National University of Lesotho

Formulating Short-Term Electricity Demand Forecasting For Lesotho

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Abbreviations of Words

SAPP: Southern African Power Pool

DAM: Day-ahead Market

IDM: Intra-day Market

FPM: Forward Physical Market

FPM-W: Forward Physical Market - Weekly

LHDA: Lesotho Highlands Development Authority

MAPE: Mean Absolute Percentage Error

MAE: Mean Absolute Error

ANN: Artificial Neural Network

STLF: Short Term Load Forecasting

LEC: Lesotho Electricity Company

EDM: Electricidade De Moçambique

LHDA: Lesotho Highlands Development Authority

SCADA: Supervisory Control and Data Acquisition

NM: Network Manager®

IPPs: Independent Power Producers

RE: Renewable Energy

GDP: Gross Domestic Product

TOU: Time of Use

ARMA: Auto Regressive Moving Average

ARIMA: Auto Regressive Integrated Moving Average

MLP: Multilayer Perception

BRT: Bagged Regression Tree

IESCO: Islamabad Electric Supply Company

LR: Linear Regression

LMBP: Levenberg-Marquardt Back Propagation

BP: Back Propagation

MCP: Market Clearing Price

MCV: Market Clearing Volume

Abstract

Electricity demand forecasting is an important process in the planning and operation of the electricity industry. Providing uninterrupted energy to consumers requires electricity demand to be predicted accurately. This study utilizes ABB Nostradamus short-term demand forecasting software, which accepts historical demand data, days of the week, time of the year and Lesotho public holidays for electricity demand forecasting. It produced day-ahead, week-ahead and hour-ahead electricity demand forecasting results with 3.06%, 4.06% and 5.09% accuracy. These MAPE results are close to or within the acceptable 5% accuracy for short-term demand forecasting, and provide crucial confidence levels for LEC to engage in power pool trading in the SAPP market for optimal power procurement.

LEC utilizes bilateral agreements with LHDA, Eskom and EDM to supply the electricity demand. During the high demand season, bilateral imports from Eskom and EDM costs LEC around 3.27 Million US Dollars (M49 Million) which is twice the money incurred (1.60 Million US Dollars (M24 Million)) during the low demand season. Compared to the average SAPP DAM, IDM and FPM-W prices, Eskom's 20 USc/kWh peak cost is higher than SAPP's 12 USc/kWh DAM and IDM, and 13 USc/kWh FPM-W peak charges. Again, EDM's 4 USc/kWh off-peak cost is higher than SAPP's 3 USc/ kWh DAM, IDM and FPM-W off-peak charges. The study therefore recommends bilateral contracts use to meet intermediate demand of around 103 MW. For demand above 103 MW, utilizing SAPP market can assist to reduce bulk purchases costs.

1. Introduction

1.1 Background

A stable and reliable electrical system depends on the balance between supply and demand. Electricity demand forecasting and electricity supply planning are crucial to attain such a balance. Nonetheless, developing countries face major challenges in performing electricity demand forecasting. These challenges from the studies conducted by Adeoye and Spataru [1] and Steinbuks [2] in 2019 include lack of quality data, electricity supply and demand gap, political instability, economic and weather conditions and technological changes and their transition. Such countries often utilize basic and simple electricity demand forecasting methods that are based on staff's experience and often yields inaccurate demand projections.

For instance, in Lesotho's situation, the national utility, Lesotho Electricity Company (LEC), performs demand forecasting using Excel Spreadsheet referred to as a schedule. This schedule is based on the historical data that is obtained from 30-minute average data generated from the supervisory control and data acquisition (SCADA) system and is sent to the local 72 MW Lesotho Highlands Development Authority (LHDA) hydropower generation station on a monthly basis. The LHDA then sets the generators accordingly to meet the demand. This schedule lacks the intelligence regarding the parameters[1] that can influence such electricity load forecast.

LEC has also subscribed to the Southern African Power Pool (SAPP) competitive market in order to perform trading. As far as trading is concerned, LEC is only selling electricity to the pool but does not purchase any. Such dual trading would be hampered by the rudimentary forecasting that does not incorporate weather, time and holiday effects as the accuracy of such forecasting is compromised due to lack of inclusion of these parameters. Therefore, such forecasting is not effective to enable LEC to engage in trading in the SAPP market, leaving it to rely on bilateral agreements with Eskom (South Africa) and EDM (Mozambique). Thus, a more accurate and automated forecasting system, incorporating weather forecasts, time and holiday effects, is required by LEC to perform trading in the SAPP market.

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[1] The parameters that are of interest in the study include things like weather conditions, public holidays, electricity price and season as well as time effects.

1.2 Problem Statement

In 2018, LEC obtained short-term demand forecasting system called Nostradamus from ABB that came with SCADA system upgrade. This software is automated to produce the electricity demand forecast after it has been trained. It is currently used sparingly and on an ad-hoc basis while LEC still maintains the manual demand schedule based on spreadsheet, despite the availability of this automated demand forecasting system.

The utility has bilateral agreement of 30 MW with Eskom and an annual agreement of 20 MW with EDM, in addition to the 72 MW obtained from LHDA. The main challenge is that LEC gets charged at the peak rate for the entire year by Eskom, if the peak demand spikes beyond the 30 MW value anticipated in the agreement. Regardless of whether this spike occurred for only 30 minutes, Eskom's charge for electricity usage remains unchanged for the next 12 months, unless a higher peak is reached. LHDA, on the other hand, schedules the electricity delivered to LEC with the amount of water being sent to South Africa. This means that when LHDA reduces the water supply to prevent excess water flow, the amount of electricity produced and dispatched to LEC is reduced. In this instance, LEC is then required to source electricity from other SAPP utilities. Mostly, it gets this power from Eskom at an extra cost of penalties or it pays wheeling charges to Eskom.

It is evident that lack of adoption of an automated and intelligent electricity demand forecasting results in non-optimal procurement of power through fixed bilateral contracts that may not be cost-effective and thus leading to higher tariffs for the final consumer. These challenges have motivated and triggered this study to be undertaken to investigate how an automated short-term electricity demand forecasting can be introduced in LEC to assist in effective and optimal power procurement through the regional SAPP market. Hence, the study seeks to show that the adoption of the short-term demand forecasting for LEC is crucial for trading in the SAPP market[2]. Moreover, the study seeks to identify and evaluate the benefits that will result from participation in the regional power trading.

1.3 Objectives

The objectives of the research are as follows:

[2] The SAPP trading markets that are applicable for this study include intra-day, day-ahead and week-ahead

- To produce accurate hour-ahead, day-ahead and week-ahead electricity forecasting for LEC using Nostradamus software,
- To use the Nostradamus electricity forecasting results to illustrate the fact that LEC can perform trading in the SAPP market,
- To perform a comparative analysis of SAPP competitive market and bilateral agreements to determine the cheaper electricity procurement option.

The research is expected to answer this main question:

How can an automated and accurate short-term electricity demand forecasting help LEC to trade in the power pool market such as SAPP?

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

1. How does LEC procure electricity?
2. What is the accuracy of Nostradamus short-term demand forecasting?
3. How does SAPP trading compare with bilateral trading?

1.4 Rationale for the study

The motivation for doing the study has been attributed to the fact that the literature around short-term electricity load forecasting suggests that accurate short-term load forecasting is crucial for the planning of power generation and purchasing of electricity. The study looks at the case of LEC and tries to illustrate the feasibility of SAPP trading. Moreover, a comparative analysis of SAPP market and bilateral agreements is undertaken to find a cheaper purchasing option. The knowledge generated by this study can be generalized to other developing countries as the challenges and opportunities faced by developing countries around producing accurate short-term load forecasting are generally the same.

The foreseen benefits of the study are:

- ❖ Increased awareness of benefits of producing an accurate short-term load forecasting using a modelling software in developing countries like Lesotho
- ❖ Inform the relevant authorities regarding importance of short-term electricity load forecasting in performing trading activities in the power pool and the supply strategies that can be adopted.

- Contribution to the body of knowledge in the area of load forecasting in developing economies around short-term load forecasting and power generation and electricity markets.

1.5 Outline of the Thesis

The research thesis comprises six chapters. Chapter 1 covers the background, problem statement, objectives and motivation for undertaking the research. Chapter 2 deals with the discussions of the existing literature related to short-term load forecasting trends, advantages, factors affecting electricity demand forecasting, forecasting techniques, artificial neural network for short-term load forecasting and load forecasting and the electricity market. Chapter 3 deals with the research methodology that will be adopted to undertake the study. The focus will be on data collection methods and analysis using the Nostradamus software to perform demand forecasting. Chapter 4 deals with the discussions and interpretation of Nostradamus demand forecasting results for the hour-ahead, day-ahead and week-ahead forecasting. Chapter 5 deals with the analysis of the results obtained in chapter 4 with the emphasis on comparative analysis of bilateral agreements that LEC uses to procure electricity against the procurement of the electricity from the SAPP competitive market which LEC can take advantage of. Lastly, chapter 6 deals with the conclusion and recommendations that are based on the results and their analysis performed in chapters 4 and 5.

2. Literature Review / Theory

2.1 Overview

Every electricity utility strives to supply its customers with quality electricity in a secured, safe and economical manner. Since electricity is a non-storable commodity [3]–[5] unlike petrol, diesel and gas, or requires an expensive solution for storage, it must be generated each time there is a demand for it. Thus, it is vital that the demand be predicted in advance. The prediction of future demand is referred to as demand forecasting. This is vital since it provides the prediction of future electricity demand. Moreover, having an understanding of the profile of electricity demand is vital for electricity producers as it aids in sustaining continuous, reliable and secure access to electricity [6]. Demand forecasting is done based on the past demand and weather data comprising the present and predicted weather and social aspects as well [7].

Accurate electricity load forecasts result in huge savings in operation and maintenance costs and improves the reliability of the electricity system [8]. Moreover, accurate demand forecasting aids the electricity utility around decisions regarding generation, selling and purchasing of electricity [7]. Also, having an accurate electricity demand forecasting facilitates scheduling, maintenance, adjustment of tariff rates and contract evaluation that are essential in power system operations [9].

In the electricity market, having precise electricity demand forecasting is important since electricity demand is the main driver of electricity prices [10]. Thus, the economy of the participants in the electricity market is extensively affected and dependent on efficient, fast and accurate demand forecasting [11]. With the deregulation of the electricity industry globally, having demand forecasting has become crucial for system operators, transmission owners, market operators and other market participants including IPPs. This aids in ensuring the scheduling of satisfactory energy transactions, creation of proper electricity bidding strategies and the operational plans [12].

2.2 Emerging Trends

Precise electricity demand forecasting translates to improved financial performance of the market participants and the electricity utility [10]. This is because having successful transactions in the electricity market requires submission of competitive bids. Thus, accurate demand forecasting is fundamental for market participants to increase their profits [13]. This means electricity market operators rely on the demand forecasting information in order to prepare their corresponding bidding strategies. This results in performing better electricity transactions in the electricity market [14].

Demand forecasting is even more crucial in deregulated environment because of energy loss, market share loss as well as decrease in shareholders values that results from unanticipated escalating operations costs [15]. Similarly, with fluctuations in electricity demand and supply, changes in weather conditions and ever increasing energy prices during peak times, demand forecasting is vital for electricity utilities and market participants [16].

Load forecasting is classified into three forms: short-term load forecasting, medium-term load forecasting and long-term load forecasting. Short-term load forecasting ranges from an hour to a week. Medium term ranges from a week to a year while long-term load forecasting ranges from a year to 20 years. Although the focus of this study will be on short-term load forecasting, it is important to take a look at the other two forecasting methods. This will result in the appreciation of the importance and value of short-term load forecasting.

Long-term demand forecasting is used in the planning department for power system planning and tariff regulation [17]. Long-term capital investment requires long-term demand forecasting more especially when making decisions regarding plant and infrastructure investment [18]. It is again crucial during strategic planning that involves capacity expansion. Medium-term demand forecasting is used in the transmission, distribution and trading departments. Scheduling unit maintenance[3], energy trading and revenue evaluation all require medium-term demand forecasting [17]. It is also applicable in arranging maintenance schedule, planning for power outages and engaging in power system upgrades[4] [19], [20].

However, for load flow[5] analysis and estimation, transfer and switching of the electricity load, medium and long-term demand forecasting are not applicable. These tasks require short-term demand forecasting. Short-term demand forecasting is also beneficial in balancing electricity demand and supply and for security, reliability and quality of electricity supply [21]. Moreover, short-term demand forecasting provides prediction of future load more

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[3] Unit maintenance here refers to maintenance of the generation units such as generators.
[4] The power system upgrades form the major work in the power system.
[5] Analysis and estimation of load flow helps prevent overloading and the power system from suffering major disturbances [21] and thus limiting occurrences of equipment failures and blackouts. This leads to improvement of network reliability. Analysis and estimation of the load flow as well as transfer and switching of electricity load are used during daily operations of the electricity utility.

accurately as opposed to the other two methods [22]. At this point, the focus for the remainder of the study will be on short-term demand forecasting.

2.3 Short-term Load Forecasting Advantages

Short-term load forecasting is used for scheduling electricity generation and electricity production and transmission planning that involves unit commitment, allocation of spinning reserves and dispatching of the generation units in an economic manner[6] [10], [23], [24]. Short-term demand forecasting is also used during load management and power interchange which are required by systems operators [11]. It is also used to set the schedule for the energy transfer and in the real-time control of the electrical system [23].

Liberalization of the electrical markets promotes participation of many agents which leads to competition[7] amongst the market players [25]. This results in less costs for the final consumer. Thus, short-term demand forecasting plays a vital role in reducing the operations costs of the electrical system. The importance of short-term demand forecasting is even more realized since the emergence of balancing market and during power exchanges [26]. Increasing the share of renewable energy into the electricity supply mix also requires precise short-term demand forecasting. This leads to reduction in greenhouse gas emissions in the atmosphere, thus conforming to Paris Agreement [25].

In determining the best approach in utilization of electricity utility resources, short-term demand forecasting is used in conjunction with information concerning wheeling transactions and availability of the transmission facilities [27]. In addition, generation cost, spot market energy pricing and spinning reserves are also crucial during determination of the best strategy for utilizing utility resources [27]. Thus, short-term demand forecasting is useful in the management and maintenance of the generation units[8] [28]. In addition, short-term demand forecasting is used by dispatchers in scheduling short-maintenance and performing cross-border trade [29]. Again, short-term load forecasting helps electricity utilities in maximizing revenues and minimizing operational and environmental costs [2]. This results from optimization of the amount of power generated by the utilities.

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[6] In economic dispatching of generation units, the least cost generator is dispatched first and the costliest unit is dispatched last.

[7] Increase in competition amongst electricity market players results in economic development of a country or a region

[8] The generation units include transformers and generators. The maintenance of these units can be tied to the generation schedule so that the generation units as well as the switch gears that are not in use during the demand supply can be maintained.

Short-term load forecasting is also used in determining the capacity required to meet the anticipated demand [6], [30] as well as the level of electrical energy provisioning needed for achieving such demand. In addition, automatic generation and control as well as distribution of the load in a cost-effective way relies on having an accurate and efficient short-term load forecasting [30]. Short-term load forecasting is used by operations engineers during network feature analysis which includes most importantly an optimal power flow [29].

2.4 Factors Affecting Electricity Demand Forecasting

Since demand forecasting results in the prediction of future consumption pattern, it is important to take into consideration time effects, economic factors, weather effects and customer type during the demand forecasting process [17], [31]–[34].

2.4.1 Time Effects

Time effects have significant impact on the electricity demand and hence the daily demand curve. These comprise calendar parameters, seasonal parameters and seasons of the year. Calendar parameters include day of the week and time of the day while seasonal parameters consist of calendar holidays, daily and weekly cycles [32], [34]. The daily demand curve is periodic and reflects the customer consumption behavior for different hours during the day. This translates to the daily lifestyle of the customers such as their working, leisure and sleeping hours [31], [34].

2.4.2 Economic Factors

The load curve is also influenced by economic factors that include industrial development, population growth, Gross Domestic Product (GDP), cost of electricity, individuals buying capability and time of use [17], [31], [33], [35]. Although the economic factors have more importance when dealing with long-term forecasting, they also have an impact on the demand curve for short-term demand forecasting. For example, time of use (TOU) and cost of electricity have more impact on short-term electricity demand forecasting. Individual buying capability (purchasing power) and the cost of electricity contribute greatly to medium-term forecasting. GDP, industrial development and population growth influence long-term forecasting.

As far as time of use is concerned, the TOU pricing has an impact on changing the duration and the time of occurrence of a peak load. For instance, countries can introduce cheaper electricity at night than during the day, thus making the night peak to vanish. The cheaper electricity can be stored in heat storage equipment for use during the day to warm houses and buildings. Thus, TOU pricing can influence domestic as well as industrial consumers to adjust their load and this aids in peak shaving [17], [31]. Therefore, for short-term electricity demand forecasting, TOU pricing is an important factor to consider since this alters the daily load curve. This results in reduction of the daily average load.

Cost of electricity and individuals purchasing power have an impact on electricity usage and ultimately on the daily load curve. This is because, as the electricity becomes expensive, its use by domestic users will decrease hence reducing the maximum demand. Therefore, economic factors comprising TOU pricing, cost of electricity, management of load and degree of industrialization have a huge impact on system average load and system maximum demand.

2.4.3 Weather Effects

Weather factors are widely used for short-term demand forecasting and include the following [17], [31], [33]:

- Temperature
- Humidity
- Wind speed
- Cloud cover
- Precipitation or dew point

Weather prediction is the most complicated task due to its variable nature and tends to exist for a short period of time in an area. It is crucial to consider the weather factors when dealing with short-term load forecasting so as to minimize the operational costs. This results from an improved forecasting accuracy that results from the combination with other factors like historical demand, time factors and economic factors. The effect of weather is mostly noticed for domestic and agricultural consumers. However, it can also change the load profile of industrial consumers as well.

2.4.3.1 Temperature

Temperature is the measure of the degree of hotness or coldness of a body [31] or the measure of warmness or coolness of the atmospheric air in a particular area at a particular time [33]. Temperature is the most important and influential factor and has a major impact and strong relationship with the electricity demand [31], [33], [34], [36]. During winter when the temperature drops, individuals require more energy to keep warm. Moreover, during summer when the temperature rises, individuals require more energy to lower the temperature. Both scenarios results in an increase in the electricity consumption. This suggests that there is positive correlation between temperature and electric load curve in summer months and negative correlation between the temperature and electric load curve in winter months [17], [31], [33], [36].

This relationship is confirmed by Figure 1 which shows the demand peaking during the summer (having highest temperatures) and winter (having the lowest temperatures) periods [36]. This is further strengthened by Figure 2 which shows the plot of electricity demand against the temperature. From Figure 2, it can be deduced that the relationship between electricity demand and temperature is non-linear, increasing both for decreasing and increasing temperatures [36].

