all households under that DPS and computed from equations 3.3. By evenly distributing the demand among household devices through Equation 3.10 to 3.12, the PAR is reduced. This is achieved through the proposed microload shedding algorithms discussed in Chanpter 4, 5 and 6.

3.4 Chapter Summary

The chapter 3 focuses on the system model and the problem formulations. The proposed model comprising microload architecture and a typically generalised microload grid structure are shown in this chapter along with the model formulation and their dependencies as the problem formulation. Some source codes relating the proposed approach are shown in the Appendix 4.

Chapter 4

Proposed General Microload Shedding

4.1 Introduction

Two main sub-algorithms accounts for the general microload shedding, namely (GSS) sub-Algorithm and GmL Meter Side (GMS) sub-Algorithm. These algorithms are discussed in this chapter along with the simulation setup and their results.

4.2 The GSS and GMS Sub-Algorithms

The first algorithm in this heuristic approach is the General Microload Shedding (GmL) Algorithm, which assumes that there are no priorities associated with the various microloads. As a result, the algorithm considers the microloads to satisfy the constraint sent to it from the server. Two sub-algorithms are used to implement the GmL Algorithm as GmL Server Side (GSS) sub-Algorithm and GmL Meter Side (GMS) sub-Algorithm to help preserve the privacy of the end users' microloads.

Algorithm 1: GmL Server Side (GSS) sub-Algorithm

Initialization;
Get Total GS Demand D;
Input Grid Section (GS);
Get N i.e. total number of SM in GS;
Input Total Expected Demand $\hat{D}$;
Compute Percentage Expected Demand d_m% per SM;
for *Grid=1 to* $Grid_{max}$ **do**
    while $m <= N$ **do**
        $d_m\% = \frac{\hat{D}}{D} * 100$;
        if $m = N$ **then**
            Return False;
        else
        end if
        Perform the SM Side Optimisation algorithm in Algorithm 2;
    end while
    Display Current Total Demand D;
    Update the GS;
end for

Figure 4 GmL Server Side (GSS) Sub-Algorithm

The GSS sub-Algorithm is responsible for acquiring and computing the percentage of demand that should be shed by a particular smart meter to achieve the intended load shedding across the entire network in context. The pseudo-code in Figure 4 shows the GSS Algorithm. The GMS sub-Algorithm computes the amount of power to be shed per meter and selects the appropriate microload to be turned OFF on to achieve the percentage reduction required in demand per the received signal from the server. It uses only the load and its magnitude to determine the curtailment or otherwise. The pseudo-code in Figure 5 shows the process and the iterations involved in the GMS sub-Algorithm.

Algorithm 2: GmL Meter Side (GMS) sub-Algorithm

initialization;
Set L_m to 0.00 kW;
Get d_m^{τ};
Compute Expected Demand per SM (d_m);
$d_m = d_m\% * d_m^{\tau}$;
for p=*1 to* p_{max} **do**
    $L_m = L_m + L_p$;
    if $L_m < d_m$ **then**
        Turn OFF L_p;
    end if
    if $L_m >= d_m$ **then**
        $L_m = L_m - L_p$;
        Update Server with L_m;
    end if
end for

Figure 5 GmL Meter Side (GMS) Sub-Algorithm

4.3 Simulation Setup

The setup is such that a single generation source is assumed to be serving the grid in context. The grid comprises twenty-six homes equipped with uniquely identifiable thirty-five microloads maximum. First, we grouped the loads into six controllable groups. Again, it is assumed that the users do not have the means to assign priorities to their appliances or the groupings. The grouped microloads are referred to as Grouped Microloads (GmL). GSS and

GMS sub-Algorithms are performed on the microloads. Secondly, each microload is identified as a unique controllable microload, this microload category is referred to as Ungrouped Microloads (UmL). The simulation is then repeated for this set of microloads (i.e. UmL). The possible combinations of microloads per household are shown in Table 2 below. The total consumption per microload was given in Equation 3.1 as l_p^m.

Table 2 Ratings for GCmL 1 to 6

Item	Loads(mL)	I/A	GCmL	UCmL
1	100W light bulb (Incandescent)	0.43	6	35
2	60W light bulb (Incandescent)	0.26	6	34
3	LED Light Bulb	0.04	6	33
4	25" colour TV	0.65	5	32
5	Clock radio	0.01	5	31
6	Desktop Computer	1.96	5	30
7	Home Internet Router	0.07	5	29
8	Scanner	0.08	5	28
9	TV (19" colour)	0.43	5	27
10	Laptop Computer	0.43	5	26
11	Smart Phone Charger	0.03	5	25
12	Inkjet Printer	0.13	5	24
13	Coffee Maker	6.09	4	23
14	Toaster	7.83	4	22
15	Electric Kettle	13.04	4	21
16	Food Blender	1.74	4	20
17	Microwave	7.39	4	19
18	Oven	9.35	4	18
19	Ceiling Fan	0.33	3	17
20	Electric Blanket	0.87	3	16
21	Electric Heater Fan	13.04	3	15
22	Electric Mower	6.52	3	14
23	Electric Shaver	0.09	3	13
24	Table Fan	0.11	3	12
25	Water Filter and Cooler	0.43	3	11
26	Clothes Dryer	17.39	2	10
27	Hair Blow dryer	10.87	2	9
28	Iron	4.35	2	8
29	Dishwasher	6.52	2	7
30	Power Shower	45.65	2	6
31	Vacuum Cleaner	3.04	2	5
32	Washing Machine	2.17	2	4
33	Lawnmower	6.09	1	3
34	Fridge / Freezer	1.74	1	2
35	Home Air Conditioner	21.74	1	1

The simulation tool was developed in python and run on the server with all the dataset locally hosted on the server. The source code can be located at the appendix sections of the thesis in Appendix 4.

4.4 GGmL and GUmL Shedding Results and Discussions

The simulation results of conducting the General microload shedding on the GmL and the UmL are presented and discussed in this section along with the performance evaluation of the General Microload Shedding (GmL) Algorithm. The accuracy of the GmL and UmL General shedding and the PAR optimization presented are also discussed. The simulation was conducted using the GCml and UCmL shown in Table 2 above, with the indicated categories of the microloads. A 30%, 20%, 15%, 10%, 5% and 2% microload shedding were requested and the expected demand along with the actual demands are compared for the GCmL and UCmL General Microload Shedding Algorithms.

4.4.1 GGmL Shedding

The requested 30%, 20%, 15%, 10%, 5% and 2% microload shedding represent a curtailment of 202.47kW, 134.98kW, 101.24kW, 67.49kW, 33.75kW and 13.50kW respectively from an overall instantaneous total demand of 674.90kW. The total demand, traditional shedding and the GGmL shedding for 30% GGml shedding request's result is shown in Figure 6 below.

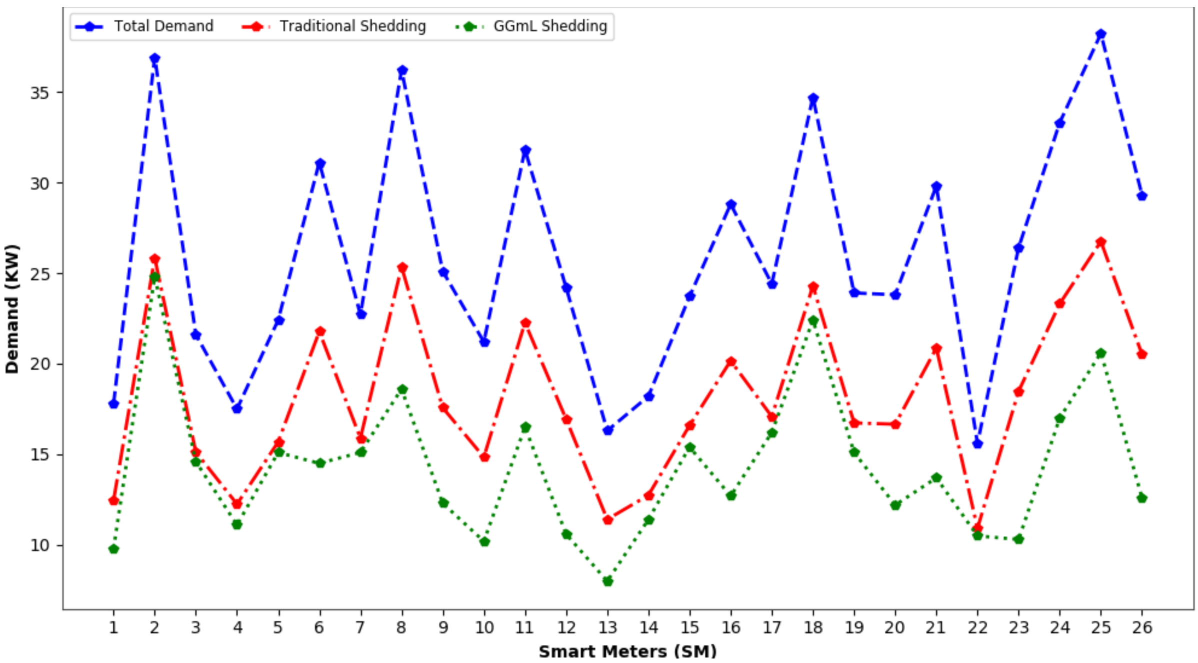


Figure 6 Results of conducting 30% GGmL Request using Grouped Microloads

30% GGmL Shedding

An expected shedding of 202.47kW, referred to as traditional shedding, was expected for the 30% GGmL shedding, but the actual overall shedding recorded was 303.60kW representing an excess overall microload shedding of 101.13kW, which appears to be very significant. The percentage of actual shedding recorded was 44.98% representing an excess percentage shedding of 14.98%. On average, the total consumption per household (SM) is 25.96. This means that the excess curtailments recorded for the 30% GGmL shedding would have been enough to cater for four houses without the need for shedding at all.

In terms of the distribution of the shedding per households, it was observed that SMs (23, 26, 16, 12, 21, 6 and 10) have experience percentage excess shedding of between 31% to 44% with the highest excess shedding recorded on SM23 and the lowest of these was recorded on SM10. The SM23 recorded an excess of 8.18kW, representing a percentage excess of 44% and SM10 recorded 4.64kW over-shedding, representing a 31% percentage excess over-shedding. The category of SMs that recorded less than 10% of percentage excess shedding is; SMs (4, 18, 15, 7, 17, 2, 5, 22 and 3) in descending order. SM4 and SM3 recorded the highest and the lowest, respectively, with SM4 recording excess shedding of 1.15kW and SM4 recording 0.52kW being 9% and 3% excess shedding, respectively. In terms of the SM excess shedding, in between (31%-40%) and (less 10%) is the (10%-30%) category. A 30%, 27%, 27% and 27% excess shedding were recorded at SM30, SM24, SM8 and SM20 representing 5.27kW, 6.31kW, 6.74 and 4.46kW respectively. The rest are SMs(11, 25, 1, 14 and 19), with the lowest excess shedding being recorded at SM19, with 1.63kW being 10% excess shedding.

20% GGmL Shedding

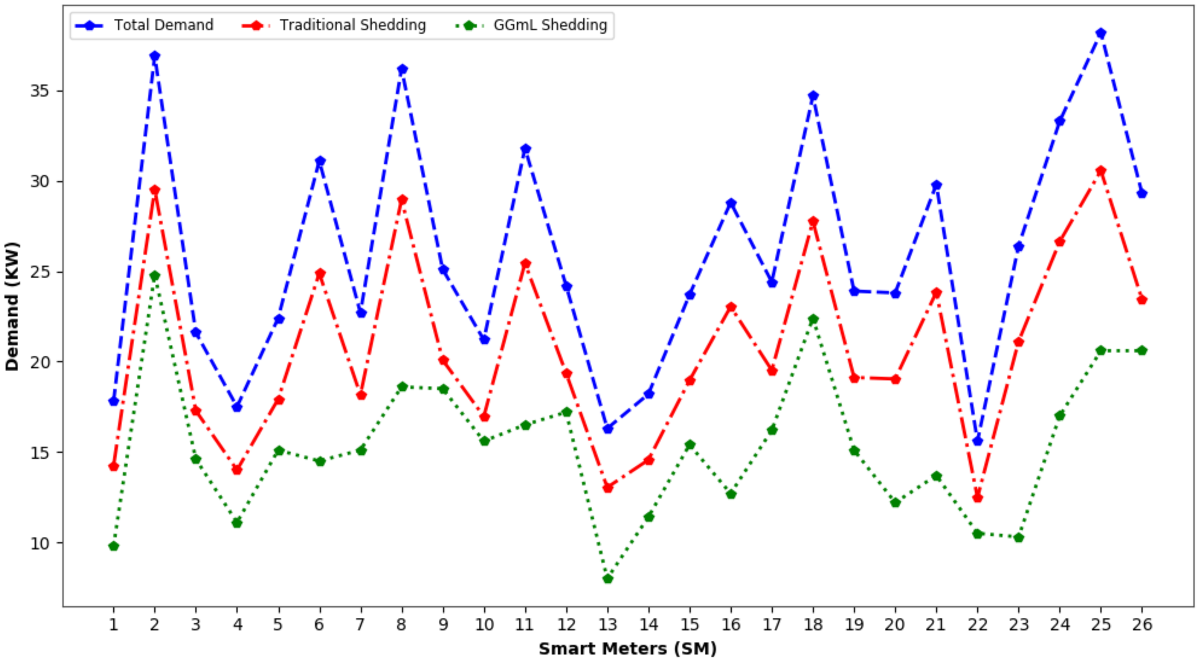


Figure 7 Results of conducting 20% GGmL Request using Grouped Microloads

The 20% GmL Shedding is categorised into three. The first represents those shedding from 45% to 61% instead of 20% representing 8kW to 16.1kW instead of the expected GmL shedding of 3.56kW to 5.28kW. This include the following SMs; SM (1, 6, 8, 11, 13, 16, 20, 21, 23, 24 and 25). The next group is those with a percentage shedding of 30% to 37%, with actual shedding from 8.7kW to 8.8kW. These actual shedding were expected to be 5.86kW to 3.5kW in that order.

The final group of the GmL shedding of 20% is relatively close to the expected shedding of 20%, which are 26%, 26% and 29% representing excess shedding of 1.36kW, 1.5kW and 2.16kW. Overall total excess shedding of 142.42kW was observed when a 20% GmL shedding was requested with an expected demand of 539.92kW, resulting in 397.5kW of actual demand from the various microloads of the 26 SMs. The summary of this result is shown in Figure 7 above.

15% GGmL Shedding

The results of the 15% GmL shedding request is shown in Figure 8 below. It was observed that the actual GmL Shedding experienced by the grid was similar to that of the 20% GmL shedding. This could be explained as being caused by the grouping of the loads, and as a result, the allotted shedding required per SM was not distributively possible. An expected shedding of 101.23kW and actual shedding of 277.4kW was observed, representing an excess shedding of 176.17kW, which is higher than even the request kilowatt. This resulted in an actual demand of 397.5kW as against the expected demand of 573.67kW. The difference between the actual and expected demand is too high for this algorithm and microload grouping to be put into a live grid.

The lowest excess shedding was observed on SMs(10, 9 and 11) with 2.84kW, 2.43kW and 3.37kW, representing percentage excess shedding of 26%, 26%, and 29%. The SMs(13,6, 21, 16 and 23) recorded percentage shedding of 51%, 53%, 54%, 56% and 61% representing over shedding of 5.86kW, 11.94kW, 11.63kW, 11.78kW and 12.14kW respectively. The rest of the SMs recorded 30% to 49% actual shedding ranging from 4.31kW to 12.17kW excess shedding.

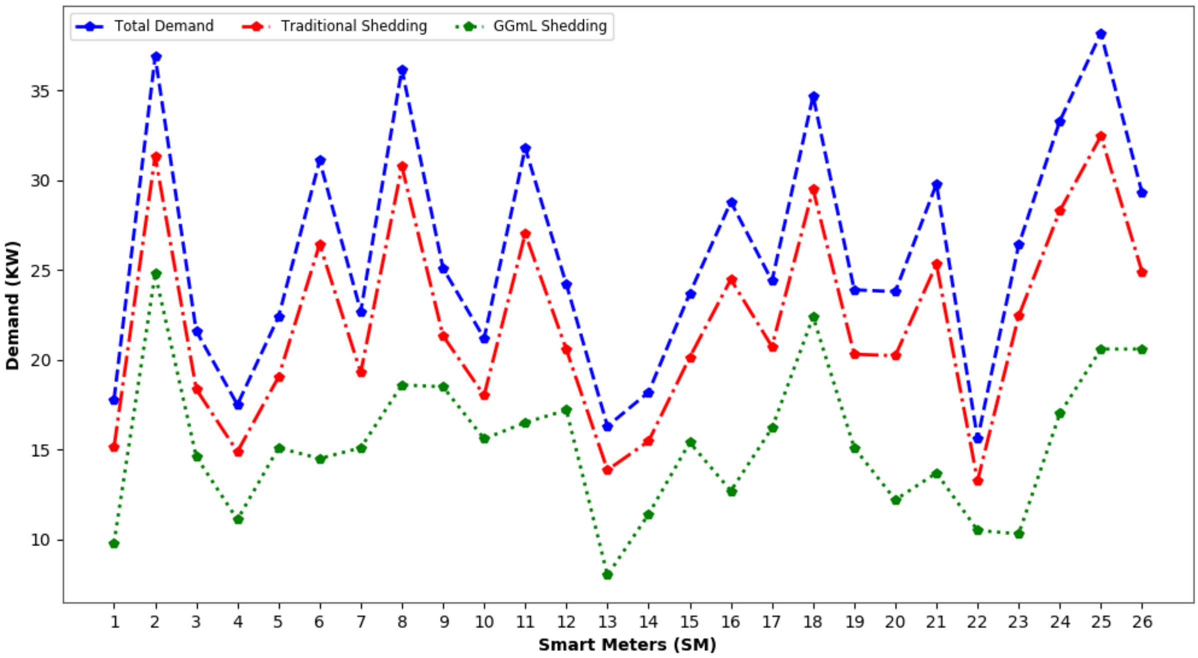


Figure 8 Results of conducting 15% GGmL Request using Grouped Microloads

10%, 5% and 2% GGmL Shedding

It was observed that requesting 10%, 5% and 2% GmL shedding resulted in the same actual demand as the results obtained from the 15% and the 20% GmL shedding. It was explained that this could be due to the grouping of the microloads into grouped microloads. The results are shown in Figure 9, 10 and 11. In terms of the relationship between the actual and expected shedding, the actual shedding is higher for all the requested shedding requested under the GmL shedding.

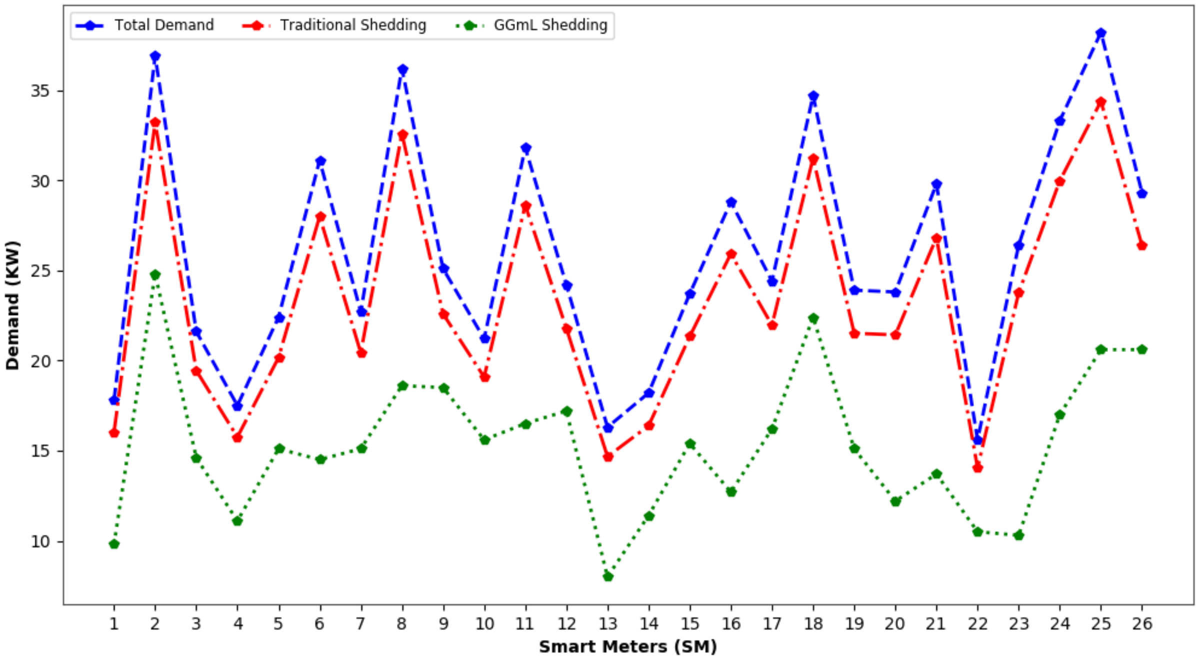


Figure 9 Results of conducting 10% GGmL Request using Grouped Microloads

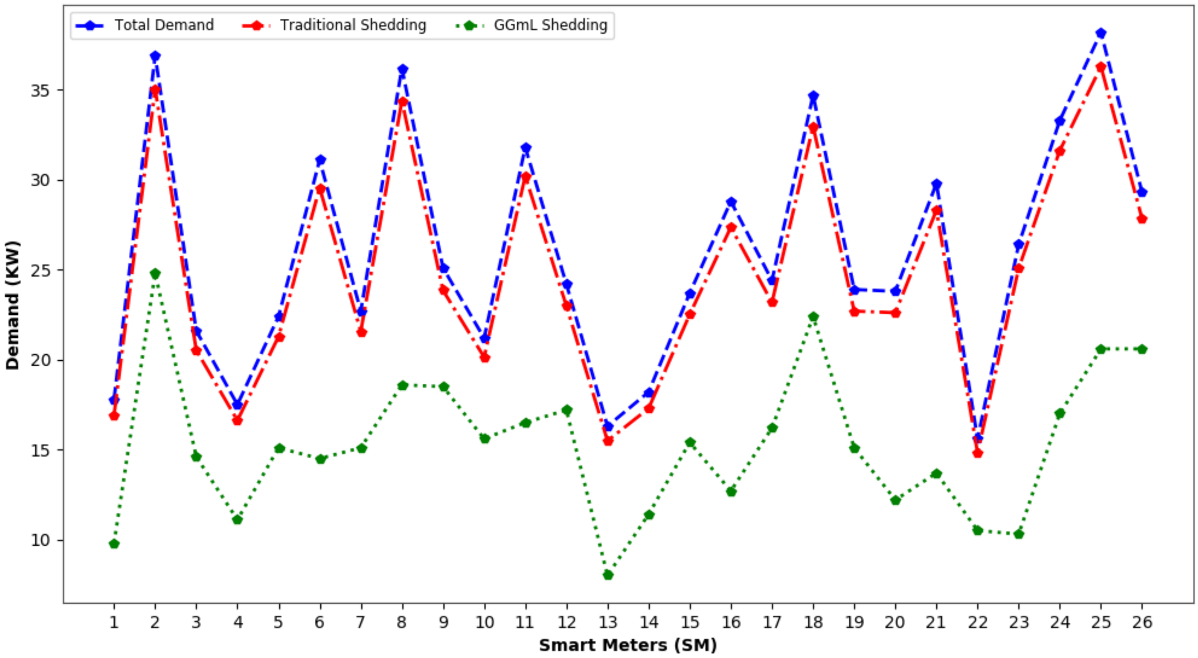


Figure 10 Results of conducting 5% GGmL Request using Grouped Microloads

The results show that the traditional shedding approach that completely cut power from a grid section would outperform this approach in terms of the actual kilowatts shed. For the 10% GmL shedding, an expected demand of 607.41kW resulted in an actual demand of 397.50kW, representing an overall shedding of 41%, far more above the required 10%. The 5% GmL shedding yielded an actual demand of 397.5kW against an expected demand of 641.16kW that is an overall eight times the expected shedding. The 2%, on the other hand, shows the highest over-shedding with a total of 263.9kW over-shedding recorded.

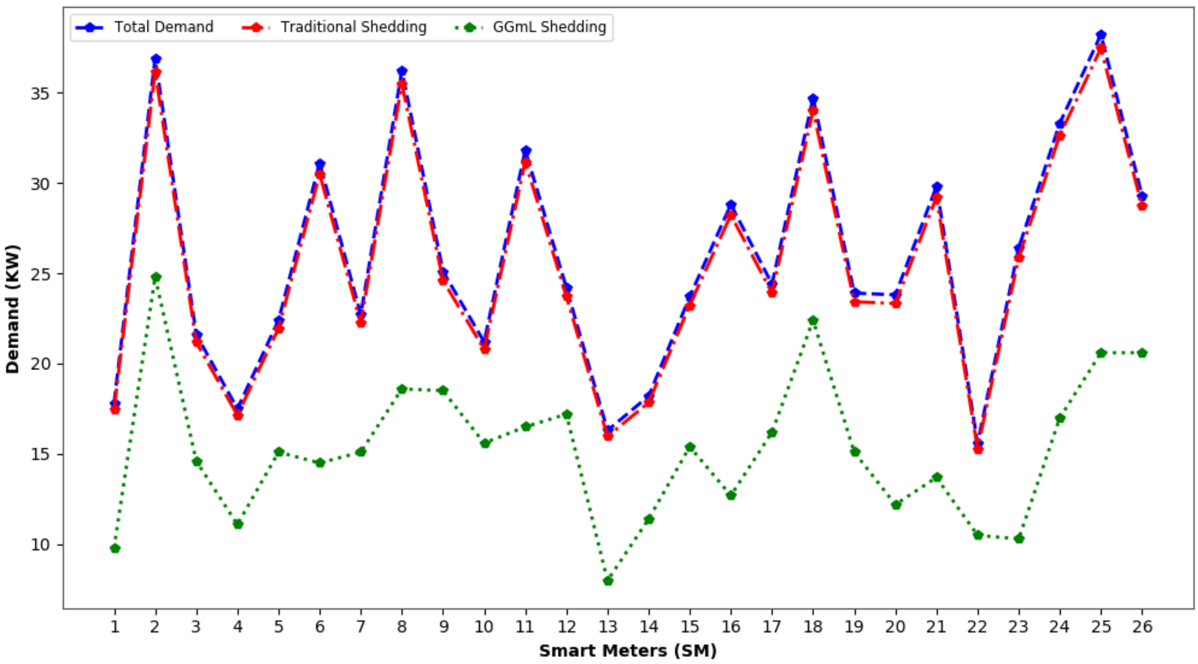


Figure 11 Results of conducting 2% GGmL Request using Grouped Microloads

To conclude, the GmL shedding shows very significant excess shedding along with the requested kilowatts, which shows that it may not be effective for effecting microload shedding that will benefit both electricity utility companies and their consumers.

4.4.2 GUmL Shedding

Similar to the GGmL shedding, curtailments of 202.47kW, 134.98kW, 101.24kW, 67.49kW, 33.75kW and 13.50kW were expected for microload shedding request of 30%, 20%, 15%, 10%, 5% and 2% respectively from an overall instantaneous total demand of 674.90kW. The actual overall microload demands observed after effecting the above percentage shedding were; 426.28kW and 481.08kW for 30% and 20% microload shedding, respectively; the 15%, 10%, 5% and 2% all recorded 494.69kW.

The figures below (i.e. Figures 12, 13, 14, 15, 16 and 17) show that the excess shedding has significantly reduced compared to those observed on the Grouped-Microload (i.e. GGmL) shedding. Overall excess shedding of 55.12kW, 69.09kW, 89.91kW, 124.26kW, 158.68kW and 179.28kW was recorded for the 30%, 20%, 15%, 10%, 5%, and 2% respectively. The excess shedding constitutes overall shedding of 37% and 29% for the expected 30% and 20% shedding. The 15%, 10%, 5%, and 2% all recorded 27% shedding. Hence, there has been an improvement in the grouped microload shedding, but the excesses remain huge and undesirable.

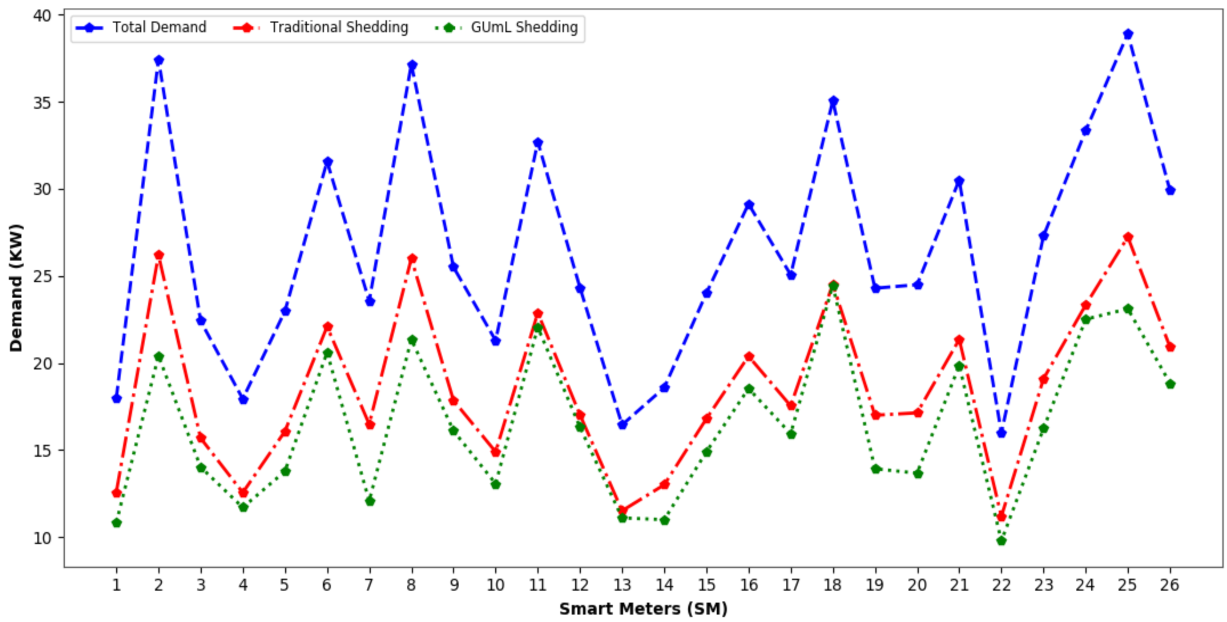


Figure 12 Results of conducting 30% GUmL Request using UnGrouped Microloads

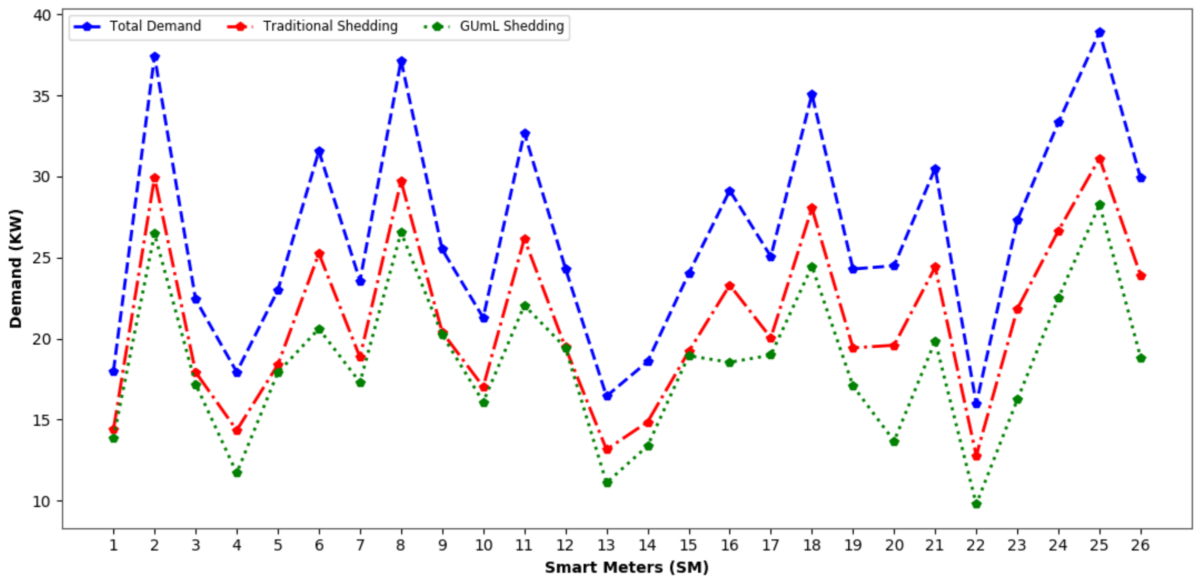


Figure 13 Results of conducting 20% GUmL Request using UnGrouped Microloads

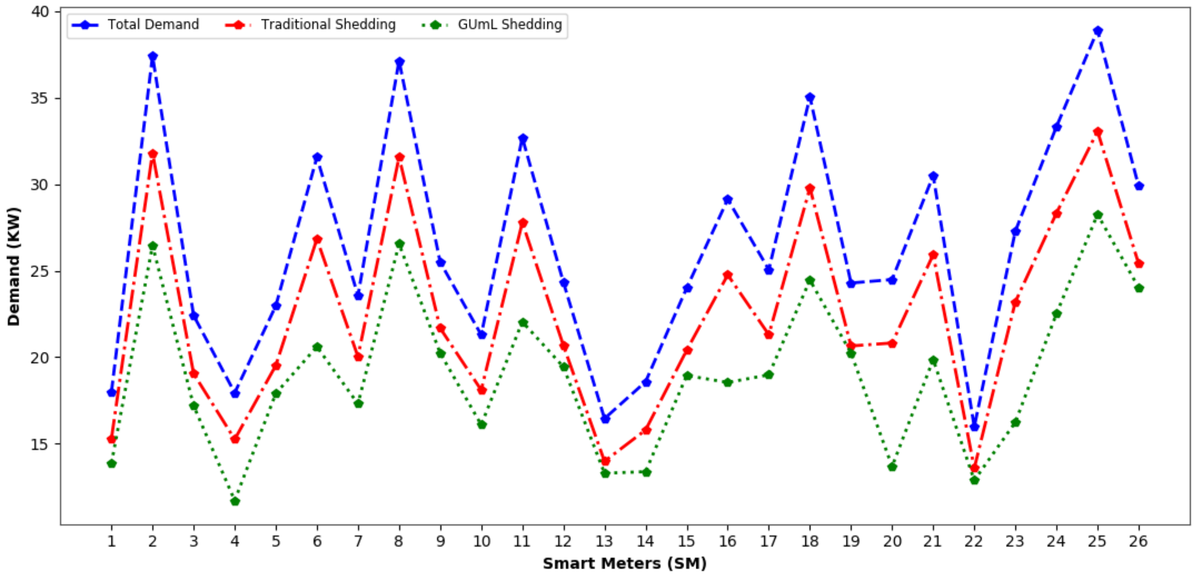


Figure 14 Results of conducting 15% GUmL Request using UnGrouped Microloads

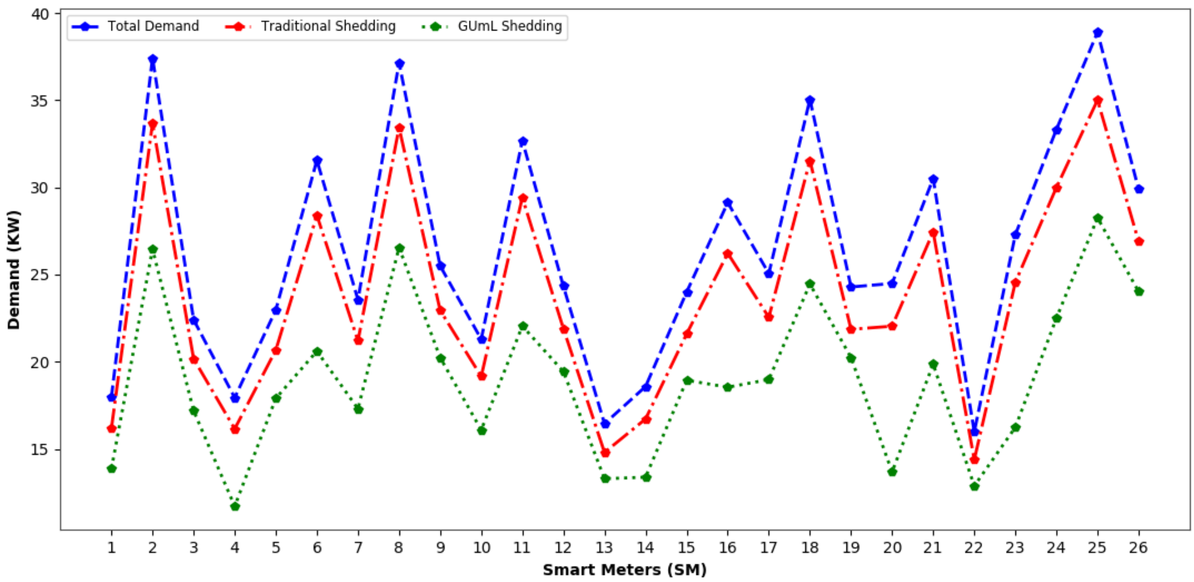


Figure 15 Results of conducting 10% GUmL Request using UnGrouped Microloads

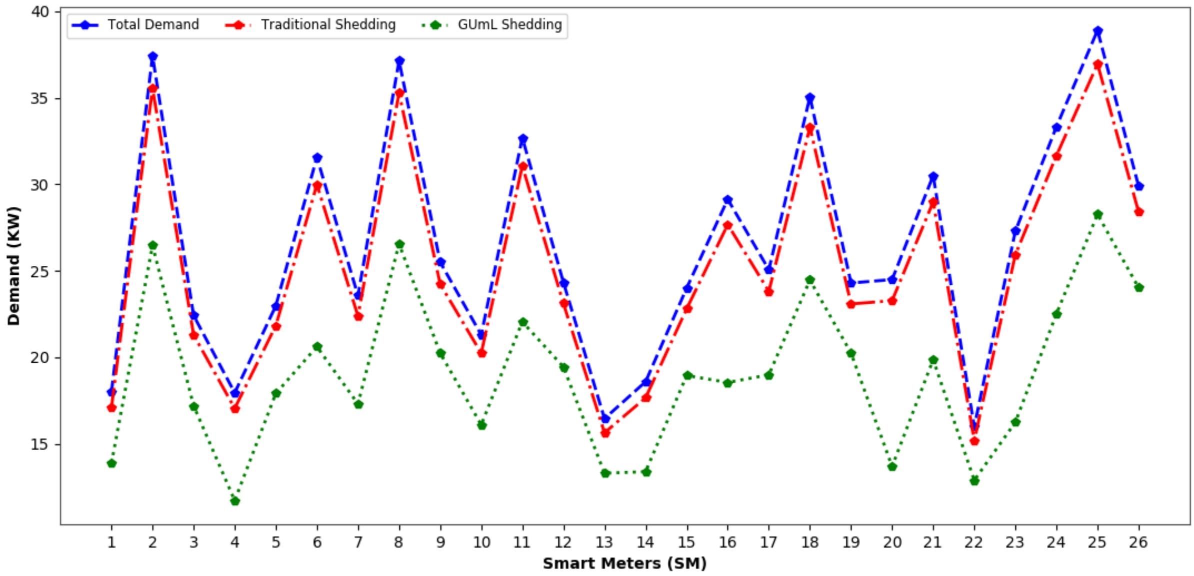


Figure 16 Results of conducting 5% GUmL Request using UnGrouped Microloads

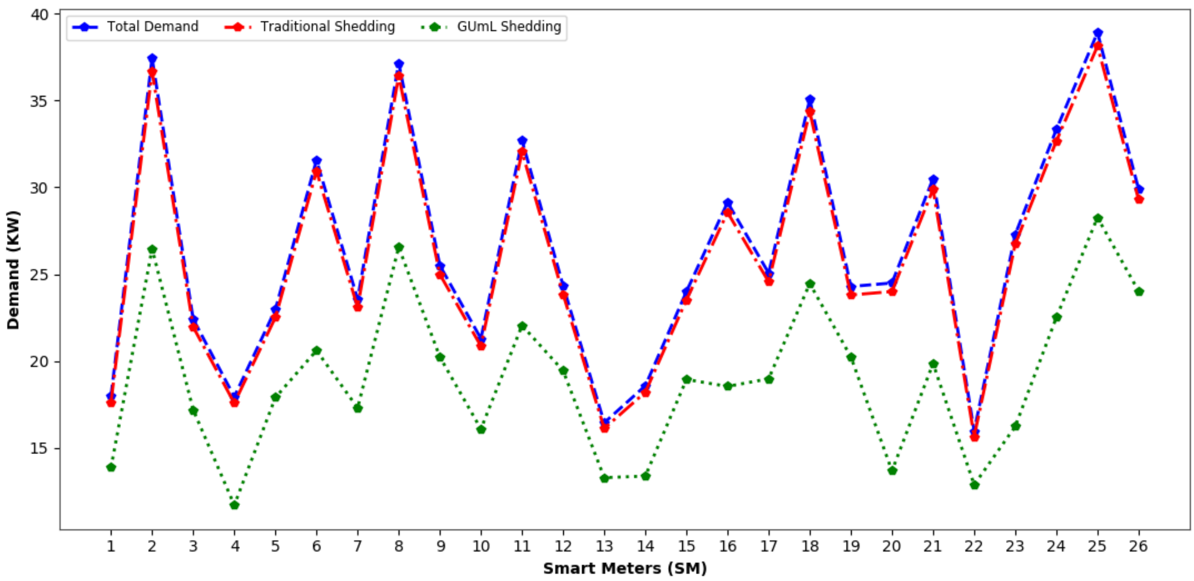


Figure 17 Results of conducting 2% GUmL Request using UnGrouped Microloads

The Table 3 below compares GGmL and GUmL Shedding.

