DATA-DRIVEN MODELING USING DEEP NEURAL NETWORKS FOR POWER SYSTEMS DEMAND AND LOCATIONAL MARGINAL PRICE FORECASTING

A THESIS SUBMITTED TO
THE BOARD OF GRADUATE PROGRAMS
OF
MIDDLE EAST TECHNICAL UNIVERSITY, NORTHERN CYPRUS CAMPUS

BY

HONEST JIMU

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN ELECTRICAL AND ELECTRONICS ENGINEERING PROGRAM

SEPTEMBER 2022

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ABSTRACT

DATA-DRIVEN MODELING USING DEEP NEURAL NETWORKS FOR POWER SYSTEMS DEMAND AND LOCATIONAL MARGINAL PRICE FORECASTING

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September 2022, 121 pages

Forecasting electricity demand and locational marginal prices (LMPs) have become critical components for power system security and management. Electricity Demand Forecasting (EDF) aids the utility in maximizing the use of power-generation plants and scheduling them for both reliability and cost-effectiveness. In this thesis, a novel Deep Neural Network Long Short-Term Memory (DNN-LSTM) forecasting model is suggested to improve accuracy and robustness for predicting hourly day ahead power system load and LMPs in two distinct markets, North Pool (NP), and New England-ISO (NE-ISO). Historical load, weather, statistical features derived from historical data, and system outage information (known as Line Outage Distribution Factors (LODFs)) will be used as input features in the proposed model. Two distinct demand-forecasting models will be modelled using two case studies that present different market patterns from different geographical locations. The deep neural network model will be compared with the state-of-the-art Lasso Estimated Autoregressive (LEAR) model using a variety of performance metrics, including Symmetric Mean Average Percentage Error (sMAPE), Root Mean Square Error (RMSE), Mean Average Percentage Error (MAPE), Relative Mean Average Error

(rMAE), Mean Average Error (MAE). The results acquired from the two experimental case studies on the markets, revealed that the proposed DNN model showed significant improvement in hourly demand and LMP forecasts and therefore outperformed contemporary statistical forecasting techniques in accuracy, computational time, and reliability.

Keywords: Deep Neural Networks, Electricity Load Forecasting, Locational Marginal Price Forecasting, Line Outage Distribution Factors (LODFs)

ÖZ

GÜÇ SİSTEMLERİ TALEBİ VE YEREL MARJİNAL FİYAT TAHMİNİ İÇİN DERİN SİNİR AĞLARI KULLANARAK VERİ DAYALI MODELLEME

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Elektrik talebini ve yerel marjinal fiyatları (LMPs) tahmin etmek, güç sistemi güvenliği ve yönetimi için kritik bileşenler haline geldi. Elektrik Talebi Tahmini (EDF), elektrik üretim tesislerinin kullanımını en üst düzeye çıkarmada ve bunları hem güvenilirlik hem de maliyet etkinliği için programlamada yardımcı olur. Bu tezde, Kuzey Havuzu (NP) ve Kuzey Havuzu (NP) ve New England-ISO (NE-ISO). Tarihsel yük, hava durumu, geçmiş verilerden türetilen istatistiksel özellikler ve sistem kesintisi bilgileri (Hat Kesintisi Dağıtım Faktörleri (LODFs) olarak bilinir) önerilen modelde girdi özellikleri olarak kullanılacaktır. İki farklı talep tahmin modeli, farklı coğrafi konumlardan farklı pazar kalıpları sunan iki vaka çalışması kullanılarak karşılaştırılacaktır. Derin sinir ağı modeli, Simetrik Ortalama Ortalama Yüzde Hatası (sMAPE), Ortalama Kare Hatası (RMSE), Ortalama Ortalama Hatası (RMSE) dahil olmak üzere çeşitli performans ölçümleri kullanılarak son teknoloji Kement Tahmini Otoregresif (LEAR) modeliyle karşılaştırılacaktır. Ortalama Yüzde Hatası (MAPE), Göreli Ortalama Ortalama Hata (rMAE), Ortalama Ortalama Hata (MAE). Piyasalardaki iki deneysel vaka çalışmasından elde edilen sonuçlar, önerilen DNN modelinin saatlik talep ve LMP tahminlerinde önemli bir gelişme gösterdiğini

ve bu nedenle doğruluk, hesaplama süresi ve güvenilirlik açısından çağdaş istatistiksel tahmin tekniklerinden daha iyi performans gösterdiğini ortaya koydu.

Anahtar Kelimeler: Derin sinir ağları, Elektrik Yük Tahmini, Lokal Marjinal Fiyat Tahmini, Hat Kesintisi Dağıtım Faktörleri (LODF'ler

ACKNOWLEDGMENTS

My experience during my Master of Science at Middle East Technical University – Northern Cyprus Campus has been an exciting journey that is full of academic discoveries and personal growth. The journey is extremely worthwhile and supportive to achieve my future endeavors. I would like to take this opportunity to acknowledge the people that help me to reach where I stand today.

First, I would like to express my sincere gratitude and appreciation to my Thesis supervisor Prof. Dr. Murat Fahrioğlu for his continued support, motivation and immense knowledge. He always steered me in the right direction whenever he thought I needed it. Besides my supervisor, I would like to thank Dr Cagil Ozansoy and Dr. Canras Batunlu for their valuable insights about my progress and achievements during this master program.

To my beloved parents Farai Jimu and Alice Jimu, my brothers Washington, Onismo, Arthur and Alfred, I must express my profound gratitude for providing me their endless love, support, and encouragement during my studies. Without them, this achievement would not have been possible. Special thanks to Nyasha for the immense support and love. Lastly, I would like to thank all my colleagues at METU-NCC especially Noorahmad Yaqubi, Amanda Mubaiwa, Shame Tatenda Chabwinja; I am grateful for the wonderful time I had with them.

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LIST OF ABBREVIATIONS

ABBREVIATIONS

RE	**Renewable Energy**
LMPs	Locational Marginal Prices
DNN	Deep Neural Networks
LSTM	Long Short-Term Memory
NP	Nord Pool
NE-ISO	New England Independent System Operator
LEAR	Lasso Estimated Autoregressive
EDF	Electricity Demand Forecasting
LODFs	Line Outage Distribution Factors
EPF	Electricity Price Forecasting
MAPE	Mean Average Percentage Error
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
sMAPE	Symmetric Mean Average Percentage Error
DML	Deep Machine Learning
rMAE	Relative Mean Average Error
TRNC	Turkish Republic of North Cyprus
PTDFs	Power Outage Distribution Factors
PM	Performance Metrics
FLR	Fuzzy Linear Regression
OPF	Optimal Power Flow
ELD	Economic Load Dispatch
PSP	Power Systems Planning

DL	Deep Learning
ML	Machine Learning
ISO	Independent System Operators
ANNs	Artificial Neural Networks
ARIMA	Autoregressive Integrated Moving Average
SVM	Space Vector Machine
CSA	Cuckoo Search Algorithm
STLF	Short Term Load Forecasting
FLNN	Fuzzy Logic Neural Network
EFNN	Evolving Fuzzy Neural Networks
NNs	Neural Networks
NARX	Non-linear Autoregressive Approaches
SVR	Support Vector Regression
RNNs	Recurrent Neural Networks
CNNs	Convolutional Neural Network
GENCOS	Generating Companies
IPPs	Independent Power Producers
DISCOS	Distribution Companies
MWh	Megawatt hour
MO	Market Operator
TRANSCO	Transmission Companies
ITC	Independent Transmission Company
AC	Alternating Current
PI	Performance Indices
LASSO	Least Absolute Shrinkage and Selection Operator
AIC	Akaike information criterion
LARS	Least Angle Regression
CV	Cross Validation
MLP	Multilayer Perceptron

CHAPTER 1

INTRODUCTION

Electricity demand management and planning has always been a difficult task for all power system utilities in all countries today, regardless of their economic status. The greatest stumbling block to economic expansion is energy unavailability, which is always in short supply due to limited or inadequate resources. The aim to reduce greenhouse gas and achieve green energy goals set by governing bodies has increased the integration of renewable energies to the power network. However, the integration of Renewable Energy (RE) sources has brought about grid instability due to their intermittent nature. As a result, there is always a need to establish approaches that can accurately anticipate electricity demand and locational marginal prices (LMPs) and allow for appropriate planning and in worst case scenarios, utility scheduling for load shedding. Very short term, short term, mid-term, and long-term load forecasting are the four types of load forecasting, with load forecast ranging from a few seconds to two decades [1]. The proper running of electric utilities necessitates the forecasting of load demand and LPMs on a short-, medium-, and long-term basis.

Electricity Demand Forecasts (EDFs) and electricity price forecasting (EPFs) techniques are really important for investment planning, having the upper hand on proper scheduling activities of generation capacity, power systems operations and maintenance, fuel purchasing as well as security assessments [2]. In general, the majority of forecasting approaches in the current literature are based on expert systems, regressive analysis, grey box systems, exponential smoothing, time series, neural network modeling, and other types of mathematical analysis [3], [4], [5], [6], [7], [8], [9]. In other literatures, many state-of-the-art load forecasting models [10]–[12] have been proposed with the goal to improve forecasting accuracy. In certain circumstances, researchers have employed a combination of approaches to create their own EDF and EPF hybrid models. For instance, in [13] a fuzzy linear regression technique was utilized to anticipate weekend power demand, whereas a conventional exponential smoothing approach was employed to forecast midweek loads. For the forecasting function, traditional econometric approaches build functional correlations between weather variables and current load demand, often assuming a linear relationship. However, because of nonlinear correlations of the load demand and the electricity prices, as pointed out in [14], the econometric approach may not adequately provide accurate results. As a result, an adaptive load forecasting technique is required [15]. Table 1. shows the time-horizon perspective of demand-forecasting and its application areas on short-term forecasting ranging from milliseconds to a week, medium-term from one week to a year, and long-term from one year to a decade.

Table 1. The forecasting mechanisms' implementation based on time spans.

Time span	Scope of applicability	Comments
Milliseconds to seconds	Assessment of a dynamic power system	
One min to one week	Unit commitment analysis Optimal power flow (OPF) analysis and economic load dispatch (ELD) Management of automated generation	
One week to one year	Maintenance scheduling	
One year – ten years	Power System Planning (PSP)	Generation planning, network planning, and load forecasting are all included. PSP's basic structure is depicted in Figure 1.

The demand for electricity is typically thought to be a result of weather parameters and human societal activities. In retrospective to contemporary econometric approaches, there is an assumption that there is a linear relationship between weather parameters and electricity load demand when it comes to forecasting. Figure 1 illustrates a basic Power Systems Planning (PSP) structure from the generation aspect, transmission, and distribution up to energy planning and policies.

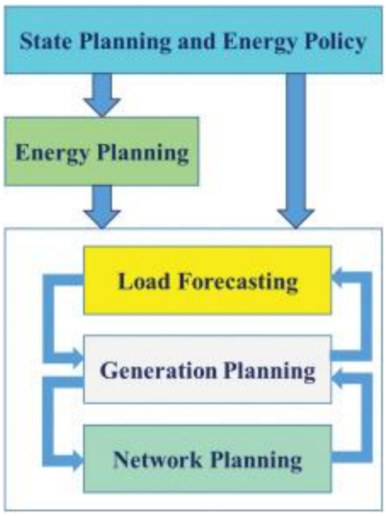


Figure 1. Power systems planning (PSP) basic structure.

