Short-Term Multiple Forecasting of Electric Energy Loads with Weather Profiles for Sustainable Demand Planning in Smart Grids for Smart Homes

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DECLARATION

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I declare that the above dissertation is my own work and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

SIGNATURE

30th April, 2018

DATE

DEDICATION

This research is dedicated to Almighty God for His mercy on my life and to my loving spouse, Oluwaseun Hannah Alani, for her endless encouragement during the programme. Words are inadequate to thank you. Another is my wonderful son, Nehemiah Akorede Alani. I accomplished the first phase of this exercise, being the submission of my research proposal, when your mother was about to give birth to you. You came at a good time. Thank you and God bless you.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS

ARIMA	Auto-Regressive Integrated Moving Average
AI	Artificial Intelligence
AVGL	Average Load
DT	Decision Tree
ICT	Information and Communication Technology
IPG	Intelligent Power Grids
K-fold CV	K-Fold Cross-validation
MAE	Mean Absolute Error
MLP	Multilayer Perceptron
PSA	Probabilistic Scenario Analysis
PSA-DT	Probabilistic Scenario Analysis with Decision Tree
STLF	Short-Term Load Forecasting
SG	Smart Grid

DEFINITION OF TERMS

Auto-Regressive Integrated Moving Average (ARIMA): A forecasting technique for predicting future value based on the weighted sum of the previous values.

Artificial Intelligence (AI): A field in computer science that emphasises the cognitive nature of systems.

Fault Location Isolation and Service Restoration (FLISR): As the name implies, it is basically intended to ensure the quality of power supply in a smart grid.

Intelligent Power Grids (IPG): System of making the traditional power grid more intuitive and smart through automation by fostering rapid diagnosis and quick recovery.

K-fold Cross-validation (K-fold CV): Technique used to measure the performance of a predictive model result by dividing the entire dataset into k subsets and picking the $k-1$ set for model training and k for testing. In each iteration, the average of all error results across all values of k will be computed.

Mean Absolute Error (MAE): This is also used for performance evaluation in predictive analytics projects. It measures the difference between two continuous variables.

Minimal Error: Predictive error for the PSA-DT with value close to zero.

Multilayer Perceptron (MLP): A form of feedforward artificial neural network with at least three layers of nodes.

Probabilistic Scenario Analysis (PSA): Analysis involving the use of different scenarios for judgement with greater consideration of the probabilities of all available options.

Probabilistic Scenario Analysis with Decision Tree (PSA-DT): A cooperative model combining probabilistic scenario analysis and decision tree.

Short-Term Load Forecasting (STLF): Prediction of the electrical system load within a short period ranging from one hour to one week.

Smart Grid (SG): System used by electricity utility, via information and communication technology (ICT) to deliver, control and manage electricity to consumers.

ABSTRACT

Energy consumption in the form of fuel or electricity is ubiquitous globally. Among energy types, electricity is crucial to human life in terms of cooking, warming and cooling of shelters, powering of electronic devices as well as commercial and industrial operations. Therefore, effective prediction of future electricity consumption cannot be underestimated. Notably, repeated imbalance is noticed between the demand and supply of electricity, and this is affected by different weather profiles such as temperature, wind speed, dew point, humidity and pressure of the electricity consumption locations. Effective planning is therefore needed to aid electricity distribution among consumers. Such effective planning is activated by the need to predict future electricity consumption within a short period and the effect of weather variables on the predictions. Although state-of-the-art techniques have been used for such predictions, they still require improvement for the purpose of reducing significant predictive errors when used for short-term load forecasting. This research develops and deploys a near-zero cooperative probabilistic scenario analysis and decision tree (PSA-DT) model to address the lacuna of significant predictive error faced by the state-of-the-art models and to analyse the effect of each weather profile on the cooperative model. The PSA-DT is a machine learning model based on a probabilistic technique in view of the uncertain nature of electricity consumption, complemented by a DT to reinforce the collaboration of the two techniques. Based on detailed experimental analytics on residential, commercial and industrial data loads, the PSA-DT model with weather profiles outperforms the state-of-the-art models in terms of accuracy to a minimal error rate. This implies that its deployment for electricity demand planning will be of great benefit to various smart-grid operators and homes.

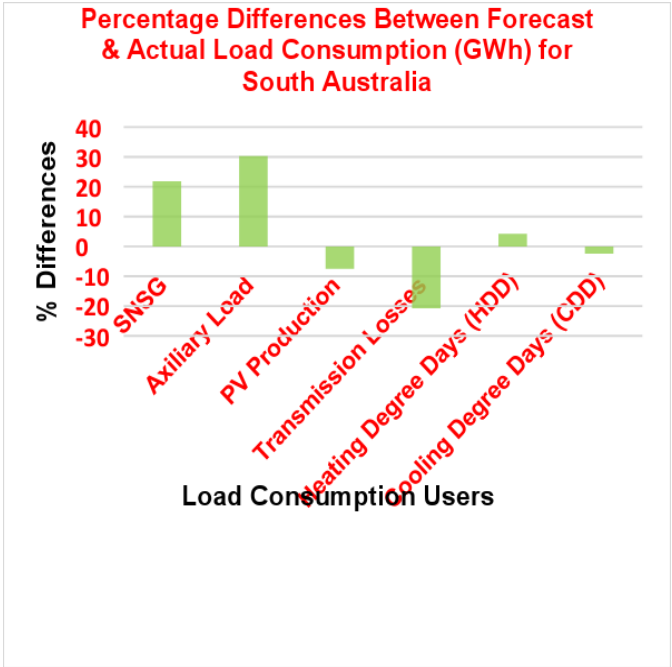
Thesis Title: Short-Term Multiple Forecasting of Electric Energy Loads with Weather Profiles for Sustainable Demand Planning in Smart Grids for Smart Homes

Keywords: Energy, Electricity, Smart Grid, Forecast, Demand, Load, Modelling, Smart Home, Predictive, Cooperative, Weather.

CHAPTER 1: INTRODUCTION

1.0 GENERAL OVERVIEW

Predicting electricity demand is crucial, since it plays a significant role in the administration, decision-making and demand planning in utility power supply operations [1]. Effectiveness and accuracy in terms of extremely reduced forecasting error of a predictive model cannot be overemphasised, as load forecasting guides power grid operations and power station construction planning. Forecasting is also important for sustainable development of the electric power industry [2]. Short-term load forecasting (STLF), the generic abbreviation for a model that can predict future load consumption, with a lead time of up to a few hours to a few days, has been undergoing constant improvement in the last few decades [3]. Inaccurate load forecasting for effective demand planning remains a difficult and critical challenge [4]–[6], especially with greater consideration of weather profiles being a critical factor in such planning [6]–[9]. This problem invariably increases the operating costs of electricity suppliers [10], [11]. Thus, there is a need for improved STLF in terms of potential error reduction, which could improve the reliability and efficiency of power generation [11]. Figure 1.1a-b is an example of the percentage differences between the actual load and forecast load consumption, used by different classes of consumers from different locations in Australia. The negative (−ve) bars and points shown above the x-axis in Figure 1.1a-b and Figure 1.2a mean the load forecasting values were low compared to the actual consumption after calculating their differences. In addition, the positive (+ve) bars and points shown below the x-axis in the same figures indicate that the forecasting values were high in relation to the actual electricity consumption after their computation differences.



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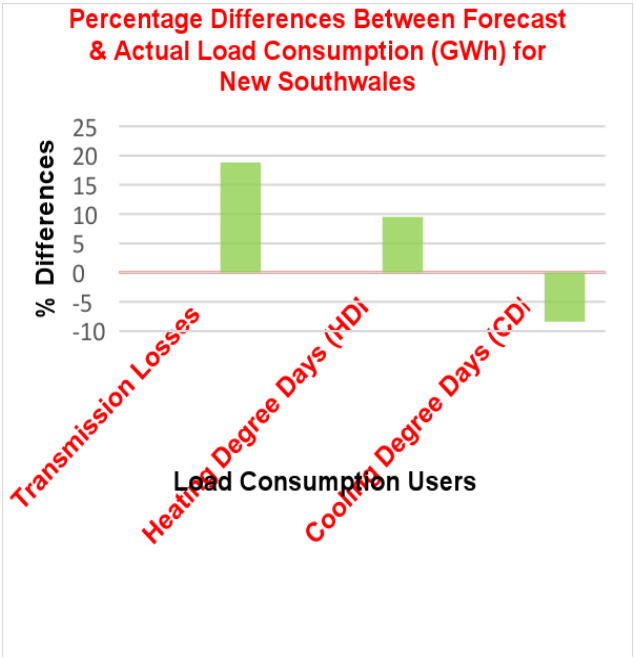
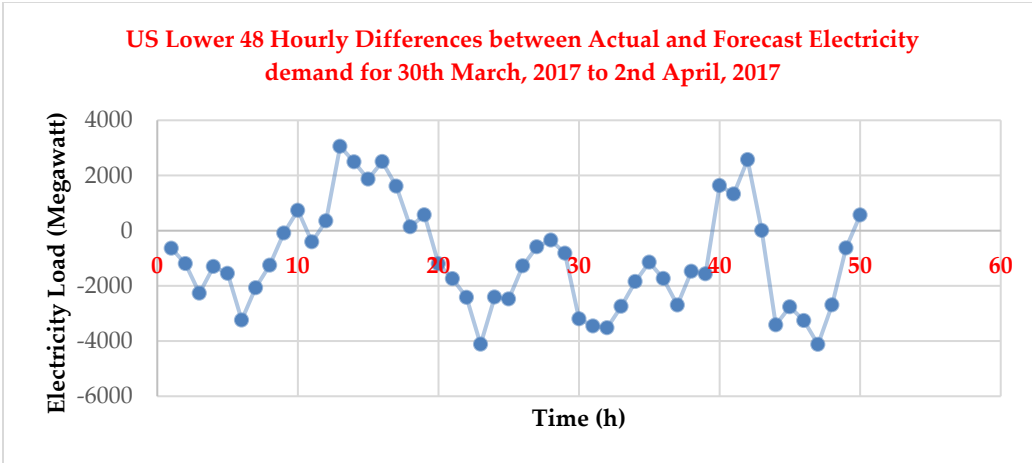


(**b**)

Figure 1.1: Electricity load consumption differences among different classes of users (Adapted from [12])



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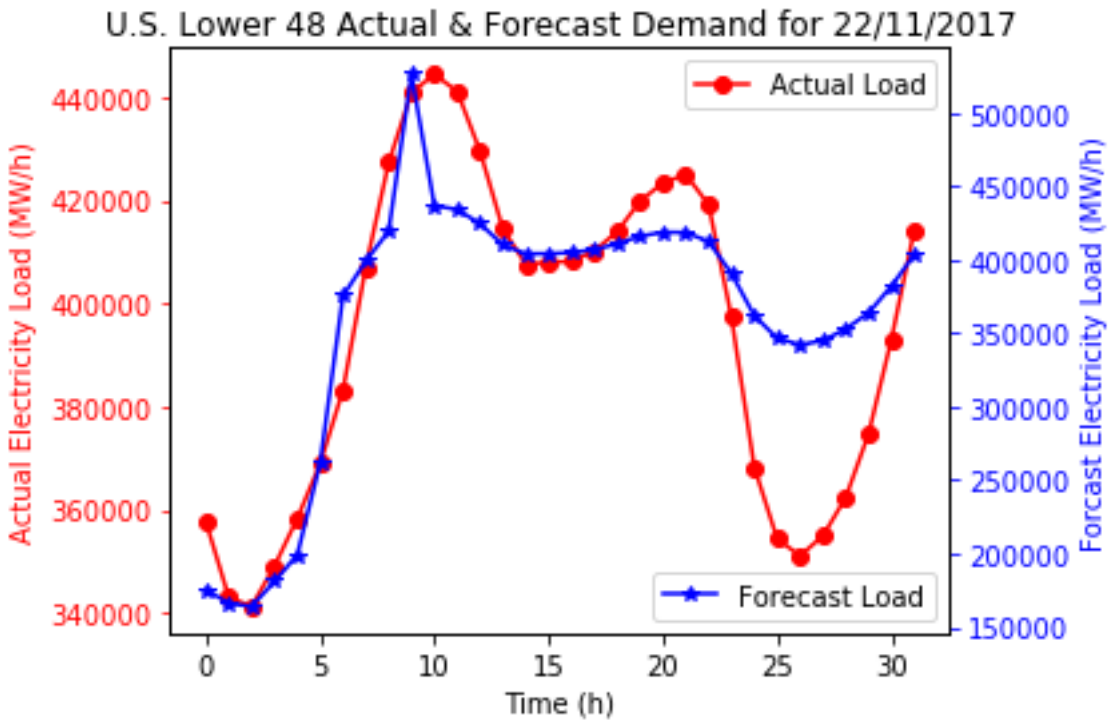


(b)

Figure 1.2: Demand and forecast differences of aggregated load consumption in US at different times of the year (Adapted from [13]).

In addition to the forecasting problem relating to disparity between electricity demand and forecast, Figure 1.2a reveals the extensive differences between the actual and the forecast load. The positive section in the trend chart depicts that the utility has over-

predicted the future load and the negative section indicates that the utility has under-predicted the future load consumption. Also, Figure 1.2b is an example of the actual load and forecast load consumption for the United States of America (USA) continental state, including the district of Columbia but excluding Hawaii and Alaska. It is obvious that there is a distinctive variation between the actual and the forecast load, as the forecast load does not agree with the actual load. In this regard, Figure 1.2b reveals the extensive differences between the two loads.

Classical models have been used but have proven inefficient in short-term load forecasting in a smart grid (SG) [8] . In statistical modelling techniques, regression and time-series models were huge successes, and more recently, computationally intelligent techniques such as artificial neural networks (ANNs), support vector machines (SVMs), self-organisation maps and fuzzy logic have contributed immensely to STLF implementation. These models are excellent and have been applied in electricity prediction; however, because of uncertainty about the nature of electricity consumption, they still require improvement in terms of accuracy when used for short-term load forecasting [3]. However, cooperative short-term load techniques, which involve collaboration of more than one model, have proven to be more efficient and accurate [8], [14]. In this regard, cooperative models can drastically reduce the large forecasting errors inherent in the classical techniques [1].

Furthermore, despite the performance of the classical models, they require improvement in accuracy when used to forecast future load consumption for short-term load in an SG, which is greatly affected by weather [8]. In addition, the inevitability of weather leads to degradation in the performance of several forecasting models used in SGs [5], [8]. Several times, the forecasting problem relating to disparity between electricity demands in smart homes and forecast was due to weather profile variations in the location where the

electricity was consumed [15]. In addition to the prediction, Luis [15], [16] stimulated greater interest by showing the relationship between weather variables in smart space and the changes in electricity load consumption; knowing the influence of weather variables in an SG on users' consumption to aid effective future planning is of great benefit.

Weather profiles such as temperature, wind speed, relative humidity, pressure and dew point at local time are essential independent factors in load forecasting [5], [6]. These weather factors have affected various classes of electricity consumers, such as domestic and agricultural consumers [7]. It has been shown that over 40% of electricity consumption of these types of consumers is attributable to heating and cooling usage in response to local weather factors. In addition, Kown et al. [6] revealed the effect of temperature, humidity, dew, pressure and wind on the actual load and the forecast load. Invariably, weather has a major impact on load consumption [5], [6], [8], [9]. Thus, there is great demand to improve load prediction, using a cooperative STLF model that incorporates weather profiles [5], [9], [17]. This will go a long way in reducing predictive errors and enhancing accuracy for effective demand planning of electrical consumption by consumers.

This study considers the development of a minimal error cooperative model, integrating probabilistic scenario analysis and a decision tree (PSA-DT) technique, and poses the question: "*How can an efficient cooperative model with minimal error predict the future load consumption and include consideration of weather variables for STLF of electric energy demands in SGs for smart homes?*" The model uses a probabilistic method to obtain the initial predictive load consumption with a high level of confidence. Prior to making a final accurate decision on productive planning, a DT model is integrated with the probabilistic

model. In this research, predicting the future load consumption using developed cooperative models with active consideration of each weather profile as essential load consumption inhibitors will be actively considered. Having predicted this, the accuracy of the prediction will be measured by using the mean absolute error (MAE).

1.1 PROBLEM STATEMENT

An SG where electricity consumers dictate the amount of electricity to be produced according to its utilisation, in other words, an accurate understanding of future load consumption, is required for sustainable and effective demand planning. However, inaccurate load forecasting remains a difficult and critical problem [4]. This problem invariably increases the operating costs of electricity suppliers and inhibits proper future planning for consumers [10].

Thus, there is a need for improved short-term load forecasting, which has the potential to improve the reliability and efficiency of power generation [8], [11], [17]–[20]. Specifically, single models have been used but have proven to be inefficient in short-term load forecasting in an SG [8].

In addition, the inevitability of weather variables such as temperature, pressure, wind speed, dew point and humidity has led to degradation in the performance of several forecasting models used in the SG [5], [8]. Therefore, there is a need for improved predictions based on cooperative models and location-specific weather profiles in an SG, which Day et al. [8] focussed on as a means of knowledge contribution.

1.2 RESEARCH OBJECTIVES

The main objective of this research is to develop a cooperative predictive model with near-zero predictive error to improve short-term load forecasting in SGs.

The specific objectives are:

i. To investigate the forecasting efficiency of the proposed model compared to the state-of-the-art model.

ii. To analyse the effects of the weather profile on load consumption, using the cooperative PSA-DT technique, and to evaluate the predictive error for each of the weather parameters.

1.3 RESEARCH QUESTIONS

The research is expected to answer this main question:

How can an efficient cooperative model with minimal error predict the future load consumption and include weather variables consideration for STLF of electric energy demands in SGs for smart homes?

The question is broken down into the following sub-questions:

Question 1: To what degree of efficiency, in terms of forecasting errors, is the proposed model better than the existing state-of-the-art model?

Question 2: To what extent can weather parameters such as temperature, pressure, wind speed, dew point and humidity be integrated with the cooperative predictive model to improve performance reliability in SGs towards near-zero predictive error?

1.4 RESEARCH DESIGN

The aim of this study is to design an efficient cooperative short-term load forecasting model that could be used by SG utility owners to plan for future electricity demand by consumers. Initially, publications related to short-term load forecasting techniques were reviewed in order to avoid repetition of what has been done. The proposed model

construction and its usage by different classes of electricity users, such as residential, commercial and industrial electricity users, were also examined in conjunction with the effects of the weather profile on the predictions. In addition, the result of the cooperative model was evaluated after conducting several experiments and testing.

Performance comparison was also conducted on the various classical techniques reviewed and the forecasting abilities of the results of some of the state-of-the-art techniques were benchmarked against the result of the cooperative model. Tests of various models, in terms of forecasting error reduction using the MAE evaluation metric, were also carried out.

Furthermore, several visualisations and experiments were done using various libraries in Python. Likewise, each weather variable was used in conjunction with hourly electricity loads from different classes of consumers. Each experiment conducted was scientifically proven by obtaining the MAE for the cooperative model and when used with an individual weather profile. The electricity load consumed by the different users was stored in the repository in conjunction with the weather profiles obtained from the smart space via a custom web service implementation. A knowledge-based system exists for various grid operational and control systems. The operational system used for planning was geared by an efficient STLF. The STLF module fetches the electricity consumption data and the corresponding weather profiles from the data warehouse, combined with the predictive model, for the SG operations to make a decision.

1.4.1 Predictive analysis processes

In this research, electricity load and weather profile data were collected from various open repositories [21], [22], cleaned and analysed prior to making predictions for future load consumption. The analytical processes involved in the experimental evaluation are

based on the CRISP model [23] and are data collection, wrangling, exploring, transforming, modelling and, finally, evaluating the performance of the model.

i. **Data Collection:** This involves collecting data of various samples and features. Features, either good or bad, cannot be neglected during data analysis; therefore, a great number of data samples have to be collected to find the best pattern when using the proposed algorithm.

ii. **Data Wrangling:** Getting rid of holes or inaccuracies in the collected data is essential to successful predictions. This promotes greater reliability of the data. Empty data will be removed with pandas implemented in our code base. It is worthy to note that pandas uses Numpy in its implementation for data wrangling. By getting rid of the data element without any value, usually called not a number, in the collected dataset, an accurate dataset and prediction can be derived from the singular action of data wrangling. In addition, incorrect or missing data could affect the proposed algorithm during its execution. In this regard, data meant to be used really needs closer inspection for accuracy.

iii. **Data Exploration:** Exploring the data makes the researcher 'feel' the data by visualising the graphical structure of such data. Important insights are obtained in this phase.

iv. **Data Transformation:** This involves using the proposed algorithm to prepare the data for computation. In most cases, it involves the selection of features of great value to the model meant to be used. In the implementation process, we transform our data into a matrix layout for ease of use by the predictive model

v. **Modelling:** At this stage, the proposed algorithm using PSA-DT will be used to model the collected data. Having trained the model, the trained model will be given test data to make predictions. Effective prediction is carried out by

avoiding overfitting through splitting the entire dataset into training and test data before use.

vi. **Evaluation:** This is the final stage where the applied algorithm is scored based on the model, involving verification of the effectiveness of the cooperative algorithm compared to the state-of-the-art algorithm.

1.5 RESEARCH CONTRIBUTIONS

This study's contribution to scientific knowledge will be viewed from two major perspectives.

1.5.1 Contribution to the body of knowledge

Contributing to the body of scientific knowledge can be achieved by developing an efficient cooperative probabilistic model with near-zero predictive error compared with the classical model. Another method is using the individual weather parameters in conjunction with the cooperative PSA-DT model for forecasting to produce a near-zero predictive error with similar comparison with the classical model. This can be proven statistically by evaluating the MAE for the proposed model when used over the historical electric load and weather profiles. Envisaged contributions include:

I. Development of a cooperative PSA-DT model, integrating the concept of probabilistic scenario analysis and DT techniques for short-term load forecasting and sustainable economic planning of electricity demand in an SG.

II. Detailed experimental evaluations of the PSA-DT and its benchmarking with many state-of-the-art models, using publicly available data from [22], [24] in terms of near-zero forecasting errors in the predictive paradigms for smart homes.

III. Deployment of a cooperative PSA-DT model integrating the concept of probabilistic scenario analysis and DT techniques for short-term load forecasting of electricity demand in smart homes when multiple weather variables matter.

IV. Detailed experimental evaluations of PSA-DT benchmarked with state-of-the-art techniques on load weather trend analytics in terms of predictive errors using publicly available electric load and weather data obtained from Texas in the USA [22] and wunderground repository [21].

1.5.2 Declaration of publications resulting from this study

The following are recent articles published from the research:

I. **A. Y. Alani** and I. O. Osunmakinde, (2017) "Short-Term Multiple Forecasting of Electric Energy Loads for Sustainable Demand Planning in Smart Grids for Smart Homes," *Sustainability journal*, vol. 9, no. 11, pp. 1–26, 2017, ISSN: 2071-1050, *(ISI journal).*

II. **A. Y. Alani** and I. O. Osunmakinde, "When Multiple Weather Variables Matter: ML-based STLF of Electricity Demand for Smart Grids," International journal of intelligent data analysis, *IOS Press,* ISSN*:* 1088-467X, (*ISI journal)*

1.6 RESEARCH ETHICAL CONSIDERATIONS

With respect to the ethics of the School of Computing, University of South Africa, the following measures were applied to protect the integrity of this research:

a. The work is presented with the focus on originality.
b. All the sources used for this study were referenced appropriately.
c. Plagiarism software has been run successfully on this dissertation.
d. Data collected were neither forged nor manipulated to ensure suitability of any form during the experiment.

e. The discoveries made during this study were reported correctly, with no form of adjustment to suit the researcher's claims.
f. The ethical clearance certificate number for the research study is 115/AAY/2017/CSET_SOC.

1.7 SCOPE AND ASSUMPTION

1.7.1 Scope

This study covers the development of a new cooperative short-term forecasting model that sets out to be more efficient in terms of MAE compared to some of the state-of-the-art models examined in the literature review. Another aim is using the cooperative model developed with each weather profile such as temperature, pressure, dew point, relative humidity and wind speed to forecast future electric load consumption for different user categories. The breadth of this study focuses on the concept of the SG, classical and cooperative short-term load forecasting techniques, detailed experimental evaluation of the cooperative model with respect to the classical models and weather variables. In each experiment, the near-zero predictive error is the major concern.

1.7.2 Assumption

Having developed the cooperative model, several experiments were conducted using Python and other compatible libraries to verify the effectiveness of the new model and the way in which it has outperformed other state-of-the-art models when tested against them to obtain the predictive error, also with each of the weather profiles. In this work, electricity data used were secondary data generated by an SG and stored in a repository for public accessibility [22], [24]. The weather data were obtained from an online weather repository [21] via the RESTful API and were based on the location where the electricity was consumed. We assumed that the weather data obtained were a true representation

of the state of weather during the users' electricity consumption in that location and at that point in time.

1.8 DISSERTATION OUTLINE

In this dissertation, our focus has been broken down into chapters.

Chapter 1 briefly discusses the general overview of the research, helping the reader to gain basic knowledge of this research focus.

Chapter 2 throws more light on the existing classical techniques that have been used for STLF and presents a detailed overview of the concept of grid transition from the traditional grid to the SG.

Chapter 3 critically explains the cooperative model and how it is used for STLF. We also consider the effect of each weather factor on the load consumption in relation to the collected data.

Chapter 4 reports various experiments conducted to evaluate the effectiveness of the new model and the addition of each weather profile.

Chapter 5 rounds off the entire discussion and proposes prospective future work to make short-term load forecasting more efficient and robust.

1.9 CHAPTER SUMMARY

This chapter explained the preliminary overview of the research by discussing the motivation for this study and giving a brief introduction of the various state-of-the-art techniques and the benefits of the cooperative model. The study was driven by various

research problems that generated different questions, which finally translated into diverse objectives to be achieved. In addition, the research process meant to be followed to answer the questions was presented.

CHAPTER 2: LITERATURE REVIEW AND BACKGROUND THEORIES

2.0 INTRODUCTION

Our aim in this chapter is to review literature and techniques that have been used for short-term load forecasting in an SG. The study is expected to yield deep understanding of the subject of this dissertation and avoid repeating work that has been done in this area of study. It will furthermore aid critical analysis of the subject matter in terms of existing problems and solutions that have been offered by different researchers, by identifying gaps related to previously proposed means and techniques of filling them, especially by identifying successful and unsuccessful approaches to resolving the issues. Above all, the literature will review the existing model for STLF and the pros and cons, including various factors that affect effective prediction of future electricity consumption.

When predicting future electricity consumption in a real-life environment by the utility, there is a need for a smart meter for periodic data acquisition at every infrastructure of choice. Acquiring electricity consumption data involves diversities in the load, ranging from where it is used to time of use and several weather determinants in the consumption location.

2.1 FORECASTING MODELLING TECHNIQUES FOR ENERGY LOAD

STLF within an SG can be effectively addressed through two major approaches, using either AI or statistical techniques. Some of the reviews given by Islam et al. [3] for electric load forecasting range from time-series to regression-based, being statistically based. Artificial intelligence (AI) techniques, ranging from ANN, fuzzy inference and SVMs to particle swamp optimisation and genetic algorithms (GAs), are mostly used for optimisation. Table 2.1 shows a brief comparison of some of the most widely used STLF

techniques in terms of their strengths, drawbacks and possible predictive error obtained from the literature.

2.1.1 Regression-Based Method

This model is a widely used statistical technique for electricity load forecasting [25], [26]. It is used for modelling the relationship between load consumption and other factors such as weather and day type, and it tends to measure the extent of the relationship between the dependent and independent variables [26]. It has been most relevant in offline (non-real time) forecasting, since it is generally unstable for online forecasting because it requires many external variables that are difficult to introduce into an online algorithm [26]. Soliman et al. [27] expatiated on the ease of use of this model, but it requires extensive initial analysis to identify the regressors and their location in each model. The model also requires continuous re-estimation of its parameters to perform accurately.

2.1.2 Time-Series Analysis Method

This involves time-series plots and extrapolating such patterns using a set of previously collected data to predict the future load [25]. The approach has gained popularity in online forecasting by making it possible to accommodate some weather information [27] and this has improved the accuracy level and ease of online implementation. Non-availability of weather parameters limits the efficiency of this technique and causes some weaknesses in predictive abilities when using it [25]. It is worthwhile to note that both stationary and non-stationary processes can be modelled by different variants of time-series models ranging from the auto-regressive moving average, auto-regressive integrated moving average to auto regressive integrated moving average with exogenous variables [25].

2.1.3 Exponential Smoothing Method

The success of this method can be traced to both online and offline forecasting. Its simplicity and cost-effectiveness make it an appealing forecasting tool [27]. However, it has poor long-range accuracy with regard to weather information. Therefore, it cannot account for weather-related load changes.