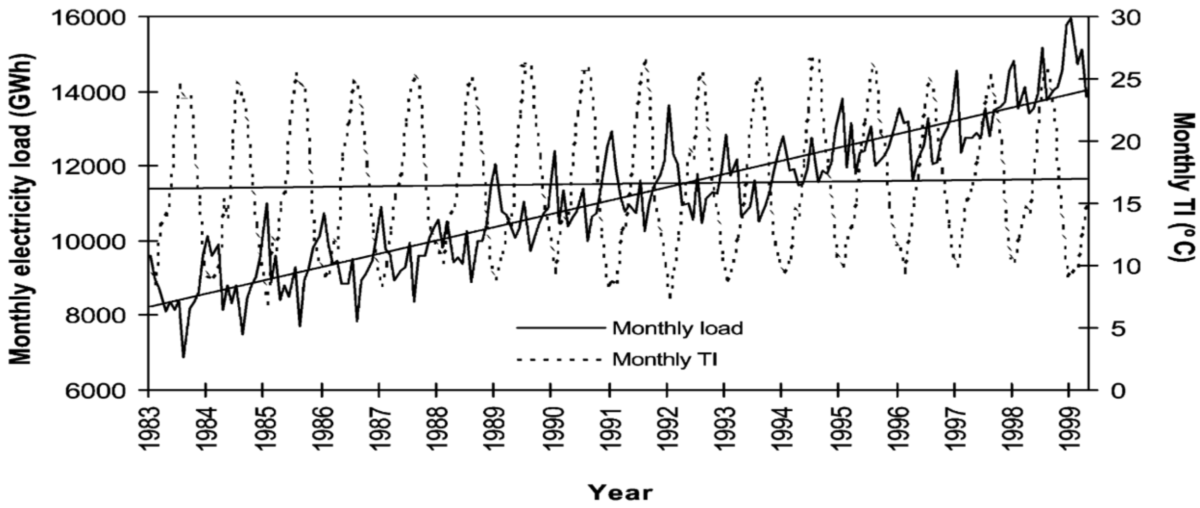


Figure 1 Monthly Evolution of Electric Load and Temperature Index (TI)[36]

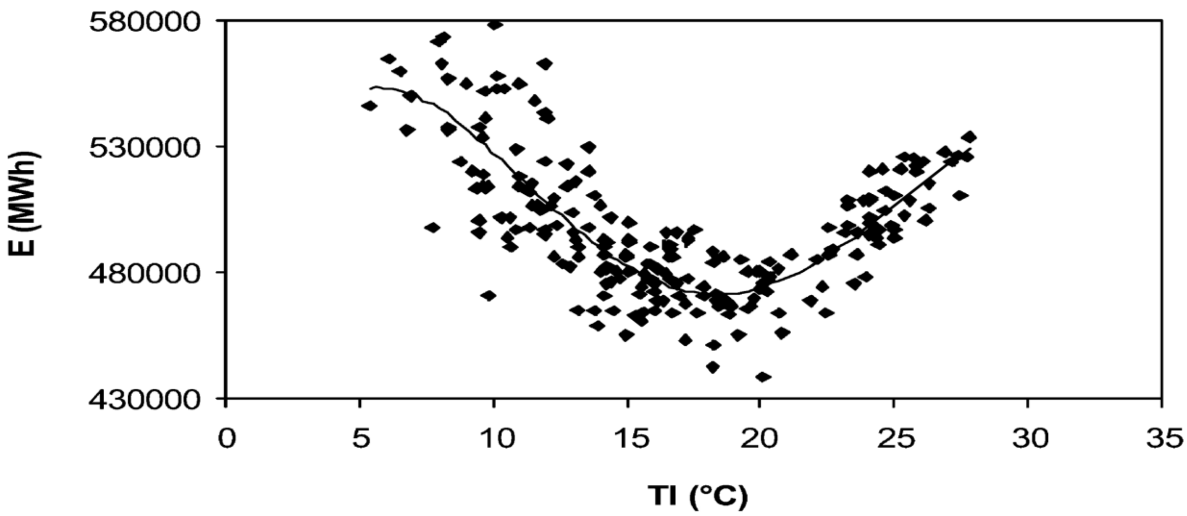


Figure 2 Variation of the total daily electricity load in Spain with Temperature Index[36]

2.4.3.2 Humidity

Humidity is the amount or the presence of water vapors in the air [31], [33]. Humidity has an effect on short term load forecasting due to the fact that it increases the feeling of severity of temperature during summer and rainy days [17]. This makes electricity consumers to use more cooling appliances thus increasing the electricity demand which has an impact on the daily load curve. When dealing with electricity consumers from domestic to industrial, the temperature humidity index is recommended to be used as the impacting factor for load forecasting [31].

2.4.3.3 Wind Speed

Wind speed is the measure of the motion of air with respect to the surface of the earth covering a unit distance per unit time [31]. Like temperature and humidity, wind speed also has an effect on electricity consumption. During the windy summer day, the fact that the human body feels comfortable at those temperatures results in less cooling appliances being used thus reducing electricity consumption. Moreover, during windy winter day, it becomes colder for the human body to accommodate, thus requiring heating appliances to be used. This increases the electricity consumption and hence increases the electricity demand.

2.4.3.4 Cloud Cover

Cloud cover is defined as the mass of cloud over all or most of the sky [33]. It is important to also consider the effect of cloud coverage on demand forecasting. The cloud cover effect on electricity consumption depend on the time of the day. During the day time especially in summer periods, the cloud cover lowers the temperature thus resulting in low consumption of electricity. During the day in winter, the cloud cover reduces the temperature. This requires electricity consumers to use heating appliances which increases the electricity consumption. However, it also has an impact on light intensity in that the intensity is lowered as the clouds block most of the sunlight. This causes consumers to use electric bulbs to light their houses which increases electricity consumption. Hence, for short term load forecasting, cloud cover effects on temperature and light intensity should be considered in order to perform an hour or day ahead load forecasting [31]. This will improve the accuracy of the short term load forecasting model.

2.4.3.5 Precipitation or dew point

Precipitation is defined as the amount of rain, snow or hail fallen at a specific place within a specific period of time which is expressed in inches or centimeter of water [31]. It has a direct and indirect effect on electricity consumption. The direct effect is realized from the fact that heavy rain or snow causes individuals to stay at home hence are likely to consume more electricity during lighting and entertainment purposes. Its indirect effect is with regards to the temperature which in turn has an effect on electricity consumption. During short term load forecasting, precipitation must be considered so as to predict the load accurately. If precipitation is not taken into account, the forecasted load may be overestimated or underestimated resulting in huge loss to the utility due to over generation or load shedding due to under generation.

2.5 Forecasting Techniques

Several short-term demand forecasting techniques have been used for the past years. The techniques are classified into three categories [37]: time series techniques, artificial intelligence techniques and hybrid techniques as depicted in Figure 3. Time series techniques such as Auto Regressive Moving Average (ARMA) and Auto Regressive Integrated Moving Average (ARIMA) are the most popular techniques for demand forecasting [28]. These use previous demand data for predictions of the next hour's load. Other time series techniques include linear regression and sessional autoregressive [37].

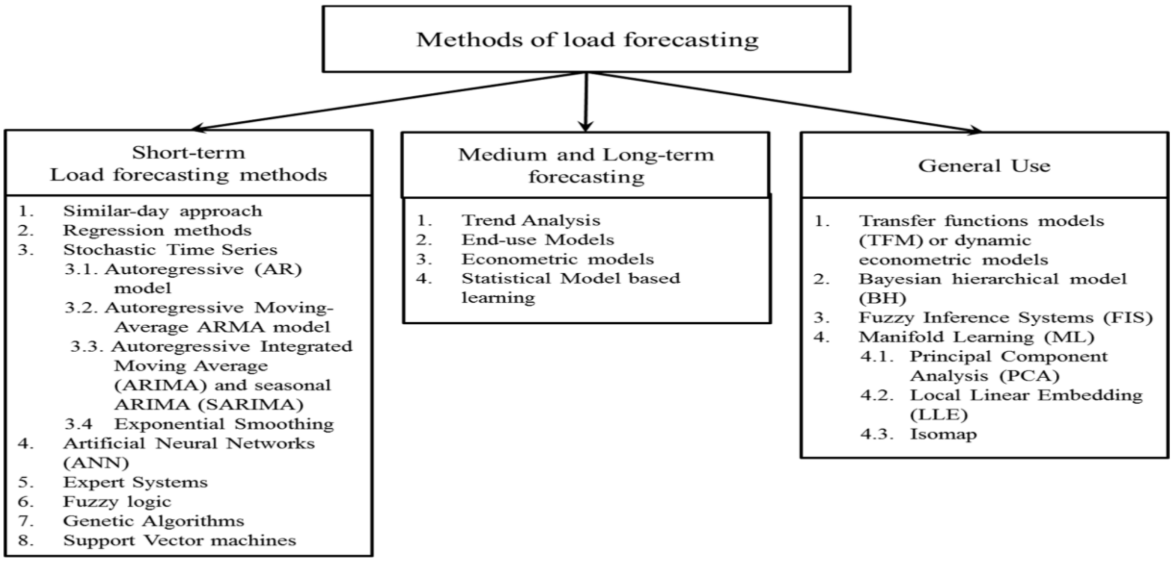


Figure 3 Load forecasting methods comprising short-term, medium-term and long term methods [29]

Since future electricity loads are complex and are nonlinear function of previous load and temperature data, time series techniques do not yield good and precise prediction. This is because electricity loads are affected by weather conditions, economic factors and time factors [8], [10], [38]. Thus, time series techniques do not produce accurate forecasting since they do not accommodate these factors.

Therefore, to address the challenges of time series techniques, the artificial intelligence techniques have been introduced to forecast the electricity loads. These techniques include expert systems, fuzzy logic, artificial neural networks, echo-state networks and support vector regression. Artificial neural network, although includes more factors for forecasting, has drawbacks such as learning-process that is time consuming [28] and there is over-training of the model [37].

Thus, in order to improve the accuracy of the forecasting model, a hybrid technique is used. In this study, the ABB Nostradamus demand forecasting software[9] is used to produce forecasting results. It uses a hybrid model that comprises ANN, smoothing techniques, regression technique and dynamic learning [39]. Nostradamus uses inputs such as demand, weather parameters and calendar information [39]. This is done to improve the accuracy of the forecasting software. Therefore, it is of utmost importance to review the work that is done by other researchers to perform short term load forecasting using ANN and incorporating several input variables in order to support such choice.

Short term load forecasting (STLF) using ANN to forecast half-hourly electricity load demand was performed for Tunisia incorporating historical load, calendar information and weather conditions [6]. The study used the hybrid model that implements MLP and Levenberg-Marquardt ANN to perform the short-term demand forecasting. The results showed that Levenberg-Marquardt algorithm performed well in forecasting half-hourly electricity demand with MAPE ranging between 1.1% and 3.4%. Moreover, the results revealed MLP with Levenberg-Marquardt algorithm as the most efficient tool in forecasting the half-hour electricity demand since it converges quickly with high accuracy.

A day-ahead load forecasting for IESCO was also performed in Pakistan using ANN and BRT [41]. The study used weather data (humidity, dew points and temperature), time factors (hour of the day, weekdays/weekends and public holidays) and past load data (previous day and hour load data and 24-hour average load data). The study have proved the effectiveness of ANN and BRT models with the MAPE of 3.72% for ANN and 3.33% of BRT

[9] ABB Nostradamus is based on neural networks and is a short-term demand forecasting system. Although the study does not focus on renewable energy technologies forecasting, it is worth mentioning that Nostradamus system can also assist in this regard.

respectively. Moreover, BRT performed better than ANN since it required less amount of data for training.

For these studies, MAPE has been used to test the performance of the models and is given by equation 1 [9], [41]–[44]. The MAPE below 5% reflects a highly precise forecasting model [11], [43].

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_t - F_t}{A_t}\right| \times 100 \quad (1)$$

Another parameter that is used to test the performance or accuracy of the forecasting model is the mean absolute error (MAE) which is given by equation 2 [9], [44],

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|A_t - F_t| \quad (2)$$

where A_t is the actual load, F_t is the forecasted load and N is the number of observations or data points and t represents a sample at a particular time.

An hour ahead STLF using Linear Regression (LR) and ANN was conducted for an Indian system incorporating historical load, weather and time factor [43]. The neural network was trained using the Levenberg-Marquardt Back Propagation (LMBP). The results showed that ANN performed better than LR when weather parameters are incorporated into the models due to its nonlinearity with a MAPE of about 0.026% and 0.028% for residential and industrial feeders respectively. This suggests that ANN gives better results with less MAPE and hence better accuracy in predicting the future load.

A study on STLF using ANN was performed for NEPOOL region of ISO New England using historical load and day of the week, hourly temperature and humidity [44]. The training of the network was done for weekdays and weekends respectively. The accuracy of the ANN was calculated using MAPE, MAE and daily peak forecasted error. The MAPE of 1.38% for weekdays and 1.39% for weekends were found portraying good prediction with high accuracy.

A week ahead STLF was constructed for ISO New England using ANN incorporating historical demand data, type of the day, temperature and due point [9]. During the analysis of the forecasting accuracy, all four seasons of the year were considered. Likewise, MAPE was used to test the accuracy of the ANN of the forecasting model. The results show that indeed the accuracy of the forecasting model is affected by the seasonal variation of the input data. The study revealed the confidence interval of 90% for training, testing and validation of the network. The study concluded by mentioning other weather variables like humidity, wind speed, cloud cover, rainfall and human body index to be included in future research so as to further improve the accuracy of the forecasted model.

2.6 Artificial Neural Network (ANN) for STLF

ANN is a nonlinear mathematical tool consisting of interconnected neurons stimulated by the human brain [6], [41]. These neurons form the basic processing units for the neural network and are arranged in layers as depicted in Figure 5 [6], [44]. Multiple neurons typically operate in parallel to process the numerical data the same way the human brain would do. The weights are associated with the connection between neurons and the information is passed in a feed-forward manner. The ANN basic architecture shown in Figure 4 comprises: scalar weights for connecting the nodes, summation function within the node to combine inputs and a transfer function which produces the scalar outputs.

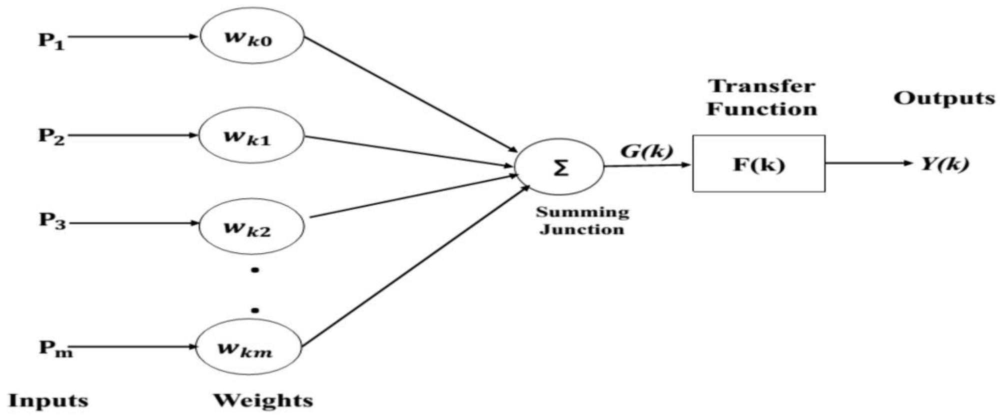


Figure 4 ANN Basic Architecture [41]

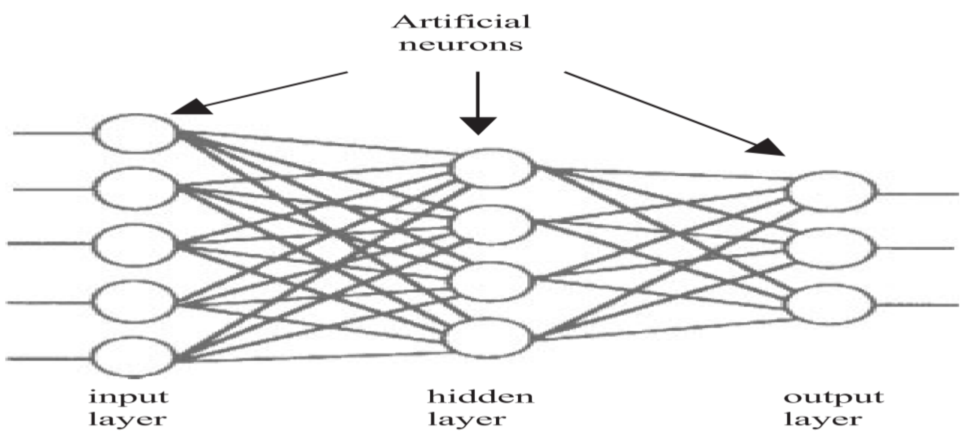


Figure 5 The basic three layer neural network [45]

The mathematical representation of a general neural network is shown in equation 3 [41].

$$Y_k = \sum_{k=1}^{m} P_k W_k \tag{3}$$

where k = 1, 2, 3 . . .,m, and P_k is the kth input, W_k is the weight allocated to the kth input and Y_k is the kth output of the ANN. Upon receiving numerical information, the neuron multiplies the value with W_k and passes them through the summing function. Several layers between the input and output are called hidden layers that act as the black box since the internal processing and means of updating the weights is not shown. In simpler words, the neurons behave like the biological neurons with respect to the way the biological neurons function and their process of learning. With the bias being introduced as shown in Figure 6, the output of the neuron is shown by equation 4 [42].

$$y_k = f(v_k) \tag{4}$$

Where v_k is given by equation 5 [42].

$$v_k = \sum_{j=1}^{m} x_j w_{kj} + b_k \tag{5}$$

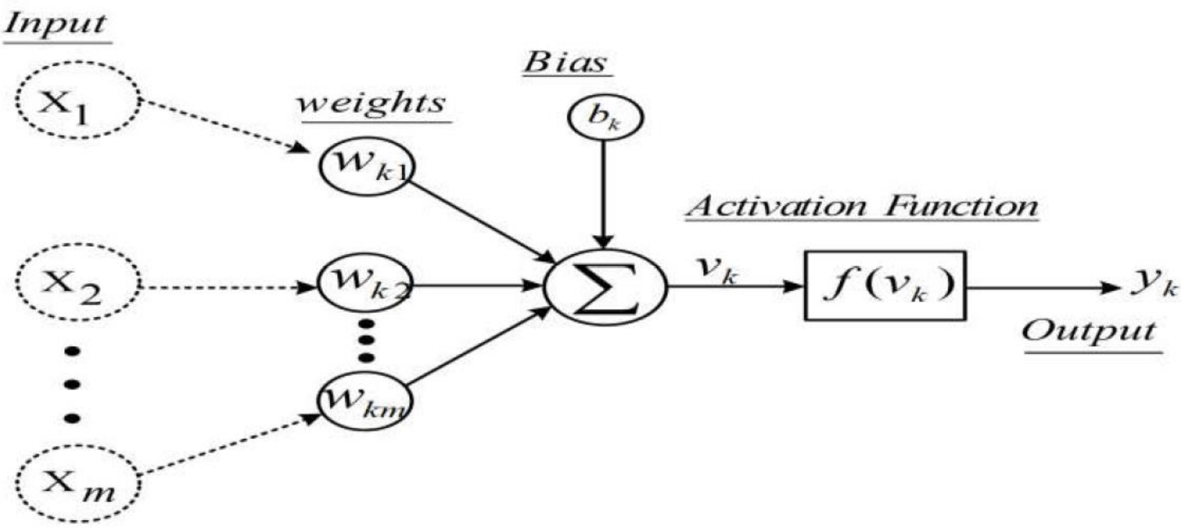


Figure 6 A basic neuron structure [42]

In a neural networks model, the input layer consists of independent variables; the hidden layer consists of unobservable nodes and the output layer consists of dependent variables. If the expected results are unknown, the hidden layer attempts to correct input to output mapping with the help of an activation function which uses the log-sigmoid transfer function shown in equation 6 [41], [43]. The activation function transfers the values coming from the input edges. The log-sigmoid allows for easier calculations of the weights since it uses first order derivatives that have non-negative values.

$$F(k) = \frac{1}{1+ e^{-k}} \quad (6)$$

Usually, the relationship between the output and the input is not known before but is determined through the training process [6]. The training process is an iterative adjustment process applied to the synaptic weights and thresholds. Thus, the power of a neural network lies in its ability to learn from its environment. Learning enables the neural network to acquire knowledge about the environment and then stores this knowledge as network weights [46]. In each iteration, the neural network becomes more informed about its environment thus improving its performance.