With the increased renewable energies integration to the power grid the overall stability of the power system has become even more erratic in nature as a result of the intermittent nature of RE sources and the irregular essence of electrical power demand. Therefore, unexpected increase in power demand can have massive instability or blackout impacts to the overall grid if forecasting techniques over estimate or under estimate future load demands. The general concept of supply and demand can be used here as a tip of the iceberg, but the overall aspect has severe consequences if generation doesn't met demand vice versa. Generation companies, transmission systems operators, retailers and all the markets players are investing in load demand LMPs forecasting techniques, which has been a focal topic of research in the energy sector in order to address the issues outlined above. If forecasting approaches employed are accurate and robust enough, the deviations of supply and demand will definitely be alleviated, gains in economic profits can be achieved and the overall grid can operate in more favorable conditions.

The main goal of this thesis is to apply a deep learning (DL) technique to reduce the gap on the real and forecasted margins and achieve a more effective and accurate model for hourly day ahead electricity load demand and locational marginal prices (LMPs) in the Nord Pool (NP) and New England ISO (NE-ISO) electricity markets over various time periods. A Deep Long Short-Term Memory Neural Network (DNN-LSTM) was developed, along with a state-of-the-art LEAR model that served as a baseline and comparative model to the proposed approach. The application of modern methodologies to the forecasting techniques, as well as the search for the optimal parameters, are the foundations of this study.

1.1 PROBLEM AND JUSTIFICATION

A highly accurate forecasting approach is a crucial contributor for planning, as stated in the abstract, because of the intermittency of renewable energies, their introduction and integration into existing power systems has created uncertainty, necessitating the development of a more precise forecasting technique allowing appropriate and meticulous planning. Therefore, newer machine learning (ML) approaches are becoming more popular as power consumption patterns change, there is a growing desire to build efficient and adaptive methods that can be applied to different sets of data or markets and still perform and achieve minimal error margins.

Since energy forecasting techniques can be classified in different timeframes and considering two unique markets, Nord Pool and New England ISO, this thesis concentrates predominantly on predicting the short-term, hourly electricity demand

and the hourly LPMs, utilizing datasets with a projection window of one day to a week with hourly phases amounting to 168 hours. Ultimately, reducing unit commitment, alleviates production-transmission costs for the power system therefore leading to efficient dispatch of popular contemporary energy sources, i.e., natural gas, RE and thermal power plants. In a nutshell, improved forecasting accuracy will also result in a substantial decrease in the operating expenses related to unit commitment and efficient dispatch of popular conventional energy sources i.e., hydro and thermal power plants will be much more attainable.

CHAPTER 2

LITERATURE REVIEW

Electrical load demand and locational marginal price forecasts are vital for efficient load scheduling, demand management, and contingency planning on power systems. Short-term forecasts, ranging from a few seconds to an hour or even days do have significant contributions to the daily operation of the overall power system. The increasing RE mix in the overall power grid and their intermittence downside issues to the grid requires system operators to push for even more accurate and reliable forecasting approaches. The reasoning behind the claims is that base generator setups usually take hours or days to get them online, and it is insanely expensive to keep large energy stocks in order to meet larger energy demand imbalances. Modern power systems have really made the load demand and LMPs forecasting an interesting work of art, because during past years, generation, transmission and distribution companies and other market players used to manage the demand imbalances by providing a higher capacity which was affecting the companies financially if the demand was over or under estimated.

However, the electricity market deregulation and the introduction of other independent system operators, have brought a greater share of shareholder and consumer participation. These changes have developed the electricity market from a physical risk of adequate capacity to a financial risk of exorbitant electricity prices, therefore the need to have accurate forecasting techniques is of much interest since any slight improvement in forecasting accuracy now leads to immense profits [16]. Deregulation has also made the electricity market to be more competitive and profit oriented. In the literature, there have been various attempts at short-term forecasting using numerous computational intelligence and statistical approaches. These models were applied to multivariate models which apply the use of exogenous variables as shown in [17] such as weather-related data (wind speed, temperature, humidity for example), economic (fuel prices), and social factors (household energy usage) or univariate models in which the load is a function of previous load data and previous LMPs and they usually forecasted using time series approaches. In this instance [18] and [19] states that there is a linear relationship between the weather variables and the electricity demand, and it's one of the most factor considered when forecasting short-term demand and LMPs.

2.1 Electricity energy models

To have a clear and better understanding and also have the concepts in a simple analogy, the principles of the prediction models will be elaborated together with the variables mentioned in the section above and their functions. LDF and LPF approaches can be classified into multivariate and univariate models as well static and dynamic models, and these topics will be explored in depth in the coming sections. These classifications have and are still being utilized by researchers in literature on Machine Learning (ML) models, deep machine learning (DML) and hybrid models to improve accuracy and stability of forecasting models [20].

2.1.1 Multivariate and univariate models

To have a better understanding of the terminologies, this thesis will explain their applications in depth from the literature in the coming sections. The terms can be defined as the absolute ability of models to depend on present variables, be it for a single variable (univariate) or on a multivariate model (two or more variables) [21].

Practically, models can be created with one or more variable depending on the objectives of the forecasting model, thus, geographical location and the intuition of the researcher. Below are tabulated differences of multivariate and univariate model approaches.

Table 2. Multivariate and univariate model differences

Multivariate	**Univariate**
Multiple variables	Single variable
Analysis - Longer time	Analysis - Short time
Purpose - Explain	Purpose - Describe
Cause and relationship – Yes	Cause and relationship - No
Tables and relationship illustrations	Frequency distribution illustrations
Uses correlations	Uses dispersion methods e.g., range and variance
Results can be shown as contingent tables	Results can be shown as charts, bar graphs etc.

2.1.2 Dynamic and Static models

Electricity demand and price forecasting models often include static or dynamic models, which enables the learning and testing phases. The process of feeding a machine learning model or any kind of model with previously obtained data in order to develop functions that characterize the variation in the data is known as the learning phase of the model.

The data that acts as the input for a model can either be one variable (univariate), in which case the model will attempt to create one function that suits the variable's changes, or multiple variables (multivariate), in which case the model would be more complex and take longer to create multiple functions in order to produce accurate trends. There is no distinction between static and dynamic models during this training phase. After completing the learning phase, the testing phase begins, during which the model's generated algorithm will be examined for accuracy and reliability. During the testing phase, the distinction between static and dynamic models becomes apparent.

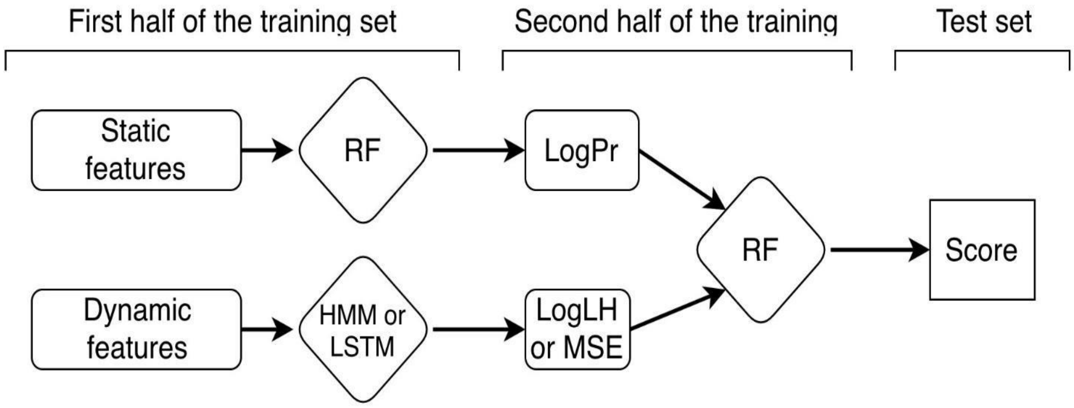


Figure 2. Combination of static and dynamic features for a multivariate classification.

The main distinction between static and dynamic system models is that, whereas a dynamic model refers to the system's runtime model, and a static model is the system's model outside of runtime. Another distinction is the differential equations used in dynamic models, which are conspicuously absent in static models. As the names implies, dynamic models are constantly evolving with respect to time, whereas the counterpart static models, are in a steady state or equilibrium over time.

Dynamic models depict the behavior of the static system components, whereas static models are more structural than behavioral. Static modeling, which helps to represent the system's static components, comprises class diagrams and object diagrams. Since static modeling provides a picture of a system independent of time, it is more rigid than dynamic modeling. Static modeling refers to an object that is constant or unchanged in real time, however dynamic models have the capacity to adapt since they display attributes of what a model can achieve with a wide range of potential future outcomes. An example of a dynamic models involves a combination of differential and algebraic equations as shown below.

$$\frac{dx_1(t)}{dt} = f_1(u_1(t), u_2(t), \ldots\ u_m(t),\ \ x_1(t), x_2(t), \ldots\ x_n(t)) \tag{2.1}$$

$$\frac{dx_2(t)}{dt} = f_2(u_1(t), u_2(t), \ldots\ u_m(t),\ \ x_1(t), x_2(t), \ldots\ x_n(t)) \tag{2.2}$$

$$\frac{dx_n(t)}{dt} = f_n(u_1(t), u_2(t), \ldots\ u_m(t),\ \ x_1(t), x_2(t), \ldots\ x_n(t)) \tag{2.3}$$

$$y_1(t) = g_1(u_1(t), u_2(t), \ldots\ u_m(t),\ \ x_1(t), x_2(t), \ldots\ x_n(t)) \tag{2.4}$$

$$y_2(t) = g_1(u_1(t), u_2(t), \ldots\ u_m(t),\ \ x_1(t), x_2(t), \ldots\ x_n(t)) \tag{2.5}$$

$$\vdots$$

$$y_k(t) = g_1(u_1(t), u_2(t), \ldots\ u_m(t),\ \ x_1(t), x_2(t), \ldots\ x_n(t)) \tag{2.6}$$

Variables of the equations are elaborated below.

- Where; U_i are the input variables,
- y_i are the output variables,
- X_i are the state variables that are independent,
- $y_i(t)$ are output variables that are related to ‘g’ functions

The defining features of a dynamic model is different to the static counterpart because it maintains a memory of combinations of the relative inputs, outputs, and internal variables.

Like what we mentioned above in respect to static models about it not having internal memory of either output variables, previously applied variables, and internal variables. Below is canonical example of a static model and the algebraic equations.

$$y_1 = f_1(u_1, u_2, \dots\ u_n,) \tag{2.7}$$

$$y_2 = f_2(u_1, u_2, \dots\ u_n,) \tag{2.8}$$

$$\vdots$$

$$y_m = f_m(u_1, u_2, \dots\ u_n,) \tag{2.9}$$

The variables of the equations are described below, where.

- y_i is the output that depends on function f_i of the inputs u_i respectively.

To efficiently run such a model, the model designer should set the parameters of the equations and provide the values for the inputs that are required and then evaluate the model.