Table 3 GGmL Shedding versus GUmL Shedding

GGmL					GUmL		GGmL - GUmL
% Requested	Expected Demand (kW)	Demand (kW)	Excess Shedding (kW)	% Excess Shedding	Excess Shedding (kW)	% Excess Shedding	Change in Excess Shedding (kW)
30	481.40	478.6	2.79	0.4%	40.43	6.0%	37.64
20	550.17	545.9	4.25	0.6%	49.72	7.4%	45.47
15	584.60	581.4	3.17	0.5%	63.87	9.5%	60.70
10	618.95	614.8	4.16	0.6%	74.01	11.0%	69.85
5	653.37	646.1	7.31	1.1%	44.66	6.6%	37.35
2	673.97	669.7	4.28	0.6%	9.50	1.4%	5.22

4.5 Chapter Summary

The result and analysis of General Microload Shedding (GmL) with Grouped and Ungrouped Microloads was investigated in this chapter. Dwindling generation, coupled with the increasing electricity demand, is compelling both developed and developing countries to explore and implement various techniques to prevent overloading the grid [125,128]. In the generation constrained powers system, load shedding is predominant, causing severe hardship for the consumers and hampers the productivity of the electric utility companies involved. An attempt has been made to reduce these burdens as seasonal and sectional load shedding is being implemented [129,130]. The microload are categorised into two groups; Grouped and Ungrouped Microloads.

A General Microload Shedding Algorithm is implemented in both categories. In general, there is a significant curtailment along with the expected load shedding resulting in over shedding. It was observed that as much as 20% microload shedding was recorded for a 2%, 5% and 10% requested microload shedding. Further, the grouped microloads experienced the highest over shedding, while the ungrouped microloads recorded less over shedding than the former. However, the excess shedding experienced under the ungrouped microload was also significant and not desirable for implementing a live grid. The need to consider other algorithms and approach for affecting the microload shedding is therefore necessary. In the next chapter, a priority-based microload shedding is investigated.

Chapter 5

Priority Based Microload Shedding

5.1 Introduction

To get the consumers involved in the proposed load shedding system, priority information is attached to the various microloads; (i.e. Grouped and Ungrouped microloads). The consumers are assumed to set the priorities of each microload as individual loads or grouped loads. This simulation's assumed priority levels are shown in Table 2 as GCmL and UCmL for the grouped and the ungrouped microloads, respectively. In this chapter, the excess microload shedding recorded in the GmL approach was significantly reduced by considering user priorities. It is assumed that at this stage the users have pre-set priorities on each microload group, and these priorities are considered by the meter side sub-algorithm shown in Figure 4 in Chapter 4. This work has contributed to the following publications: [127, 128].

5.2 The Priority Based Microload Shedding

As discussed earlier in Chapter 4, concealing the actual microloads consumptions from the server preserves the user's privacy. As a result, the Server Side GmL Shedding sub-algorithm is the same as that of the Priority Based Microload Shedding server-side sub-algorithm as in Figure 4. The Priorities are therefore considered only in the Meter Side sub-algorithm shown in Figure 18. The server only allocates the amount of energy to be curtailed by each smart meter. The smart meter computes which microload to be cut-off to achieve the desired curtailment based on the assigned user priorities. The meter side sub-algorithm for the priority-based microload shedding is shown in Figure 18 below.

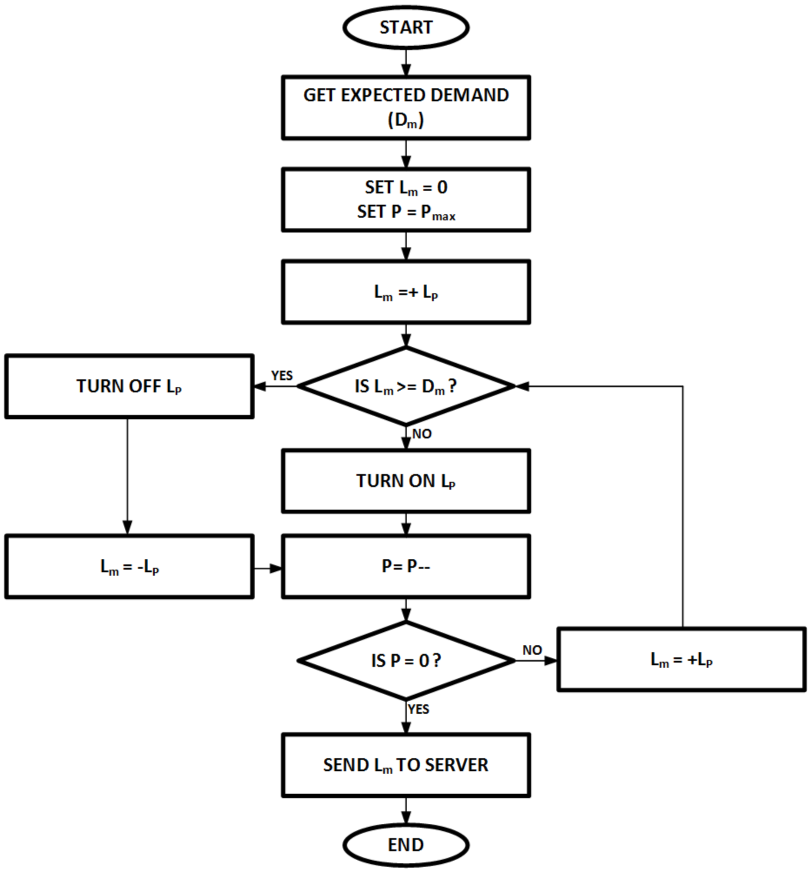


Figure 18 Meter Side Sub-algorithm

5.3 Results and Discussions

The proposed system is evaluated on the GmL and the UGmL, and the results are discussed under their subheadings, respectively. The setup is similar to those discussed in the previous chapter. The GmL Server Side (GSS) sub-Algorithm is the same as the Priority-based one as reported in Figure 12 of Chapter 4, but the algorithms utilise the priority of the loads at the meter side as shown in Figure 18 above.

5.3.1 Priority Based Grouped Microload (PbGmL) Shedding

This subsection discusses the simulation results obtained from grouping the microloads into six priorities groups. High priorities are assigned high priority numbers such that the higher the priority, the more user prefers that microload group in that category remain unaffected (ON) during microload shedding periods. 2%, 5%, 10%, 15%, 20% and 30% microload shedding requests were conducted in that order, and the results are discussed, respectively. The PbGmL shedding assumes that the user sets the priorities of all the microloads (i.e. P = 1 for Grouped Microloads 1 to P = 6 for Grouped Microloads 6), implying each grouped microload category has a unique priority as shown in Table 2. Expected Demand is given as (Dm) where Priority Based Grouped Microload (PbGmL) Shedding and Priority Based Ungrouped Microload (PBUmL) Shedding were performed.

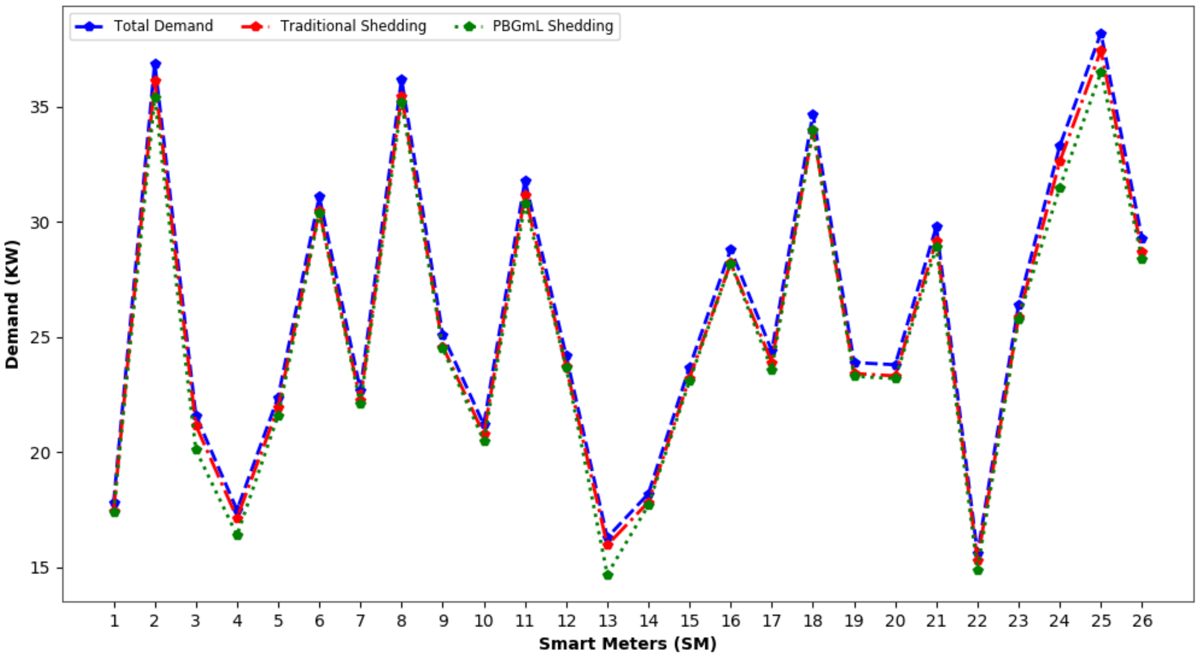


Figure 19 Results of conducting 2% PBGmL Request using Grouped Microloads

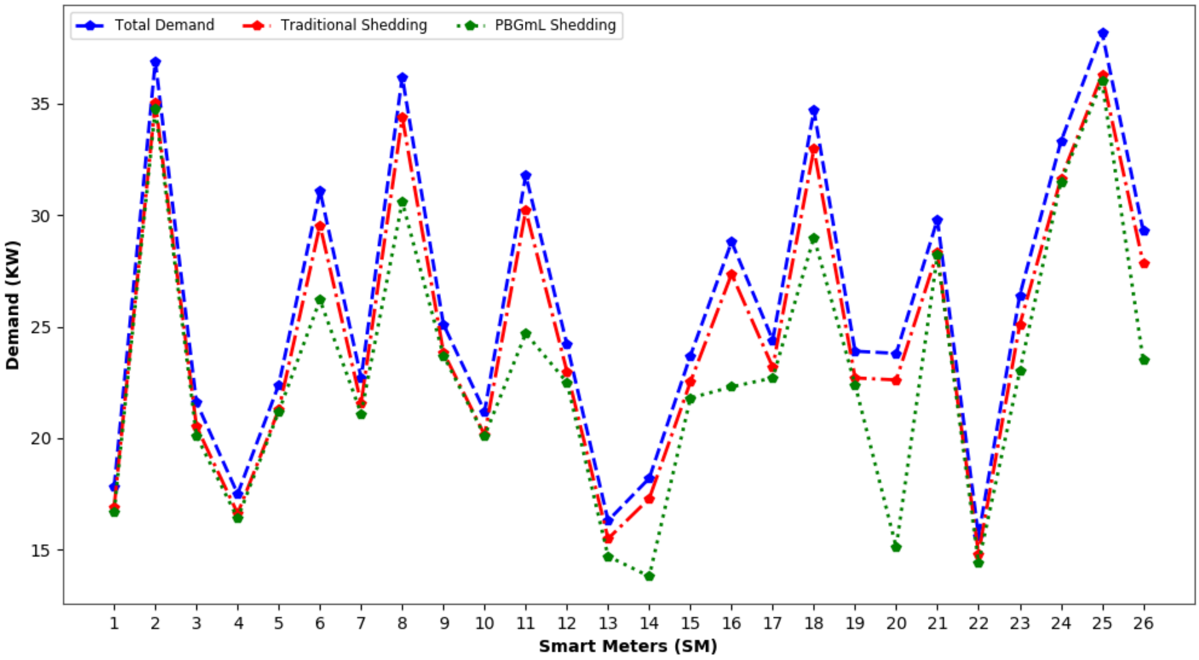


Figure 20 Results of conducting 5% PBGmL Request using Grouped Microloads

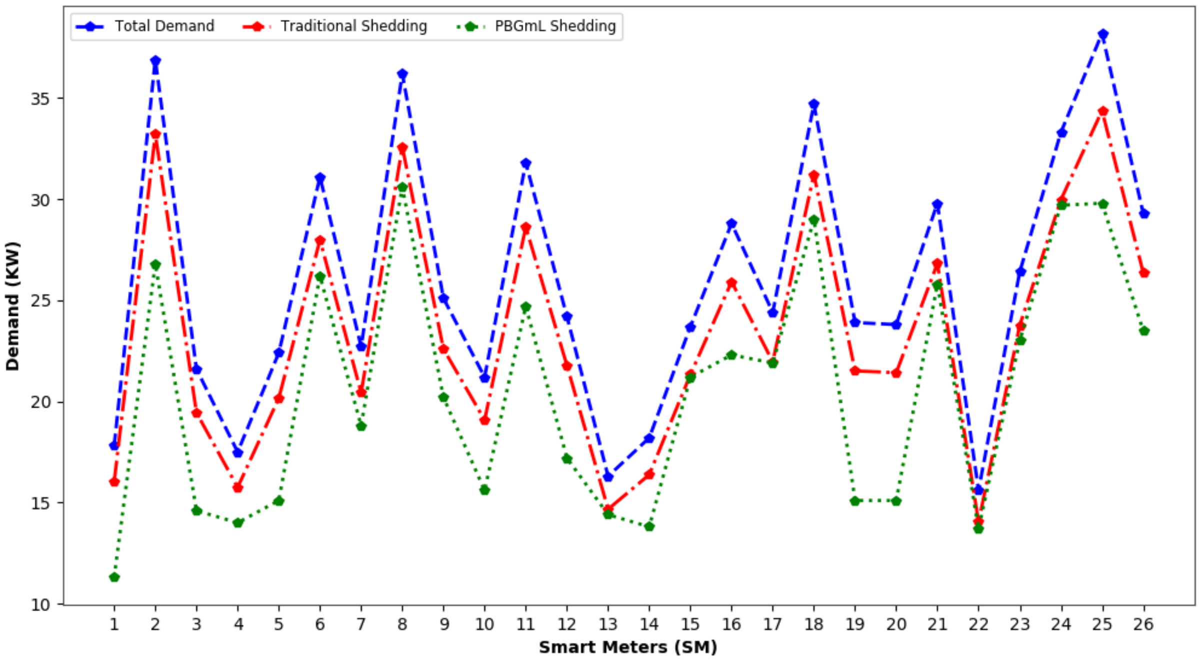


Figure 21 Results of conducting 10% PBGmL Request using Grouped Microloads

The total demand from the 26 SMs was observed to be 674.90kW at the beginning of all simulations. Figure 19 to Figure 24 show the results of Priority Based Grouped Microload (PbGmL) for the 2%, 5%, 10%, 15%, 20% and 30% requests for microload shedding, respectively. As shown in the figures; 2%, 5%, 10%, 15%, 20% and 30% microload management was performed on the same consumption profile of 26 SMs consuming a total of 674.90kW with expected demand of 661.40kW, 641.16kW, 607.41kW, 573.67kW, 539.92kW and 472.43kW respectively.

Table 4 PBGmL Excess Shedding

% Requested	Expected Demand (kW)	Demand (kW)	Excess Shedding (kW)	% Excess Shedding
30	472.43	432.0	40.43	6.0%
20	539.92	490.2	49.72	7.4%
15	573.67	509.8	63.87	9.5%
10	607.41	533.4	74.01	11.0%
5	641.16	596.5	44.66	6.6%
2	661.40	651.9	9.50	1.4%

However, the actual total demands recorded for these microload shedding request were 651.9kW, 596.5kW, 533.4kW, 509.8kW, 490.2 and 432.0kW in ascending order of the percentage request made. The lowest percentage of excess shedding is observed on 1.4% request with a total excess of 9.50kW, and the largest excess shedding is seen to be 74.01kW on 11%. Table 4 shows the excess shedding amongst the percentage requests made.

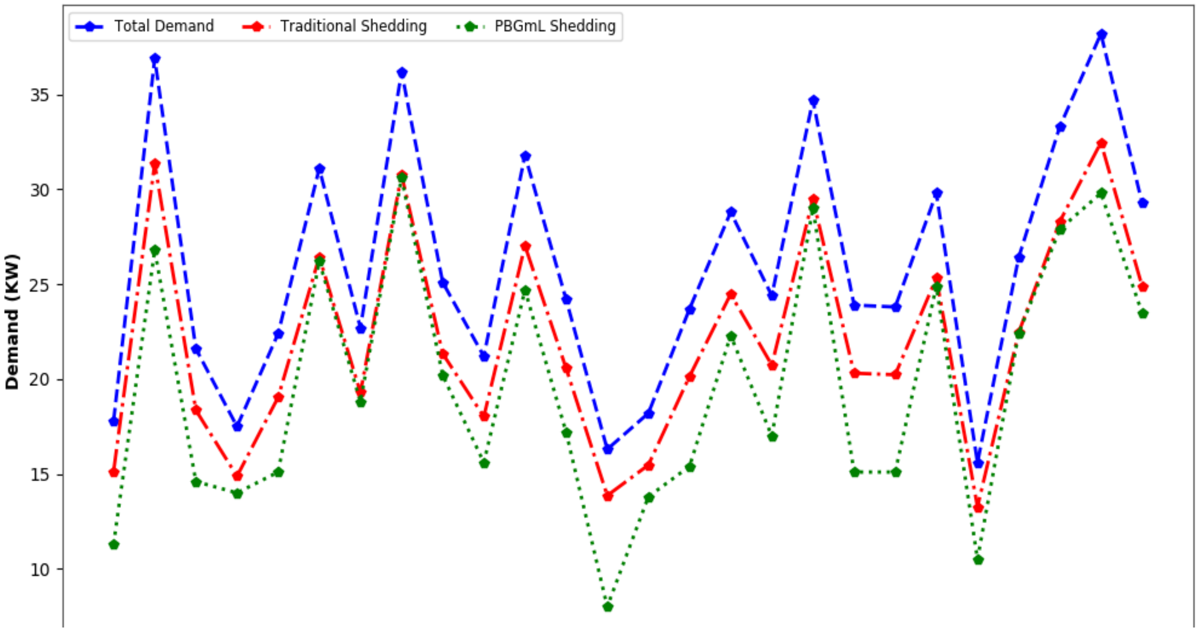


Figure 22 Results of conducting 15% PBGmL Request using Grouped Microloads

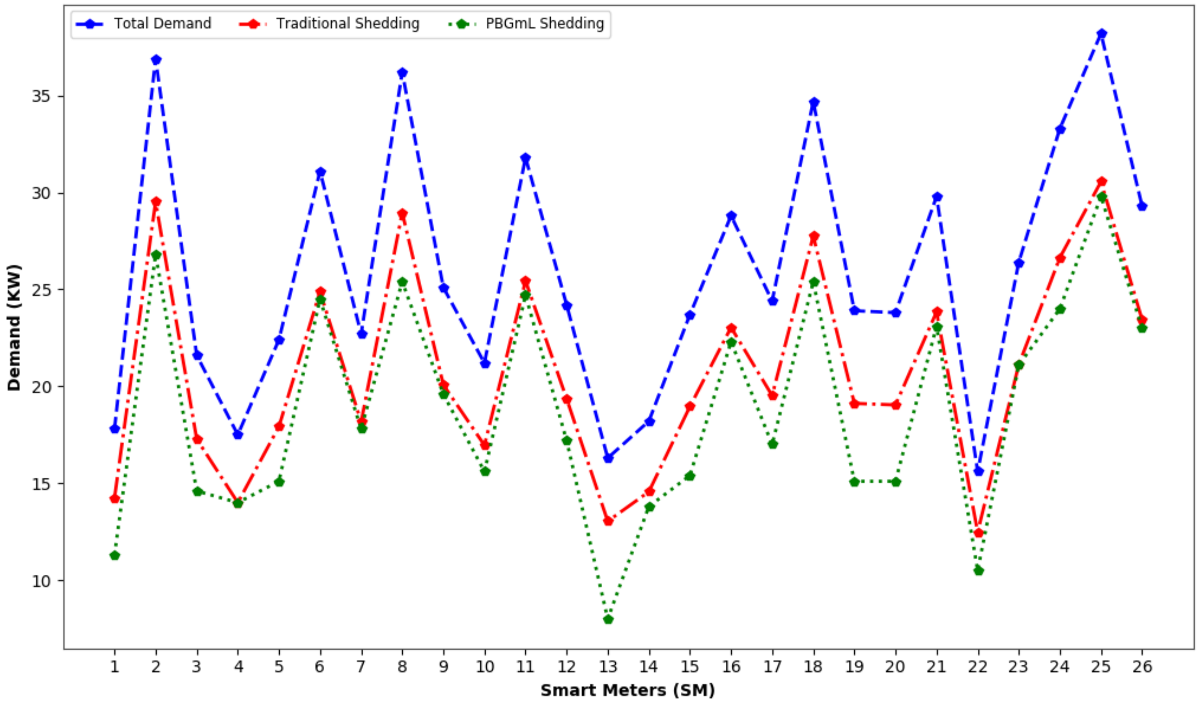


Figure 23 Results of conducting 20% PBGmL Request using Grouped Microloads

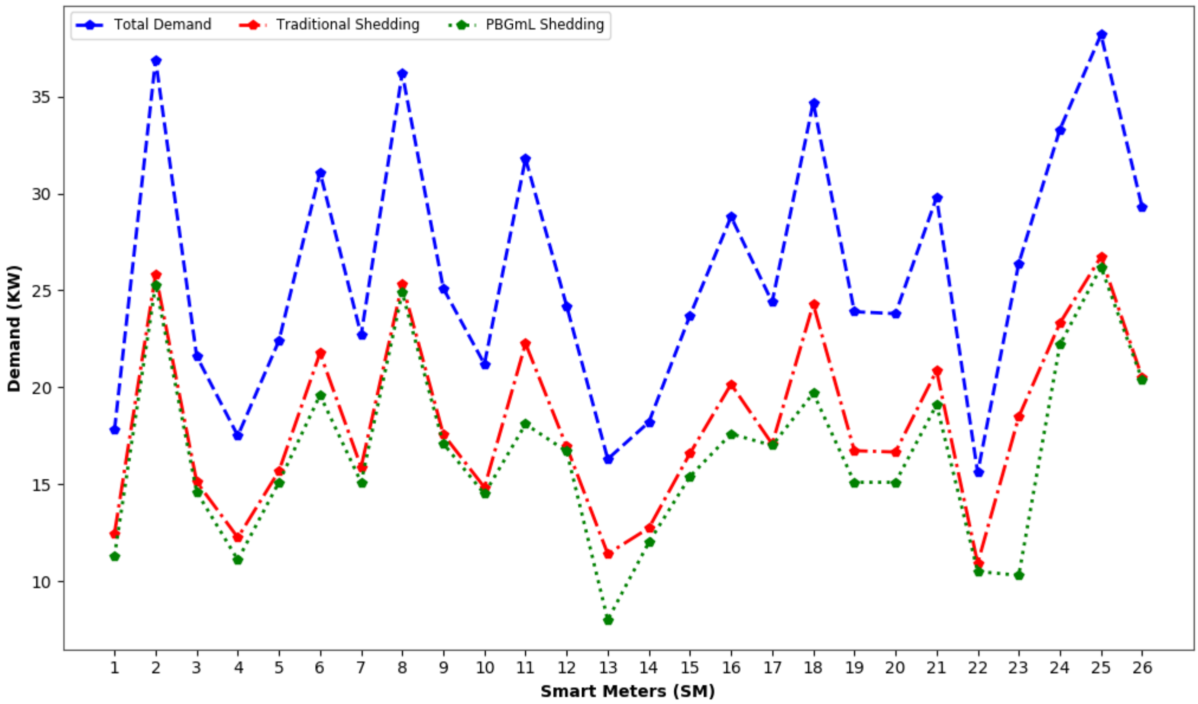


Figure 24 Results of conducting 30% PBGmL Request using Grouped Microloads

5.3.2 Priority Based Ungrouped Microload (PBUmL) Shedding

The ungrouped microloads are subjected to the same priority-based algorithm as the grouped microloads. The simulation results of the ungrouped microloads shedding are discussed in this subsection. Overall, there appears to be a very significant reduction in the excess microload shed, along with the expected values. The performance of the PBUmL is shown in Figure 25 to Figure 30.

There was a huge gap between the excess load shed and a comparison between PBGmL shedding and PGUmL shedding. The PBGmL shedding recorded 40.43kW, 49.72kW, 63.87kW, 74.01kW, 44.66kW and 9.5kW representing over-shedding of 6.0%, 7.4%, 9.5%, 11.0%, 6.6% and 1.4% for the 30% to the 2% PBGmL shedding. The PBUmL shedding on the other hand recorded excess shedding of 2.79kW, 4.25kW, 3.17kW, 4.16kW, 7.31kW and 4.28kW which represents fractional percentage over-shedding of 0.4%, 0.6%, 0.5%, 0.6%, 1.1% and 0.6% for the requested shedding of 30% to 2% PBUmL shedding. Hence, the PBUmL performs significantly better than the PBGml shedding. This can be explained by the number of controllable microloads available to share the required demand level.

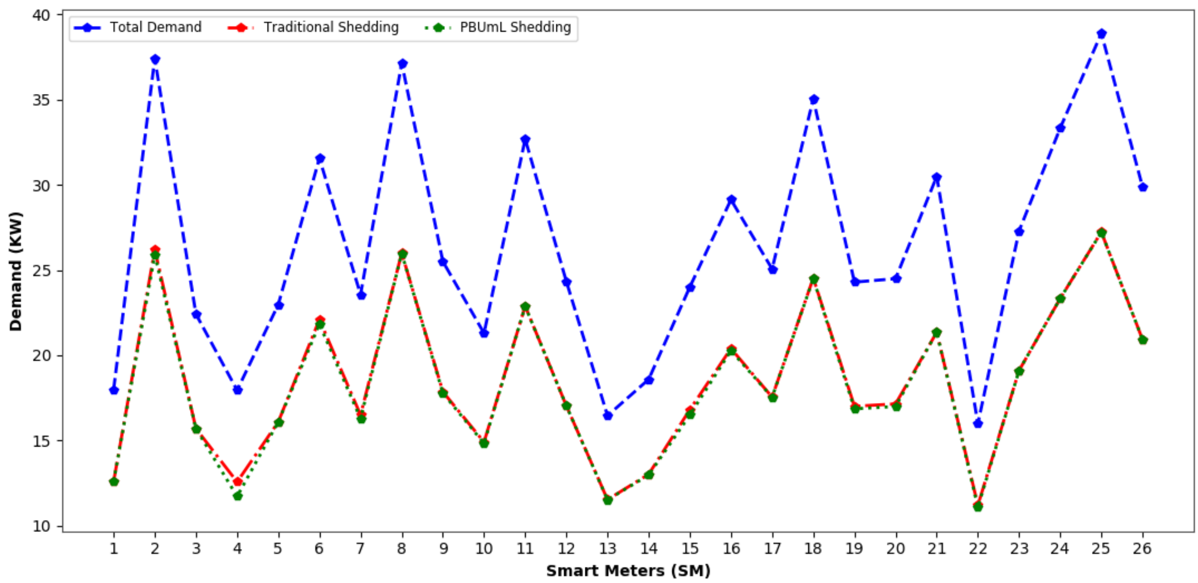


Figure 25 Results of conducting 30% PBUmL Request using UnGrouped Microloads

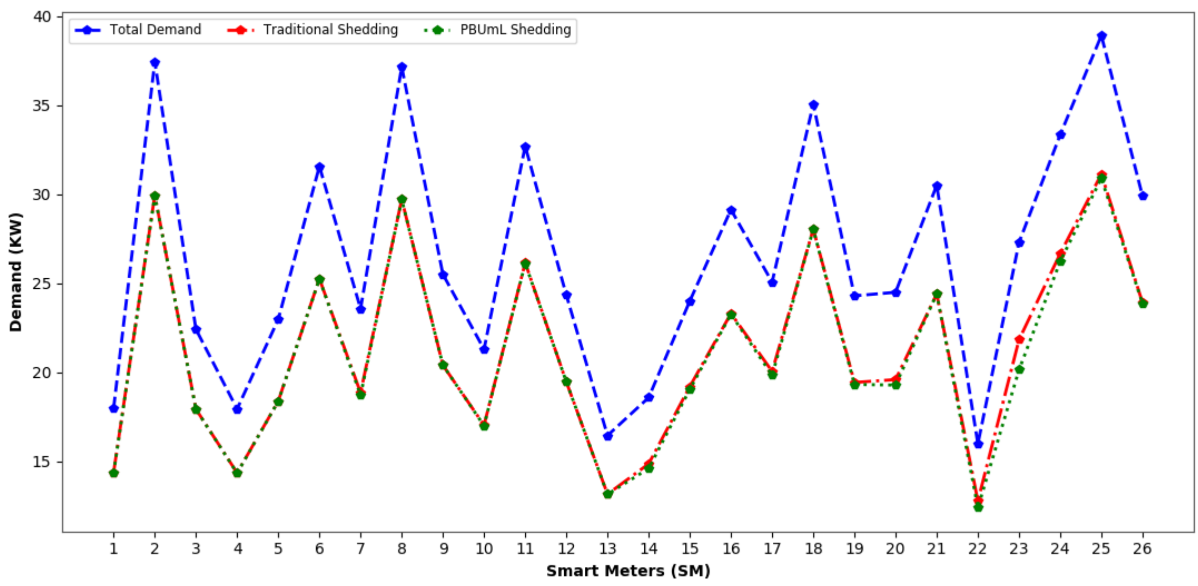


Figure 26 Results of conducting 20% PBUmL Request using UnGrouped Microloads

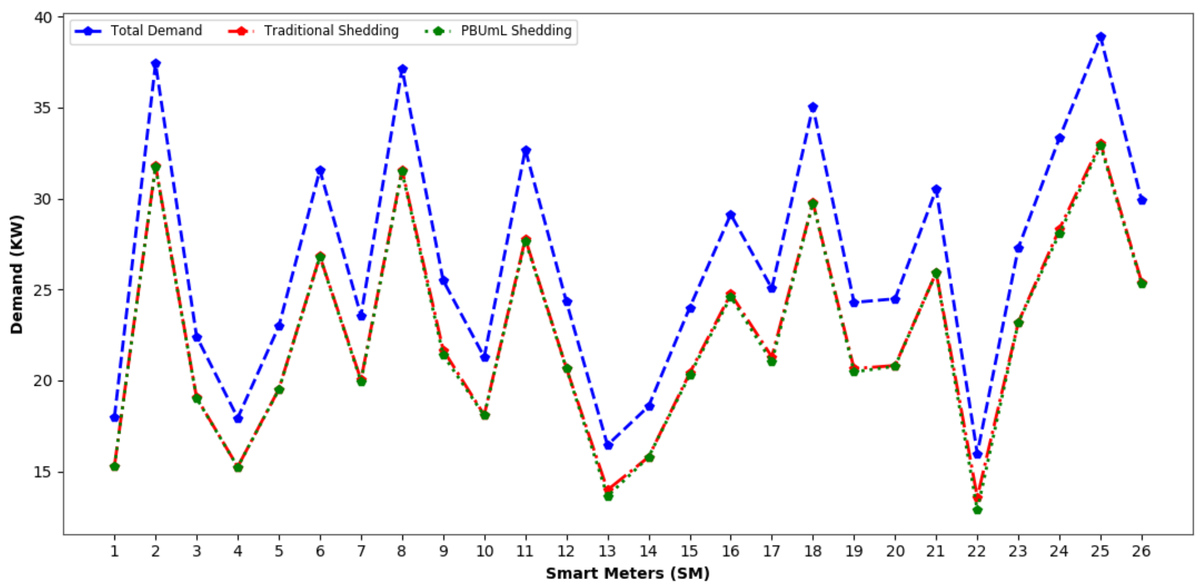


Figure 27 Results of conducting 15% PBUmL Request using UnGrouped Microloads

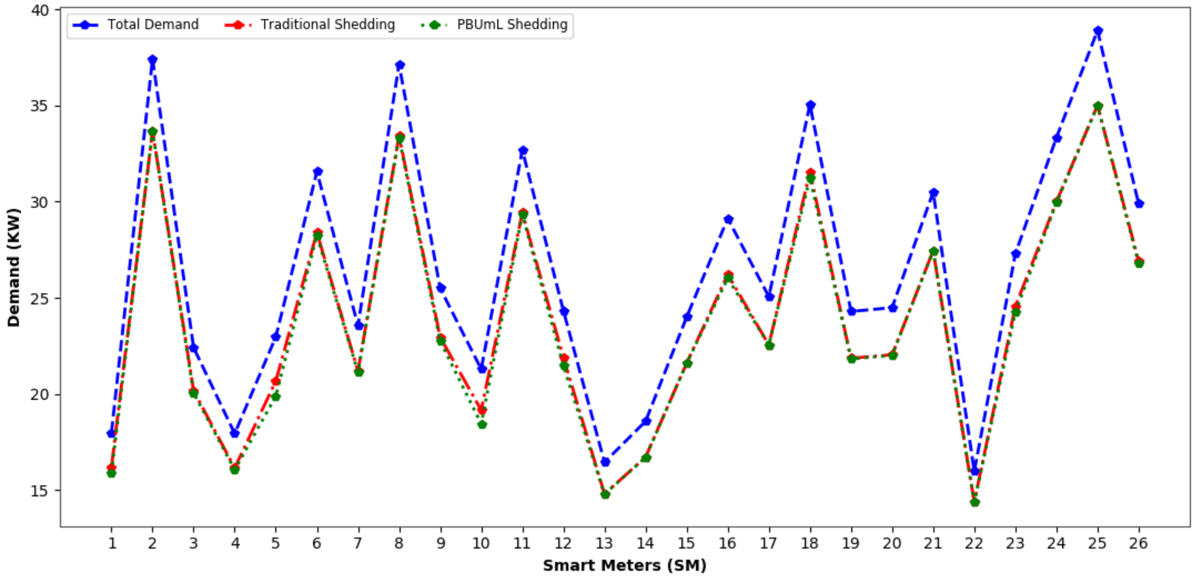


Figure 28 Results of conducting 10% PBUmL Request using UnGrouped Microloads

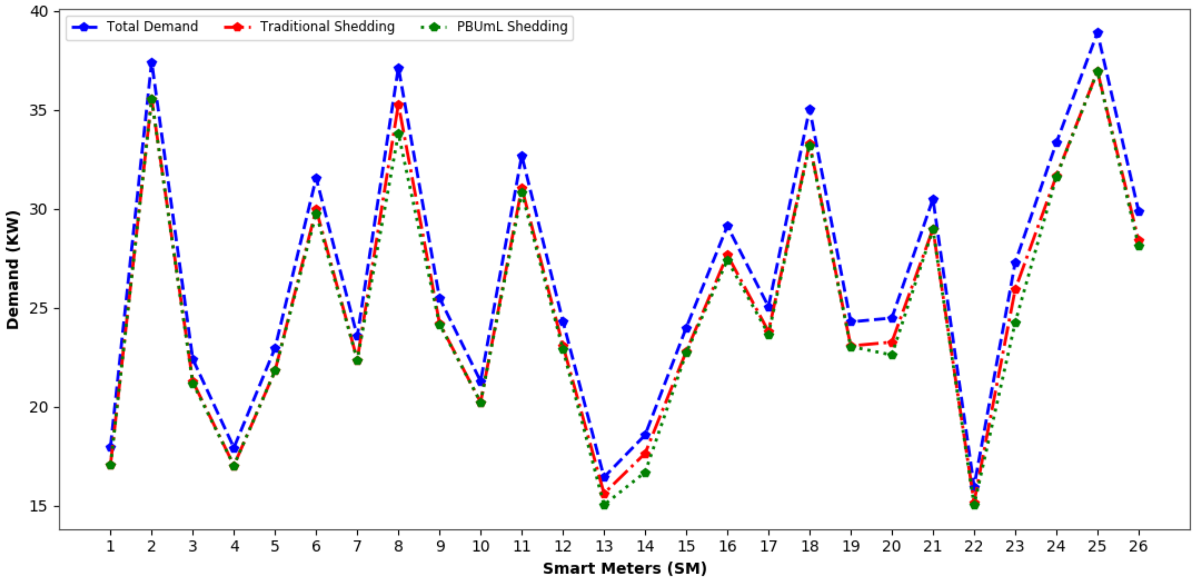


Figure 29 Results of conducting 5% PBUmL Request using UnGrouped Microloads

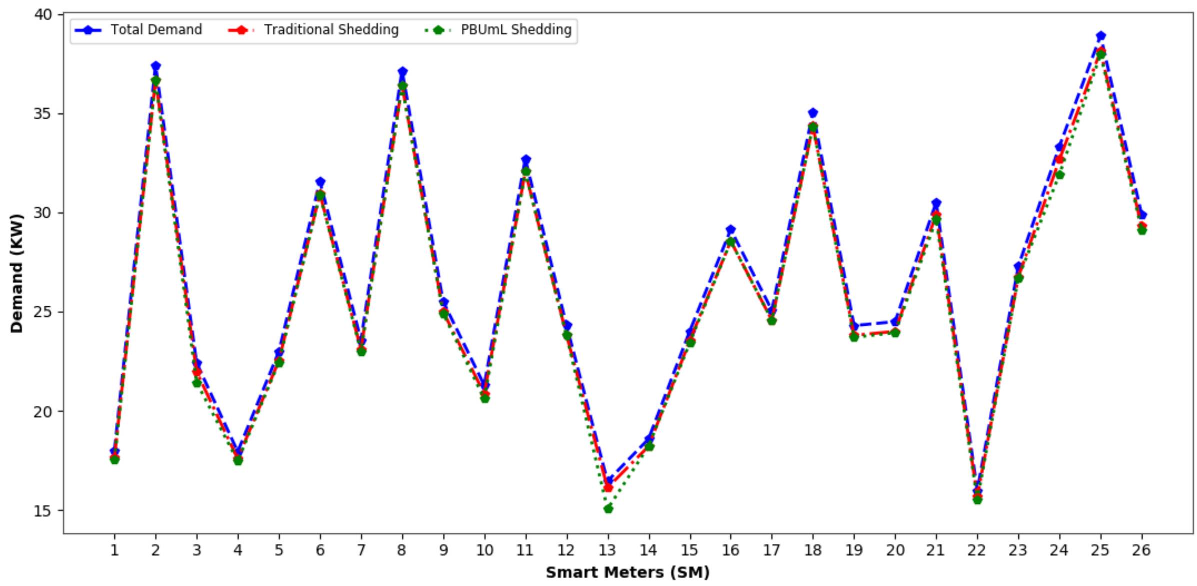


Figure 30 Results of conducting 2% PBUmL Request using UnGrouped Microloads

5.4 Chapter Summary

In this chapter, the most effective ways of reducing the impact of traditional load shedding of electricity in generation constrained power systems on the consumers within the context of the smart grid was examined after the general grouped and ungrouped microload shedding show that there is significant excess shedding along with the intended one. Therefore, algorithms to efficiently allocate the available generation without incurring high excess shedding are investigated. Dynamic programming-based algorithms are developed to achieve this constraint by uniquely controlling home appliances to reduce the overall electricity demands in two ways; Grouping the microloads and controlling them as one controllable group of microload (Grouped Microload) and uniquely controlling each microload (Ungrouped Microload).

A significant reduction in the excess curtailment was achieved as it helps the utility companies to reduce wastage and ultimately reduce losses resulting from over shedding. There was a reduction of the over-shedding from 74.01kW to 4.16kW after employing the Priority-based microload shedding techniques using the Ungrouped Priority Loads (UPL) consumption profiles. Additionally, the actual percentage shedding was also improved from 11% to 0.6%

when subjected to a 10% microload shedding using the UPL load profiles. The next chapter considers the re-use of the excess in the implementation of the various algorithms discussed previously.

Chapter 6

Excess Reuse Microload Shedding

6.1 Introduction

This chapter introduces the excess reuse concept to reuse the excess microload shedding experienced in the previous approaches, namely, General Microload Shedding [125,126] and Priority Based Microload Shedding [127]. It was previously seen that there were high values excess shedding when the households' microload demands were curtailed using the General and Priority Based Microload Shedding techniques for the Grouped and UnGrouped Microloads. Similar to the previous approach, the microloads used for the simulation are shown in Table 2. Most of the work reported in this chapter has contributed to the publication in [128]. The simulation and the subsequent results are discussed in the subsections below.

6.2 The Excess Reuse General Microloads Shedding

After observing the excess shedding that comes along with the intended values termed as over-shedding as seen in the work reported in [125] and [126], the Excess Reuse General Microloads (ERGmL) Shedding is developed to reuse the excess from the first household (SM) in the sequence to the next successive house (SM). ERGmL Shedding Algorithms in Figure 31 shows the sequence of this approach. To validate the ERGmL shedding, it was subjected to both Grouped Controllable Microloads (GCmL) and Ungrouped Controllable Microloads (UGCmL), as shown in Table 2 in Chapter 4.