2.1.4 Expert System Approach

Being a rule-based technique, resulting from the improvement in the AI domain, the expert system approach has a retractable reasoning instinct with adjustable cognitive abilities with new information [25]. It uses an "*if-then*" rule base for its inference; therefore, such rules require constant updates for effective performance. It resulted from improvement in the AI domain. It is a computer program with reasoning instincts and its cognition base expands as new information becomes accessible [25], [28]. It has the capacity to retrace its logical reasoning if requested by a user; this feature is built as an illustrative network of elements. In the prediction process, where some of the rules remain static over time, some change gradually, and others change dynamically. Therefore, the expert system needs to be updated continuously.

2.1.5 Artificial Neural Network-Based Techniques

This is an unsupervised machine-learning method that involves inter-connection of numerous neurons, which can be used to learn the characteristics of non-linear relationships of input and output pairs of data accurately. This is one of the major merits of the model compared to other statistical approaches [29]. In addition, Hahn et al. [17] found that several neural networks performed best with a small mean percentage error between 2.35% and 2.65%, and less spreading of the errors. However, neural networks require significant training to understand the model [29].

2.1.6 Support Vector Machine

An SVM is very powerful, especially for solving classification and regression issues [25]. The SVM is used for non-linear mapping of datasets into prominent dimensional features via kernel functions, a class of pattern analysis algorithm that performs better than statistical techniques. Chen et al. [30] discovered that support vector regression avoids under-fitting and over-fitting as well as regularisation. However, choosing a suitable kernel during the analytical phases and difficulties in its interpretation are major concerns in this technique [25].

2.1.7 Fuzzy Logic

Fuzzy logic deduces output from input logically via the use of Boolean logic, which forms the basis of the fuzzy rules. In this technique, mathematical model mapping between inputs and outputs is not necessary. In addition, precise or noise-free input is not a necessity [30]. Fuzzy inferences used for STLF models help utilities economically by reducing the error in load predictions [31]. In addition, it benefits load forecasting owing to its numerical aspect and the uncertainty of the system load [25]. It is strenuous in developing fuzzy rules and its membership functions. Likewise, analysis might be difficult because of different interpretations of fuzzy outputs [32].

2.1.8 Adaptive Neuro Fuzzy Inference System

The adaptive neuro fuzzy inference system (ANFIS) is a hybrid model combining ANN and fuzzy logic. It combines the benefits of both techniques. It has proven to be more efficient compared to ANN and GA techniques [31]. It has better training processes and improved forecasting ability due to effective data processing. The ANFIS approach gives lower mean absolute percentage error values than ANN and GA [31]. The concept behind these adaptive neuro-techniques is to enhance the dataset information to be learnt using fuzzy modelling procedures. Several rules are formed and they constitute the membership function of the fuzzy inference system.

2.1.9 Genetic Algorithm Techniques

GA is inspired by biology and improved fitness evolution, and was proposed in [33]. It involves simulation of biological evolution and genetic evolution processes. GA comprises three different stages, namely selection, crossover and mutation [34]. These operations enhance the creation of a new operation that is better than the predecessor [35]. Its main merits are the ability to conduct global searching, ease of expansion, and need for very little specialised knowledge when applied. The shortcomings are premature convergence, indefinite time of convergence, low computational speed and lack of local optimisation capacity [35], [36].

2.1.10 Particle Swarm Optimisation

Particle swarm optimisation is an evolutionary computational technique and an extremely simple algorithm that is effective for optimising a broad range of functions [37]. This technique imitates swarms of birds, which invariably search for optimal solutions within a vector space of several particles. Each element in the space represents a potential solution with a moving velocity. At every point in time, a best fitness function is evaluated and obtained. Such a particle best function is tracked. In the vector space of the best particle, there is another best position in the swarm, which is also being tracked. Finally, all the information is allotted by all the particles for confluence to the overall best solution [35]. Despite the difficulties of selecting probable inertia weight, it only works effectively for small test functions by considering the best value found by its neighbours. In summary, it fails when used for a larger population [38]

2.1.11 Bayesian Network

A Bayesian network (BN) has the ability to handle missing values very well and yield a positive result during queries compared to a training dataset in the case of machine learning techniques such as ANN or SVM [39]. Being a probabilistic model, it shows the

relationship among the random electricity and weather variables in smart space. For example, it finds the probability of a load being high, given a weather parameter.

Having discussed the various techniques used in STLF, Table 2.1 shows the comparisons of the methods used, strengths, weaknesses and the error rates obtained when using the model for predictions

Table 2.1: Performance Comparison of Frequently Used Load Forecasting Methods

Energy Load Forecasting Techniques	Specific Model Used	Strength	Weakness	Error Rate with Respect to the Data Used
Regression [30], [40]–[42]	Linear Regression and Multiple Linear Regression.	Very useful in non-real time forecasting. Functional relationship between previous, forecast load and other factors such as weather, time of the day.	Not accurate for real time load and unable to handle non-linear load consumption. Adding parameters makes it unstable.	4.665% 21.87%
Time-series Analysis [17], [41], [42]	Auto-regressive Moving Average, Auto-regressive Integrated Moving Average, Deterministic Decomposition.	They possess abilities to accommodate seasonal component effects.	They suffer numerical instability.	1.48–1.99%

	Artificial Neural Network [40], [43]	Multilayer Perceptrons, Back Propagation Algorithm, Steepest Descent Error Back Propagation.	Ability to handle nonlinear relationships in load consumption by adjusting its weight during the training process.	Large amounts of data are needed to train the model and the training of such data is complex.	2.9% 6.609%
	Fuzzy Inference System[44]–[46]	Defuzzification Method Using Centre of Area, Middle of Maxima, Last of Maxima and Centre of Gravity	Faster and more accurate in performance, including simplicity in rule formation.	Selection of membership function to form its rule is based on trial and error.	2.58%, 5.831% and 1.794%, 9.53%
	Support Vector Machine [25], [47]	Support Vector Regression Using Incremental Learning Algorithm Support Vector Regression	It enhances higher feature space dimensionality by using ε-insensitive loss for linear regression computation and reduction in model complexity.	Choosing a suitable kernel and difficulties in its interpretation are major concerns.	4.2306% 1.57–4.28% 1.95–3.48

Despite the classical methods in Table 2.1 that show the strengths, weaknesses and some error rates of the most widely used state-of-the-art techniques, there have been good testimonies of cooperative methods compared to classical methods in terms of performance [8], [14], [47].

However, the state-of-the-art techniques can also be differentiated by using some criteria for further comparison, as shown in Table 2.2.

Table 2.2: Criteria Comparison of Load Forecasting Methods

Criteria	**Regression**	**Time-series Analysis**	**ANN**	**Fuzzy Logic**	**SVM**
Functional relationship between previous load or weather parameters and forecast load [18], [20]	Yes	Yes	Yes	Yes	Yes
Learning by training processes between input and output [18], [20], [47]	No	No	Yes	No	Yes
Number of parameters used for prediction per time [18], [20], [48]	Two	Two or more	Two or more	Two or more	Two or more
Linear relationship of input and output data pairs [20], [49]	Yes	Yes	No	Yes	No
Non-linear mapping of input and output pairs of data, especially in classification [20], [29], [50], [51]	No	No	Yes	Yes	Yes
Use of a linguistic variable (If ... Then... Else) [8], [50]	No	No	No	Yes	No
Handling of complex and robust data [8], [49]	No	No	Yes	No	Yes

2.2 THEORETICAL TECHNIQUES

In this section, the discussion will be based on the theoretical frameworks that support the research study and development of the cooperative PSA-DT model.

2.2.1 Probabilistic Scenario Analysis

Probabilistic scenario analysis (PSA), being the use of a probabilistic model over various scenarios, foresees and evaluates various possible occurrences of an event in the future [52], [53]. It is mostly used in the financial world to make extensive projections into the future. Considering the technique and its vast usage in management for forecasting, several researchers have come up with diverse processes for performing good scenario analysis [54], which can easily be combined with the probability model [55] to generate a sampled expected outcome based on randomly generated events [56]. In summary, the scenario process depicted in Figure 2.1 will aid any activity considering scenario analysis as a method of future prediction. In conjunction with the probabilistic theory, the expected mean, deviation from mean and the degree of confidence of accepting the mean are essential statistical tools meant to be used for each scenario. The expected mean will be computed as a random variable X between two load points shown in Equation 1, where $f(x)$ is a probability density function between two loads, a and b.

In the proposed technique, especially during simulation processes, the cumulative probability $f(x)$ of the load is computed as a non-decreasing function with probability values between 0 and 1. In this regard, the expected mean in Equation 1, generated during this random process, will have a certain level of confidence, which falls between the confidence interval for all the load samples, usually known as the $t_{interval}$, as shown in Equation 2.

$$mean(\mu) = E(X) = \int_{-\infty}^{\infty} x f(x)\, \delta x \text{ Where } f(x) = P(a \leq x \leq b) \qquad (1)$$

$$t_{interval} = x \pm T_{\alpha/2,n-1} \times \frac{\sigma}{\sqrt{N}} \quad (2)$$

where $E(X)$ *is a* ***point estimate*** *of* μ , $\frac{\sigma}{\sqrt{N}} =$ ***standard error of the mean***

and $T_{\alpha/2,n-1} \times \frac{\sigma}{\sqrt{N}} =$ ***error margin*** with **N** as the total number of observations for the random value of $\boldsymbol{x}$.

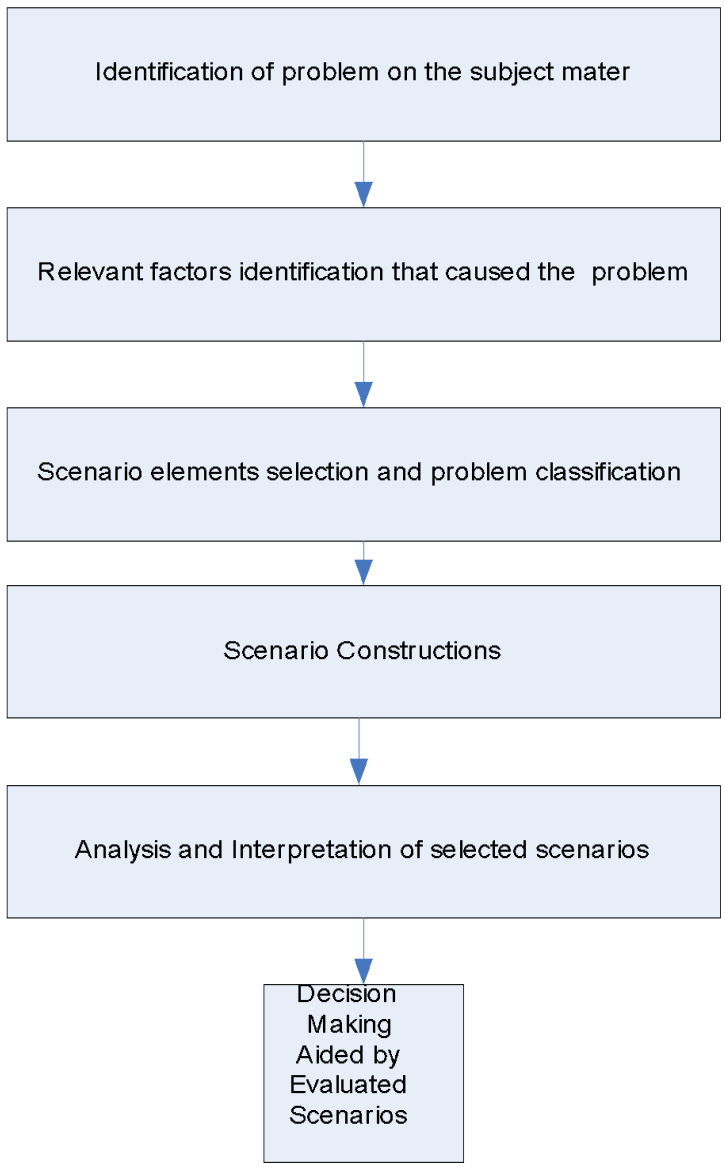


Figure 2.1: Scenario Analysis Processes.

2.2.2 Decision Tree

A DT uses a tree-like pattern to present various possibilities for its decision route and the result of each route in order to decide effectively on the path to take, depending on whether it is a classification or regression problem. Concepts such as entropy and information gain must be predetermined for an effective split in the classification problem, while standard deviation from the mean forms the major criterion for a split in the regression problem.

2.2.3 Entropy

This is a measure of disorderliness or impurities in the sample space. In every sample space, there are data that might not contribute to the decision made by the DT model; the model tries to make its decision by ensuring that the decision boundaries are void of impurities as far as possible. Entropy computation has been formalised by Shannon [57], shown in Equation 3. The equation assumed a random variable X with values x_i and probability $Pr(x_i)$:.

$$H(X) = -\sum_{i} \Pr(x_i)\, log2\Pr(x_i). \tag{3}$$

In addition, information gain, which is meant to be maximised in the decision processes, has the lowest value as zero (0) and the highest value as one (1). In some other texts, this is called gain ratio, which draws many relationships from the entropy. It is mostly defined by the difference between the initial and the final entropy, as shown in Equation 4. The value of X is the predicted class and i is the feature used by the predicted label:

$$IG(X, i) = H(X) - H(X|i). \tag{4}$$

In general, let us define the training samples T containing time-series load data $(x, y) = (x_1, x_2, x_3, x_4, \ldots\ldots, x_n, y)$ where $x \in vals(i)$ is a value of the ith attribute of the sample x

and y. The information gain for the ith attribute in terms of $H(T)$ entropy is given in Equation 5.

$$IG(T,i) = H(T) - \sum_{v \in val(i)} \frac{abs(\{x \in T | x_i = v\})}{abs(T)} . H(\{x \in T | x_i = v\}) \quad (5)$$

Standard deviation (SD), otherwise called standard error (SE), describes the expected variations in the mean of a population with total samples N; Y_i is each load observation and Y is the average of the entire load consumption. It can be written mathematically as presented in Equation 6.

$$SD = \sqrt{(\frac{1}{N-1} \sum_{i=1}^{N} (Yi' - Y)^2)} \quad (6)$$

A DT can be built using Greedy top-down construction, which is the most widely used technique in tree growing [58]. It is structured in a top-down pattern considering all the data and then builds up various subsets of the tree, which are managed in a recursive manner. Having constructed the tree, one has to deal with the problem of finding the right tree size, which can be managed by pruning [59].

Briefly, in Chapter 4, during the PSA-DT model evaluation, we used the DT regression function in scikit-learn that implemented these concepts, and improved the learning algorithm by making such a prediction more generalised and sensitive to new datasets through bias-variance trade-off.

2.3 GOVERNMENT ELECTRICITY DISTRIBUTION IN CITIES

Recently, electricity distribution in various cities has gone beyond the usual norms of traditional electricity distribution; new technologies have been combined to distribute electricity effectively to different cities [60], [61]. Governments, especially in the USA,

have focused on improving the electricity network via information and communication technology (ICT) [62]. They have grown distribution over the years with the assistance of organisations such as IBM and Malta among others by initiating some effective policies in the Energy Independent and Security Act of 2007.

2.3.1 Traditional Load Distribution

The traditional electricity power grid is a one-way electrical transmission and distribution system in which electricity can only flow in one direction from a generating station to the consumers [61]. This has been in existence for centuries and it suffers several challenges from the distribution point until it gets to the destination where the electricity is consumed. Such challenges, according to departments of energy [63], are 6% distribution and transmission losses in the USA and even more in less developed economies, greenhouse gas emission and more recent threats such as security issues from energy suppliers and alarming demand for more electricity, as well as poor management and control of the electricity distribution grid.

2.3.2 Electricity Value Chain

Several processes, such as transmission, substation step-down and the distribution chain, are involved between the generation of electricity from the source and the point of consumption by customers [63], [64]. Shown in Figure 2.2 is a typical electricity power chain delivery framework that shows the transition from generation to various consumers. Principally, the substation and primary consumers are the medium and large businesses that are financially sufficiently buoyant to own personal transformers, while the secondary consumers are mostly associated with residential purposes and small businesses.

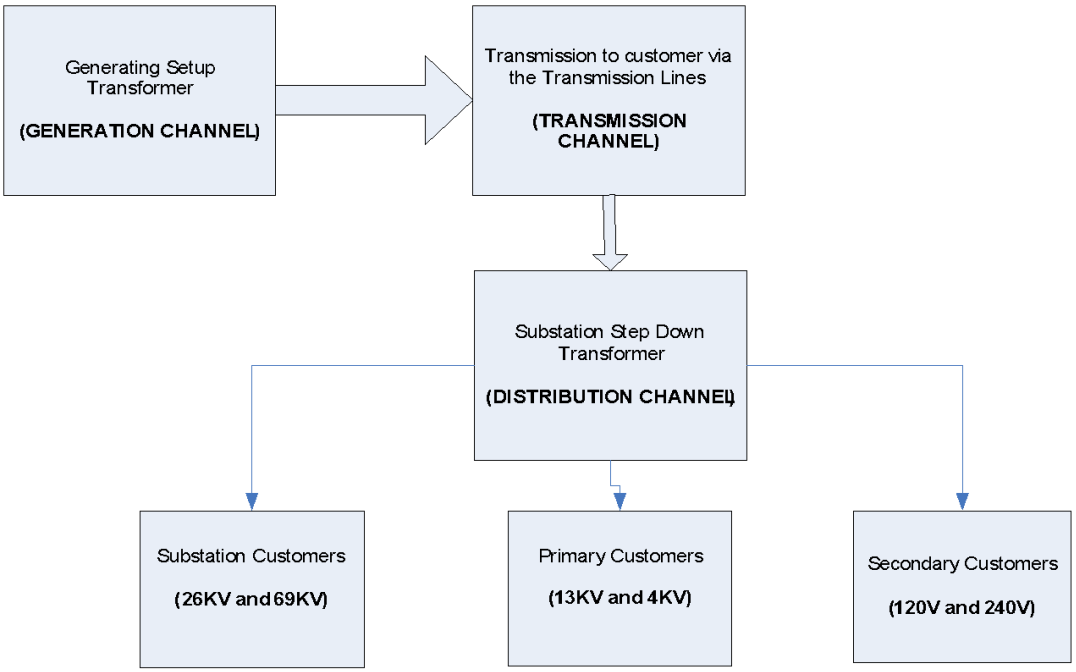


Figure 2.2: Typical Electricity Value Chain in Classical Power Delivery System.

According to the Department of Energy [63], classical power chain delivery poses various challenges, such as losses at each stage ranging from generation to transmission and before the electricity reaches the final consumers, as shown in Figure 2.3.

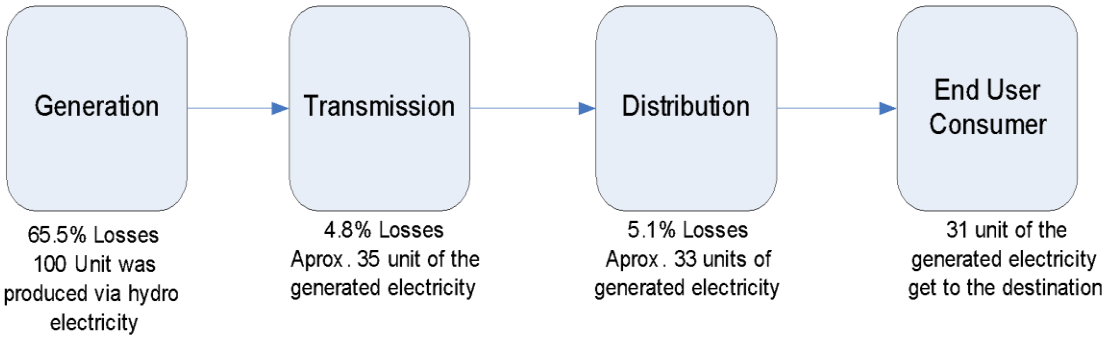


Figure 2.3: Power Losses in the Grid.

Despite the losses at every stage in the electricity value chain, the current grid, being the traditional type, is faced with imbalance between the energy supply and the aged electromechanical elements. In addition, increase in demand, insufficient thermal generation, inability to integrate with other renewable energy resources, aging grid

infrastructure and security setbacks, as well as inconsistent regulatory and legislative environments, constitute the major challenges confronting the traditional grid. These make such a system inconsistent and unsustainable. However, moving into a sustainable grid through the invention of the SG introduces characteristics that include an increase in power transmission and efficiency, optimisation of grid assets, intelligent and end-to-end monitoring, control with cyber security focus, customer engagement and extensive demand response.

2.3.3 Transition from Traditional Load Distribution to Smart Grid

In today's world, information technology has transformed every facet of the economy including the realm of electricity generation, distribution and transmission. The traditional grid is characterised by customers' non-participation in the power system and their slow responses, central generation of power supply featuring many obstacles and power losses, inefficient operation and asset management and, above all, inefficient responses to asset handling. The reverse is the situation in the SG known as the grid of the future. The future grid might be subject to certain threats such as vulnerability increment that makes the grid prone to cyber attack, un-standardised technology usage, upfront consumer expenses and infrastructure management. Furthermore, Table 2.3 shows some quick functional differences between the SG and the traditional grid, based on this review [65]–[67].

Table 2.3: Classical Differences between Traditional and Smart Grid

Factors Considered	**Smart Grid**	**Traditional Grid**
Easy and quick resolution of fault location isolation and service restoration	Yes	No

Real time and ease of management (transmission, delivery and monitoring) [67], [68]	Yes and remote	No and Onsite
Enhances data analysis of the collected data	Yes	No
Consumers playing a critical role in the grid operation, especially in optimisation	Yes	No
System design	Digital and microprocessor or microcontrollers	Electromechanical and solid state
Communication flow	Global two-way communication	One-way or local two-way communication
Resiliency	Self-healing and automated	Manual restoration
Reliability	Predictive reliable	Estimated reliable

2.4 SMART-GRID METERING

ICT is one of the essential components of technology-driven industries in today's economy and its uses in renewable energy are significant. ICT has been integrated into renewable energy, especially the power grid, to make such grids more intelligent; this

development is popularly referred to as SG. SG is one of the most critical components in a classical power grid containing several smart objects such as smart meters, smart devices, sensors, actuators and communication infrastructure for seamless communication, among others. SGs can be denoted as intelligent power grids (IPG). An IPG forms its chain from the energy generation point through power-transmitting infrastructure and distribution networks to smart homes (*final electricity consumer*), such as houses, factories, public lighting, smart appliances and electric vehicle charging infrastructure, as shown in Figure 2.4, which captures the SG conceptual model. In addition, making such a power grid an intelligent one requires some level of ICT involvement such as hardware, software and firmware aimed at ensuring proper control and remote monitoring of the grid, as well as maintaining a real-time balance between electricity generation and consumption. Moreover, electricity consumers drive the production from the power grid, and it is necessary to have foreknowledge of its future demand owing to population expansion.

Forecasting the future consumption of electricity in an SG is an essential aspect of power system planning and operation of SG systems. In every utility, load forecasting forms the key yardstick for pricing the required load generation for consumers. Electricity load forecasting, being the focus, can involve a short-term, medium-term or long-term load. These differences depend solely on the requisite forecasting period, that is, short-term forecasting focuses on one-hour to one-week future prediction, the medium term corresponds to one-week to one-year future prediction, while long-term forecasting focuses on more than a year in advance [11]. The focus of this research is short-term load forecasting and the data used for the future prediction are hourly and 15-minute interval data obtained from components of SG, being the result of electricity consumption at different times of the year. Different residential properties, commercial offices and industrial sectors form the consumer section of an SG, as shown in Figure 2.5-2.7.

Furthermore, various sensors, such as temperature and pressure sensors and other data collection devices, are installed on customers' premises to aid data collection before transmitting the data to a central repository for further analysis. It is noteworthy that in a 21st century electrical power grid infrastructure, the aims are to improve efficiency, security and reliability via intelligent control, power converters, ICT (hardware and software), sensing and metering and effective energy management techniques based on electricity demand optimisation and network availability.

Prior to any prediction of the future load, it is essential to visualise the trends in historical electricity load consumption, as shown in Figures 2.5–2.7. Figures 2.5-2.7 depict the load consumption over time. This trend helps to reveal the various patterns of consumption in the residential, commercial and industrial sectors from the collected data.

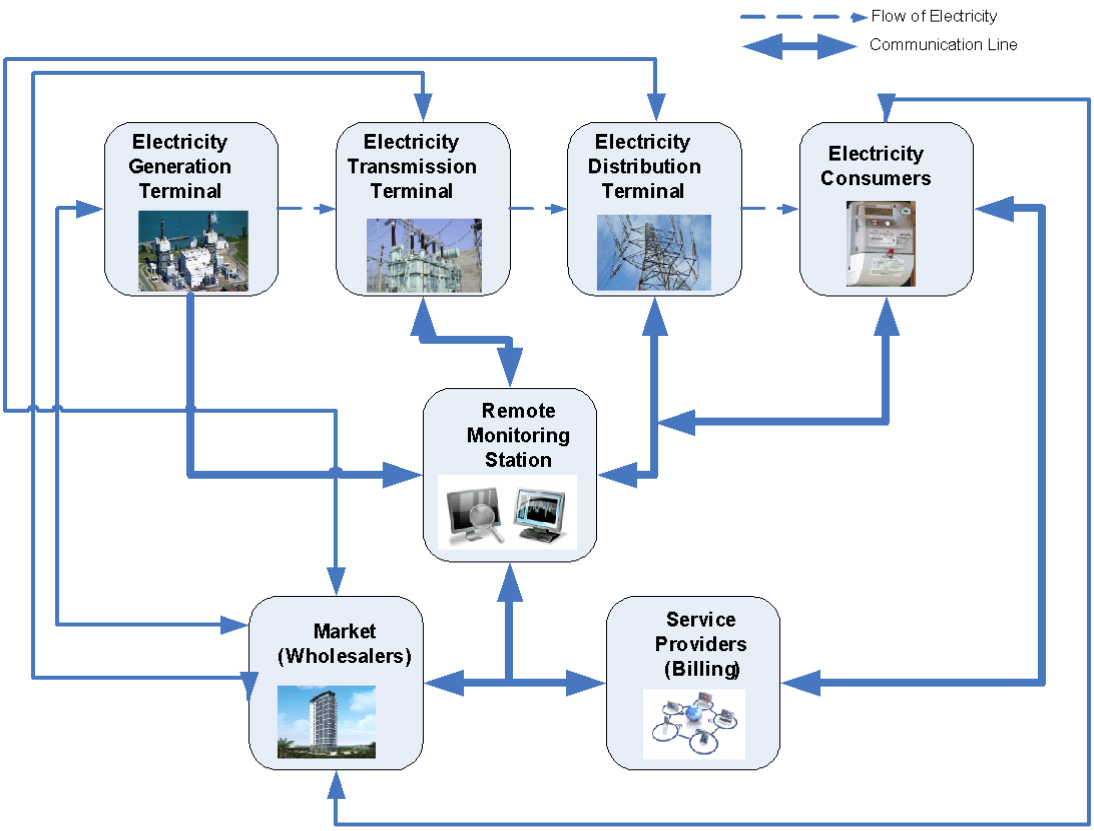


Figure 2.4: Smart Grid Conceptual Model (Adapted from [60]).

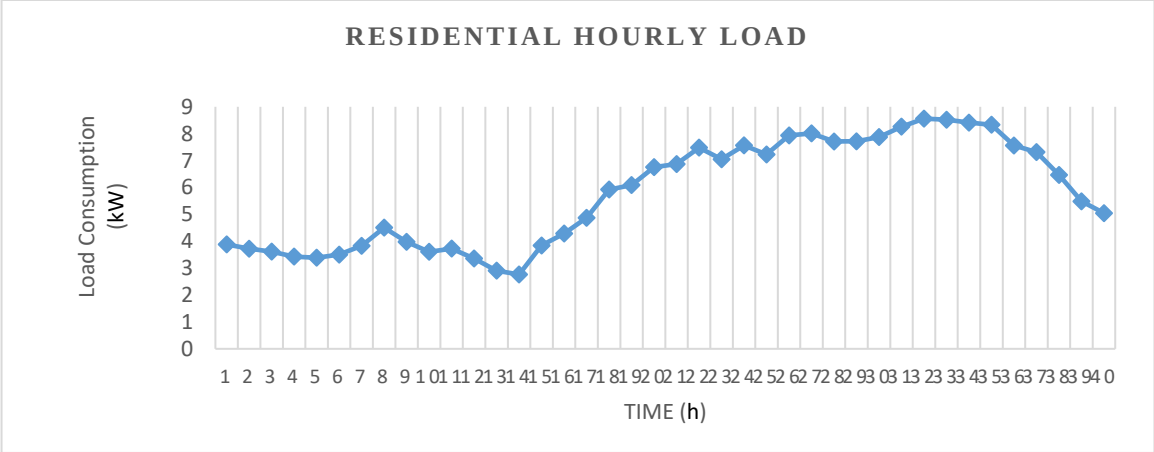


Figure 2.5: Hourly Load Trends for Residential Consumers.