2.2 INPUT DATA

In today's modern markets, various countries have active deregulated electricity markets, and each of these markets may comprise of coexisting submarkets. There is no predetermined list of inputs that can be defined to produce an effective energy model due to the sheer diversity of market trends, market players and different geographical locations that is accessible. It is crucial to keep in mind that within a single energy market, demand forecasting organizations may use several prediction models that follow various operating ideologies, as stated in the preceding section, as well as their choice of inputs, this is also valid for suppliers and Independent System Operators (ISOs). Therefore, this results in the application of several models that operate with various inputs provided by various entities all with the aim of precisely forecasting the demand for electricity and its prices.

All kinds of data are always available to all entities, but because electricity demand is unpredictable, there is an infinite possibility that different types of externalities will occur. Depending on the type of externality, this causes variations in the reliability of each model being used. The many input kinds can be divided primarily into the qualitative and quantitative categories [22].

2.2.1 Qualitative Inputs

Qualitative inputs are non-numerical in nature, and they are usually acquired through an interactive process that includes one-on-one interviews, open-ended surveys, methods of observation, etc. The analysis is then given in the form of categories or clusters of people who share the same characteristics or traits [23].

The following statement is a suitable illustration of such data in the power market: As a result of the rise in greenhouse gas emissions, temperature changes are more drastic, and many nations regularly experience extreme heat or cold waves. There are broad neighborhoods in country "X" where the bulk of the people are army officers, and new regulations there have been issued that state a rise in the pay for army officers. Following the overall pay increase, these folks might tend to use more electricity throughout the summer or winter by using their heaters and chillers for longer periods of time. Since there is no prior data indicating this new consumption trend, this behavioral change must be accounted for in the prediction model.

2.2.2 Quantitative Inputs

Data or variables that can be represented by numbers are considered quantitative inputs [24]. This makes it simple to input this kind of data into a computer model. For forecasting power demand, some of the often utilized quantitative data are [25]:

- Temperature
- Line outage information (LODFs and PTDFs)
- Humidity
- Past Consumption
- Income and price elasticity
- Number of customers • Population
- Climate factors:
    - Dry bulb temperature
    - Dew point temperature
    - Global solar radiation
    - Humidity
    - Wind speeds
- Energy price
- Technology and advancements
- Previous years' energy's demand

Therefore, open-ended questionnaires or surveys could be used to segment the population into groups and somehow quantify this intangible data to improve the predictive model's accuracy. Table 3.2 can be used to summarize the differences between qualitative and quantitative inputs [26].

Table 3. Shows the difference between qualitative and quantitative data

Comparison Point	Quantitative Research	Qualitative Research
Scope of research	Quantity aspect (how much and how many)	Quality aspect (essence and nature)
Objectives and goals of research	Hypothesis testing, forecasting, confirmation, and control	Description, generating hypothesis, understanding and discovery
Data collection	Surveys, scales, questionnaires, and scales	Interviews, researcher as the ground instrument and observations
Findings	Mostly precise, relative, and narrow	Can be expanded, comprehensive and integrated
Setting	Artificial and queer	Familiar and natural

2.3 TREND VARIATIONS

Any form of data will vary with respect to a pre-set datum (time in the instance of electricity demand), regardless of the type of input used or the operating principles of the system. These fluctuations come in a variety of forms, including seasonal variation, nonlinear variation, and linear variation [27].

2.3.1 Trend regression analysis (Linear variations)

Also known as Trend regression analysis, they use equations to analyze the relationship between one or more quantitative variable in order to pick up traits and forecast the variable traits based on the other. In this thesis we will have X and Y variables, X variables being the input variables, and Y being the output variable based on the input parameters. In this case X has 16-18 columns of the historical data ranging from, temperature, LMPs, to systems minimum, maximum, and peak demands etc. Trend regression analysis are there to measure the relationship between X and Y variables where X is always independent and Y acts as the dependent variable. If we are to graphically represent the linear variations, the data will appear as a straight line angled diagonally upwards or downwards, therefore the trends are concluded to be upward or downward trends.

Most linear trends have a simple equation that can be illustrates as follows; $y = mx + c$. Where y is the variable on the y-axis and m is the slope or coefficient of the x variable and lastly c can be either the constant or value if no x value is present.

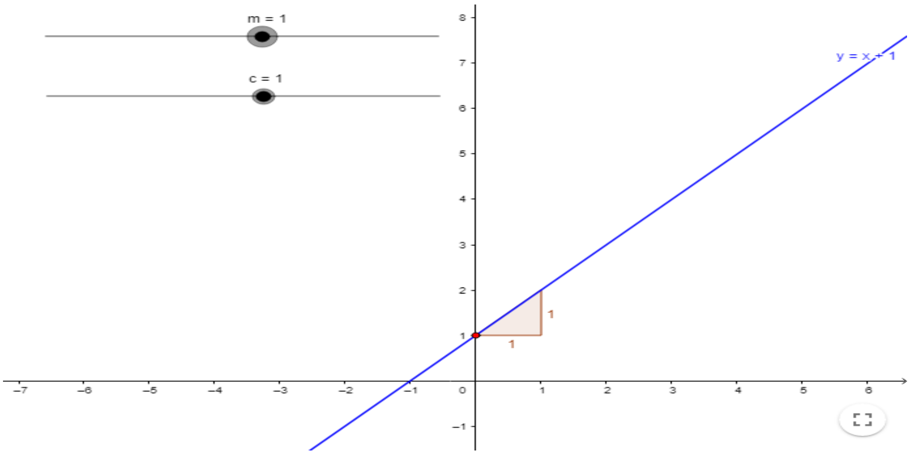


Figure 2.1. Graphical representation of a linear variation

2.3.2 Non-Linear variation

For non-linear relationships to be modelled, the forecasted variable/s (y) and the input or predictor variable (x) has to be transformed, this will provide the model with a non-linear functional form even through the model parameters. The commonly used transformation is the natural logarithm which is elaborated as a log-log function in the given form below.

$$\log \log y = \beta_o + \beta_1 \log \log x + \varepsilon \tag{2.10}$$

In this case, lets interpret the slope β_1 as electricity, simply meaning that β_1 is the average percentage change in y, resulting from a percentage increase in (x). There is some instance where simply transforming the data won't be sufficient and therefore a more sophisticated specification may be required. In order to have a more specific model. We can structure the model as below.

$$y = f(x) + \varepsilon \tag{2.11}$$

In this instance f is the function for a non-linear equation, in standard terms for non-linear regression, $f(x) = \beta_0 + \beta_1 x$. This equation allows for f to be more flexible compared to when he's applied to simple logarithmic or other transformations. Now the question bags to how we can apply these models to contemporary forecasting models? The application of quadratic equations or advanced high order equations can be achieved if input (predictor) variables are carefully specified. Using the piecewise approach yields similar results since, the approach can change formats because it responds to data variations. Such ability makes it a non-linear trend constructed of linear pieces and the equation below illustrates such claims.

$$x_{1,t} = t \tag{2.12}$$

$$x_{2,t} = (t - \tau)_+ = \{\ 0 \qquad t < \tau\ (t - \tau) \quad t \geq \tau$$

Where τ is when the model can be readjust it's trend at time τ therefore elaborative specifications can be made by replacing $c = \tau$ and $x = t$ respectively.

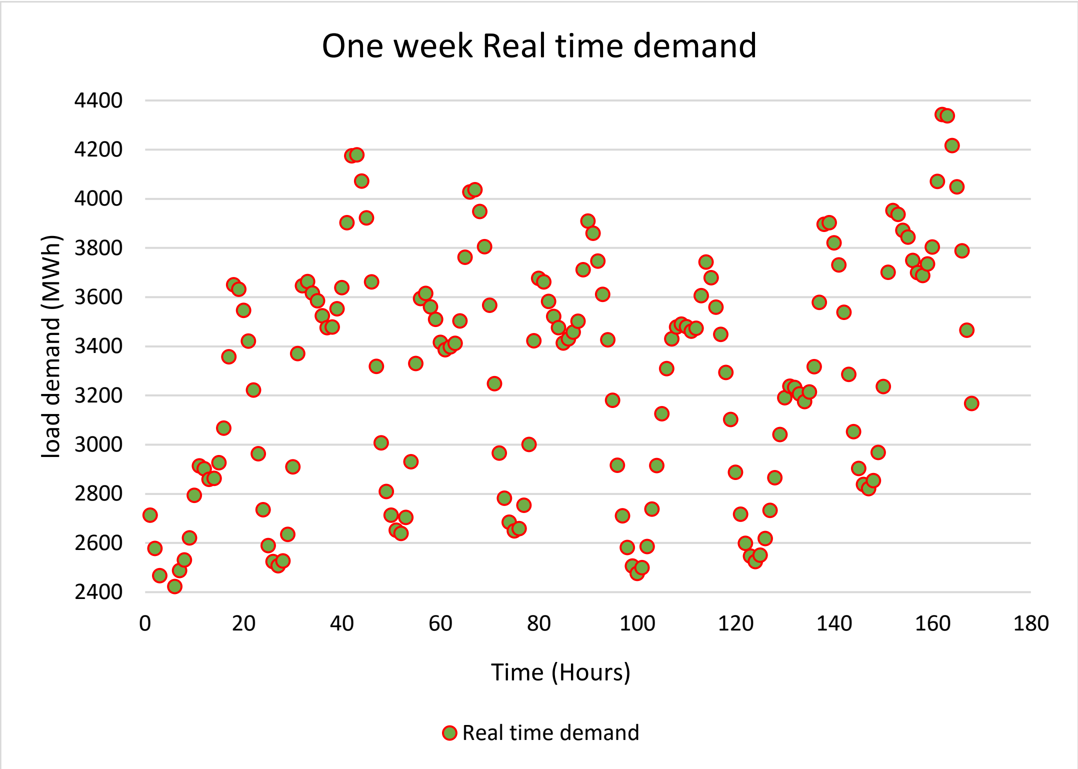


Figure 2.2. Shows a non-linear variation of load demand

2.4 SEASONAL VARIATIONS

Seasonal trends or traits are systematic and calendar related effects. Some examples include the increased demand of electricity in summer periods compared to any other periods. Some basic seasonal variations are increase in water consumptions in summer due to hotter weather conditions.