Depending on the path followed by the information in the neural network, it can be classified as either a feed-forward network or feed-back network. A feed-forward network allows the information to flow in one way from input to output. The input layer is usually built from the source nodes into which the input data are fed. Nostradamus for instance uses a three layer feed-forward neural network as depicted in Figure 7.

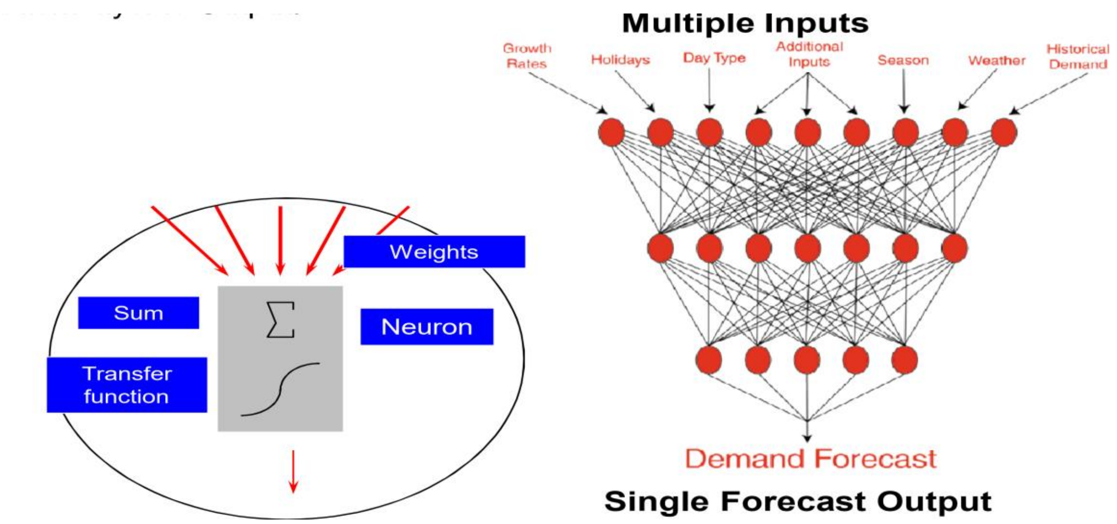


Figure 7 Nostradamus Three-layer feed-forward Neural network [47]

With feed-back, the network has the capability to provide at least one path back to the input where the network first started [6].

2.7 Load Forecasting and the Electricity Market

Many utilities around the world make various short-term resource commitments involving load forecasting that spans a few minutes up to a week ahead of time. The decisions around short-term resource commitment includes amongst many: commitment of generating units, economic dispatch of committed units, spinning reserve scheduling, estimation of available transfer capability, stability margins, short-term energy purchases and sales and real-time prices [48], [49]. These decisions are taken as the utility performs trading in the competitive electricity markets.

The short-term energy purchases and sales as well as the real-time prices play a crucial role for short-term electricity trading. This type of trading enables the electricity producers to sell excess or surplus electrical energy since electricity is a non-storable commodity. In addition, short-term electricity trading is used by electricity buyers to meet the unplanned demand requirements. This helps to improve the reliability of the power system by taking care of intermediate load requirements.

Market participants perform electricity trading through bilateral contracts and the power pool [50]–[52]. The short-term electricity trading is performed in the power pool. In the power pool, market participants (producers and consumers) submit supply and demand bids or offers to a central market place for buying or selling energy [51], [52]. Supply bids correspond to the quantity of energy that the producers are willing to sell at a particular price. The demand bids correspond to the amount of energy the consumers are willing to buy at a particular price. The bid format consists of pair of values such as quantity (MW) and price ($/MWh).

The market operator clears the market comprising energy and reserves once a day and produces the market clearing price for the electricity. Moreover, the market operator prepares the sets of accepted supply and demand bids [52]. The market participants prepare the bids such that they can recover variable costs of operating their power plants [53]. This is called the marginal price. Moreover, participants submit the bids that are closer to the market clearing price [51]. If the seller bid is too high, the seller may end up without selling the energy and if the buyer bid is too low, the buyer may not be able to purchase the energy [54]. In this market, low costs generators would essentially be rewarded during the dispatch of power to the consumer.

Thus, in a power pool, the market operator produces an aggregated supply and demand curves for suppliers and consumers resulting from the submitted bids as depicted in Figure 8. The supply bids are put in increasing order while the demand bids are put in decreasing order. This arrangement of the supply bids determines the order of the dispatch of the power plants where the generation costs, physical aspects of the transmission system and the network constraints become the determining factors [53], [55].The market clearing price is determined at the point of intersection of the supply and demand curves [53]. The quantity of energy corresponding to the market clearing price (MCP) is called market clearing volume (MCV). This is the price at which the quantity of energy that the supplier is willing to offer is equal to the quantity that the customer is willing to take.

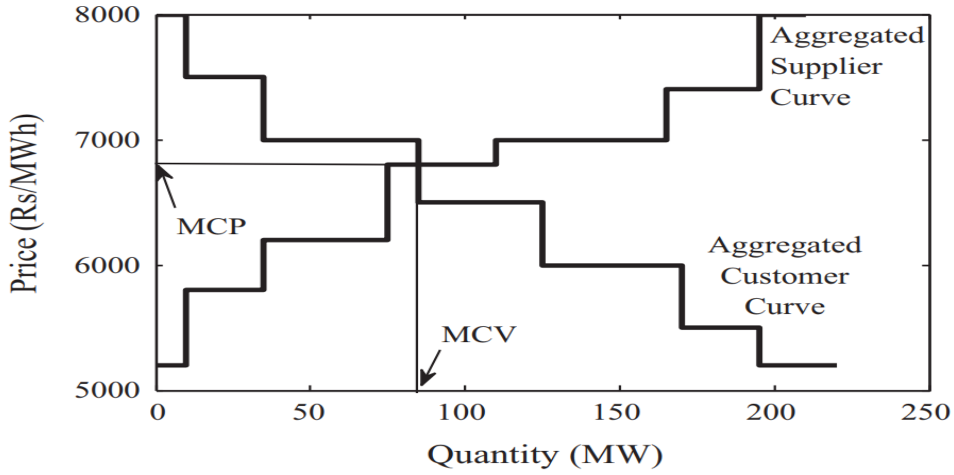


Figure 8 The Market Clearing Process in the Electricity Market [51]

Apart from the power pool, the energy can be traded through bilateral contracts which constitutes major portion or majority of the energy traded. A bilateral contract is an agreement between two parties to trade power which is governed by specified conditions consisting of MW amount, time of delivery, duration as well as price [56], [57]. In a bilateral contract model, the energy transactions take place directly between producer and consumer. This contract is negotiated privately without the involvement of the market operator to determine the price and quantity to be traded [50].

Bilateral contracts can be physical or financial where physical contract means that all the traded power traded must be generated and consumed at a pair of specified network buses [56]. Financial contract implies that the power traded can be transferred to the power pool at the short-term market-clearing time if power produced has not all been consumed.

In the competitive wholesale market offered by the power pool, time dimension which covers the time when the electricity transaction is produced to the time the actual delivery of electricity happens is crucial. The physical delivery of power is referred to as the physical power flow. With this in mind, then the wholesale market comprise two categories which are the spot market and the forward market [57]. The spot market happens 24 hours ahead of the actual delivery and comprises three distinct submarkets: the day-ahead, the hour-ahead and the real-time markets [57]. If trading happens more than 24 hours then the physical delivery becomes part of the forward market as depicted in Figure 9. In the spot market, the market operator does not only determine price and quantity to be traded but also performs system scheduling and control.

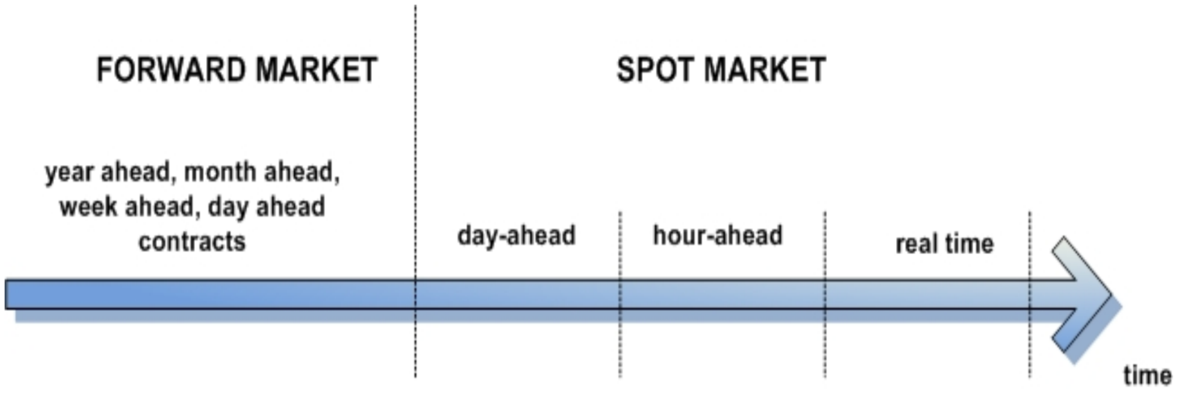


Figure 9 Time Horizon of the Wholesale Electricity Market [57]

The day-ahead market is regarded as a financial market instead of the physical market. This means the seller is not committed to the physical delivery of electricity but is bound to the financial obligation provided their bids are accepted [58]. For instance, to fulfil the contractual obligations, the producer will not be physically be generating power to the consumer. Instead, the system operator will continually be balancing the available generation with the demand. Thus, the day-ahead market allows the consumers and producers to hedge their transactions in the real-time market which is a physical spot market. This happens if the producer cannot provide power in the previous day and must obtain it from the real-time market. This suggest that the real-time market guarantees the physical delivery of electricity to the consumers.

Real-time market, regarded as the balancing market or intraday market, is also used to address the real-time incidences that impact the supply and demand. This includes malfunction of the generator resulting in its unavailability or a substation or transmission line outage resulting in unavailability of power to the consumer. Thus, available capacity or reserves which are operating reserves, spinning reserves and planning reserves [58] are necessary during such incidences to continually supply electricity to the end customer. These operational risks results in real-time prices to become more volatile than the day-ahead prices. Since the day-ahead prices are more stable than real-time prices, they are used to hedge against volatile market prices. Apart from these operational risks, technical constraints resulting from dispatching units can limit maximum or minimum power produced. These comprise maximum or minimum output restrictions, ramp rates, startup and shutdown procedures and minimum uptime or downtime [52].

Apart from the forward market which constitute forward contracts, reserves market also exist. The producer in the reserves market acts as a price taker by reacting to a forecasted price curve [52] regarded as the residual demand curve or price quota curve as depicted in Figure 10. This curve is determined based on demand forecasting results and the competitor's supply offers for every hour of the market period. Moreover the residual demand curve reveals how the energy market clearing price changes as the quota of the producer changes. Market participants are often exposed to different residual demand curves on the same market. There are basically two approaches of scheduling the energy and reserve services: first approach employs sequential scheduling of energy and reserves starting with clearing the energy market and the clearing the reserves market; the second approach involves simultaneous scheduling of the energy and reserves market where they are both cleared at almost the same time.

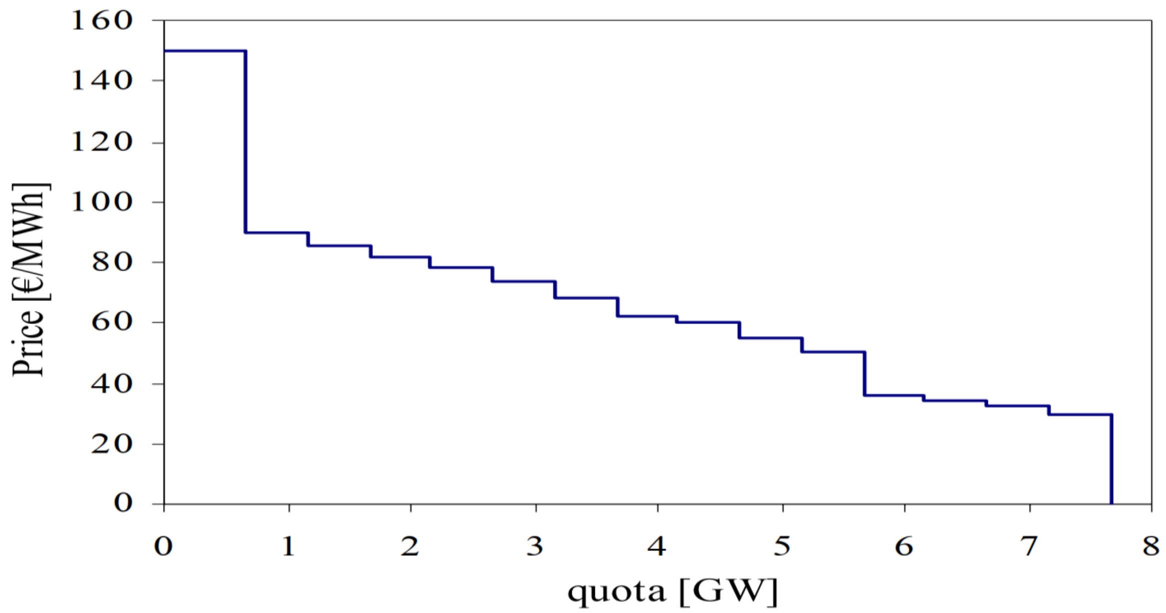


Figure 10 The residual demand curve [52]

3. Methodology

The purpose of the study is to show that the adoption of an automated short-term demand forecasting for LEC is crucial for effective participation in the SAPP markets to perform trading. Moreover, the study will evaluate or identify the benefits that will results from such participation.

3.1 Load-Forecasting Procedure

The study involves quantitative techniques for data collection. The study uses computer modelling and simulation tool called ABB Nostradamus® to produce the results that will be used during the discussion. The procedure and the flowchart used by Nostradamus to perform demand forecasting are the same as those shown in Figure 11 and Figure 12.

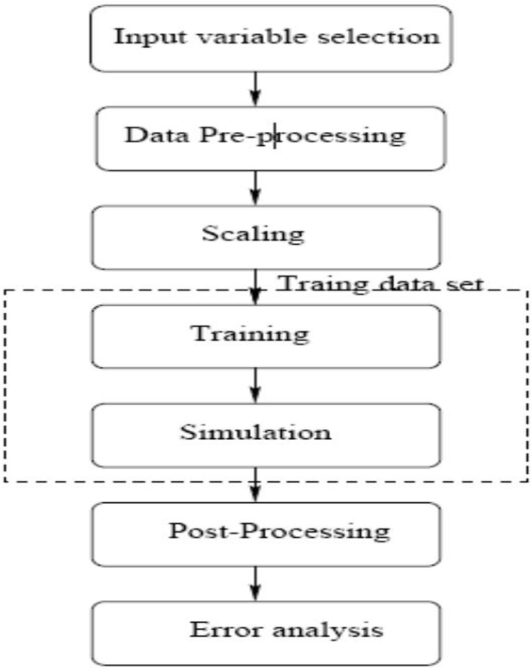


Figure 11 The ANN Load forecasting procedure [5], [12], [46], [59]

- *Input variable selection*: This is where the factors affecting demand forecasting are determined. These include historical loads, day type, temperature, humidity just to mention a few. This is usually the initial and most important step for the ANN.
- *Data pre-processing:* This is where raw data is transformed using mathematical operations such as normalizing, ranking and correlation. Irregular or incorrect data and observation errors are also identified and are either adjusted or discarded to avoid contamination of the model.

- *Scaling:* The input data is scaled between the upper and lower bands of the transfer function using two schemes. The first scheme allows the input and output variables to be scaled such that they are in the 0 and 1 range as shown in equation 7 [12], [46].

$$X_i{}^{(\acute{k})} = X_i{}^{(k)} / max(X_i{}^{(k)})$$
$$O_i{}^{(\acute{k})} = O_i{}^{(k)} / max(O_i{}^{(k)}) \quad (7)$$

where k is the index of the input and output vectors or patterns, X_i and O_i are input and output variables respectively.

The second scheme is where the input and output variables are scaled such that they are in the range -1 and 1 as shown in equation 8 [12].

$$X_i{}^{(\acute{k})} = (X_i{}^{(k)} - \tilde{X}_i) / S_i$$
$$O_i{}^{(\acute{k})} = (O_i{}^{(k)} - \tilde{O}_i / SO_i \quad (8)$$

where S_i and SO_i are the estimates of the standard deviation of input and output i respectively.