6.2.1 ERGmS using GCmL Consumption Profiles

The GCmL Consumption profiles of 26 homes fitted with a 6-grouped controllable microload were subjected to the ERGmL shedding Algorithm. At the start of the simulation, the overall demand from the 26 homes was seen to be 674.90kW before curtailments of 202.47kW, 134.98kW, 101.24kW, 67.49kW, 33.75kW and 13.50kW was initiated, representing percentage microload shedding requests of 30%, 20%, 15%, 10%, 5% and 2% respectively. This load shedding is referred to as Excess Reuse General Grouped Microload (ERGGmL) Shedding.

```
Initialization;
Get Total GS Demand D;
Input Grid Sections (GS);
Get N i.e. total number of SM in GS;
Set ER = 0.00 kW;
Input Total Expected Demand D̂;
Compute Percentage Expected Demand d_m% per SM;
d_m% = D̂/D * 100;
for Grid = 1 to Grid_max do
    Set L_m = 0.00 kW;
    for m = 1 to N do
        Compute Expected Demand per SM (d_m);
        d_m = d_m% * d_m^τ;
        D_m = d_m + ER;
        if ER < 0 then
            D_m = d_m;
        end if
        for p = 1 to p_max do
            L_m = L_m + L_p;
            if L_m < D_m then
                Turn OFF L_p;
            end if
            if L_m > D_m then
                L_m = L_m - L_p;
                ER = D_m - L_m;
                Update Server with L_m & ER ;
            end if
        end for
        Display Current Total Demand D;
        Update the GS;
    end for
end for
```

Figure 31 ERGmL Algorithm

30% ERGGmL Shedding

The results of requesting 202.47kW microload shedding reveal 261.9kW representing 38.81% microload shedding which shows an excess of 8.81% shedding. This is a marginal over-shedding compared to the previous techniques discussed. It was also observed that a significant number of households experienced less shedding than the requested values, which was demonstrated by the negative excess shedding seen from these smart meters. SMs (7, 9, 12, 17, 22 and 26) experienced this negative over-shedding at values of 6.8kW, 0.93kW, 0.26kW, 7.32kW, 4.68kW and 0.09kW respectively. This observation could be attributed to the fact that excesses from previous houses are redistributed on the successive ones leading to more available electric energy for the affected houses. Figure 32 below shows how the houses (SMs) performed under the 30% ERGGmL Shedding.

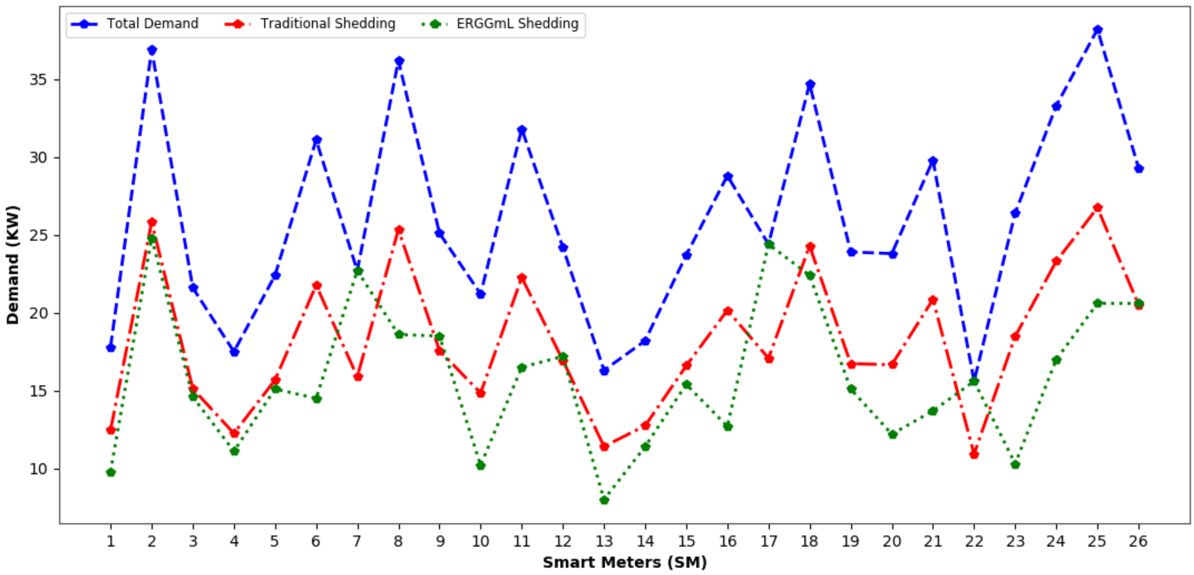


Figure 32 Results of conducting 30% ERGGmL Request using Grouped Microloads

The lowest excess shedding was observed on the SM3 and SM6 at 0.52kW and 0.58kW in that order. On the other hand, the highest excess shedding observed were seen from SM 16, SM6 and SM 21, which recorded 7.46kW, 7.27kW and 7.16kW. On average, the excess shedding per request observed was 2.29kW.

20% ERGGmL Shedding

When a 20% microload shedding was requested under this context, an excess shedding of 7.31% was observed, representing 49.32kW actual excess shedding with an expected demand of 539.92kW and an actual demand of 490.6kW. Regarding individual households' microload shedding, several households experienced under-shedding resulting from the excess reuse of the previous successive houses. The average excess shedding recorded for all households under the 20% ERGGmL shedding request was 1.90kW.

An average of 5kW was observed to have been reused, with 50.50kW being the total reused among the following smart meters; SMs (3, 7, 9, 12, 14, 17, 19, 21, 24 and 26). Among these houses, SM24 recorded under-shedding of 6.66kW and 3.64 was recorded by SM14. The summary of the ERGGmL shedding performance at a request of 20% microload shedding is shown in Figure 33. In terms of excess shedding, 10.34kW, 10.36kW and 10.82kW were seen as the highest recorded for SM16, SM8 and SM23, respectively and a low of 1.36kW and 1.98kW were recorded at SM10 and SM22.

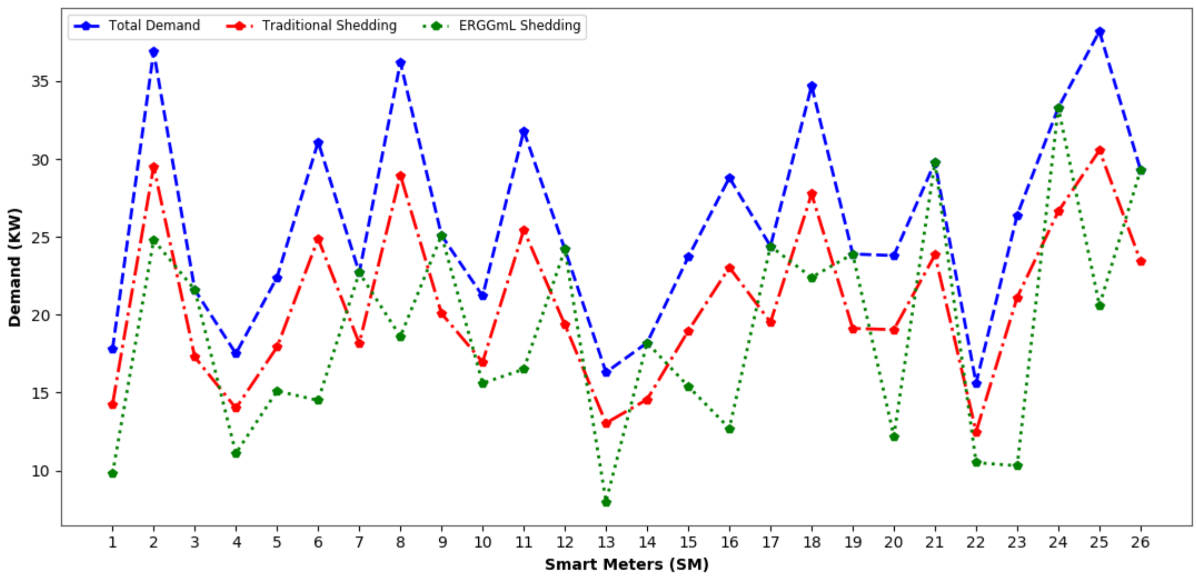


Figure 33 Results of conducting 20% ERGGmL Request using Grouped Microloads

15% ERGGmL Shedding

When a 15% ERGmL was requested, an expected shedding of 101.23kW yielded an actual shedding of 167.10kW, representing a 67.87kW over-shedding. This amounted to an actual demand of 505.8kW instead of an expected demand of 573.67kW. An average of 2.61kW was observed for the 26 houses when subjected to the 15% ERGmL shedding. While there was apparent general over-shedding, there are some houses that experience some levels of under-shedding.

SMs (3, 5, 7, 9, 12, 14, 16, 19, 21, 24 and 26) experienced various levels of under-shedding with the highest recorded at SM24, SM21 and SM26 with 5.00kW, 4.47kW and 4.39kW, respectively. The lower margin was recorded at 2.73kW. Apart from the under-shedding, some houses experienced excess shedding of 2.42kW, 2.73, 2.76kW, and others. The highest excess sheddings were recorded at SM6, SM8, SM23 and SM25, recording 11.94kW, 12.17kW, 12.14kW and 11.85kW, respectively. Figure 34 shows the demand, expected shedding and the actual ERGGmL Shedding recorded per household.

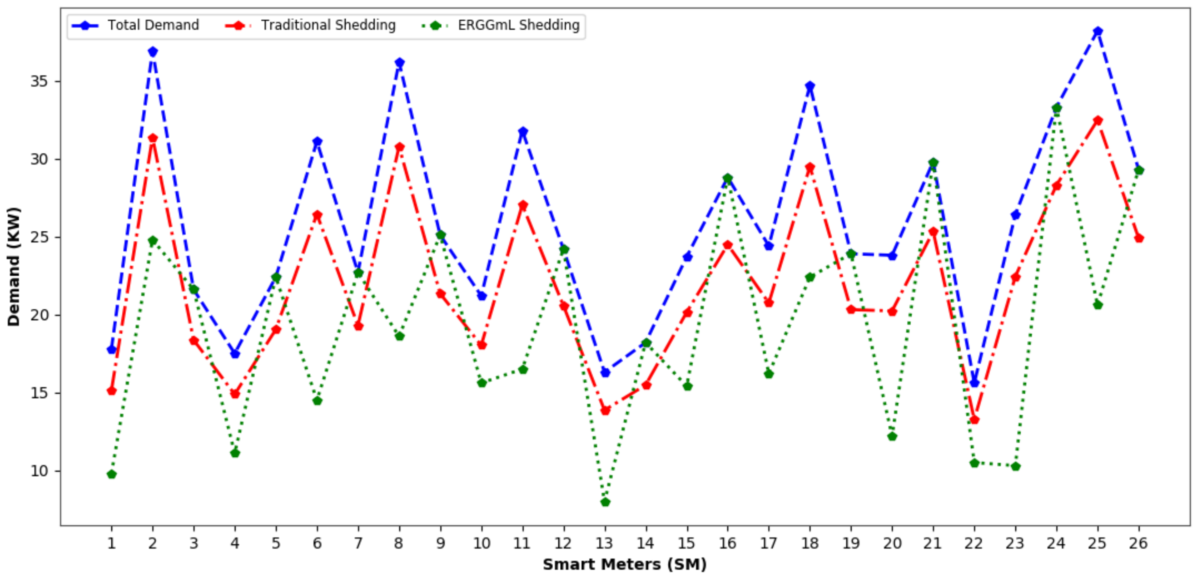


Figure 34 Results of conducting 15% ERGGmL Request using Grouped Microloads

10% ERGGmL Shedding

The results of the 10% ERGGmL shedding request is shown in Figure 35 below. It shows that 13 households experienced over-shedding at various magnitudes, and the rest were completely under-shed. On average, the 26 households recorded 2.60kW with a total expected demand of 607.41kW yielding 539.7kW, which is an excess shedding of 67.71kW.

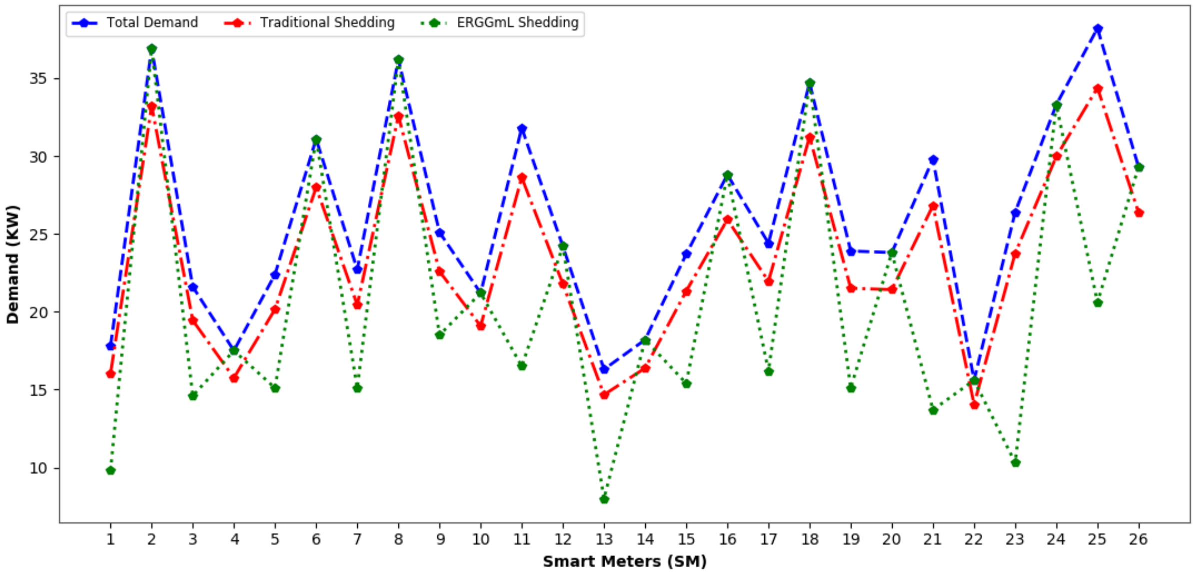


Figure 35 Results of conducting 10% ERGGmL Request using Grouped Microloads

The maximum over-shedding were recorded on SM11, SM21, SM23 and SM25 as 12.12kW, 13.12kW, 13.46kW and 13.78kW. SM3 and SM9 recorded 4.84kW and 4.09kW as the lowest over-shedding as previously indicated, 13 SMs experienced negative excess shedding, which means that they were under-shed. The smallest of these values were observed on SM4, SM14 and SM22 as 1.75kW, 1.82kW and 1.56kW, respectively.

.

2% and 5% ERGGmL Shedding

After requesting 2% and 5% microload shedding, an average of 4.68kW and 3.90kW were observed for the 2% and the 5% requests, respectively. Similar to the other shedding observed under the ERGGmL shedding, 2% and 5% all showed similar households over-shed in various magnitudes. The over-shedding experience values in the 2% request were higher than that of the 5% shedding requests, but the under-shedding of the 5% were also higher than that of the 2% requests.

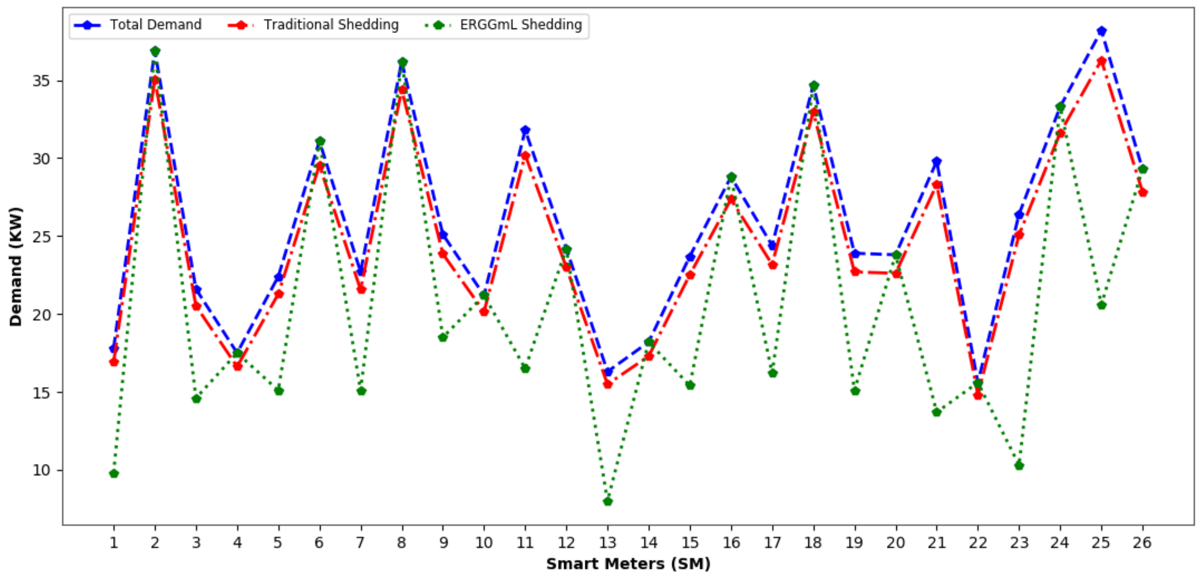


Figure 36 Results of conducting 5% ERGGmL Request using Grouped Microloads

Expected demands of 661.4kW and 641.16kW resulted in 539.7kW and 539.7kW, respectively, for the 2% and the 5% microload shedding requests. These developed excess shedding of 121.7kW and 101.46kW for 2% and 5%. While the 2% shedding yielded 18.03% excess shedding, the 5% was 15.03%, which appears to be even lower than that of the 2%. The 2% and the 5% results are shown in Figure 36 and Figure 37.

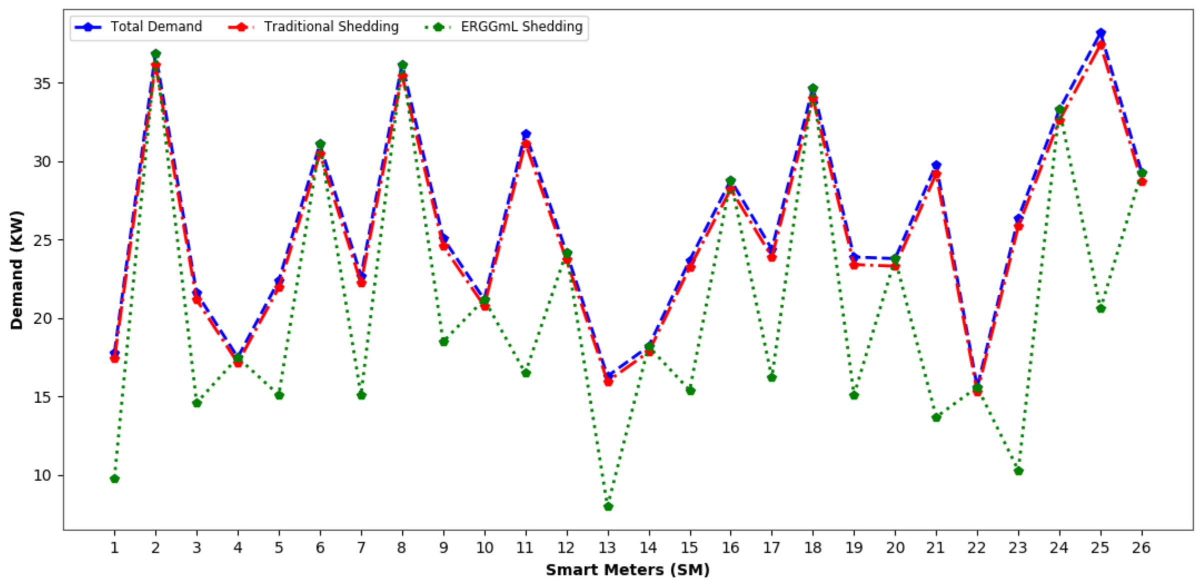


Figure 37 Results of conducting 2% ERGGmL Request using Grouped Microloads

6.2.2 ERGmS using UGCmL Consumption Profiles

The ERmL shedding algorithm is further evaluated on the ungrouped microloads presented in Table 2. The average excess shedding for requesting 2%, 5%, 10%, 15%, 20% and 30% ERGUmL shedding were 2.83kW, 2.03kW, 2.12kW, 0.99kW, 2.10kW and 1.12kW respectively. This shows an improvement from the previous techniques that yielded higher average excesses. Part of this work has been published in [128]. Details of the performance of this approach are discussed below.

2% and 5% ERGUmL Shedding

A 13.77kW and 33.37kW requests using the ERGUmL shedding representing 2% and 5% of the instantaneous demand resulted in actual demands of 600.49kW and 600.49kW, respectively, amounting to excess shedding of 73.48kW and 52.88kW. These excesses represent 11% and 8% of the original demand. The effective demand for a 2% and 5% ERGUmL shedding appeared to be the same (i.e. 600.49kW). This can be explained from the minimum selectable loads' perspective under the 2% being similar or the same as those of the 5%.

Though 73.48kW and 52.88kW were observed as excess shedding for the 2% and 5%, respectively, most of the houses were not negatively affected. Households represented by SM (2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22, 24 and 26) effectually experienced under-shedding during both 2% and 5% microload shedding. The rest of the households, on the other hand, are those that experienced over-shedding, which resulted in the excesses recorded 2% and the 5% shedding requests under the ERGUmL approach.

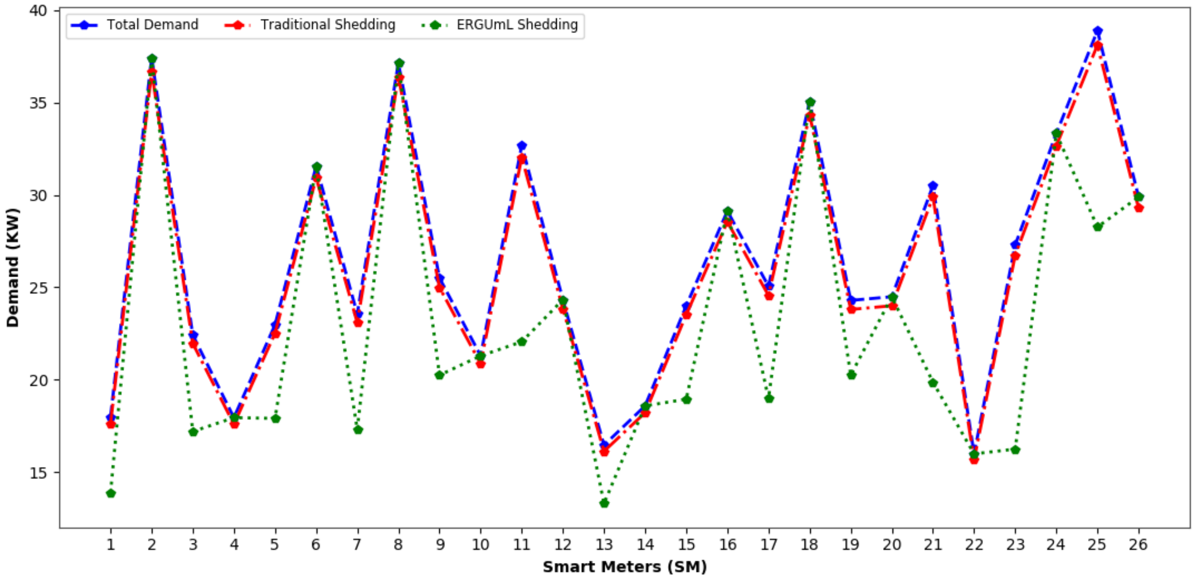


Figure 38 Results of conducting 2% ERGUmL Request using UnGrouped Microloads

In terms of the 2% request, the minimum and the maximum over-shedding were observed at SMs (13, 1, and 19) and SMs (11, 21 and 23). On the other hand, the maximum and the minimum under-shedding were observed at SMs (2, 8 and 18) and SMs (4, 14 and 22). The 5% microload shedding requests also yielded a minimum and maximum over-shedding at SM (13 and 19) and SMs (11, 21 and 23).

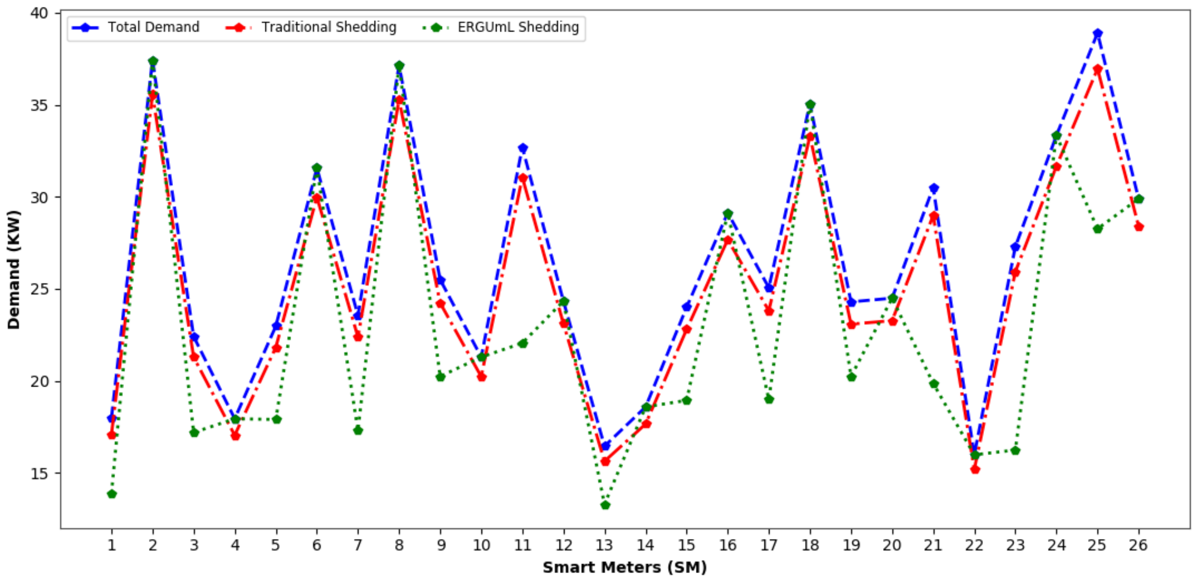


Figure 39 Results of conducting 5% ERGUmL Request using UnGrouped Microloads

While the maximum and the minimum under-shedding were observed at SMs (2 and 8) and SMs (4 and 14), overall, the excess shedding recorded for these two requested were 11% and

8% for 2% and 5% requests, respectively. This improved from the previous technique, which yielded a percentage of excess shedding of 18.03% and 15.03% for 2% and 5% ERGGmL requests. The 2% and 5% ERGUmL shedding results are shown in Figure 38 and Figure 39, respectively.

10% ERGUmL Shedding

A 68.79kW microload shedding request resulted in 563.91kW as an actual demand with an expected demand of 618.25kW. On average, a 2.12kW excess was observed when a 10% microload was initiated, a slight improvement from the 2.6kW obtained from the 10% ERGGmL shedding request. SMs (1, 2, 4, 6, 8,10, 11, 13, 14, 16, 18, 20, 22, 23 and 25) experienced over-shedding in various magnitudes, with the lowest being recorded at SMs (13 and 22) and the highest values at SMs (20 and 23). This result is summarized in Figure 40 below.

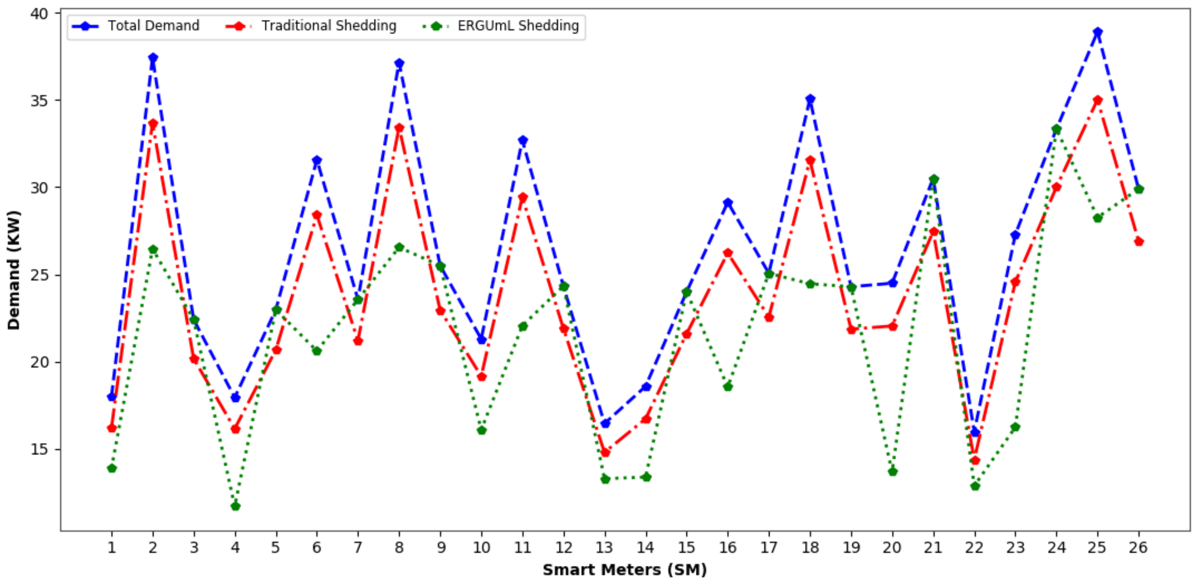


Figure 40 Results of conducting 10% ERGUmL Request using UnGrouped Microloads

Despite this, many households were observed to have experienced under-shedding, which is the aim of this approach. In terms of the under-shedding, SM4 recorded the lowest with 2.24kW and SMs (21 and 24) recorded the highest with 3.05kw and 3.33kW, respectively.

15% ERGUmL Shedding

The minimum excesses recorded when a request of 103.14kW was made under the ERGUmL shedding representing a 15% request, was seen at SMs (1, 13, 15, and 22) with 1.42kW, 0.69kW, 1.46kW and 0.7kW. SMs (20 and 23) obtained the highest excesses with 7.14kW and 6.96kW, respectively. The result obtained from the 15% microload shedding is shown in Figure 41.

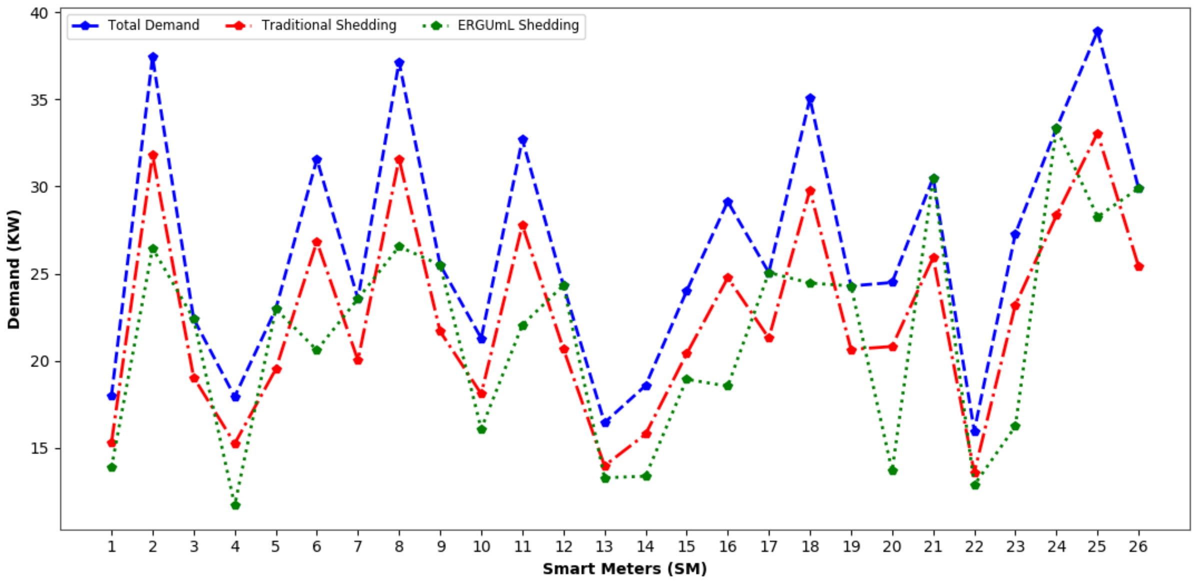


Figure 41 Results of conducting 15% ERGUmL Request using UnGrouped Microloads

The excesses' presence did not affect the negative shedding obtained on SMs (24, 21, 26, etc.) recording -5.00kW, -4.57kW, -4.48 etc., as excesses representing the highest under-shedding. The minimum under-shedding was recorded at SM3 with -3.36kW. A 4% excess shedding was recorded under the ERGUmL compared to that of the ERGGmL under the same request was 10.06% showing an improvement of over 6% of the total demand.

20% ERGUmL Shedding

An excess of 8% was recorded when a request of 137.57kW was made, representing 20% actual request. In terms of the individual households, 5.91kW and 5.59kW were recorded as the highest excess shedding experienced under SM20 and SM23. Comparing the ERGGmL shedding, which recorded an average excess of 1.90kW and an overall excess of 7.31%, performed better than the ERGUmL shedding, which resulted in an average excess of 2.10kW and 8% for the overall excess.

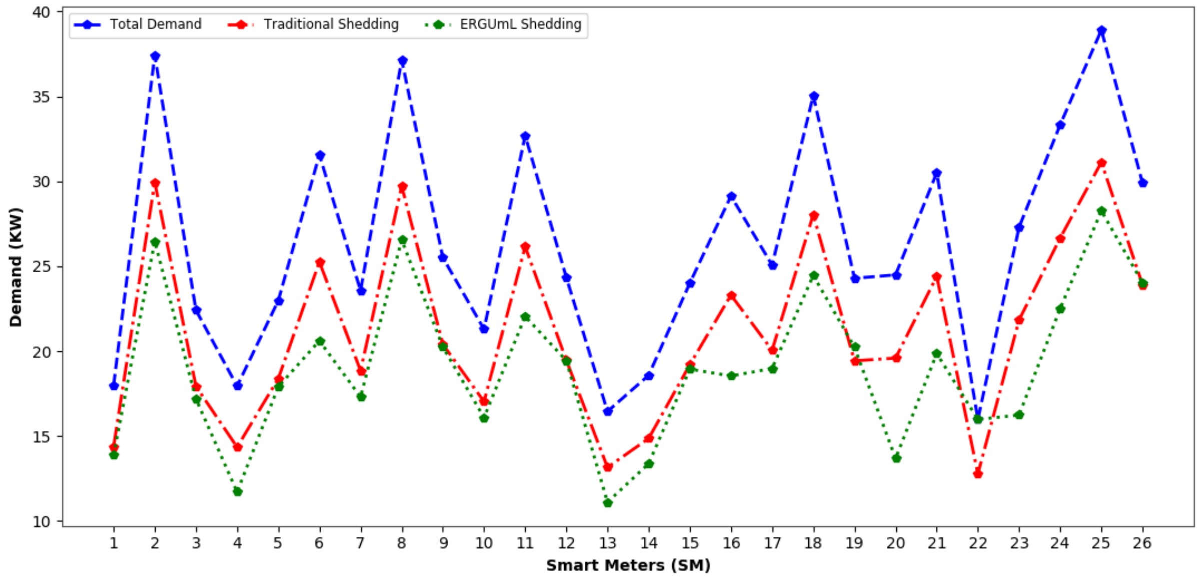


Figure 42 Results of conducting 20% ERGUmL Request using UnGrouped Microloads

The expected demand for 550.17kW yielded 495.61kW. Despite the non-conformance of the 20% ERGUmL shedding with the rest, SM19, SM22, and SM26 recorded under-shedding of 0.81kW, 3.20kW and 0.11kW, respectively. The highest of the negative excess shedding were recorded at SM22 the lowest was seen on SM26. The results are shown in Figure 42 above.

30% ERGUmL Shedding

A 30% microload shedding request made under the ERGUmL resulted in 452.27kW as the actual demand with an expected demand of 498.4kW representing an excess shedding 29.13kW. On average, the individual smart meters had an average excess shedding of 1.12 kW compared to the ERGGmL shedding, which resulted in 2.29kW on the average and an overall excess of 59.43kW was recorded.

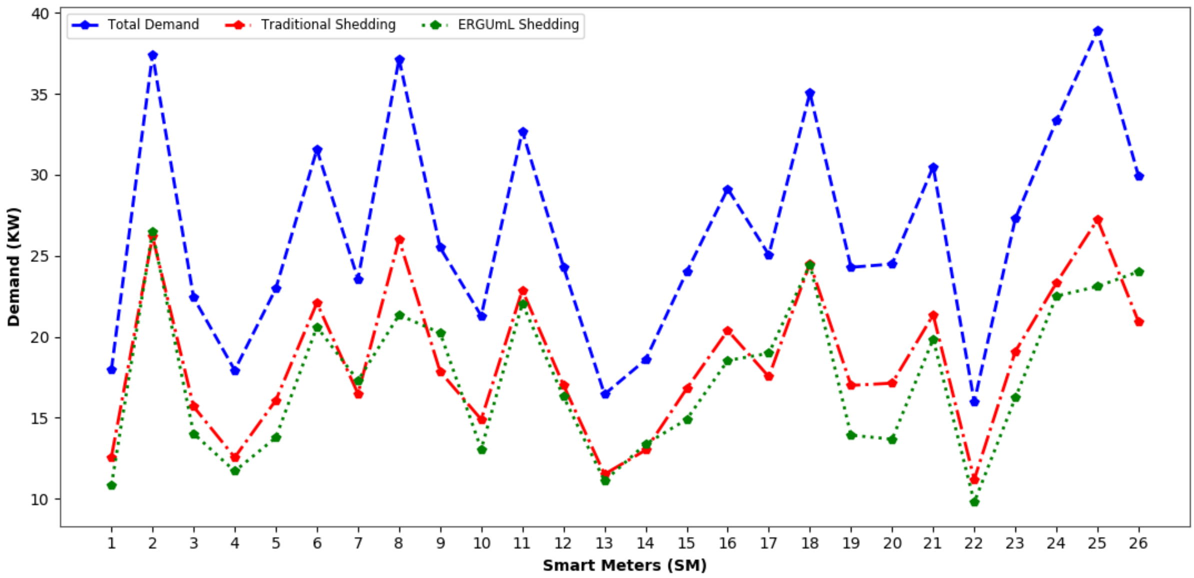


Figure 43 Results of conducting 30% ERGUmL Request using UnGrouped Microloads

Regarding the negative excess shedding, the 30% ERGUmL shedding request yielded 0.27kW, 0.81kW, 2.39kW, 0.37kW, 1.44kW and 3.10kW at SMs (2, 7, 9, 14, 17 and 26) and the highest at SM26 with the lowest at SM2. The rest of the households experienced excess shedding, with the lowest at SM13 with 0.41kW and 4.12kW was recorded as the highest at SM25. These can be observed in the Figure 43.

6.3 The Excess Reuse Priority Based Microloads Shedding

The excess reuse priority-based microload shedding (ERPBmS) is similar to the ERGS but takes into account the priorities assigned to the microloads in deciding which of the devices or group of devices (i.e. in the case of the grouped priority microloads) to be cut off to meet the minimum requirements from the grid.

Initialization;
Get Total GS Demand D;
Input Grid Sections (GS);
Get N i.e. total number of SM in GS;
Set ER = 0.00 kW;
Input Total Expected Demand $\hat{D}$;
Compute Percentage Expected Demand $d_m\%$ per SM;
$d_m\% = \frac{\hat{D}}{D} * 100$;
for $Grid = 1$ *to* $Grid_{max}$ **do**
  Set $L_m = 0.00\ kW$;
  Set $P_T = 0$;
  for $m = 1$ *to* N **do**
    Compute Expected Demand per SM (d_m);
    $d_m = d_m\% * d_m^{\tau}$;
    $D_m = d_m + ER$;
    if $ER < 0$ **then**
      $D_m = d_m$;
    end if
    Sort Priority P per microload i in SM m as (P_i) *in Ascending order*;
    for $i = 0$ *to* $I - 1$ **do**
      $HoldSub = i$;
      for $k = i + 1$ *to* $I\text{-}1$ **do**
        if $P[k] < P[HoldSub]$ **then**
          $HoldSub = k$;
        end if
      end for
      $HoldTemp = P[i]$;
      $P[i] = P[HoldSub]$;
      $P[HoldSub] = HoldTemp$;
    end for
    for $p = 1$ *to* p_{max} **do**
      $L_m = L_m + L_p$;
      $P_T = P_T + P[i]$;
      if $L_m < D_m$ **then**
        Turn OFF L_p;
      end if
      if $L_m >= D_m$ **then**
        $L_m = L_m - L_p$;
        $P_T = P_T - P[i]$;
        $ER = D_m - L_m$;
        Update Server with L_m, P_T and ER;
      end if
    end for
    Display Current Total Demand D;
    Update the GS;
  end for
end for

Figure 44 ERPBmL Algorithm

Like the previous approach discussed, two sets of microloads are considered. These are Grouped Controllable Loads (GCmL) and the Ungrouped Controllable Loads (UGCmL). The algorithm performing the ERPBmS is shown in Figure 44 above.

6.3.1 ERPBmS using GCmL Consumption Profiles

Generally, a 202.47kW, 134.98kW, 101.24kW, 67.49kW, 33.75kW and 13.50kW microload shedding requests representing 30%, 20%, 15%, 10%, 5% and 2% under the Excess Reuse Priority Based Grouped Microload (ERPBGmL) shedding resulted in actual demands of 456.8kW, 521.00kW, 550.50kW, 588.20kW, 620.5kW and 656.80kW respectively for the 26 households considered. The specifics of each of the requests are discussed in their respective subheadings below.

30% ERPBGmL Shedding

The expected microload demand of 472.43kW resulted in an actual demand of 456.80kW, representing an excess shedding of 2% on the expected 30% request. The result shown in Figure 45 depicts many households experiencing under-shedding, with very few experiencing visible over-shedding. On average, there was 0.60kW over-shedding across the 26 households. Visible over-shedding were seen at SMs (1, 6, 10, 11, 13, 15, 18, 19, 20 and 23), with the highest being 8.18kW recorded at SM23. The lowest of the over-shedding was seen at SM10, recording 0.34kW. In terms of the negative excesses recorded, the maximum was seen at SM24 with 7.69kW and SM12 recorded 0.26kW as the minimum under-shedding.