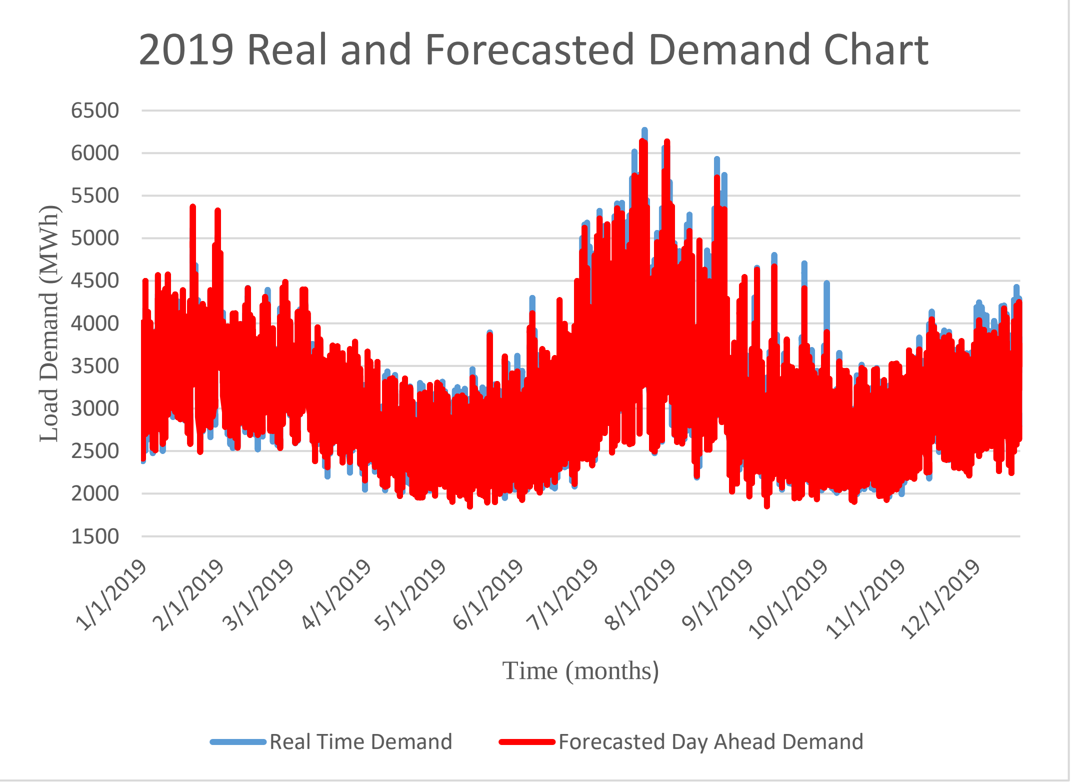


Figure 2.3. Seasonal variation of load demand over time.

The figure above shows a seasonal variation of load demand for Connecticut, as shown by the figure there is a sharp increase in electricity demand in summer more than during other seasons and the cycle repeats yearly.

To further understand seasonal trends, seasonal graphical representation of the NE-ISO electricity market will be given, where the total NE-ISO hourly electricity load in general is at its peak during afternoon summer months due to businesses and households using air-conditioning on the hotter days. Figure 2.4 illustrates these seasons and the peak demands during seasons. It can be seen that electricity demand follows a certain seasonal variation and these trends are affected by many factors but the most important are time of the day and temperature.

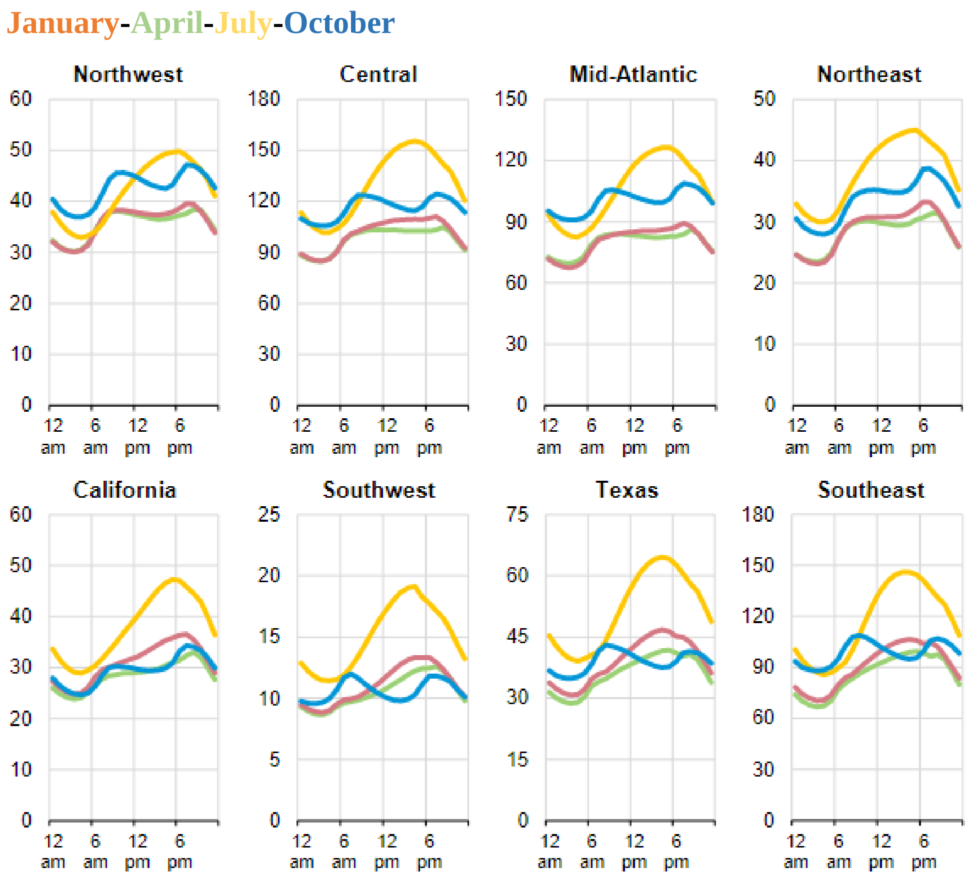


Figure 2.4. Average hourly electricity load during typical day by region

2.5 FORECASTING MODELS

Due to global warming, increasing household capacity and extreme temperatures in different regions has increased power demand significantly over the years, therefore, a variety of forecasting models are being implemented to counter for uncertainties in power grids. The integration of renewable energy sources and the increase in electrical vehicles also pose a huge threat on the smooth operation of electrical power systems. As huge amounts of data are being made public, researchers are now implementing state of the art forecasting techniques and others are even going to the extent of combining traditional methods with current technologies to enhance accuracy and model robustness. The development of deep neural network architectures and other hybrid methods have seen huge improvements in forecasting accuracy, reduced computational timing and generally have helped improve forecasting in different regions of available data.

Electricity load demand, on all aspects from short-term, medium, and long term is very much unpredictable as demand fluctuations all the time. The demand for electricity does not only change at the utility but also at regional or zonal level and major factors like economic profile of the country plays a vital role. Forecasting models can then be classified into three main categories; firstly, hybrid models, which are combinations of parametric and non-parametric models. Secondly, we have parametric models which consist of time series models and regression analysis models. Lastly, we have non-parametric models that implements the use of machine learning models under the artificial intelligence umbrella term.

2.5.1 Hybrid models

As seen in the literature, different models perform differently depending on the end goals of the researcher and the available data presented. Every model has its strengths and weaknesses when explored to different datasets or different market structures.

Hybrid models are being used because they promise to advance the existing time-series forecasting approaches by combining high performing machine learning and statistical models.

A combination of Artificial neural networks (ANNs) and Autoregressive Integrated Moving Average (ARIMA) were implemented in some literature to map the linear and non-linear trends for Jeddah's monthly peak loads. According to [28], the concept of using ARIMA as the initial forecaster and then feed the results into an ANN model showed significant improvement in the overall accuracy of the load forecaster. Another hybrid model was implemented in [29] where a combination of Support Vector Machine (SVM), Cuckoo Search Algorithm (CSA) and ARIMA showed again an improved accuracy of the forecaster but in this instance ARIMA was used as the primary forecaster and the data was fed into an SVM model structure.

Another author in [30] suggested the combination of ANN model and a fuzzy logic (FL) where FL was solely used on the training the neural network in a Short Term Load Forecasting (STLF) and this combination was given the name Fuzzy Logic Neural Network (FLNN) because of the combination model names and it showed improved forecasting accuracy than the conventional neural network model.

Another author in [31] implemented further the concept introduced in [30] and introduced a combination of advanced and evolving fuzzy neural networks which is known as Evolving Fuzzy Neural Networks (EFuNN) which was used to forecast short-term demand of about 48 hours ahead demand forecasting.

In a nutshell, there is quite an extensive amount of hybrid combinations available in the literature and to some extend they have been superior to other contemporary forecasting models available in the literature. With the increase of data and research interests there is going to be strong technological or model advancements in the area of hybrid electricity forecasting models. However, hybrid models don't have fixed set of combinations; contrary, the literature is constantly looking for fresh concoctions that will perform well given a specific sort of data to be employed.

2.5.2 Machine learning and DL models

In this section, we delve in the application of non-parametric approaches and their implementations in the literature. Machine learning approaches are a bit complicated in nature compared to some of the established approaches mentioned in this thesis. Therefore, a throughout analysis on them can be difficult since due to their immense theories and computational structures. The need to deal with various datasets with different trends and behavioral structures in different markets, is the reason why a deep machine learning model was introduced in this thesis because of its capacity to execute feature engineering on its own. Since huge amounts of data are now available from electricity markets, deep learning algorithms have an advantage since they have the ability to scan the data and attentively search for features that correlates and then combine them to unleash even faster learning without being instructed to do so. Numerous researchers has revealed that, while automated forecasting have consistently proven to be highly effective and accurate than human forecasts, many decision makers are still skeptical around the approaches and some don't fully commit in the technologies [32].

The implementation of computational intelligence approaches has been a popular area of study especially in load demand and LMPs forecasting. Over the years, researchers have implemented these machine learning techniques, with ANN being one of the popular techniques under study. The ability of ANN to model non-linear traits of load demand data was the reason researchers turned their focus on it. The author in [33] was one of the very first researcher to successfully explore the abilities of ANN and apply it in a competitive market to predict short-term load demand. The results showed high forecasting accuracy on hourly day ahead demand forecasting in the US electricity market [33].

The study of weather ensembles implemented by [34] showed great model stability with highly accurate forecasting metrics since he used a variety of weather variables as input with 51 different scenarios unlike other authors who only implemented a single scenario when it comes to weather variables. His results were accurate for a ten day ahead load demand forecasting but however, his model underestimated quite a number of demand forecasts periods which can results in systems black outs and higher electricity prices. To some extend his model was considered stable and reliable because used weather variables unlike the cut-throat models.

Over the years, neural networks (NNs) popularity has increased significantly and efforts to enhance its performance and accuracy, has become research's primary concern. For instance, the author in [35] carried out a study that included Bayesian structure for optimal decision making in choosing which ANN model can be employed and its internal characteristics like the number of hidden layers, the input feature selection to be used in the model. In contrast with other approaches in the literature, other authors have made use Non-linear Autoregressive Approaches (NARX) for short-term load forecasting a special type of neural network with an optimized architecture that shortens feedback time. However, the research examining their performance are limited.

Another popular approach for electricity demand and electricity price forecasting is the Support Vector Regression (SVR). This method has been used since the turn of the century, and it falls under the of support vector machines (SVM) machine learning category. Numerous comparisons have been made in literature, for example the comparison of auto regression (AR) with SVR by [36] on the Saudi Arabia and his contributions were involved in the pilot stages of SVR implementations in short term demand forecast. [37] employed all models mentioned in [36] for an extensive model that predicted monthly electricity demand in China and in that study the results showed that SVM was superior that ANN based on the evaluation of accuracy metrics.

In recent literature deep machine learning models have taken the center stage as they are proving to have more reliable and accurate forecasting models. The three common issues that has driven this thesis to strictly focus on deep learning is the lack of details to produce research that has been presented by some authors. The issues are stated below.

i. Insufficient evidence or explanation on the exact split of data for training and testing[38]–[44],
ii. The authors not being able to specify the datasets used [40], [45], [46], [47] and thus limiting other researchers to fully validate and compare research results and
iii. Poor indication of the used inputs or features for the forecasting model [42], [43], [48]–[50]
iv. Comparison of forecasting data from different markets.