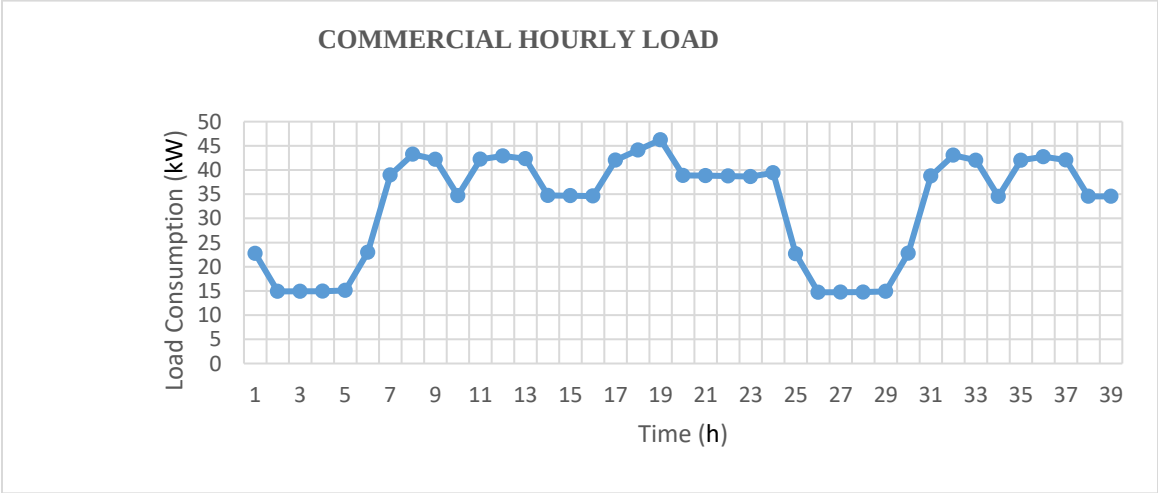


Figure 2.6: Hourly Load Trends for Commercial Consumers.

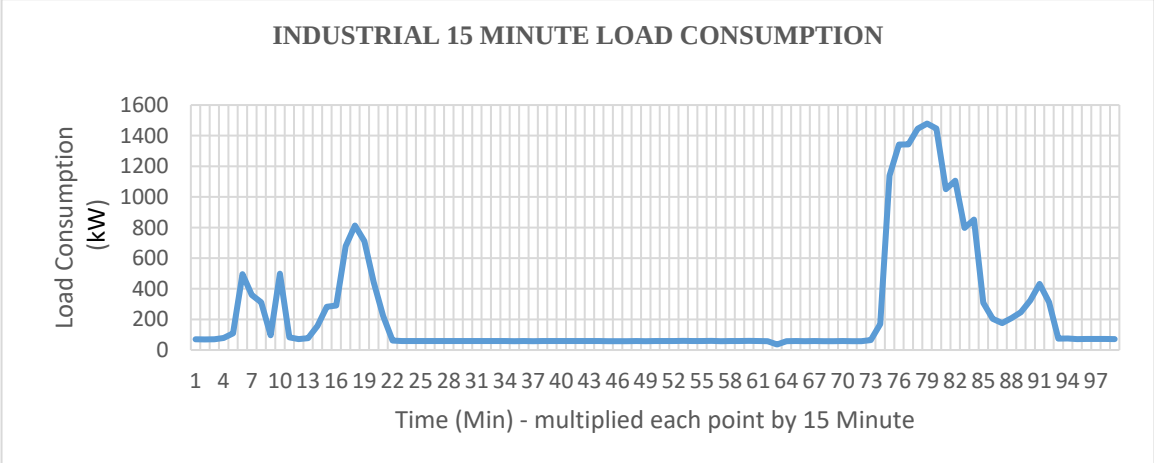


Figure 2.7: 15-minute Load Trends for Industrial Consumers.

From the virtualisations in Figures 2.5 to 2.7, one can see different patterns of electricity consumption from the classes of data. These figures show diverging low, medium and high load consumptions for residential, commercial and industrial users. The consumption disparity depicts how loads are consumed by different groups at different times, and this helps most utilities determine load behaviour on a class-by-class consumer basis.

It will be helpful to have the key drivers that determine the continuous growing of the SG world and various benefits derived from such inventions. The drivers for SG are:

I. Growing energy demands;
II. Energy-independent infrastructure, reliability and security necessities;
III. Economic growth and sustainability;
IV. Technology advancements;
V. Necessities for quality power;
VI. Safety for all the grid workers.

In summary, various benefits highlighted below can be derived from a SG over the usual traditional grid:

I. Quick recovery after storms;
II. Reduction in the cost of the utility;
III. Effective customer engagements.

2.5 SHORT-TERM LOAD INFLUENCING FACTORS

Several factors, such as time of day, economic constraints and weather, have complicated the development of a global short-term load forecasting technique [5], [6]. Time has an

effect on demand patterns, especially as consumption progresses during the day, and load consumption tends to decrease as night-time approaches [5].

Economic constraints cannot be underestimated, but are quite unsuitable for load forecasting owing to their convoluted statistical methods that require significant time and effort [10] and their variations based on different economic features such as economic growth and development [5], [6].

Weather is the atmospheric condition of a certain location over a period and it includes temperature, wind speed, pressure, dew point and humidity. These play a crucial role in predicting short-term load by modifying the daily load curve [68]. However, the effects of some factors are stronger than others. Kown et al. [6] use a neural network with weather factors such as temperature and dew point to predict electricity load demand, using hourly intervals. In addition, Hobby et al. [69] use different weather parameters and previous load consumption in conjunction with least squares fitting to predict the next load consumption for short-term loads. They collected several datasets from different locations to prove their argument of accurate forecasts; however, only the least square fitting algorithm was used for their prediction. In order to produce an effective short-term load forecast, Day et al. [8] emphasised the effective performance of hybrid forecasting methods for short-term load forecasting and Rothe [68] pointed out the use of an adaptive approach to short-term load forecasting. Thus, weather factors are critical for short-term load forecasting.

2.6 CHAPTER SUMMARY

This chapter discussed various valuable state-of-the-art techniques used for energy forecasting alongside their strengths and weaknesses in relation to the predictive error rates. Though these techniques have proven excellent in terms of short-term load forecasting and its corresponding predictive error, the cooperative method of electricity

load consumption will aid improvement in the load prediction by reducing the predictive error further.

The study explained the theoretical framework of the cooperative PSA-DT and components such as PSA, DT, entropy and standard deviation, which form the major components of the PSA-DT framework.

The research also discussed the electricity transition from the traditional design to the SG and indicated how several energy losses occur during distribution of electricity to stakeholders. The differences between the traditional grid and SG were highlighted, in conjunction with the necessity of smart metering devices for electricity consumption data capture for future analysis, which is one of the key components of an SG. In addition, a brief discussion on several conditions such as weather, seasons, price, etc., which affect electricity consumption by various categories of users, was conducted.

CHAPTER 3: RESEARCH METHODOLOGY AND PROPOSED SYSTEM

3.0 INTRODUCTION

This section focuses mainly on the development of a cooperative model for short-term load forecasting in an SG environment. It uses the predictive result for effective future demand and operational planning. In this model, load consumption from various classes of consumers, such as residential, commercial and industrial, was considered, and the collected historical load data from different classes of consumers were cleaned and formatted for effective integration. The PSA-DT cooperatively functions as an interaction between scenario analysis with probabilistic focus and a DT model, as shown in Figure 3.1. Probabilistic results of each scenario analysis form a list structure. In addition, the lists generated have some confidence value to show that the contents of the list have a high degree of confidence belief. This list is then passed to the DT to generate predictive value with low MAE.

The current study claims are based on the fact that the PSA-DT model might enhance the predictive performance for short-term load forecasting in an SG. This might improve the electricity distribution planning activities based on accurate predictions.

3.1 ESTABLISHING FRAMEWORK OF PSA-DT MACHINE LEARNING MODEL

Considering some of the components in Figure 3.1, these were divided into a historical data repository, grid operational planning systems and the PSA-DT framework. The historical data were generated from various power sensors installed in the SG to record the different categories of users' electricity consumption. Users such as residential, commercial and industrial producers generate time-based load consumption, filtered via

the knowledge-based system and stored in a repository for future prediction and research. The grid operational system comprises the control systems and the various operational components such as smart meters and several planning tools, among which is the STLF model for effective load planning. The PSA-DT framework details the process of using both Monte Carlo PSA and a DT for a minimal error short-term load predictive solution, as shown in Figure 3.1.

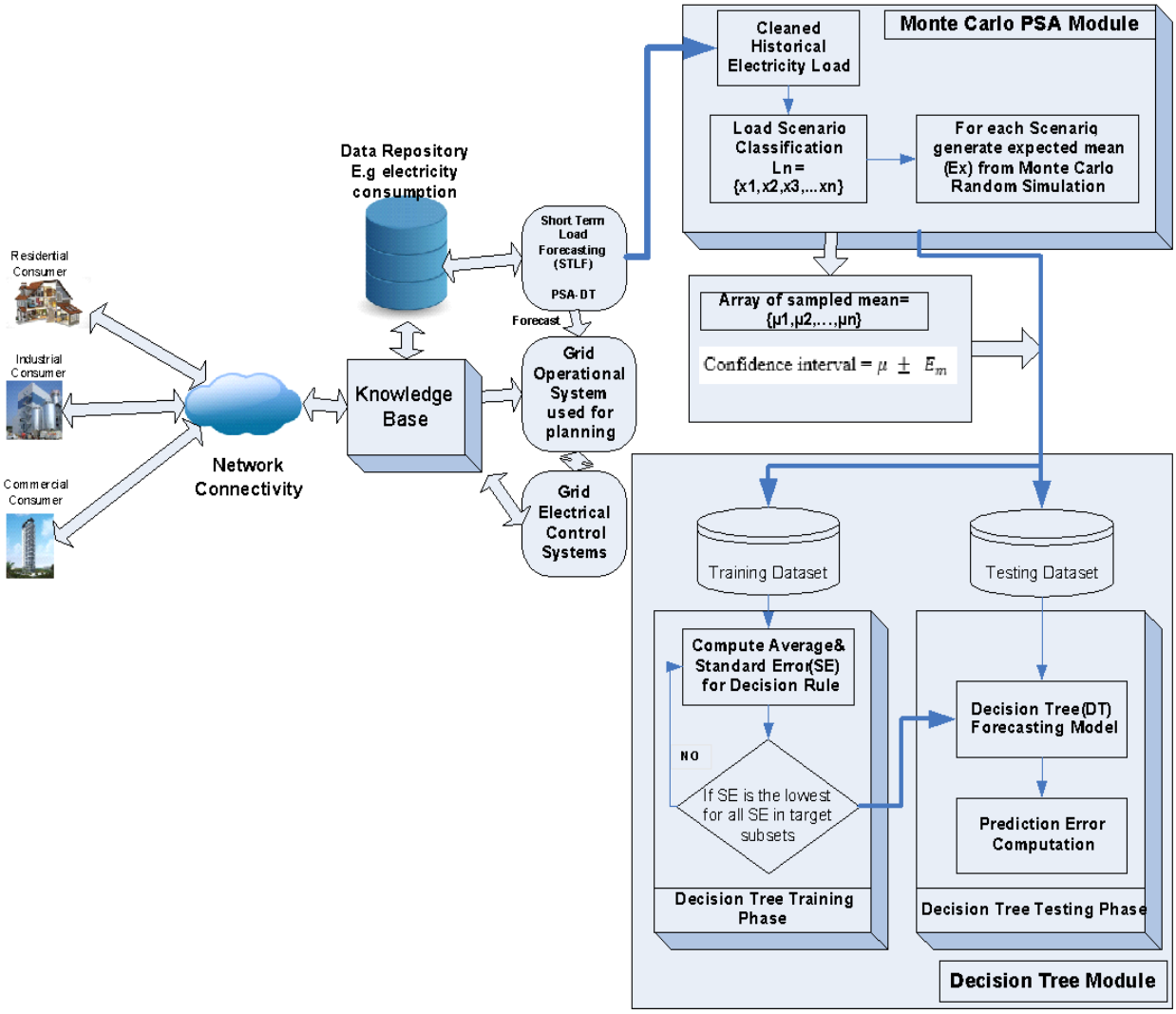


Figure 3.1: PSA-DT Framework.

3.2 CONFIDENCE INTERVAL AND DEGREES OF FREEDOM

This is usually in range and defined as the probability value within which the value of a parameter falls. It is an indicator of how stable an estimate (E(X)) is and it measures how close the measurements are to the initial estimate in some repeated experiments. With the mean (μ), E_m being the acceptable error level and standard deviation (σ), the estimate at 90%, 95% or 99% confidence level can be computed before such an estimate of a high confidence degree and with uniform probability of occurrence can be fed into the DT for final prediction of future load consumption.

$$\text{Confidence interval} = \mu \pm E_m \tag{7}$$

Degree of Freedom: The degree of freedom (DF) is the number of independent items of information used for calculating an estimate. Usually, the DF is one less than the sample size.

$$\text{DF} = \text{Sample Size (N)} - 1 \tag{8}$$

3.3 PSA-DT: MONTE CARLO PROBABILISTIC SA MODELLING

The PSA model was based on the Monte Carlo method because of uncertainty about future load consumption. It involves the use of probabilistic simulation techniques to compute the future sampled demand of load consumption. This process uses both probability and scenario analysis. In the scenario section shown in Figure 3.2, PSA was built around the cleaned and formatted historical load $L = \{l_{1,}\ l_{2,},\ l_{3,},\ l_{4,} \ldots\ldots l_{n,}\}$. The load was split into four major parts, namely very low (VL), low (L), high (H) and very high (VH), forming each scenario case. At every point in time, any load consumption (L_o) can be a member of any of the subsets of the entire load-set. For each subset, we then found the probability of each scenario to generate its expected value. The expected mean of each

scenario was also obtained through various random experiments using Monte Carlo simulations. For each event generated in the random experiment, the mean was calculated repeatedly to generate another future mean during the subsequent random experiment. In the final set of mean loads, the confidence interval of the mean, shown numerically in Section 3.2, is calculated and stored in conjunction with the mean in the array structure for further analysis with the DT model, as also shown in Figure 3.2.

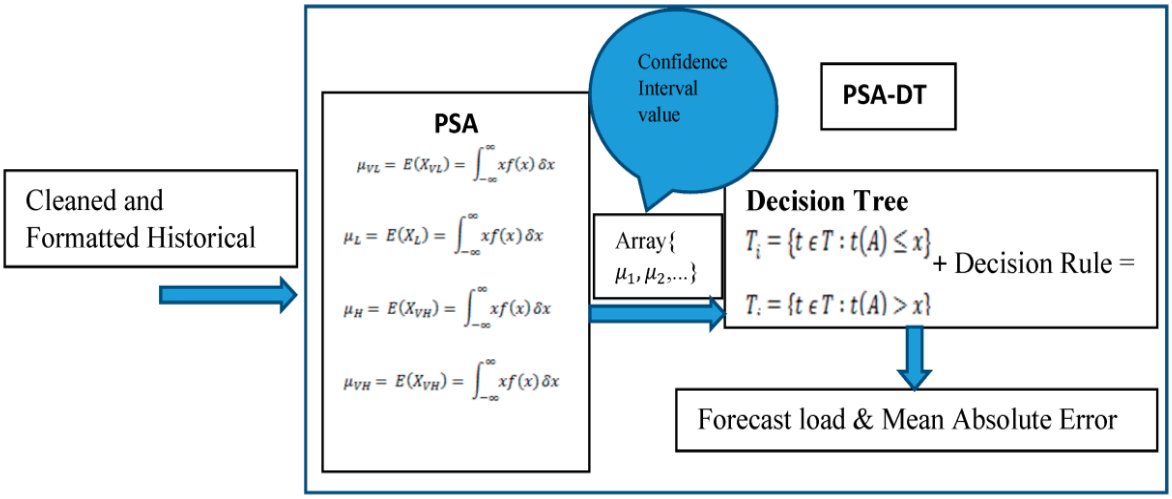


Figure 3.2.PSA-DT Model Flow.

3.4 PSA-DT: DECISION TREE MODELLING

Using the DT model for final prediction of the short-term load requires the expected mean in the list generated from the Monte Carlo experiment to be divided into training and test data. In each of the features in the training set, a set average and the standard error for each of the training features were calculated; a target variable within the training set with least standard error was selected to enhance the split point of the training set into two sets, namely S_1 and S_2. These operations were then carried out recursively until the leaf nodes were reached. In addition, the lowest error used in determining the split point shows how close the predicted value can effectively fit the test value with a minimal error

value. The prediction and the MAE for the load consumption were finally computed. Based on the DT section in the framework shown in Figure 3.2, the operations described above were broken down for quick view and comprehension for similar approaches, using the decision rule in Figure 3.3.

Definition: Consider the DT structure for the load recognition problem described by the following properties:

i. X_L is the load consumption, X_p is the absolute weather status and Y constitutes a set of possible behaviour exhibited by the entities in X, which are {very low load (VLL), moderate load (ML), and very high load (VHL)}.

In this case, Figure 3.3 shows the model situation where Y depends on X after the average load (AVGL) has been computed.

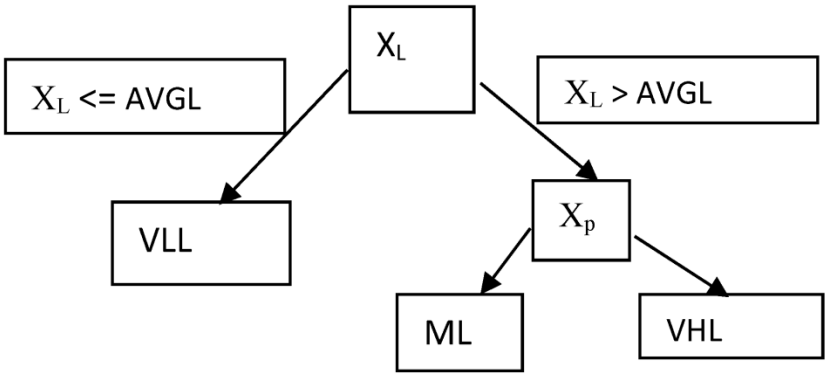


Figure 3.3: A Typical DT Structure.

Considering Figure 3.3, the tree has a root as X_L growing downwards to X_p and several leaf nodes, namely VLL, ML and VHL. This formation was based on the following decision rule:

1. If X_L<= AVGL, *Y* = "*VLL*".

2. If $X_L \in Z$, where Z > AVGL and X_p = "*average weather*", then *Y* = "*ML*".

3. If $X_1 \in Z$, where Z > AVGL and X_p= "*hash weather*", then *Y* ="*VHL*".

ii. The VLL, ML and VHL form the predicted load at every decision node such as X_L and X_P. As described in Section 2.2.2, these nodes were formed based on the computation of standard errors for each of the sample elements and selecting the least error in conjunction with the corresponding samples.

3.5 PSA-DT WITH WEATHER PROFILE IN SMART GRID: MONTE CARLO PROBABILISTIC SA MODELLING WITH WEATHER PROFILES

Using PSA-DT for the future prediction of loads involves active consideration of the expected loads obtained from the sample loads. This result was achieved through a Monte Carlo random experiment because of the unpredictability of the future load consumption. The process uses a flow process that includes obtaining the historical loads and corresponding weather locations and generating the expected load via a Monte Carlo random experiment to obtain loads of high confidence value. For the selected sample load, the corresponding expected weather profiles were also obtained for easy synchronisation during the training with the DT model. This flow can be seen clearly in the model pseudo-code shown in Figure 3.1.

However, the relationship between electricity load consumption and weather parameters can be seen in terms of the cumulative mean generated from the random sampling in a Monte Carlo experiment, as shown in Equation 9,

$$E_{demand} = (\alpha_0 + \alpha_1\gamma^1_{mean[1]} + \alpha_2\gamma^2_{mean[2]} + \cdots + \alpha_{t-1}\gamma^{t-1}_{mean[t-1]})/n + \varepsilon_{margin}$$

$$E_{demand} = \varepsilon_{margin} + \frac{1}{n}\sum_{t=0}^{t-1}\alpha_t\,\gamma^{t-1}_{mean[t-1]} \quad (9)$$

where E_{demand} is the expected load demand, γ is the average summation of load and weather variables at every time t generated through Monte Carlo simulation while α

depicts the constant factor for each of the experiments and ε_{margin} means the possible error margin generated during the process of simulation. The expected load demand can then be predicted using the PSA-DT model in Figure 3.1 with detailed processes published in [70]. The main difference between the pseudo-code in Figure 3.1 and the referenced PSA-DT model is the addition of the weather variables during the process of prediction.

Furthermore, using the DT model for final prediction of the short-term load requires the expected mean in the list generated from the Monte Carlo experiment to be divided into training and test data. In each of the features in the training set, a set average and the standard error for each of the training features were calculated; a target variable in the training set with least standard error was selected to enhance the split point of the training set into two sets, namely S_1 and S_2. These operations were then carried out recursively until the leaf nodes were reached. In addition, the lowest error used in determining the split point shows how close the predicted value can effectively fit the test value with a minimal error value. The prediction and the MAE for the load consumption were finally computed. Based on the DT framework, the operations described above were broken down for quick view and comprehension for similar approaches, using the decision rule in Figure 3.3.

3.6 SCORING AND EVALUATION MECHANISMS

3.6.1 Cross-validation Scheme

One of the major scoring and evaluation schemes is a cross-validation scheme, popularly known as *K-fold* cross-validation (K-fold CV). Its primary aim is to improve predictive performance in a statistical model. It is a systematic repetition of the training and testing procedure several times, which aims to lower the associated variance that dominates the

single run of training/testing splitting techniques. When this method serves as an improvement mechanism, the entire dataset will be split into *k* equal sizes known as folds. A combination of $k - 1$ folds will be used to train the model and testing will make use of the remaining one fold, but the fold for testing will be unique at every iteration of the *k-fold* space. In summary, the major aim of cross-validation is to avoid overfitting.

Implementing the cross-validation task, the following procedure is followed by each of the k-folds:

1. Model training using $k - 1$ of the folds as training data; and
2. Validating the resulting model on the remaining set of data; i.e., it is used as test data to compute its accuracy, which is a performance measurement.

The average of the computed value in the loop therefore forms the measured performance by *k-fold* cross-validation.

3.6.2 Mean Absolute Error

In addition, MAE is an evaluation metric for predictive modelling performance used to measure the level of closeness of the prediction to the actual outcome. It can be calculated via Equation 10,

$$MAE = \frac{1}{N}\sum_{i=1}^{n} |y_i - x_i| \tag{10}$$

where N is the number of observations, and $|y_i - x_i|$ is the absolute errors between the predicted and actual load.

3.7 PSA-DT ALGORITHMIC AND MATHEMATICAL ANALYSIS

The algorithm in this section is divided into two parts; the first is the algorithm without weather profile and the second algorithm contains the weather profile, though the

process flows in the two algorithms are similar because the two models used the concept of PSA-DT.

PSA-DT algorithmic and mathematical analysis without the weather profile in Figure 3.4 is the algorithm used to develop implementation for the PSA-DT model. Having read all the electricity load data from the repository, the number of simulations for the experiment was inserted. An empty list was generated and the load was finally classified into different scenarios, as discussed earlier. The random number of sampled mean was also computed to produce the expected mean being stored in an array. The resulting list was used to compute the confidence interval, as revealed in the algorithm in Figure 3.4. Between lines 10 and 23 in Figure 3.4, each of the randomly generated load consumption lists produces a list of expected loads meant for confidence interval generation. If the generated confidence interval is within the desire value, such as 90%, 95% or 99%, a decision will be made on the list of expected loads. Prior to the decision, the expected load list will be divided into training and test sets. The training set will be used to train the DT model while the test set will be used to test the effectiveness of the trained model. The strategy of splitting the dataset was to avoid overfitting of the model.

PSA-DT – Cooperative Probabilistic Scenario Analysis With Decision Tree

```
allLoads ← readAllElectricityLoad()
//Initialization
numOfSimulation ← input(number)
possibleAverageTuple ← input(List[])
averageLoad ← mean(allLoads)
//Division all Loads to very low-VL, low-L, high-H and very high-VH Scenarios
scenarioClasses ← ScenarioClassifier(averageLoad, possibleAverageTuple)
emptyLoadList = generateEmptyList(lenght(allLoads))
loadRandomNumberList ← generateLoadRandomNumber(emptyLoadList)
for i in loadRandomNumberList do
    //Compute the expected mean of the randomly selected load
    expectedLoadList ← MeanLoad(loadRandomNumberList[0:i])
    for j in expectedLoadList do
        confidenceInterval ← GenerateConfidenceValue(expectedLoadList[j])
        confidenceStatus ← isConfidenceValueValid(confidenceInterval)
        if confidenceStatus then
            //Split into Training and Test Data
            TrainingSet, TestSet ← Split(expectedLoadList)
            DecisionTreeAnalysis(TrainingSet)
            RootMeanSquareError ← GenerateRootMeanSquareError(TestSet, predictedValue)
        end if
    end for
end for

function DecisionTreeAnalysis(TrainingSet)
    //Checkifthetrainingsetisnotemptyandterminationnodeisnotreached
    if TrainingSet ≠ emptySet then
        if TerminationNode ≠ reached then
            StandardError[] ← ComputeStandardError(TrainingSet)
            LeastError, TargetVariable, RemainingTrainingSet ← SearchLeastStandardError(StandardError[])
            PredictedValue ← DecisionNode(TargetVariable, mean(RemainingTrainingSet))
            DecisionTreeAnalysis(RemainingTrainingSet)
        else
            ReturnPredictedValue()
        end if
    else
        PrintNoDataset
    end if
end function
```

Figure 3.4.PSA-DT Algorithm.

3.7.1 Numerical Scenario for Residential Load Consumption

Supposing there is a sample set of very high residential load consumption from an SG, RL_{vh}, which is equal to {3.8809, 3.7225, 3.6137, 3.4286, 3.3893, 3.5024, 3.8319, 3.74693021, 3.74657042, 3.74643688} in Kw/h. Based on the randomly generated estimated load data from Monte Carlo simulations through randomly sampled residential load from the set RL_{vh}, the following list, μ_{vh} = {3.74747941, 3.74715633, 3.74683391, 3.74706542, 3.74670404, 3.74693522, 3.74679607, 3.74693021, 3.74657042, 3.74643688}, was generated as expected load in the simulated experiment with mean (μ) equals 3.7499 and standard deviation (σ) equals 0.1224.

From Equation 7, the 95% confidence level, sometimes called the margin error (E_m), can be obtained from the calculation in this section.

Using Equation 2,

N = sample size = 10

$\mu = \mathbf{3.7499}$ *and* σ = Standard deviation = **0.1224**

α = Confidence Level = 95% = 0.95.

From Equation 8 DF = 10 − 1 = 9

$\frac{\sigma}{\sqrt{n}}$ = Standard Error = $\frac{\mathbf{0.1224}}{\sqrt{\mathbf{10}}}$ = 0.0387.

Being a component in Equation 2, $T_{\alpha/2}$ = Confidence Coefficient = T_{value} (1-confidence level)/2 = (1 − 0.95)/2 = 0.025.

One can then extract the result of T_{value} (0.025) = 2.262 from the T distribution section in [71] and also E_m = 2.262 x 0.0387 = 0.0875.

Therefore, the confidence interval at 95% confidence degree = **3.7499** ± 0.0875:

lower limit with 95% confidence interval = 3.7499− 0.0875 = 3.6624; and

upper limit with 95% confidence interval = **3.**7499+ 0.0875 = 3.8375.

Despite some low load consumption in RL_{vh}, such as 3.4286 Kw/h and 3.3893 Kw/h, the expected load for future planning at 95% confidence interval falls within the range of **3.6624 kW/h** and **3.8375 kW/h**. In this case, the expected mean μ_{vh} generated from Monte Carlo simulation will be between the calculated confidence intervals. Once the statement is valid, the estimated mean has 95% confidence.

Selecting the set of mean load obtained from the Monte Carlo experiment as PSA_{result} = {3.7403, 3.74, 3.7401, 3.7398, 3.7397, 3.7398, 3.7406, 3.7408, 3.7416, 3.7415}, it is appropriate to note that PSA_{result} falls within the confidence interval and these results are split into training and test sets for DT processing using K-fold CV described in Section 3.6.1.

$DT_{trainingSet}$ = {3.7416, 3.7398, 3.7403, 3.7401, 3.7406, 3.7415, 3.7397, 3.7398} and the mean of $DT_{trainingSet}$ = 3.7404

$DT_{testSet}$ = {3.7408, 3.74}.

From Equation 6, the SD from the mean for $DT_{trainingSet}$ is shown in Table 3.1 for different split sessions.

Table 3.1: Residential Load Standard Deviation for Different Splitting Session of the $DT_{trainingSet}$.