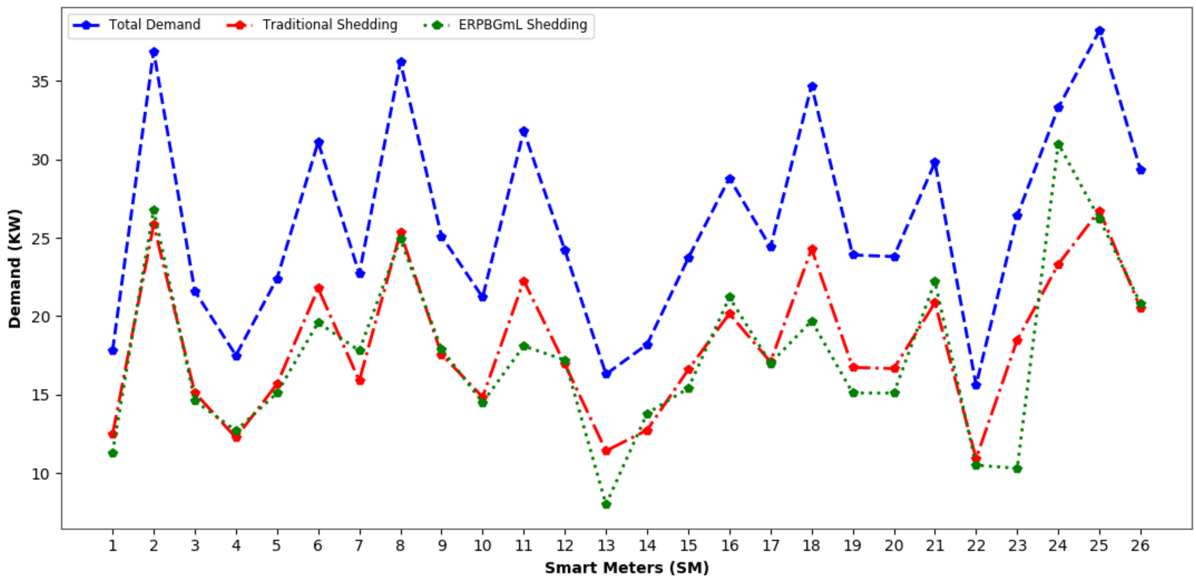


Figure 45 Results of conducting 30% ERPBGmL Request using Grouped Microloads

20% ERPBGmL Shedding

When the same load profiles were subjected to a 20% ERPBGmL shedding representing a load shedding of 134.98kW, the result obtained was 521.00kW as an actual demand resulting in 15.63kW excess shedding. On average, 0.73kW (i.e. 3%) excess shedding was observed across all the smart meters. The highest excess recorded was seen at SM19 with 4.02kW, and its minimum was 0.36kW seen at SM7. Besides, SM4 did have all its expected demand met.

The maximum under-shedding recorded under the 20% request was 3.66kW at SM20. SM26 recorded 0.06kW as the minimum under-shedding. The result of the 20% microload shedding is shown in Figure 46 below.

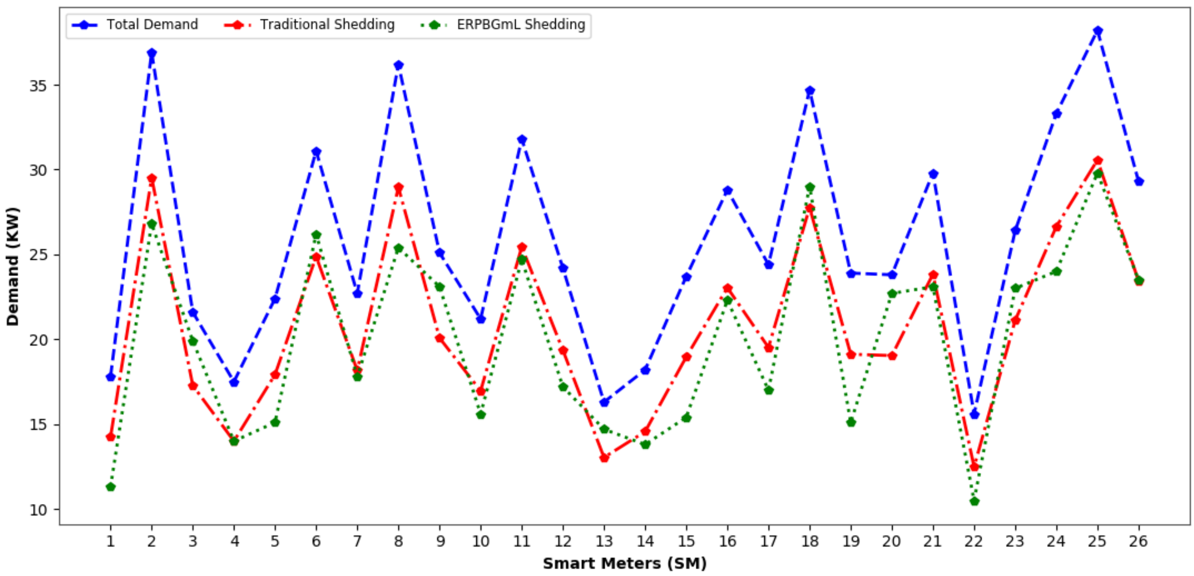


Figure 46 Results of conducting 20% ERPBGmL Request using Grouped Microloads

15% ERPBGmL Shedding

The expected demand for 573.67kW produced 550.50kW as an actual demand representing excess shedding of 23.18kW. The average excess shedding recorded was 0.89kW amounting to 3% extra shedding. The maximum excess shedding was observed at SM19 with 5.21kW excess. 0.17kW was recorded as the minimum excess. Figure 47 shows the result of requesting 101.24kW under the ERPBGmL shedding.

Like the other results under the ERPBGmL shedding, the 15% request also experienced various under-shedding per household. The maximum of these was seen at SM16 with 4.32kW, and SM23 recorded the minimum as 0.56kW.

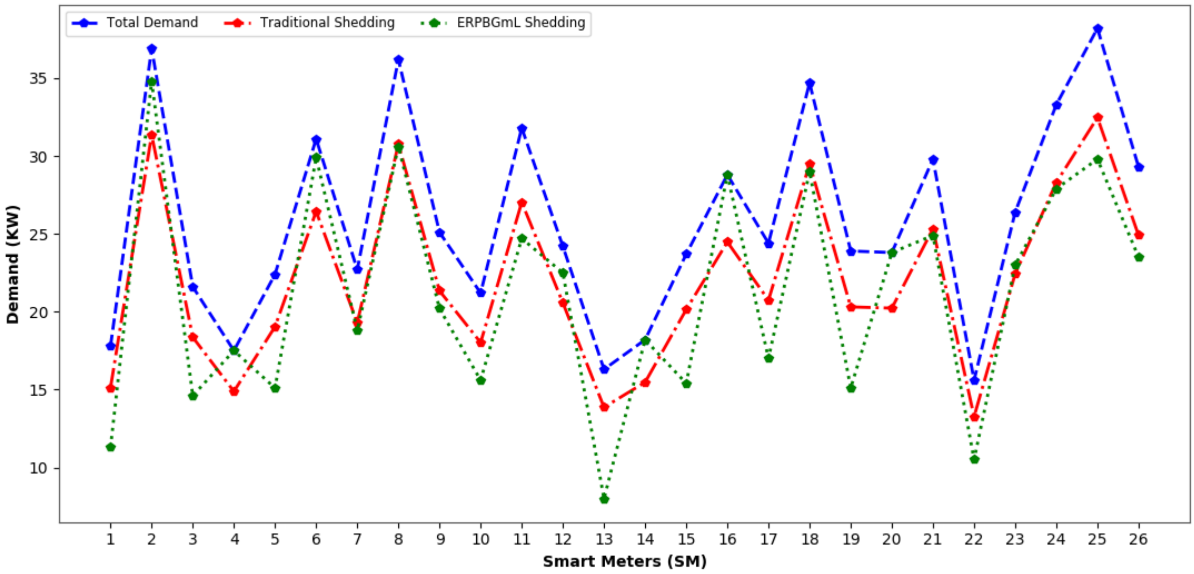


Figure 47 Results of conducting 15% ERPBGmL Request using Grouped Microloads

10% ERPBGmL Shedding

A 67.49kW microload shedding request resulted in an actual demand of 588.20kW against an expected demand of 607.41kW, amounting to an excess of 19.21kW, representing 3% excess. On average, 0.74kW was shed across the smart meters. The highest excess shedding was seen at SM20 with 6.32kW, and the lowest was 0.27kW at SM24.

In terms of under-shedding, 3.69kW recorded at SM2 was the highest, and the minimum was observed at SM4 with 1.75kW. Figure 48 shows the result of the 10% ERPBGmL Shedding request.

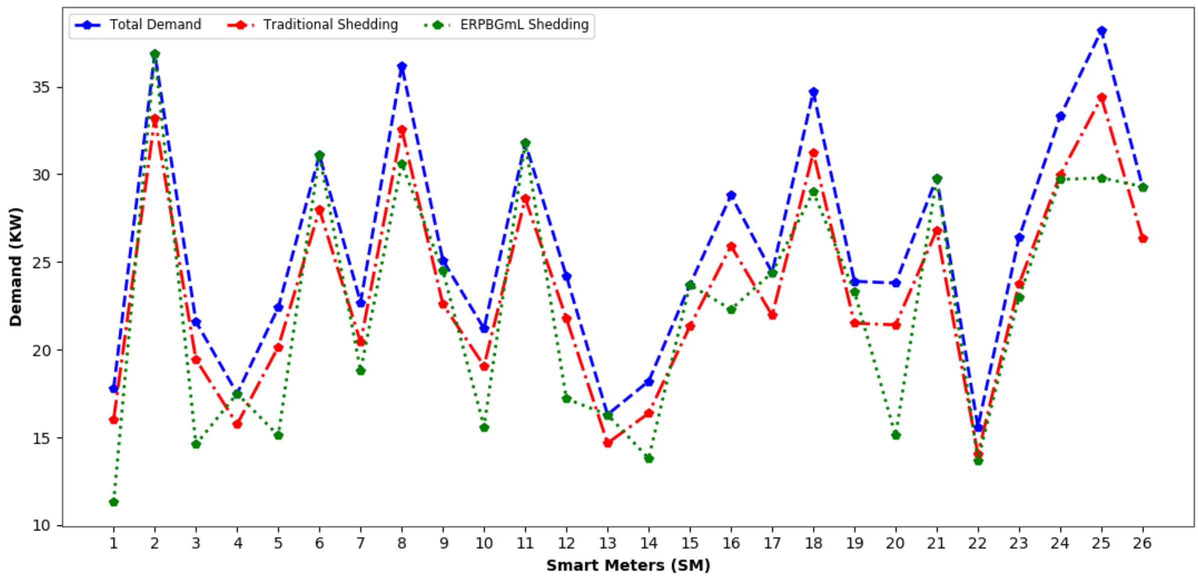


Figure 48 Results of conducting 10% ERPBGmL Request using Grouped Microloads

2% and 5% ERPBGmL Shedding

Request to shed 13.50kW and 33.75kW representing 2% and 5% yielded 656.80kW and 620.50kW as actual demands. Therefore, these demands resulted in excess shedding of 4.60kW and 20.66kW at an average of 0.18kW and 0.79kW excess shedding. The performance of the ERPBGmL shedding algorithm on the 2% and 5% shedding are shown in Figure 49 and Figure 50 below.

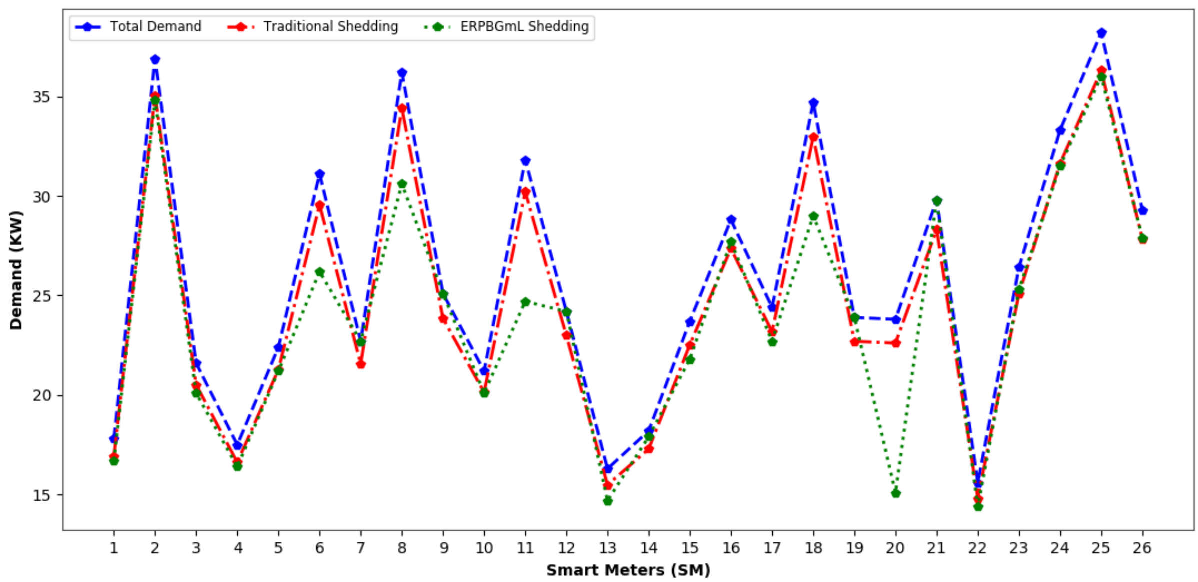


Figure 49 Results of conducting 5% ERPBGmL Request using Grouped Microloads

The highest excess recorded for the 5% shedding request was observed on SM20 with 7.51kW excess and SM10 recorded 0.04kW as the lowest excess recorded.

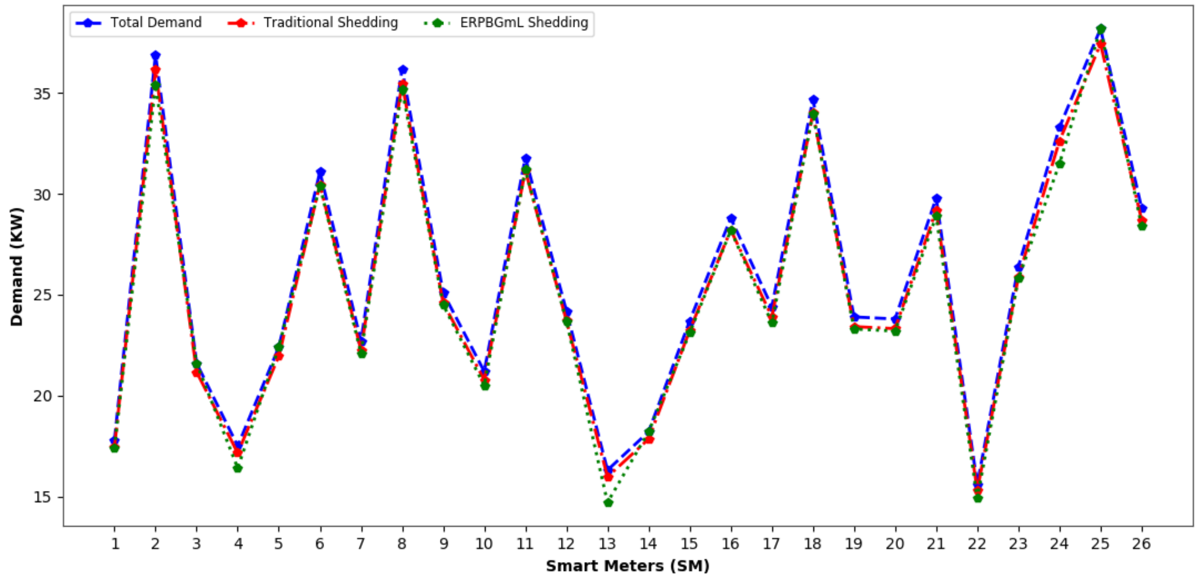


Figure 50 Results of conducting 2% ERPBGmL Request using Grouped Microloads

It was also observed that most of the households recorded excess shedding when the 5% shedding request was made. The lowest under-shedding was observed on SM26 with 0.06kW and SM21 recorded 1.49kW as the highest under-shedding.

The biggest excess shedding under the 2% request was seen at SM24 with 1.13kW and the smallest was 0.01kW seen at SM18. In terms of the negative excesses representing under-shedding, 0.76kW was observed to be the highest under-shedding, and the lowest was seen at SM11, recording 0.04kW.

6.3.2 ERPBmS using UCmL Consumption Profiles

The Excess Reuse approach was further evaluated on the ungrouped controllable microloads with assigned priorities and the results discussed within this subsection.

2% and 5% ERPBUmL Shedding

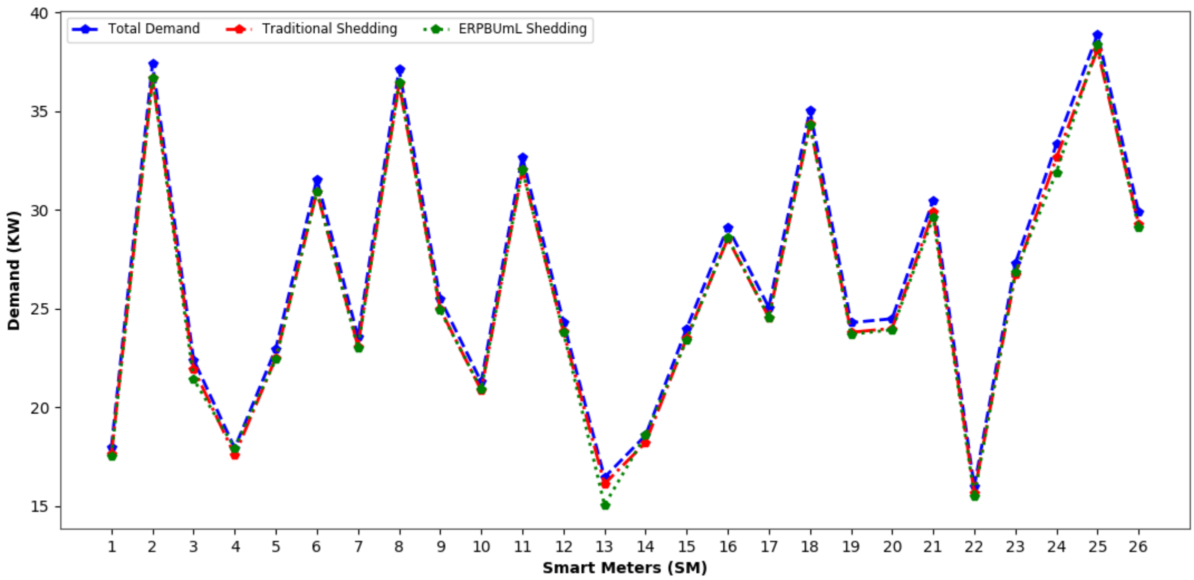


Figure 51 Results of conducting 2% ERPBUmL Request using UnGrouped Microloads

The above result in Figure 60 shows how the algorithm performed when subjected to a 2% microload shedding. That of the 5% microload shedding is shown in Figure 52. The highest excess recorded is seen in SM13 as 1.07kW for the 2% when a request of 13.75kW was made. A 34.39kW requested resulted in an actual demand of 652kW, yielding the highest excess at SM8 with 1.48kW for the 5% microload shedding. The lowest excess of 0.01kW was recorded for both 2% and 5% requests at SM18 and SM25, respectively. The average excess shedding recorded for the 2% and the 5% microload shedding was 0.09kW and 0.05kW, respectively. An increasing number of smart meters experience no excess shedding at all. These were observed at SMs (6, 11 and 16) and SMs (5 and 10), respectively, where they recorded 0.0kW over-shedding for both 2% and the 5% shedding requests. Eight households recorded negative excesses representing under-shedding, with the highest of 0.37kW recorded at SM14 and the lowest of 0.02kW at SM2 when the 2% microload shedding request was made. The 5% microload shedding request also resulted in nine households experiencing under-shedding with the highest of 1.67kW at SM24 and the lowest of 0.03kW at SM2 and SM16.

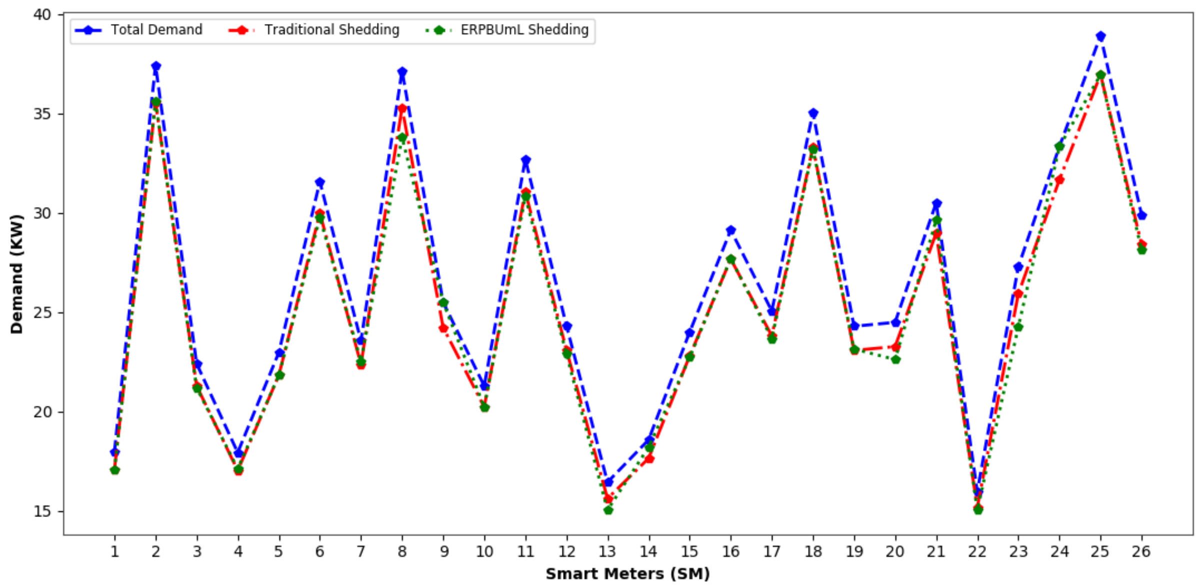


Figure 52 Results of conducting 5% ERPBUmL Request using UnGrouped Microloads

10% ERPBUmL Shedding

Subjecting the households to a 10% microload shedding request with an expected demand of 618.95kW resulted in an actual demand of 617.51kW, representing a marginal over-shedding of 1.44kW compared to all the previous techniques applied. On average, the excess recorded was 0.06kW from all the 26 households in context. The highest excess was recorded at SM5 with 0.79kW and 0.01kW was recorded for both SM22 and SM25.

Like the 2% and the 5% shedding, the 10% shedding SM17 recorded no change in expected demand resulting in zero excess shedding. However, eight households experienced negative excess shedding, with the highest under-shedding at SM6 0.76kW. The relationship shared between the expected and the actual demands are shown in Figure 53 below.

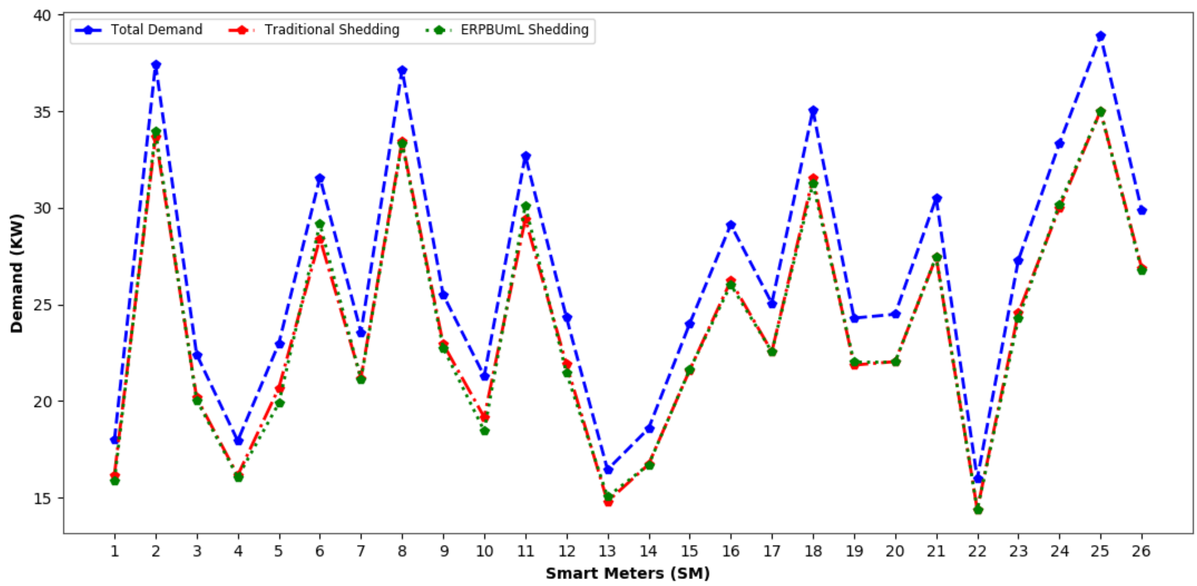


Figure 53 Results of conducting 10% ERPBUmL Request using UnGrouped Microloads

15% ERPBUmL Shedding

A microload shedding request of 103.16kW representing a 15% request resulted in an actual shedding of 104.05kW, a 0.91kW excess shedding recorded. On average, across the 26 households, a 0.03kW excess shedding was recorded. This is a significant improvement from all the previous ones. The percentage of excess shedding recorded was computed as 0.13%.

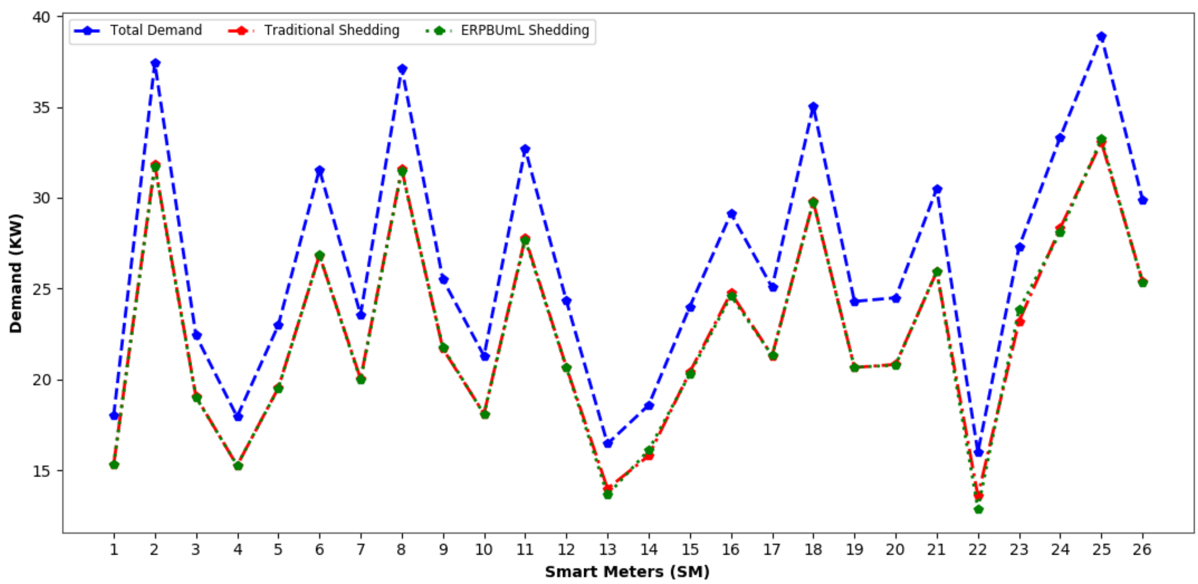


Figure 54 Results of conducting 15% ERPBUmL Request using UnGrouped Microloads

The excess shedding distribution was such that the maximum was recorded at SM22, recording 0.70kW, and the minimum excess was recorded at SM1, which recorded 0.01kW. The contribution of under-shedding to improving the overall performance was recorded in SMs (4, 6, 9, 14, 17, 19, 21, 23 and 25). Among these, the highest was recorded at SM23 with negative excess of 0.65kW. The lowest negative value was 0.01kW recorded at SM6, SM17 and SM19. The results of this are shown in Figure 54.

20% ERPBUmL Shedding

From the 20% microload shedding shown in Figure 55, there is visible marginal over-shedding and under-shedding across the various households. It is difficult to see any significant changes between the expected demands and the actual demands. An average of 0.09% excess shedding was recorded across the households when 137.55kW microload shedding request being the 20% was made. An expected 550.17kW resulted in 549.54kW producing an excess of 0.63kW. 0.44kW was recorded as the maximum excess at SM24 while SM4, SM6 and SM13 recorded 0.01kW as the excess shedding. SM5, SM9 and SM12 recorded no change between the expected and the actual demands. Negative excess was recorded in SMs (3, 8, 15, 18, 21, 23 and 25). Amongst these, the highest value was seen at SM25 as 0.43kW and 0.01kW at SM3, representing the lowest of the under-shedding.

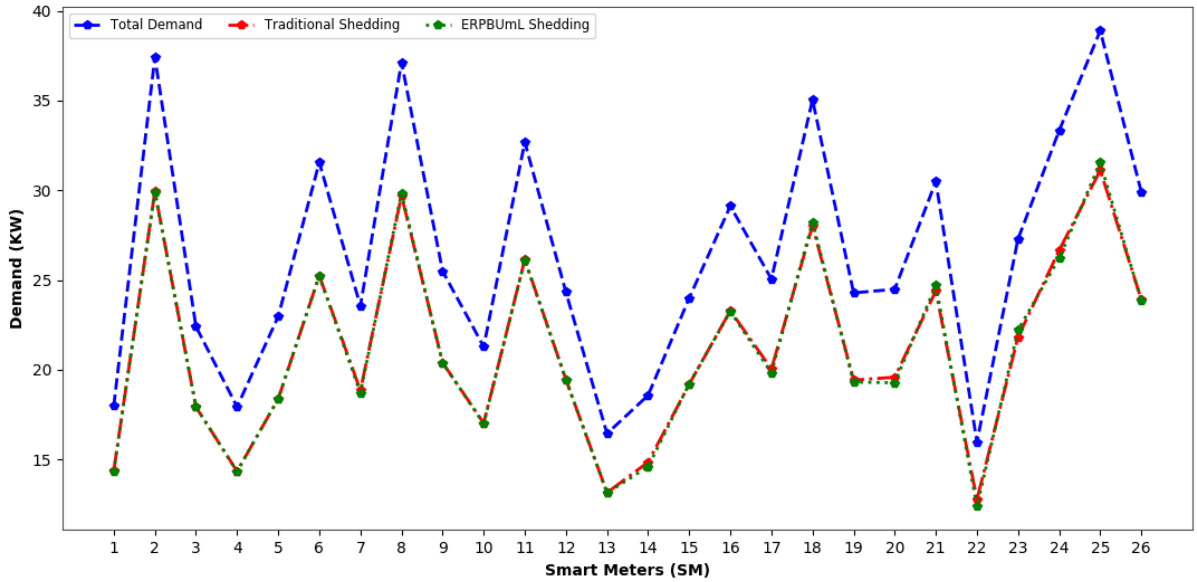


Figure 55 Results of conducting 20% ERPBUmL Request using UnGrouped Microloads

30% ERPBUmL Shedding

A 30% microload shedding request amounting to 206.32kW resulted in an actual demand of 481.05kW against an expected demand of 481.40kW. An excess microload shedding of 0.35kW was recorded, representing 0.05% of the instantaneous demand. The result of the 30% microload shedding is summarised in Figure 56. 0.01kW was recorded on average across all the households.

SMs (12, 21, 24 and 26) recorded no change in the expected demands when compared to the actual values obtained. The highest excesses were recorded at SM4 with 0.85kW, and SM1, SM13 and SM25 all recorded 0.01kW as the lowest of the excesses recorded. On the other hand, negative excesses were observed in eight houses, with the highest observed at SM5, which recorded it was 0.85kW. The lowest of the under-shedding was seen at SM20 with 0.04kW.

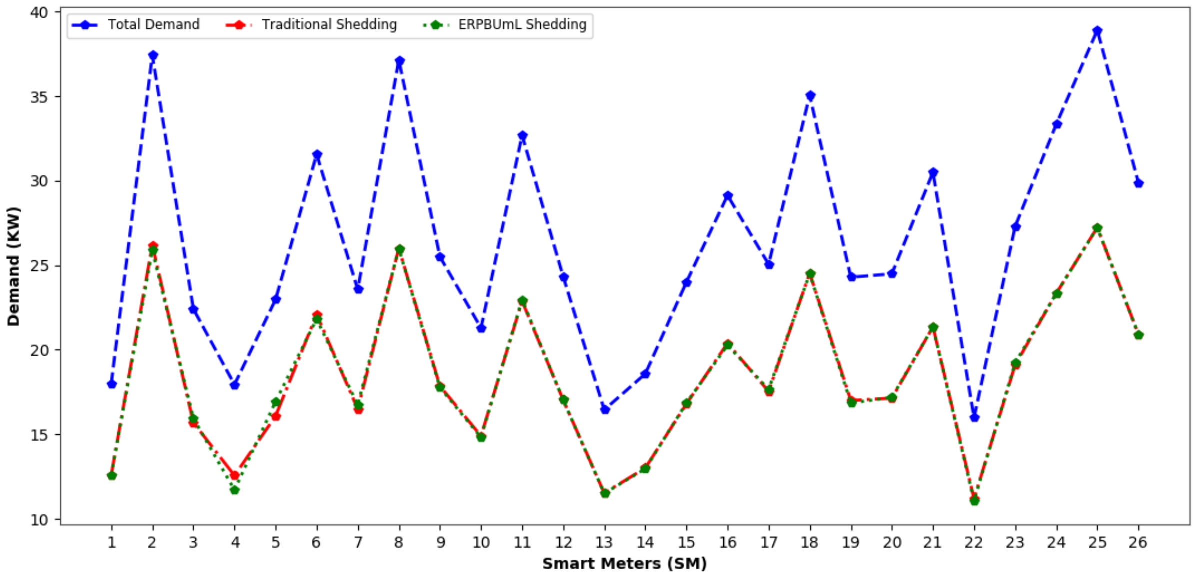


Figure 56 Results of conducting 2% ERPBUmL Request using UnGrouped Microloads

6.4 Chapter Summary

The microload shedding algorithm has been further extended to reuse the excess shedding observed from the General Shedding and Priority Based Shedding Algorithms. The novel algorithm in these heuristics is referred to as Excess Reuse Microload (ERmL) Shedding Algorithm. Two techniques were derived from the ERmL; Excess Reuse General Microload (ERGmL) shedding and Excess Reuse Priority Based Microload (ERPBmL) Shedding techniques.

First and foremost, the ERGmL was evaluated on six grouped microloads referred to as Excess Reuse General Grouped Microload (ERGGmL) shedding where on the average 4.68kW, 3.90kW, 2.60kW, 2.61kW, 1.90kW and 2.29kW were observed across the smart meters as excess shedding for the 2%, 5%, 10%, 15%, 20% and 30% microload shedding requests. The same technique is then applied on the Ungrouped Controllable microloads as Excess Reuse General Ungrouped Microload (ERGUmL) shedding in which the average excess shedding across all the households was seen as 2.83kW, 2.03kW, 2.12kW, 0.99kW, 2.10kW and 1.12kW for the 2%, 5%, 10%, 15%, 20% and 30% microload shedding requests respectively.

Secondly, the ERPBmL shedding approach was evaluated on the grouped microloads as Excess Reuse Priority Based Grouped Microload (ERPBGmL) shedding in which the average excess shedding obtained across the smart meters were 0.18kW, 0.79kW, 0.74kW, 0.89kW and 0.60kW for the 2%, 5%, 10%, 15%, 20% and 30% microload shedding requests respectively. After which it was tested on the ungrouped microloads as Excess Reuse Priority Based Ungrouped Microload (ERPBUmL) shedding resulting in 0.33kW, 0.20kW, 0.21kW, 0.09kW and 0.05kW as the average of the excess shedding for 2%, 5%, 10%, 15%, 20% and 30% request for shedding.

A progressive reduction in the excess shedding has been observed from the ERGmL to the ERPBUmL, producing the lowest excess shedding. The level of excess produced under the ERPBUmL makes it ideal for implementation in live grid infrastructure. In the next chapter, the impact of predicting the demand to prepare both consumers and the electric utility companies for potential load shedding is discussed.

Chapter 7

Generation and Demand Predictions for Microload Shedding

7.1 Introduction

Five prediction models are developed and tested as an initial step towards the aim of preparing all stakeholders in the smart grid ahead of any significant load shedding. The ultimate importance of forecasting will be that the current grid demand is considered, and the next 24 hours' demand is predicted along with the granular consumption of the microloads. The predicted overall demand and the microload demand are then compared to evaluate the next 24-hour load-shedding requirements. If there is a need to curtail some of the microloads, it is communicated to the end-users and other parties affected as predicted microload shedding.

The end users can then readjust the priorities to meet their energy needs in the coming hours. According to related research, the prevailing weather conditions significantly influence electricity demand. Therefore, the weather conditions such as Temperature (Temp (C)), Dew Point Temperature (Dew Point Temp (C)), Relative Humidity (Rel Hum (%)), Wind Direction (Wind Dir (10s deg)), Wind Speed (Wind Spd (km/h)), Visibility (Visibility (km)) and Saturation Pressure (Stn Press (kPa)) were considered as the independent variables in this experimental setup.

However, to evaluate the forecasting, minutely consumption data of various microloads obtained from Makonin et al., in [142] was used instead. This data set comprises microload consumption from one home in Vancouver, Canada, from April 2012 to the end of March 2014. The different microloads' data were cleaned and processed. The weather data was hourly, and the microload consumptions were in minute intervals. The time interval of one hour was processed into minutely weather data. Three months of data comprising the weather and the microloads was selected from the process data and used for the evaluation. The extracted data set used can be found at https://tinyurl.com/e4nb5h2 with a one-hour extract in Appendix 2.

The microloads and their respective IDs are as follows; North Bedroom (B1E), Master/South Bedroom (B2E), Basement Plugs & Lights (BME), Clothes Dryer (CDE), Clothes Washer (CWE), Dining Room Plugs (DNE), Dishwasher (DWE), Electronics Workbench (EBE), Security/Network (EQE), Kitchen Fridge (FGE), HVAC/Furnace (FRE), Garage (GRE), Heat Pump (HPE), Instant Hot Water Unit (HTE), Home Office (OFE), Outside Plug (OUE), Ent Tv/PVR/AMP (TVE), Utility Room Plug (UTE), Wall Oven (WOE), and Rental Home (RSE). The weather information used as the independent variables in this research are; Temperature (Temp (C)), Dew Point Temperature (Dew Point Temp (C)), Relative Humidity (Rel Hum (%)), Wind Direction (Wind Dir (10s deg)), Wind Speed (Wind Spd (km/h)), Visibility (Visibility (km)) and Saturation Pressure (Stn Press (kPa)). The predictive models used in this research are discussed in the next subsection.

The metric of evaluation obtains the measure of prediction model quality in statistic or machine learning. Two main metrics identify predictions techniques in energy prediction evaluation. These are Root Mean Square Error (RMSE) and Accuracy [156,156]. Additionally, computational complexity, which refers to the computational resources required for the practical application of learning algorithms [193, 194].

7.3.1 Root Mean Square Error (RMSE)

When the errors of a prediction model are averaged and the result's square root is obtained, this is referred to as RMSE. It ranges from zero upward and never a negative number. It does depict the measure of the difference between the predicted and the actual values. Its interpretation can be subjective to the data in context. Therefore, the values are only important when the test and the predicted values are well understood.

$$RMSE = \sqrt{\frac{\Sigma(Xi_{Predicted} - Xi_{Actual})^2}{n}} \qquad (Equation\ 7.1)$$

where, $i = 1,2,3, \dots, n$ and n is the total number of predictors, Xi_{Actual} is the actual demand from the microloads and $Xi_{Predicted}$ is the predicted demand.

7.3.2 Accuracy

Accuracy is the most popular performance metric for predictive models in terms of energy demand forecasting. As indicated through its name, it represents how accurate a predictive model performed. It is a percentage measure of the predicted and the actual demands. It can be computed from Equation 7.2 below.

$$Accuracy = \frac{\sum_i^n (|(Xi_{Actual} - Xi_{Predicted})|) \times 100 \leq err}{n} \qquad \textit{(Equation 7.2)}$$

7.3.3 Computational Complexity

The resources needed by a computing system to enable a learning algorithm to solve a given real-world problem, in this case, prediction and classification is computed as computational complexity. There are two basic types of computational complexity; sample and computational complexity [193, 194]. In this research, the focus is on the RMSE and the accuracy of the prediction models, as discussed in [144] and [192].

7.4 Results and Discussions

In this section, the results obtained for the various models used are discussed. To compare the accuracy of the predictions, the data is subdivided into training and testing sets. Consistent with the work reported in [144], the data set was divided into 70% training and 30% testing data. The first ten headers of the training and the test data sets are shown in Appendix 2 as Forecasting Dataset Samples. The results of the various techniques are discussed below.

7.4.1 KNNR Prediction Results

As indicated earlier, the elbow technique for obtaining the appropriate K value was used for the KNN predictive method, where the values obtained for the KNN approach are shown in Figure 57, 58, and the rest can be found in Appendix 6 as K-values. Once the K value is known, the next is to make a prediction.