The above-mentioned issues have gone overboard for some time now and the introduction of deep learning (DL) techniques looks to mitigate them by solely employing a programming environment (e.g., python) which has powerful open sources libraries and hence making available the forecasting methods to be used by other researchers. Another path that can be used, is setting up best practices on EDF and EPF studies so that conclusions on similar types of models can be easily made and fair comparisons can be attained.

2.5.3 Deep learning

There have been 28 deep learning studies published in the topic of EPF over the past five years. The number has now been progressively rising from just one paper in 2017 to 11 in 2018 and 16 in 2019. Notwithstanding this pattern, the majority of the published research have relatively restricted scope, use outdated statistical techniques, and have generalizable results.

The first DL paper to be published was [51] and it consisted of a deep learning network using stacked denoising autoencoders. Despite being the first, the research offers a more thorough review than other studies because it compares the novel method not just to machine learning techniques but also to two state of the art statistical methodologies. However, the evaluation is constrained because it only considers models test period with three months' worth of data. An idea for a DNN for modeling market integration is put forth in the second published DL article [52]. The drawback of this proposed model was that, it was not examined against other machine learning or statistical approaches, even if the method is evaluated across a year's worth of data.

Four DL models—two Recurrent Neural Networks (RNNs), a Convolutional Neural Network (CNN), and a DNN—are proposed in the third published paper [52]. To the best of my research knowledge, this study is the most comprehensive one to date. A benchmark comprising 23 alternative models, including 7 machine learning models, and 15 statistical approaches were used to compare the suggested DL models in particular using a full year of data. Additionally, the state-of-the-art statistical approaches, fARX-Lasso and fARX-EN, are included in the comparison of statistical methodologies. Although the study demonstrates the advantages of DL algorithms, it is impossible to draw particularly firm conclusions because it only considers one market.

The subsequent papers in 2018 primarily addressed one of three issues: comparing the effectiveness of various deep recurrent networks [44], [53], [54], [55], suggesting novel hybrid techniques based on CNNs and LSTMs [56], [57], [58], [59] or using conventional DNN models [54]. Regardless of the area of study, they were all more constrained than the first and third research [51], [52] because they did not evaluate the new DL models with cutting-edge statistical techniques and/or did not use lengthy datasets to draw firm findings.

The primary objectives of the papers in 2019 were similar to those in 2018:

i. assessing the performance of various deep recurrent networks, primarily LSTMs [60], [61], [62], [63], [64], [65], [66],
ii. presenting novel hybrid deep learning techniques, typically based on LSTMs and CNNs [67], [68], [43], [64], [69], [70], [71], or
iii. utilizing conventional DNN models [72], [73], [74].

While some studies [60], [75] attempted to compare the suggested approaches with already-existing DL models [52] in this context, they either neglected to re-estimate the benchmark models for the new case study [60] or over fit the DL benchmark models [75].

Furthermore, the author in [75], investigated a neural network that uses order book data, and it was then compared with DL techniques previously proposed in the literature, such as those in [52]. The DL approaches from the literature are taught to over fit the training dataset, even though the new model performs better than the existing DL methods. As a result, it is impossible to judge how well the new model performs because the comparison is misleading (thus the DL benchmark models would inevitably do poorly on the test dataset). The author in [69], employed and presented a DL hybrid forecasting technique based on normal auto encoders for feature selection, stacked denoising auto encoders for pre-training the dataset, and a crude DNN as a forecasting method.

The approach was solely evaluated against the conventional machine learning methods, as seen in earlier publications. Additionally, the significance of each of the hybrid method's four modules is not examined, and the models are trained only once and evaluated throughout a full year by the authors without being re-calibrated with fresh data. Similar to this, [70] suggests a CNN hybrid model for feature selection that makes use of consensual information, gray correlation analysis, random forests, and recursive feature elimination. The algorithm is taught to classify prices rather than predict their scalar values, which is different from most models; nevertheless, the specifics of how this process is carried out are not given. Furthermore, the strategy is only tested for less than a year of data and only compared against standard ML algorithms (the study uses one year for testing and training, but the split is not specified). Similar to other studies, [43] suggests a hybrid approach for micro grids based on CNNs and RNNs. However, unlike other studies, [43] only evaluates the method on a small dataset and does not compare it to cutting-edge statistical techniques or specify the precise split between training and test datasets.

2.5.4 State of the art models

It is exceedingly difficult to determine which techniques are the state-of-the-art because of the issues that have been mentioned when comparing EDF and EPF models. Nevertheless, it may be argued that the LEAR is a very accurate (if not the most accurate) linear model based on the experiments conducted in recent years. It may also be claimed that by utilizing variance stabilizing operations on the prices, combining forecasts from various calibration windows, and/or employing long-term seasonal decomposition, the accuracy of this model can be increased even further.

The selection process is more difficult in the case of machine learning models because the quality of the current comparisons is low. A straightforward DNN with two layers appears to be among the best ML models when considering the most comprehensive benchmark study in terms of forecasting models in [52]. Particularly, whereas more intricate models, like LSTMs may be more accurate, there is currently no solid evidence to support this assertion.

It is impossible to determine which hybrid model is the best in this situation. First off, despite the fact that numerous hybrid techniques have been put forth, neither they nor the LEAR or DNN models have been put side by side for comparison. Second, it is impossible to determine the optimal algorithms for each hybrid component because the majority of research do not assess the individual influence of each hybrid component. For example, it is unknown which clustering, feature selection, or data decomposition approaches are best.

In light of this, this thesis considered the LEAR and the DNN as the ultimate model candidates for the research. In instance, these two approaches are not only very accurate but also quite straightforward. As a result, they serve as the ideal comparison points for new, complicated EDF and EPF forecasting techniques.

CHAPTER 3

ELECTRICITY ECONOMICS

3.1 INTRODUCTION

It is essential to distinguish the various organizations and entities that are involved in electricity markets before we begin to analyze the markets. Presumably, we will go into a deeper discussion about the motivations and functions of each of these market players in the sections that follow.

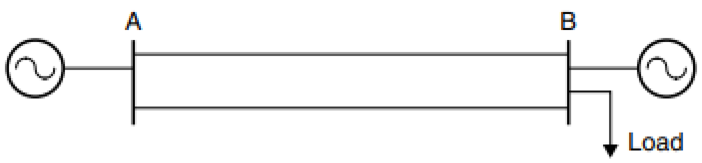


Figure 3. Two-bus power system used to illustrate a simple power systems network.

Since electricity markets have been evolving due to power systems technological advancements, overall capacity increase, economic growth, and other individual factors in electricity markets. It is really difficult to find common patterns that can be used as conclusive evidence for different electricity markets in different countries or regions. For example, in some regions one company might be responsible for the electricity generation, transmission and distribution and also be responsible for a wide range of functions that are described in detail below. Not all of these entities will be present in every market because markets have evolved at varying paces and in substantially distinct patterns in each country or region. One business or organization might occasionally handle more than one of the responsibilities listed below. Figure below shows an entire power system from the generation aspect to loads for Northern Cyprus.

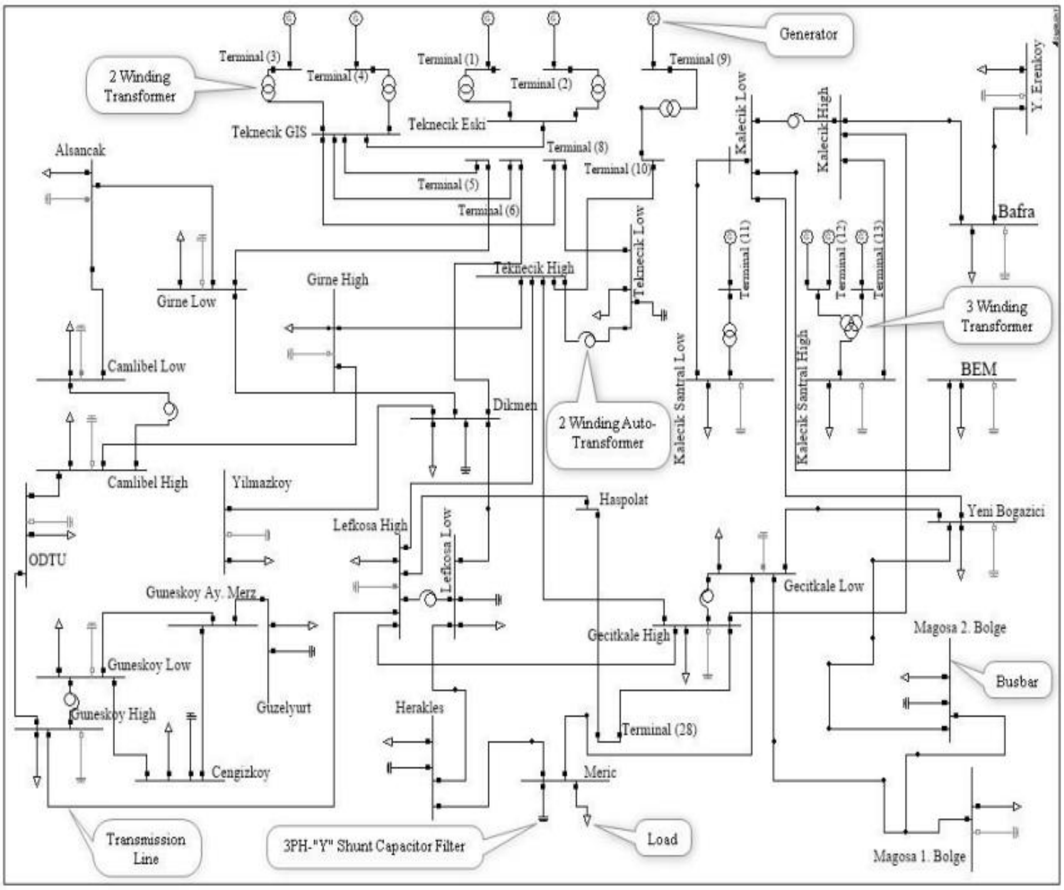


Figure 3.1. TRNC Transmission system network

3.1.1 Vertically integrated utilities

These set of utilities own the power generation plants, transmission networks and the distribution networks. Such an organization exercises monopolistic rights over the supply and transmission of power within a specific geographical area in a conventional regulated environment. Now that the electricity market is a more liberated playing ground, the generation, transmission, and distribution networks are largely decoupled.

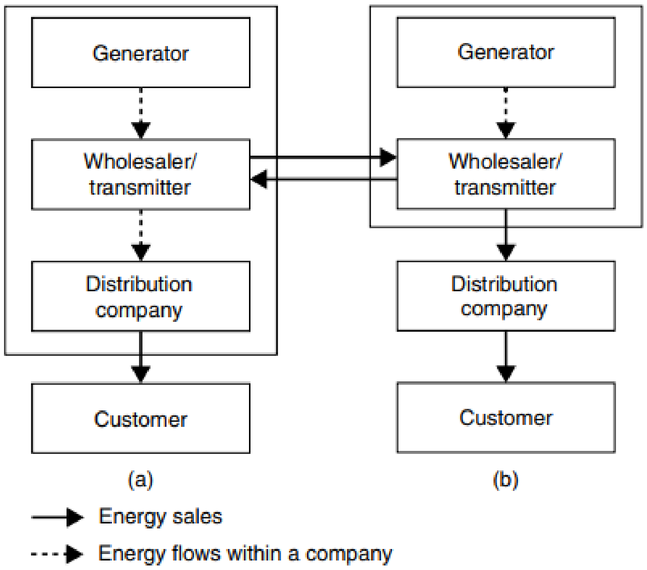


Figure 3.2. Shows a monopolistic electricity market model

The monopolistic electricity market was derived from [76]. Where sub-model (a), the utility is completely vertically integrated, whilst in sub-model (b), the distribution is handled by one or more separate companies

3.1.2 Generating companies (gencos)

These entities generate and sell the electrical energy to retailers or to big consumers and they are called (gencos). Additionally, they might offer ancillary services that the system operator needs in order to maintain the reliability and security of the electrical supply, such as regulation, systems reserve, and voltage profile management. An energy producer may own various generating plants or a single plant that are based on a diverse technological advancement. Independent power producers (IPPs) can be somewhat be simplified as entities or individuals that can generate power independently and coexist with the vertically integrated utilities.