- *Training:* Training allows adjusting of the weights until the appropriate transformation linking the inputs and outputs is learned. It involves four steps in general [46]: (1) data collection for network training, (2) determining the network object, (3) training the network, and (4) computing the network outputs. Also, the ANN weights and the biases are initialized and the data windows that are used for training are moved one day ahead [5]. To ease the training process, the adopted practice is to divide the time series into the training, testing and validation sets [59]. The training set, being the largest of the three distinct sets, is used by the neural network to learn the patterns that exists in the data.
- *Simulation:* This allows the predicted results to be produced from the input patterns. Simulation is done after the neural network has been trained.
- *Post*-processing: This allows for the analysis of the simulated result sets. To perform proper analysis of the output results, the outputs need to be de-scaled to achieve the desired predicted loads [5], [46]. If required, special events can be factored in at this stage.
- *Error Analysis:* This allows the accuracy of the ANN to be tested using either MAPE or MAE represented by equations (1) and (2).

A more simplified ANN flowchart is shown in Figure 12.

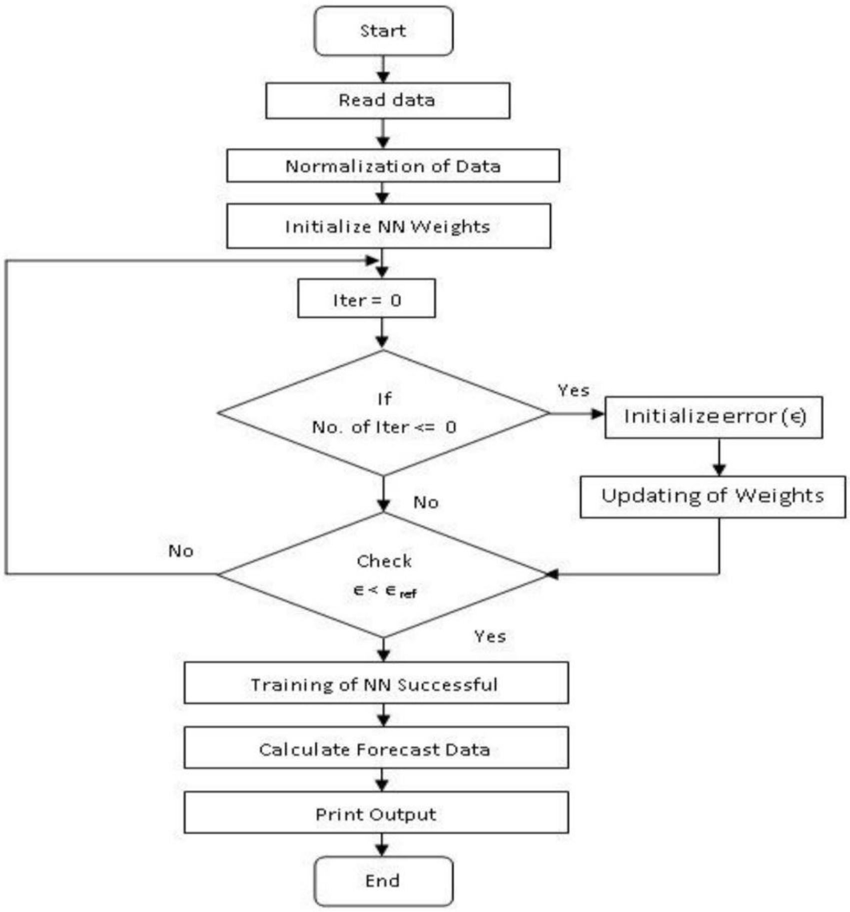


Figure 12 Flowchart for Artificial Neural Network Procedure [11]

3.2 Inputs to Nostradamus

The following are the inputs used by Nostradamus software employed in this research:

- *Historical Demand Data:* This includes 30-minute demand data from 03rd March 2017 and 08th March 2018 obtained from LEC Network Manager system as shown in Figure 13. This data, which was in Microsoft Excel format, was exported into the Nostradamus software. An export and import script have been implemented to automate the demand data export from NM into Nostradamus. Automatic data access together with accuracy, fast speed, automatic data detection, friendly interface and automatic forecasting result generation are the important requirements of a good short-term load forecasting system. To improve the accuracy of the model results, the data have been cleaned to remove the outliers or bad data. Sudden increase or decrease in demand and communication breakdown between central SCADA system and monitored equipment can result in having outliers or missing data.

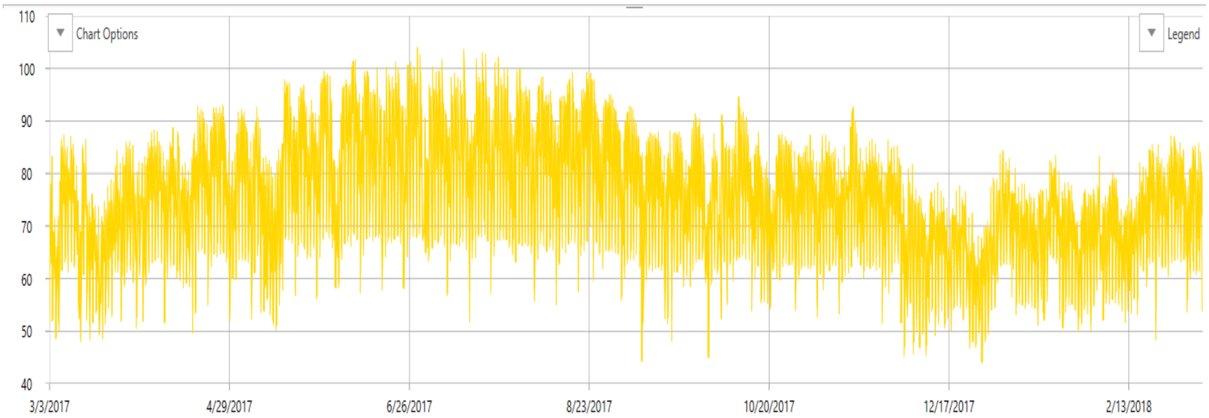


Figure 13 Exported 30-minute Data from Network Manager into Nostradamus for training the model

- *Day of the week, time of the year and public holidays:* Time parameters used in the research include day of the week (Monday – Sunday), time of the year (January – December) and Lesotho public holidays. The public holidays were created in groups where each group name represents the name of the holiday as depicted in Figure 14. The date of occurrence of such holiday was added to the group.

Figure 14 Nostradamus Lesotho Holiday Setup

During training, the hour ahead demand forecasting represented as LEC_INTRADAY in Nostradamus, accepted the previous 2-day (-48 hours), 4-day (-96 hours) and 14-day (-336 hours) demand data as depicted in Figure 15. The day-ahead demand forecasting represented as LEC_TOMORROW accepted the previous 4-day (-96 hours), 6-day (-144 hours) and 14-day (-336 hours) demand data as depicted in Figure 16. The week-ahead demand forecasting represented as LEC_FORWARD accepted the previous 14-day (-336 hours) demand data as depicted in Figure 17.

Based on these inputs, the hour-ahead, day-ahead and week-ahead forecasted results are produced. The training and verification results for each forecasting type are shown and discussed. The accuracy of Nostradamus was tested using MAPE shown in equation (1). The MAPE graph and correlation for each forecasting type are also presented and discussed. Moreover, the forecasted seasonal morning and evening peak occurrences are presented and discussed and these were linked with the daily load profiles for holiday, normal day, winter weekend and normal winter day. These results are crucial to enable LEC to trade in the SAPP competitive market in order to balance supply and demand. Next, the comparative analysis of Eskom and EDM bilateral peak, standard and off-peak prices against those of SAPP market prices was conducted. As the analysis was done, Eskom and EDM energy consumptions and energy shares were considered. The purpose was to determine which option will be cost effective for LEC in order to address the power deficit. During the comparative analysis, the risks and the opportunities under each procurement options are discussed.

Lag Table Size (Forecasted Variable Interval)

30 Minutes

Input Variable -->	Demand(0)	Demand(1)	Demand(2)
1	-336	-96	-48
2	-336	-96	-48
3	-336	-96	-48
4	-336	-96	-48
5	-336	-96	-48
6	-336	-96	-48
7	-336	-96	-48
8	-336	-96	-48
9	-336	-96	-48
10	-336	-96	-48
11	-336	-96	-48
12	-336	-96	-48
13	-336	-96	-48
14	-336	-96	-48
15	-336	-96	-48
16	-336	-96	-48

Figure 15 Historical Demand Data Lag for Hour-ahead (LEC_INTRADAY) Forecasting

Lag Table Size (Forecasted Variable Interval)

30 Minutes

Input Variable -->	Demand(0)	Demand(1)	Demand(2)
1	-336	-144	-96
2	-336	-144	-96
3	-336	-144	-96
4	-336	-144	-96
5	-336	-144	-96
6	-336	-144	-96
7	-336	-144	-96
8	-336	-144	-96
9	-336	-144	-96
10	-336	-144	-96
11	-336	-144	-96
12	-336	-144	-96
13	-336	-144	-96
14	-336	-144	-96
15	-336	-144	-96
16	-336	-144	-96

Figure 16 Historical Demand Data Lag for Day-ahead (LEC_TOMORROW) Forecasting

Lag Table Size (Forecasted Variable Interval)

30 Minutes

Input Variable -->	Demand(0)
1	-336
2	-336
3	-336
4	-336
5	-336
6	-336
7	-336
8	-336
9	-336
10	-336
11	-336
12	-336
13	-336
14	-336
15	-336
16	-336

Figure 17 Historical Demand Data Lag for Week-ahead (LEC_FORWARD) Forecasting

4. Data Analysis and Nostradamus Load Forecasting Results

4.1 LEC Demand Data Analysis

Figure 18 illustrates how LEC daily load profile varies for normal day, for holiday, for normal winter day and for winter weekend. The peak demand for all profiles occurs in the evening and morning hours. This normally happens for residential/domestic customers where cooking, showering and heating occur. At midnight, majority of the people are sleeping hence the demand is at the minimum. However, industries and offices experience less demand during weekends and holiday due to less production activities. This figure will be referenced a lot during the discussion of LEC demand peaks obtained from Nostradamus for different seasons of the year.

The morning peak for the normal day which occurs at around 0900 HRS as illustrated by Figure 18 lags that of the holiday by about an hour. The normal winter day morning peak which happens at around 0830 HRS also lags that of winter weekend by about an hour. However, in the evening, the holiday peak which occurs at around 1930 HRS lags the normal day peak which happens at around 2000 HRS. Moreover, the normal winter day and the winter weekend evening peaks occur at around the same time at about 1830 HRS. But the duration of the evening peak for the normal winter day is longer than that of the winter weekend.

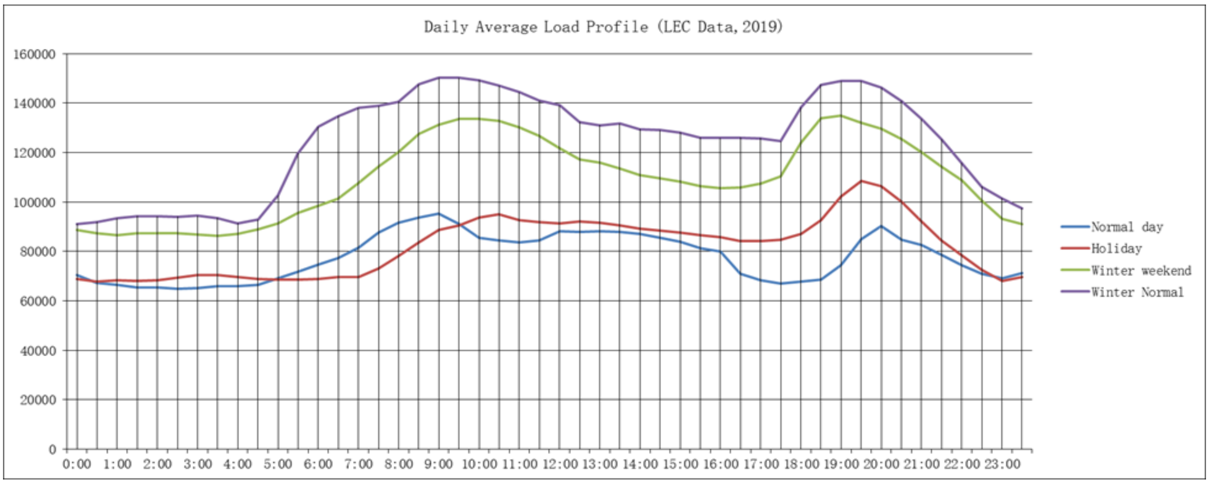


Figure 18 A 24 hour LEC Load Profile for Normal, Holiday and Winter Periods

4.2 Training and Verification Results

The purpose of any forecasting tool is to produce the forecasted results with the least error. In order to determine the accuracy of such tools, MAPE is used. Table 1 shows the MAPE results obtained during the training and verification phases for the hour-ahead, day-ahead and week-ahead forecasting. 21409 samples were used during training and resulted in the MAPE of 3.06 % for hour-ahead forecasting, 4.06 % for day-ahead forecasting and 5.09 % for week-ahead forecasting respectively. The MAPEs' obtained are all within the 5 % accuracy limit [11], [43] thus showing highly accurate forecasted results.

The verification of the Nostradamus software was done with 4415 samples as seen in Table 1 This resulted in the MAPE of 2.94 % for hour-ahead forecasting, 3.63 % for day-ahead forecasting and 4.54 % for week-ahead forecasting. The MAPEs' for the verification are below those for the training since less samples were used. This means with less data samples, there are less chances of getting bad data that results from outliers or missing data which then improves the prediction accuracy.

Predicting electricity demand with high accuracy such as the one attained in this study increases the confidence level of a utility to rely on the predicted results. This facilitates electricity trading, load flow analysis, automatic generation control (AGC) scheduling and maintenance scheduling. The MAPE results shown in Table 1 reveal the fact that LEC can rely on the Nostradamus forecasted results to engage in trading in the SAPP competitive market. The bids that are produced in order to trade in the competitive market such as the SAPP market are dependent on the demand forecasting results. What Table 1 depicts is that Nostradamus software produced the hour-ahead, day-ahead and week-ahead forecasting with 3%, 4% and 5% confidence levels respectively.

Table 1 also shows the maximum and minimum forecasted and actual power in MW during the training and verification periods for the hour-ahead, day-ahead and week-ahead forecasting. What was noticed was that the day-ahead forecasting produced the forecasted maximum power of 112 MW which was closest to the maximum actual power of 104 MW. This was followed by week-ahead forecasting and finally the day-ahead forecasting with 115 MW and 123 MW respectively.

Table 1 MAPE results for Hour-ahead, Day-ahead and Week-ahead Demand Forecasting

Type of Forecasting	Training MAPE in %	Verification MAPE in %	Number of smaples used for training	Number of samples used during verification	Training maximum forecasted power in MW	Training maximum actual power in MW	Training minimum forecasted power in MW	Training minimum actual power in MW	Verification maximum forecasted power in MW	Verification maximum actual power in MW	Verification minimum forecasted power in MW	Verification minimum actual power in MW
Hour-ahead	3.06	2.94	21409	4415	112	104	44	44	136	138	55	55
Day-ahead	4.06	3.63	21409	4415	123	104	48	44	136	138	57	55
Week-ahead	5.09	4.54	21409	4415	115	104	48	44	132	138	59	55

4.3 Hour-ahead Forecasting Results

Figure 19 shows the hour-ahead electricity demand forecasting results from the 12th to 18th July 2019 with the MAPE of 3.06 %. It can be realized that Nostradamus was able to track the actual demand quite well. Thus, the prediction of these results using Nostradamus was done with high accuracy. Moreover, it was able to forecast the morning and evening peak demands very well and these were very close to the actual peak demand. It is critical for the forecasting tool to predict the peak demand accurately so that the generation dispatchers can generate precise generation schedules to supply the peak demand. If the peak demand is not predicted accurately, this may lead to load shedding caused by generation that is not sufficient to meet the demand. It can also lead to unnecessary costs of generating more electricity than required.

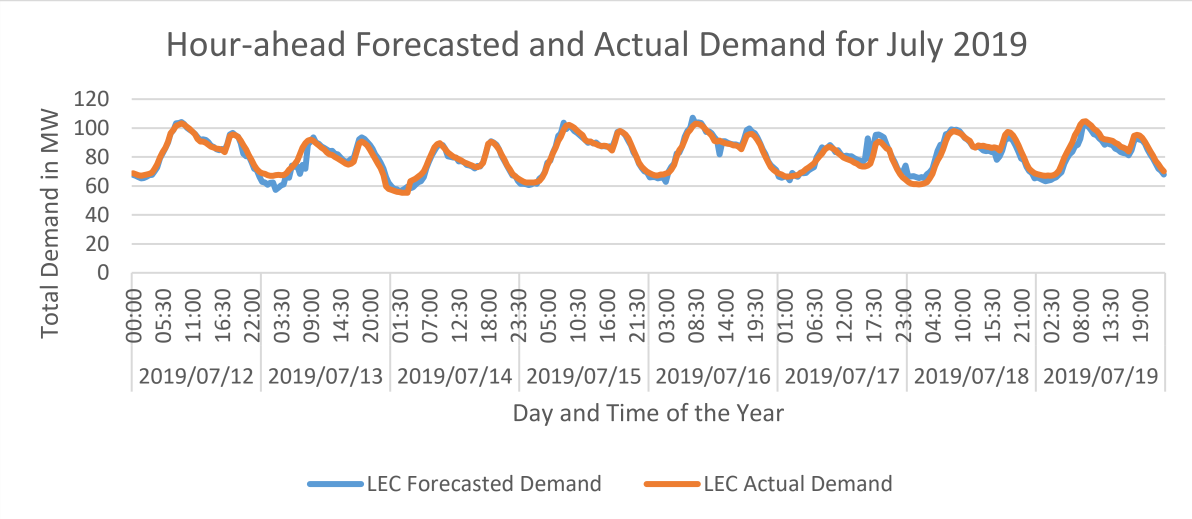


Figure 19 Hour-ahead (Intraday) Results of the Forecasted and Actual Demand of the July Week (12th – 19th July) with the MAPE of 3.06%

Figure 20 shows the MAPE graph for the hour ahead forecasting. It can be realized that the forecasting error is high when the iterations (number of passes) are small. As the number of iterations increases, the forecasting error is reduced to an acceptable value of around 3 % (3.22). The reduction of the forecasting error is attributed by adjusting of the weights as the error is fed back (back propagation) into the model. This error is along the lines of the accuracy error of 3.06 % obtained during the training of the model which is depicted in Table 1.