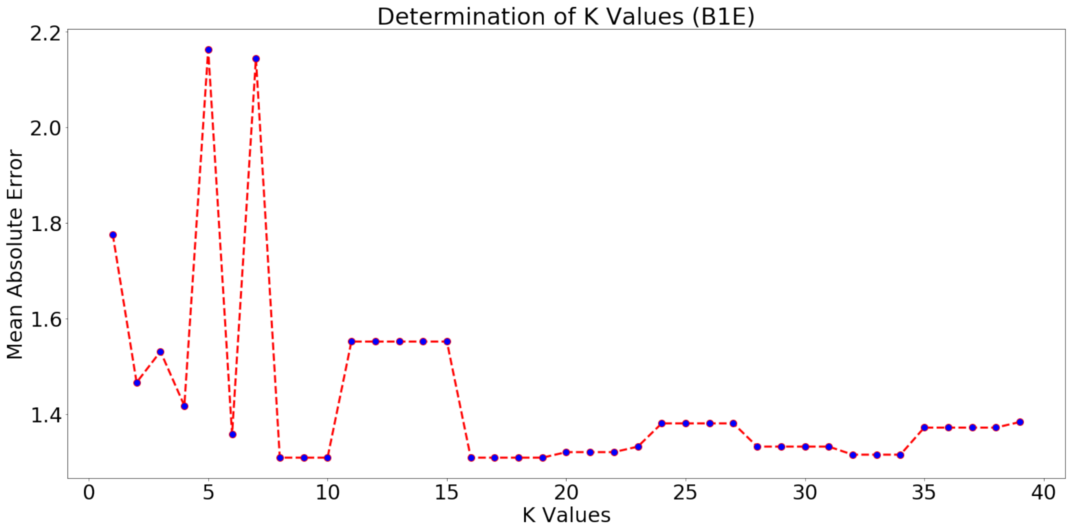


Figure 57 K values for North Bedroom (B1E)

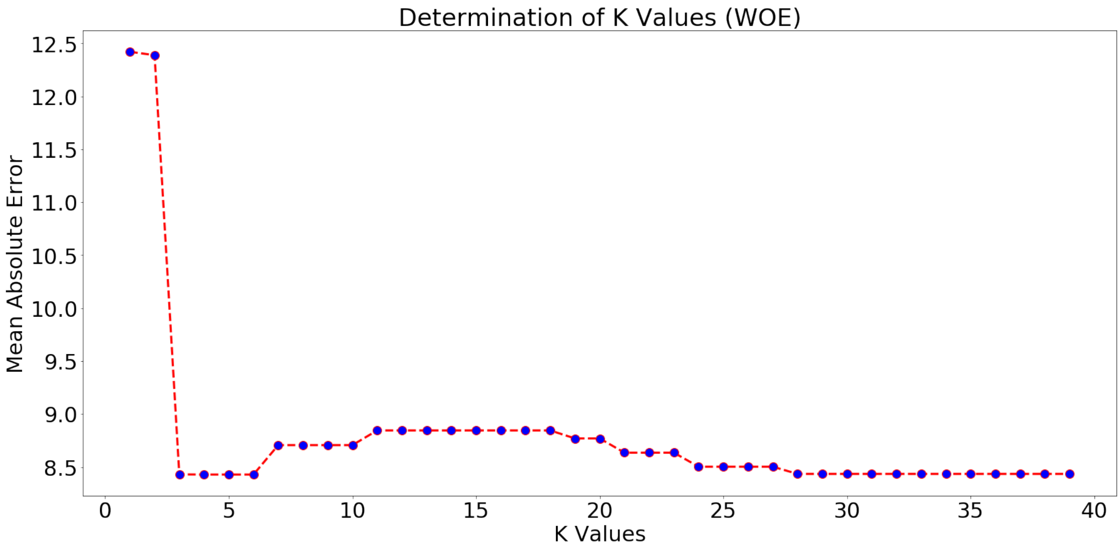


Figure 58 K Values for Wall Oven (WOE)

The evaluation metrics Root Mean Square Error (RMSE) and Accuracy for the KNN approach are shown in Figure 68 and Figure 69 below for all the microloads. It can be observed that the majority of the microloads resulted in RMSE around 100 with CDE, HPE, RSE and WOE recording 524.95, 651.88, 455.71 and 158.5, respectively. The lowest RMSE values were observed from OUE, EBE, EQE, DNE, B1E, UTE and THE, respectively, recording 0.11, 0.12, 2.64, 3.62, 7.47, 7.68 and 8.58.

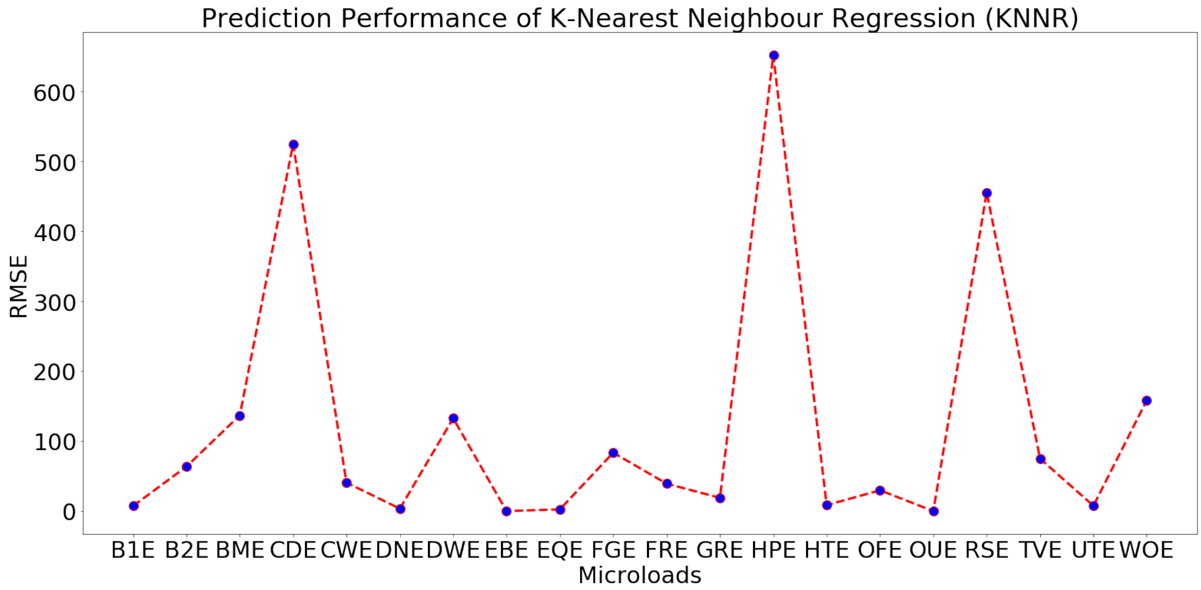


Figure 59 KNNR RMSE values

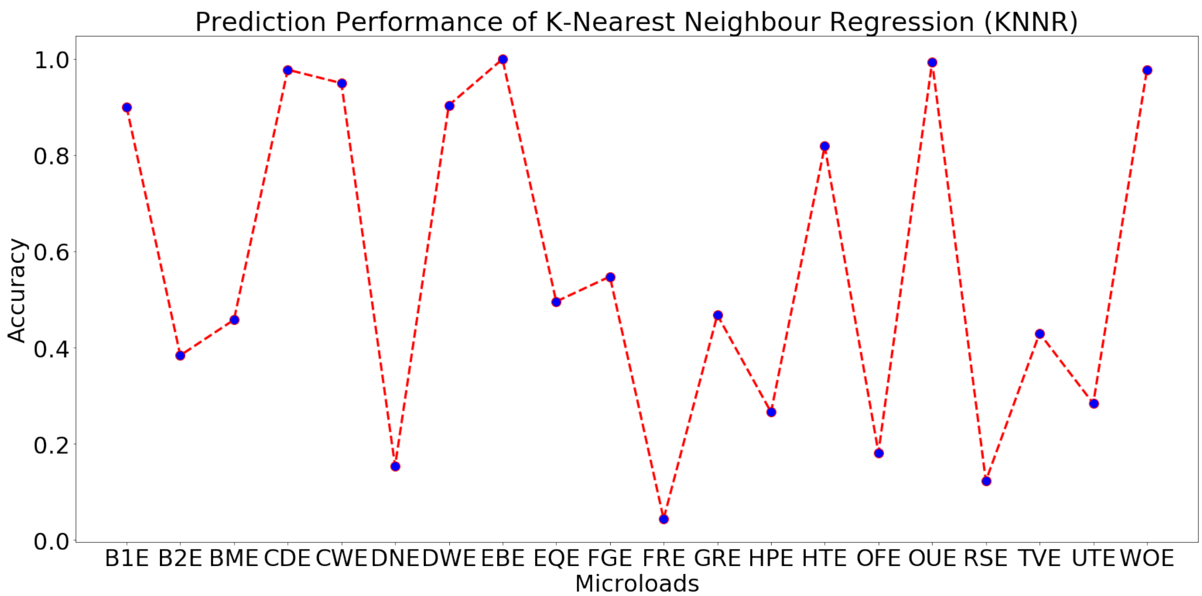


Figure 60 KNNR Accuracy values

The best accuracy values were observed on EBE, OUE, CDE, WOE, B1E and DWE, all 90% and above, with EBE recording 100% accuracy. The worse results were seen on FRE, RSE, DNE, OFE, HPE, UTE, B2E, TVE, BME and GRE all recording below 50% with 43% and 47% being observed at TVE and GRE and 4%, 12%, 15% and 18% were observed on FRE, RSE, DNE and OFE respectively. FGE and EQE recorded 55% and 50%, respectively too.

7.4.2 SVR Prediction Results

The results obtained from the SVR predictions are shown in Figure 61 and Figure 62 for the RMSE and the Accuracy, respectively, below. Regarding the RMSE values obtained, three key peaks were observed at CDE, HPE and RSE, being 524.94, 644.73 and 432.73. The values of 6.96, 3.38, 0.12, 2.57, 8.56, 0.14 and 3.81 were all recorded as the lowest for B1E, DNE, EBE, EQE, THE, OUE and UTE, respectively. The rest of the microloads recorded RMSE values between 19 and 131.92 as observed on GRE and BME.

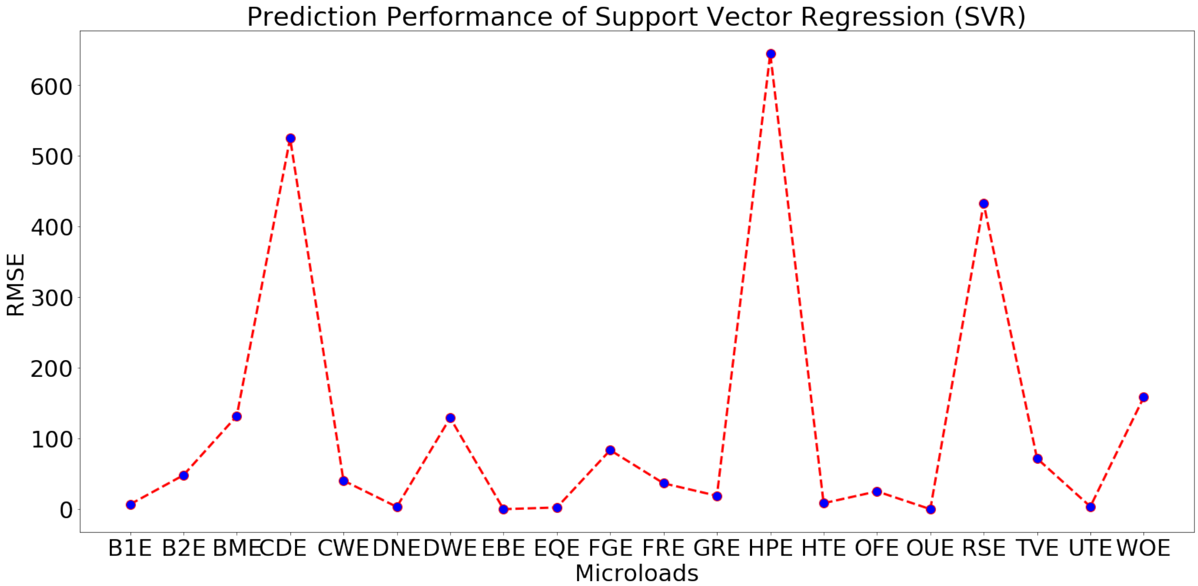


Figure 61 SVR RMSE values

An accuracy value of 100% was recorded for EBE, while 99%, 98%, 98%, 97%, 95% and 94% were recorded for OUE, CDE, WOE, CWE, B1E and EBE, respectively. On the other hand, RSE, FRE, DNE, and OFE recorded 1%, 5%, 17% and 17%, respectively, as their Accuracy values for the SVR prediction. B2E, EQE, FGE, GRE and HTE all were observed to record values from 50% to 82%.

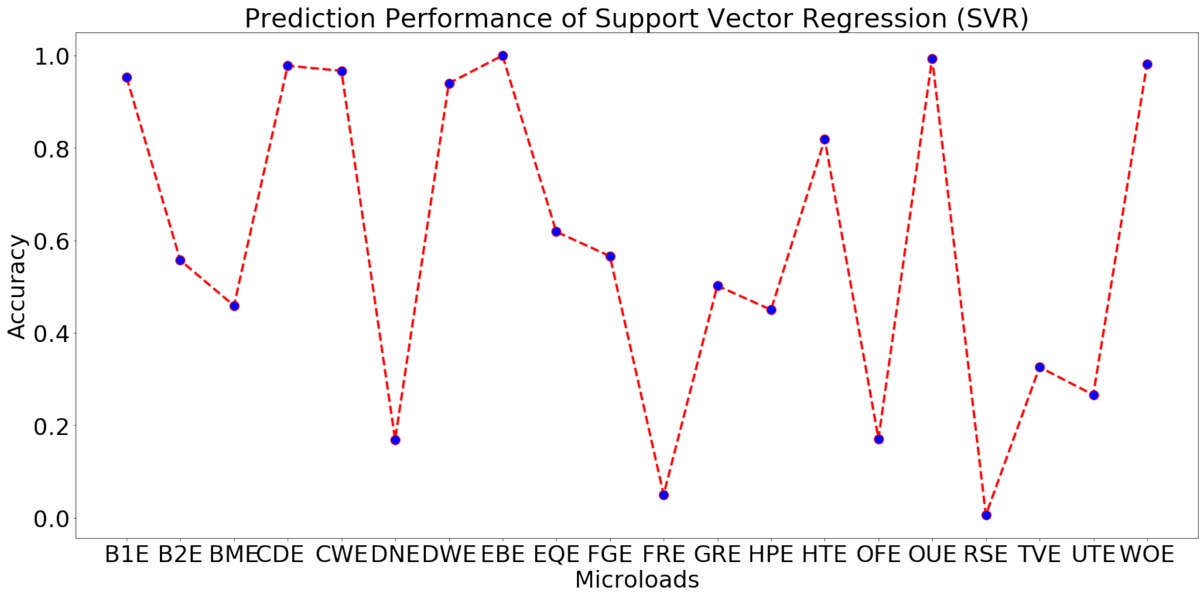


Figure 62 SVR Accuracy values

7.4.3 RF Prediction Results

The RMSE values obtained from the RF prediction are shown in Figure 63 below, where it can be observed that CDE, HPE and RSE recorded 620.31, 712.65 and 532.89, respectively, as the highest RMSE values recorded. RMSE values of 0.11 to 8.31 were observed for B1E, DNE, EBE, EQE, THE, OUE and UTE. The microload OUE recorded 0.11, and the 8.31 was recorded on the HTE. RMSE values of 127.14, 134.17 and 161.09 were observed on BME, HPE and RSE, respectively. Also, B2E, FGE and TVE recorded 61.30, 69.01 and 77.03, respectively. CWE, FRE, OFE and GRE recorded 43.79, 43.67, 26.35 and 19.09, respectively, as their RMSE values.

The Accuracy values obtained for the RF predictions are shown in Figure 64. The results show that the RF has performed very poorly compared to all the previously discussed results. As observed from the graph in Figure 73, EQE recorded 100%, OUE and WOE recorded 99% and 82%, respectively; 58% was recorded on EQE. FGE, HTE and RSE all recorded 0% for the accuracy under the RF prediction model. 1% was observed for B2E and HPE; 2% was also observed for BME and OFE; similarly, 4% was observed for the FRE microload. 11%, 11%

and 17% were observed at GRE, TVE and UTE, respectively. B1E, CDE, CWE, DNE and DWE all recorded accuracies of 21% to 35%.

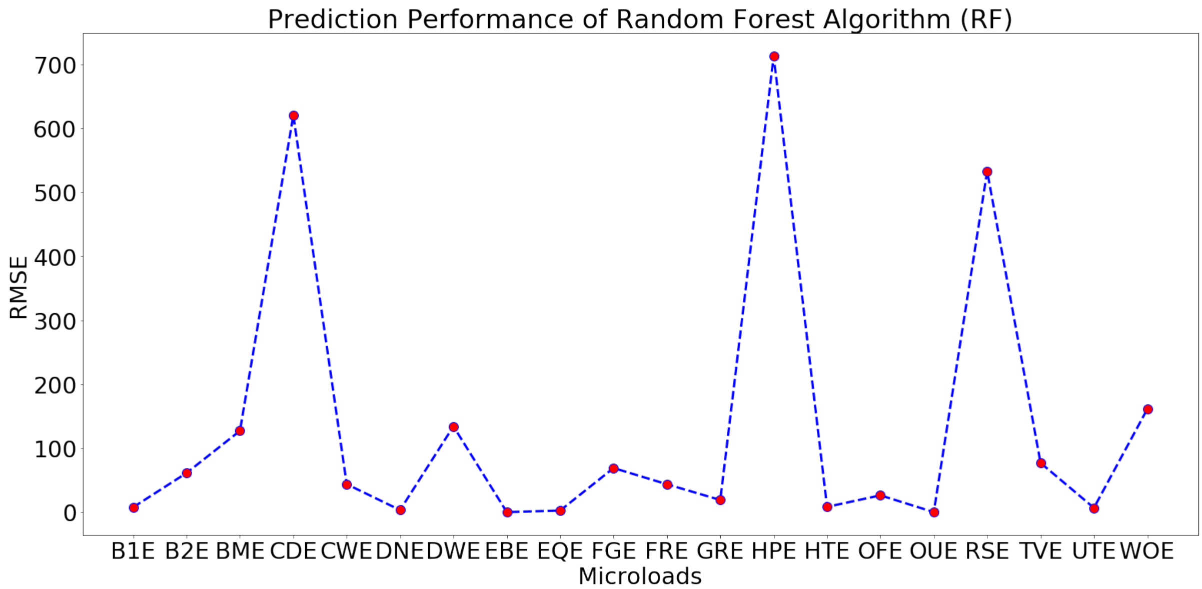


Figure 63 RF RMSE values

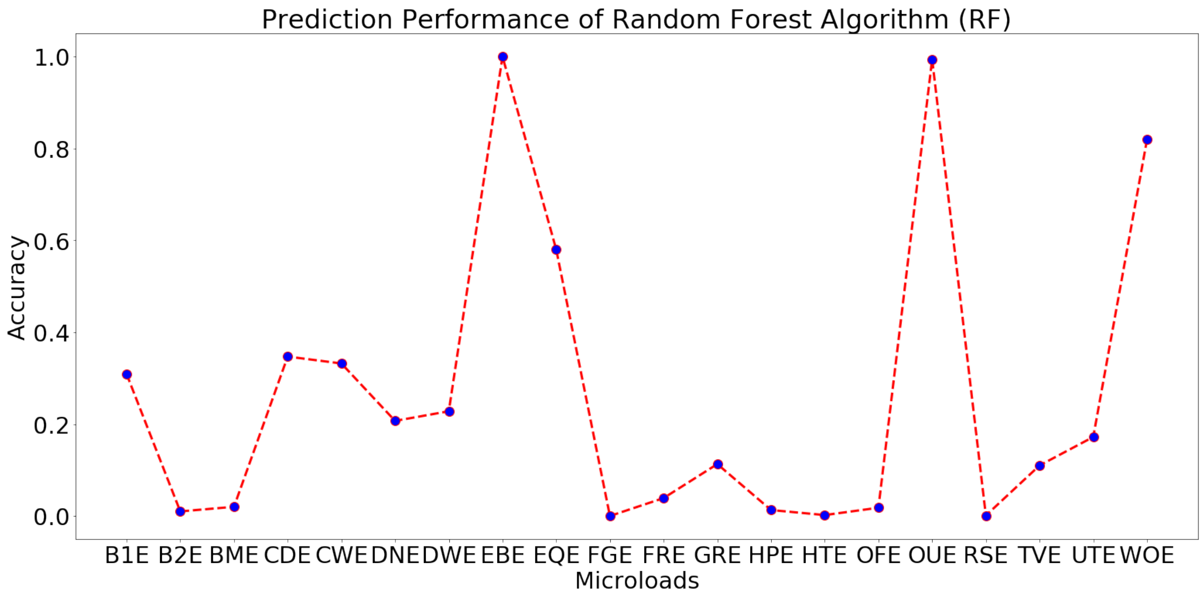


Figure 64 RF Accuracy values

7.4.4 ANN Prediction Results

The ANN prediction results show three key peaks from the graph in Figure 65 below for the RMSE values. These were observed on CDE, HPE and RSE with RMSE values of 524.95, 644.73 and 474.33. RMSE values between 129 and 159 were observed on BME, DWE and WOE, where 158.48 was observed on the WOE and 129.30 were observed on DWE. Single digits of MSE values from 0.11 to 8.58 were seen on B1E, DNE, EBE, EQE, THE, OUE and UTE, where OUE recorded the 0.11 and 8.58 were recorded for the HTE on the other hand. FGE and TVE were observed to record 83.69 and 71.73, respectively. RMSE values of 48.38, 40.62 and 38.02 were recorded for B2E, CWE and FRE as their respective. The rest of the microloads recorded RMSE values of 19.08 and 26.37 on GRE and OFE.

The Accuracy observed during the ANN prediction shows that over 90% accuracy values were observed on B1E, CDE, CWE, DWE, OUE, WOE and EBE where 100% was recorded for EBE and 99% was observed for OUE. Accuracy values of 74%, 62%, and 82% were also observed for B2E, EQE, and HTE. Accuracy values of 30% to 57% were observed on BME, FGE, GRE, HPE, OFE, TVE and UTE, with 57% recorded on FGE and TVE recorded 30%. DNE, FRE and RSE recorded 15%, 4% and 29%, respectively. The Accuracy results are shown in Figure 66 below.

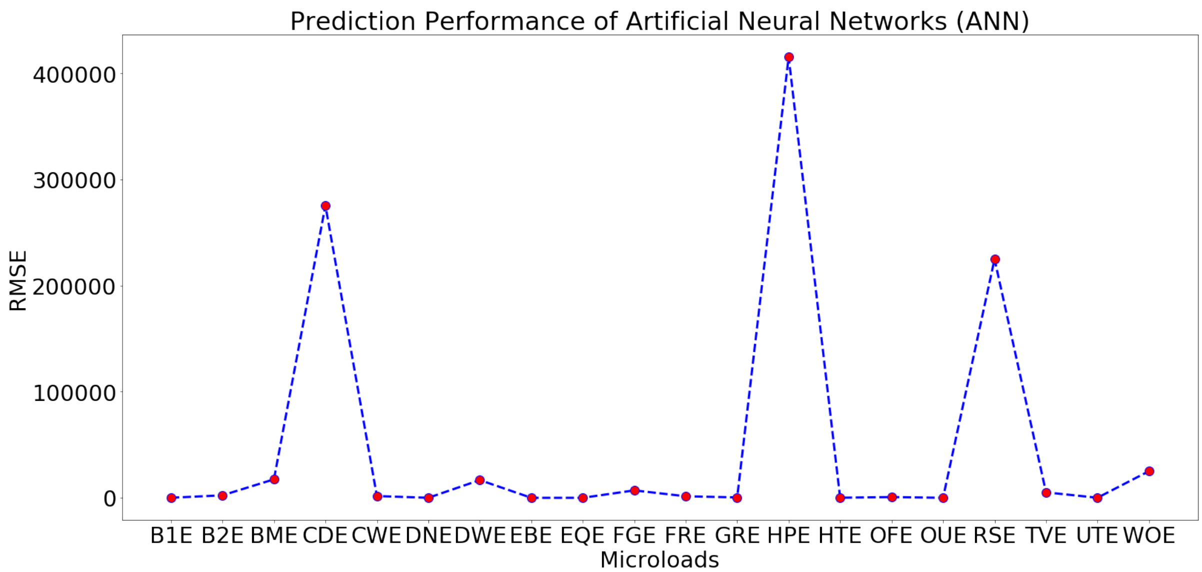


Figure 65 ANN RMSE values

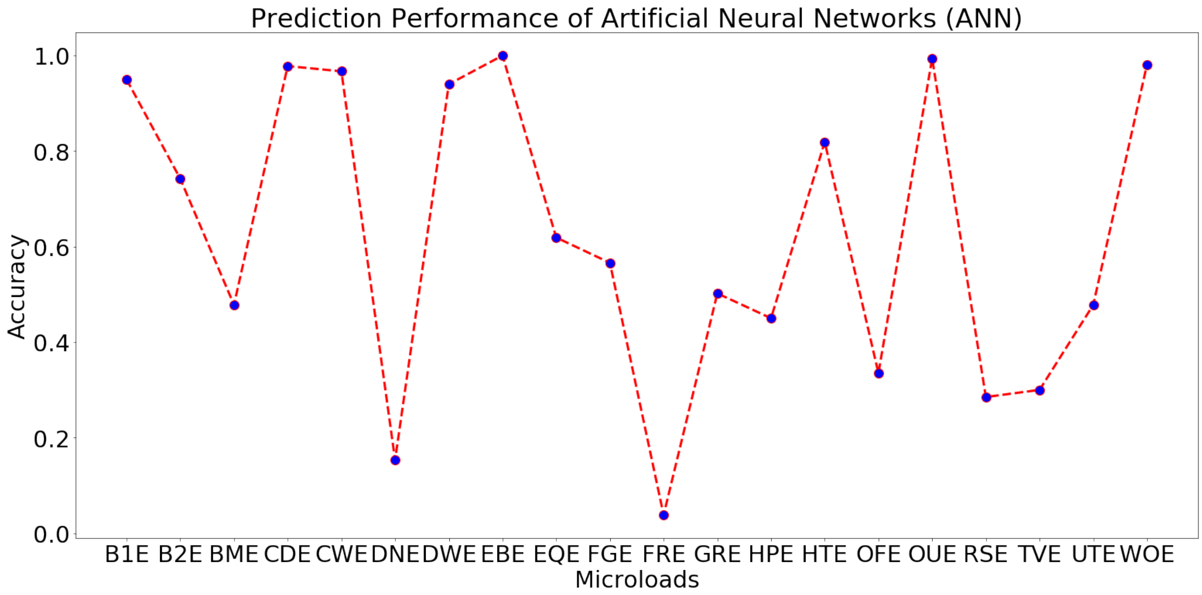


Figure 66 ANN Accuracy values

7.4.5 DT Prediction Results

The RMSE and the Accuracy values observed from the DT predictions are shown in Figure 67 and Figure 68 respectively.

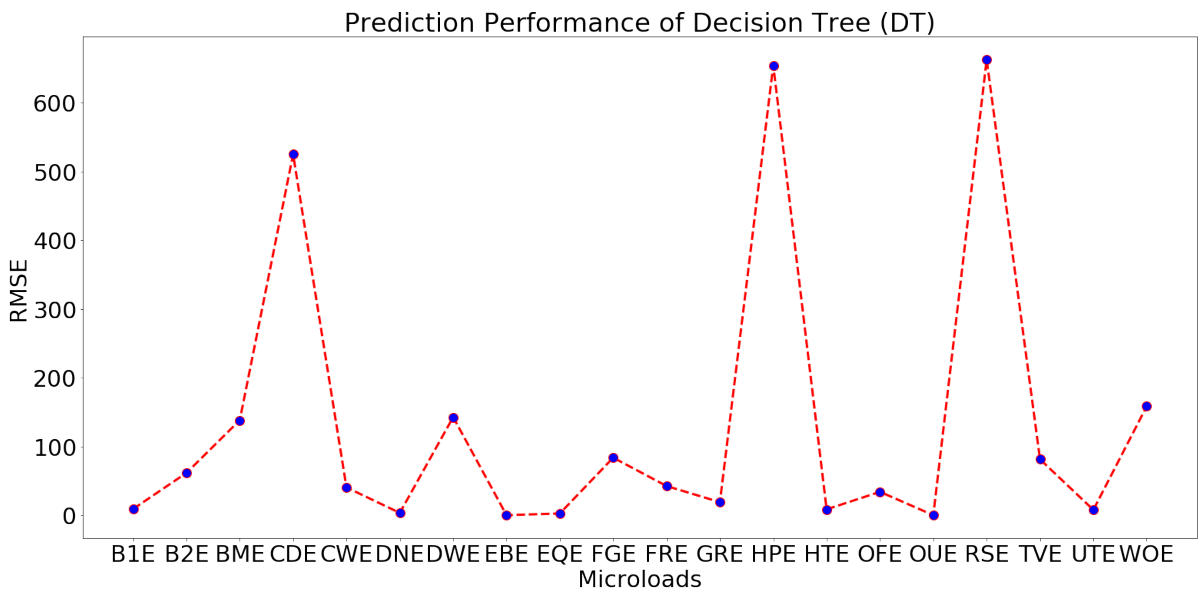


Figure 67 DT RMSE values

RMSE values of 9.07, 3.45, 0.12, 2.63, 8.58, 0.11 and 7.85 were observed on B1E, DNE, EBE, EQE, THE, OUE and UTE, respectively, being the lowest RMSE values observed. 19.09 and 34.05 RMSE values were observed on GRE and OFE, respectively. RMSE values of 40.51 to

83.75 were observed on B2E, CWE, FGE, FRE and TVE microloads. 138.18, 142.72 and 158.49 were observed on BME, DWE and WOE, respectively. The highest was observed at CDE, HPE and RSE with RMSE values of 523.95, 654.33 and 662.68, respectively.

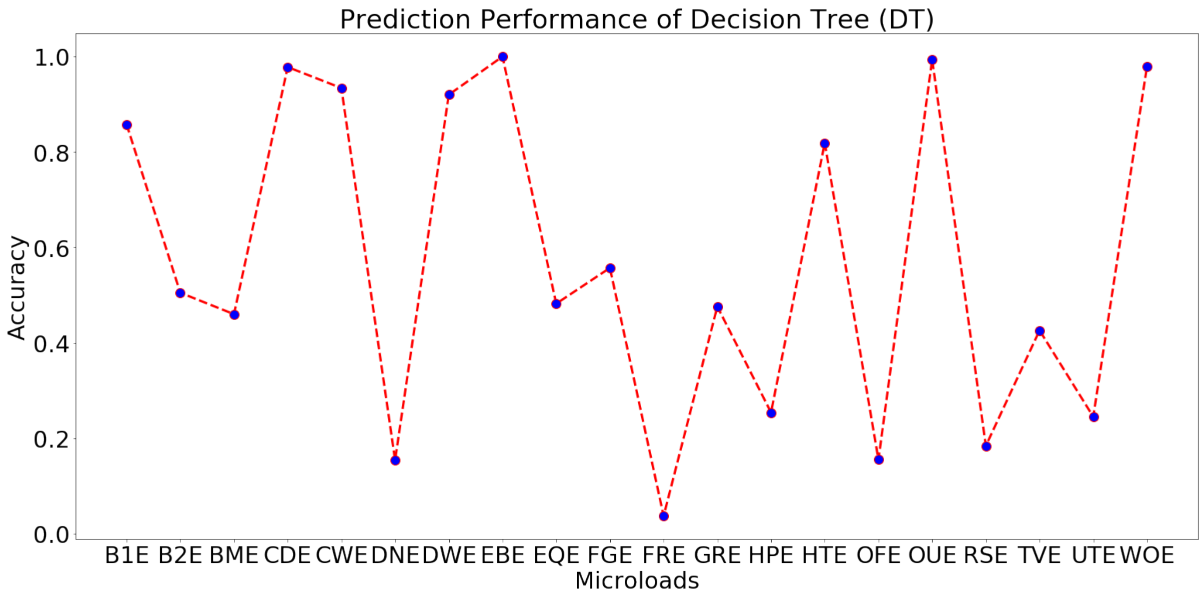


Figure 68 DT Accuracy values

As shown in Figure 68 above, the accuracy values observed under the DT predictions has CDE, CWE, DWE, EBE, OUE and WOE, all recording from 92% to 100% where the 100% was recorded on EBE, and 92% was observed on the DWE. Accuracies of 82% and 86% can be observed on HTE and B1E, respectively. Accuracies of 43% to 56% were observed on B2E, BME, EQE, FGE, GRE and TVE where FGE recorded 56% and TVE recorded 43%; 25% was recorded for HPE and UTE; 15%, 16% and 18% were also recorded for DNE, OFE and RSE microloads respectively. The lowest accuracy value obtained was seen on FRE, being 4%.

7.5 Comparative Analysis of Results

The existing literature reviewed showed that the approach reported in this thesis outperformed most of the works reported in [192]. The microload forecasting by Gajowniczek and Zabkowski in [192] evaluated various prediction models, including some of those discussed in this research where 24-hour microload consumption data was used to predict the next 24-hour consumption of the microloads. In this research, 42 days microload consumption was used to predict the next 18 days microload demands based on the 70% training and 30% testing data comprising minutely consumption data of 20 microloads.

Gajowniczek and Ząbkowski in [192] obtained 41.07% for accuracy when the RF model was evaluated, but the result here shows an average of 26.57%, 47.02% and 41.37% was also obtained for SVR and KNNR where this research shows an average of 58.87%, 56.78% which shows that the evaluation reported in this research outperformed those of Gajowniczek and Zabkowski.

The specific results obtained for each microloads are discussed subsequently, with Figure 69 showing their respective accuracies, and their RMSEs are shown in Figure 70, Figure 71 and Figure 72.

B1E

RMSE values of 6.97, 9.07, 7.76, 6.96 and 7.47 were observed for ANN, DT, RF, SVR and KNNR with accuracies of 95%, 86%, 31%, 95% and 90%, respectively, when the B1E microload was subjected to the prediction techniques under evaluations. The best accuracy was observed on both ANN and SVR. The lowest accuracy was seen during the RF algorithm, with 31%. It was expected that a lower RMSE recorded by RF compared to the rest of the techniques should have yielded a better accuracy, but that was not the case for the RF technique.

B2E

In terms of the B2E microload consumption predictions, the lowest observed accuracy was seen from the KNNR and RF techniques with 1% and 38% and RMSE of 61.30 and 63.75, respectively. Accuracies of 74%, 56% and 51% were observed for ANN, SVR and DT with RMSEs of 48.38, 63.75 and 61.53, respectively.

BME

None of the techniques recorded up to 50% accuracy; ANN recorded 48% as the highest accuracy, with the lowest being observed at RF with 2%. The RMSEs of ANN and RF were 131.95 and 127.14, respectively. DT, SVR and KNNR all recorded accuracy of 46%, with RMSEs of 138.18, 131.92 and 137.05, respectively.

CDE

Apart from RF, which shows an RMSE of 620.31 and an accuracy of 35%, all the rest of the algorithms were observed to have recorded 524,95 for the RMSE, an accuracy of 98%.

CWE

RMSEs of 40.61 to 43.79 was recorded for the CWE microload prediction with an accuracy of mostly 93% to 98%, except RF recording 33% accuracy with RMSE of 43.79, lowest in terms of the accuracy metric.

DNE

The RMSEs recorded for this microload ranged from 3.34 to 4.24, and an accuracy of 15% was observed for ANN, DT and KNNR. SVR yielded 17%, and RF recorded 21%, being the highest in accuracy with an RMSE of 3.34.

DWE

Most of the algorithms recorded 90% to 94% accuracy, but RF recorded 23%, being the lowest with RMSE of 134.17. The rest of the RMSEs were between 129.28 to 142.72, with the highest accuracy at ANN and SVR with an accuracy of 94%.

EBE

All algorithms recorded 0.12 and 100% accuracy for the EBE microload.

EQE

The RMSEs observed for this microload was 2.57 to 2.64, with the best accuracy being recorded by ANN and SVR as 62%. The lowest accuracy was observed at DT with an accuracy of 48%. RF recorded 58% and 2.59 as its REMSE.

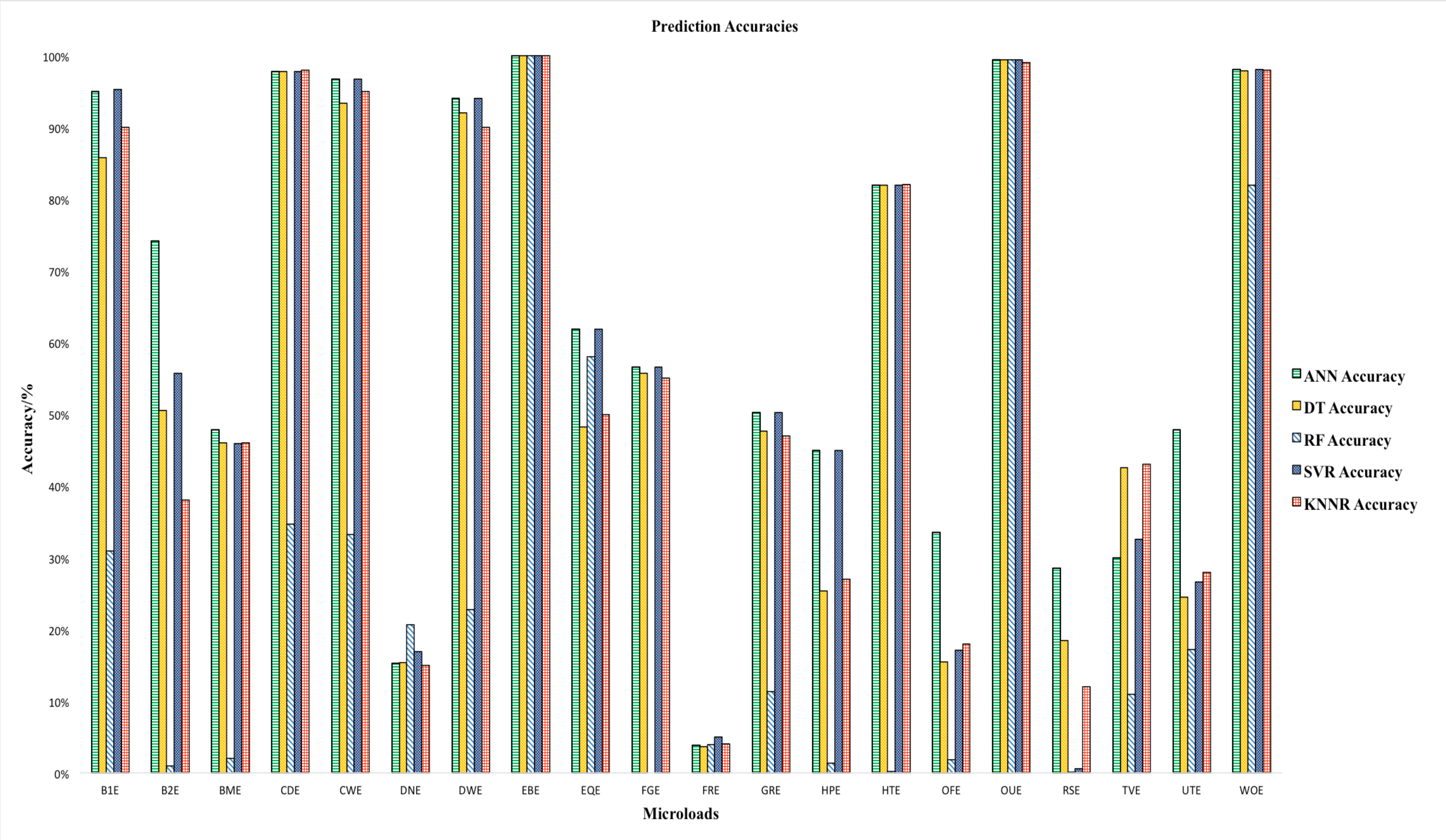


Figure 69 Prediction Accuracies of microloads consumptions

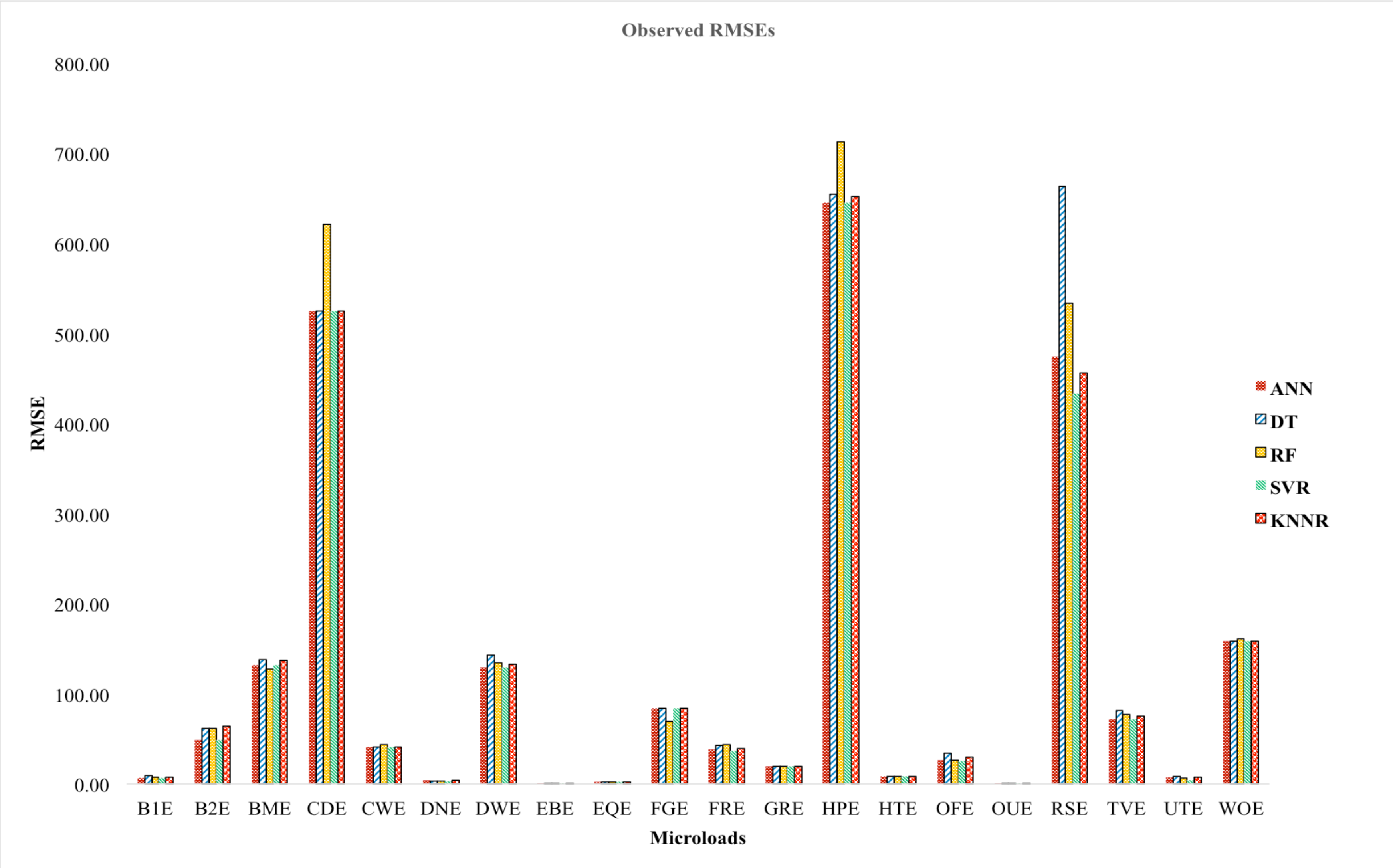


Figure 70 Prediction RMSEs of microloads consumptions ALL

FGE

RF recorded 0% for accuracy with RMSE of 69.01. The rest of the techniques yielded RMSEs ranging between 83.62 to 83.75 and accuracy of 55% to 57%, with the highest accuracy was observed at ANN and SVR with an accuracy of 57%.