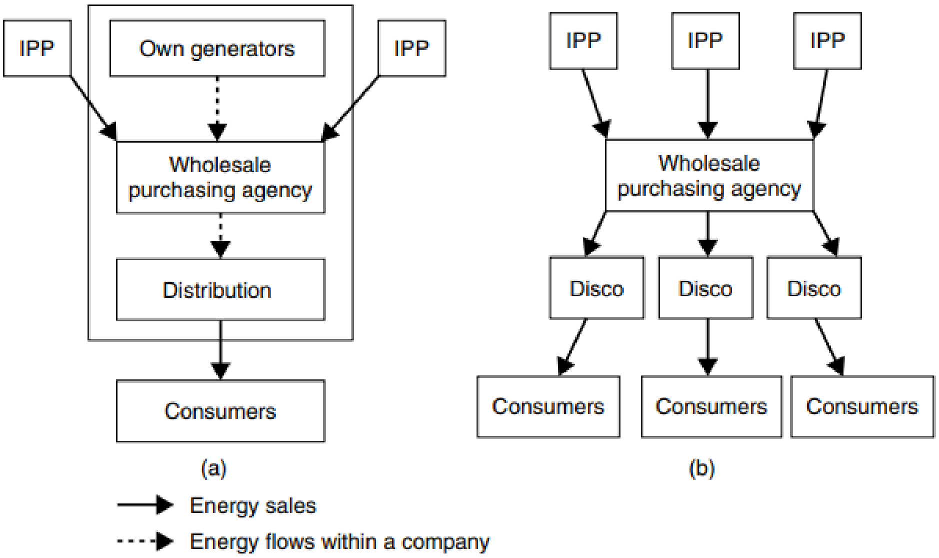


Figure 3.3. Shows the purchasing agency model of electricity market based on [77]. (a) integrated version; (b) disintegrated version

As depicted in part (a) of figure 3.3, the model shows a complete vertical structure where one single company own the generation, wholesale purchasing and distribution, while in part (b) the distribution of power is managed by different entities. Since IPPs are directly connected to the network, they can effectively sell electricity to the utility they are connected to, which in this case acts as the purchasing agent, as shown in part (b), as a result of being linked to the network. A further analysis to the model can be made in figure 3.3 (b), where the grid utility doesn’t own the generation, therefore it has to buy the electricity from independent IPPs. Additionally, the retail and distribution activities are broken down. The energy used by their patrons is subsequently purchased by discos from the wholesale purchasing organization. The issue of monopoly can be mitigated by regulating the rates issues by the purchasing agency since they have purchasing power over the generating and IPPs entities.

3.1.3 Distribution companies (discos)

Distribution networks are owned and run by distribution companies (discos). In an orthodox setup, discos do possess a monopolistic power over the sale of electricity to all the customers connected to their network. In recent times the selling of electricity to customers is now separated from the running, maintaining, and expansion of the distribution network due to regulation of power systems. Following that, retailers will then have to compete to be involved in the activity to sell energy. In some cases, these entities might be a subsidiary to a local distribution company.

3.1.4 Retailers.

Since the markets have approved market players, buying, and selling electricity as a commodity must be monitored. Since we have some consumers who do not wish or are not allowed to participate in the buying and selling of electricity, retailers can act as middle structures that purchase the commodity on the market and deliver it to the designated customers. In modern regulated markets, retailers can be market players that necessarily don't have to own any sort of generational, transmission and distribution as they have the capability to just be business oriented. A retailer's customer base must not be linked to the same distribution company's network.

As this thesis is forecasting the hourly day ahead demand and price, an example was suggested on how the approach can assist retailers in the market. A retailer acquired an amount of electricity to satisfy demand after forecasting client demand for 12 hours. Each hour's buying price is determined by a combination of contracts (short-term, long-term bilateral, screen-based transactions, future, and forward contracts. The average and total energy costs purchased for each time are displayed on the 4th and 5th lines of the table below. When demand is at its peak, the average price tends to increase because entities will have to resort to much more expensive generators to cater for increased demand. It is nearly impossible to not have negative and positive imbalances between power generated and load demand because the power system can never forecast such scenarios at a hundred percent rate but can design models that improve accuracy metrics to reduce the deviations which is what this thesis is also working on.

Period	**Units**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Average**	**Total**
Load forecast	(MWh)	221	219	254	318	358	370	390	410	382	345	305	256	325	3828
Contract purchases	(MWh)	221	219	254	318	358	370	390	410	382	345	305	256	325	3828
Average costs	($/MWh)	24.70	24.5	27.50	35.20	40.70	42.40	45.50	48.60	44.20	38.80	33.40	27.70	36.10	
Contract costs	($)	5459	5366	6985	11 194	14 571	15 688	17 745	19 926	16 884	13 386	10 187	7091	12 040	144 482
Actual loads	(MWh)	203	203	287	328	361	401	415	407	397	381	331	240	330	3954
Imbalances	(MWh)	−18	−16	33	10	3	31	25	−3	15	36	26	−16	10.5	
Spot prices	($/MWh)	13.20	12.50	17.40	33.30	69.70	75.40	70.10	102.30	81.40	63.70	46.90	18.30	50.35	
Balancing costs	($)	−238	−200	574	333	209	2337	1753	−307	1221	2293	1219	−293	742	8901
Total costs	($)	5221	5166	7559	11 527	14 780	18 025	19 498	19 619	18 105	15 679	11 406	6798	12 782	153 383
Total revenues	($)	7815.5	7815.5	11 050	12 628	13 899	15 439	15 978	15 670	15 285	14 669	12 744	9240	12 686	152 229
Profits	($)	2595	2650	3491	1101	−882	−2587	−3521	−3950	−2821	−1011	1338	2442	−96	−1154
Profits w/o error	($)	3050	3066	2794	1049	−788	−1443	−2730	−4141	−2177	−104	1556	2765	241	2896

Figure 3.4. illustrates the daily operation of a retailer.

These imbalances are compelled to be then cleared at the spot market price displayed in row 8th of figure 3.4, which increases our retailer's revenue or balancing costs (given a scenario that the power imbalances are negative). The entire energy cost for each hour can be calculated by adding the balancing and contract expenses. In this example we will presume that the market player (retailer) has opted for a fixed charge tariff structure and requires all the consumers to pay a minimum fee of $38.50 per megawatt-hour (MWh). The amounts that accrue for each hour are displayed in the table's "Total Revenues" and "Profits" lines. When prices are low, our retailer generates an operational profit; but when prices are high, they make a loss.

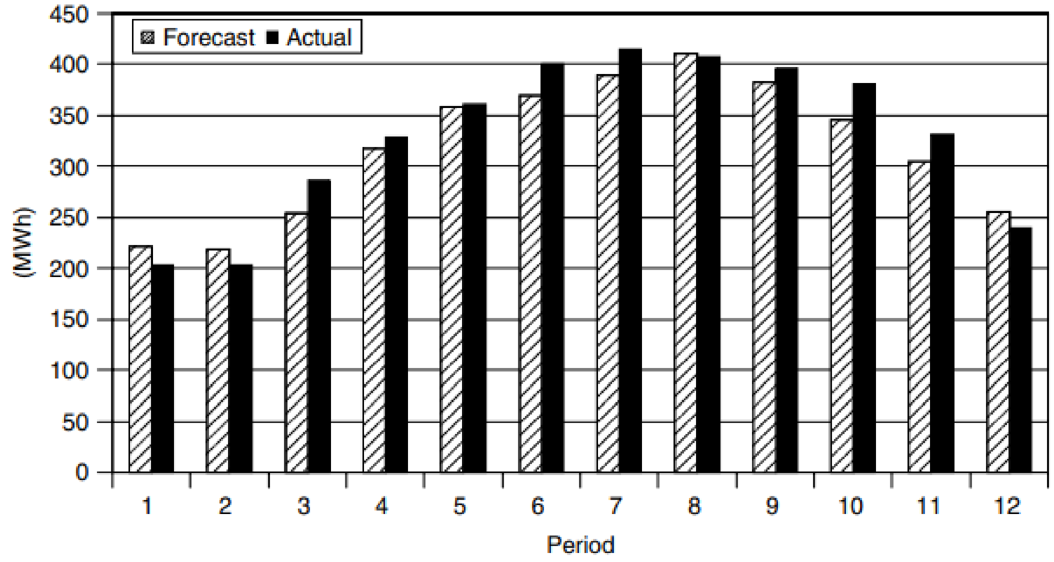


Figure 3.5. Forecast and actual demand for Example 1

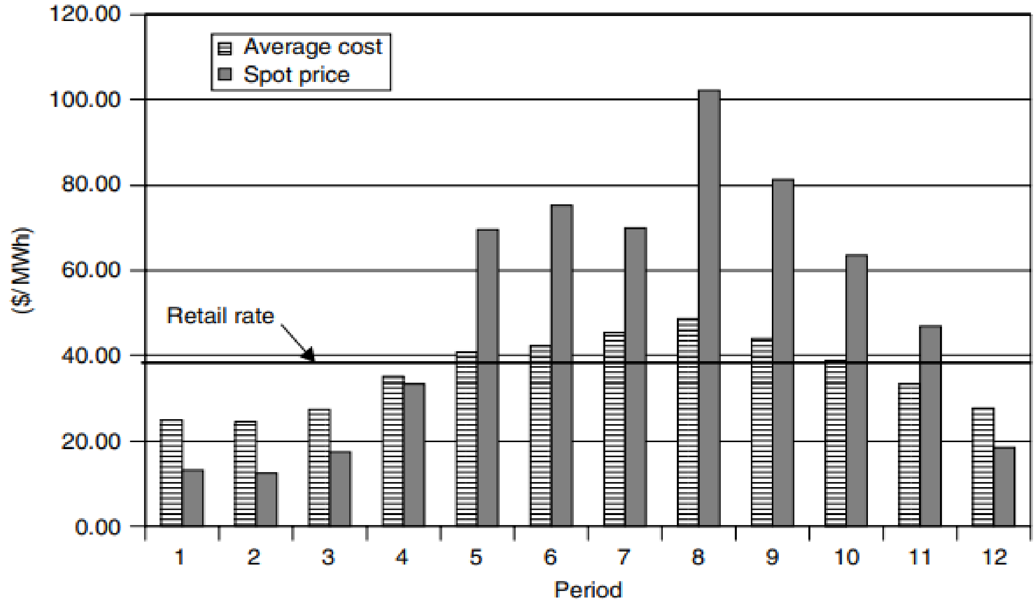


Figure 3.6. Costs and prices cost analysis for Example 1

Overall, the bottom line for these 12 hours' electricity price reveals a $1154 deficit accumulated due to high electricity prices. The retailer should, therefore, try to counter for such occurrences and hope it's the markets cycle, and that other days will have lower average electricity purchase prices. The retailer can reduce losses and improve the comparatively balancing costs if he employs accurate forecasting techniques, which in turn will reduce the overall imbalances on the supply and demand curve. To demonstrate this idea, the final line of the chart displays the profits that would be realized if actual demand matched predicted demand and the store was not susceptible to spot prices. Our retailer would have generated $2896 in profit if this ideal projection had come true during this time.