$DT_{trainingSet}$ at Split 1	SD at Split 1	$DT_{trainingSet}$ at Split 2	SD at Split 2	$DT_{trainingSet}$ at Split 3	SD at Split 3
3.7416	0.0012	3.7416	0.0012	3.7416	0.00095
3.7398	0.0006	3.7398	0.0006	3.7415	0.00085
3.7403	0.0001	3.7401	0.0003	3.7397	0.00095
3.7401	0.0003	3.7406	0.0002	3.7398	0.00085
3.7406	0.0002	3.7415	0.0011		
3.7415	0.0011	3.7397	0.0007		
3.7397	0.0007	3.7398	0.0006		

3.7398	0.0006

Split 1: The DT was split where the SD is at minimum value, which is at the point where the load value is 3.7403 KW/h. This is S_1, while the remaining members in the $DT_{trainingSet}$ will form set S_2 as described in Section 3.4. The S_1 becomes the leaf node while S_2 will go through recursive processes of extracting the member set with minimal SE carried out in Split 2, as shown in Table 3.1.

Split 2: During this split process, the SD of the remaining dataset in Table 3.1 will be recalculated to obtain the lowest SD value. The load value 3.7406 Kw/h with SD 0.0002, being the minimum value among others, is selected as the decision node for further splitting. When the split result is more than one, an average of this result is computed for the leaf node, e.g. (3.7398 + 3.7401 + 3.7406)/3 = 3.7401 KW/h.

Split 3: At this juncture, the corresponding dataset was used to calculate the SD in order to obtain its lowest SD value. Load values 3.7415 and 3.7398 have the same SD value (0.00085) but the average of the two loads has an approximate value of 3.7407 Kw/h, which will form the decision point to aid the final decision. The final leaf nodes in Figure 3.3 form the model checked against $DT_{testSet}$ for effective testing of the model. $DT_{testSet}$is a new dataset that has never been used during the DT training process and this was used against the training model to obtain an MAE that indicates the predictive performance of the model.

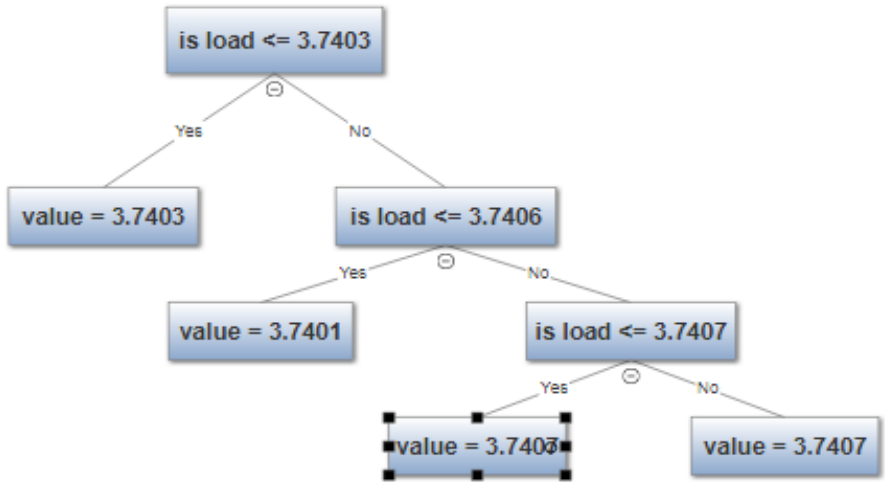


Figure 3.5: Generated DT for Residential Load.

Based on the size of $DT_{testSet}$, the same data size was obtained from the DT result in Figure 3.5, preferably the last unique leaf nodes {3.7407, 3.7401}. Therefore, from Equation 10,

$$\text{MAE} = \frac{|3.7407-3.7408|+|3.7401-3.74|}{2} = \frac{0.0001+0.0001}{2} = 0.0001.$$

In brief, the result of the predictive error (MAE) is a minimum value for the few datasets considered in this mathematical analysis and compared with the result of the predictive error produced in Experiment 2 shown by Figure 4.3a(ii), one can see that using the cooperative model PSA-DT produces a minimum predictive error close to zero for residential load consumption.

3.7.2 Numerical Scenario for Commercial Load Consumption

CL_{vh} = {22.7436, 14.901, 14.9245, 14.9408, 15.1012, 22.9898, 38.9705, 43.2523, 42.1958, 34.702} in Kw/h.

$\mu = 25.6743$ *and* σ = Standard deviation = 1.0486

$\frac{\sigma}{\sqrt{n}}$ = Standard Error = $\frac{1.0486}{\sqrt{10}}$ = 0.3316, at 99% Confidence level

$T_{\alpha/2}$ = Confidence Coefficient = T_{value}(1-confidence level)/2 = (1 − 0.99)/2 = 0.005 using Equation 2

T_{value} (0.005) = 3.250 obtained from T distribution in [71]

E_m = 3.250 x 0.3316 = 1.0777

Therefore, the confidence interval at 99% confidence degree = 25.6743 ± 1.0777.

Lower limit with 95% confidence interval = 25.6743 − 1.0777 = 24.5966.
Upper limit with 95% confidence interval = 25.6743 + 1.0777 = 26.752.

From the set CL_{vh} with a sample load such as 22.7436, 14.901, ..., the load expectation at 95% confidence interval is between 24.5966 Kw/h and 26.752 Kw/h for the class of load users considered. In this situation, using a Monte Carlo experiment, the expected mean generated and this value fall within the computed confidence interval.
The mean loads obtained from the Monte Carlo experiment as PSA_{result} = {26.5359, 26.5485, 26.5369, 26.5333, 26.5295, 26.5453, 26.5535, 26.5418, 26.5586, 26.5547} fell within the confidence interval and this result was also split into training and test sets for DT processing using K-fold CV described in Section 3.6.1.

$DT_{trainingSet}$ = {26.5586, 26.5453, 26.5359, 26.5369, 26.5535, 26.5547, 26.5295, 26.5333} and the mean of $DT_{trainingSet}$ = 26.5435, which can also be used as the initial root node.

$DT_{testSet}$ = {26.5418, 26.5485}

From Equation 6, SD from the mean for $DT_{trainingSet}$ is shown in Table 3.2 for a different split session.

Table 3.2: Commercial Load Standard Deviation for Different Splitting Sessions of the $\boldsymbol{DT_{trainingSet}}$.

$\boldsymbol{DT_{trainingSet}}$ **at Split 1**	**SD at Split 1**	$\boldsymbol{DT_{trainingSet}}$ **at Split 2**	**SD at Split 2**	$\boldsymbol{DT_{trainingSet}}$ **at Split 3**	**SD at Split 3**
S_1(initial)					
26.5359	0.0020	26.5359	0.0005	26.5359	0.0005
26.5369	0.0030	26.5369	0.0015	26.5369	0.0005
26.5295	0.0044	26.5333	0.0021		
26.5333	0.0006				
S_2 (initial)					
26.5586	0.0056	26.5586	0.0030	26.5586	0.0025
26.5453	0.0077	26.5535	0.0021	26.5535	0.0026
26.5535	0.0005	26.5547	0.0009		
26.5547	0.0017				

Initially, the average load of 26.5435 Kw/h forms the first root node, as shown in Figure 3.6. The first decision shows the split result of $DT_{trainingSet}$ into S_1 and S_2 based on the validity of the condition that the initial average load is less or greater than the average load of 26.5435 Kw/h.

S_1 (initial) = {26.5359, 26.5369, 26.5295, 26.5333} was formed when $DT_{trainingSet} \leq total\ mean(\mu)$.

S_2 (initial) = {26.5586, 26.5453, 26.5535, 26.5547} was formed when $DT_{trainingSet} > total\ mean(\mu)$.

Considering Tree S_1 (initial) **with** $\boldsymbol{\mu(S_1)} =$ 26.5339 Kw/h:

Split 1: The split point through S_1 was determined by the lowest SD with value equal to 0.0006 and the corresponding load value is 26.5333 Kw/h, as shown in Table 3.2. Therefore, another set of S_1 and S_2 was formed.

S_1 = {26.5295} was formed when SD is at its lowest value of 0.0006 and S_1 average ≤ 26.5339 Kw/h.

S_2 = {26.5359, 26.5369, 26.5333} was formed when SD was at its lowest value of 0.0006 and S_1 average > 26.5339 Kw/h with new S_2 average as 26.5354 Kw/h.

Split 2: In this section, the split point is at the lowest SD of 0.0005 with a load value of 26.5359 Kw/h and another set of S_1 and S_2 was formed.

S_1 = {26.533} was formed when SD is at its lowest value of 0.0005.

S_2 = {26.5359, 26.5369} was formed when SD was at its lowest value of 0.0005 with a new decision node of 26.5364 Kw/h, being an average of S_2.

Split 3: In this last recursive iteration, the average of S_2 in Split 2 forms the decision node for the final split with an average of the remaining member set because they both have the same SD value of 0.0005.

Considering Tree S_2 (initial) with $\boldsymbol{\mu(S_2)} = 26.5530$ Kw/h:

Split 1: The split point through S_1 was determined by the lowest SD with value equal to 0.0005 and the corresponding load value is 26.5535 Kw/h, as shown in Table 3.6. Therefore, another set of S_1 and S_2 was formed.

S_1 = {26.5453} was formed and S_2 = {26.5586, 26.5535, 26.5547} was also formed with new S_2 average as 26.5556 Kw/h forming the next decision node, as shown in Figure 3.3.

Split 2: In this section, the split point is at least an SD of 0.0009 with a load value of 26.5547 Kw/h and another set of S_1 and S_2 was formed.

S_1 = {26.5535} was formed, and S_2 = {26.5586, 26.5547} was also formed with a new decision node of **26.5566 Kw/h**, being an average of S_2.

Split 3: In this last recursive iteration, the previous set S_2 forms the leaf node, as shown in Figure 3.6.

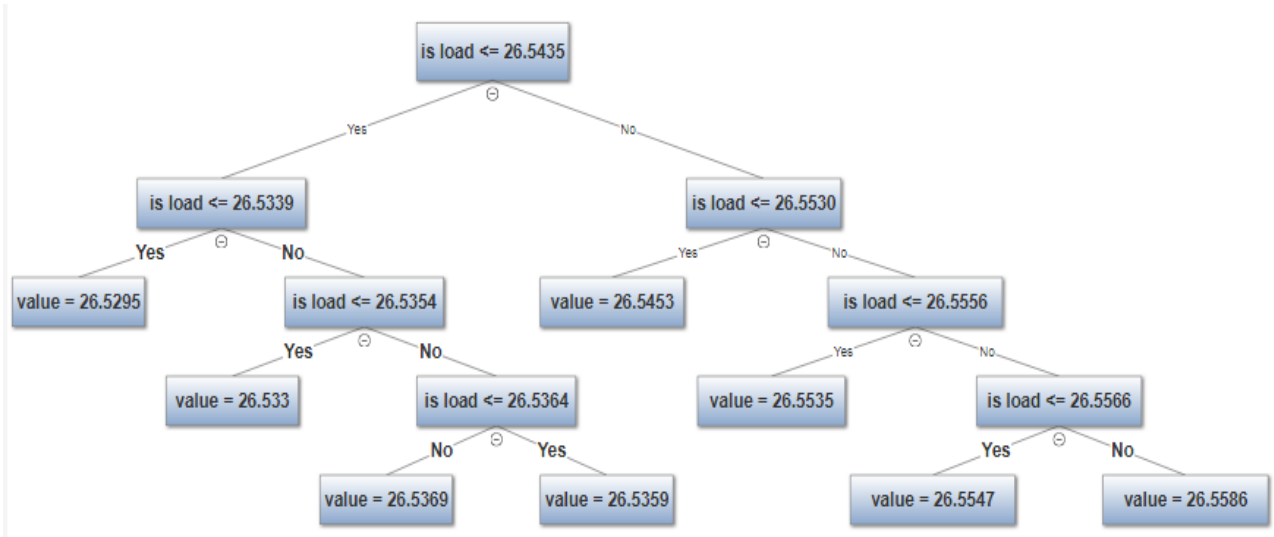


Figure 3.6: Generated DT for Commercial Load.

Based on the size of $DT_{testSet}$, the same data size was obtained from the DT result in Figure 3.6, preferably the last unique leaf nodes {26.5586, 26.5547}. Therefore, from Equation 10,

$$\text{MAE} = \frac{|26.5418-26.5586|+|26.5485-26.5547|}{2} = \frac{0.0168+0.0062}{2} = 0.0115.$$

From the MAE result obtained from the mathematical analysis of a commercial load using cooperative PSA-DT, one can also see the near-zero predictive result. This result also falls within the predictive error shown in Figure 4.3b (ii).

3.8 PSA-DT WITH WEATHER PROFILES: ALGORITHMIC AND MATHEMATICAL ANALYSIS

Figure 3.7 is the pseudo-code used to develop implementation for the PSA-DT model with weather variables. Having read all the electricity load data from the repository and fetched the load corresponding weather parameter through the custom RESTful web service, the number of simulations for the experiment was inserted. An empty list was generated and the load was finally classified into different load scenarios. The random

number of sampled mean was also computed in order to produce the expected mean stored in an array. The resulting list was used to compute the confidence interval, as revealed in the pseudo-code in Figure 3.7.

```
STLF with Weather Profiles Using PSA-DT
allLoads ← readAllElectricityLoad()
//Initialization
numOfSimulation ← input(number)
possibleAverageTuple ← input(List[])
averageLoad ← mean(allLoads)
//Division all Loads to very low-VL, low-L, high-H and very high-VH Scenarios
scenarioClasses ← ScenarioClassifier(averageLoad, possibleAverageTuple)
emptyLoadList = generateEmptyList(lenght(allLoads))
loadRandomNumberList ← generateLoadRandomNumber(emptyLoadList)
emptyWeatherParaList = generateEmptyList(lenght(allLoads))
loadRandomNumberList ← generateLoadRandomNumber(emptyLoadList)
weatherProfileList ← getlCorrespondingExpectedWeather(geolocation, loadRandomNumberList)
for i in loadRandomNumberList do
    //Compute the expected mean of the randomly selected load and corresponding weather profile
    expectedLoadList ← MeanLoad(loadRandomNumberList[0:i])
    correspondExpectedWeatherProfile ← getWealtherProfile(weatherProfileList[i], expectedLoadList[i])
    for j in expectedLoadList do
        confidenceInterval ← GenerateConfidenceValue(expectedLoadList[j])
        confidenceStatus ← isConfidenceValueValid(confidenceInterval)
        if confidenceStatus then
            //Split into Training and Test Data
            TrainingSet, TestSet ← Split(expectedLoadList, correspondExpectedWeatherProfile)
            DecisionTreeAnalysis(TrainingSet)
            RootMeanSquareError ← GenerateRootMeanSquareError(TestSet, predictedValue)
        end if
    end for
end for
```

Figure 3.7: PSA-DT with Weather Profile Algorithm

3.8.1 Numerical Scenario Residential Load Consumption with Temperature Weather Variable

Supposing there is a sample set of very high residential load consumption from an SG, RL_{vh}, which is equal to {3.8809, 3.7225, 3.6137, 3.4286, 3.3893, 3.5024, 3.8319, 3.74693021, 3.74657042, 3.74643688} in Kw/h with {6.1,5.6,3.9,2.8,2.2,1.1,0.6,1.1,3.9,6.1} as corresponding temperature at the location of each load consumption. Based on the randomly generated estimated load data from Monte Carlo simulations through randomly sampled residential load from the set RL_{vh}, the following list, μ_{vh}= {3.74747941, 3.74715633, 3.74683391, 3.74706542, 3.74670404, 3.74693522, 3.74679607, 3.74693021, 3.74657042, 3.74643688}, was generated as expected load in the simulated experiment with mean (μ) equals 3.7499 Kw/h and standard deviation (σ) equals 0.1224.

From Equation 7, the 95% confidence level, sometimes called the margin error (E_m), can be obtained from the calculation in this section.

Using Equation 2,

N = sample size = 10

μ =$\mathbf{3.7499}$ $and \sigma$= Standard deviation = **0.1224**

α= Confidence Level = 95% = 0.95.

From Equation 6 DF = 10 − 1 = 9

$\sigma/\sqrt{n}$= Standard Error = $\mathbf{0.1224}/\sqrt{\mathbf{10}}$= 0.0387.

Being a component in Equation 2, $T_{\alpha/2}$= Confidence Coefficient = T_{value} (1-confidence level)/2 = (1 − 0.95)/2 = 0.025.

One can then extract the result of T_{value}(0.025) = 2.262 from the T distribution section in [71] and also E_m = 2.262 x 0.0387 = 0.0875.

Therefore, the confidence interval at 95% confidence degree = **3.7499** ± 0.0875:

lower limit with 95% confidence interval = 3.7499 − 0.0875 = 3.6624; and

upper limit with 95% confidence interval = **3.**7499 + 0.0875 = 3.8375.

Despite some low load consumption in RL_{vh}, such as 3.4286 Kw/h and 3.3893 Kw/h, the expected load for future planning at 95% confidence interval still falls within the range of **3.6624 kW/h** to **3.8375 kW/h**. In this case, the expected mean μ_{vh} generated from Monte Carlo simulation will be between the calculated confidence intervals. Once the statement is valid, the estimated mean has 95% confidence.

Selecting the set of mean load obtained from the Monte Carlo experiment as PSA_{result} = {3.7403, 3.74, 3.7401, 3.7398, 3.7397, 3.7398, 3.7406, 3.7408, 3.7416, 3.7415} with corresponding weather equal {6.1,5.6,3.9,2.8,2.2,1.1,0.6,1.1}, it is appropriate to note that PSA_{result} falls within the confidence interval and the result is split into training and test sets for DT processing using K-fold CV described in [72].

$DT_{trainingSet}$ = {3.7416, 3.7398, 3.7403, 3.7401, 3.7406, 3.7415, 3.7397, 3.7398} the mean of $DT_{trainingSet}$ = 3.7404 and the average weather (AVG_{temp}) = 2.93 ^{o}C

$DT_{testSet}$ = {3.7408, 3.74}.

Split 1: The initial split was determined by the weather profile being greater or less than the average weather value. This generated two distinctive sets S_1 and S_2, titled Set of jth load and Set of ith load respectively, as shown in Figure 3.8.

S_1 = {3.7416, 3.7398, 3.7403, 3.7401, 3.7406, 3.7415, 3.7397, 3.7398} = Set of jth load

S_2 = { } = Set of ith load

The S_2 becomes the terminated node for the tree while S_1 follows the process of determining further splitting using the concept of lowest SD from the mean for all the sets obtained at every tree level.

From Equation 6, the SD from the mean for $DT_{trainingSet}$ is shown in Table 3.3 for subsequent and different split sessions.

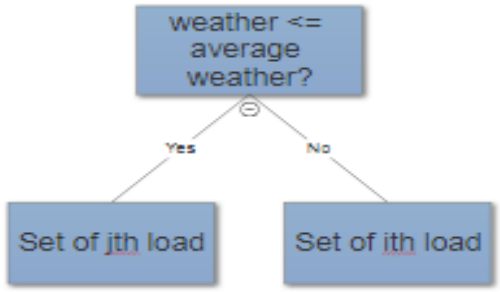


Figure 3.8: Initial Decision for Weather Split.

Table 3.3: Standard Deviation for Different Splitting Sessions of $DT_{trainingSet}$.

$DT_{trainingSet}$ at Split 1	SD at Split 1	$DT_{trainingSet}$ at Split 2	SD at Split 2	$DT_{trainingSet}$ at Split 3	SD at Split 3
3.7416	0.0012	3.7416	0.0012	3.7416	0.00095
3.7398	0.0006	3.7398	0.0006	3.7415	0.00085
3.7403	0.0001	3.7401	0.0003	3.7397	0.00095
3.7401	0.0003	3.7406	0.0002	3.7398	0.00085
3.7406	0.0002	3.7415	0.0011		
3.7415	0.0011	3.7397	0.0007		
3.7397	0.0007	3.7398	0.0006		
3.7398	0.0006				

Split 1: The DT is split where the SD is at minimum value, which is at the point where the load value is 3.7403 KW/h. This is S_1, while the remaining members in the $DT_{trainingSet}$ will form set S_2, as described in Section 3.4. The S_1 becomes the leaf node while S_2 will go through recursive processes of extracting the member set with minimal SE carried out in Split 2, as shown in Table 3.3.

Split 2: During this split process, the SD of the remaining dataset in Table 3.3 will be recalculated to obtain the lowest SD value. The load value 3.7406 Kw/h with SD 0.0002, being the minimum value among others, is selected as the decision node for further splitting. When the split result is more than one, an average of this result is computed for the leaf node, e.g. (3.7398 + 3.7401 + 3.7406)/3 = 3.7401 KW/h.

Split 3: At this juncture, the corresponding dataset was used to calculate the SD in order to obtain its lowest SD value. Load values 3.7415 and 3.7398 have the same SD value (0.00085) but the average of the two loads has an approximate value of 3.7407 Kw/h, which will form the decision point to aid the final decision. The final leaf nodes in Figure 3.9 form the model checked against $DT_{testSet}$ for effective testing of the model. $DT_{testSet}$is a new dataset that had never been used during the DT training process and this was used against the training model to obtain an MAE that indicates the predictive performance of the model.

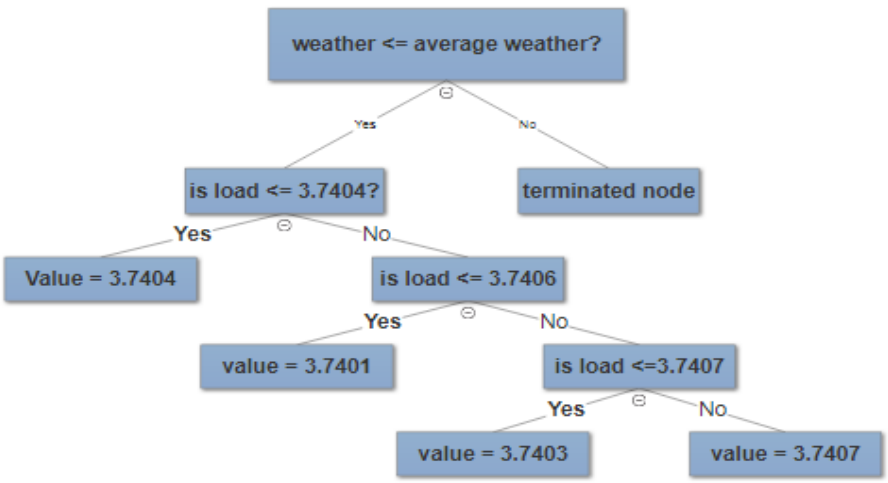


Figure 3.9: Generated DT for Residential Load.

Preferably the last unique leaf nodes are {3.7407, 3.7403}. Therefore, from Equation 10,

$$\text{MAE} = \frac{|3.7407-3.7403|+|3.7404-3.7401|}{2} = \frac{0.0004+0.0003}{2} = 0.00035.$$

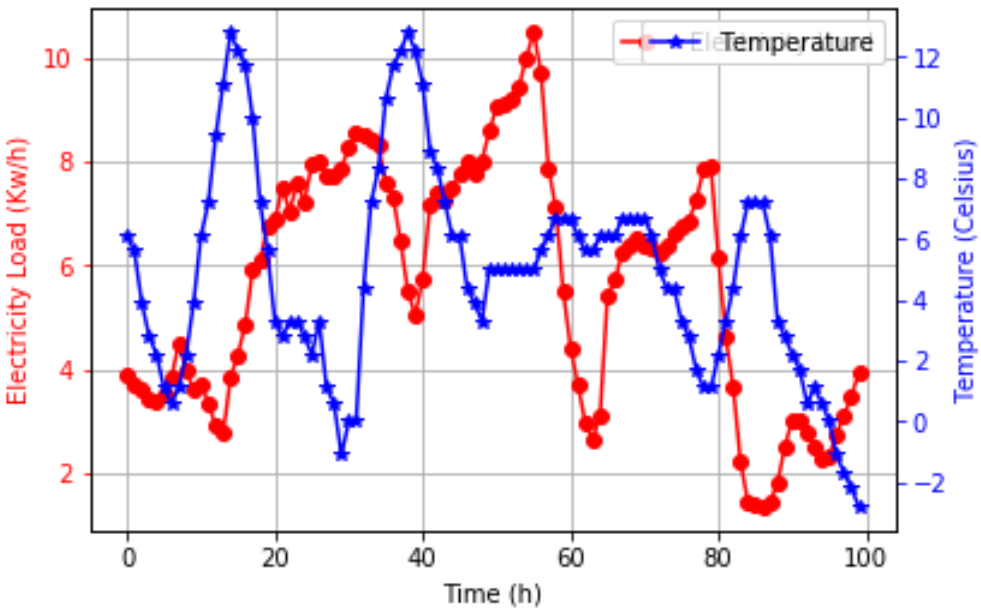
In brief, the result of the predictive error (MAE) is a minimal value, tends to zero for the few datasets considered in this mathematical analysis, complemented by the results of the predictive error produced in Experiment 2 shown by Figure 4.2(ii) and Figure 4.3(ii). One can see that using the cooperative model PSA-DT produces a near-zero predictive

error for residential load consumption. Apparently, most of the error points in the figure revolve around near-zero value.

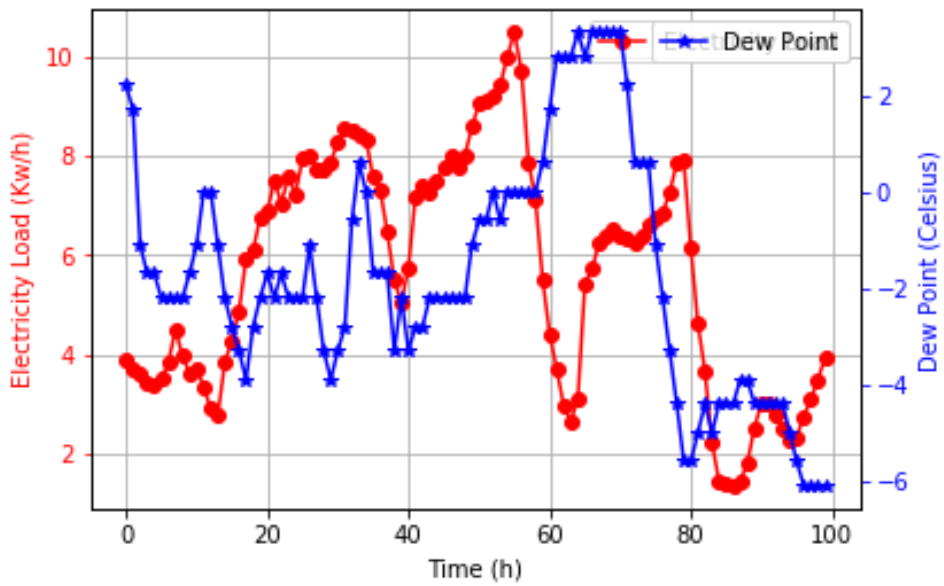
3.9 WEATHER ANALYSIS OF USERS' LOAD CONSUMPTION

3.9.1 Weather Analysis of Residential Load Consumption

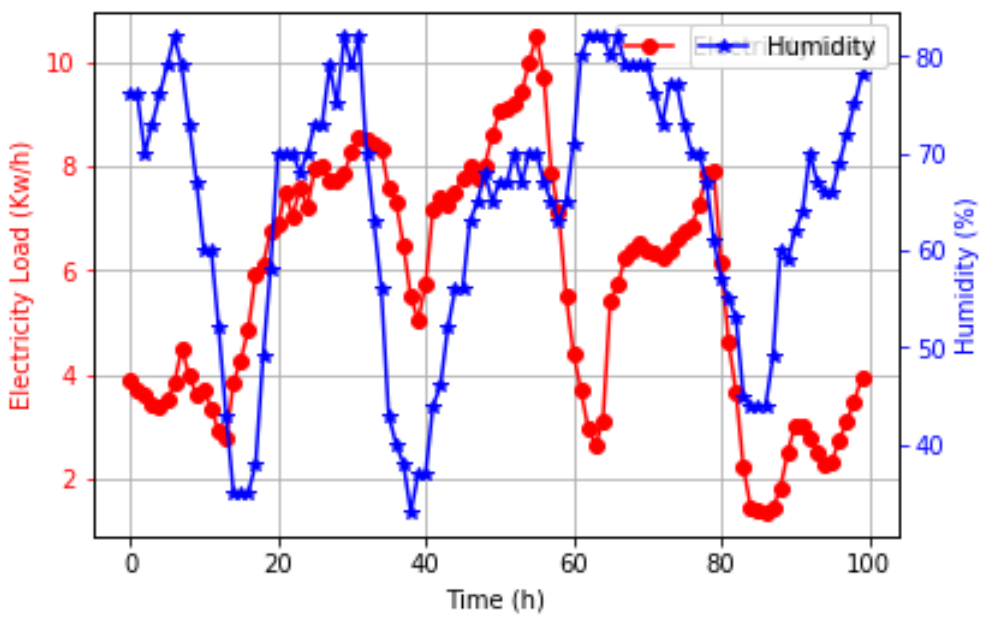
Various weather parameters in smart space form a critical factor towards effective load consumption and it will be necessary to visualise them individually with respect to their corresponding residential load consumption at different time intervals in order to discern the relationships in the variables prior to the prediction of future load. Such virtualisation will aid a quick overview of how the weather parameter affects the load consumption and instant overview by the power demand planners for decision making for any location concerned. Shown in Figure 3.10a-e are the several analytical trend plots for the residential demand with the respective weather variables obtained from the location where the load was consumed.