FRE

SVR recorded 5% as the highest accuracy for this category of microload with RMSE of 36.72. All other techniques recorded 4% with RMSE from 38.02 to 43.67.

GRE

Accuracy of 11% and RMSE of 19.09 was observed for RF as the lowest accuracy representing the lowest accuracy observed. ANN and SVR recorded 19.08 for their RMSEs and 50% for their accuracies as the highest. The rest recorded 48% accuracies and 19.09 for their RMSEs.

HPE

RMSEs of 644.73 was recorded for ANN and SVR, with an accuracy of 45% being the best-recorded accuracy for the HPE microload predictions. DT and KNNR recorded 25% and 27% for their accuracies, respectively, with RMSEs of 654.33 and 65185. The lowest accuracy was observed on the RF with 10% and RMSE of 712.65.

HTE

Accuracy of 82% was recorded for ANN, DT, SVR and KNNR with RF recording 0% with RMSE of 8.31. ANN, DT and KNNR were observed to have recorded RMSEs of 8.58 and SVR recorded 8.56 for its RMSE.

OFE

RMSEs of 25.35 to 34.05 were observed for all the techniques. The lowest accuracy was recorded from RF as 2% and the highest of 34% was observed on ANN.

OUE

Accuracies of 99% were observed for all the approaches with RMSEs of 0.11 except for SVR, which recorded RMSE of 0.14.

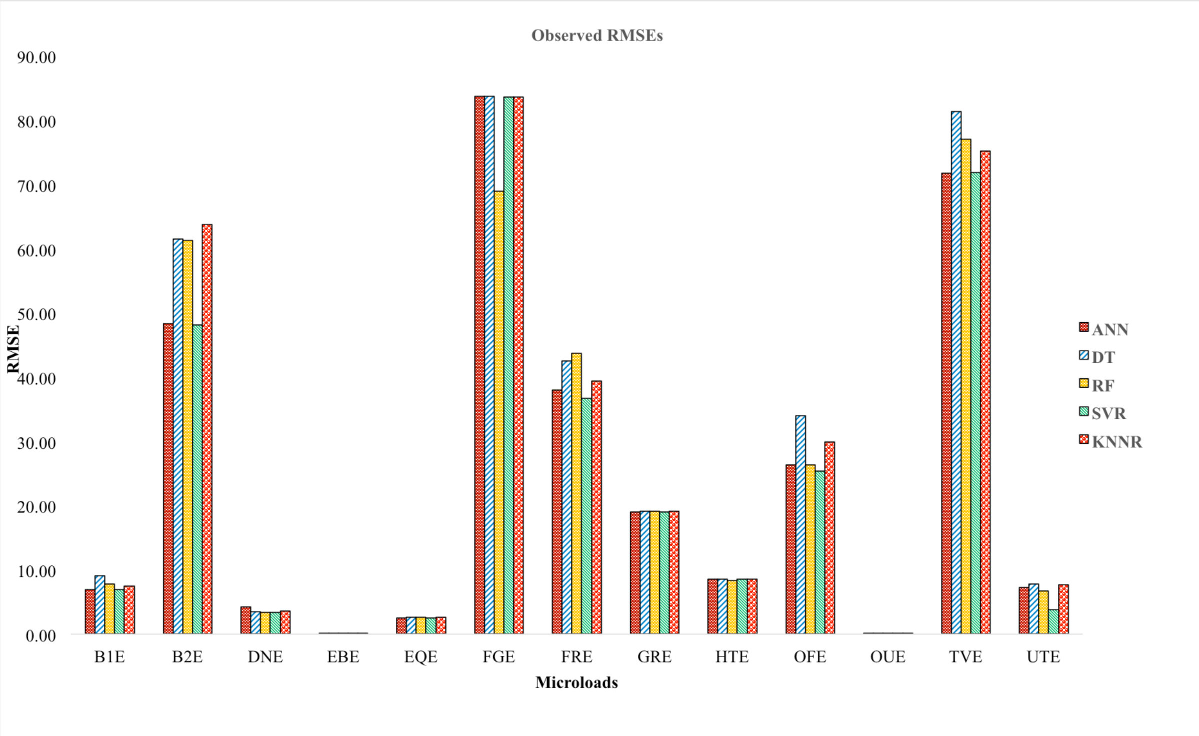


Figure 71 Prediction RMSE less than 90 of microloads consumptions

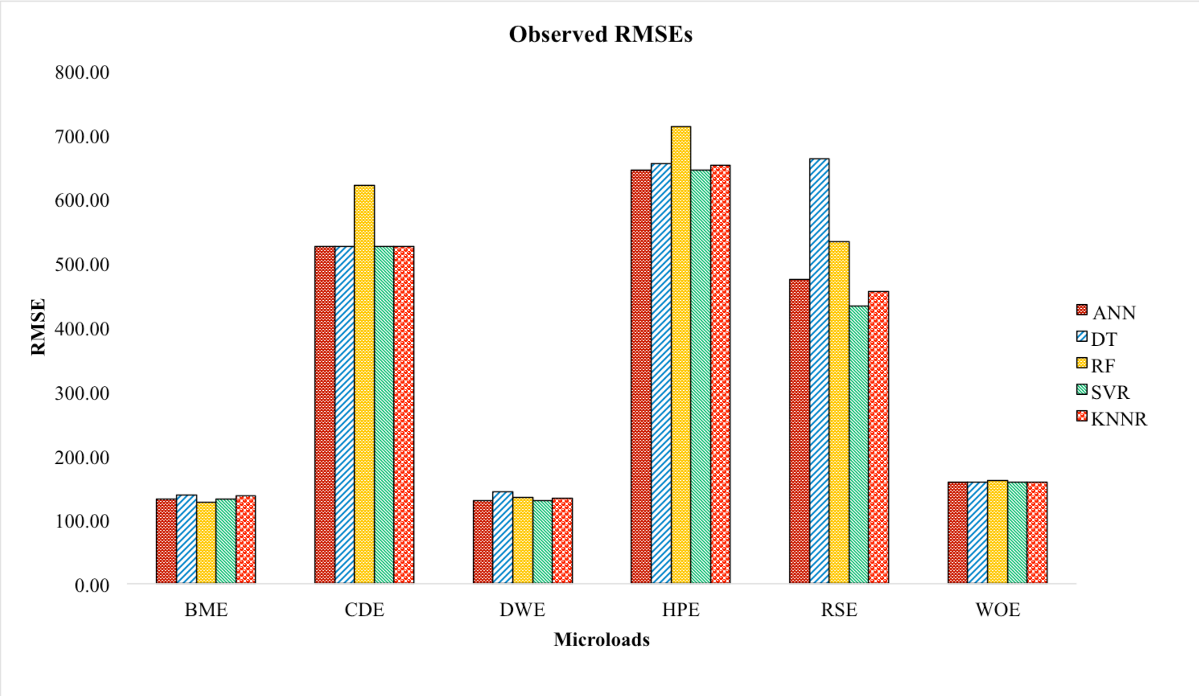


Figure 72 Prediction RMSEs greater than 90 of microloads consumptions

RSE

RMSEs of 432.73, 455.71, 474.33, 532.89 and 662.68 for SVR, KNNR, ANN, RF and DT respectively with accuracies of 1%, 12%, 29%, 0% and 18% with the highest accuracy on ANN and RF recorded the lowest accuracy.

TVE

RMSEs ranging from 71.73 to 81.37 were observed when predicting the microload consumption of TVE. The lowest accuracy was observed on RF with 11%. 30% and 33% were observed on ANN and SVR respectively. DT and KNNR recorded 43% as their accuracies.

UTE

The UTE microload consumption prediction yielded 48% as the best accuracy for ANN with RMSE of 7.27 and the lowest accuracy of 17% was observed on RF with RMSE of 6.76. DT, SVR and KNNR were observed to recorded 25%, 27% and 28% for accuracy respectively with RMSE of 7.85, 3.81 and 7.68.

WOE

The lowest accuracy for predicting this microload was observed on RF as 82% with RMSE of 161.09. Accuracy of 98% was observed for all the rest of the approaches evaluated with RMSEs of 158.48, 158.49, 158.47 and 158.50 for ANN, DT, SVR and KNNR respectively.

7.6 Chapter Summary

Microloads' prediction to reduce the burdens associated with the proposed microload shedding techniques has been considered in this chapter. Various predictive algorithms have been discussed and evaluated on minutely microload consumption data from a Canadian home over three months. Summaries of prediction experiments based on KNNR, SVR, RF, ANN and DT are presented.

The independent variable considered are Temp (C), Dew Point Temp (C), Rel Hum (%), Wind Dir (10s deg), Wind Spd (km/h), Visibility (km) and Stn Press (kPa). The corresponding dependent variables are the microload consumptions. The dataset was split into 70% for the training and 30% for the testing, consistent with previously reported works. Two evaluation metrics were used for examining the efficacy of the methods; RMSE and Accuracy values obtained are consistent with those reported in [144,156,159].

However, the reported works made use of hourly consumption data for the forecasting. The results show significant potential for forecasting in microload shedding where the predicted microload demands could be used to predict the generation requirements of any constrained electric grid.

Chapter 8

Conclusion and Future Works

8.1 Introduction

This chapter reviews the extent to which the aim and objectives of this research have been achieved. The research is aimed at proposing and designing microload management algorithms, and optimisation techniques for microload shedding in generation constrained power systems.

8.2 Conclusion

The research presented here seeks to address one of the important electricity load management issues focusing on generation constrained power systems. The research commenced with getting a broader understanding of the causes and effects of the severe load shedding experience in generation constrained power systems by undertaking various investigations to validate and substantiate the problem in context. The need for different microload shedding algorithms to systematically effect microload shedding was identified through the review of related literature on smart grid.

Further, the modern smart grid and its related research works were reviewed, focusing on load shedding. It was deduced that modern endeavours have mostly focused on peak demand reductions and electric bill payment reductions. However, load shedding as a result of the lack of sufficient generating capacity to meet the increasing electricity demand has not been fully explored. The heuristic technique was used to propose various algorithms to systematically distribute the generation among various domestic devices in residential households to reduce the identified burdens on the end-users.

Firstly, General Microload Shedding Algorithm was proposed and validated using Grouped and UnGrouped Microloads. It was observed that there was significant excess shedding along with the required values. In some cases, the excesses recorded exceeded the actual demands.

The Grouped microload recorded even higher excesses as compared to the UnGrouped microloads.

Secondly, to solve the significant excesses recorded using the previous technique, a Priority Based Microload Shedding Algorithm was proposed. The Grouped and Ungrouped microload were used to validate this algorithm, where the microloads were assumed to have priorities set on them by the end-user. Even though the excesses recorded under this approach was lower than those recorded for the General microload shedding algorithm, the excess values were still of great concern. Some of the excesses were enough to supply full electricity to some houses. The results obtained from this approach show that the Ungrouped microloads experience less excess shedding than the Grouped microloads.

Excess Reuse Microload Shedding algorithm was further proposed to reduce the excesses recorded. This algorithm was in twofold, General Excess Reuse Microload shedding algorithm and Priority Based Excess Reuse Algorithm. Both Grouped and UnGrouped microloads show a significant reduction in the excesses observed when the two algorithms were tested. The Priority Based Excess Reuse Algorithm outperformed the General Excess Reuse Algorithm. The Ungrouped microloads showed almost no excesses, but rather negative excesses were recorded, meaning that the available electricity was efficiently distributed among the microloads.

Furthermore, the potential of energy forecasting on microload shedding was investigated using real minutely microload consumption data obtained from a single house in Canada. The future consumption of the microloads was predicted to alert both the electricity utility companies and their end-users about an impending load shedding to prepare ahead of time. It is hoped that when implemented, it will go a long way to help household set appropriate priority for those periods of load shedding and at the same time give enough time to the electric utility companies to make necessary adjustments on the generations and distribution before effecting any load shedding. The evaluation metrics used showed the efficacy of the forecasting.

8.3 Limitations

Even though this research contributes to both theory and practice by way of the publications and the proposed approach to microloads management, there are some limitations identified; The data used to validate the proposed microload management algorithms were obtained through the random selection of domestic appliances consumption profile cross-sectional (i.e. instantaneous consumptions) created 26 households. The instantaneous demand may not give the true complexities associated with microloads.

Also, the consumption data used for the prediction were collected from a single household and may not represent the other houses in the area. Additionally, using a single household's consumption, the independent variables were obtained hourly and later converted to minutely data to match the consumptions before being used for the experiment.

8.4 Future Outlooks

Logically, the next stage of this work will be to use real-time consumption data for effecting microload management. Further research is also needed in the area of consumption prediction using weather conditions as the independent variable. Other predictive algorithms could be used to predict the consumption and the generation, and the best performing models are retained in terms of their accuracies and minimum errors.

8.9 Chapter Summary

The contributions of this research are summarised in this chapter along with some future works. The limitation of the research has also been discussed in this concluding chapter.

References

[1] Samarakoon, K. and Ekanayake, J., 2011, August. Selective load control to provide primary frequency response in the wake of introducing new large thermal power plants to Sri Lanka. In 2011 6th International Conference on Industrial and Information Systems (pp. 204-209). IEEE.

[2] Muratori, M. and Rizzoni, G., 2015. Residential demand response: Dynamic energy management and time-varying electricity pricing. IEEE Transactions on Power systems, 31(2), pp.1108-1117.

[3] Sugarman, V. and Lank, E., 2015, April. Designing persuasive technology to manage peak electricity demand in ontario homes. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (pp. 1975-1984).

[4] Trovato, V., Sanz, I.M., Chaudhuri, B. and Strbac, G., 2016. Advanced control of thermostatic loads for rapid frequency response in Great Britain. IEEE Transactions on Power Systems, 32(3), pp.2106-2117.

[5] Trovato, V., Sanz, I.M., Chaudhuri, B. and Strbac, G., 2016. Advanced control of thermostatic loads for rapid frequency response in Great Britain. IEEE Transactions on Power Systems, 32(3), pp.2106-2117

[6] Wang, Y., Yang, W. and Liu, T., 2017. Appliances considered demand response optimisation for smart grid. IET Generation, Transmission & Distribution, 11(4), pp.856-864.

[7] Ibrahim, A.M., Attia, M.A., Othman, M.M. and Abdelaziz, A.Y., 2017. A Survey on Demand Side Management in Electrical Power Systems. i-Manager's Journal on Power Systems Engineering, 5(1), p.40.

[8] Samarakoon, K. and Ekanayake, J., 2009, December. A survey of frequency control methods and demand side contribution in Sri Lanka and in Great Britain. In 2009 International Conference on Industrial and Information Systems (ICIIS) (pp. 454-459). IEEE.

[9] Shahgholian, G. and Salary, M.E., 2012. Effect of load shedding strategy on interconnected power systems stability when a blackout occurs. International Journal of Computer and Electrical Engineering, 4(2), p.212.

[10] Ramchurn, S., Vytelingum, P., Rogers, A. and Jennings, N., 2011. Agent-based control for decentralised demand side management in the smart grid.

[11] Fiorentino, G., Corsi, A. and Fragnito, P., 2015, July. A smarter grid with the internet of energy. In Proceedings of the 2015 ACM Sixth International Conference on Future Energy Systems (pp. 301-306).

[12] Samarakoon, K. and Ekanayake, J., 2011, August. Selective load control to provide primary frequency response in the wake of introducing new large thermal power plants to Sri Lanka. In 2011 6th International Conference on Industrial and Information Systems (pp. 204-209). IEEE.

[13] Yaghmaee, M.H., Moghaddassian, M. and Leon-Garcia, A., 2016. Autonomous two-tier cloud-based demand side management approach with microgrid. IEEE Transactions on Industrial Informatics, 13(3), pp.1109-1120.

[14] Daily News. (2014, April) www.dailynewsegypt.com. [Online]. http://www.dailynewsegypt.com/2014/04/13/preventing-summer-blackouts-egypt-impossible-minister/

[15] Free Press Release. (2014, April) http://www.free-press-release.com. [Online]. http://www.free-press-release.com/news-electricity-and-power-shortage-holding-india-back-1182330309.html

[16] N. Madhavan. (1999) Low voltage story kernel description. [Online]. Available: http://www.businesstoday.in/magazine/features/tamil-naduelectricity-board-measures-to-revive/story/185965.htm

[17] CBC News. (2014, January) CBC News. [Online]. http://www.cbc.ca/news/canada/newfoundland-labrador/newfoundland-power-outage-worsens-after-holyrood-incident-1.2484663

[18] Daily News. (2014, April) www.dailynewsegypt.com. [Online]. http://www.dailynewsegypt.com/2014/04/13/preventing-summer-blackouts-egypt-impossible-minister/

[19] GhanaNews.Com. (2015, January) www.ghanaweb.com/. [Online]. http://www.ghanaweb.com/GhanaHomePage/NewsArchive/artikel.php?ID=344788

[20] Free Press Release. (2014, April) http://www.free-press-release.com. [Online]. http://www.free-press-release.com/news-electricity-and-power-shortage-holding-india-back-1182330309.html

[21] Billewicz, K., 2015. Smart Meters and Under-Frequency Load Shedding. Journal of Energy and Power Engineering, 9, pp.905-911.

[22] Slavickas, R.A., Alden, R.T.H. and El-Kady, M.A., 1999. Distribution utility's trade-off decisions in obtaining sources of electricity. IEEE Transactions on Power Delivery, 14(4), pp.1495-1503.

[23] Miller, A.I. and Duffey, R.B., 2006, May. Integrating large-scale co-generation of hydrogen and electricity from wind and nuclear sources (NUWIND©). In 2006 IEEE EIC Climate Change Conference (pp. 1-9). IEEE.

[24] Farret, F.A. and Simoes, M.G., 2006. Integration of alternative sources of energy. John Wiley & Sons.

[25] Azasoo, J.Q. and Boateng, K.O., 2012, October. Smart metering: A GSM approach in Ghana. In 2012 IEEE 4th International Conference on Adaptive Science & Technology (ICAST) (pp. 158-163). IEEE.

[26] Hosseinzadeh, M. and Salmasi, F.R., 2015. Robust optimal power management system for a hybrid AC/DC micro-grid. IEEE Transactions on Sustainable Energy, 6(3), pp.675-687.

[27] Frank Heinz. (2011, February) http://www.nbcdfw.com/. [Online]. http://www.nbcdfw.com/news/local/Power-Grid-Taxed-Rolling-Blackouts-Ordered-115093224.html

[28] Zhong, J., Kang, C. and Liu, K., 2010, July. Demand side management in China. In IEEE PES General Meeting (pp. 1-4). IEEE.

[29] Yang, P., Tang, G. and Nehorai, A., 2012. A game-theoretic approach for optimal time-of-use electricity pricing. IEEE Transactions on Power Systems, 28(2), pp.884-892.

[30] Ekanayake, J.B., Jenkins, N. and Strbac, G., 2008. Frequency response from wind turbines. Wind Engineering, 32(6), pp.573-586.

[31] Mohsenian-Rad, A.H., Wong, V.W., Jatskevich, J., Schober, R. and Leon-Garcia, A., 2010. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. IEEE transactions on Smart Grid, 1(3), pp.320-331.

[32] The Chronicles, Ghana. (2015, March) http://thechronicle.com.gh. [Online]. http://thechronicle.com.gh/ghana-electricity-crisis-dumsor-the-causes-disadvantages-and-solutions/

[34] Alhaji Mustapha Iddrisu. (2015, November) https://www.modernghana.com. [Online]. https://www.modernghana.com/author/AlhajiMustaphaIddrisu

[33] Kelkar, S., Kothari, N. and Ramamritham, K., 2015, July. Brownout energy distribution scheme for mitigating rolling blackouts. In Proceedings of the 2015 ACM Sixth International Conference on Future Energy Systems (pp. 193-194).

[35] Antoinette Slabbert. (2014, December) http://mybroadband.co.za/news. [Online]. http://mybroadband.co.za/news/government/115267-this-is-a-catastrophe-electricity-expert.html

[36] Karnouskos, S., Colombo, A.W., Lastra, J.L.M. and Popescu, C., 2009, June. Towards the energy efficient future factory. In 2009 7th IEEE International Conference on Industrial Informatics (pp. 367-371). IEEE.

[37] Whetten, D.A., 1989. What constitutes a theoretical contribution?. Academy of management review, 14(4), pp.490-495.

[38] Corley, K.G. and Gioia, D.A., 2011. Building theory about theory building: what constitutes a theoretical contribution?. Academy of management review, 36(1), pp.12-32.

[39] Jian, Z., Lijuan, S., Lirong, W., Jun, L., Qinsheng, D. and Shalobanov, S.V., 2015, August. The Research of Human-Computer Interaction Model Based on the Morhpable Model Based 3D Face Synthesis in the Speech Rehabilitation for Deaf Children. In 2015 IEEE Fifth International Conference on Big Data and Cloud Computing (pp. 191-194). IEEE.

[40] Warwick, W.M., 2002. A primer on electric utilities, deregulation, and restructuring of US electricity markets (No. PNNL-13906). Pacific Northwest National Lab.(PNNL), Richland, WA (United States).

[41] D. of Energy. (2009, Jun) The smart grid: An introduction. [Online]. Available: https://energy.gov/oe/downloads/smart-grid-introduction-0

[42] Agarwal, Y., Weng, T. and Gupta, R., 2007. Micro-systems driving smart energy metering in smart grids. DAC'07.

[43] Kamble, P. and Bodkhe, S., 2011. A new approach for design and implementation of AMR in Smart Meter. International journal of advanced engineering sciences and Technology, 2, pp.57-61.

[44] Tweneboah-Koduah, S., Skouby, K.E. and Tadayoni, R., 2017. Cyber security threats to IoT applications and service domains. Wireless Personal Communications, 95(1), pp.169-185.

[45] Azasoo, J.Q. and Boateng, K.O., 2012, October. Smart metering: A GSM approach in Ghana. In 2012 IEEE 4th International Conference on Adaptive Science & Technology (ICAST) (pp. 158-163). IEEE.

[46] Popa, M., 2011, June. Gateway design and implementation in an automatic meter reading system based on power line communications. In The 7th International Conference on Networked Computing and Advanced Information Management (pp. 295-298). IEEE.

[47] Oksa, P., Soini, M., Sydanheimo, L. and Kivikoski, M., 2006, March. Considerations of using power line communication in the AMR system. In 2006 IEEE International Symposium on Power Line Communications and Its Applications (pp. 208-211). IEEE.

[48] Bera, S., Misra, S. and Obaidat, M.S., 2014, December. Energy-efficient smart metering for green smart grid communication. In 2014 IEEE Global Communications Conference (pp. 2466-2471). IEEE.

[49] Owen, G. and Ward, J., 2006. Smart meters: commercial, policy and regulatory drivers. Sustainability First, 54.

[50] Apperley, M. and Kalyan, J., 2015, July. A mobile personal residential electricity dashboard. In 2015 19th International Conference on Information Visualisation (pp. 195-199). IEEE.

[51] Chetty, M., Tran, D. and Grinter, R.E., 2008, September. Getting to green: understanding resource consumption in the home. In Proceedings of the 10th international conference on Ubiquitous computing (pp. 242-251).

[52] Mohamed, A.R. and Lee, K.T., 2006. Energy for sustainable development in Malaysia: Energy policy and alternative energy. Energy policy, 34(15), pp.2388-2397.

[53] Goh, H.H., Goh, K.C., Sukri, W.N.Z.S.W. and Chua, Q.S., 2016. Introductory Of Renewable Energy Sources In Asean Countries And Green-Y Model For Predicting Fit-In Tariff In Malaysia. Project Management Development–Practice and Perspectives, 14, p.94.

[54] Ahmad, M.R.B., Rauf, M., Fakharuddin, A. and Abdalla, A.N., 2010, October. Design of embedded automated monitoring system; an intelligent application to reduce peak load demand. In 2010 International Conference on Power System Technology (pp. 1-5). IEEE.

[55] Nunoo, S. and Attachie, J.C., 2011. A Methodology For The Design Of An Electricity Theft Monitoring System. Journal of Theoretical & Applied Information Technology, 26(2).

[56] Azasoo, J.Q. and Boateng, K.O., 2015, June. A retrofit design science methodology for smart metering design in developing countries. In 2015 15th International Conference on Computational Science and Its Applications (pp. 1-7). IEEE.

[57] Buse, D.P. and Wu, Q.H., 2007. IP network-based multi-agent systems for industrial automation: information management, condition monitoring and control of power systems. Springer Science & Business Media.

[58] Newbury, J. and Miller, W., 2001. Multiprotocol routing for automatic remote meter reading using power line carrier systems. IEEE transactions on power delivery, 16(1), pp.1-5.

[59] Nguyen, D., Negnevisky, M., Jiang, D. and de Groot, M., 2008, December. A model of domestic energy management enabling low-cost technology. In 2008 Australasian Universities Power Engineering Conference (pp. 1-6). IEEE.

[60] Yang, P., Tang, G. and Nehorai, A., 2012. A game-theoretic approach for optimal time-of-use electricity pricing. IEEE Transactions on Power Systems, 28(2), pp.884-892.

[61] Moore, I. and Ekanayake, J., 2009, September. Frequency response from wind turbines. In 2009 44th International Universities Power Engineering Conference (UPEC) (pp. 1-5). IEEE.

[62] Ma, J., Chen, H.H., Song, L. and Li, Y., 2015. Residential load scheduling in smart grid: A cost efficiency perspective. IEEE transactions on smart grid, 7(2), pp.771-784.

[63] Koschel, L., Mahler, K., Felbecker, R. and Frey, M., 2014, October. RF-MIMO for smart metering communication under harsh conditions. In 2014 IEEE Conference on Wireless Sensors (ICWiSE) (pp. 55-60). IEEE.

[64] Erlinghagen, S., Lichtensteiger, B. and Markard, J., 2015. Smart meter communication standards in Europe–a comparison. Renewable and Sustainable Energy Reviews, 43, pp.1249-1262.

[65] Singh, L., Paliwal, A. and Shekhawat, R., 2014, March. Extending battery life of smart meters by optimizing communication subsystem. In 2014 IEEE Students' Conference on Electrical, Electronics and Computer Science (pp. 1-7). IEEE.

[66] Christou, G., 2017. The EU's approach to cybersecurity.

[67] Luan, S.W., Teng, J.H., Chan, S.Y. and Hwang, L.C., 2009, November. Development of a smart power meter for AMI based on ZigBee communication. In 2009 International Conference on Power Electronics and Drive Systems (PEDS) (pp. 661-665). IEEE.

[68] Kistler, R., Knauth, S. and Klapproth, A., 2008. EnerBee-example of an advanced metering infrastructure based on ZigBee. In Proceedings of 2nd European ZigBee Developers Conference, EuZDC (pp. 1-11).

[69] Chang, Y.H., Jirutitijaroen, P. and Ten, C.W., 2010, September. A simulation model of cyber threats for energy metering devices in a secondary distribution network. In 2010 5th International Conference on Critical Infrastructure (CRIS) (pp. 1-7). IEEE.

[70] Igure, V.M. and Williams, R.D., 2008. Taxonomies of attacks and vulnerabilities in computer systems. IEEE Communications Surveys & Tutorials, 10(1), pp.6-19.

[71] Rial, A. and Danezis, G., 2011, October. Privacy-preserving smart metering. In Proceedings of the 10th annual ACM workshop on Privacy in the electronic society (pp. 49-60).

[72] Le, S.P., Zeng, H., Qiu, J. and Zhang, S., 2011, August. Design and implementation of wireless power monitoring system for public buildings. In Proceedings of 2011 International Conference on Electronic & Mechanical Engineering and Information Technology (Vol. 1, pp. 291-294). IEEE.

[73] Bennett, C. and Highfill, D., 2008, November. Networking AMI smart meters. In 2008 IEEE Energy 2030 Conference (pp. 1-8). IEEE.

[74] Khan, M.A., Javaid, N., Arif, M., Saud, S., Qasim, U. and Khan, Z.A., 2014, May. Peak load scheduling in smart grid communication environment. In 2014 IEEE 28th International Conference on Advanced Information Networking and Applications (pp. 1025-1032). IEEE.

[75] Liu, Y., Yuen, C., Huang, S., Hassan, N.U., Wang, X. and Xie, S., 2014. Peak-to-average ratio constrained demand-side management with consumer's preference in residential smart grid. IEEE Journal of Selected Topics in Signal Processing, 8(6), pp.1084-1097.

[76] Tsagarakis, G., Thomson, R.C., Collin, A.J., Harrison, G.P., Kiprakis, A.E. and McLaughlin, S., 2016. Assessment of the cost and environmental impact of residential demand-side management. IEEE Transactions on Industry Applications, 52(3), pp.2486-2495.

[77] Huang, H., Cai, Y., Xu, H. and Yu, H., 2016. A multiagent minority-game-based demand-response management of smart buildings toward peak load reduction. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 36(4), pp.573-585.

[78] Ru, Y., Kleissl, J. and Martinez, S., 2012. Storage size determination for grid-connected photovoltaic systems. IEEE Transactions on sustainable energy, 4(1), pp.68-81.

[79] Gatsis, N. and Giannakis, G.B., 2012. Residential load control: Distributed scheduling and convergence with lost AMI messages. IEEE Transactions on Smart Grid, 3(2), pp.770-786.

[80] Dittawit, K. and Aagesen, F.A., 2014, September. Home energy management system for electricity cost savings and comfort preservation. In 2014 IEEE Fourth International Conference on Consumer Electronics Berlin (ICCE-Berlin) (pp. 309-313). IEEE.

[81] Nunna, K.H. and Doolla, S., 2014. Responsive end-user-based demand side management in multimicrogrid environment. IEEE Transactions on Industrial Informatics, 10(2), pp.1262-1272.

[82] Cao, Y., Tang, S., Li, C., Zhang, P., Tan, Y., Zhang, Z. and Li, J., 2011. An optimized EV charging model considering TOU price and SOC curve. IEEE Transactions on Smart Grid, 3(1), pp.388-393.

[83] Ding, Z., Sarikprueck, P. and Lee, W.J., 2015, May. Medium-term operation for an industrial customer considering demand side management and risk management. In 2015 IEEE/IAS 51st Industrial & Commercial Power Systems Technical Conference (I&CPS) (pp. 1-9). IEEE.

[84] Wang, Z. and Paranjape, R., 2015. Optimal residential demand response for multiple heterogeneous homes with real-time price prediction in a multiagent framework. IEEE transactions on smart grid, 8(3), pp.1173-1184.

[85] Kinhekar, N., Padhy, N.P., Li, F. and Gupta, H.O., 2015. Utility oriented demand side management using smart AC and micro DC grid cooperative. IEEE Transactions on Power Systems, 31(2), pp.1151-1160.

[86] Prema, V., Rao, K.U. and Closepet, A.S., 2014, May. A novel predictive DSM strategy to match power outage pattern for optimal cost with solar and diesel power. In 2014 IEEE Innovative Smart Grid Technologies-Asia (ISGT ASIA) (pp. 377-382). IEEE.

[87] Nguyen, H.K., Song, J.B. and Han, Z., 2014. Distributed demand side management with energy storage in smart grid. IEEE Transactions on Parallel and Distributed Systems, 26(12), pp.3346-3357.

[88] Margellos, K. and Oren, S., 2015. Capacity controlled demand side management: A stochastic pricing analysis. IEEE Transactions on Power Systems, 31(1), pp.706-717.

[89] Khomami, H.P. and Javidi, M.H., 2013, November. An efficient home energy management system for automated residential demand response. In 2013 13th international conference on environment and electrical engineering (EEEIC) (pp. 307-312). IEEE.

[90] Baharlouei, Z. and Hashemi, M., 2014. Efficiency-fairness trade-off in privacy-preserving autonomous demand side management. IEEE Transactions on Smart Grid, 5(2), pp.799-808.

[91] Hayes, B., Hernando-Gil, I., Collin, A., Harrison, G. and Djokić, S., 2014. Optimal power flow for maximizing network benefits from demand-side management. IEEE transactions on power systems, 29(4), pp.1739-1747.

[92] Soliman, H.M. and Leon-Garcia, A., 2014. Game-theoretic demand-side management with storage devices for the future smart grid. IEEE Transactions on Smart Grid, 5(3), pp.1475-1485.

[93] Stephens, E.R., Smith, D.B. and Mahanti, A., 2014. Game theoretic model predictive control for distributed energy demand-side management. IEEE Transactions on Smart Grid, 6(3), pp.1394-1402.

[94] Ma, J., Deng, J., Song, L. and Han, Z., 2014. Incentive mechanism for demand side management in smart grid using auction. IEEE Transactions on Smart Grid, 5(3), pp.1379-1388.

[95] Sheikhi, A., Rayati, M., Bahrami, S. and Ranjbar, A.M., 2015. Integrated demand side management game in smart energy hubs. IEEE Transactions on Smart Grid, 6(2), pp.675-683.

[96] Guo, Y., Pan, M. and Fang, Y., 2012. Optimal power management of residential customers in the smart grid. IEEE Transactions on Parallel and Distributed Systems, 23(9), pp.1593-1606.

[97] Conejo, A.J., Morales, J.M. and Baringo, L., 2010. Real-time demand response model. IEEE Transactions on Smart Grid, 1(3), pp.236-242.

[98] Joe-Wong, C., Sen, S., Ha, S. and Chiang, M., 2012. Optimized day-ahead pricing for smart grids with device-specific scheduling flexibility. IEEE Journal on Selected Areas in Communications, 30(6), pp.1075-1085.

[99] Wang, Y., Yang, W. and Liu, T., 2017. Appliances considered demand response optimisation for smart grid. IET Generation, Transmission & Distribution, 11(4), pp.856-864.

[100] Braun, P., Grüne, L., Kellett, C.M., Weller, S.R. and Worthmann, K., 2016. A distributed optimization algorithm for the predictive control of smart grids. IEEE Transactions on Automatic Control, 61(12), pp.3898-3911.

[101] Carta, J.A., Ramirez, P. and Velazquez, S., 2009. A review of wind speed probability distributions used in wind energy analysis: Case studies in the Canary Islands. Renewable and sustainable energy reviews, 13(5), pp.933-955.

[102] Nogales, F.J. and Conejo, A.J., 2006. Electricity price forecasting through transfer function models. Journal of the Operational Research Society, 57(4), pp.350-356.

[103] Giannakis, G.B., Kekatos, V., Gatsis, N., Kim, S.J., Zhu, H. and Wollenberg, B.F., 2013. Monitoring and optimization for power grids: A signal processing perspective. IEEE Signal Processing Magazine, 30(5), pp.107-128.

[104] Wang, G., Kekatos, V., Conejo, A.J. and Giannakis, G.B., 2016. Ergodic energy management leveraging resource variability in distribution grids. IEEE Transactions on Power Systems, 31(6), pp.4765-4775.

[105Gan, L., Li, N., Topcu, U. and Low, S.H., 2014. Exact convex relaxation of optimal power flow in radial networks. IEEE Transactions on Automatic Control, 60(1), pp.72-87.

[106] Fischer, D., Stephen, B., Flunk, A., Kreifels, N., Lindberg, K.B., Wille-Haussmann, B. and Owens, E.H., 2016. Modeling the effects of variable tariffs on domestic electric load profiles by use of occupant behavior submodels. IEEE Transactions on Smart Grid, 8(6), pp.2685-2693.

[107] Ileri, O., Mau, S.C. and Mandayam, N.B., 2005. Pricing for enabling forwarding in self-configuring ad hoc networks. IEEE Journal on Selected Areas in Communications, 23(1), pp.151-162.

[108] Liu, Y., Yuen, C., Huang, S., Hassan, N.U., Wang, X. and Xie, S., 2014. Peak-to-average ratio constrained demand-side management with consumer's preference in residential smart grid. IEEE Journal of Selected Topics in Signal Processing, 8(6), pp.1084-1097.

[109] Manasseh, E., Ohno, S., Kalegele, K. and Tariq, R., 2015, May. Demand side management to minimize peak-to-average ratio in smart grid. In Proceedings of the ISCIE International Symposium on Stochastic Systems Theory and its Applications (Vol. 2015, pp. 102-107). The ISCIE Symposium on Stochastic Systems Theory and Its Applications.

[110] Reka, S.S. and Ramesh, V., 2016. A demand response modeling for residential consumers in smart grid environment using game theory based energy scheduling algorithm. Ain Shams Engineering Journal, 7(2), pp.835-845.

[111] Nguyen, H.K., Song, J.B. and Han, Z., 2012, March. Demand side management to reduce peak-to-average ratio using game theory in smart grid. In 2012 Proceedings IEEE INFOCOM Workshops (pp. 91-96). IEEE.

[112] Hajj, N. and Awad, M., 2015. A game theory approach to demand side management in smart grids. In Intelligent Systems' 2014 (pp. 807-819). Springer, Cham.

[113] Yaghmaee, M.H., Moghaddassian, M. and Leon-Garcia, A., 2016. Autonomous two-tier cloud-based demand side management approach with microgrid. IEEE Transactions on Industrial Informatics, 13(3), pp.1109-1120.

[114] Latifi, M., Khalili, A., Rastegarnia, A., Zandi, S. and Bazzi, W.M., 2017. A distributed algorithm for demand-side management: Selling back to the grid. Heliyon, 3(11), p.e00457.

[115] Bozchalui, M.C., Hashmi, S.A., Hassen, H., Canizares, C.A. and Bhattacharya, K., 2012. Optimal operation of residential energy hubs in smart grids. IEEE Transactions on Smart Grid, 3(4), pp.1755-1766.

[116] Uturbey, W., Duarte, A.P., Coura, I.M. and Araújo, T.F., 2015, October. An optimization framework to assess TOU tariffs. In 2015 IEEE PES Innovative Smart Grid Technologies Latin America (ISGT LATAM) (pp. 525-530). IEEE.

[117] Chiş, A. and Koivunen, V., 2017. Coalitional game-based cost optimization of energy portfolio in smart grid communities. IEEE Transactions on Smart Grid, 10(2), pp.1960-1970.

[118] Akasiadis, C. and Chalkiadakis, G., 2017. Mechanism design for demand-side management. IEEE intelligent systems, 32(1), pp.24-31.

[119] Shaheen, N., Javaid, N., Nisa, N., Zeb, A.M., Khan, Z.A. and Qasim, U., 2016, July. Appliance scheduling for energy management with user preferences. In 2016 10th International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS) (pp. 328-334). IEEE.

[120] W. in Africa. (2016) Ghana promises end to black outs. [Online]. Available: http://www.wantedinafrica.com/news/ghana-promises-endto-black-outs/

[121] A. N. Online. (2017) Sa heatwave forces blackouts to cope with electricity demand, angering government. [Online]. Available: http://www.abc.net.au/news/2017-02-08/sa-heatwave-forcesrolling-blackouts-angering-government/8252512

[122] News24. (2014) Tripped coal stations add to load shedding burden. [Online]. Available: http://www.fin24.com/Economy/Trippedcoal-stations-add-to-load-shedding-burden-20141205.

[123 Khalid, A., Javaid, N., Guizani, M., Alhussein, M., Aurangzeb, K. and Ilahi, M., 2018. Towards dynamic coordination among home appliances using multi-objective energy optimization for demand side management in smart buildings. IEEE access, 6, pp.19509-19529.

[124 Khalid, A., Javaid, N., Mateen, A., Khalid, B., Khan, Z.A. and Qasim, U., 2016, July. Demand side management using hybrid bacterial foraging and genetic algorithm optimization techniques. In 2016 10th International Conference on Complex, Intelligent, and Software Intensive Systems (CISIS) (pp. 494-502). IEEE.

[125 Azasoo, J.Q., Kuada, E., Boateng, K.O. and Agyeman, M.O., 2017, June. An algorithm for micro-load shedding in generation constrained electricity distribution network. In 2017 IEEE PES PowerAfrica (pp. 396-401). IEEE.

[126] Azasoo, J.Q., Kanakis, T., Al-Sherbaz, A. and Agyeman, M.O., 2019, April. Improving electricity network efficiency and customer satisfaction in generation constrained power system. In 2019 6th international conference on control, decision and information technologies (CoDIT) (pp. 2010-2015). IEEE.