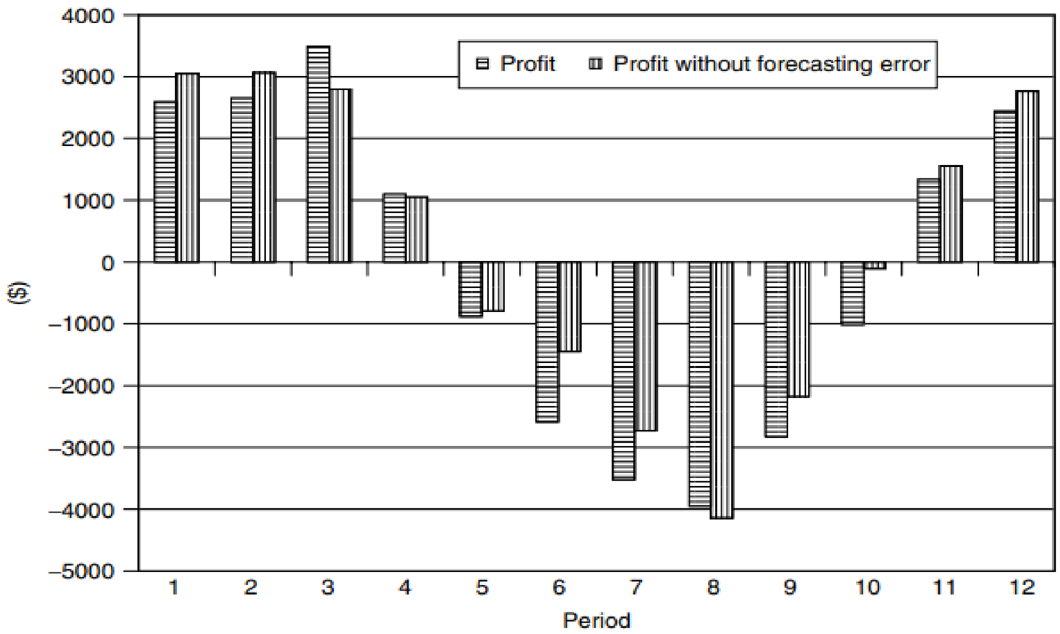


Figure 3.7. Costs and prices forecast analysis for example 1

3.1.5 Market Operator (MO)

Since short-term electrical transactions are cleared in a matter of few seconds to hours, a sophisticated computer system is in place to match the offers made by buyers and bids submitted by sellers to be cleared in real time. These computer systems or structures are monitored by the market operator (MO). Additionally, it handles the payment of bids that have been accepted and also submitted proposals, it then transfers payments made by buyers into the seller's accounts automatically only when the energy delivery has been triggered. The market of last resort, or the market where load and generation are constantly balanced, is often run by ISOs. Independent for-profit market operators frequently oversee markets that close ahead of actual time.

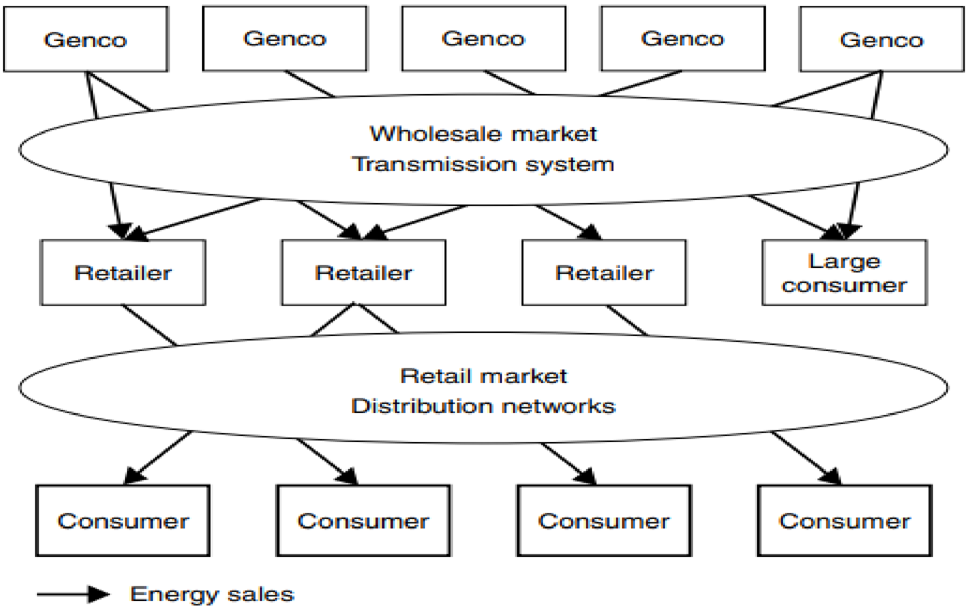


Figure 3.8. Retail structure for a competitive electricity market model.

The ideal competitive power market, where each consumer can select their supplier, is depicted in the Figure above. Some of the biggest consumers like mines, manufacturing companies, etc. do have the options to buy electricity directly from the wholesale market due to the low transaction expenses unlike the majority of small and medium-sized consumers which acquire the purchasing power from local distribution companies. Retail prices no longer need to be regulated once markets are sufficiently competitive since small consumers can switch retailers when given a better deal. Such a structure is quite appropriate from an economics point of view since market interactions determine energy prices, as we will discover in the following chapter sections. However, implementing this paradigm necessitates a large amount of data processing, communication, and metering.

3.1.6 Independent system operator (ISO)

ISOs are primarily in charge of preserving the electrical system's safety and security, because power system networks are obliged to run smoothly to avoid contingencies and penalties that might come to one market participant over another if any rules are violated in an independent competitive environment. In comparison to MO mentioned in section 3.1.5 the ISO only have access to the computational and communication resources needed to oversee and monitor the status and operations of the power system. An ISO often combines the responsibilities of the market operator as a last resort if other market structures are inoperable.

3.1.7 Transmission companies (Transco)

Reactive compensation devices, lines, cables, transformers, and other transmission assets are owned by transmission companies (Transco). They run these machinery following the independent system operator's instructions. Occasionally, firms that also operate producing facilities have subsidiaries that are transmission companies. A separate transmission company (ITC) is a transmission firm that also serves as an independent system operator but does not own any power facilities.

3.1.8 The regulator

The regulatory body is in charge of guaranteeing the equitable and effective electricity market and grid operation. Its main purpose is to establish and adopt the regulatory body governing the electricity market and looks into alleged instances of power abuse. The regulator also sets the price of commodities and services offered by market players to mitigate monopolistic behavior and improve overall competition.

3.1.9 Large and Small consumers

Large and small consumers play a vital role in the electricity market. Small users like residential areas, shops and electric vehicles sign an agreement to have a power connection from their local distribution entity or municipality so they can have the purchasing power to buy electricity at a smaller scale. When individuals have this option, their involvement in the power market typically only entails picking one retailer from a list of options.

On the other hand, large customer like industrial companies, heavy duty mines etc., are directly involved in the market due to them purchasing huge quantities of energy, therefore usually buying direct from the generating companies. Some might provide the ISO with a resource, their capacity to manage their load, so the ISO can control the system. Large customers may occasionally be directly connected to the transmission system.

3.2 ELECTRICITY MARKETS

Since storing vast amounts of electrical energy is very costly, it therefore must be produced or generated concurrently with demand or consumption. Therefore, any electrical energy that’s traded-in is always related to specific time periods and for specific number of MWh to be filled. Such assumptions do vary depending on the nation or region where the market is located, these time frames are classified in a range starting from 15 minutes, 30 minutes up to an hour. Therefore, having classified time slots will obviously mean that the price will vary according to time because commodity prices change over time due to different delivery and generation timings. However, the beginning of each era does not see a clean transition in demand, hence, to keep the system in balance, some production modifications must be performed much more frequently. Even if these changes result in energy trades, it is best to approach them as services rather than commodities.

The concept put in place to trade electricity as a commodity has been the foundation for the growth of electricity markets. The markets behavior between various commodities like barrels of oil, gas, bushels of wheat to electricity significantly differs. Since electricity energy cannot be kept for when its needed or the process is costly as compared to other commodities, therefore such distinctions have significant impacts on the structure and regulations of the power markets. The primary importance is those physical systems that work considerably quicker than markets tightly tied to electrical energy. To reiterate the importance of power systems security, electricity generation and load demand should be balanced in every normal power system, and if the equilibrium fluctuates, the system can collapse with disastrous results.

Such a failure is intolerable since it might leave an entire country or region without electricity for several days, and the trading system fails. In major industrialized nations, bringing a power grid back online after a total breakdown can take up to 24 hours. Since a regular customer cannot purchase power directly from a single generating company, instead, the power produced by all generating companies is combined and delivered to various end users. The indistinguishability of the electrical energy units generated by various sources makes this pooling possible. Because pooling produces significant economies of scale, it is preferable to do so rather than summing the maximum individual needs. The most remarkable generation capacity must match the maximum aggregate demand. On the other hand, everyone, not just the parties to a specific transaction, is impacted when a system where the commodity is pooled fails.

Finally, there are regular daily and weekly cyclical variations in the demand for electrical energy. It is not the only item for which demand is cyclical. To provide a straightforward example, daily coffee consumption shows two or three firm peaks, followed by periods of decreasing demand. Coffee may be stored by customers readily in solid or liquid form; hence unique processes are not needed for trading coffee.

The kinetic energy held in electricity-generating units is much smaller than the amount of energy contained in gas pipes, therefore, it would take significantly longer for a gas production/consumption to turn back the system on and off in the event of a system outage or blackout.