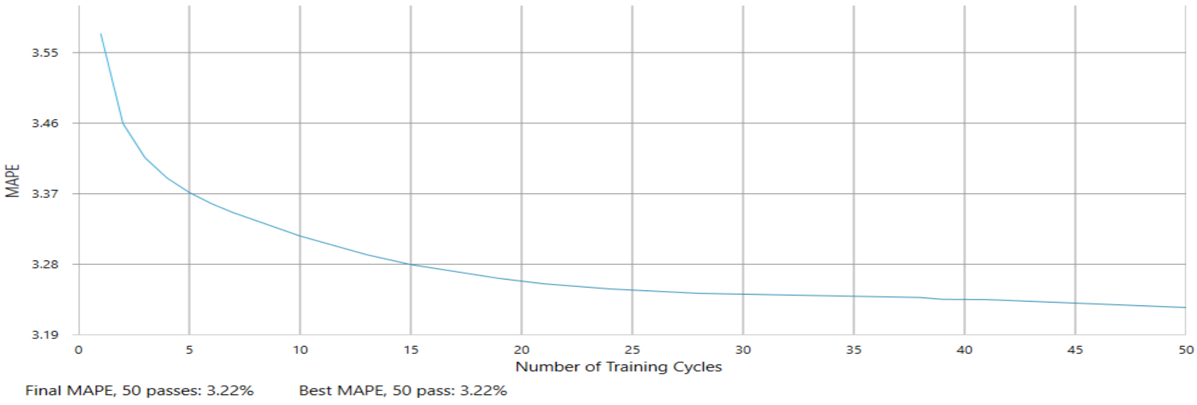


Figure 20 Hour-ahead (LEC_INTRADAY) Forecasting MAPE Graph

Figure 21 shows the correlation of the data from 2015 to 2018 for the hour-ahead forecasting. There is less correlation of 73 % of the electricity demand in the year 2015 due to time factors (season, days of the week and holidays). This was attributed by the fact that it was a year of great drought. Thus, the behavior of the electricity demand was not dependent on any time effects as discussed in section 2.4. The year that had the greatest correlation was 2018 with 92 % followed by years 2016 and 2017 with 91 % and 87 % respectively. This simply means that in the year 2018 yearly seasons, holidays and weekdays had the greatest influence on the electricity demand than in years 2016 and 2017.

Figure 21 Correlation of Data from 2015 – 2018 for Hour-ahead (LEC_INTRADAY) Forecasting

4.4 Day-ahead Load Forecasting Results

Figure 22 shows the day-ahead electricity demand forecasting results captured from the 06th to 07th June 2019 with the MAPE of 4.06 %. The forecasted and the actual demand results are recorded for every 30 minutes. It can be seen that the forecasted demand profile seem to follow the actual demand profile proving that the tool is performing very well since the gap between the two profiles is relatively small.

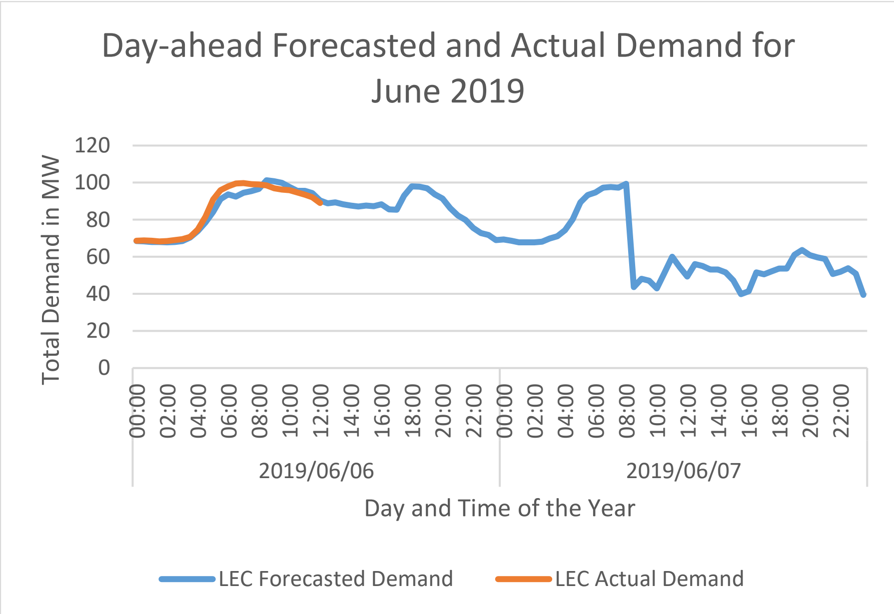


Figure 22 Day-ahead (LEC_TOMORROW) Demand Forecasting for June 2019 (06th – 07th June) with the MAPE of 4.06 %

Figure 23 shows the MAPE graph for the day-ahead forecasting. The forecasting error started being high with fewer number of passes or iterations. As the number of iterations or passes increases, the forecasting error is reduced gradually until an acceptable forecasting error of around 4 % (4.23) is reached. Although slightly higher than the accuracy error obtained during the training as depicted in Table 1, it is also around 4 % confirming that the forecasting accuracy for the day-ahead forecasting is 4 %.

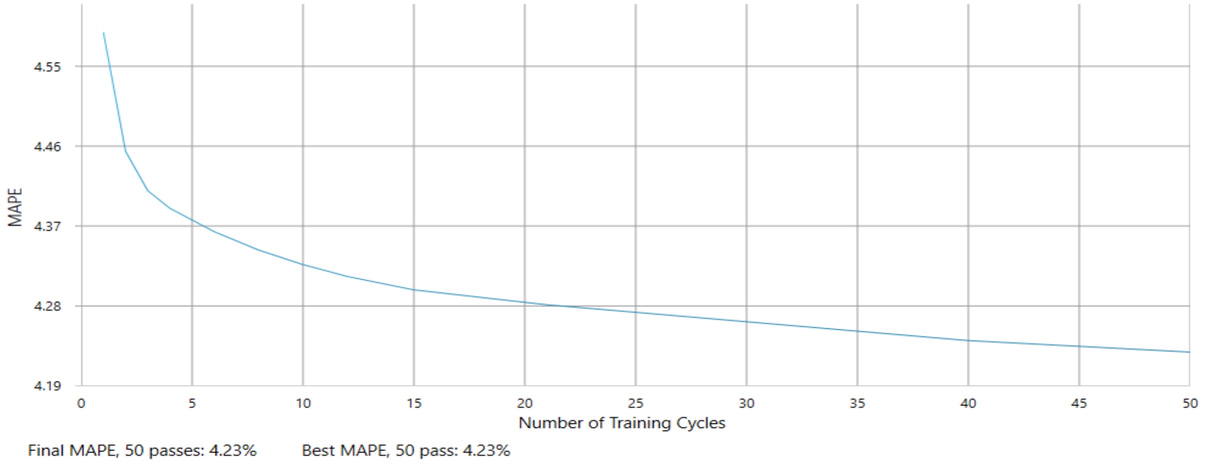


Figure 23 Day-ahead (LEC_TOMORROW) Forecasting MAPE Graph

Figure 24 shows the correlation of the data from 2015 to 2018 for the day-ahead forecasting. Just like with the hour-ahead forecasting, there is less correlation of 73 % of the electricity demand in the year 2015 due to time factors (season, days of the week, time of the year and holidays) and the weather effects (temperature, humidity wind speed, etc.). Moreover, 2016 had greatest correlation of 91 % followed by 2017 and 2018, each with 87 % correlation. This suggests that in the year 2016 time and weather effects had the greatest influence on the electricity demand than in years 2017 and 2018.

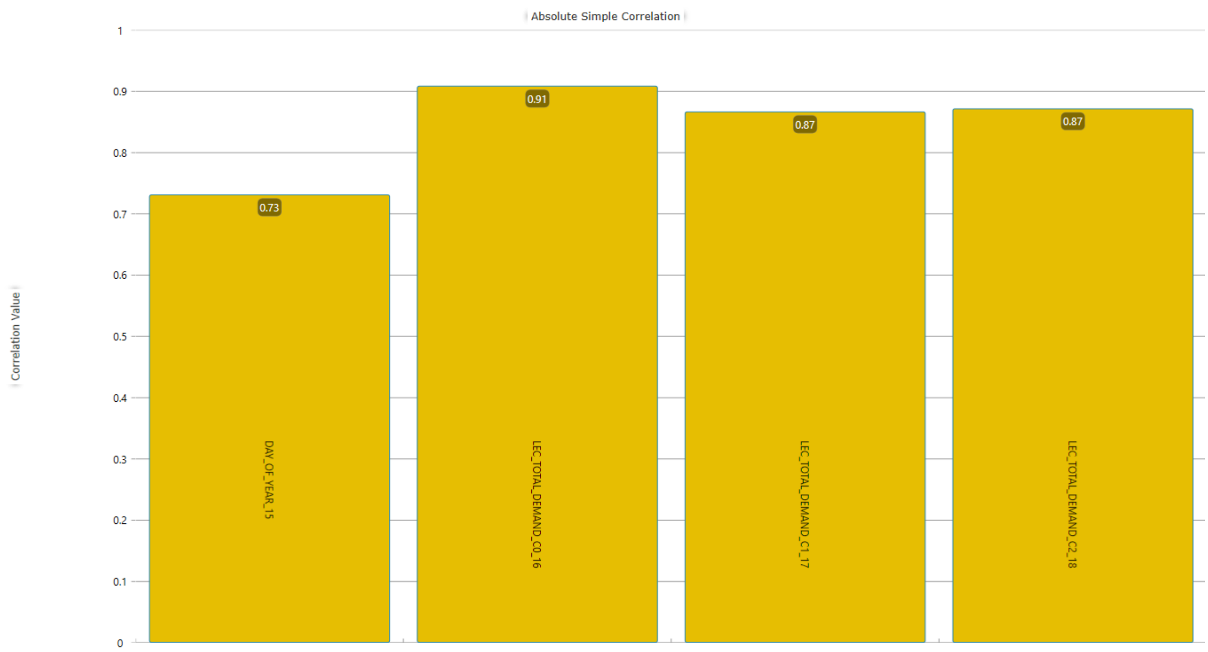


Figure 24 Correlation of Data from 2015 – 2018 for Day-ahead (LEC_TOMORROW) Forecasting

4.5 Week-ahead Load Forecasting Results

Figure 25 shows the week-ahead electricity demand forecasting results from the week of 22nd to 30th September 2019 with the MAPE of 5.09 %. It can be realized that the demand was predicted with high accuracy and the 22nd demand profile was tracked very well by Nostradamus.

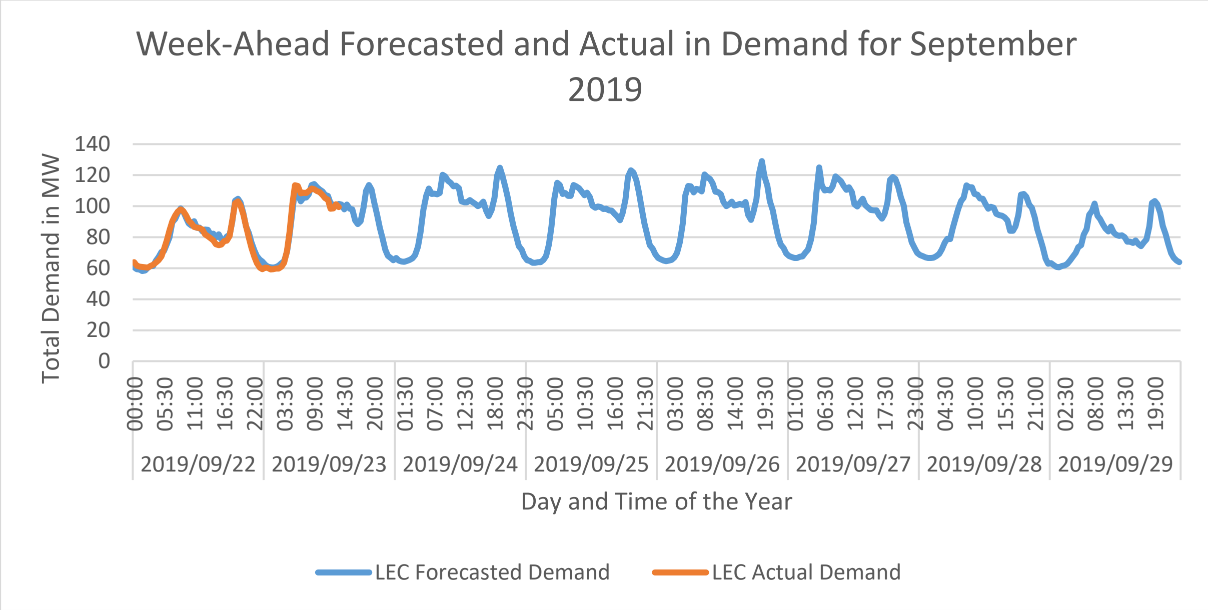


Figure 25 Week-ahead (LEC_FORWARD) Demand Forecasting for September 2019 with the MAPE of 5.09 %

Figure 26 shows the MAPE graph for the week-ahead forecasting. The figure simply portrays the behavior of the forecasting error starting being higher at the beginning of forecasting when there are few passes. This behavior was similar with the hour-ahead and day-ahead MAPE graphs. In addition, the error was reduced to a minimum acceptable value with an increase in the number of iterations. The final error obtained was 5.23 %. This error seems slightly higher than the training error found in Table 1. However this error is around 5 % which confirms that the forecasting accuracy for the week-ahead forecasting is 5 %.

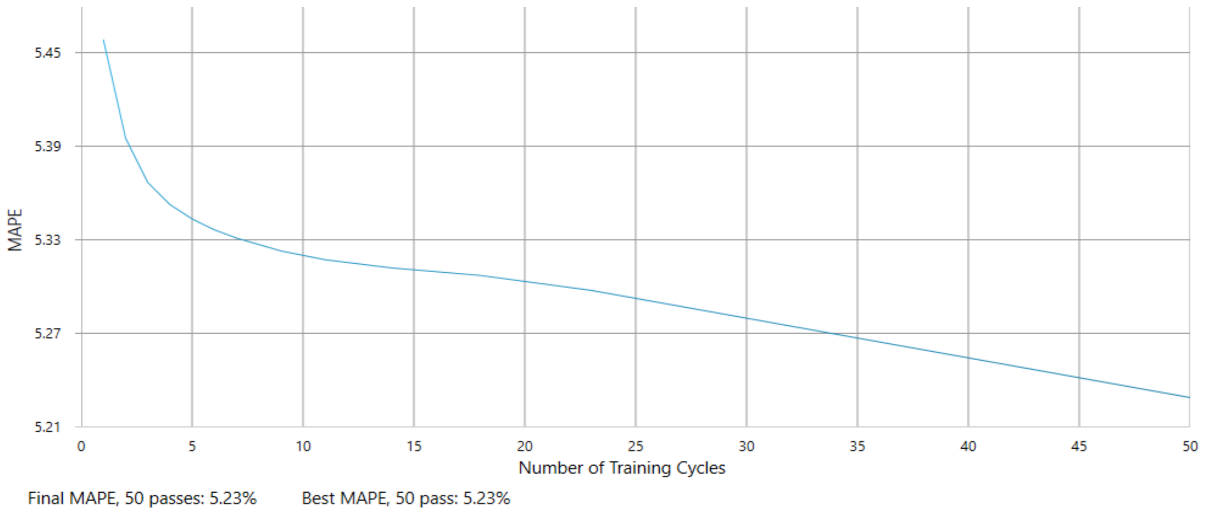


Figure 26 Week-ahead (LEC_FORWARD) Forecasting MAPE Graph

Figure 27 shows the correlation of the demand data from 2015 to 2016 for the week-ahead forecasting. It can be seen that there was a correlation of 73 % of the electricity demand in the year 2015 due to time factors and weather effects. Also, in year 2016, there was a correlation of 91 %. This implies that the time and weather effects had more influence on the electricity demand represented by the load curve in 2016 in comparison with the year 2015.

Figure 27 Correlation of Data from 2015 – 2016 for Week-ahead (LEC_FORWARD) Forecasting

4.6 Forecasted Seasonal Peaks

Figure 28 and Figure 29 show morning and the evening peak demands during the winter period. The morning and evening peak demands in MW occur at around 0900 AM and 0630 PM respectively. This seems to agree with the winter daily LEC load profile shown in Figure 18. Although these peak times occur for a short period of time, LEC experiences higher price charges for the consumed energy. The prices are based on the peak demand charge. This behaviour applies for the hour-ahead, day-ahead and week-ahead demand forecasting. For other periods, LEC gets charged at the standard and off-peak prices which are lower than the peak prices. Thus, the higher the demand, the higher the price per the energy consumed. This is attributed by the dispatch of the peak generators (high cost generators) to meet the peak demand. Moreover, the lower the demand, the lower the charge per the energy consumed. This is attributed by the use of least-cost generators to meet such demand.

Figures 30 through 32 portray the morning peak demands and evening peak demand in MW occurring during the spring period. There are two morning peaks, one happens at around 0830 AM while the other occurs at around 0530 AM. The evening peak occurs at around 0700 PM. The occurrence of these peaks seems to also agree with the normal day load profile shown in Figure 18. The shift of the morning peak from 0830 AM to 0530 AM seem to happening from the 23rd September as shown in Figure 31.

Figure 33 and Figure 34 shows the morning and the evening peak demands for the summer period. The morning peak happens around 0830 AM while the evening peak happens at 0800 PM. Again, referring to Figure 18, it also reveals the same behavior for the summer period.