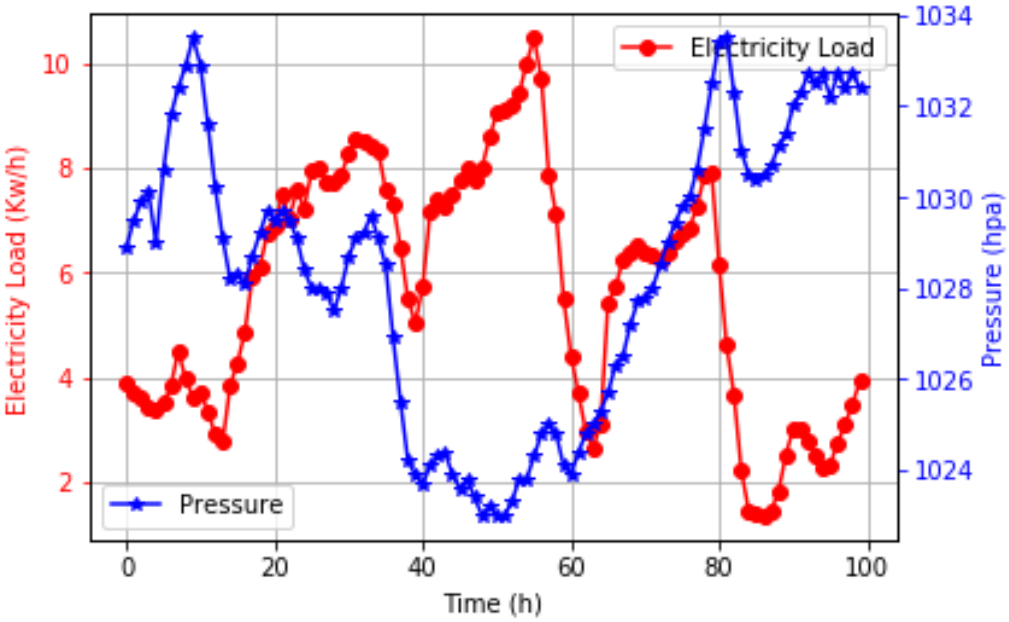
(a)


Dew Point
Electricity Load (Kw/h)
Dew Point (Celsius)
Time (h)

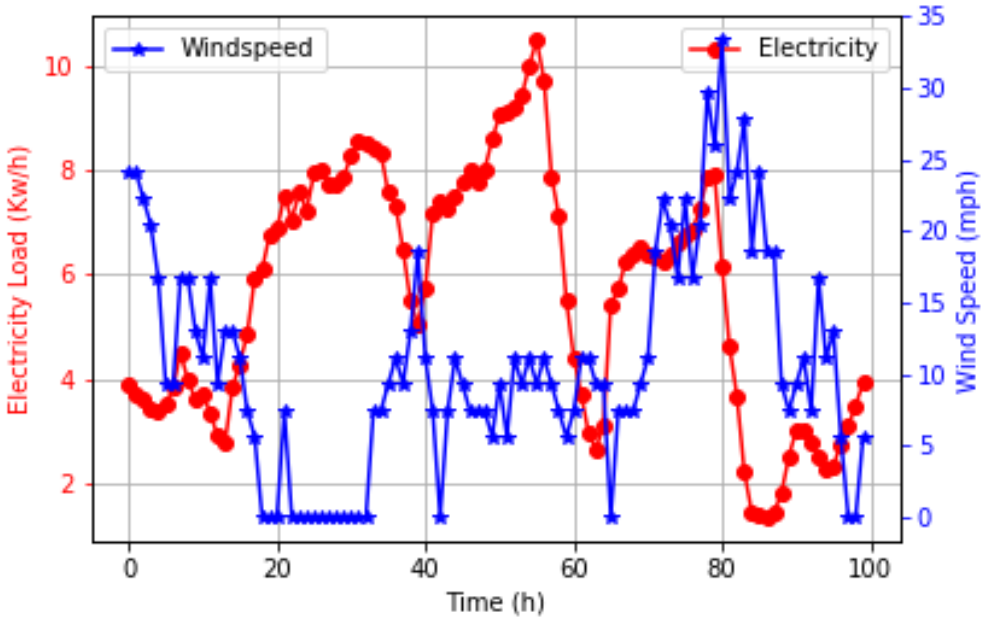
(b)


Humidity
Electricity Load (Kw/h)
Humidity (%)
Time (h)

(c)



(d)



(e)

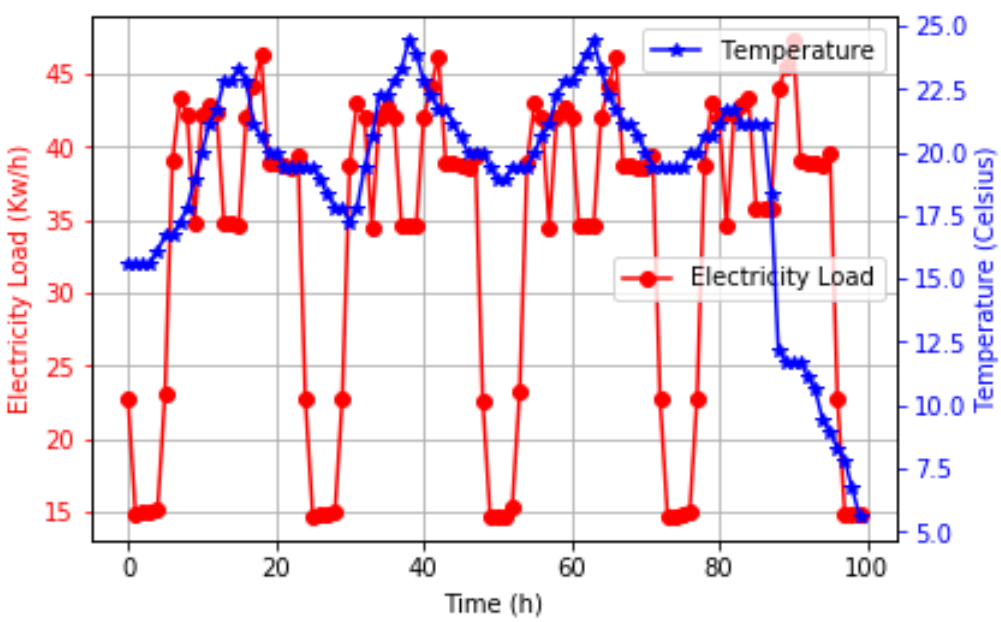
Figure 3.10: Trend Analytics with Residential Data.

The electricity load consumption behaves in a different way for each of the weather parameters. By super-positioning the electricity load and weather profiles, it is obvious

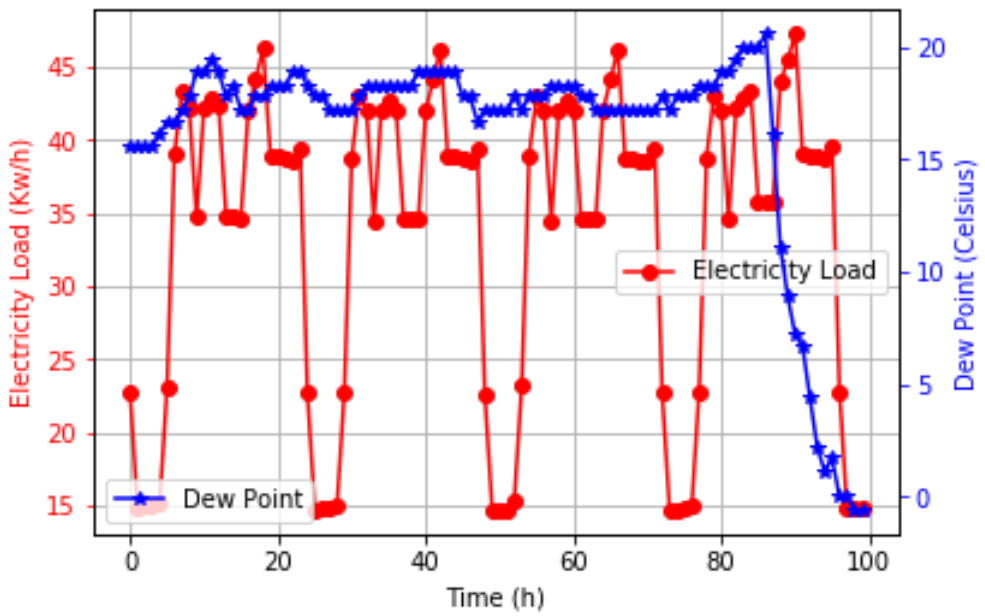
that there is a direct and inverse relationship between the two variables at every point in time. One can then deduce generally from Figure 3.10c that weather variables have some level of direct relationship to the load consumption at time 15 h-42 h and an inverse relationship between 40 h and 60 h in Figure 3.10d, 20 h and 60 h in Figure 3.10e, 15 h and 80 h in Figure 3.10a. Though these variations in direct and inverse relationship between the electricity load and each of the weather profiles resulted in uncertain behaviour during electricity prediction, this effect simply shows that there are other factors that affect the load consumption apart from the weather variables, but in this dissertation, the major aim is to evaluate the extent to which weather variables can aid predictive error reduction when forecasting future load consumption.

3.9.2 Weather Analysis of Commercial Load Consumption

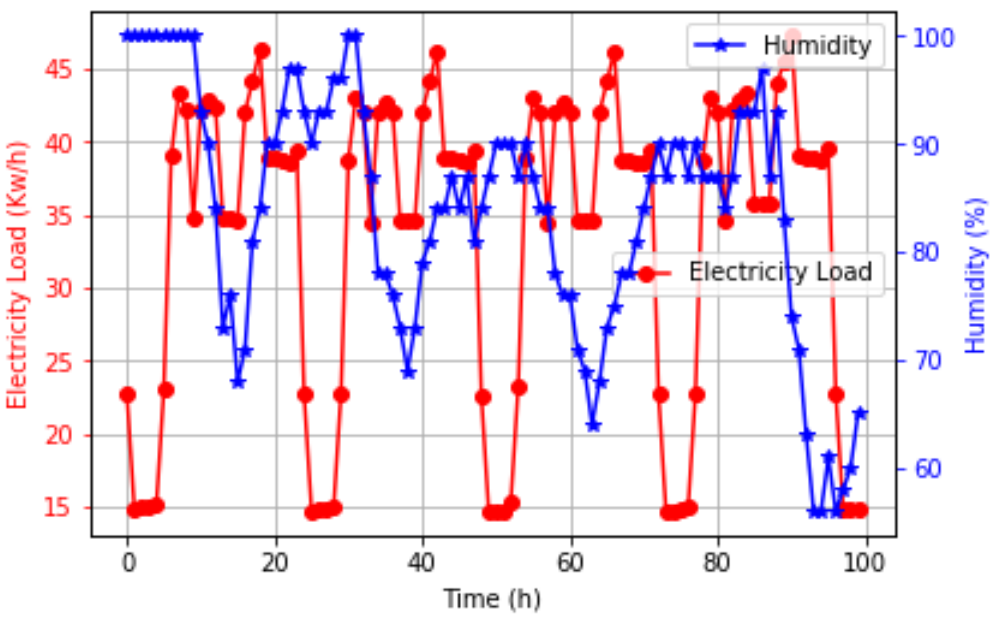
In this section, the aim is to visualise the commercial load consumption in relation to the various weather parameters to see the effect of the variables on one another, as shown in Figure 3.11a-e.



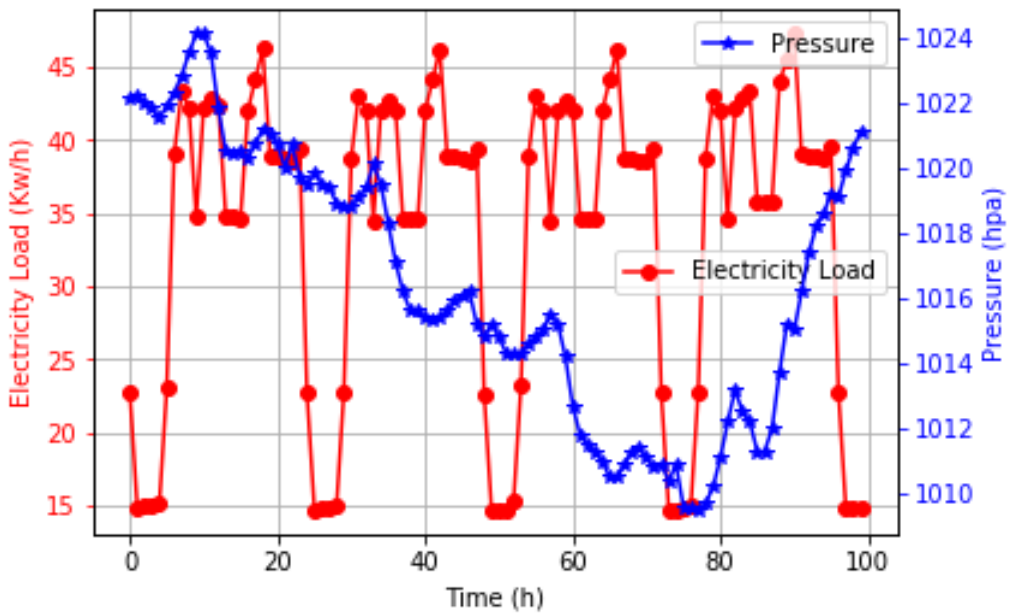
(a)


Electricity Load (Kw/h)
Dew Point (Celsius)
Time (h)
Electricity Load
Dew Point

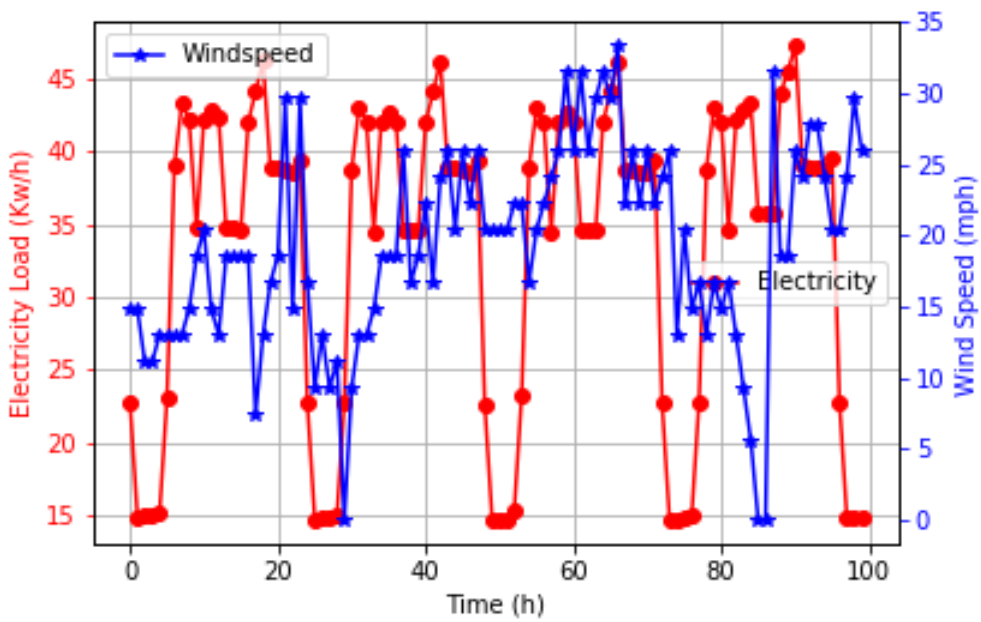
(b)


Electricity Load (Kw/h)
Humidity (%)
Time (h)
Humidity
Electricity Load

(c)



(d)



(e)

Figure 3.11: Trend Analytics with Commercial Data.

Looking at the pattern in Figure 3.11(a-e), one can deduce that load consumption reduces at a particular time of the day, especially around 20 h-25 h, 45 h-50 h, 70 h-75 h for all

weather variables. Most likely, this is the off-peak business period when the load consumers have closed and office equipment has been powered off. The weather variables, drawn over the load trends, show the behaviour of the load with respect to the weather factors. Generally, the behavioural patterns of the weather parameters were mostly inversely proportional to the load consumption, with some exceptions such as 75 h for pressure and 30 h for wind speed where load and weather were directly proportional.

Having considered the trend analytics from each of the load consumptions in Sections 3.8 and 3.9, one can see that there is no linear relationship between the load and the weather variables. In addition, the relationship might be directly proportional and a few hours later, it becomes an inverse relationship. This shows how uncertain the electricity load could be. In this regard, PSA-DT, being a probabilistic model, will be excellent to address the uncertainty relationship.

3.10 CHAPTER SUMMARY

The chapter discussed extensively the development process of the cooperative PSA-DT, including the mathematical and algorithm processes. The process flow, from the data consumption until the prediction is made, was detailed in Figure 3.2 and the stepwise algorithms shown in Figures 3.4 and 3.7. The PSA-DT algorithm in Figure 3.4 and the PSA-DT with weather profile algorithm in Figure 3.7 gave a clear pictorial view of the entire design of the cooperative PSA-DT model. In this chapter, the study also emphasised the use of PSA-DT with the weather profile and the evaluation techniques used for validating the cooperative PSA-DT model.

The different splitting sessions were also explained to see the anatomy of the DT component of the PSA-DT. Finally, visualisation of each of the weather profiles was done

to aid understanding of the effects of the weather on electricity load consumption by different user categories.

CHAPTER 4: EVALUATION OF PSA-DT FOR SHORT-TERM LOAD FORECASTING TOWARDS ECONOMIC SUSTAINABILITY

4.1 EXPERIMENTAL SETUP FOR SMART GRIDS

As described earlier, short-term load forecasting corresponds to predictions ranging from one minute to one week ahead. In this research, data collected include **residential**, **commercial** and **industrial** loads. The residential and commercial loads were from a location in Texas, USA, obtained as secondary data from open energy information [22] and industrial data were collected from Terni Energy in Germany [24]. A brief overview of the data layout, shown in Figure 4.1, is the snapshot of the various data meant for different classes of electricity consumers. Each electricity consumer serves as an entry point to the PSA-DT model, as shown in Figure 3.1. These time-series loads were then stored in the data repository after being processed via the knowledge-based system. During electricity forecast planning by the grid owners, historical records stored in this repository were fetched by the model to make its prediction.

Time(h)	Load(kW)
01/01 01:00:00	3.8809
01/01 02:00:00	3.7225
01/01 03:00:00	3.6137
01/01 04:00:00	3.4286
01/01 05:00:00	3.3893
01/01 06:00:00	3.5024
01/01 07:00:00	3.8319
01/01 08:00:00	4.5068
01/01 09:00:00	3.9758

(**a**)

Time(h)	Load(kW)
01/01 02:00:00	14.901
01/01 03:00:00	14.9245
01/01 04:00:00	14.9408
01/01 05:00:00	15.1012
01/01 06:00:00	22.9898
01/01 07:00:00	38.9705
01/01 08:00:00	43.2523
01/01 09:00:00	42.1958
01/01 10:00:00	34.702

(**b**)

Time(h)	Load(kW)
12/3/2015 13:45	70.0000
12/3/2015 14:00	69.0000
12/3/2015 14:15	70.0000
12/3/2015 14:30	79.0000
12/3/2015 14:45	109.0000
12/3/2015 15:00	495.0000
12/3/2015 15:15	360.0000
12/3/2015 15:30	312.0000
12/3/2015 15:45	96.0000

(**c**)

Figure 4.1: Snapshot of Load Consumption by Different Classes of Consumers: (**a**) Residential data; (**b**) Commercial data; and (**c**) Industrial data.

The major raw input data fed into the designed model were the time series load data for different categories of data collected. The predictive problem was approached by systematically following the PSA-DT pseudo-code in Figure 3.4. During the implementation, several libraries and software in addition to *pandas* for data analysis were used. These are *matplotlib* for data visualisation, *sklearn* package [72], a repository of diverse machine learning algorithms, where the DT model and other algorithms were obtained for the experiments. In addition, *scipy* [73] was used for both descriptive and inferential statistics such as mean, variance and standard deviation. Using the random sample experiment, a high confidence-level estimated mean was generated prior to final decision making via the use of a DT model. This forms the basis of the model explanation in this dissertation.

In summary, Feinberg and Genethliou [41] suggested that researchers should investigate several applications of the developed model and argued that there is no single model or algorithm that is superior for all utility firms. This is due to variation in the consumption pattern of different categories of consumers at different locations. In addition, variation includes geographical, climatic, economic and social attributes. In selecting the most appropriate algorithm, the utility will require to test it on real data. According to Feinberg [41], there is no system that could predetermine which forecasting technique is most accurate for given load data. Nevertheless, every model needs to be well-trained and tested over the load data.

4.1.1 Experiment 1: Electric Load Forecasting with Classical Models on Residential Load Consumption with no Weather Profile Consideration

In Figures 4.2a–c, the residential load consumption in Kw/h, shown on the *y*-axis and the hourly consumption time on the *x*-axis, were used during the various experimental setups. The load was predicted in parallel with the actual load using the forecasting line

till the 50th hour, as shown in Figure 4.2, the 51st and 60th hour being the 10-step forecasting horizon that depicts the future predictions for each of the classical models based on the residential data in Figure 4.1a. The aim is to verify the predictive performance in terms of reduced MAE in each model considered. The models exhibited differences in their predictive error, as shown in Figure 4.2a (ii), Figure 4.2b (ii), and Figure 4.2c (ii) for SVM, ANN and BN, respectively. Based on the behaviour of the three models, the following reasoning analysis guides the actions of future electricity consumption planners in their decision processes:

Decision making: The sampled quantitative analysis between the 51st and 60th hour for this experiment gave a corresponding answer to some of the questions asked.

Question (Q)1: **What is happening to the predictive behaviour?**

Answer (A)1: The predictive error in SVM is reduced with peak values ranging between −5.8 kw/h and 3.0 kw/h; BN predictive error is slightly higher than SVM error with a value between −6.8 kw/h and 3.8 kw/h; and predictive error from ANN is relatively higher than the results of the other classical models and ranges from −9 kw/h to 1.8 kw/h.

Although the SVM could predict slightly better compared with the other classical models considered in terms of low predictive errors, its predictive performance can still be improved with the PSA-DT model. Although BN could predict up to 6 kw/h for an actual load of 10 kw/h, as shown in Figure 4.2c (i), the predictive error was still higher than the SVM predictive error. In addition, the ANN forecasting result in Figure 4.2b (i) could not fit the actual load for different load consumption periods. This irregularity occurred because large amounts of data were needed to train the ANN model for effective predictions. Therefore, these shortfalls contributed to the high predictive error generated by the ANN model in Figure 4.2b (ii).

Q2: Why is it happening?

A2: Inability of the forecasting models to predict the actual electricity load consumption accurately; this proposition can be seen clearly in Figure 4.2a(i), Figure 4.2b(i), and Figure 4.2c(i), meant for SVM, ANN and BN, respectively, where their forecasting lines in blue do not "fit" their corresponding actual load lines in red. Overall, there was under-estimation.

Q3: What can be done about it?

A3: The forecasting error can be improved by deploying an effective cooperative model for the predictive analysis.

Q4: What will happen next?

A4: The SVM model tends to predict well in terms of low predictive error depicted by Figure 4.2a (ii), with a predictive error value of −5.8 kw/h to 3.0 kw/h when compared with the predictive error result of BN and ANN.

In Figure 4.2a(i), SVM predicts the future load consumption as between 4 Kw/h and 5 Kw/h even when the actual load at some approximate time such as 12 h, 22 h and 32 h rises to 10 Kw/h and sometimes reduces to as low as 1 kw/h. In brief, one can also deduce that the predictive result rises and drops with respect to increases and decreases in actual load consumption, respectively. To address the results of high predictive errors produced by the classical models, the use of an *uncertainty* model could be of great assistance to achieve more reliable electricity load predictions and near-zero predictive errors.

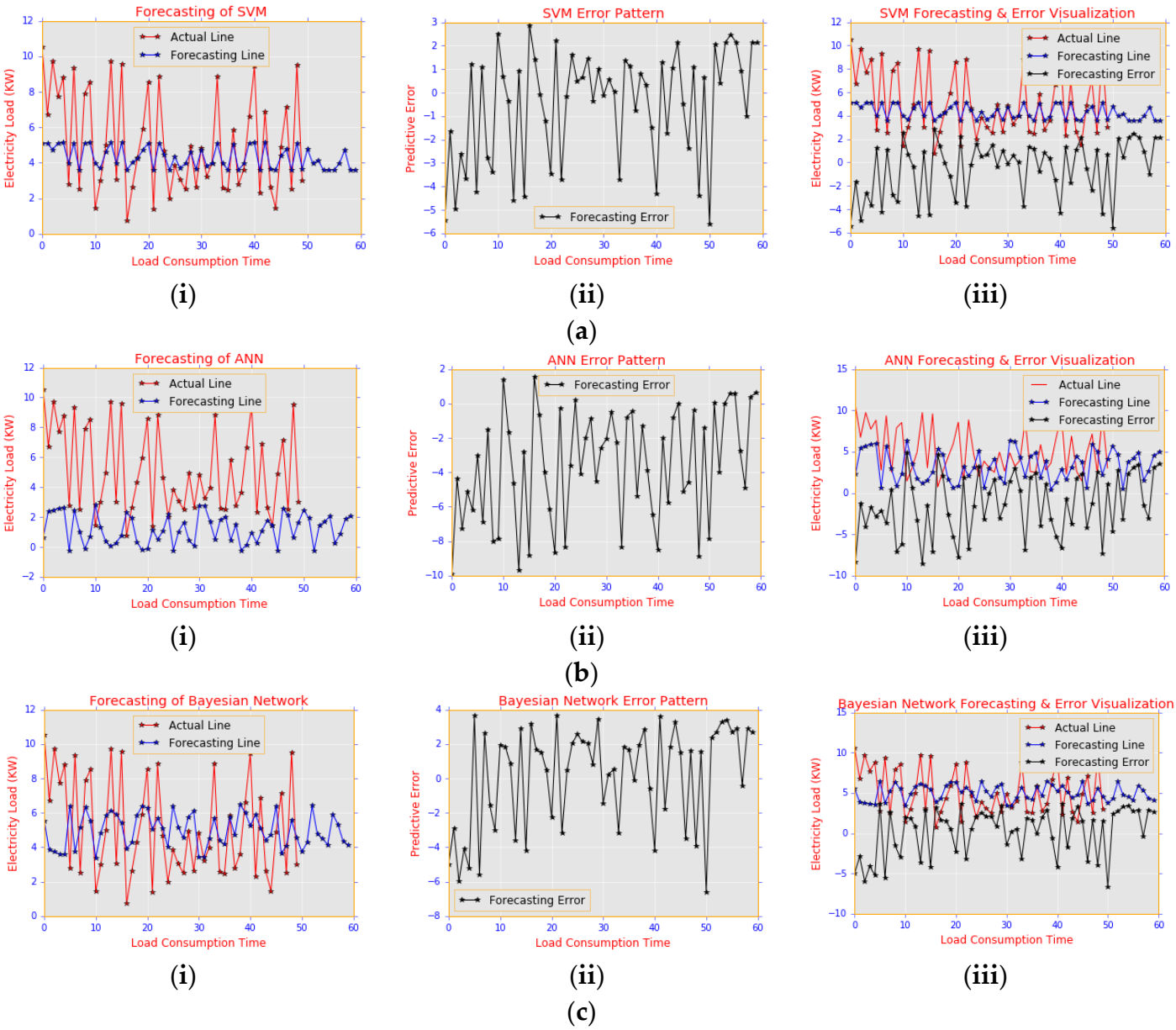


Figure 4.2: (**a**) SVM for residential electricity load consumption; (**b**) ANN for residential electricity load consumption; and (**c**) BN for residential electricity load consumption.

However, one might have noticed the fluctuating nature of the predictive error over time; this is due to the unpredictable nature of the load consumption feature, implying that there will be a great need for a probabilistic model such as PSA-DT that can handle the uncertain conditions better.

4.1.2 Experiment 2: Electric Load Forecasting with PSA-DT on Three Classes of Consumers in Smart Homes

The objective of this test and the results obtained, as shown in Figures 4.3a–c, is to affirm effectiveness in the predictive ability of PSA-DT in terms of the low predictive error computed using Equation 10 and comparing the PSA-DT predictive error and the classical model error.