[127] Azasoo, J.Q., Kanakis, T., Al-Sherbaz, A. and Agyeman, M.O., 2019, August. Optimal demand side management in generation constrained power systems. In 2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI) (pp. 29-36). IEEE.

[128] Azasoo, J.Q., Kanakis, T., Al-Sherbaz, A. and Agyeman, M.O., 2020. Heuristic optimization for microload shedding in generation constrained power systems. IEEE Access, 8, pp.13294-13304.

[129] Tripped Coal Stations Add to Load Shedding Burden, 2014, [online] Available: http://www.fin24.com/Economy/Tripped-coal-stations-add-to-load-shedding-burden-20141205.

[130] Sa Heatwave Forces Blackouts to Cope with Electricity Demand Angering Government, 2017, [online] Available: http://www.abc.net.au/news/2017-02-08/sa-heatwave-forces-rolling-blackouts-angering-government/8252512.

[131] Siddiqui, I.F., Lee, S.U.J., Abbas, A. and Bashir, A.K., 2017. Optimizing lifespan and energy consumption by smart meters in green-cloud-based smart grids. IEEE Access, 5, pp.20934-20945.

[132] Quijano Cetina, R., Roscoe, A.J. and Wright, P.S., Challenges for Smart Electricity Meters due to Dynamic Power Quality Conditions of the Grid.

[133] Mahmood, D., Javaid, N., Alrajeh, N., Khan, Z.A., Qasim, U., Ahmed, I. and Ilahi, M., 2016. Realistic scheduling mechanism for smart homes. Energies, 9(3), p.202.

[134] Pipattanasomporn, M., Kuzlu, M. and Rahman, S., 2012. An algorithm for intelligent home energy management and demand response analysis. IEEE Transactions on Smart Grid, 3(4), pp.2166-2173.

[135] Lin, S.W., Ying, K.C., Chen, S.C. and Lee, Z.J., 2008. Particle swarm optimization for parameter determination and feature selection of support vector machines. Expert systems with applications, 35(4), pp.1817-1824.

[136] Rodrigues, F., Cardeira, C. and Calado, J.M.F., 2014. The daily and hourly energy consumption and load forecasting using artificial neural network method: a case study using a set of 93 households in Portugal. Energy Procedia, 62, pp.220-229.

[137] Butt, F.M., Hussain, L., Mahmood, A. and Lone, K.J., 2021. Artificial Intelligence based accurately load forecasting system to forecast short and medium-term load demands. Mathematical Biosciences and Engineering, 18(1), pp.400-425.

[138] Juan, Y.K., Gao, P. and Wang, J., 2010. A hybrid decision support system for sustainable office building renovation and energy performance improvement. Energy and buildings, 42(3), pp.290-297.

[139] Lazos, D., Sproul, A.B. and Kay, M., 2014. Optimisation of energy management in commercial buildings with weather forecasting inputs: A review. Renewable and Sustainable Energy Reviews, 39, pp.587-603.

[140] Kong, W., Dong, Z.Y., Jia, Y., Hill, D.J., Xu, Y. and Zhang, Y., 2017. Short-term residential load forecasting based on LSTM recurrent neural network. IEEE Transactions on Smart Grid, 10(1), pp.841-851.

[141] Makonin, S., Ellert, B., Bajić, I.V. and Popowich, F., 2016. Electricity, water, and natural gas consumption of a residential house in Canada from 2012 to 2014. Scientific data, 3(1), pp.1-12.

[142] Makonin, S., 2016. Ampds2: the almanac of minutely power dataset (version 2). Harvard Dataverse, p.V2.

[143] Makonin, S., 2016. Ampds2: the almanac of minutely power dataset (version 2). Harvard Dataverse, p.V2.

[144] Kaur, J. and Bala, A., 2019. Predicting power for home appliances based on climatic conditions. International Journal of Energy Sector Management.

[145] Paresh, S., Thokala, N.K. and Chandra, M.G., 2019, November. Electrical Load Disaggregation using a two-stage deep learning approach. In Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (pp. 366-367).

[146] Cottone, P., Gaglio, S., Re, G.L. and Ortolani, M., 2015. User activity recognition for energy saving in smart homes. Pervasive and Mobile Computing, 16, pp.156-170.

[147] López, M., Valero, S., Sans, C. and Senabre, C., 2020. Use of available daylight to improve short-term load forecasting accuracy. Energies, 14(1), p.95.

[148] Tian, W., Song, J. and Li, Z., 2014. Spatial regression analysis of domestic energy in urban areas. Energy, 76, pp.629-640.

[149] Gottwalt, S., Ketter, W., Block, C., Collins, J. and Weinhardt, C., 2011. Demand side management—A simulation of household behavior under variable prices. Energy policy, 39(12), pp.8163-8174.

[150] Rasheed, M.B., Javaid, N., Ahmad, A., Jamil, M., Khan, Z.A., Qasim, U. and Alrajeh, N., 2016. Energy optimization in smart homes using customer preference and dynamic pricing. Energies, 9(8), p.593.

[151] Vellei, M., Le Dréau, J. and Abdelouadoud, S.Y., 2020. Predicting the demand flexibility of wet appliances at national level: The case of France. Energy and Buildings, 214, p.109900.

[152] Zhu, G., Chow, T.T. and Tse, N., 2018. Short-term load forecasting coupled with weather profile generation methodology. Building Services Engineering Research and Technology, 39(3), pp.310-327.

[153] Haq, E.U., Lyu, X., Jia, Y., Hua, M. and Ahmad, F., 2020. Forecasting household electric appliances consumption and peak demand based on hybrid machine learning approach. Energy Reports, 6, pp.1099-1105.

[154] Y Chen, Y., Xu, P., Chu, Y., Li, W., Wu, Y., Ni, L., Bao, Y. and Wang, K., 2017. Short-term electrical load forecasting using the Support Vector Regression (SVR) model to calculate the demand response baseline for office buildings. Applied Energy, 195, pp.659-670.

[155] Dinesh, C., Makonin, S. and Bajić, I.V., 2020. Residential power forecasting based on affinity aggregation spectral clustering. IEEE Access, 8, pp.99431-99444.

[156] Torabi, M., Hashemi, S., Saybani, M.R., Shamshirband, S. and Mosavi, A., 2019. A Hybrid clustering and classification technique for forecasting short-term energy consumption. Environmental progress & sustainable energy, 38(1), pp.66-76.

[157] Khakimova, A., Kusatayeva, A., Shamshimova, A., Sharipova, D., Bemporad, A., Familiant, Y., Shintemirov, A., Ten, V. and Rubagotti, M., 2017. Optimal energy management of a small-size building via hybrid model predictive control. Energy and Buildings, 140, pp.1-8.

[158] Kaur, J. and Bala, A., 2019, December. A hybrid energy management approach for home appliances using climatic forecasting. In Building Simulation (Vol. 12, No. 6, pp. 1033-1045). Tsinghua University Press.

[159] Divina, F., Gilson, A., Goméz-Vela, F., García Torres, M. and Torres, J.F., 2018. Stacking ensemble learning for short-term electricity consumption forecasting. Energies, 11(4), p.949.

[160] Muralitharan, K., Sakthivel, R. and Vishnuvarthan, R., 2018. Neural network based optimization approach for energy demand prediction in smart grid. Neurocomputing, 273, pp.199-208.

[161] Dong, B., Li, Z., Rahman, S.M. and Vega, R., 2016. A hybrid model approach for forecasting future residential electricity consumption. Energy and Buildings, 117, pp.341-351.

[162] P.-Y. Yin and C.-H. Chao, "Automatic selection of fittest energy demand predictors based on cyber swarm optimization and reinforcement learning," Applied Soft Computing, vol. 71, pp. 152–164, 2018.

[163] Candanedo, L.M., Feldheim, V. and Deramaix, D., 2017. Data driven prediction models of energy use of appliances in a low-energy house. Energy and buildings, 140, pp.81-97.

[164] Wang, Z., Wang, Y., Zeng, R., Srinivasan, R.S. and Ahrentzen, S., 2018. Random Forest based hourly building energy prediction. Energy and Buildings, 171, pp.11-25.

[165] Wei, Y., Zhang, X., Shi, Y., Xia, L., Pan, S., Wu, J., Han, M. and Zhao, X., 2018. A review of data-driven approaches for prediction and classification of building energy consumption. Renewable and Sustainable Energy Reviews, 82, pp.1027-1047.

[166Subbiah, R., Pal, A., Nordberg, E.K., Marathe, A. and Marathe, M.V., 2017. Energy demand model for residential sector: a first principles approach. IEEE Transactions on Sustainable Energy, 8(3), pp.1215-1224.

[167] Gupta, N., Ahuja, N., Malhotra, S., Bala, A. and Kaur, G., 2017. Intelligent heart disease prediction in cloud environment through ensembling. Expert Systems, 34(3), p.e12207.

[168] Sharma, N., Sharma, P., Irwin, D. and Shenoy, P., 2011, October. Predicting solar generation from weather forecasts using machine learning. In 2011 IEEE international conference on smart grid communications (SmartGridComm) (pp. 528-533). IEEE.

[169] Ha, D.L., Joumaa, H., Ploix, S. and Jacomino, M., 2012. An optimal approach for electrical management problem in dwellings. Energy and Buildings, 45, pp.1-14.

[170] Ardakani, F.J. and Ardehali, M.M., 2014. Long-term electrical energy consumption forecasting for developing and developed economies based on different optimized models and historical data types. Energy, 65, pp.452-461.

[171] Al-Shetwi, A.Q., Hannan, M.A., Jern, K.P., Mansur, M. and Mahlia, T.M.I., 2020. Grid-connected renewable energy sources: Review of the recent integration requirements and control methods. Journal of Cleaner Production, 253, p.119831..

[172] Sinsel, S.R., Riemke, R.L. and Hoffmann, V.H., 2020. Challenges and solution technologies for the integration of variable renewable energy sources—a review. renewable energy, 145, pp.2271-2285.

[173] Chen, X., Cao, W., Zhang, Q., Hu, S. and Zhang, J., 2020. Artificial intelligence-aided model predictive control for a grid-tied wind-hydrogen-fuel cell system. IEEE Access, 8, pp.92418-92430.

[174] Ahmad, T., Zhang, H. and Yan, B., 2020. A review on renewable energy and electricity requirement forecasting models for smart grid and buildings. Sustainable Cities and Society, 55, p.102052.

[175] Bunodiere, A. and Lee, H.S., 2020. Renewable Energy Curtailment: Prediction Using a Logic-Based Forecasting Method and Mitigation Measures in Kyushu, Japan. Energies, 13(18), p.4703.

[176 Tharani, K., Kumar, N., Srivastava, V., Mishra, S. and Pratyush Jayachandran, M., 2020. Machine learning models for renewable energy forecasting. Journal of Statistics and Management Systems, 23(1), pp.171-180.

[177 Cai, H., Jia, X., Feng, J., Li, W., Hsu, Y.M. and Lee, J., 2020. Gaussian Process Regression for numerical wind speed prediction enhancement. Renewable energy, 146, pp.2112-2123.

[178] Kabir, M.A. and Chowdhury, A.H., 2020. A dynamic-adaptive load shedding methodology to improve frequency resilience of power systems. International Journal of Electrical Power & Energy Systems, 122, p.106169.

[179 Małkowski, R. and Nieznański, J., 2020. Underfrequency load shedding: an innovative algorithm based on fuzzy logic. Energies, 13(6), p.1456.

[180 Shi, Q., Li, F., Olama, M., Dong, J., Xue, Y., Starke, M., Winstead, C. and Kuruganti, T., 2021. Network reconfiguration and distributed energy resource scheduling for improved distribution system resilience. International Journal of Electrical Power & Energy Systems, 124, p.106355.

[128] Azasoo, J.Q., Kanakis, T., Al-Sherbaz, A. and Agyeman, M.O., 2020. Heuristic optimization for microload shedding in generation constrained power systems. IEEE Access, 8, pp.13294-13304.

[181] Jabian, M.E., Funaki, R. and Murata, J., 2020. Consumer appliance-level load shedding optimisation for real-time application. The Journal of Engineering, 2020(11), pp.1103-1111.

[182] Yu, X., Jin, L., Wang, Q. and Zhou, D., 2019. Optimal path for controlling pollution emissions in the Chinese electric power industry considering technological heterogeneity. Environmental Science and Pollution Research, 26(11), pp.11087-11099.

[184] Chen, W., Zhou, K. and Yang, S., 2017. Evaluation of China's electric energy efficiency under environmental constraints: A DEA cross efficiency model based on game relationship. Journal of Cleaner Production, 164, pp.38-44.

[185] IPCC, C.C., 2014. Impacts, Adaptation and Vulnerability: Regional Aspects.

[186] Friedman, J.H., 1991. Multivariate adaptive regression splines. The annals of statistics, 19(1), pp.1-67.

[187 Al-Qahtani, F.H. and Crone, S.F., 2013, August. Multivariate k-nearest neighbour regression for time series data—A novel algorithm for forecasting UK electricity demand. In The 2013 international joint conference on neural networks (IJCNN) (pp. 1-8). IEEE.

[188] Vapnik, V., 1999. The nature of statistical learning theory. Springer science & business media.

[189] Biau, G. and Scornet, E., 2016. A random forest guided tour. Test, 25(2), pp.197-227.

[190] McCulloch, W.S. and Pitts, W., 1943. A logical calculus of the ideas immanent in nervous activity. The bulletin of mathematical biophysics, 5(4), pp.115-133.

[191] Breiman, L., Friedman, J.H., Olshen, R.A. and Stone, C.J., 2017. Classification and regression trees. Routledge.

[192] Gajowniczek, K. and Ząbkowski, T., 2017. Electricity forecasting on the individual household level enhanced based on activity patterns. PloS one, 12(4), p.e0174098.

[193] Bovet, D.P., Crescenzi, P. and Bovet, D., 1994. Introduction to the Theory of Complexity (Vol. 7). London: Prentice Hall.

[194] Roos, M. and Rothe, J., 2010. Introduction to computational complexity. Institut fur Informatik, Dusseldorf, Germany, Tech. Rep.

[195] Chen, F., Zhou, J., Wang, C., Li, C. and Lu, P., 2017. A modified gravitational search algorithm based on a non-dominated sorting genetic approach for hydro-thermal-wind economic emission dispatching. Energy, 121, pp.276-291.

Appendix 1

The demands of the 26 households

Table 5 Grouped Microloads Extracts

id	grid_id	meter_id	load_id	voltage	load	current	app_power	rea_power	status
1	1	1	1	251	0.4	1.594	0.4	0.4	On
2	1	1	2	263	0.7	2.662	0.7	0.7	On
3	1	1	3	218	6.5	29.817	6.5	6.5	On
4	1	1	4	240	1.8	7.5	1.8	1.8	On
5	1	1	5	256	8	31.25	8	8	On
6	1	1	6	237	0.4	1.688	0.4	0.4	On
7	1	2	1	233	0.6	2.575	0.6	0.6	On
8	1	2	2	225	1.5	6.667	1.5	1.5	On
9	1	2	3	232	10.1	43.534	10.1	10.1	On
10	1	2	4	242	6.2	25.62	6.2	6.2	On
11	1	2	5	239	12.1	50.628	12.1	12.1	On
12	1	2	6	237	6.4	27.004	6.4	6.4	On
13	1	3	1	233	0.2	0.858	0.2	0.2	On
14	1	3	2	225	1.5	6.667	1.5	1.5	On
15	1	3	3	232	7	30.172	7	7	On

Table 6 UnGrouped Microloads Extracts

id	grid_id	meter_id	load_id	voltage	load	current	app_power	rea_power	priority_id	status
1	1	1	1	251	0.32379	1.29	0.32379	0.32379	35	On
2	1	1	2	263	0.13676	0.52	0.13676	0.13676	34	On
3	1	1	3	218	0.01744	0.08	0.01744	0.01744	33	On
4	1	1	4	240	0.156	0.65	0.156	0.156	32	On
5	1	1	5	256	0.00256	0.01	0.00256	0.00256	31	On
6	1	1	6	237	0.46452	1.96	0.46452	0.46452	30	On
7	1	1	7	233	0.01631	0.07	0.01631	0.01631	29	On
8	1	1	8	225	0.018	0.08	0.018	0.018	28	On
9	1	1	9	232	0	0	0	0	27	On
10	1	1	10	242	0.10406	0.43	0.10406	0.10406	26	On
11	1	1	11	239	0	0	0	0	25	On
12	1	1	12	237	0	0	0	0	24	On
13	1	1	13	233	0	0	0	0	23	On
14	1	1	14	225	1.76175	7.83	1.76175	1.76175	22	On
15	1	1	15	232	3.02528	13.04	3.02528	3.02528	21	On
16	1	1	16	242	0	0	0	0	20	On
17	1	1	17	218	1.61102	7.39	1.61102	1.61102	19	On
18	1	1	18	240	0	0	0	0	18	On
19	1	1	19	256	0.08448	0.33	0.08448	0.08448	17	On
20	1	1	20	237	0	0	0	0	16	On
21	1	1	21	233	0	0	0	0	15	On
22	1	1	22	225	1.467	6.52	1.467	1.467	14	On
23	1	1	23	232	0	0	0	0	13	On
24	1	1	24	242	0.02662	0.11	0.02662	0.02662	12	On
25	1	1	25	239	0.20554	0.86	0.20554	0.20554	11	On
26	1	1	26	237	4.12143	17.39	4.12143	4.12143	10	On

27	1	1	27	233	2.53271	10.87	2.53271	2.53271	9	On
28	1	1	28	225	0.97875	4.35	0.97875	0.97875	8	On
29	1	1	29	251	0	0	0	0	7	On
30	1	1	30	263	0	0	0	0	6	On
31	1	1	31	218	0	0	0	0	5	On
32	1	1	32	240	0.5208	2.17	0.5208	0.5208	4	On
33	1	1	33	256	0	0	0	0	3	On
34	1	1	34	237	0.41238	1.74	0.41238	0.41238	2	On
35	1	1	35	233	0	0	0	0	1	On
36	1	2	1	225	0.387	1.72	0.387	0.387	35	On
37	1	2	2	232	0.18096	0.78	0.18096	0.18096	34	On
38	1	2	3	242	0.02904	0.12	0.02904	0.02904	33	On
39	1	2	4	239	0.15535	0.65	0.15535	0.15535	32	On
40	1	2	5	237	0.00474	0.02	0.00474	0.00474	31	On
41	1	2	6	233	0.91336	3.92	0.91336	0.91336	30	Off
42	1	2	7	225	0.0315	0.14	0.0315	0.0315	29	On
43	1	2	8	232	0.03712	0.16	0.03712	0.03712	28	On
44	1	2	9	242	0.10406	0.43	0.10406	0.10406	27	On
45	1	2	10	218	0.18748	0.86	0.18748	0.18748	26	On
46	1	2	11	240	0.0144	0.06	0.0144	0.0144	25	On
47	1	2	12	256	0.03328	0.13	0.03328	0.03328	24	On
48	1	2	13	237	1.44333	6.09	1.44333	1.44333	23	Off
49	1	2	14	233	1.82439	7.83	1.82439	1.82439	22	Off
50	1	2	15	225	2.934	13.04	2.934	2.934	21	Off

Appendix 2

Forecasting Data

Table 7 One-Hour Extract from Weather Data

Date/Time	Temp (C)	Dew Point Temp (C)	Rel Hum (%)	Wind Dir (10s deg)	Wind Spd (km/h)	Visibility (km)	Stn Press (kPa)
01/01/14 00:00	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:01	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:02	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:03	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:04	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:05	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:06	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:07	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:08	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:09	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:10	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:11	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:12	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:13	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:14	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:15	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:16	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:17	5.2	4.9	98	9	8	0.4	102.88

01/01/14 00:18	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:19	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:20	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:21	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:22	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:23	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:24	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:25	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:26	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:27	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:28	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:29	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:30	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:31	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:32	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:33	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:34	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:35	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:36	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:37	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:38	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:39	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:40	5.2	4.9	98	9	8	0.4	102.88

01/01/14 00:41	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:42	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:43	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:44	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:45	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:46	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:47	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:48	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:49	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:50	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:51	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:52	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:53	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:54	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:55	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:56	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:57	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:58	5.2	4.9	98	9	8	0.4	102.88
01/01/14 00:59	5.2	4.9	98	9	8	0.4	102.88

Table 8 One-Hour Extract from Microload Consumption Data

Date/ Time	B1E (w)	B2E (w)	BME (w)	CDE (w)	CWE (w)	DNE (w)	DWE (w)	EBE (w)	EQE (w)	FGE (w)	FRE (w)	GRE (w)	HPE (w)	HTE (w)	OFE (w)	OUE (w)	RSE (w)	TVE (w)	UTE (w)	WOE (w)
01/01/14 00:00	0	55	0	0	0	0	0	0	39	0	103	0	38	5	19	0	63	22	51	0
01/01/14 00:01	0	56	0	0	0	0	0	0	38	0	103	0	38	5	19	0	63	22	51	0
01/01/14 00:02	0	56	0	0	0	0	0	0	38	0	102	2	38	5	19	0	63	22	51	0
01/01/14 00:03	0	56	0	0	0	0	0	0	40	0	103	0	39	5	19	0	61	21	52	0
01/01/14 00:04	0	55	0	0	0	0	0	0	38	0	103	0	37	5	19	0	63	21	51	0
01/01/14 00:05	0	55	0	0	0	0	0	0	38	0	103	2	37	5	19	0	59	21	51	0
01/01/14 00:06	0	55	0	0	0	0	0	0	41	0	102	2	38	5	19	0	61	21	51	0
01/01/14 00:07	0	55	0	0	0	0	0	0	38	0	103	2	38	5	19	0	63	22	51	0
01/01/14 00:08	0	55	0	0	0	0	0	0	38	0	103	0	37	5	19	0	63	22	51	0

01/01/14 00:09	0	56	0	0	0	0	0	0	44	0	103	0	37	5	36	0	217	22	51	0
01/01/14 00:10	0	55	0	0	0	0	0	0	38	0	103	0	38	5	20	0	196	22	51	0
01/01/14 00:11	0	54	0	0	0	0	0	0	38	0	103	0	38	5	19	0	191	22	51	0
01/01/14 00:12	0	55	0	0	0	0	0	0	38	0	103	0	37	5	19	0	191	21	51	0
01/01/14 00:13	0	55	265	0	0	0	0	0	38	0	102	2	36	5	19	0	191	22	51	0
01/01/14 00:14	0	54	0	0	0	0	0	0	38	0	103	0	38	5	67	0	191	22	51	0
01/01/14 00:15	0	55	0	0	0	0	0	0	38	0	103	2	38	5	67	0	189	23	51	0
01/01/14 00:16	0	55	0	0	0	0	0	0	39	0	102	0	38	5	66	0	191	21	51	0
01/01/14 00:17	0	55	0	0	0	0	0	0	38	0	103	2	38	5	70	0	194	21	51	0
01/01/14 00:18	0	55	0	0	0	0	0	0	38	0	102	0	38	5	68	0	61	22	51	0

01/01/ 14 00:19	0	55	0	0	0	0	0	0	39	0	102	2	38	5	68	0	61	22	51	0
01/01/ 14 00:20	0	55	0	0	0	0	0	0	38	0	103	2	38	5	67	0	61	21	51	0
01/01/ 14 00:21	0	55	0	0	0	0	0	0	38	0	103	2	37	5	67	0	63	22	51	0
01/01/ 14 00:22	0	55	0	0	0	0	0	0	41	0	104	2	37	5	66	0	61	21	51	0
01/01/ 14 00:23	0	55	0	0	0	0	0	0	39	0	103	2	38	5	72	0	61	21	51	0
01/01/ 14 00:24	0	55	0	0	0	0	0	0	39	0	103	0	38	5	66	0	63	21	51	0
01/01/ 14 00:25	0	55	0	0	0	0	0	0	42	0	102	0	38	5	68	0	66	23	51	0
01/01/ 14 00:26	0	55	0	0	0	0	0	0	39	141	103	4	39	5	66	0	61	21	51	0
01/01/ 14 00:27	0	55	0	0	0	0	0	0	38	130	103	0	37	5	66	0	63	22	51	0
01/01/ 14 00:28	0	55	0	0	0	0	0	0	29	128	102	0	38	5	66	0	63	21	51	0

01/01/14 00:29	0	55	0	0	0	0	0	0	38	127	102	4	37	5	65	0	66	22	51	0
01/01/14 00:30	0	55	0	0	0	0	0	0	39	130	103	2	38	5	66	0	61	22	51	0
01/01/14 00:31	0	55	0	0	0	0	0	0	38	127	103	2	38	5	68	0	63	22	51	0
01/01/14 00:32	0	55	0	0	0	0	0	0	39	126	103	0	38	5	66	0	63	22	51	0
01/01/14 00:33	0	55	0	0	0	0	0	0	38	124	103	2	38	5	20	0	207	22	51	0
01/01/14 00:34	0	55	0	0	0	0	0	0	38	125	103	0	38	5	19	0	196	21	51	0
01/01/14 00:35	0	55	0	9	0	0	0	0	39	0	102	0	37	5	19	0	194	22	51	0
01/01/14 00:36	0	54	0	4765	0	0	0	0	38	0	103	0	37	5	19	0	191	22	50	0
01/01/14 00:37	0	55	0	4741	0	0	0	0	38	0	102	0	38	5	19	0	191	22	50	0
01/01/14 00:38	0	54	0	4732	0	0	0	0	39	0	103	4	37	5	19	0	189	21	50	0

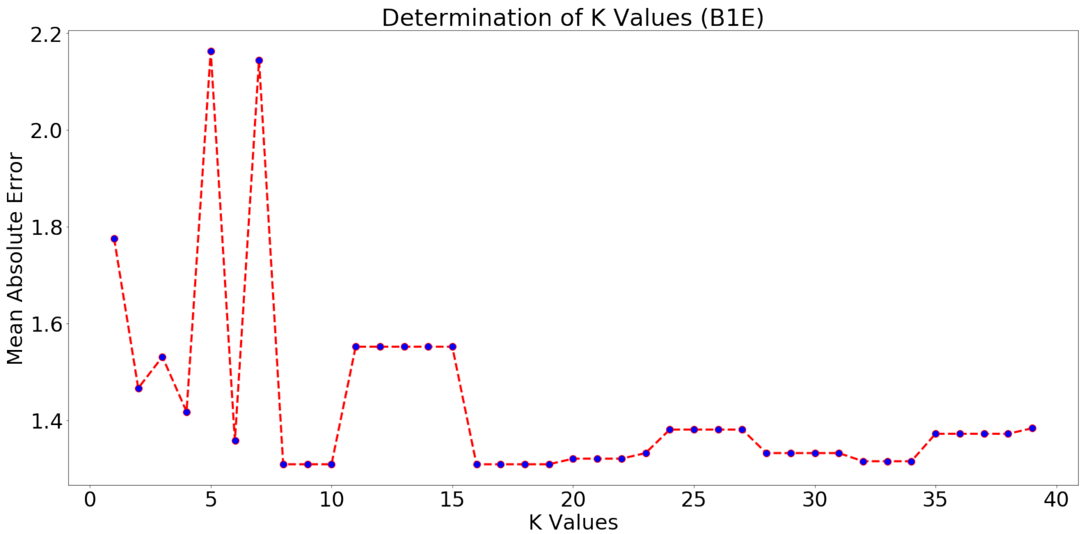
01/01/ 14 00:39	0	54	0	4748	0	0	0	0	38	0	103	2	37	5	19	0	189	22	51	0
01/01/ 14 00:40	0	5	0	4720	0	0	0	0	38	0	102	4	37	5	19	0	189	22	50	0
01/01/ 14 00:41	0	5	0	4725	0	0	0	0	41	0	103	2	38	5	19	0	61	22	50	0
01/01/ 14 00:42	0	5	0	260	0	0	0	0	38	0	103	0	37	5	19	0	66	21	51	0
01/01/ 14 00:43	0	5	0	4742	0	0	0	0	38	0	103	2	37	5	19	0	63	22	51	0
01/01/ 14 00:44	0	5	0	259	0	0	0	0	37	0	103	2	38	5	19	0	63	22	51	0
01/01/ 14 00:45	0	5	0	5041	0	0	0	0	38	0	103	0	37	5	19	0	61	22	51	0
01/01/ 14 00:46	0	5	0	4751	0	0	0	0	38	0	103	2	38	5	19	0	63	22	51	0
01/01/ 14 00:47	0	5	0	260	0	0	0	0	38	0	103	4	38	5	19	0	63	21	51	0
01/01/ 14 00:48	0	5	0	4758	0	0	0	0	38	0	103	0	38	5	19	0	61	21	51	0

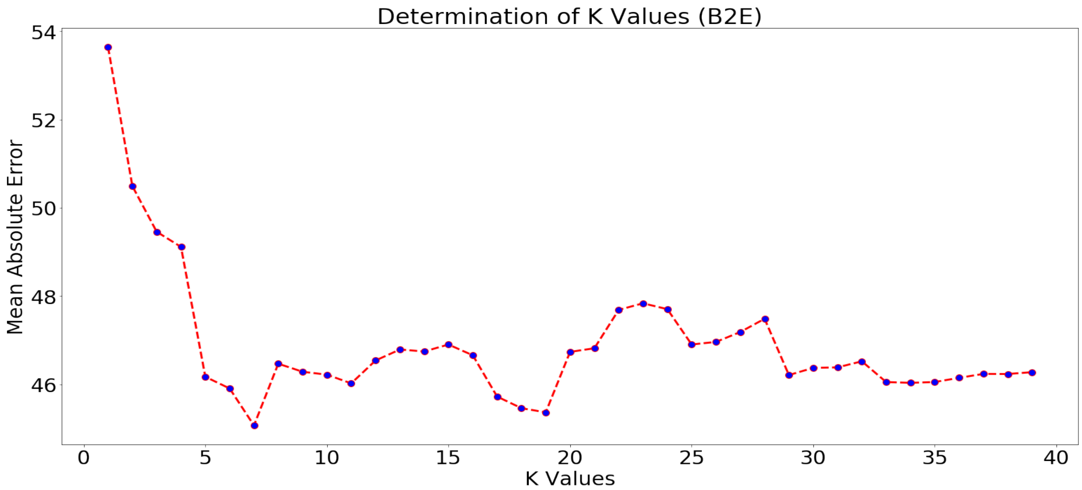
01/01/14 00:49	0	5	0	255	0	0	0	0	38	0	103	0	38	5	19	0	59	21	51	0
01/01/14 00:50	0	5	0	5320	0	0	0	0	38	0	102	2	38	5	19	0	61	22	50	0
01/01/14 00:51	0	4	0	259	0	0	0	0	39	0	102	2	37	5	19	0	61	21	51	0
01/01/14 00:52	0	5	0	252	0	0	0	0	38	0	103	2	38	5	19	0	61	22	51	0
01/01/14 00:53	0	5	0	4749	0	0	0	0	38	0	103	2	37	5	19	0	61	21	51	0
01/01/14 00:54	0	5	0	255	0	0	0	0	39	0	103	0	39	5	19	0	63	21	51	0
01/01/14 00:55	0	5	0	4794	0	0	0	0	38	0	102	0	38	5	19	0	61	22	51	0
01/01/14 00:56	0	5	0	259	0	0	0	0	38	0	103	0	38	5	19	0	212	22	51	0
01/01/14 00:57	0	5	0	253	0	0	0	0	40	0	103	0	38	5	19	0	194	22	51	0
01/01/14 00:58	0	5	0	252	0	0	0	0	38	0	102	2	38	5	19	0	191	21	51	0

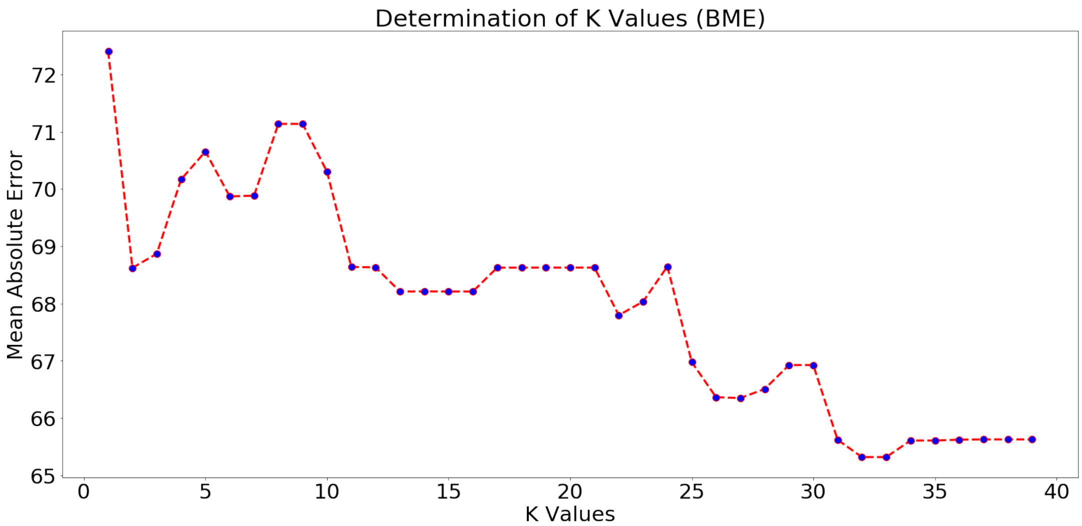
01/01/14 00:59	0	5	0	254	0	0	0	0	38	0	102	0	39	5	20	0	191	21	51	0
01/01/14 01:00	0	5	0	253	0	0	0	0	42	0	102	4	37	5	19	0	189	22	51	0