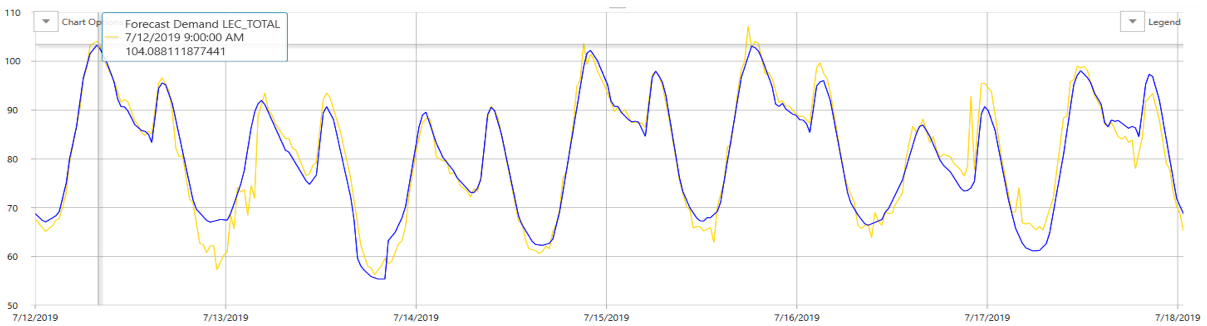


Figure 28 LEC Total Demand Morning Peak Time in Winter

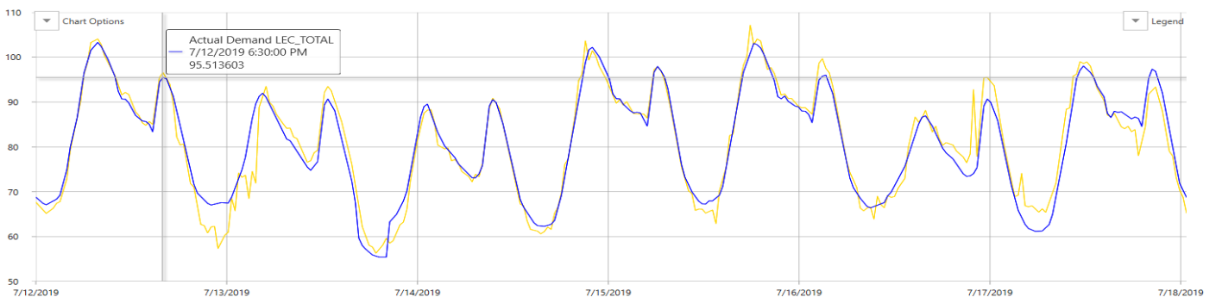


Figure 29 LEC Total Demand Evening Peak Time in Winter

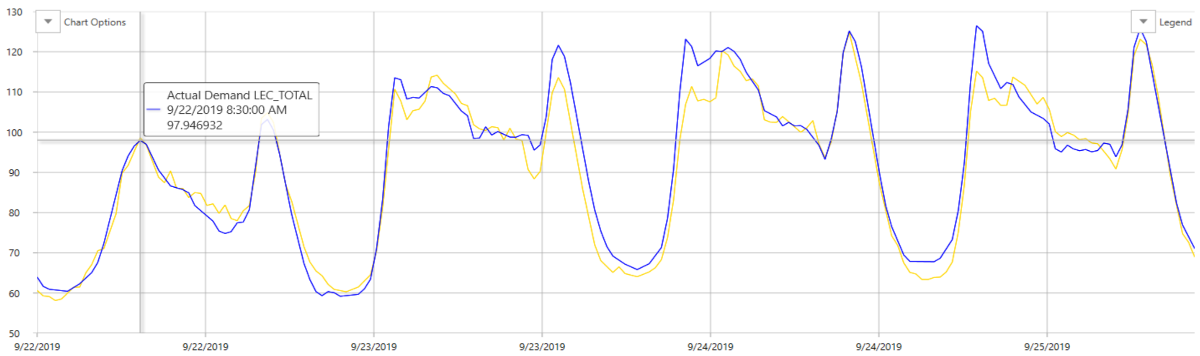


Figure 30 LEC Total Demand Morning Peak Time in Spring

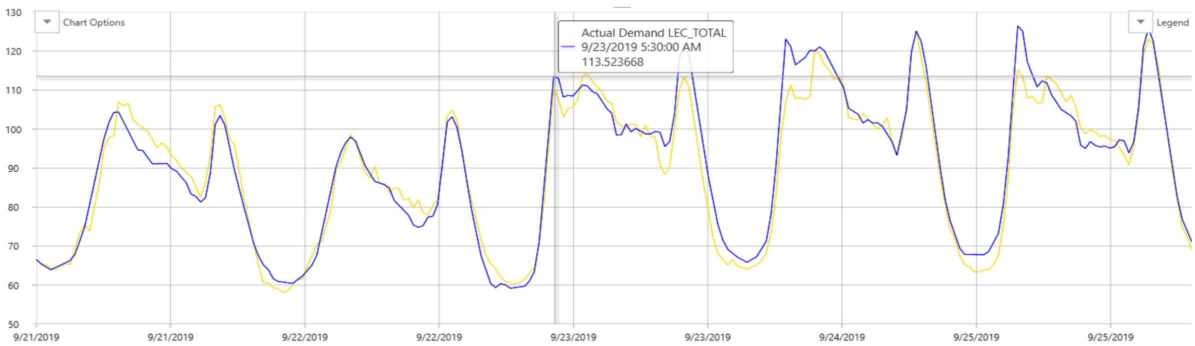


Figure 31 LEC Total Demand Morning Peak Time in Spring

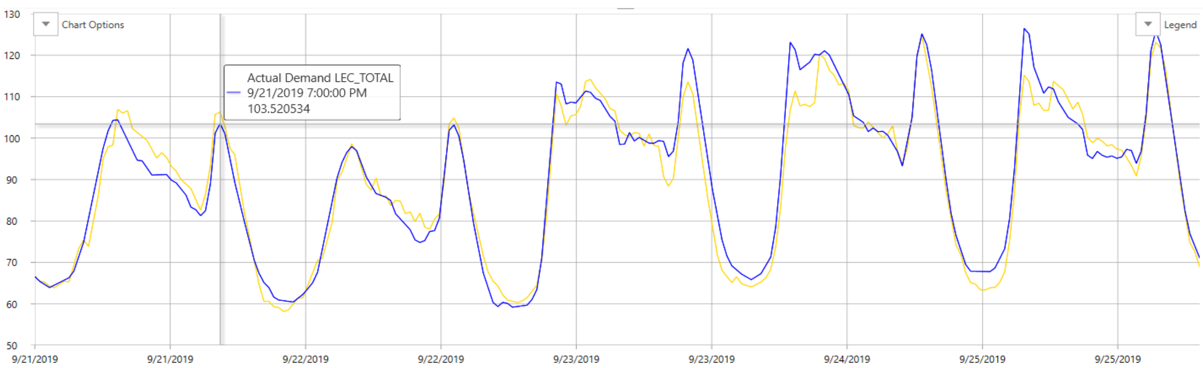


Figure 32 LEC Total Demand Evening Peak Time in Spring

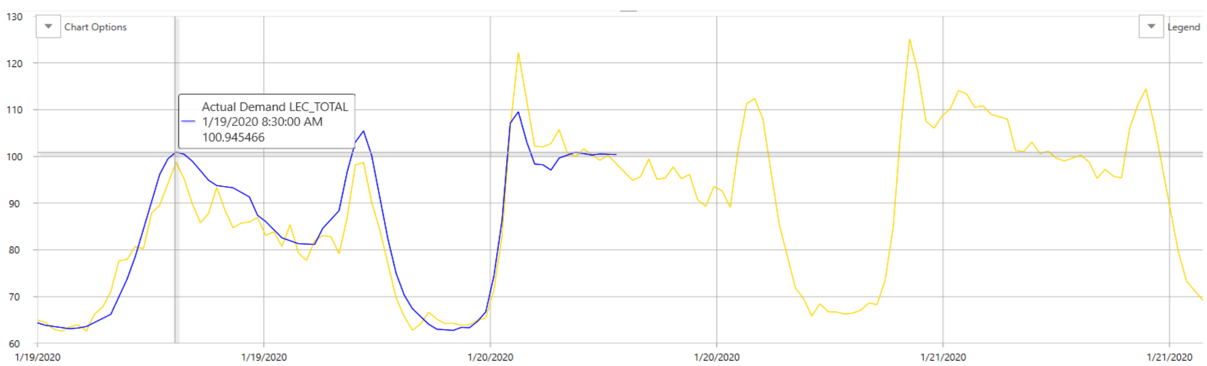


Figure 33 LEC Total Demand Morning Peak Time in Summer

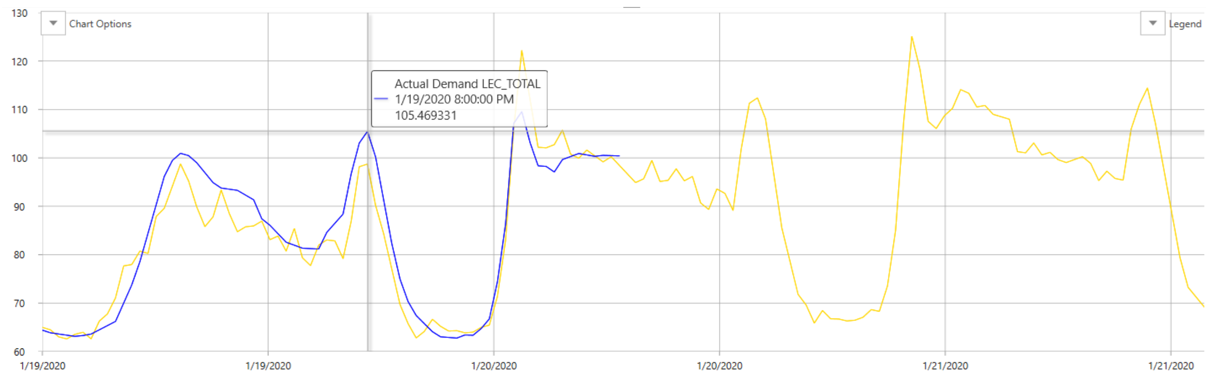


Figure 34 LEC Total Demand Evening Peak in Summer

5. Results Analysis and Discussions

From the discussion of the hour-ahead, day-ahead, and week-ahead forecasting results, it has been seen that the Nostradamus software has produced the forecasted results with high accuracy. As a reminder, Nostradamus has produced the hour-ahead forecasting with around 3 % accuracy, day-ahead forecasting with around 4 % accuracy and week-ahead forecasting with around 5 % accuracy. These forecasting results are crucial for LEC to participate in the SAPP competitive market. The bids that are produced in order to trade in the SAPP market are dependent on the demand forecasting results. Thus, with the demand forecasting results produced by Nostradamus, LEC is ready to participate in the SAPP competitive market.

The focus for the remainder of this section will be on the electricity procurement options that LEC can utilize to meet the forecasted demand. These options include the bilateral agreements with Eskom and EDM and the electricity market provided by SAPP. Under each option, the pros and cons as well as the associated risks will be discussed. Moreover, the comparative analysis of these options will be considered with the purpose of finding the option that results in cheaper electricity for LEC.

5.1 Power Procurement through Bilateral Agreements

Lesotho has an installed capacity of 72 MW generated from LHDA's hydro power plant at Muela, of which LEC has signed a bilateral agreement in order to obtain this power to supply electricity to the country. However, as depicted in Figure 35 which shows Lesotho maximum demand against LHDA installed capacity captured during 2019/20 period [60], LEC is not able to fulfil the country's demand with LHDA generation. Figure 35 further reveals that the demand can even be more than double the installed capacity increasing the power deficit even more. This happens in winter. Although, the assumption made is that Muela delivers maximum power throughout the 2019/20 period, this is not the case. For instance, during the month of December 2019 as depicted in Figure 36, Muela seems to be delivering power that is slightly above 60 MW except on the 1st to the 3rd where the plant was not delivering power due to plant maintenance hence the total dependency on electricity imports.

Due to inadequate electricity supply from local generation, LEC has to import electricity from Eskom and EDM. These electricity imports occur through fixed bilateral agreements which aid in addressing security of supply since they are always guaranteed first priority on the transmission network. Moreover, they provide LEC with the assurance of guaranteed electricity supply regardless of any load shedding that Eskom and EDM may experience. However, these contracts are all physical bilateral contracts meaning LEC must consume all dispatched power at the transmission network buses. If not, LEC gets penalized by the utility that will consume the dumped energy on its behalf.

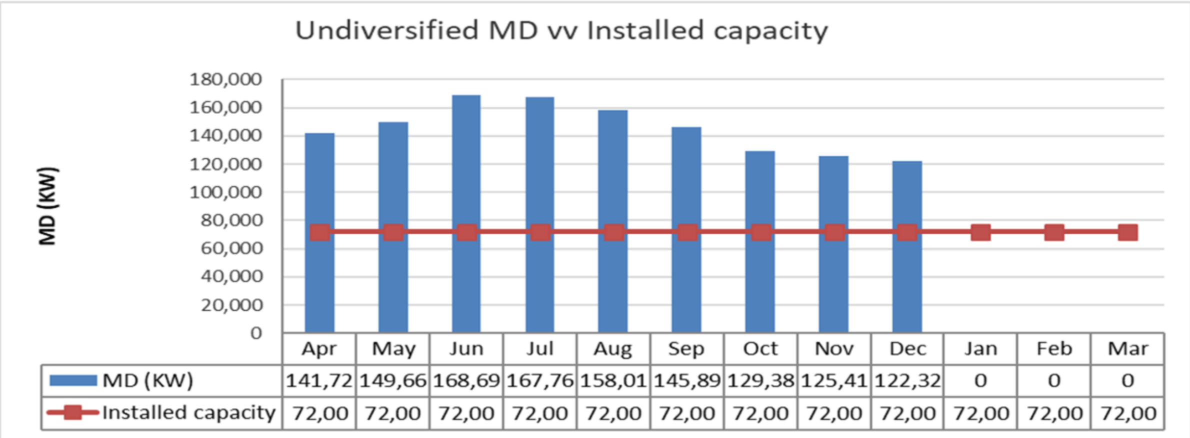


Figure 35 LEC Total Demand (Maximum Demand) against Lesotho Installed Capacity for the Period of April 2019 to March 2020 [60]

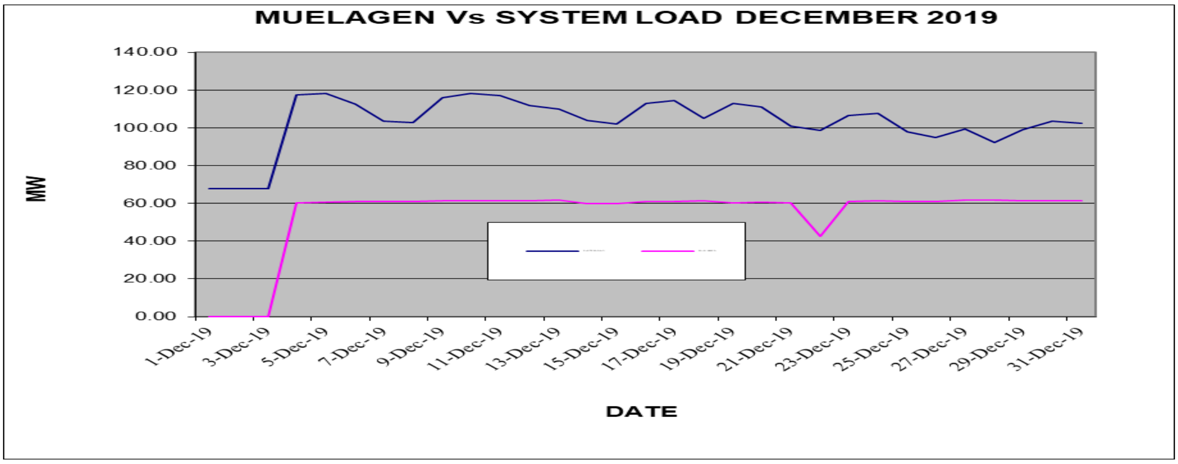
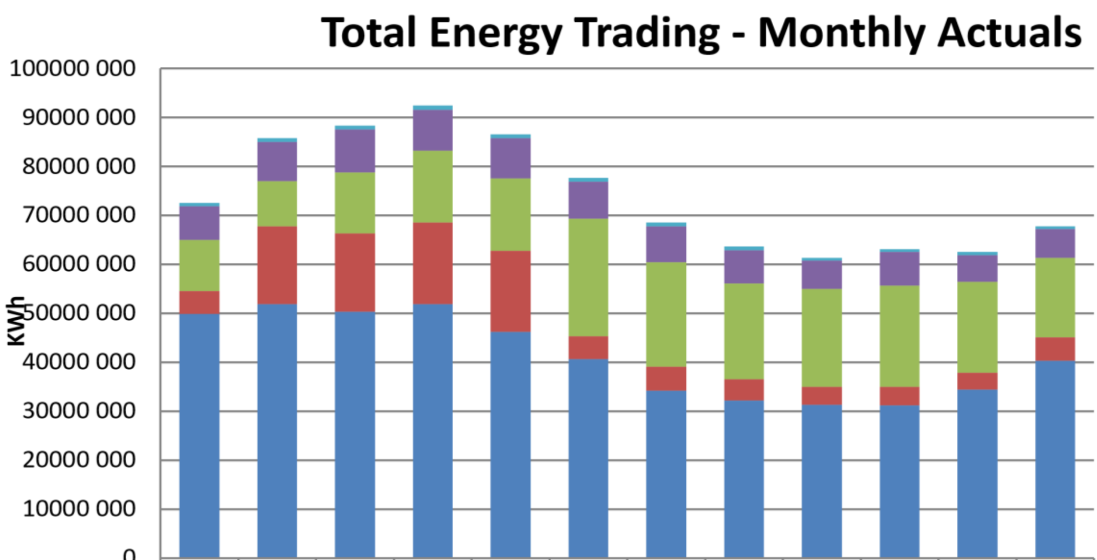


Figure 36 The Actual Total System Demand against the Actual Total Generated Power for December 2019 [60]

Figure 37 shows the amount of energy that has been traded through bilateral agreements with LHDA, Eskom and EDM for the period of 2018/19. Table 2 has presented the energy shares of these bilateral agreements as percentages. What is noticed from Table 2 is that throughout the 2018/19 period, LEC's largest portion of energy consumption comes from LHDA with the highest share occurring in April 2018 at 69 % and the lowest share occurring in January 2019 at 49 %. Figure 37 confirms Table 2 results where it is realized that around 50 % or more of the total energy traded comes from the local generation (LHDA).

What is also noticed from Table 2 is that during the high demand season where LEC attains the peak demand, LEC consumes more energy from EDM than Eskom with average energy shares being around 18 % (EDM) and 15 % (Eskom) respectively. However, during the low demand season occurring in summer, LEC consumes more energy from Eskom than EDM, with the average energy shares sitting at around 28 % (Eskom) and 6 % (EDM) respectively. Figure 37 again confirms these discussions where it is realized that more energy is traded from Eskom than EDM during the high demand season while the opposite happens during the low demand season.