Decision making: Sampled quantitative analysis between load consumption hour 0 to hour 50 and beyond.

Q1: What is happening to the predictive behaviour?

A1: The predictive error for the PSA-DT model was reduced to a range of −0.01 to 0.01 for residential load consumption, as shown in Figure 4.3a (ii); error values ranged from −0.04 to 0.04 for a commercial load user category in Figure 4.3b (ii) and −1.5 to 0.5 for an industrial load user. The negative predictive error value occurred because under-prediction and over-prediction produce a positive predictive error value. Since this error is extremely small compared to the value generated by the classical model shown in experiment Figure 4.2a–c (ii), the forecasting result generated by the PSA-DT model tends towards higher accuracy than the result obtained from the classical model for all classes of users being considered.

Q2: Why is it happening?

A2: This predictive error reduction occurred because of the cooperative nature of the PSA-DT model formed by combining the merits of both PSA and the DT model described in Chapter 3. Because of the uncertain nature of electricity load consumption, we obtained the expected mean load with high confidence value via the Monte Carlo experiment before passing the result into a DT for effective learning and predictions.

Q3: What can be done about it?

A3: To maintain the efficiency of the cooperative model, data used for such predictions can be obtained with a low time interval, less than an hourly data interval. In addition, the classical models, such as ANN and SVM, can be improved by acquiring more data for effective learning of the model and for better representation of the future data point in the training data.

Q4: What will happen next?

A4: Deploying this predictive model during future load planning within an SG has huge potential to yield an effective forecasting result with high confidence of low predictive error.

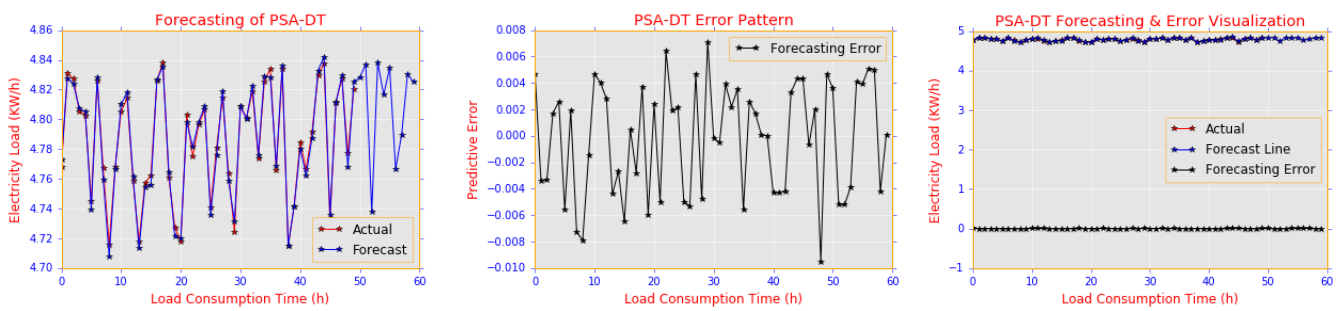
This experiment shows the different forecasting abilities and the forecasting error of the cooperative PSA-DT model when used for different classes of user load consumption, such as residential, commercial and industrial.

In this section, the result of Figure 4.3a (i) depicts how well the forecast load fitted the actual residential load with near-zero error, as shown in Figure 4.3a (ii). With the near-zero error of value ranging from −0.01 to 0.007, a periodic peak error value was obtained at 10 h, 22 h and 29 h. According to Figure 4.3a (ii), the predictive error is still lower than the error results of the classical model used for residential load consumption. Moreover, these possibilities occurred as a result of effective PSA-DT model usage with low standard deviation from the mean load in residential electricity load consumption.

This research deduced from Figure 4.3b(ii) that the result of the cooperative predictive model produces a predictive error close to zero with value ranges from −0.03 to 0.04 and the peak error found at among others 2 h, 12 h, 20 h, 23 h and 40 h. This reduction aids the model predictive abilities for economic sustainability. Though the standard deviation from the mean load is slightly higher than the corresponding residential load

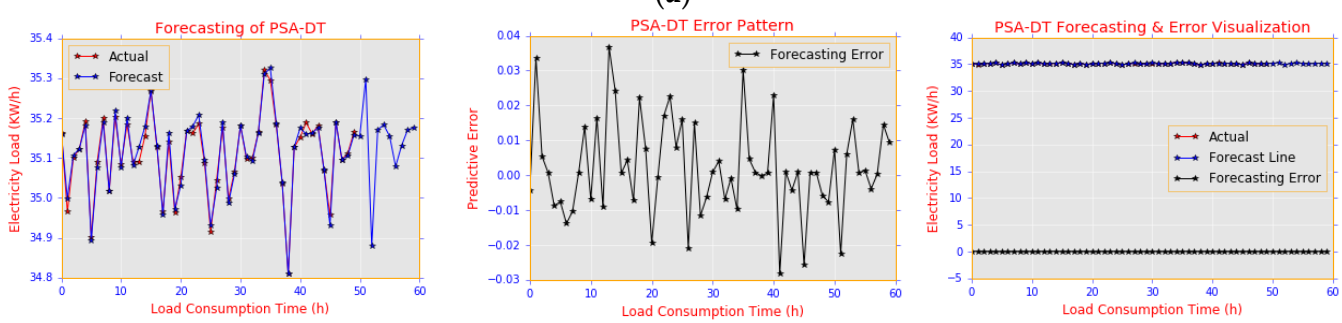
consumption, the predictive error remained within the range value, which is lower than the predictive error of the classical model when used by the same load user category as shown in Table 4.1.

In Figure 4.3c, the predictive error was a little higher between −1.9 and 1.6. This peak value was achieved occasionally in Figure 4.3c(ii) at 8 h, 21 h, 22 h and 49 h, but it is better than the predictive result produced by other classical models when used for industrial load prediction with the detailed experiment shown in Table 4.1. However, this was a result of high standard deviation in the historical load for industrial electricity load consumption.



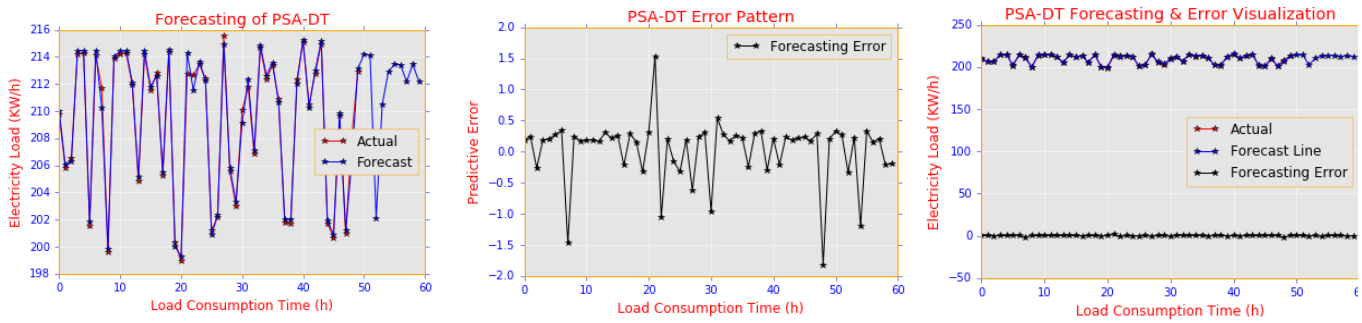
(i) (ii) (iii)

(a)



(i) (ii) (iii)

(b)



(i) (ii) (iii)

(c)

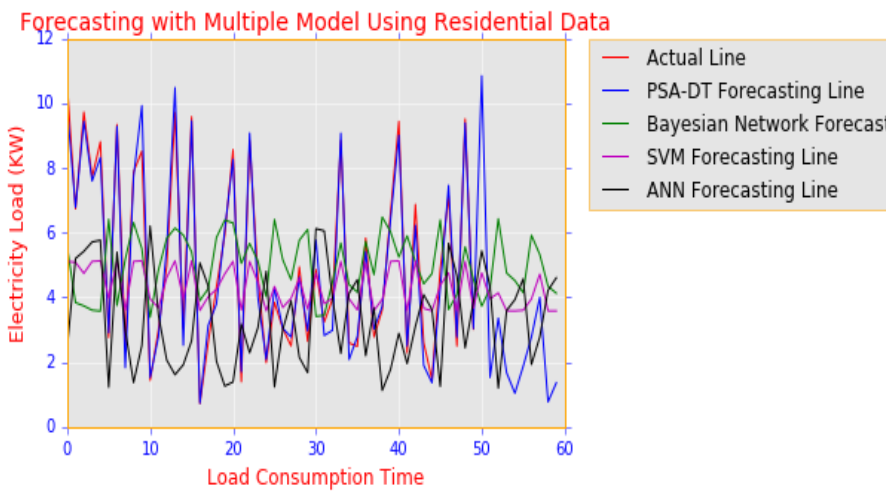
Figure 4.3: (**a**) PSA-DT for residential electricity load consumption in smart homes; (**b**) PSA-DT for commercial electricity load consumption; and (**c**) PSA-DT for industrial electricity load consumption.

Generally, the predictive result of the experiment (Figure 4.3a–c) was extrapolated after the 50th load data in order to predict the next few hours between the hours of 51 and 60 for each of the experiments. The corresponding reduced near-zero predictive error in Figures 4.3a–c(ii) shows how well the cooperative PSA-DT model can predict using interpolated results ranging from 0 to 50th load data value and after the 50th load data value.

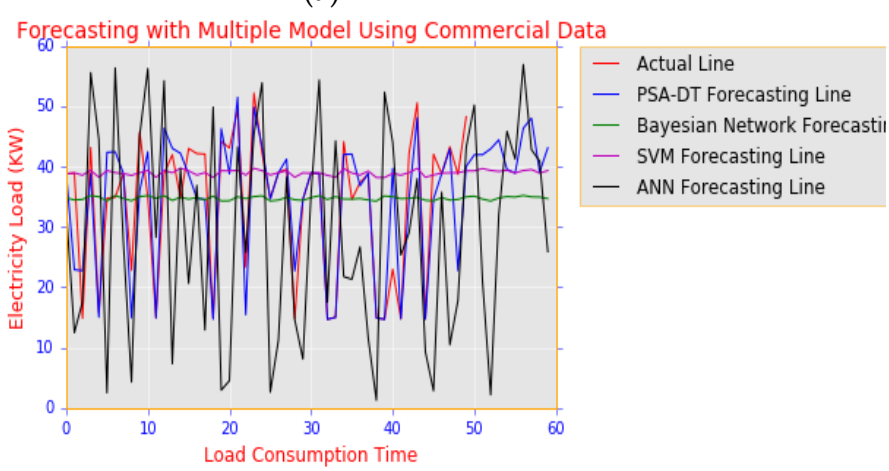
From the visualisation result, the blue line depicts the forecast load, which almost "maps" the red line that shows the actual load with a near-zero forecasting error in Figure 4.3a–c(ii). In addition, ranging from the residential load to the industrial load, the analytical plots in experiments 1 and 2 denote that different user categories have different load consumption patterns and the cooperative PSA-DT can predict the consumption to a high degree of predictive accuracy with reduced forecasting error, but it is notable that the level of errors also varies among load categories considered owing to variations in their load standard deviation from the mean load.

4.1.3 Performance Evaluation of Electric Load Forecasting with PSA-DT and Classical Models

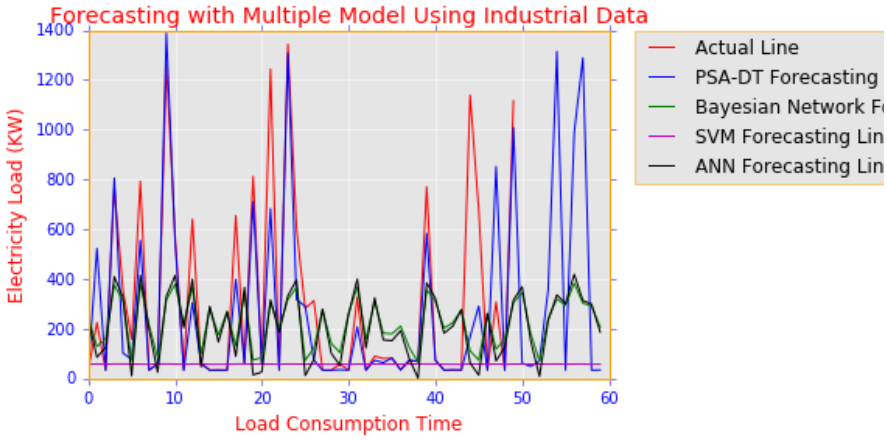
Another fascinating observation was the cooperative model fitting the actual load consumption compared to other models at load times up to the 50th hour and till the 60th hour for future prediction, as shown in Figures 4.4a–c. In the residential load category, one could see in residential load consumption the "overlap" of the red and blue lines depicting the actual and PSA-DT forecasting line in Figure 4.4a; but, in Figure 4.4c, the PSA-DT could not fit very well from 20 h-22 h and 44 h-46 h. This was a result of wide deviation of the load from the mean load in industrial load with a value of 395.4969 kw/h compared to the residential load consumption having a mean deviation of 2.9295.



(**a**)



(**b**)



(**c**)

Figure 4.4. (**a**) Residential electricity load consumption; (**b**) Commercial electricity load consumption; and (**c**) Industrial electricity load consumption.

This research made differential analysis in terms of forecasting error levels between PSA-DT and the classical models. The experimental result in Tables 4.1a–c shows the various predictive error results of PSA-DT compared with each of the classical models for different hourly load data, training and test sizes. In each table and for each of the SG user categories, the corresponding experiment produced different predictive errors for PSA-DT and each of the classical models. In a more elaborate form, Tables 4.1a–c show the predictive error comparison between PSA-DT and SVM, PSA-DT and BN and finally, PSA-DT and ANN for different categories of load users with different hourly load data sizes of 100, 200 and 500 in each category. We also considered different percentages of training and test sizes of 60% and 40%, 80% and 20%, as detailed in Table 4.1. Going through each of these variations and performing the corresponding experiment, different predictive error values were obtained, as highlighted in Table 4.1.

Table 4.1a shows the comparison between PSA-DT and SVM in terms of their predictive errors. The tabular result enables a quick comparison, using different variations of datasets with diverse training and test sets, for all the classes of electricity user

consumption. In each of the experiments and, having obtained the MAE, using Equation 10, for both PSA-DT and SVM with different variations in training and test set sizes, the MAE of PSA-DT is lower than SVM results in all the experiments shown in Table 4.1a. These differences explain how PSA-DT outperforms SVM in predicting the future electricity load consumption in smart homes. One can deduce that for each of the experiments in Table 4.1a, the predictive error value in PSA-DT is lower than the corresponding result from SVM. In the residential user category, using 100 data size in conjunction with 60% training and 40% test data size, the corresponding predictive error of PSA-DT is **0.0018**, while the result of the SVM model is **0.0105**. In the commercial load user category, the predictive error value of PSA-DT is **0.0093**, SVM is **0.05** and, in the industrial user group, the predictive error of PSA-DT is **0.2375** and that of SVM is **1.2713**.

Experimental results in Table 4.1b show the different variations of the training and test set for various hourly load sizes of 100, 200 and 500 used by each user category. In the tabular analysis, there is still a high level of significant differences between PSA-DT and BN predictive errors. Considering the data size of 200 in the commercial user category with training and test sizes of 80% and 20% respectively, the PSA-DT predictive error was **0.0093**, while that of BN was **0.0178**. In addition, in the residential category of the same data size, the PSA-DT predictive error was **0.002** while that of BN was **0.00475**. This gave the PSA-DT improved performance over BN by generalising the predictive results of PSA-DT performance over BN in each of the experiments.

In Table 4.1c, PSA-DT predictive abilities were also benchmarked against ANN, as shown by the various experiments. In addition to the numerical justification from Tables 4.1a and b, one can see the differences in PSA-DT and ANN predictive error values. The predictive error in an industrial hourly load data size of 500 with training and test size of 60% and 40% resulted in **0.4369** and **2.2818** for PSA-DT and ANN respectively. In this

regard, Table 4.1 presented a clear difference in their performance for various observations among different classes of electricity consumers.

Table 4.1: (a) Predictive errors from SG categories of users using PSA-DT and SVM; (b) Predictive errors from SG categories of users using PSA-DT and BN; and (c) Predictive error comparison from SG categories of users using PSA-DT and ANN

(**a**)

Predictive Model	Smart-Grid Data (User Category)	Hourly Load Data Size	Training Size (%)	Test Size (%)	Predictive Error (MAE) for PSA-DT	Predictive Error (MAE) for SVM
PSA-DT and SVM	Residential	100	60	40	0.0018	0.0105
			80	20	0.002	0.0100
		200	60	40	0.0028	0.007
			80	20	0.002	0.02
		500	60	40	0.0032	0.0463
			80	20	0.0038	0.0336
	Commercial	100	60	40	0.0093	0.05
			80	20	0.0095	0.078
		200	60	40	0.0093	0.0544
			80	20	0.0093	0.0715
		500	60	40	0.0150	0.1059
			80	20	0.0129	0.08
	Industrial	100	60	40	0.2375	1.2713
			80	20	0.2345	1.9485

		200	60	40	0.20438	1.3151
			80	20	0.2185	1.6672
		500	60	40	0.4369	1.8399
			80	20	0.4252	4.062

(**b**)

Predictive Model	Smart-Grid Data (User Category)	Hourly Load Data Size	Training Size (%)	Test Size (%)	Predictive Error (MAE) for PSA-DT	Predictive Error (MAE) for BN
PSA-DT and BN	Residential	100	60	40	0.0018	0.0028
			80	20	0.002	0.0045
		200	60	40	0.0028	0.0075
			80	20	0.002	0.00475
		500	60	40	0.0032	0.0053
			80	20	0.0038	0.0109
	Commercial	100	60	40	0.00925	0.011
			80	20	0.0095	0.0145
		200	60	40	0.0093	0.0178
			80	20	0.0093	0.0193
		500	60	40	0.0150	0.0315
			80	20	0.0129	0.0323

	Industrial	100	60	40	0.2375	1.3978
			80	20	0.2345	1.996
		200	60	40	0.204375	0.653875
			80	20	0.2185	0.7785
		500	60	40	0.4369	1.1663
			80	20	0.4252	1.7514

(**c**)

Predictive Model	**Smart-grid Data (User Category)**	**Hourly Load Data Size**	**Training Size (%)**	**Test Size (%)**	**Predictive Error (MAE) for PSA-DT**	**Predictive Error (MAE) for ANN**
PSA-DT and ANN	Residential	100	60	40	0.0018	0.0118
			80	20	0.002	0.013
		200	60	40	0.0028	0.0124
			80	20	0.002	0.0235
		500	60	40	0.0032	0.0569
			80	20	0.0038	0.0466
	Commercial	100	60	40	0.00925	0.0643
			80	20	0.0095	0.086
		200	60	40	0.0093	0.0575
			80	20	0.0093	0.078
		500	60	40	0.0150	0.1283
			80	20	0.0129	0.0904

Industrial	100	60	40	0.2375	2.3153
		80	20	0.2345	2.0225
	200	60	40	0.204375	1.558
		80	20	0.2185	1.6768
	500	60	40	0.4369	2.2818
		80	20	0.4252	4.0605

It is worth noting that the huge predictive errors in the industrial user category, compared to the residential and commercial categories, were due to a large statistical variance in the industrial dataset, as shown by sample data in Figure 4.1c. However, increasing the size of the dataset can result in a further decrease in the predictive error.

Therefore, it was observed that the cooperative probabilistic scenario analysis with DT in forecasting future electricity load consumption for smart homes is more accurate, as it produces a near-zero predictive error for all the categories of users considered in this research, as shown in Table 4.1. The experimental results show that various classes of load, such as residential, commercial and industrial, of diverse data size, behave differently, revealing sustainable economic consumption patterns.

Hence, the PSA-DT model could predict the future load more accurately for smart homes with a low predictive error in relation to the analysed dataset and the particular structure of the classical models adopted in BN, SVM and multilayer perceptron, which is a class of feedforward ANN considered in this research.

4.2. EXPERIMENTAL SETUP FOR SMART GRIDS WITH WEATHER PROFILE

As described earlier, short-term load forecasting corresponds to predictions ranging from one minute to one week ahead. In this research, data collected included **residential** and **commercial** loads. The residential and commercial loads were from a location in Texas, USA, obtained as secondary data from open energy information [25]. A brief overview of the data layout, shown in Figure 4.5, is the snapshot of the various data meant for different classes of electricity consumers and the corresponding weather variables obtained from wunderground [27]. Each electricity consumer and the corresponding weather status at the location of such consumption serve as an entry point to the PSA-DT model, as shown by the processes in Chapter 3. Data repository stored times-series loads were then processed via the knowledge-based system with the weather dataset based on the load consumption geolocation. During electricity forecast planning by the grid owners, stored historical records in this repository were fetched by the model to make its prediction.

time (h)	load (kw)	temperature (°C)	dew point (°C)	humidity (°C)	pressure (hPa)	wind speed (mph)
01/01 01:00:00	3.8809	6.1	2.2	76	1028.9	24.1
01/01 02:00:00	3.7225	5.6	1.7	76	1029.5	24.1
01/01 03:00:00	3.6137	3.9	-1.1	70	1029.9	22.2
01/01 04:00:00	3.4286	2.8	-1.7	73	1030.1	20.4
01/01 05:00:00	3.3893	2.2	-1.7	76	1029	16.7
01/01 06:00:00	3.5024	1.1	-2.2	79	1030.6	9.3
01/01 07:00:00	3.8319	0.6	-2.2	82	1031.8	9.3
01/01 08:00:00	4.5068	1.1	-2.2	79	1032.4	16.7
01/01 09:00:00	3.9758	2.2	-2.2	73	1032.9	16.7
01/01 10:00:00	3.6089	3.9	-1.7	67	1033.5	13
01/01 11:00:00	3.7261	6.1	-1.1	60	1032.9	11.1
01/01 12:00:00	3.3567	7.2	0	60	1031.6	16.7
01/01 13:00:00	2.905	9.4	0	52	1030.2	9.3
01/01 14:00:00	2.7651	11.1	-1.1	43	1029.1	13

(a)

time (h)	load (kw)	temperature (°C)	dew point (°C)	humidity (°C)	pressure (hPa)	wind speed (mph)
01/01 01:00:00	22.7436	15.6	15.6	100	1022.1	14.8
01/01 02:00:00	14.901	15.6	15.6	100	1022.2	14.8
01/01 03:00:00	14.9245	15.6	15.6	100	1022	11.1
01/01 04:00:00	14.9408	15.6	15.6	100	1021.8	11.1
01/01 05:00:00	15.1012	16.1	16.1	100	1021.5	13
01/01 06:00:00	22.9898	16.7	16.7	100	1021.9	13
01/01 07:00:00	38.9705	16.7	16.7	100	1022.3	13
01/01 08:00:00	43.2523	17.2	17.2	100	1022.8	13
01/01 09:00:00	42.1958	17.8	17.8	100	1023.5	14.8
01/01 10:00:00	34.702	18.9	18.9	100	1024.1	18.5
01/01 11:00:00	42.224	20	18.9	93	1024.1	20.4
01/01 12:00:00	42.9088	21.1	19.4	90	1023.5	14.8
01/01 13:00:00	42.3217	21.7	18.9	84	1021.8	13
01/01 14:00:00	34.7378	22.8	17.8	73	1020.5	18.5

(b)

Figure 4.5: Snapshot of Load Consumption and Weather Variables by Different Classes of Consumers: (**a**) Residential data; and (**b**) Commercial data.

4.2.1 Experiment 1: Electric Load Forecasting Analysis with Classical Model for Each Weather variable on Residential Load Consumption

In Figures 4.6a–e and Figures 4.7a-e, the residential load consumption in Kw/h shown on the y-axis and the hourly consumption time on the x-axis were used during the various experimental setups. The load was predicted in parallel with the actual load using the forecasting line till the 50th hour, as shown in Figure 4.6 to 4.8, the 51st and 60th hour being the 10-step forecasting horizon that depicts the future predictions for each of the classical models based on the residential data in Figure 4.6a. The aim is to verify the predictive abilities in terms of reduced MAE for each of the weather variables used with the load consumption during classical model prediction. Each experiment exhibited slight differences in its predictive error, as shown in Figures 4.6a-e (ii) and Figures 4.7a-e (ii), for temperature, wind speed, dew point, humidity and pressure. Based on the behaviour of the five experiments, the following reasoning analysis guides the actions of future electricity consumption planners in their decision processes.

Decision making: The sampled quantitative analysis between the 51st and 60th hour for this experiment gave a corresponding answer to some of the questions asked.

(Question) Q1: **What is happening to the predictive behaviour?**

(Answer) A1: **For SVM in Figures 4.6a-e (ii)**, the predictive errors with temperature and pressure are minimal, with peak values ranging between −1.8 kw/h and 3.0 kw/h; followed by the predictive error of dew point, which is slightly lower than the result obtained from temperature and pressure with error values ranging from -1.2 kw/h and 2.6 kw/h. The predictive error values for wind speed and humidity are higher than temperature and pressure error, with a value between −2.8 kw/h and 3.9 kw/h.

For ANN in Figures 4.7a-e (ii), the predictive error with dew point is reduced with peak values ranging between −0.85 kw/h and 1.20 kw/h; followed by the predictive error of temperature, which is slightly higher with error values of -1.5 kw/h and 0.6 kw/h. Though both temperature and wind speed had an outlier error at 10 h and 30 h respectively, the predictive error results obtained from dew point and humidity range from -0.85 kw/h to 1.5 kw/h and -8.0 kw/h to 8 kw/h respectively. In Figures 4.7a-e (ii), wind speed has many data points with huge predictive errors ranging from 1 kw/h to 19 kw/h, with the exception of the outlier data point at 30 h.

The ANN could predict slightly better in terms of low predictive errors compared with the SVM classical model for temperature and dew point, and vice versa with wind speed, humidity and pressure where SVM predictive errors results are lower than their ANN counterpart their predictive performance can still be improved with the PSA-DT model. In addition, the ANN forecasting result in Figure 4.7b (i) could not fit the actual load for different load consumption periods with humidity and the inabilities are more obvious with wind speed and pressure. This irregularity occurred because large amounts of data were needed to train the ANN model for effective predictions. The drawbacks of

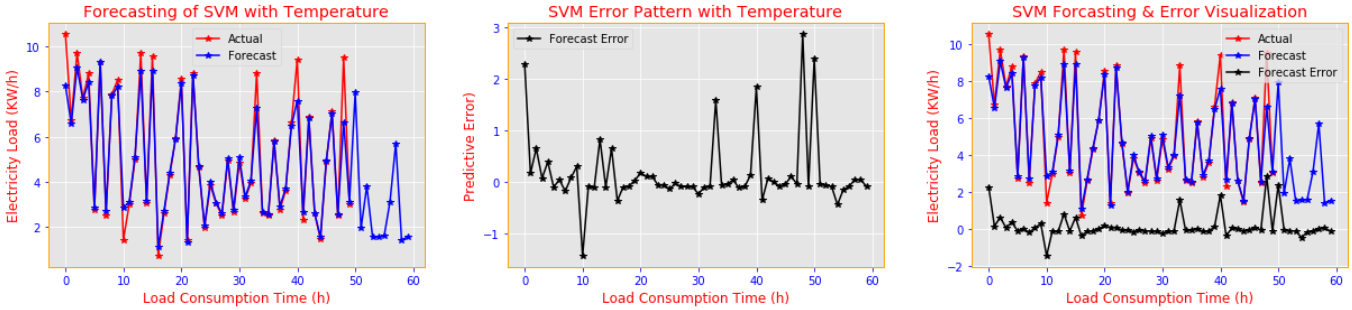
inaccurate predictions and proper fitness of the forecast load with the actual load for each of the weather variables exist with SVM as well, but such ineffectiveness in the predictive performance could also be abated with the PSA-DT model.

Q2: Why is it happening?

A2: Looking at Figures 4.6a-e (i) and Figures 4.7a-e (i) meant for SVM and ANN respectively, weather parameters seem to affect the predictive accuracy, especially seeing the different variations in the predictive error for each weather profile. The forecasting lines do not accurately "fit" their corresponding actual load lines either. Overall, there was under-estimation.