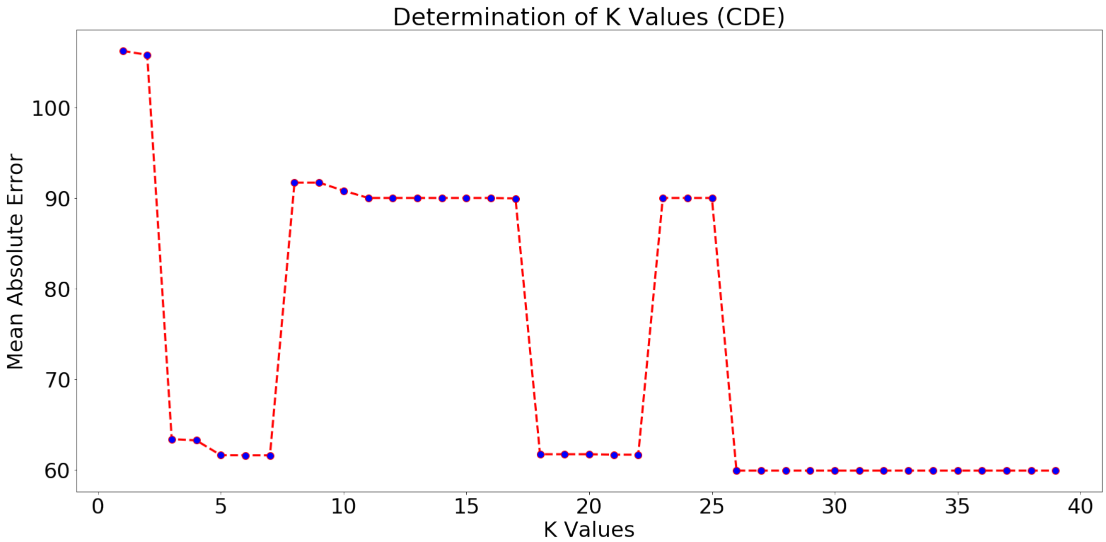
Appendix 3

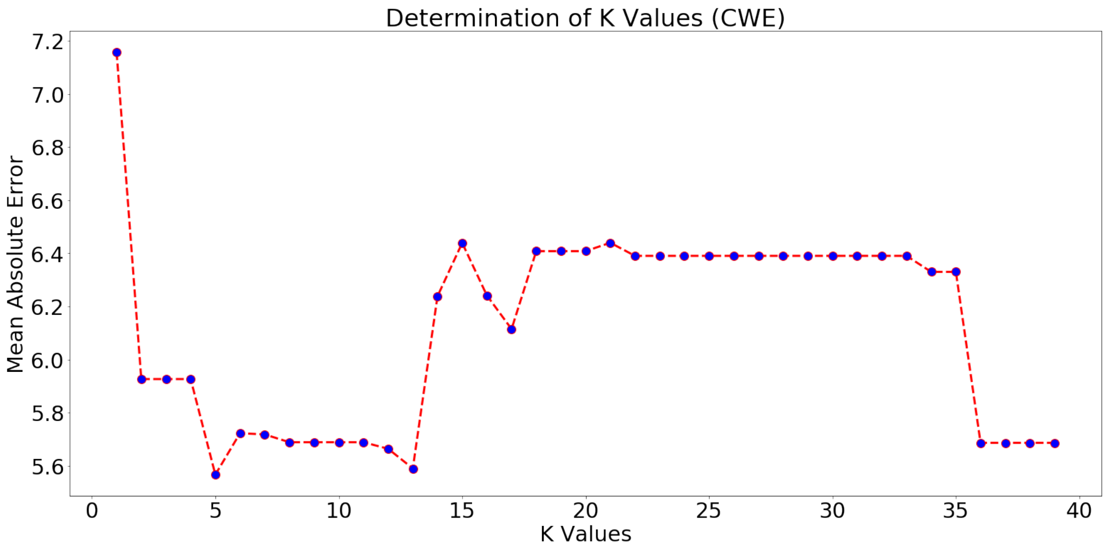
K Values

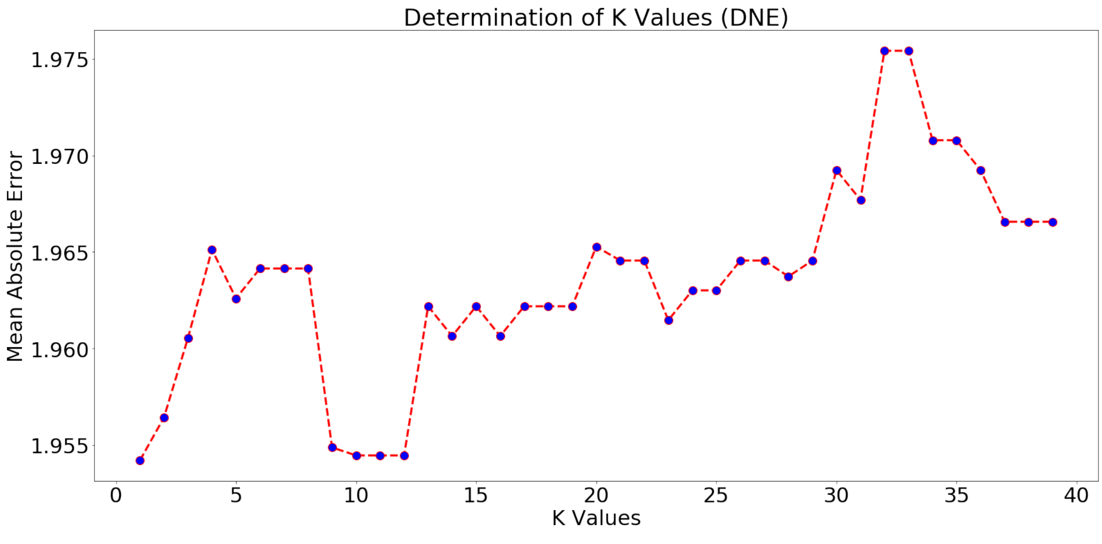


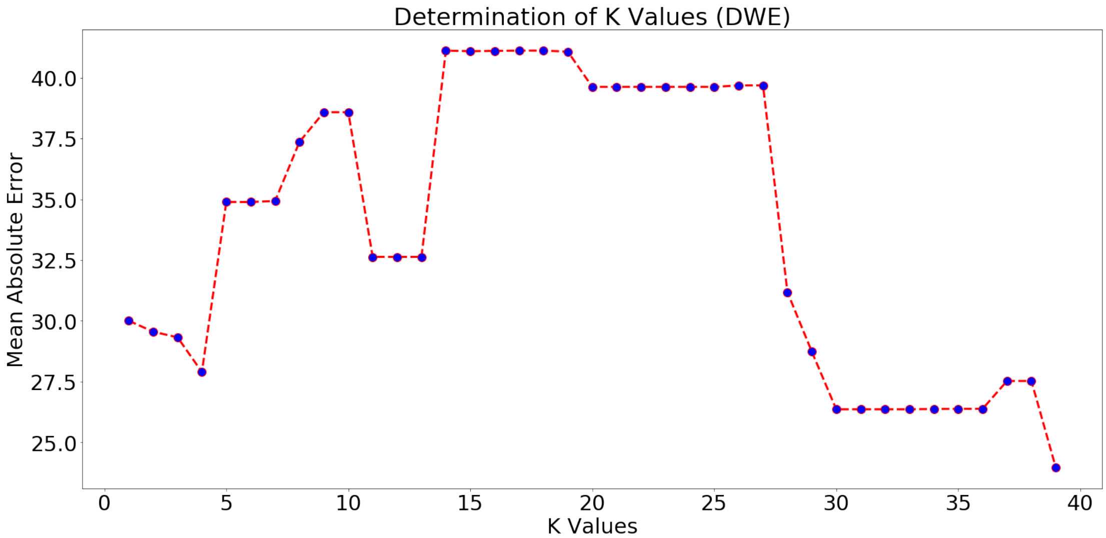


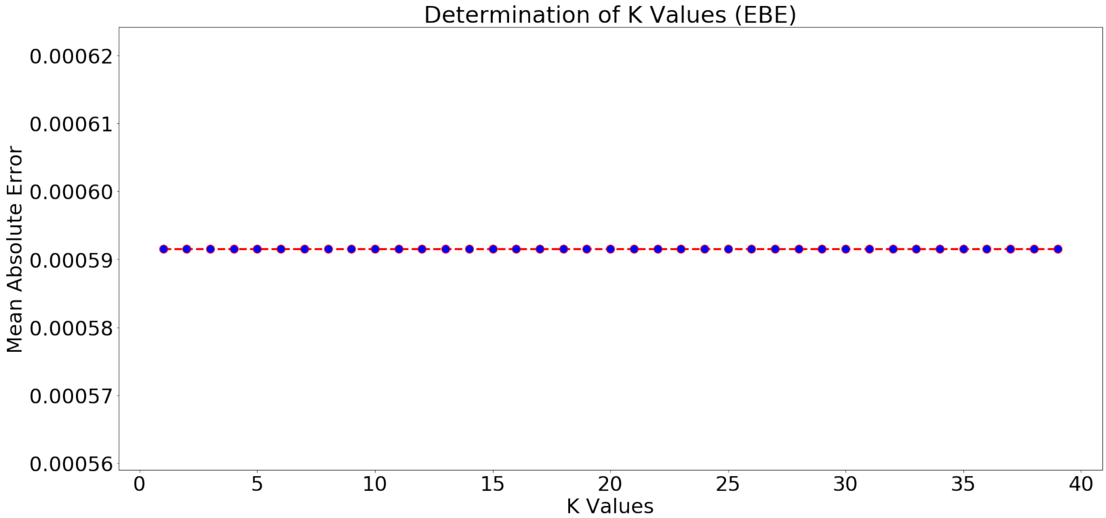


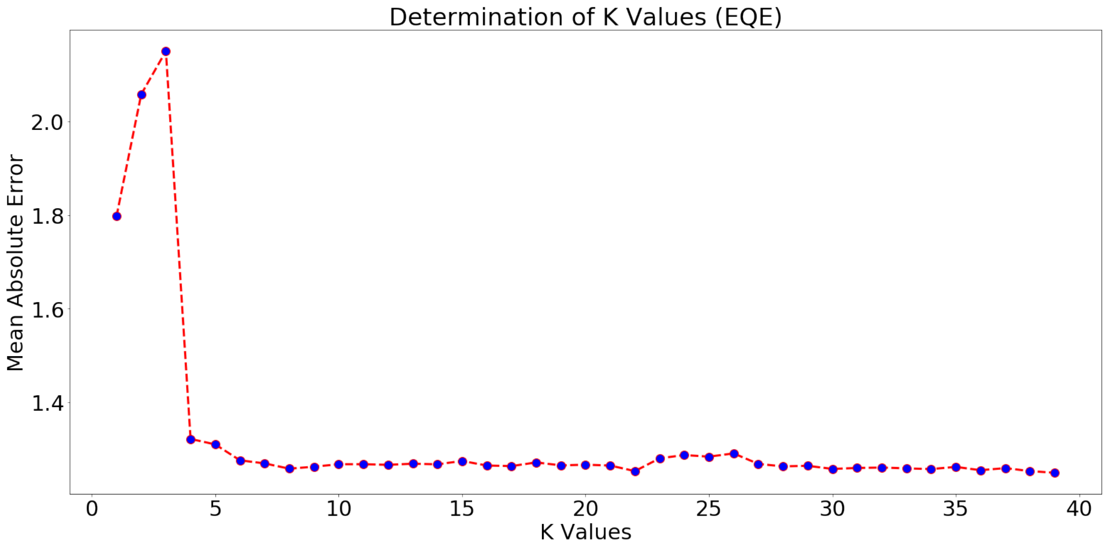

Determination of K Values (CDE)
Mean Absolute Error
K Values

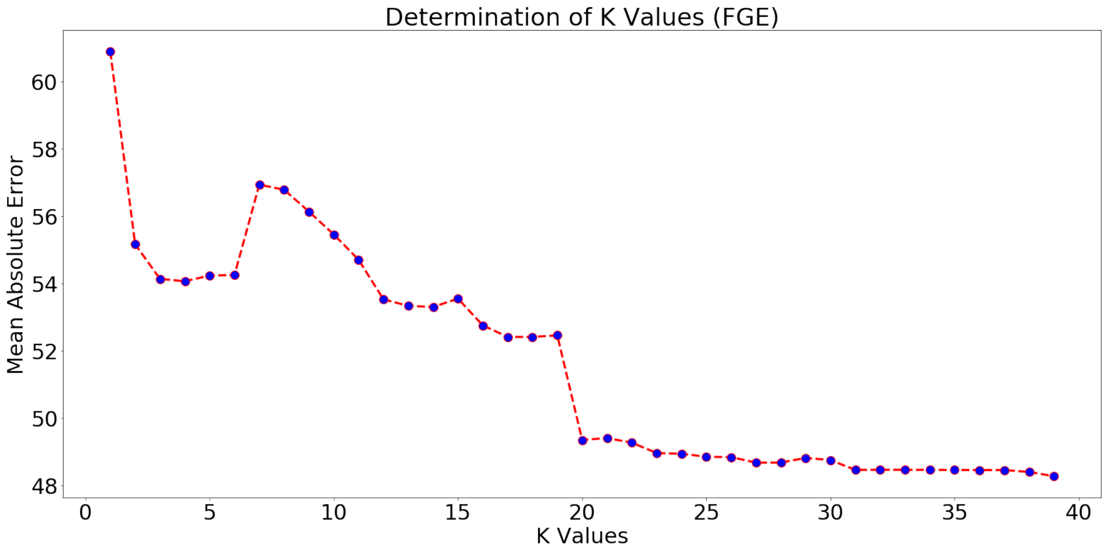

Determination of K Values (CWE)
Mean Absolute Error
K Values

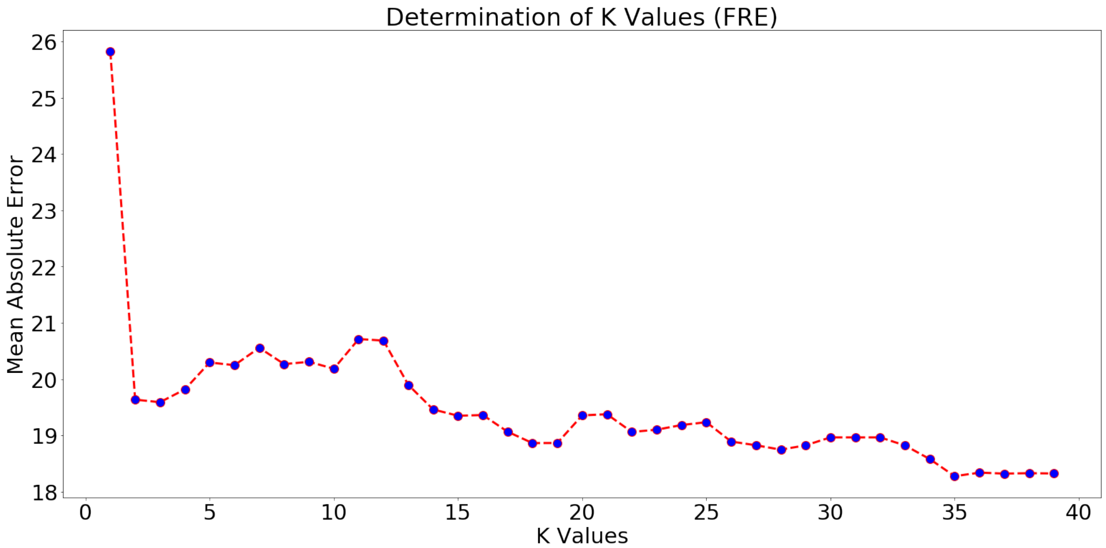

Determination of K Values (DNE)
Mean Absolute Error
K Values

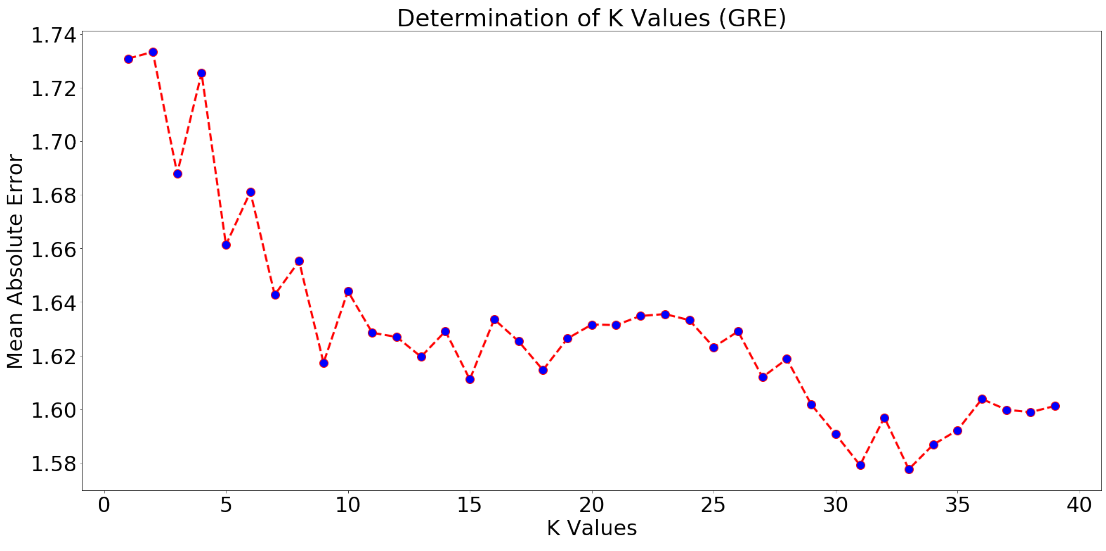

Determination of K Values (DWE)
Mean Absolute Error
25.0
27.5
30.0
32.5
35.0
37.5
40.0
0
5
10
15
20
25
30
35
40
K Values

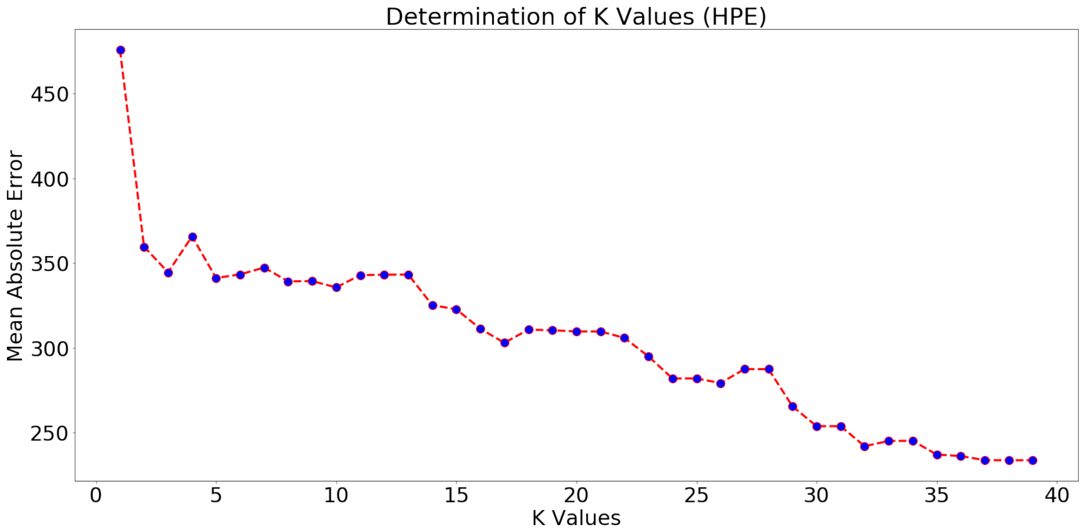

Determination of K Values (EBE)
Mean Absolute Error
0.00056
0.00057
0.00058
0.00059
0.00060
0.00061
0.00062
0
5
10
15
20
25
30
35
40
K Values

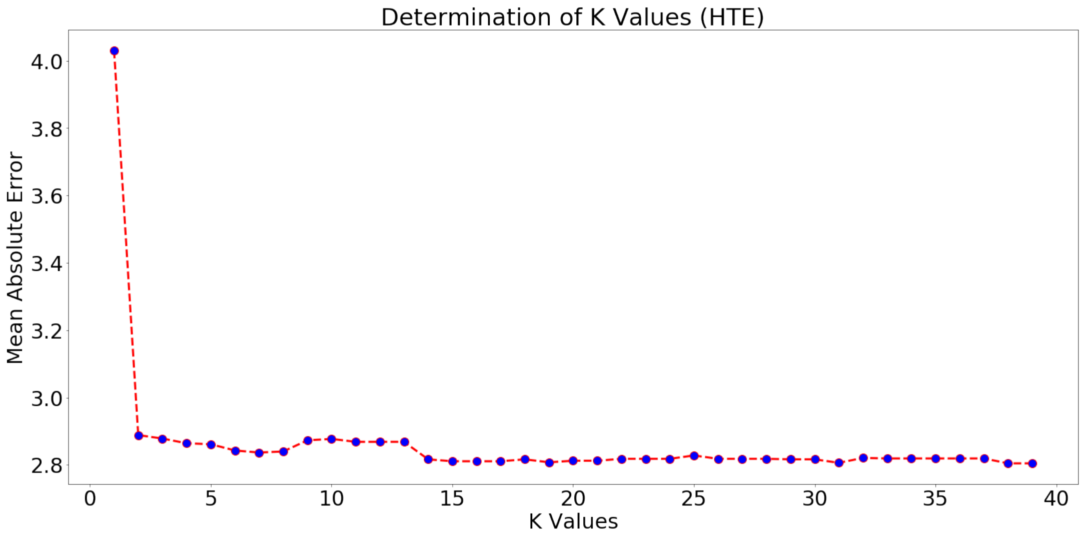

Determination of K Values (EQE)
Mean Absolute Error
1.4
1.6
1.8
2.0
0
5
10
15
20
25
30
35
40
K Values

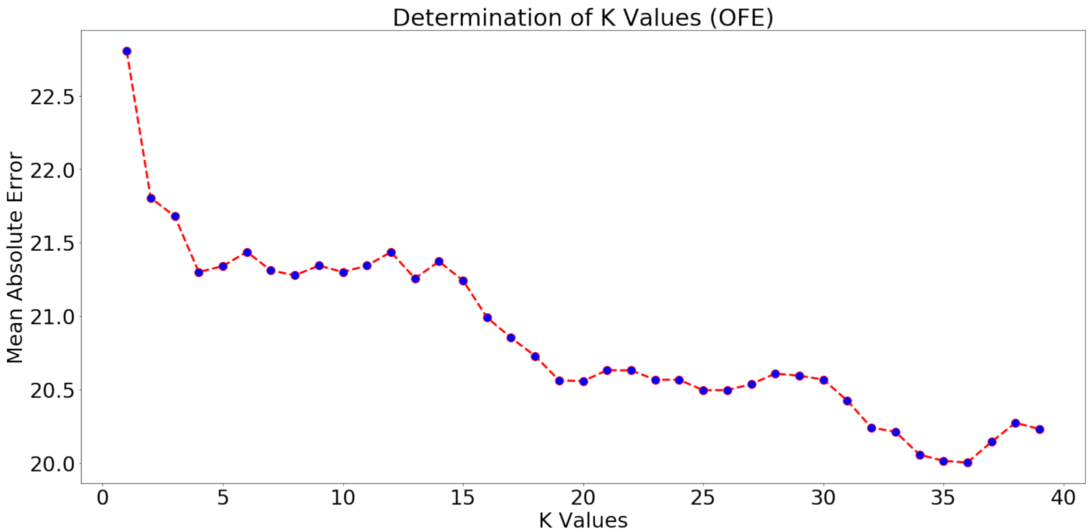

Determination of K Values (FGE)
Mean Absolute Error
K Values

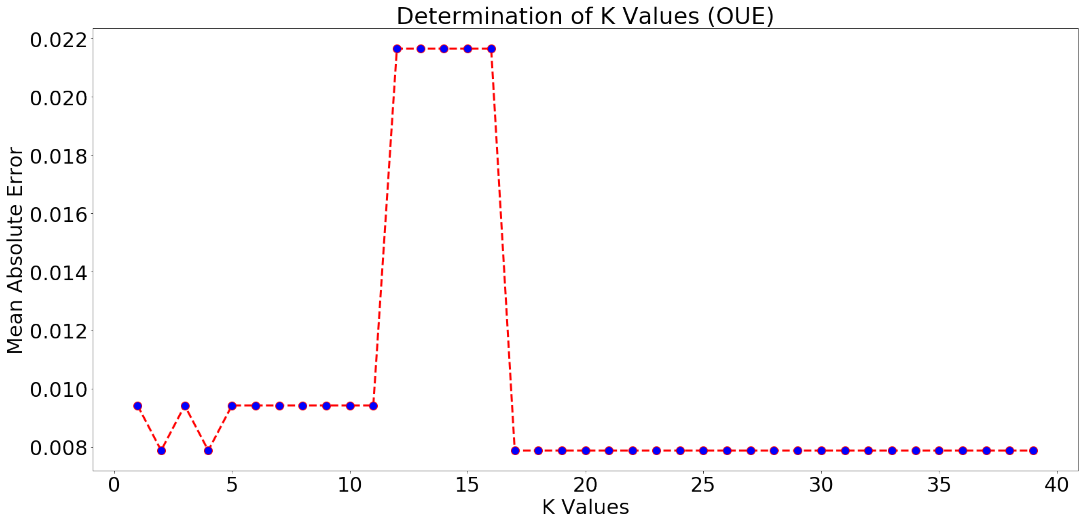

Determination of K Values (FRE)
Mean Absolute Error
K Values

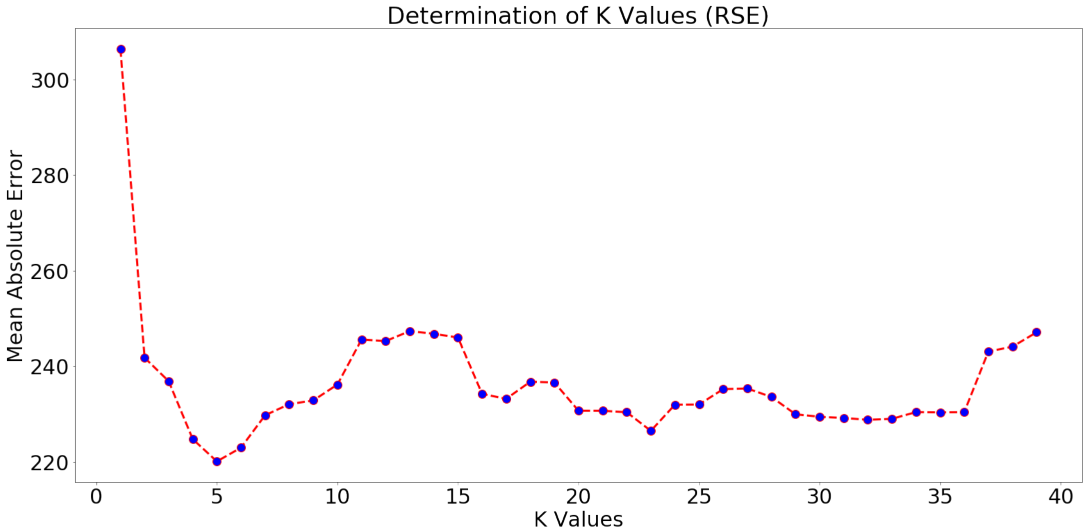

Determination of K Values (GRE)
Mean Absolute Error
K Values

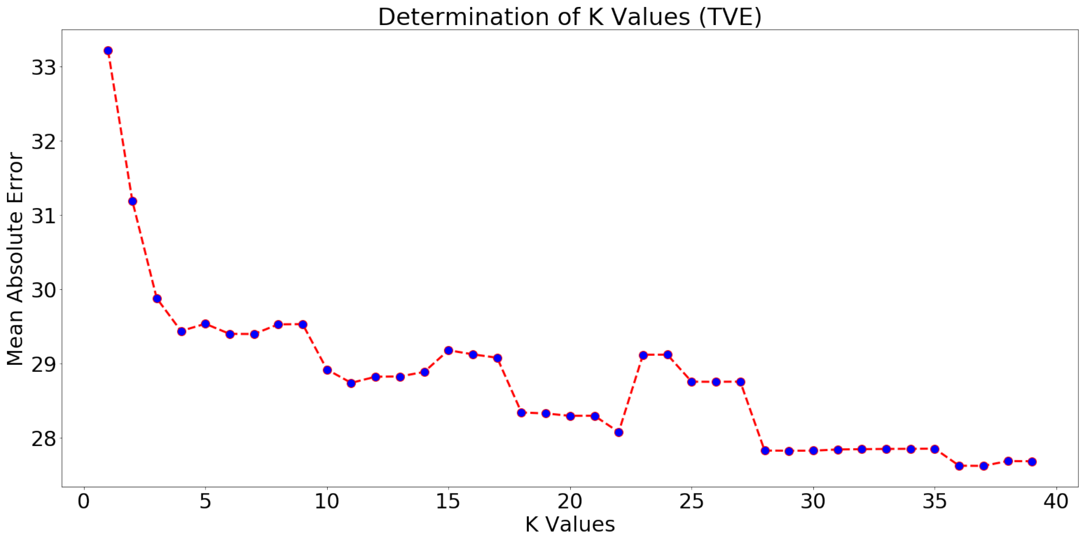

Determination of K Values (HPE)
Mean Absolute Error
K Values
450
400
350
300
250
0
5
10
15
20
25
30
35
40

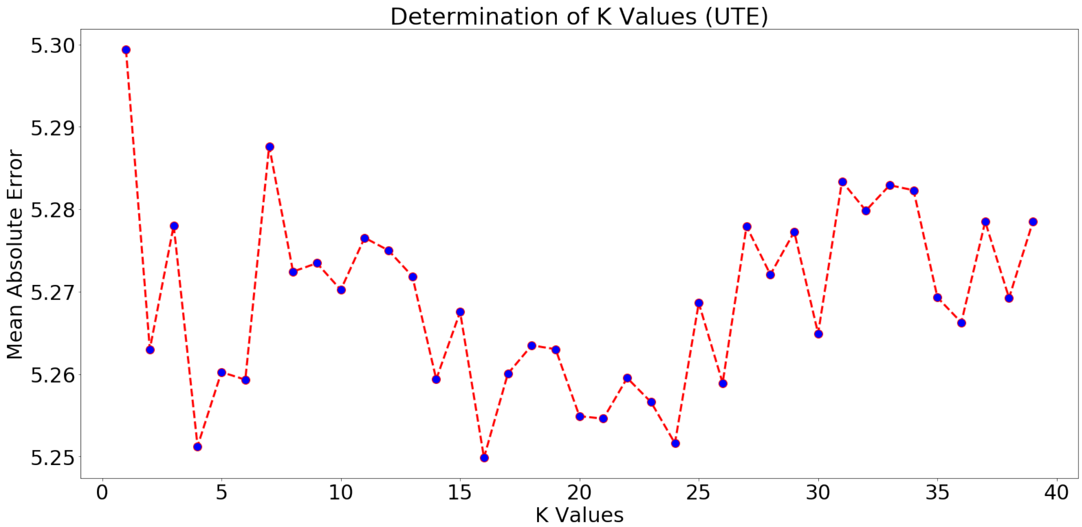

Determination of K Values (HTE)
Mean Absolute Error
K Values
4.0
3.8
3.6
3.4
3.2
3.0
2.8
0
5
10
15
20
25
30
35
40

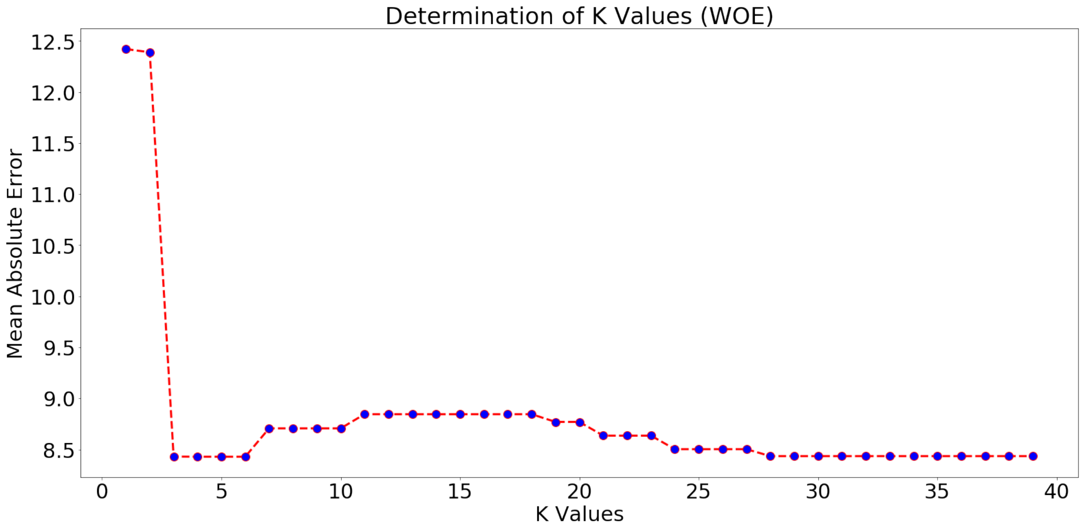

Determination of K Values (OFE)
Mean Absolute Error
K Values
22.5
22.0
21.5
21.0
20.5
20.0
0
5
10
15
20
25
30
35
40

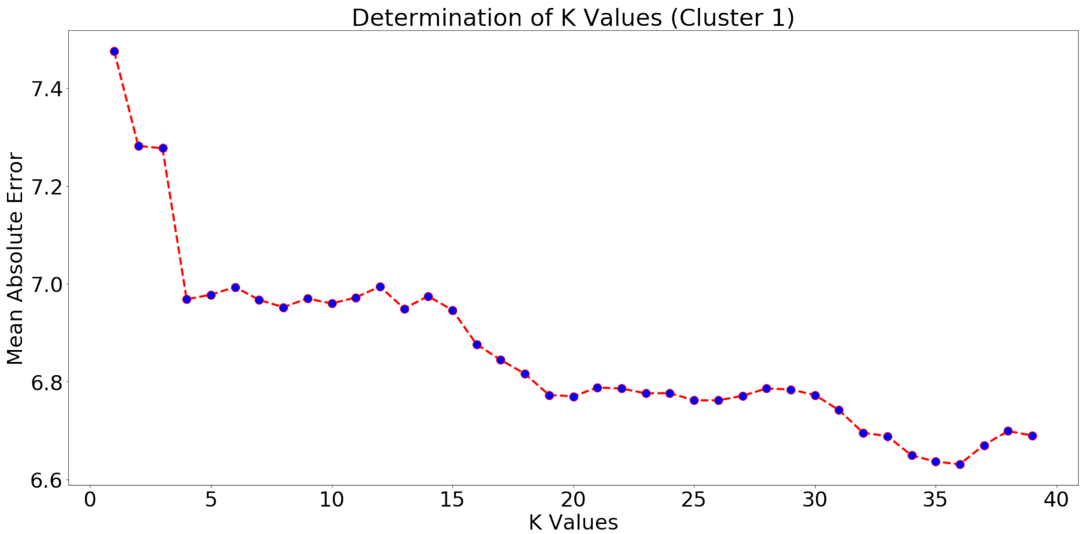

Determination of K Values (OUE)
Mean Absolute Error
K Values

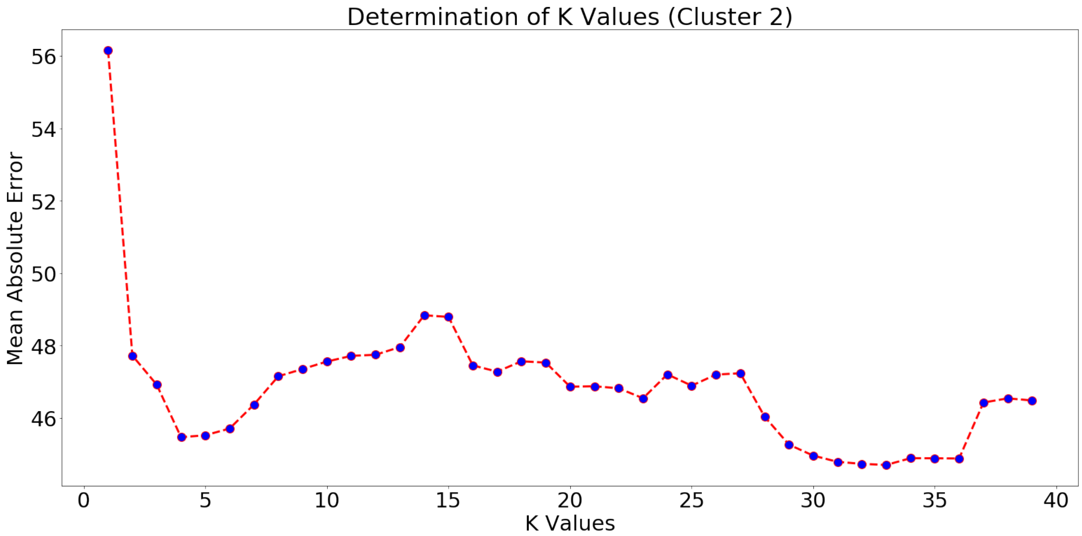

Determination of K Values (RSE)
Mean Absolute Error
K Values

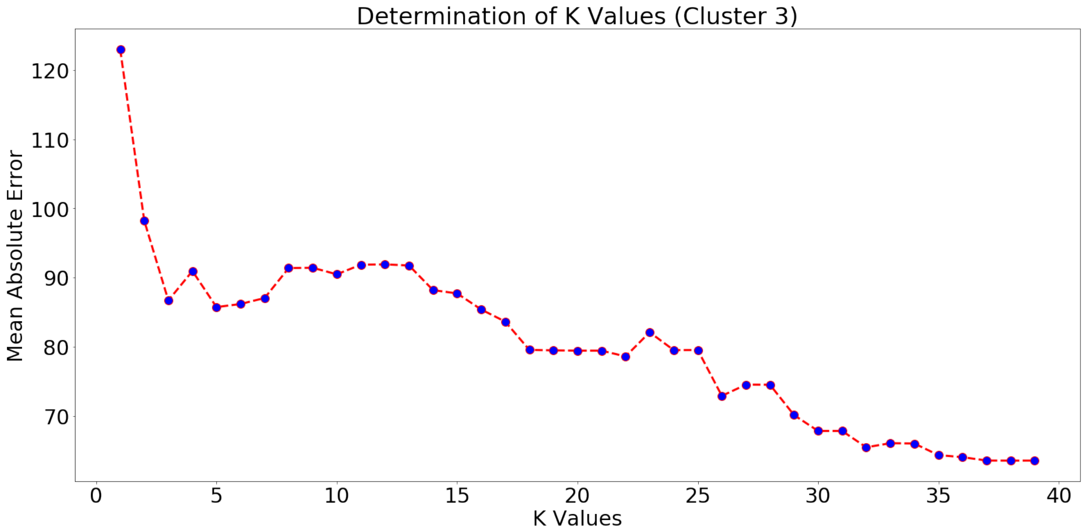

Determination of K Values (TVE)
Mean Absolute Error
K Values


Determination of K Values (UTE)
Mean Absolute Error
K Values
5.30
5.29
5.28
5.27
5.26
5.25
0
5
10
15
20
25
30
35
40


Determination of K Values (WOE)
Mean Absolute Error
K Values
12.5
12.0
11.5
11.0
10.5
10.0
9.5
9.0
8.5
0
5
10
15
20
25
30
35
40


Determination of K Values (Cluster 1)
Mean Absolute Error
K Values
7.4
7.2
7.0
6.8
6.6
0
5
10
15
20
25
30
35
40


Determination of K Values (Cluster 2)
Mean Absolute Error
K Values
56
54
52
50
48
46
0
5
10
15
20
25
30
35
40


Determination of K Values (Cluster 3)
Mean Absolute Error
K Values
120
110
100
90
80
70
0
5
10
15
20
25
30
35
40

Appendix 4

Source Code of the Main Microload Shedding Function

```
from Quarshie import UserLoad
import json as json
from models.Energy import EnergyModel
from models.Load import LoadModel
from models.Reuse import ReuseModel
from multiprocessing import Process

import matplotlib.pyplot as plt

if __name__ == '__main__':
  """"
  # setup database
  energy = EnergyModel()
  load = LoadModel()
  reuse = ReuseModel()



  worker = UserLoad()

  while (True):
    grid_id = input("Select Grid (1-3 for range and 1 for a single grid): ").split('-')
    if int(grid_id[0]) <= 0:
      print("Grid ID can't be 0")
      continue


    meter_id = input("Select Meters (1-3 for range and 1 for a single Smart Meter): ").split('-')
    if int(meter_id[0]) <= 0:
      print("Meter ID can't be 0")
      continue

    shed = input("Enter Percentage to be shed: Whole numbers from 1 to 100: ")

    if int(shed) <= 0:
      print("% Shedding cannot be less than 1")
      continue

    grid_id_start = int(grid_id[0])

    grid_id_end = (int(grid_id[1]) + 1 if len(grid_id) > 1 else int(grid_id_start) + 1)
    meter_id_start = int(meter_id[0])
    meter_id_end = (int(meter_id[1]) + 1 if len(meter_id) > 1 else int(meter_id_start) + 1)
    shed = int(shed)
    break

  print("Grid Id      Meter Id       Total Demand       Expected Demand     Actual Demand  % Shedding")

  for k in range(grid_id_start, grid_id_end):
    koko=0
    for i in range(meter_id_start, meter_id_end):
      koko = worker.calculateDemand(k, i, shed, koko)
```

```
    # show graph
    graph = load.raw_query("select meter_id, total_demand, expected_demand, demand from tbl_load
group by meter_id")

    m_id = []
    t_demand = []
    e_demand = []
    demand = []

    plt.style.use('fast')
    fig, ax = plt.subplots()
    fig.set_facecolor('w')
    ax.patch.set_facecolor('w')
    for i in graph:
        m_id.append(i[0])
        t_demand.append(i[1])
        e_demand.append(i[2])
        demand.append(i[3])

    ax.spines['bottom'].set_color('0.3')
    ax.spines['top'].set_color('0.3')
    ax.spines['right'].set_color('0.3')
    ax.spines['left'].set_color('0.3')

    ax.plot(m_id, t_demand, "p--", label='Total Demand', color="blue", linewidth="2")
    ax.plot(m_id, e_demand, "p-.", label='Traditional Shedding', color="red", linewidth="2")
    ax.plot(m_id, demand, 'p:', label='ERPBUmL Shedding', color="green", linewidth="2")

    plt.legend(loc='upper left', fontsize='small', ncol=3, facecolor='w')
    plt.title(str(shed) + "% Load Shedding", fontsize=11, fontweight='bold')
    plt.xlabel('Smart Meters (SM)', fontsize=10, fontweight='bold')
    plt.ylabel('Demand (KW)', fontsize=10, fontweight='bold')
    plt.xticks(m_id)
    plt.subplots_adjust(top=0.96, left=0.05, right=0.99)
    plt.show()
```

Source Code of the Quarshie Function

```
# Smart Grid
koko=0
from models.Energy import EnergyModel
from models.Load import LoadModel
from models.Reuse import ReuseModel

class UserLoad:
    def __init__(self):
        self.max_voltage = 240
        self.smarID = 0
        self.meterID = 0
        self.Load_ID = 0
        self.Load = 0
        self.priority = 0
        self.status = 'On'
        self.pf = 0.8
        self.Voltage = 0
        self.total_load = 0

        self.load = LoadModel()
```

```
        self.energy_table = EnergyModel()
        self.reuse = ReuseModel()

    def createNewLoad(self, smartID, meterID, Load_ID, watt, priority, state):
        min_ = self.max_voltage - (10 / 100) * self.max_voltage
        max_ = self.max_voltage + (10 / 100) * self.max_voltage
        self.Voltage = np.random.randint(min_, max_, 1)
        self.smarID = smartID
        self.priority = priority
        self.meterID = meterID
        self.Load_ID = Load_ID
        self.Load = watt / 1000.0
        self.current = self.currentCalculation()
        self.reactivePower = self.Voltage * self.current
        self.activePower = self.Voltage * self.current
        self.state = state
        self.excess= 0


    def currentCalculation(self):
        return (self.Load / (self.Voltage))

    def showGridLoad(self, gridId):
        load = self.energy_table.raw_query(
            "select sum(load) as total_load, sum(current) as total_curr from " +
self.energy_table.gettableName() + " where grid_id =" + gridId)
        if len(load) == 0:
            print('Data Does not Exist')
        else:
            print(load)
            self.total_load = load[0]['total_load']
            self.current = load[0]['total_curr']
            print('Total Load of Grid ID {} = {} KW'.format(gridId, self.total_load))

    def showMeterLoad(self, gridId, meterId):
        load = self.energy_table.raw_query(
            "select sum(load) as total_load, sum(current) as total_curr from " +
self.energy_table.gettableName() + " where grid_id = " + gridId + " and meter_id = " + meterId)
        if len(load) == 0:
            print('Data Does not Exist')
        else:
            print(load)
            self.total_load = load[0]['total_load']
            self.current = load[0]['total_curr']
            print('Total Load of Grid ID {},Meter ID {} = {} KW'.format(gridId, meterId, self.total_load))

    def showUserLoad(self, gridId, meterId, loadId):
        load = self.energy_table.raw_query(
            "select sum(load) as total_load, sum(current) as total_curr from " +
self.energy_table.gettableName() +
            " where grid_id = " + gridId + " and meter_id = " + meterId + " load_id = " + loadId)
        if len(load) == 0:
            print('Data Does not Exist')
        else:
            self.total_load = load[0]['total_load']
            self.current = load[0]['total_curr']
            print('Total Load of Grid ID {}, Meter ID {}, Load ID {} = {} KW'.format(gridId, meterId, loadId,
                                                                    self.total_load))

    def knapsack(self, p, w, e):
```

```
        p_sort, w_sort = (list(t) for t in zip(*sorted(zip(p, w))))

        prior = p_sort
        weight = w_sort
        d = 0
        state = []
        for i in range(len(weight)):
            d = d + weight[i]
            if d <= e:
                state.append(prior[i])
            else:
                d = d - weight[i]

        return d, state

    def calculateDemand(self, gridId, meterId, shed, koko):

        newkoko = koko
        where_clause = " where grid_id=" + str(gridId) + " and meter_id=" + str(meterId)
        load = self.energy_table.find(["* "], where_clause)
        print("koko before= ", koko)
        state = []
        if len(load) == 0:
            print('Data Does not Exist')
        else:
            total_demand = round(self.energy_table.find(["sum(load) "], where_clause)[0][0],2)
            expected_demand = round(total_demand - (shed / 100) * total_demand, 2)
            priority_tmp = self.energy_table.find(["priority_id "], where_clause)
            priority = []
            for i in priority_tmp:
                priority.append(i[0])

            weight_tmp = self.energy_table.find(["load "], where_clause)
            weight = []
            for i in weight_tmp:
                weight.append(i[0])

            #demand, state = self.knapsack(priority, weight, expected_demand)
            #koko = expected_demand-demand
            sacksize = expected_demand + koko
            if koko<=0:
                sacksize = expected_demand
            demand, state = self.knapsack(priority, weight, sacksize)
            print('Sacksize= ', round(sacksize, 4), '  ')
            #BEFORE demand, state = self.knapsack(priority, weight, expected_demand + koko)
            newkoko = expected_demand - demand
            print('Difference= ', round(koko, 4), '  ')
            #kokoko= koko
            #print("Kokoko = ", kokoko)
            print(str(gridId)+"            "+str(meterId)+"              "+str(total_demand)+ "               " +
str(expected_demand)+ "               "+str(round(demand,2))+"         "+ str(shed))

            self.load.set("grid_id", gridId)
            self.load.set("meter_id", meterId)
            self.load.set("total_demand", total_demand)
            self.load.set("expected_demand", expected_demand)
            self.load.set("demand", round(demand, 2))
            self.load.set("shed", shed)
            self.load.save()
```

```
self.energy_table.update(["status='On'"], " where grid_id=" + str(gridId) + " and meter_id=" + str(
    meterId) + " and priority_id in (" + ",".join(str(x) for x in state) + ")")
self.energy_table.update(["status='Off'"], " where grid_id=" + str(gridId) + " and meter_id=" + str(
    meterId) + " and priority_id not in (" + ",".join(str(x) for x in state) + ")")

return newkoko
```

Appendix 5

Source Code for Selected Forecasting Functions

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn
from sklearn.neural_network import MLPClassifier
from sklearn.neural_network import MLPRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from math import sqrt
from sklearn.metrics import r2_score
from sklearn import metrics
# reading data from csv to pandas dataframe
df =
pd.read_csv("/Users/julius/Desktop/Predictions/My_Data_for_Minutely/ALL_Data_minutely_Weather_coded_
clean2_Months.csv")
dataset = df
X = dataset.iloc[:, :-21].values
y = dataset.iloc[:, 27].values
# splitting the dataset into testing and training sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=False)
mlp = MLPRegressor(hidden_layer_sizes=(8,8,8), activation='relu', solver='adam', max_iter=100)
mlp.fit(X_train,y_train.ravel())
pred = mlp.predict(X_test)
df1 = pd.DataFrame(pred)
print('Mean squared error: {}'.format(metrics.mean_squared_error(y_test, pred)))
print('Mean absolute error: {}'.format(metrics.mean_absolute_error(y_test, pred)))
# predicting B2E (w) with temperature
X = df['Temp (C)']
y = df['B2E (w)']
X = np.array(X).reshape(-1,1)
y = np.array(y).reshape(-1,1)
# splitting the dataset into testing and training sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=False)
mlp = MLPRegressor(hidden_layer_sizes=(8,8,8), activation='relu', solver='adam', max_iter=1000)
mlp.fit(X_train,y_train.ravel())
pred = mlp.predict(X_test)
df1 = pd.DataFrame(pred)
print('Mean squared error: {}'.format(metrics.mean_squared_error(y_test, pred)))
print('Mean absolute error: {}'.format(metrics.mean_absolute_error(y_test, pred)))
```