	Apr-18	May-18	Jun-18	Jul-18	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18	Jan-19	Feb-19	Mar-19
Qacha (KWh)	695 449	709 000	780 106	817 700	780 106	698 904	698 904	762 810	586 950	588 367	653 313	555 185
Clarens (KWh)	6790 460	8014 978	8867 962	8319 560	8149 879	7538 060	7342 588	6767 927	5802 090	6898 802	5462 966	5964 344
Msu Bulk (KWh)	10471 005	9281 866	12372 124	14753 414	14815 912	24036 371	21439 420	19577 267	19933 467	20715 750	18646 574	16209 362
EDM (KWh)	4650 000	15810 000	16050 800	16585 000	16585 000	4650 000	4805 000	4340 000	3720 000	3720 000	3360 000	4805 000
Muela (KWh)	49937 995	51937 803	50332 033	51937 803	46222 237	40701 868	34254 346	32197 954	31325 829	31252 622	34481 110	40286 217

Figure 37 LEC Traded Energy Quantum from Bilateral Agreements with Eskom, LHDA and EDM for 2018/19 Period [61]

Table 2 Percentage Share of Bilateral Agreements to the Total Energy Consumption

Month	Apr-18	May-18	Jun-18	Jul-18	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18	Jan-19	Feb-19	Mar-19
Eskom MSU Bulk Energy Share in %	14%	11%	14%	16%	17%	31%	31%	31%	32%	33%	30%	24%
EDM MSU Bulk Energy Share in %	6%	18%	18%	18%	19%	6%	7%	7%	6%	6%	5%	7%
Eskom Clarens Energy Share in %	9%	9%	10%	9%	9%	10%	11%	11%	9%	11%	9%	9%
Eskom Qacha Energy Share in %	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
LHDA Energy Share in %	69%	61%	57%	56%	53%	52%	50%	51%	51%	49%	55%	59%

Figure 38 shows electricity imports costs from fixed bilateral agreements for the 2018/19 period. What is noticed is that LEC incurs more costs during high demand season[10] of which around 50 % of it comes from Eskom at Maseru Bulk while the other 50 % is shared by EDM and Eskom (Clarens and Qacha's Nek). For instance, during the months of July and August 2018, LEC incurred around M23 million for each month from Eskom at Maseru Bulk intake point. Moreover, Eskom at Clarens tie line charged LEC around M9 million while Eskom at Qacha's Nek tie line charged LEC slightly above M1 million for each of these months. EDM charged LEC around M14 million and M16 million for July and August respectively. What is also noticed from Figure 38 is that in August 2018, LEC is incurring the highest charge from EDM than in the other months. Furthermore, in June 2018, LEC is incurring the highest charge (which is slightly above M10 million) from Clarens than in the other months.

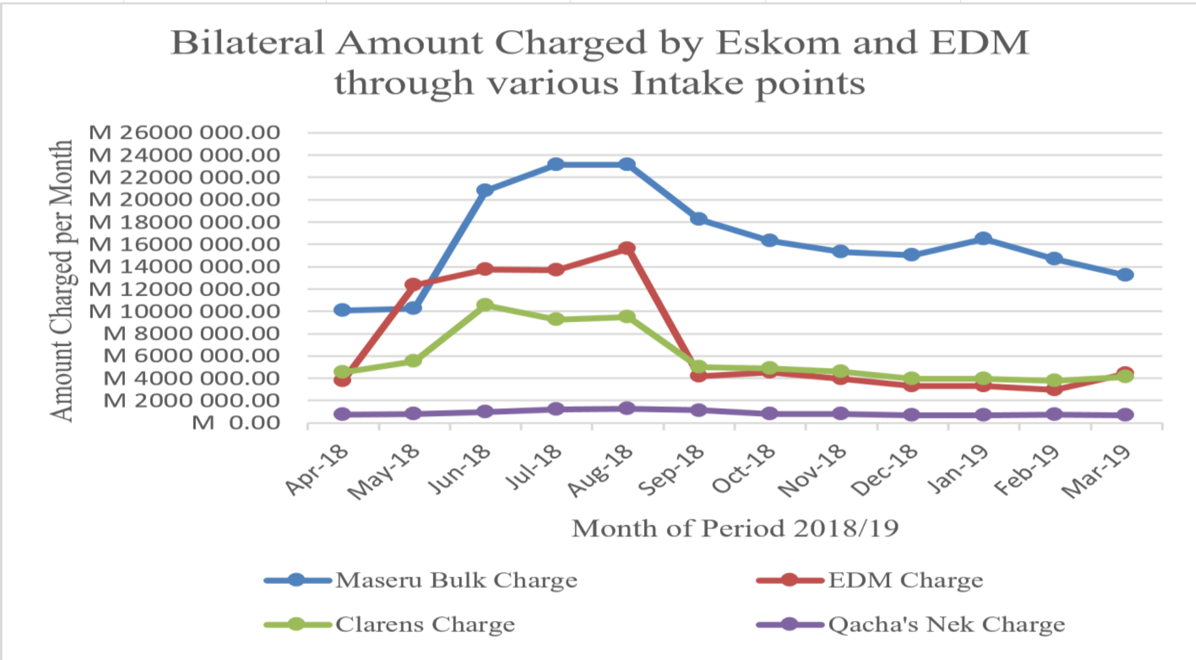


Figure 38 Bilateral Charges from Maseru Bulk, EDM, Clarens and Qacha's Nek for the period 2018/19 Period

[10] High Demand Season for LEC is from June to August

Similarly, just like in the high demand season, Eskom (Maseru Bulk) contributes to total of low demand season[11] electricity import costs around 50 % or more. Taking for instance the month of January 2019, the contribution of around M16 million of electricity costs from Eskom (Maseru Bulk) is more than twice the contribution of around M7,7 million from EDM, Clarens and Qacha's Nek. Of the M7,7 million, EDM charged LEC around M3 million whereas Clarens and Qacha's Nek charged LEC around M4 million and M700 thousand respectively. However, the low demand costs are lower than the high demand costs.

The total amount of electricity imports from bilateral agreements is depicted in Figure 39. What is noticed is that the highest amount of about M49 million was paid in August 2018 while the lowest amount of about M19 million was paid in May 2018. During the summer months comprising November 2018 to January 2019, LEC has paid an amount averaging M24 million. What can also be noticed from Figure 39 is that, that during the high demand season[12] LEC pays around twice as much money than in the low demand season[13].

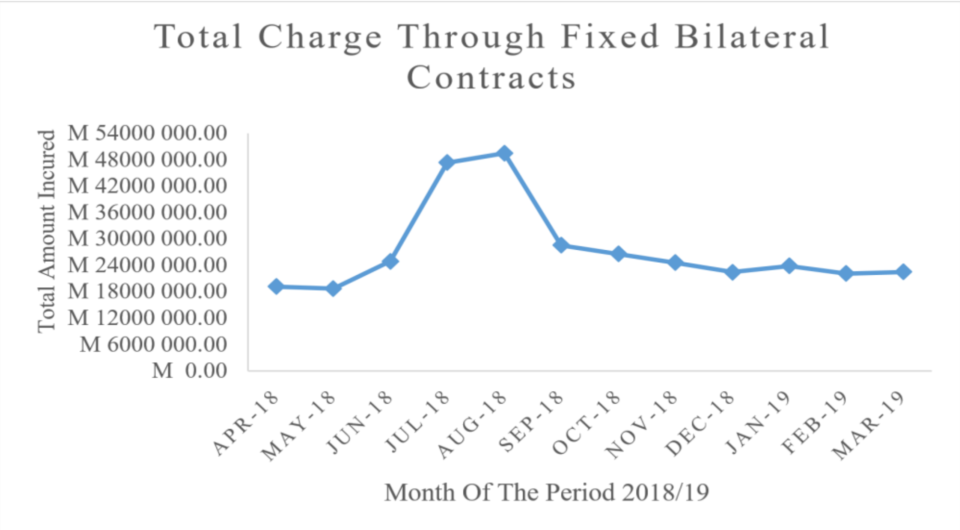


Figure 39 Total Charge from Bilateral Agreements from Maseru Bulk, Clarens, EDM and Qacha's Nek for 2018/19 period

5.2 Analysis of Possibilities Offered by the Power Pool

The focus at this point will be on the day-ahead, intra-day and flexible forward electricity markets offered by SAPP. For each market type, the discussion around whether LEC could be saving by engaging in such markets will be done.

[11] Low Demand Season for LEC is from September to May
[12] High demand season for LEC is from June to August
[13] Low demand season for LEC is from September to May

Figure 40 and Figure 41 show the import unit costs from bilateral agreements with Eskom and EDM during peak, standard and off-peak hours for 2018/19 period. The peak, standard and off-peak hours differ for high demand and low demand seasons. During weekdays, 0600 HRS to 0900 HRS and 1700 HRS to 1900 HRS are peak hours for high demand season whereas 0900 HRS to 1700 HRS and 1900 HRS to 2200 HRS are standard hours. 2200 HRS to 0600 HRS are off-peak hours for high demand season. On Saturday, 0700 HRS to 1200 HRS and 1800 HRS to 2000 HRS are standard hours while all other hours are off-peak hours. There are no peak hours on weekends. Sunday is an off-peak day. 0700 HRS to 1000 HRS and 1800 HRS to 2000 HRS are peak hours for low demand season while 0600 to 0700 HRS, 1000 HRS to 1800 HRS and 2000 HRS to 2200 HRS are standard hours. Lastly, 2200 HRS to 0700 HRS are off-peak hours. On Saturday, standard hours are from 0700 HRS to 1200 HRS and 1800 HRS to 2000 HRS while off-peak hours are from 2000 HRS to 0700 HRS. Sunday hours are all off-peak hours.

What is demonstrated by Figures 40 and 41 is that during the high demand season, Eskom peak prices (~20 USc/kWh) are about twice EDM peak prices (~10 USc/kWh). However, during the low demand season, Eskom peak prices fall significantly (~6.5 USc/kWh) to the point where they are below EDM peak prices. Moreover, Eskom standard and off-peak prices are lower than those of EDM during both the low and the high demand seasons. It is also noticed that EDM peak, standard and off-peak prices are flatter throughout the 2018/19 period while Eskom peak price is spiking in the high demand season and becomes flatter in the low demand season.

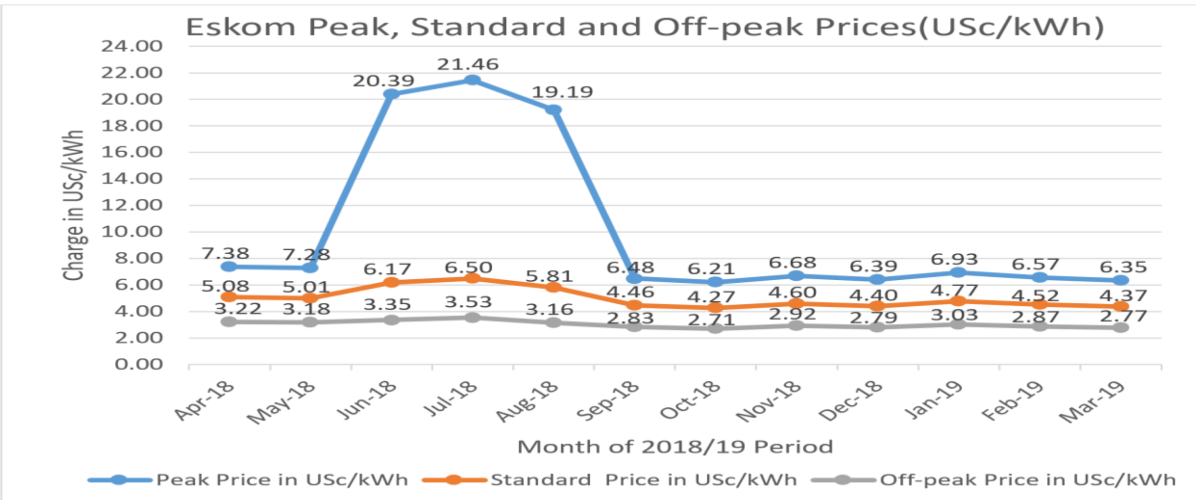


Figure 40 Eskom Average Peak, Standard and Off-peak Prices at Maseru Bulk Intake Point

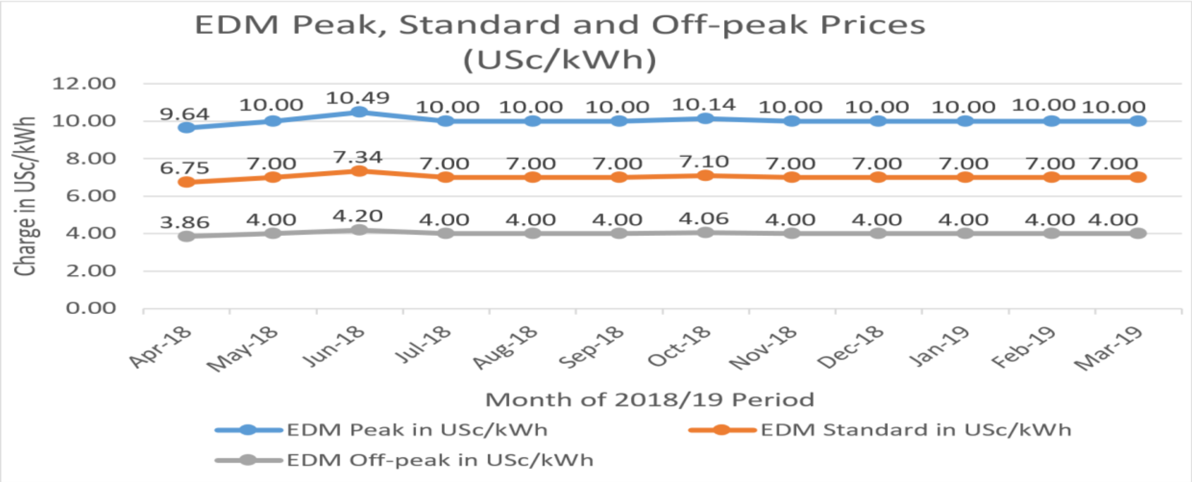


Figure 41 EDM Average Peak Standard and Off-peak Prices at Maseru Bulk Intake Point

Figures 42 through 44 show the unit costs for SAPP DAM, FPM-W and IDM during peak, standard and off-peak hours for 2018/19 period. Table 3 represents the average unit costs for bilateral contracts and SAPP markets obtained from Figures 42 through 44 for high demand and low demand seasons respectively. What is noticed from **Error! Reference source not found.** is that Eskom average peak price for high demand season (~20 USc/kWh) is way higher than those of SAPP DAM and IDM (~12 USc/kWh each) and FPM-W (~13 USc/kWh). However, EDM average peak price for high demand season (~10 USc/kWh) is lower than SAPP DAM, IDM and FPM-W average peak prices. Moreover, EDM and SAPP FPM-W average peak prices for the low demand season are about the same (~10 USc/kWh). However, those of SAPP DAM (~9USc/kWh) and IDM (~8 USc/kWh) are lower than EDM's average peak price. Similarly, EDM's standard price (~7 USc/kWh) and off-peak price (~4 USc/kWh) for the low demand season are higher than those of DAM, IDM and FPM-W. However, during the low demand season, Eskom's average peak (~7 USc/kWh) and standard (~5 USc/kWh) prices unlike those of EDM are lower than SAPP's DAM, IDM and FPM-W average peak and standard prices. Eskom's average off-peak price (~3 USc/kWh) is about the same as SAPPs' DAM, IDM and FPM-W average off-peak prices. Furthermore, what is noticeable from figures 42 through 44 is the price variability offered by the power pool. On the other hand, lack of flexibility of bilateral charges is noticeable as shown in figures 40 and 41.

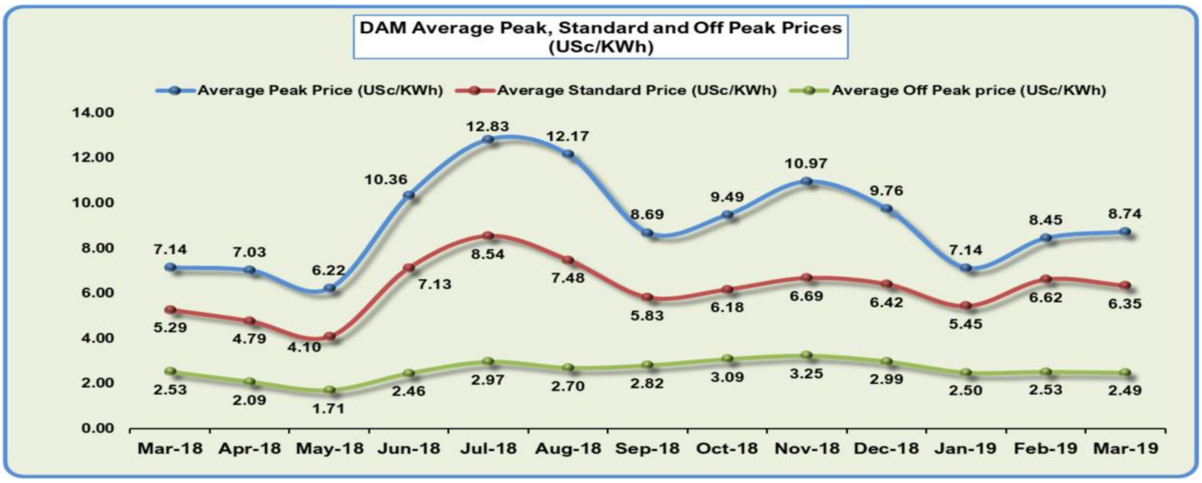


Figure 42 Average SAPP DAM Time of Use Prices for the 2018/19 Period [62]

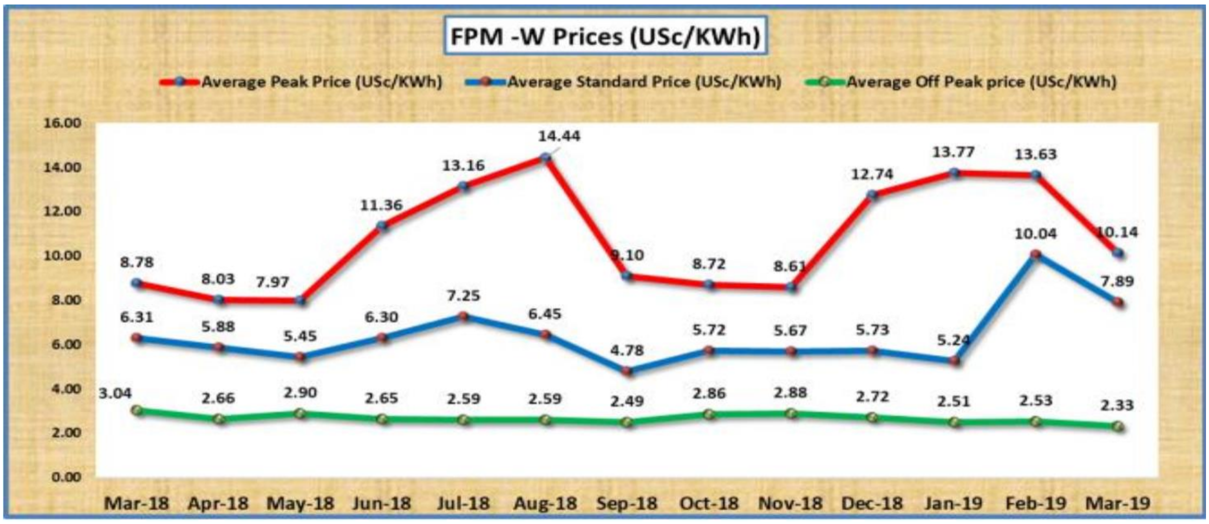


Figure 43 Average SAPP FPM-W Time of Use Prices for 2018/19 Period

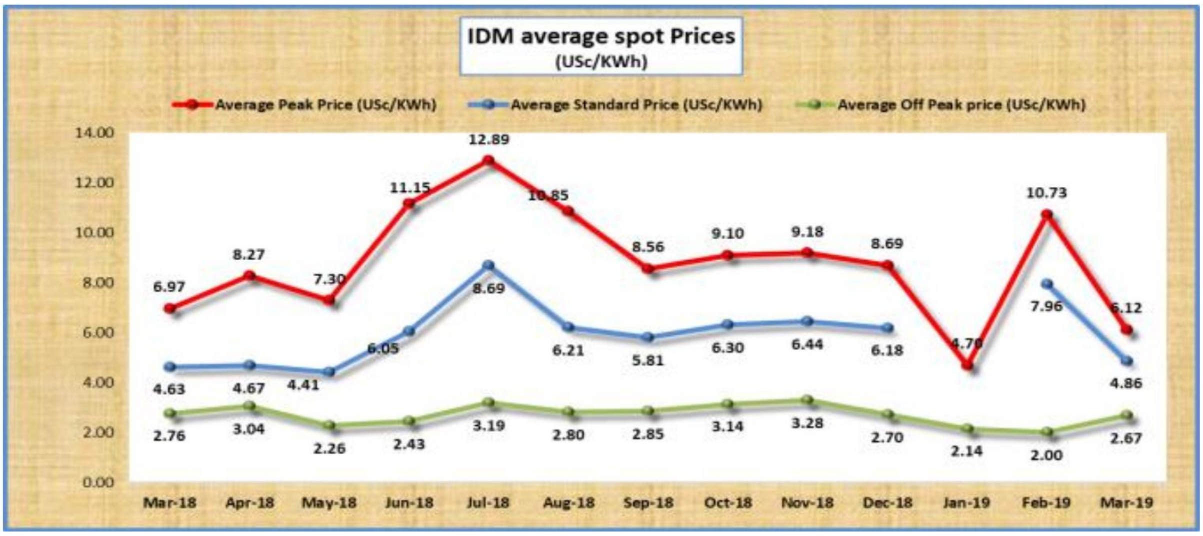


Figure 44 Average SAPP IDM Time of Use Prices for 2018/19 Period

Table 3 Average Peak, Standard and Off-peak Prices for Bilateral contracts and SAPP Market