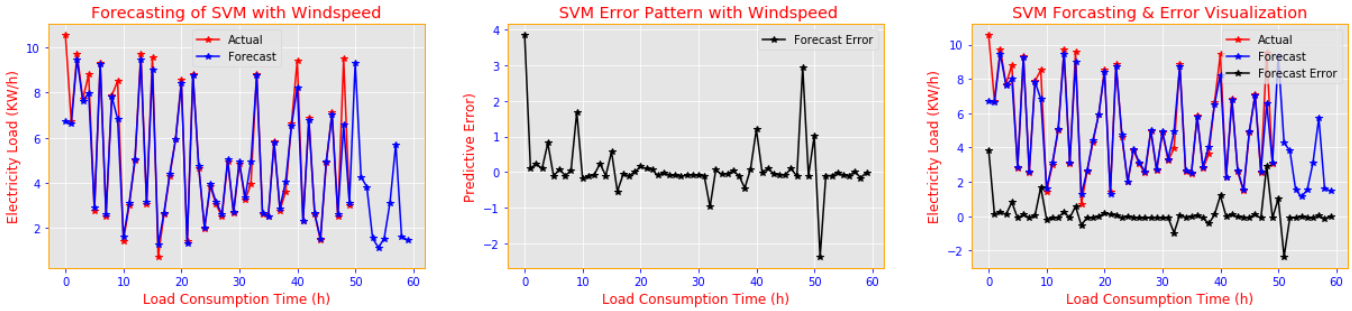
Q3: What can be done about it or what is happening next?

A3: The forecasting error can be improved by deploying an effective cooperative model to track the inherent uncertainties for the predictive analysis with weather profile. The ANN model tends to predict well in terms of low predictive error for temperature and dew point depicted by Figure 4.7a (ii) and Figure 4.7c (ii), with a predictive error value of −1.5 kw/h to 0.6 kw/h and -0.85 kw/h to 1.20 kw/h respectively when compared with the corresponding predictive error result of the SVM model with weather profile in Figure 4.6. In brief, one can also deduce that the predictive result rises and drops with respect to an increase and a decrease in actual load consumption, respectively. To address the results of high predictive errors produced by the classical models, the use of an *uncertainty* model could be of a great assistance for more reliable electricity load predictions and near-zero predictive errors.



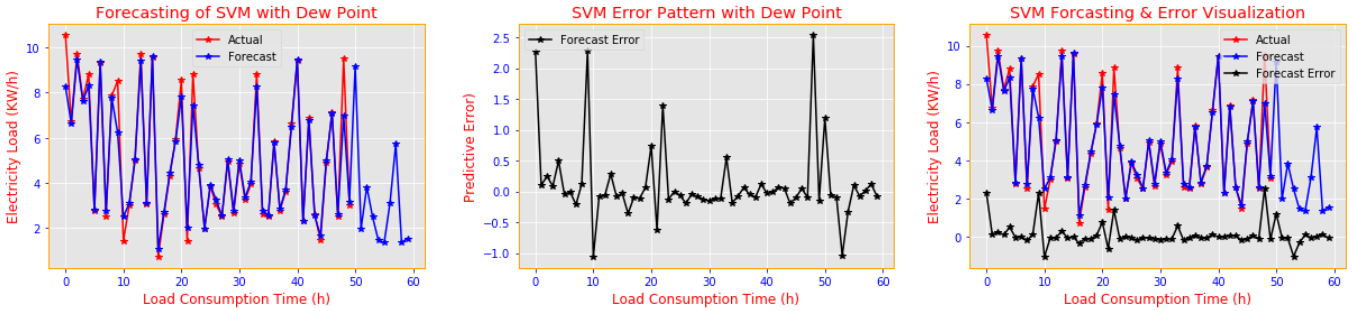
(i) (ii) (iii)

(a)



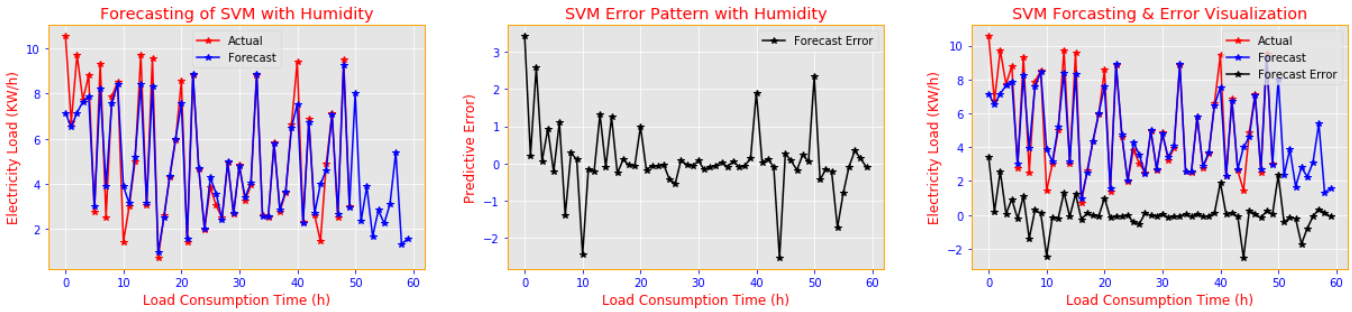
(i) (ii) (iii)

(b)



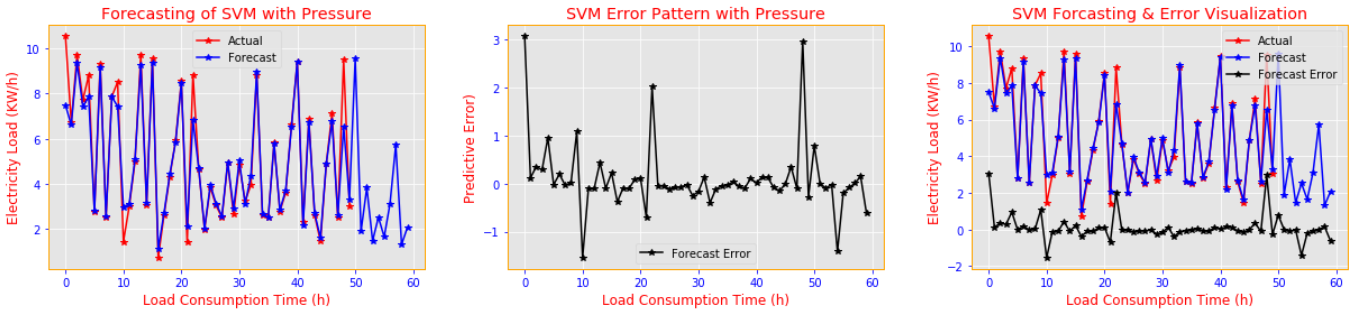
(i) (ii) (iii)

(c)



(i) (ii) (iii)

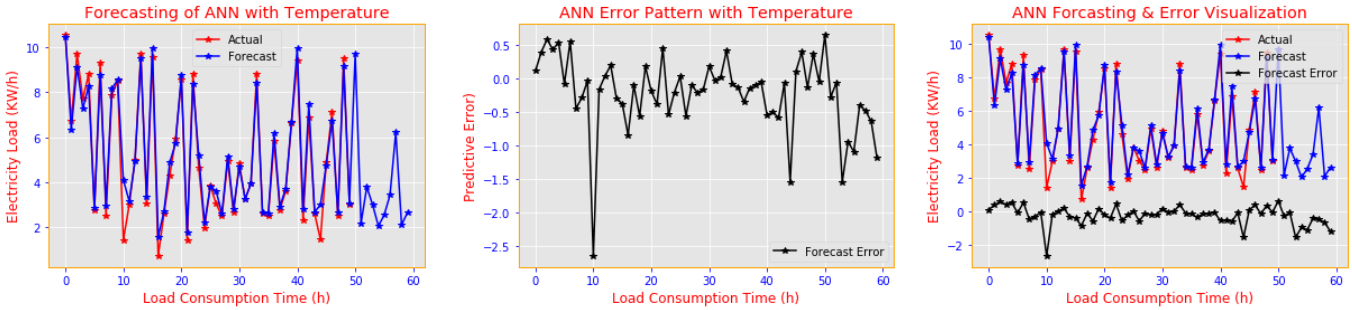
(d)



(i) **(ii)** **(iii)**

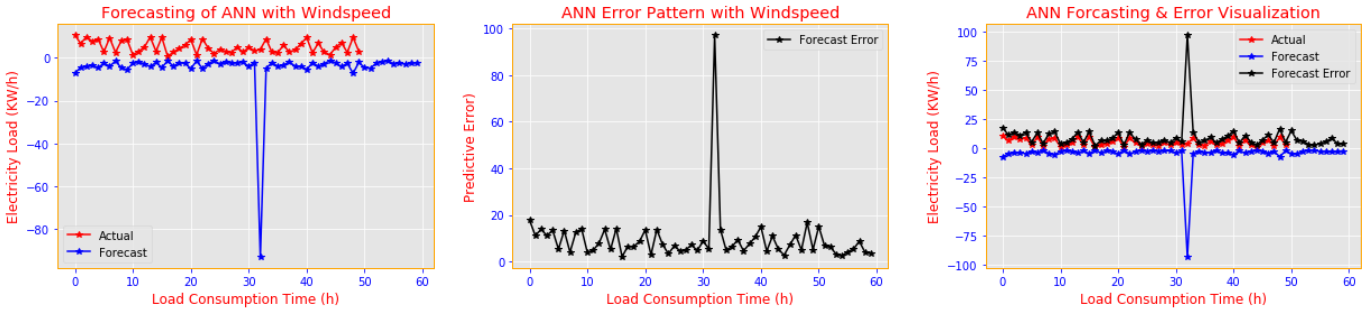
(e)

Figure 4.6: SVM for residential electricity load consumption with (**a**) Temperature; (**b**) Wind speed; (**c**) Dew point (**d**) Humidity and (**e**) Pressure.



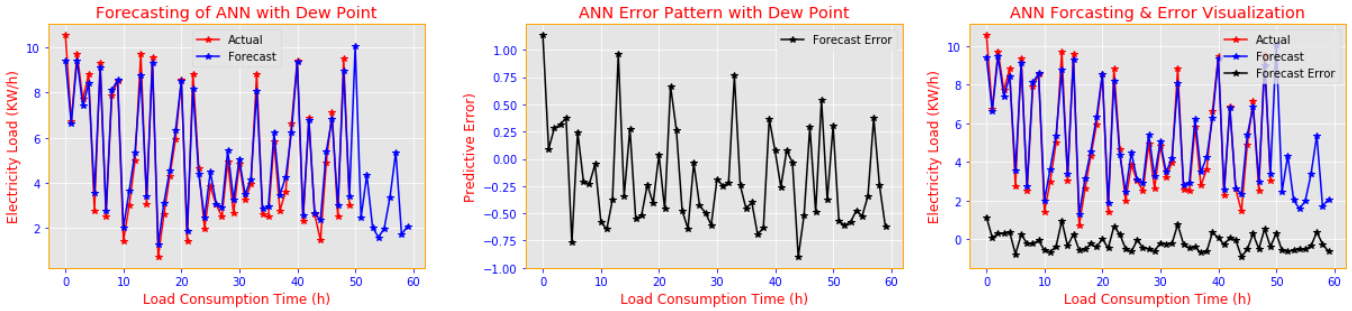
(i) **(ii)** **(iii)**

(a)



(i) **(ii)** **(iii)**

(b)



(i) **(ii)** **(iii)**

(c)

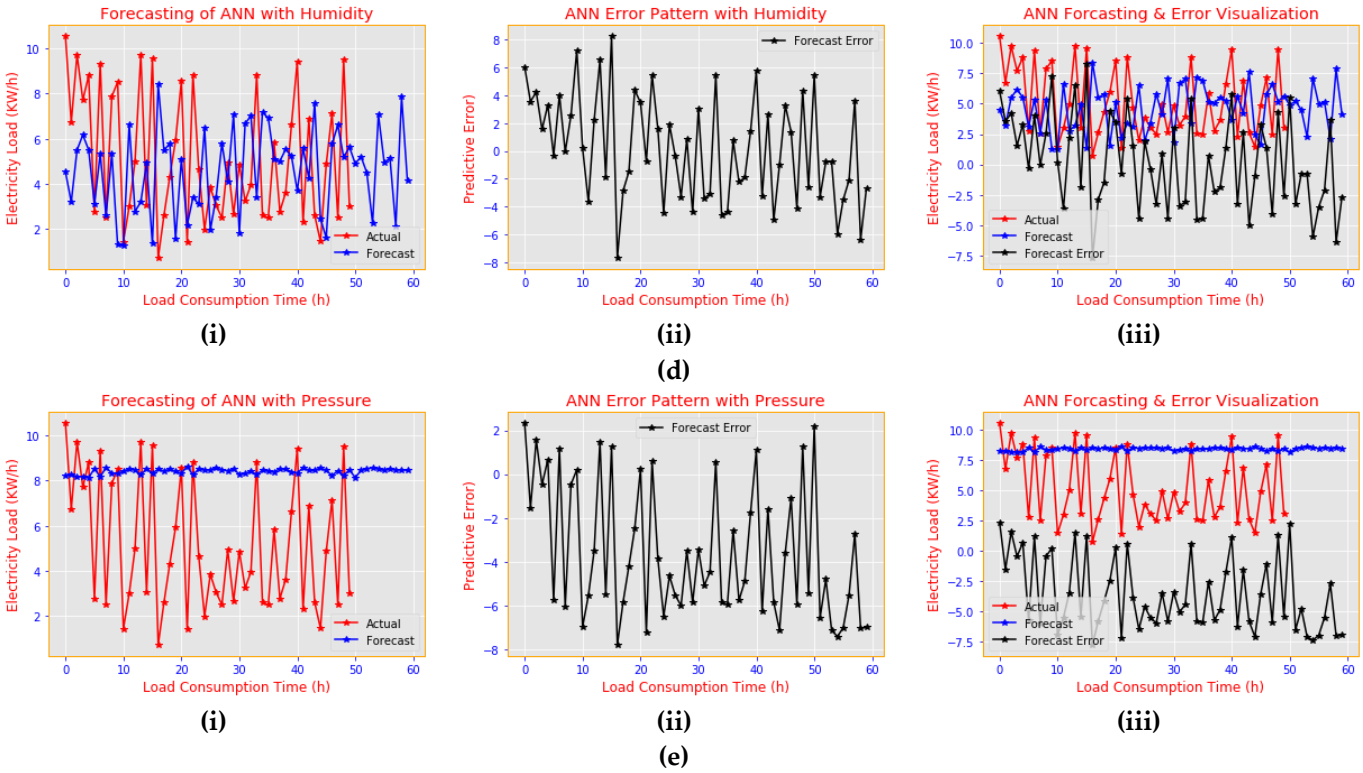


Figure 4.7: ANN for Residential Electricity Load Consumption with (**a**) Temperature; (**b**) Wind speed; (**c**) Dew point (**d**) Humidity and (**e**) Pressure.

However, one might have noticed the fluctuating nature of the predictive error over time; this is due to the unpredictable nature of the load consumption feature and its corresponding weather profiles, implying that there will be a great need for a probabilistic model such as PSA-DT that can handle the uncertain conditions better.

4.2.2 Experiment 2: Electric Load Forecasting with PSA-DT on Commercial Consumers with Weather Profiles in Smart Homes

The objective of this test and the results obtained, as shown in Figures 4.8a–e, is to affirm effectiveness in the predictive ability of PSA-DT in terms of the low predictive error computed using Equation 10 and comparing the PSA-DT predictive error with the classical model error in the context of each weather profile.

Decision making: Sampled quantitative analysis from load consumption in 0 h-50 h and beyond.

Q1: What is happening to the predictive behaviour?

A1: The predictive error for each of the experiments in Figures 4.8a (ii)-e(ii) has its error values for most of the load consumption time with each weather variable close to zero, with the exception of a few outliers at 21 h for temperature, 22 h and 42 h for wind speed effect, 32 h and 37 h for dew point, 22 h and 42 h for humidity and 9 h for pressure. This near-zero performance was aided by the probabilistic predictive ability of PSA-DT coupled with the weather effect. Since the errors generated by PSA-DT with each weather parameter are extremely small compared to the value generated by the classical model shown in Figures 4.6a–e(ii) and Figures 4.7a-e(ii), the forecasting result generated by the PSA-DT model tends towards higher accuracy than the result obtained from the classical model for all classes of users being considered.

Q2: Why is it happening?

A2: This predictive error revolving around the zero points on the axis occurred because of the meaningful weather parameters with the cooperative nature of the PSA-DT model formed by combining the merits of both PSA and the DT model described in Chapter 3. Because of the uncertain nature of electricity load consumption, the expected mean load with high confidence value was obtained via the Monte Carlo experiment before passing the result into a DT for effective learning and predictions.

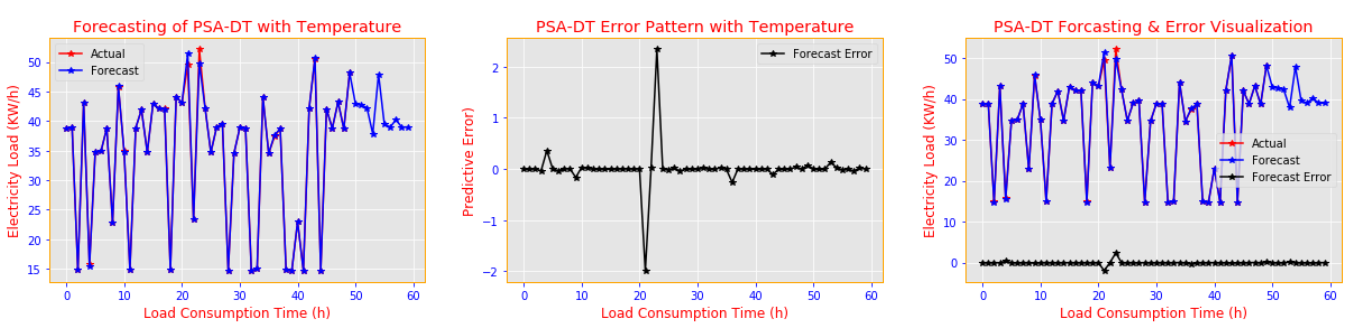
Q3: What can be done about it or what will happen next?

A3: To maintain the efficiency of the cooperative model with weather profiles, data used for such predictions can be obtained with a low time interval, less than an hourly data interval. In addition, acquiring more datasets to train the PSA-DT model could also improve the predictive error. Considering weather variables during predictive analytical processes within an SG has huge potential to yield an effective forecasting result with

high confidence of low predictive error. This experiment shows the different forecasting abilities and the forecasting error of the cooperative PSA-DT model when used with weather parameters and for commercial users of electricity load.

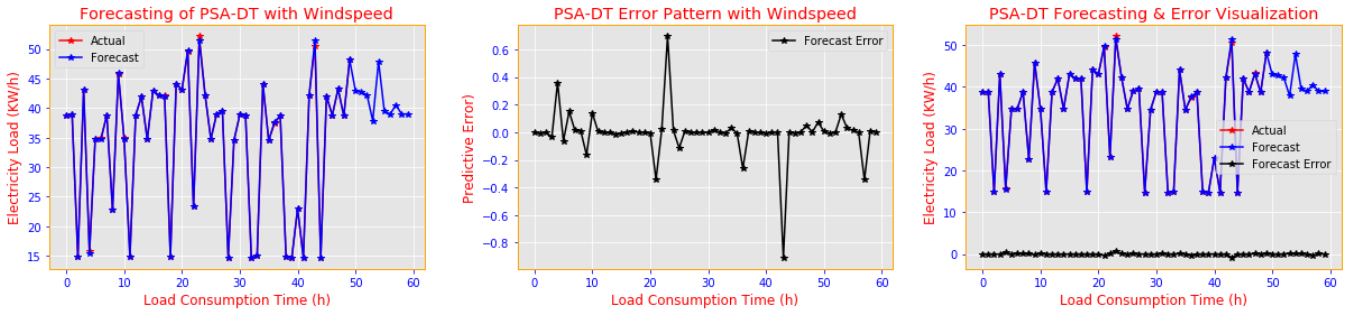
In this section, the results of Figures 4.8a-e (i) depict how well the forecast load fitted the actual commercial load with near-zero error. The highlighted Figure 4.8a-e (i) exhibited absolute average predictive error values of 0.0057685, 0.026702, 0.0036875, 0.007436 and 0.0031815 for electricity load with temperature, wind speed, dew point, humidity and pressure respectively, which can be seen as a near-zero error value. Moreover, these possibilities occurred as a result of effective PSA-DT model usage, with the weather parameter being considered during the predictive analytics.

This research deduced from Figure 4.8b(ii) that the result of the cooperative predictive model induced with weather profiles produces a predictive error close to zero with most of the absolute value ranges between 0.01 and the peak error found at 20 h and 22 h for all the weather profiles, 36 h for dew point, 42 h for both dew points and humidity, as well as 10 h for pressure. The peak error must have been caused by other electricity load influencers, which can be considered in future research. This reduction aids the model predictive abilities for economic sustainability. The predictive error remains within the range value, which is lower than the predictive errors of the classical models when used by the same load user category, as shown in Table 4.2.



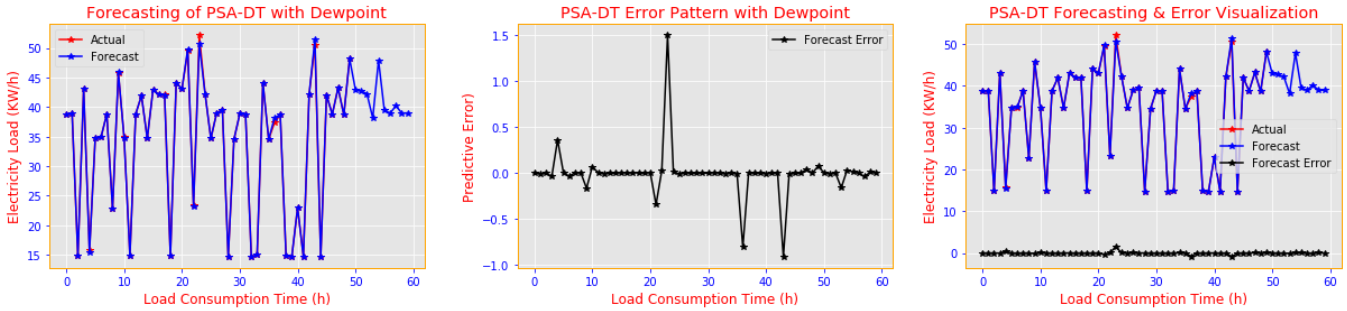
(i) (ii) (iii)

(a)



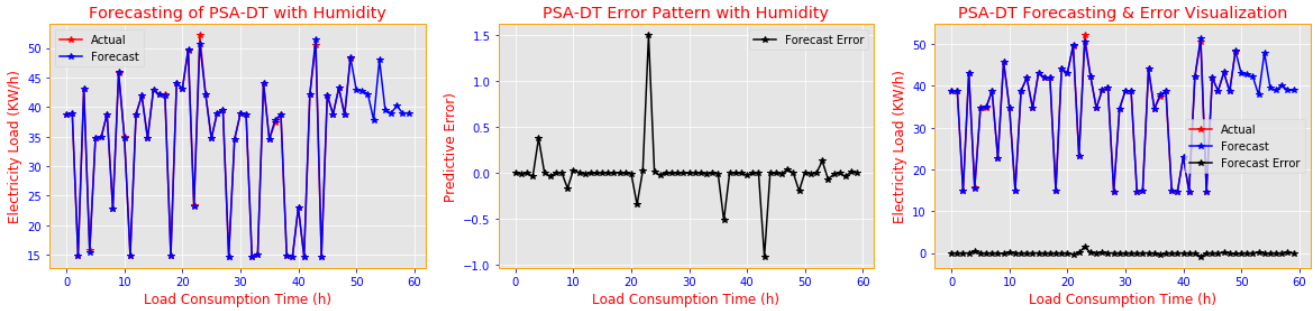
(i) (ii) (iii)

(b)



(i) (ii) (iii)

(c)



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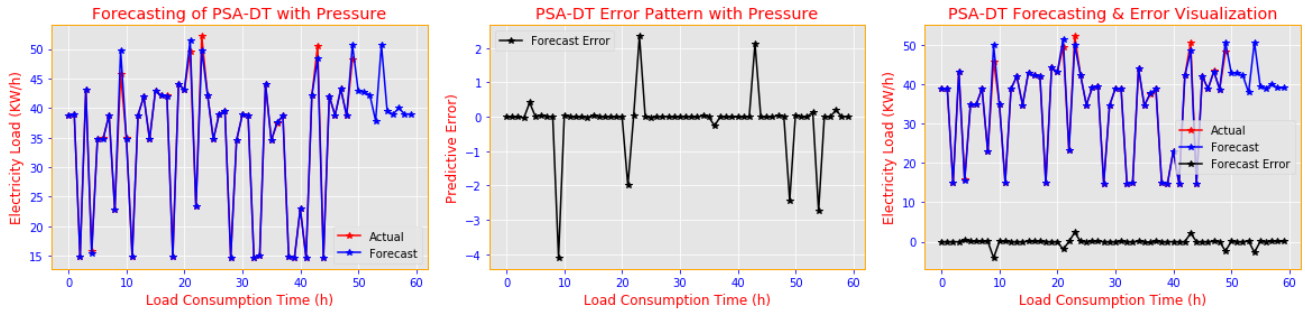
(d)



(i) (ii) (iii)

(e)

Figure 4.8: PSA-DT for Commercial Electricity Load Consumption in Smart Homes with (**a**) Temperature; (**b**) Wind speed; (**c**) Dew point; (**d**) Humidity and (**e**) Pressure.

4.2.3 Experiment 3: Electric Load Forecasting with PSA-DT of Residential Consumers with Weather Profiles in Smart Homes

In this section, the objective of this test and the results obtained, as shown in Figures 4.9a–e, is to affirm effectiveness in the predictive ability of PSA-DT in terms of low predictive errors computed, using Equation 10 and comparing the PSA-DT predictive error and the classical model error in the context of each weather profile for residential load consumers.

Decision-making: Sampled quantitative analysis from load consumption 0 h-50 h and beyond.

Q1: What is happening to the predictive behaviour?

A1: The predictive error for each of the experiments in Figures 4.9a(ii)-e(ii) has error values for each weather parameter as follows: temperature ranges between -0.1 to -0.085; wind speed ranges between -0.08 to 0.14; -0.1 to 0.055 was the error value of dew point; humidity also ranges between -0.08 to 0.13 and finally, the pressure profile produces an error value of -0.1 to 0.13. This near-zero performance was aided by the probabilistic predictive ability of PSA-DT coupled with the weather effect. Since the errors generated by PSA-DT with each weather parameter are extremely small compared to the value generated by the classical model shown in Figures 4.6a–e(ii) and Figures 4.7a-e(ii), the forecasting results generated by the PSA-DT model tend towards higher accuracy than the result obtained from the classical model for all classes of users being considered.

Q2: Why is it happening?

A2: This predictive error revolving around the zero points on the axis occurred because of the meaningful weather variables with the cooperative nature of the PSA-DT model formed by combining the merits of both PSA and the DT model described in Chapter 3. Because of the uncertain nature of electricity load consumption, the expected mean load with high confidence value was obtained via the Monte Carlo experiment before passing the result into a DT for effective learning and predictions.

Q3: What can be done about it or what will happen next?

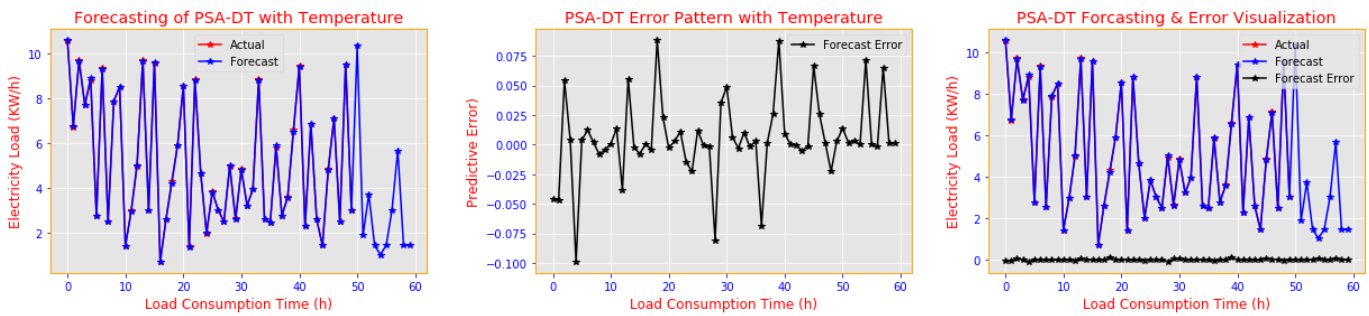
A3: To maintain the efficiency of the cooperative model with weather factors, data used for such predictions can be obtained with a low time interval, less than an hourly data interval. In addition, acquiring more data for effective learning of the model and for better representation of the future data point in the training data can also improve the predictive error. Furthermore, greater consideration can be given to the price of electricity being supplied to various residents across different locations.

Considering a weather factor during predictive analytical processes in an SG has huge potential to yield an effective forecasting result with high confidence of low predictive error. This experiment shows the different forecasting abilities and the forecasting errors of the cooperative PSA-DT model when used with weather parameters and for residential load consumption.