	High demand season average peak charge (USc/kWh)	High demand season average standard charge (USc/kWh)	High demand season Average Off-peak charge (USc/kWh)	Low demand season average peak charge (USc/kWh)	Low demand season average standard charge (USc/kWh)	Low demand season average off-peak charge (USc/kWh)
Eskom	20.35	6.16	3.35	6.74	4.61	2.92
EDM	10.16	7.11	4.07	9.98	6.98	3.99
SAPP DAM	11.79	7.72	2.71	8.50	5.83	2.61
SAPP IDM	11.63	6.98	2.81	8.07	5.70	2.68
SAPP FPM-W	12.99	6.67	2.61	10.30	6.27	2.65

When looking at the energy consumptions during peak, standard and off-peak periods from the bilateral contracts with Eskom and EDM depicted in Table 4, it can be established that the peak energy consumptions from Eskom and EDM for high demand season are around the same at an average of about 4 GWh. The standard energy consumption from Eskom of about 8 GWh is more than that of EDM of about 6 GWh while the energy consumed during the off-peak period from Eskom of about 2 GWh is much less than that of EDM at about 8 GWh. However, during the low demand season, energy consumed from Eskom during peak period is still 4 GWh while that of EDM has been reduced to about 1 GWh. During the standard and off-peak periods, energy consumption from Eskom has increased to 10 GWh for standard and 7 GWh for off-peak. However, EDM energy consumption has decreased to about 1 GWh for standard and 2 GWh for off-peak.

Table 4 LEC Peak, Standard and Off-peak Volumes from Eskom and EDM for 2018/19 Period

Month	Apr-18	May-18	Jun-18	Jul-18	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18	Jan-19	Feb-19	Mar-19
Eskom Peak Volume in GWh	2.88	3.28	3.54	3.79	3.79	4.84	4.48	3.69	3.32	4.42	3.57	3.28
Eskom Standard Volume in GWh	5.19	4.78	7.23	8.89	8.02	10.48	9.08	9.55	8.79	10.72	8.86	7.85
Eskom Off-peak Volume in GWh	2.41	1.22	1.60	2.08	3.01	8.72	7.88	6.43	7.83	5.58	6.22	5.09
EDM Peak Volume in GWh	0.84	2.30	2.42	5.53	2.65	0.80	0.92	0.88	0.55	0.55	0.50	0.84
EDM Standard Volume in GWh	1.67	5.47	5.55	5.58	5.80	1.65	1.81	1.64	1.33	1.33	1.24	1.72
EDM Off-peak Volume in GWh	2.14	8.04	8.09	8.48	8.14	2.20	2.08	1.82	1.87	1.87	1.62	2.25

When focusing on the LEC load duration curve (LDC) which is depicted in Figure 45, it can be established that, at 50 percent of the time during the 2019/20 period, Lesotho's demand is sitting at around 103 MW (103, 116.06 kW) while around 170 MW of demand occurs about once since the percentage of occurrence is very low (approaching 0 % occurrence). Again, at 100 % of the time, the demand is around 34 MW which is slightly above 30 MW. The demand obtained at 50 % occurrence provides the intermediate load requirements which LEC needs to supply, while the demand obtained when occurrence is around 0 % provides the peak load requirements. Moreover, 100% occurrence provides the base load or the minimum load requirements. Thus the LDC gives an indication of how often or seldom has a certain demand occurred throughout the year.

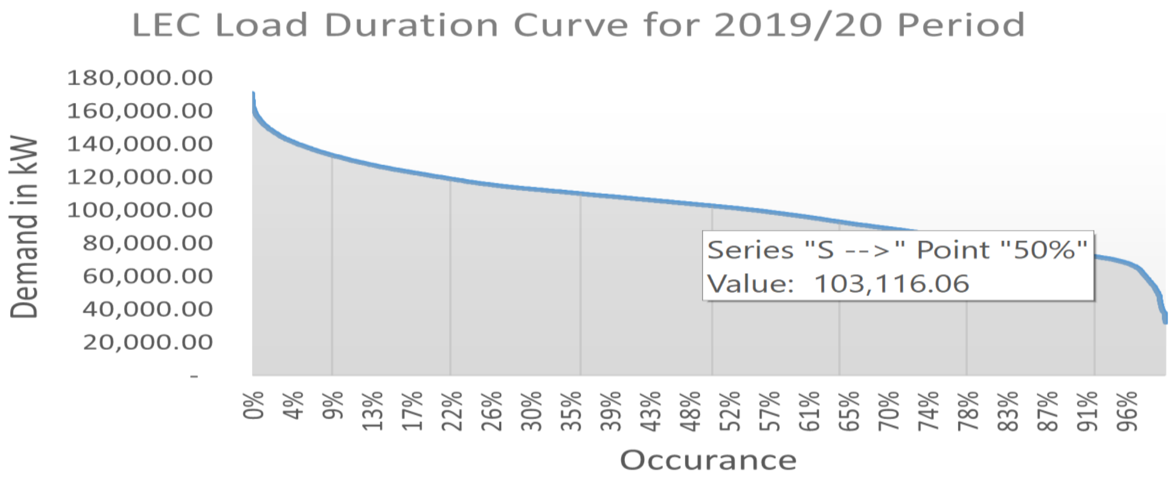


Figure 45 LEC Load Duration Curve for 2019/20 Period

Based on these deductions, it can be realized that LEC could meet the intermediate load and the base load requirements occurring during standard and off-peak periods by utilizing the bilateral agreements from LHDA (local generation), Eskom and EDM. This is based on the fact that bilateral agreements offer security of supply and guarantee long term electricity supply. Also during these periods, it was realized that bilateral imports standard and off-peak charges are around the same as SAPP’s standard and off-peak prices. The exception here is EDM charges (7 USc/ kWh standard charge and 4 USc/ kWh off-peak charge) though they do not differ much from SAPP’s charges (3 USc/ kWh off-peak charge and 6 USc/ kWh standard charge). To meet the peak demand requirements, LEC can utilize the SAPP’s competitive market. This is based on the fact that Nostradamus software is able to project the peak demand with high accuracy. Moreover, it was realized that peak charges from Eskom are costing LEC about twice the total charge. Adoption of SAPP’s market can help reduce the bulk purchases costs which will then reduce the tariff charges to the final consumer.

LEC charges its consumers using a flat tariff. However, SAPP market prices are based TOU. Similarly, bilateral agreements from Eskom and EDM are based on TOU except that SAPP peak prices are higher than Eskom and EDM bilateral peak prices. Time of use pricing results in higher prices during the peak period. Hence, this influences electricity users to shift their loads to the period where the cost of energy is lower. Thus, if LEC could shift the peak demand to where the SAPP prices are lower, then it could benefit from SAPP market resulting in reduction of bulk purchases costs.

The share of energy traded bilaterally and in the SAPP market from 2012 to 2020 is presented in Figure 46. An increasing trend of the percentage share of the energy traded in the SAPP competitive is noticed while the percentage share of energy traded bilaterally portrayed a decreasing trend. For instance, energy traded in SAPP market increased from 0.2 % in 2012/13 to 32 % in 2018/19 as depicted in Figure 46. However, energy traded bilaterally decreased from 99.8 % in 2012/13 to 68 % in 2018/19. The decreasing trend of energy traded bilaterally is confirmed by Figure 47 which shows a decrease from 7,992 GWh in 2015/16 period to 3,343 GWh in 2019/20 period. An increase in energy traded in SAPP competitive market and decrease in energy traded bilaterally are attributed by the fact that utilities have started to take advantage of the SAPP competitive market and are thus slowly decreasing or moving away from the bilateral contracts.

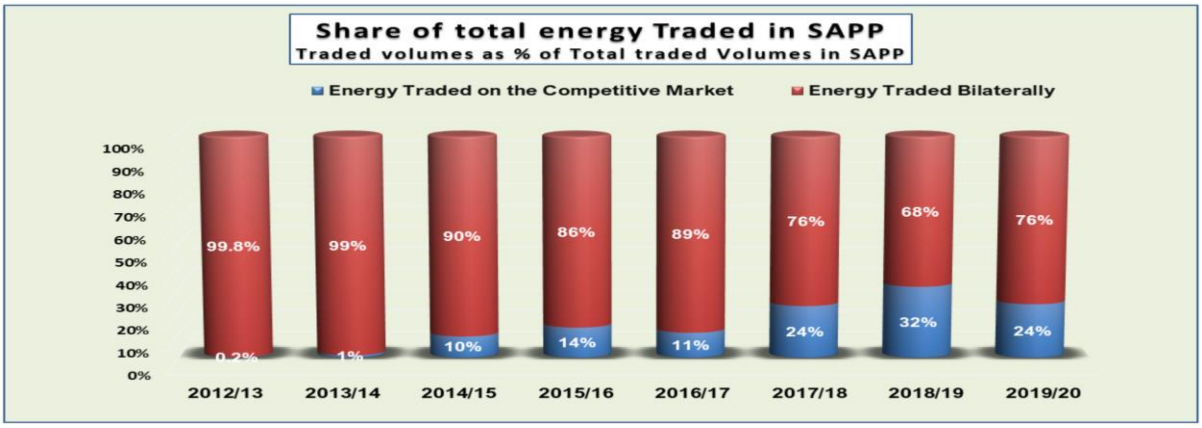


Figure 46 Percentage of Energy Traded Bilaterally versus the Competitive Market in SAPP from 2012 to 2020 [62]

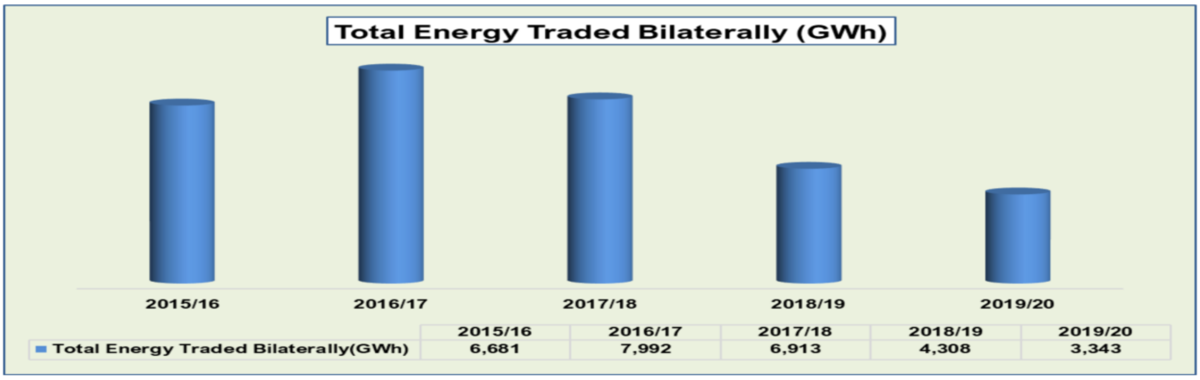


Figure 47 The share of the Total Energy Traded Bilaterally in the SAPP Market from 2015 to 2020 [62]

Likewise, LEC can also take advantage of SAPP market to procure electricity instead of increasing bilateral agreements to meet the demand. This can help reduce the cost of bulk purchases. In the competitive market, electricity demand forecasting and price forecasting play a major role. With the accurate demand forecasting results produced by Nostradamus, LEC is ready to engage in the competitive market offered by SAPP to procure and sell electricity.

Although the SAPP competitive market offers price variability, transmission constraints continue to be the prohibiting factor towards trading in the market [62]. This is confirmed by Figure 48 which shows the amount of energy matched with the amount of energy traded on the market. For instance, in 2016/17, 37 % of energy was traded resulting in 1,023 GWh traded energy against 2,780 GWh matched energy. However, 2017/18 and 2018/19 periods resulted in 99 % of the energy traded on the market showing a huge improvement from 2016/17 period. 2019/20 showed a decrease of the energy traded in the market resulting in 87 % of the traded energy.

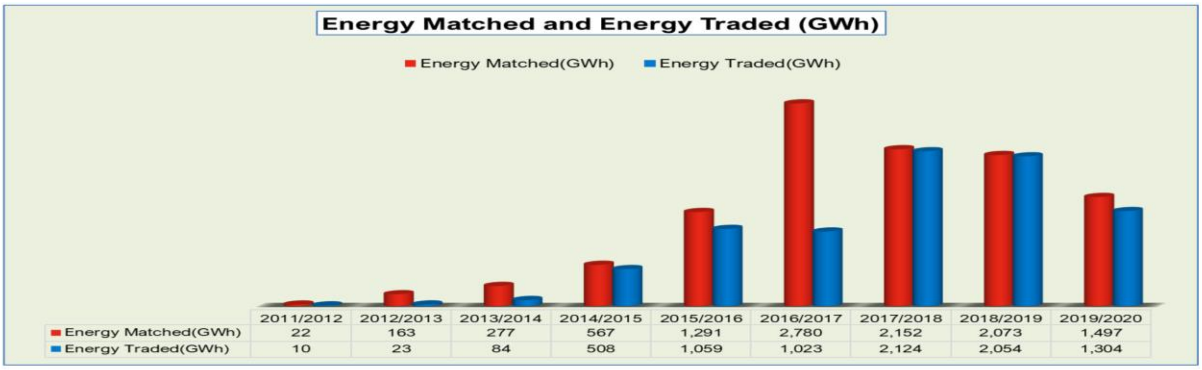


Figure 48 The Volume of Energy Matched against Energy Traded through SAPP Competitive Market from 2011 to 2020 [62]

In the context of LEC, the transmission constraints lie with the 132 kV tie line from Maseru bulk to Mabote substation. Depending on how far the electricity dispatch point in the power pool is from Mabote substation, the electricity that will be traded will not match the electricity that will be matched. This may result in LEC not being able to supply enough electricity to meet the demand.

6. Conclusions and Recommendations

In this research, Nostradamus short-term demand forecasting software was used to produce accurate hour-ahead, day-ahead and week-ahead electricity demand forecasting for Lesotho. Nostradamus produced an hour-ahead, day-ahead and week-ahead demand forecasting with 3 %, 4 % and 5 % accuracy. These MAPE values are within 5 % acceptable accuracy for short-term load forecasting model portraying high accuracy. To produce the results, historical demand data for March 2017 to March 2018, days of the week, months of the year and Lesotho public holidays were utilized. With these results, LEC is ready to perform trading in the SAPP short-term market. However, the accuracy can be improved further by incorporating weather data such as temperature and humidity into the model. The improvement of the accuracy can addressed through further research. In addition to short-term demand forecasting, further research on short-term price forecasting needs to be undertaken since short-term demand and price forecasting are mandatory for trading in the SAPP market.

As far as the electricity procurement is concerned, LEC is using bilateral agreements with LHDA, Eskom and EDM to supply electricity to its consumers. During the high demand season, electricity imports from Eskom and EDM costs LEC around twice (M49 Million) as much money as it incurs during the low demand season (M24 Million). In order to reduce the bulk purchases costs, LEC can utilize bilateral agreements with the local generation to address intermediate load requirements of 103 MW since they guarantee long term electricity supply. To address the demand beyond the intermediate load, LEC can sort to the SAPP market given the fact that Nostradamus software predicts the demand, more especially the peak demand with high accuracy. Moreover, SAPP electricity costs for peak hours were realized to be lower by around half than the bilateral costs.

Since the bilateral contracts with Eskom and EDM are fixed agreements with take-or-pay clauses, LEC is bound to consume that energy as per the contractual agreement, unless they are reviewed, even if it had better offers from other markets. One recommendation is for the country to invest in a pump storage generation system and then get cheaper electricity from SAPP markets during off-peak periods. This water can then get discharged during the peak hours to meet the peak load. As such, Lesotho needs to implement policies promoting generation projects such as pump storage to optimally and cost-effectively meet the country's current and future electricity needs. Another recommendation would be for LEC to negotiate the financial bilateral agreements with Eskom and EDM that allows for selling of unused power in the SAPP competitive market.

It was realized however that the transmission constraints are limiting trading in the SAPP market. This results in traded energy and the matched energy to differ. LEC for instance is constrained by the 132 kV tie line at Maseru bulk. The recommendation here is for LEC to invest in upgrading this tie line to at least 275 kV under medium term investment of 3 to 5 years. LEC can also increase 88 kV tie line at Clarens to at least 132 kV and 22 kV at Matatiele to at least 66 kV. Thus, the electricity intake points will be increased resulting in the power flow not only through Maseru Bulk but also Clarens and Matatiele. This way LEC is at liberty to negotiate cheaper power from anywhere with EDM included. This would benefit LEC during the peak period where it was realized that EDM peak prices are cheaper than Eskom peak prices. Moreover, having more tie lines will increase the possibility of purchased energy to lend in the LEC power network.

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