In this section, the result of Figure 4.9a (i) depicts how well the forecast load fitted the actual residential load with near-zero error, as shown in Figure 4.9a (ii). For all the weather variables, most of the predictive error points revolved around -0.02 to 0.03 and a periodic peak error value was obtained at 28 h for all the weather profiles. According to Figures 4.9a-e (ii), the predictive errors were still lower than the error results of the classical model used for residential load consumption. Moreover, these possibilities

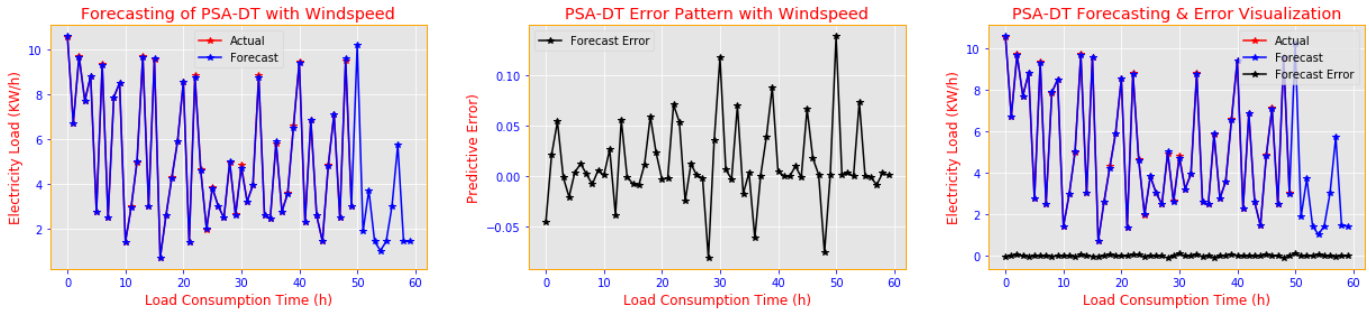
occurred as a result of effective PSA-DT model usage with low standard deviation from the mean load in residential electricity load consumption.

This research deduced from Figures 4.9a-e(ii) that the results of the cooperative predictive model combined with weather profiles to produce predictive errors close to zero with most of the absolute value ranges between 0.02 and the peak error found at 28 h for all the weather profiles, 50 h for wind speed, 3 h and 12 h for humidity. This reduction aids the model predictive abilities for economic sustainability. The predictive error remains within the range value, which is lower than the predictive error of the classical model when used by the same load user category as shown in Table 4.2.



(i) (ii) (iii)

(a)



(i) (ii) (iii)

(b)

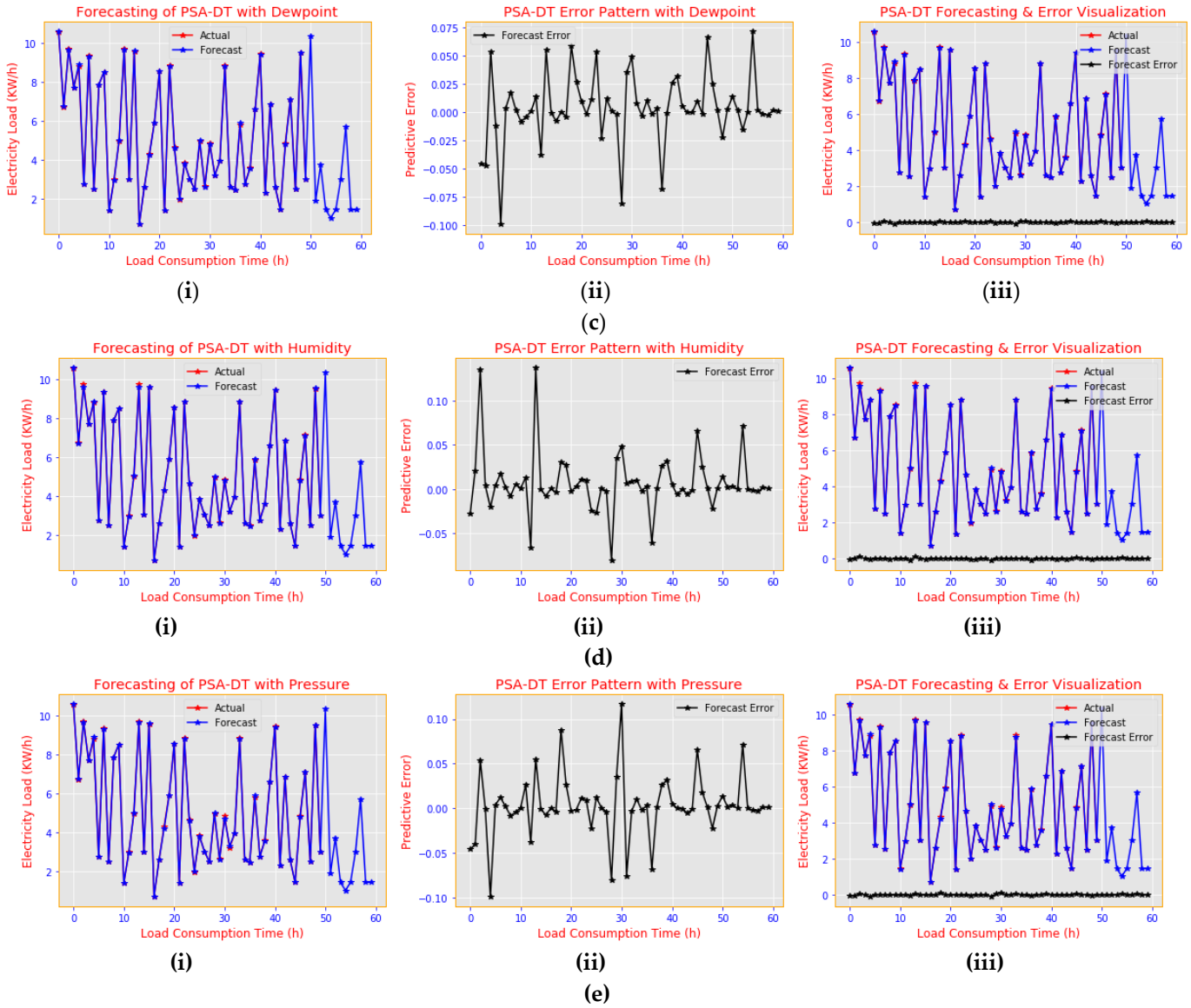


Figure 4.9: PSA-DT for Residential Electricity Load Consumption in Smart Homes with (**a**) Temperature; (**b**) Wind speed; (**c**) Dew point; (**d**) Humidity and (**e**) Pressure.

Generally, the predictive results in Figures 4.8a–e and Figures 4.9a–e were extrapolated after the 50th load data in order to predict the next few hours between the hours of 51 and 60 for each of the experiments. The corresponding reduced near-zero predictive errors in Figures 4.8a-e(ii) and Figures 4.9a–e(ii) show how well the cooperative PSA-DT model

with weather variables can predict using interpolated results ranging from 0 to 50th load data value and after the 50th load data value.

From the visualisation result, the forecast load line almost "maps" the actual load line with a near-zero forecasting error in the error patterns in Figure 4.9. In addition, ranging from temperature to pressure for both residential and commercial load, the analytical plots in experiments 2 and 3 in Section 4.2 denote that different weather profiles have different load consumption patterns and the cooperative PSA-DT with weather profiles can predict the consumption to a high degree of predictive accuracy with reduced forecasting errors, but it is notable that the level of errors also varies among load categories considered because of the load consumption behaviour of consumers at different points in time for different locations.

4.2.4 Performance Evaluation for PSA-DT with all the Weather Parameters on Residential and Commercial Load Consumption in Smart Homes

Another interesting observation was the cooperative model with all the weather parameters. Considering temperature, wind speed, dew point, humidity and pressure simultaneously with the residential and commercial load consumption during the predictive process gave a more pleasing result of near-zero predictive error. The actual load consumption with the predicted load up to the 50th hour and till the 60th hour for future prediction can be seen in Figures 4.10a–b. In the residential load category, one could see in residential load consumption that most of the predictive error falls within -0.1-0.05 and within zero range for commercial electricity load consumption. However, this arose from the applaudable abilities of PSA-DT used with weather variables in SG.

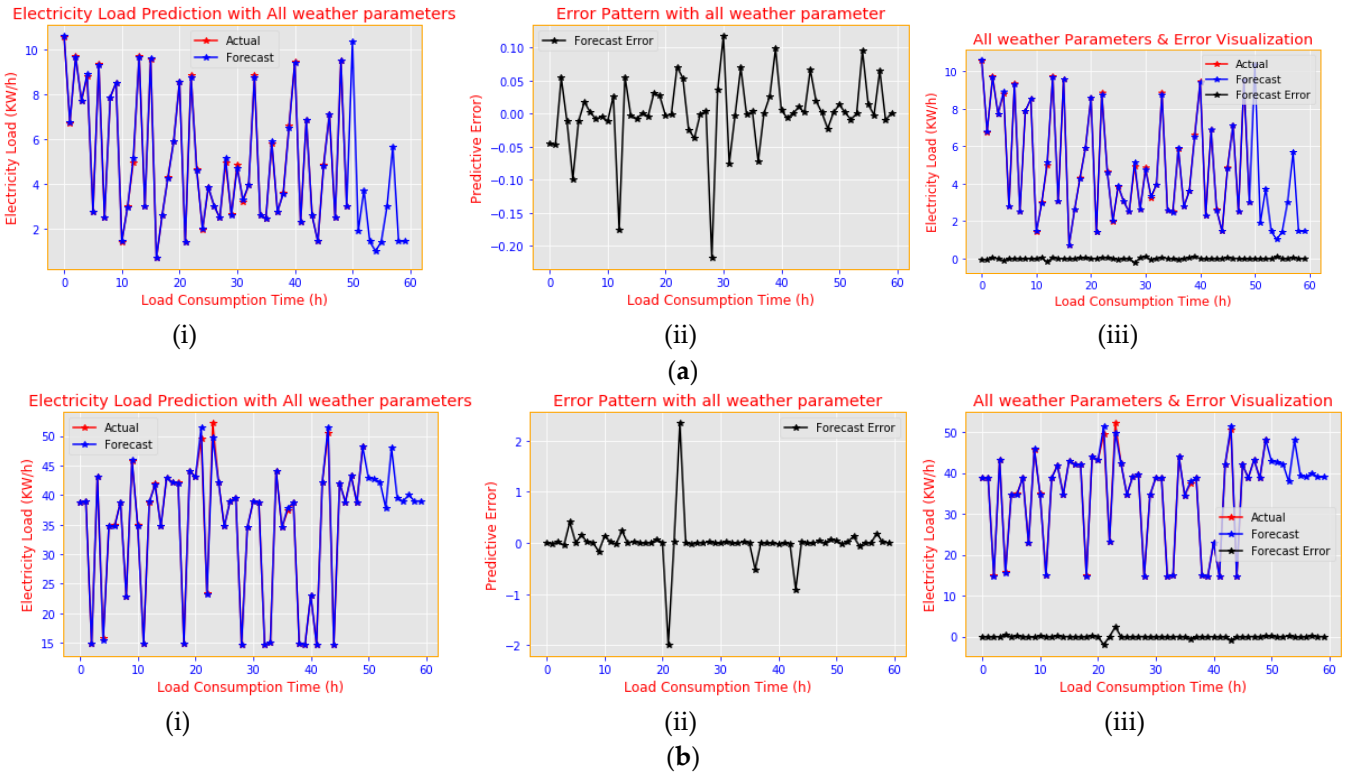
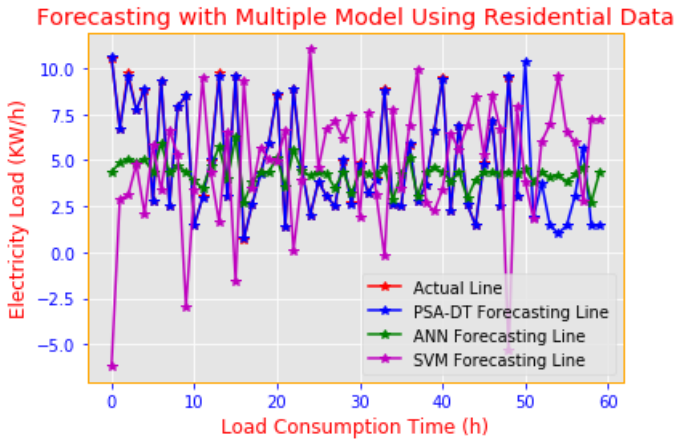


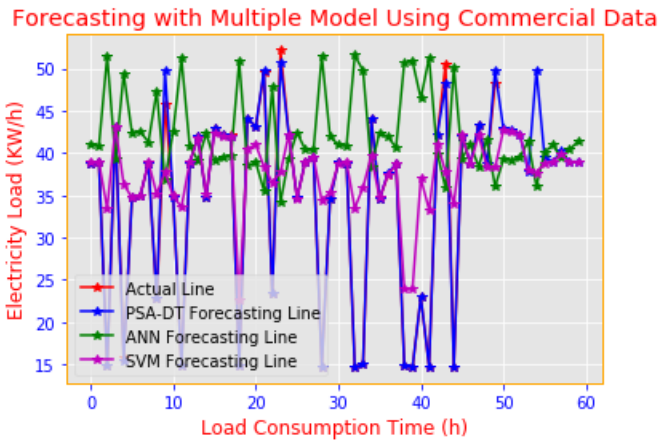
Figure 4.10: (**a**) Residential Electricity Load Consumption Prediction with all the Weather Parameters; and (**b**) Commercial Electricity Load Consumption Prediction with all the Weather Parameters

4.2.5 Performance Evaluation of Electric Load Forecasting with PSA-DT and Classical Models

Finally, a more interesting observation was the cooperative model fitting the actual load consumption compared to other state-of-the-art models at load times up to the 50th hour and to the 60th hour for future prediction, as shown in Figures 4.11a-b. In the residential load category, one could see in residential load consumption the "overlap" of the actual load and PSA-DT forecasting load in Figure 4.11a; but, in Figure 4.11b, the PSA-DT could fit very well in this category, whereas it is otherwise for other classical models. The absolute fitting of the actual load and the predicted load for the classical model for both the residential and commercial datasets with all the weather profiles could not be established owing to their performance compared with the PSA-DT.



(a)



(b)

Figure 4.11: (**a**) Residential Electricity Load Consumption; and (**b**) Commercial Electricity Load Consumption.

This research made differential analysis in terms of the forecasting abilities of PSA-DT when used with weather variables by justifying its performance in reducing forecasting error levels to near-zero when compared with the classical model. The experimental results in Tables 4.2a–b show the various predictive error results of PSA-DT with each of the weather parameters for different hourly load data, training and test sizes and each of the classical models. In each table, and for each of the SG user categories including the individual weather variable, the corresponding experiment produced different but negligible predictive errors. In a more elaborate form, Tables 4.2a–b show the predictive error analytical result for different categories

of load users with different hourly load data sizes of 100, 200 and 500 in each category and for different weather variables. Consideration was also given to different percentages of training and test sizes of 60% and 40%, 80% and 20%, as detailed in Table 4.2. Going through each of these variations and performing the corresponding experiment, different predictive error values were obtained, as highlighted in Table 4.2.

Table 4.2a shows the analytical breakdown of the predictive error for residential load consumption in an SG. The tabular result gives a quick overview using different variations of datasets with diverse training and test sets for each of the weather variables in smart space. In each of the experiments and having obtained the MAE, using Equation 10, for different variations in the training and test set used by each of the weather parameters, one could deduce that the predictive error reduces during each experiment compared to the classical model counterpart as the hourly load size is increased from 100 to 200 and also 500, as shown in Table 4.2a. This reduction is more prominent when the training size is 60% and the test size is 40%. These insights explain how the predictive performance of PSA-DT with the weather parameter can be improved if one has a large dataset to train and test the model and such a performance will result in effective prediction of the future electricity load consumption in smart homes.

The experimental results in Table 4.2b show the different variations of the training and test set for various hourly load sizes of 100, 200 and 500 used by each weather parameter for the commercial users' category. In the tabular analysis, the predictive error values are always near zero, which is similar to the result from Table 4.2a. These both exhibited similar characteristics, as the predictive error for each round of experiment tends to a near-zero value regardless of the load size. This result was also obvious at load size 500

for temperature and wind speed with of 0.0174 and 0.0178 respectively at 80% training size and 20% test size.

One notices that the predictive error values obtained from the commercial load users are significantly higher than those obtained from residential load users with the classical models. This difference could be caused by several other factors, such as the season of business activities and the nature of business in the location where the data were collected. Also, load user categories have different consumption preferences. In Figures 3.11a-e, there is a more pronounced reduction in load consumption at every specific point in time, such as 0 h-3 h, 22 h-25 h, 48 h-50 h and 72 h-75 h, compared to Figures 3.10a-e meant for residential users. This shows that different categories of users come with different consumption pattern and this goes a long way in affecting the predictive abilities of any model used. However, PSA-DT, with each of the weather variables, produces near-zero predictive error for all the instances of the experiment.

Table 4.2. (a) Predictive errors analysis from residential SG categories of users using PSA-DT with each weather parameter; (b) Predictive errors analysis from commercial SG categories of users using PSA-DT with each weather parameter

Predictive Model	Smart-Grid Data (User Category)	Weather Parameter	Hourly Load Data Size	Training Size (%)	Test Size (%)	Predictive Error (MAE) for PSA-DT	Predictive Error (MAE) for SVM	Predictive Error (MAE) for ANN
	Residential	Temperature	100	60	40	0.1304	0.4832	0.1933
							0.4778	0.1015
				80	20	0.0485		
			200	60	40	0.0727	0.9400	0.1800
				80	20	0.0331	0.8737	0.2053

		500	60	40	0.0256	0.3982	0.0670
						0.3432	0.0631
			80	20	0.0174		
		100	60	40	0.0796	0.9583	0.1078
	Wind Speed					1.0049	0.2198
			80	20	0.0577		
		200	60	40	0.0760	1.2784	0.2310
						1.1294	0.3225
			80	20	0.0340		
PSA-DT, SVM & ANN		500	60	40	0.0254	0.4728	2.3143
						0.3067	2.5430
			80	20	0.0178		
		100	60	40	0.1083	0.2854	0.1298
	Dew Point					0.2813	0.0903
			80	20	0.0391		
		200	60	40	0.0779	0.8712	0.1486
			80	20	0.0400	0.6856	0.2170

	500	60	40	0.0231	0.3904	0.0881
		80	20	0.0155	0.3060	0.0804
Humidity	100	60	40	0.0695	1.1679	2.7189
		80	20	0.0340	1.1265	3.1245
	200	60	40	0.0698	1.5626	2.5699
		80	20	0.0334	1.6662	2.0236
	500	60	40	0.0222	0.6914	2.3905
		80	20	0.0158	0.4915	3.0925
Pressure	100	60	40	0.0881	0.2869	22.9099
		80	20	0.0378	0.3042	16.6074
	200	60	40	0.0569	0.8489	22.2804
		80	20	0.0336	0.7568	25.9642
	500	60	40	0.0281	0.4249	11.9023

							0.3636	21.6266
				80	20	0.0171		

(b)

Predictive Model	Smart-Grid Data (User Category)	Weather Parameter	Hourly Load Data Size	Training Size (%)	Test Size (%)	Predictive Error (MAE) for PSA-DT	Predictive Error (MAE) for SVM	Predictive Error (MAE) for ANN
			100	60	40	0.1304	6.7932	1.3000
		Temperature					6.6163	2.5646
				80	20	0.0485		
			200	60	40	0.0411	5.1058	0.1600
							5.9021	0.9478
				80	20	0.0331		
			500	60	40	0.0256	4.1001	10.3863
	Commercial						4.0072	9.6386
				80	20	0.0174		
			100				7.9246	2.4969
				60	40	0.0796		
		Wind Speed					8.0650	0.1839
				80	20	0.0889		
			200				5.6213	2.1923
				60	40	0.0435		
				80	20	0.0340	6.2756	2.3509

		500	60	40	0.0254	4.1971	5.0263
			80	20	0.0178	4.1798	25.4792
PSA-DT, SVM & ANN	Dew Point	100	60	40	0.1083	6.2173	2.3699
			80	20	0.0391	5.9263	1.5508
		200	60	40	0.0403	5.0893	0.5360
			80	20	0.0400	6.1913	0.3269
		500	60	40	0.0210	4.2980	10.9675
			80	20	0.0401	4.1979	25.3955
	Humidity	100	60	40	0.1069	8.1552	0.0680
			80	20	0.0340	8.3999	7.9907
		200	60	40	0.0438	6.1060	0.2448
			80	20	0.0334	6.7130	0.6997
		500	60	40	0.0212	5.1015	4.9780

					5.1737	5.0207
		80	20	0.0349		
Pressure	100	60	40	0.1506	7.5879	21.5362
					7.8270	25.5629
		80	20	0.0378		
	200	60	40	0.0429	5.3103	8.7335
					5.7600	21.8680
		80	20	0.0336		
	500	60	40	0.0261	4.4845	6.7242
					4.7290	28.8212
		80	20	0.1362		

Following the analytical presentation of the weather effects on the predictive error, it is worth noting that increasing the size of the dataset can also decrease the predictive error when the PSA-DT model is used. In addition, further consideration should be given to other factors that affect electricity consumption in an SG for further reduction of the predictive error to near zero.

Hence, the PSA-DT model, when used with weather variables, could also predict the future load more accurately for smart homes with a low predictive error, but additional improvement of the prediction can be enhanced with further attention being paid to other electricity consumption factors, such as the price of electricity.

4.3 CHAPTER SUMMARY

The chapter mainly covered the experimental evaluations of the PSA-DT model using different hourly electricity loads collected from residential, commercial and industrial users in conjunction with each user's weather profile. The experimental analysis was divided into two sections. The first section was the experimental evaluation of the PSA-DT model with respect to the classical models such as SVM, ANN and BN, while the second section was the experimental evaluation of the PSA-DT model when used with each of the weather profiles such as temperature, dew point, wind speed, pressure and humidity. In each of the experiments, different hourly data sizes such as 100, 200 and 500 were considered, as well as for each variation in the data size of training and test data.

In the first section, the predictive errors of the experimental evaluations for the classical models considered were presented and also when used with the PSA-DT model. The PSA-DT model showed excellent performance in terms of near-zero predictive errors for all classes of electricity users considered in this research.

In addition, the second section of the evaluation extensively considered the use of the PSA-DT model for residential and commercial load users and for each weather profile considered in this study. Consideration was also given to comparison with SVM and ANN in terms of how well they were able to predict and produce predictive errors compared to the near-zero predictive errors produced by the PSA-DT model.

CHAPTER 5: CONCLUSION

5.1 RESEARCH SUMMARY

This research was undertaken principally to examine the predictive performance of PSA-DT with and without weather profiles following the techniques in Chapter 3.0. Critical analysis was conducted, as shown in experiments 4.1 and 4.2 with various tabular results on the cooperative PSA-DT model performance. When PSA-DT was used in both situations, the aim was to gauge its performance in terms of near-zero predictive errors when used with and without weather profiles, with the study focus placed on reducing the predictive error that can result in high accuracy for electricity load forecasting in an SG. This will aid effective planning for sustainable economic development, especially when used by SG owners for electricity demand planning. Such near-zero error forecasting will minimise wastage by assisting utility managers to know the possible total amount of electricity that will be supplied to various smart homes for future electricity consumption.

The cooperative model for sustainable demand planning in an SG was developed using a probabilistic simulation of the load to obtain a list of cumulative loads via successive random generation. Such loads generate a high level of confidence interval for their expected mean acceptability. Following the model flow in Figure 3.2, the accepted list was fed into the DT model, trained and fitted; it finally predicted the future load consumption.

Overall, PSA-DT proved more efficient than the state-of-the-art models by producing a near-zero predictive error for the different categories of users considered, as shown in the various experiments in Section 4.1. This implies that such a probabilistic model will enhance accurate decision-making on the load consumption in various smart homes. In addition, weather profiles such as temperature, wind speed, dew point, humidity and pressure (being the critical factors during the electricity predictive activities in an SG),

were variables used with PSA-DT and experiments were conducted as detailed in Section 4.2. One could see that a near-zero predictive error value was obtained for each of the experiments when compared with the classical model.

However, future prediction of short-term loads is affected by various other factors. Therefore, consideration should be given to some of the factors, such as the number of customers in different categories, the appliances being used in those areas and electric load (in turn reflecting consumers' personal characteristics, e.g. age, economic and demographic data, as well as appliances' sales data and other related factors). Other factors, such as the price of electricity, days of the week and time of the year, should also be considered.

5.2 RESOLUTION TO RESEARCH QUESTIONS

In this study, various questions asked in Section 1.3 were addressed by implementing a PSA-DT model and carrying out several experiments detailed in Chapter 3 and Chapter 4 respectively. The main question on how an efficient cooperative model with minimal error can predict future load consumption and include consideration of weather variables for STLF of electric energy demands in SGs for smart homes was addressed with extensive description and algorithms in Section 3.1, 3.3 and 3.4.

The main question was broken down into two, as question 1 and question 2. To what degree of efficiency, in terms of forecasting errors, is the proposed model better than the existing state-of-the-art model? The first question was addressed via experimental evaluations in Section 4.1. In Section 4.1, descriptions and experiments on the behaviour of state-of-the-art techniques were carried out in Section 4.1.1 and Figure 4.2 respectively. The forecasting errors obtained from each of the state-of-the-art methods, such as SVM, ANN and BN, using the residential load consumption dataset, were visualised in Figure

4.2 a(iii) - c(iii). The results of the forecasting error for each of the state-of-the-art models and how well the forecasting line fits the actual load consumption line were compared, as shown in Figure 4.2. The forecasting error results in Figure 4.3 show a minimal predictive error value close to zero compared to similar errors produced by the state-of-the-art forecasting techniques in Figure 4.2. This shows that PSA-DT could make predictions with minimal forecasting error compared to a similar error produced by the classical models.

In addition, Figure 4.4 superimposed the PSA-DT forecasting model and each of the classical models that was considered in this research. One could see that PSA-DT model was able to predict very close to the actual load consumption for all classes of electricity load consumption users. Further justification of the predictive performance of PSA-DT was shown in Table 4.1. It was obvious from a comparison of the PSA-DT predictive error value and the state-of-the-art model. In each experimental setup using various data samples, the predictive error of PSA-DT tends to zero.

Furthermore, question 2 considered the extent of the weather profiles, such as temperature, pressure, dew point, humidity and wind speed, on the SG by using the PSA-DT model to predict the future electricity load consumption, as explained in Section 3.5 and Section 3.7, with a detailed experiment carried out in Section 4.2. In Figure 4.8, consideration was given to temperature, pressure, wind speed, dew point and humidity as weather factors influencing the PSA-DT predictive results. An experiment was conducted for each of the weather parameter generated forecasting errors highlighted in Figure 4.8 and 4.9. The forecasting error results show that the PSA-DT model could accurately predict future electricity consumption by residential and commercial users and reduced the huge forecasting error that inhibited effective prediction of future electricity load consumption by these categories of users.

To justify the effective performance of the PSA-DT model over the classical model discussed in this study further, we have extracted the predictive error results in Table 4.2 for PSA-DT, SVM and ANN when used with weather profiles and electricity load consumed by both residential and commercial users. In Table 4.2, the predictive errors produced by PSA-DT are very low compared to the results produced by SVM and ANN.

Finally, in order to address the questions raised in this study formally, a PSA-DT algorithm was developed and experimental results were obtained for different load user categories. To support the minimal predictive error generated by PSA-DT further, mathematical analyses were undertaken in Sections 3.7 and 3.8. These mathematical frameworks also show the near-zero performance of the PSA-DT developed and deployed in this study.

5.3 RECOMMENDATION

The main goal of this study is to provide electrical power system planners with a correct and dependable short-term load forecast of electricity consumption in an SG through the cooperative PSA-DT model.

The research observed some improved predictive ability by producing minimal forecasting errors for short-term load forecast of electricity consumption in an SG for a smart home. The study also posed minimal predictive error when used with weather profiles as one of the critical factors affecting electricity consumption. The findings have some management implications for SG infrastructure owners by reducing the cost incurred through electricity consumption. In addition, this implies that its deployment for electricity demand planning will be of great benefit to various smart-grid operators providing electricity distribution to homes. Reduced forecasting error will translate into

accurate prediction of future electricity consumption, and this inevitably means that there will be insignificant energy losses during the supply of electricity for consumption.

5.4 LIMITATIONS AND FUTURE WORK

In summary, future research might focus on the effect of electricity consumer behaviour on load consumption. Prices of electricity paid by consumers and the season of such consumption form a critical factor for effective predictive results of load consumption in an SG. It will be valuable to analyse the effect of various prices and seasonal changes on consumers' electricity load consumption as well as determine how PSA-DT can be used in the prediction of load consumption for improved decision-making by SG electricity planners for smart homes. In addition, another probabilistic model, such as a BN, can be investigated exhaustively for further reduction in predictive error obtained by forecasting the future load, taking cognisance of weather variables at load consumption locations.

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