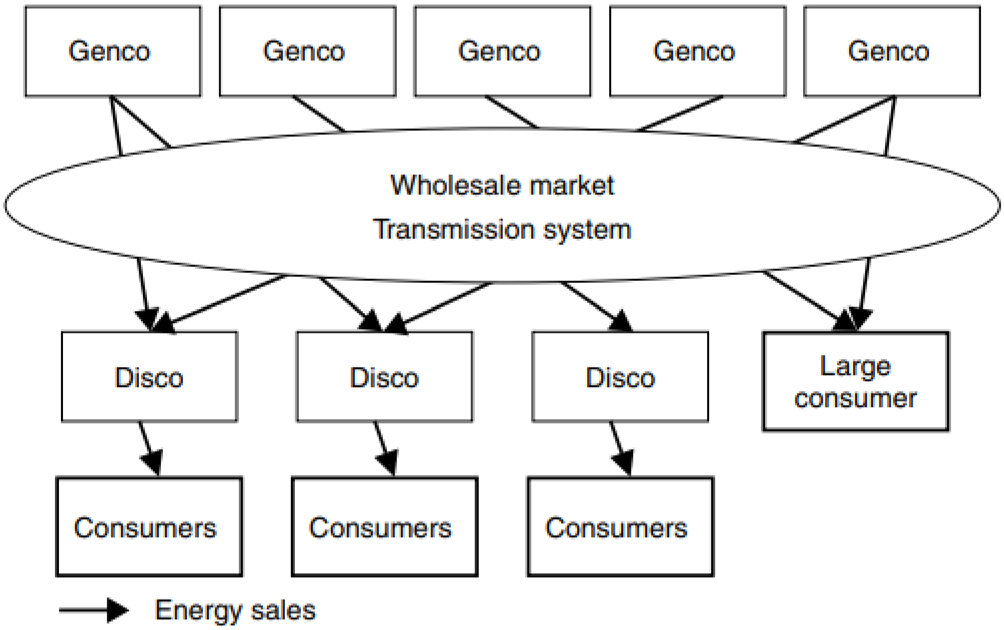


Figure 3.9. Electricity market wholesale model.

The illustration above demonstrates that no single entity is in charge of supplying electricity. Conversely, discos buy the electricity, and their clients use it directly from generating firms. These exchanges happen in a market for wholesale electricity. Heavy users are frequently permitted to purchase electrical energy straight from producers on the wholesale market. The system is essentially centralized just in the commercial sector because each disco manages the local distribution network and makes energy purchases on behalf of the customers within its service area.

The fact that supply and demand interact to set the wholesale price under this model significantly increases the competitiveness of the generating companies. However, the retail price of electrical energy must continue to be regulated because small consumers cannot switch to a different supplier if they feel the price is too high. As a result, the distribution firms are vulnerable to abrupt, significant rises in the cost of energy at the wholesale level.

3.2.1 Spot market

To simplify how a spot market works, we use the everyday fruit and vegetable market example, you notify the seller of the number of fruits you want let's say cucumbers, the sellers' hands them over to you, you check if it's the correct product and quantity and the seller immediately expects the payment, then the transaction is done. The regulations governing these markets may initially seem to be relatively similar because they have centuries of tradition bearing down on them. Due to the more significant trade volumes and the usage of electronic trading, modernized spot markets for other commodities e.g., barely, coffee and oil operate in a much flexible way compared to an electricity spot market. The fundamentals, however, remain the same. The immediate nature of the spot market is advantageous. I can sell the available goods if a buyer shows up because I am a producer.

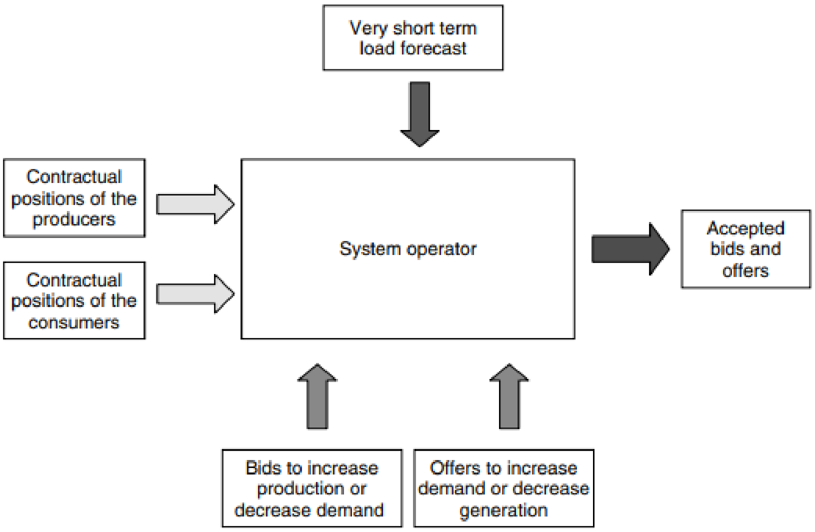


Figure 3.10. Shows an operated electricity spot market

I can buy just what I need as a consumer. Unfortunately, prices in a spot market frequently fluctuate. The supply of items available for immediate delivery may be restricted, which causes the price to soar in the event of a sudden spike in demand (or decrease in output). Similarly, a surplus of supply or a drop in demand lowers prices. Spot markets also reacted to information about a commodity's upcoming availability. For instance, if enough purchasers have the patience to wait until a predicted bountiful harvest of an agricultural item hits the market, the spot price of that commodity could plummet.

Since market players wouldn't anticipate changes in the spot price if they were predictable, changes in the spot price are effectively unpredictable. Both sellers and purchasers of a commodity experience more difficulty due to the large and unexpected price fluctuations. Each of them is an entrepreneur; thus, they both incur the risk of various dangers.

A harvest can be ruined by bad weather or a bug. Production may halt if a machine malfunctions. Employees going on a strike can hinder production and in worst cases terminate the transport of readymade items. The downside of being in business is the issue of taking risks, too much risk imperils a company's ability to survive. Therefore, most organizations will work to minimize their exposure to price concerns. For instance, a commodity producer will try to avoid selling their product for a meager price. A consumer also doesn't want to be forced to pay a high price for a necessary good. Several kinds of transactions and markets have been introduced as a result of this goal to minimize risk of wildly fluctuating electricity price typical in spot markets. The following sections provide insights and descriptions of other contemporary markets.

3.2.2 Forward markets and contracts

To better understand the concept of forward markets and contracts an example will be used, suppose Honest Jimu is a wheat-raising farmer, although it is only the beginning of summer, he is certainly sure to supply one-hundred tons of wheat upon harvest to food enterprise Pretty Good Breakfast. However, he takes price changes quite seriously therefore he would prefer to "lock in" a fair price right away and stop worrying about selling once the wheat is ready and probably at a loss due to a flooded market. Will he be able to locate someone willing to accept such a bargain? The food enterprise Pretty Good Breakfast is skeptical on paying a higher price for the wheat it uses to manufacture its famous pancake recipe, just as farmers are anxious about selling at a low price in case it might be cheaper in the future. If both parties agree on a certain fee to buy and sell the product on their stipulated terms, we can define that as forward contracts and basically how forward markets works.

- Delivery date and payments following delivery
- Quality and quantity of wheat to be delivered

- Stipulated price to be paid
- Penalties for both parties if they fail to honor such commitments

Each party begins by estimating the spot price at the delivery time as accurately as possible. This prediction considers past spot pricing data and any other knowledge the farmer and the food-processing business may have on harvest yields, long-term weather predictions, and demand forecasts. The estimations of both sides at any one time are unlikely to be drastically different because a lot of that information is readily accessible to the general public. Nevertheless, due to varying negotiating stances, the price settled upon for the contract may vary outside the best projections. Farmer Honest Jimu might commit to a price lower than what he anticipated the spot market price to be if he worries about the potential of a meager price. The premium he is prepared to spend to lessen his vulnerability to an unfavorable price fluctuation is the difference between the anticipated spot market price and the forward contract price. The farmer, Honest Jimu can suggest a premium price that might be slightly higher than the expected spot market price to counter for price increase risks from the food processing company. The seller can sustain some losses if the delivery spot price exceeds the predetermined price and can obtain huge profits if the situation is otherwise. The forward contract indicates a loss for the buyer and an income for the seller; however, if the spot price is higher than the agreed price.

3.2.3 Future contracts and futures markets

Owing to the growth of a secondary market where producers (generation companies) and consumers (loads) of the commodity (electricity) can purchase and sell standardized electricity market forward contracts, such players in the market can better manage their exposure to price swings. In such a market, companies that generate (produce) or consume (loads) the product i.e., electrical energy in this case are the only entities allowed to take part in such a market. There can be companies not allowed to participate or don’t have the privilege in other markets, do prefer to be involved in future markets and future contracts. These companies are usually a set of investors that are profit oriented, in the aspect that they want to buy electricity and sell it at a later date for profit or sell an existing contract to buy another later at a cheaper price.

They are known as futures contracts rather than forwards since they are not backed by actual delivery. Since they can create, utilize, or retain the commodities, the participants should adjust their stance as the delivery date draws near.

We could be wondering at this point why any sane individual would want to operate in this manner. To keep the market substantially competitive the future prices should mirror or not deviate much from the expected spot price and all market players should be carefully informed. So, it would appear more like gambling than a wise business approach to purchasing low and expecting to sell high. Thus, one needs an edge over other investors to succeed as a trader. Being less risk-averse than other market players typically give you this benefit. Some companies' shareholders anticipate steady but typical returns. Therefore, risk aversion in an electricity market is really important because it avoids the business from negative exposure that brings huge losses if not carefully assessed.

On the other hand, shareholders in businesses that speculate on commodities aspire for extremely high profits, but they shouldn't be shocked if they occasionally experience significant losses. Participants are better positioned to balance losses against earnings over a lengthy period of time since they do not incur additional risks and have substantial financial resources. Additionally, most traders don't stick to trading a single commodity. They further limit their risk exposure by diversifying into marketplaces for various entities, even though market participants usually profit from electricity trading, the market gains from their trades since their participation broaden the players' pool and this improved liquidity aids in the market's determination of a commodity's price. The downside of that is, it is simpler for other market players to discover counterparties for their trades (i.e., generation and loads behavior and trends)

CHAPTER 4

CONTINGENCY ANALYSIS FOR POWER SYSTEMS

The aspect of reliability in power system networks has huge implications on the overall system operations, particularly in large, interconnected modern networks where severe blackouts are a huge possibility. To optimally design a power system network, reliability constraints, such as the economical aspect of the system should be taken into consideration for smooth operations. Transmission lines should always be available to sustain and deliver the power from the generation plants to the end users (loads), and there should always be equilibrium between generation and load demand as to mitigate cascading system outage scenarios. When no system components malfunction, power systems ought to function smoothly. On the basis of the N-1 contingency principle, power systems must also be built so that they can operate effectively without violating their limitations when a system component fails.

4.1 CONTINGENCY ANALYSIS

Electrical power systems are massive infrastructures that are susceptible to various malfunctions due to internal factors such as short circuits or external factors like bad weather i.e., typhoons, hailstorm etc. It is difficult to build a power system with enough security to protect against all potential failures but doing so increases power system security and lessens the likelihood of unplanned blackouts. Since the working conditions of the system are continuously changing, reliability of the power system should be tested periodically. The most frequent power system failures are interruptions in transmission lines and generators. Failures in transmission and distribution lines alter the bus voltages and power flows of the remaining lines therefore posing severe consequences on the remaining parts of the power network.

To counter for future system black outs and transmission line outages, line flows and bus voltages for every given outage scenario should be forecasted so that preventative and remedial measures can be taken when there are line outages. The operational conditions of the other generators as well as the transmission lines alter when a generator outage occurs in the power system. The balance between loads and generators is disrupted when generation units fail, which lowers the frequency of the power system. The remaining generators, assuming they are working within their maximum output restrictions, should take the remaining generated burden in order to restore the frequency which might lead to catastrophic outages when the generation does not meet the demand. Load shedding will occur to restore electricity system frequency if the remaining generators are unable to make up the shortfall.

In order to avoid this such instances, all the other generators should be run at a capacity greater than the slack bus in the power system. This unoccupied capacity from the slack bus is known as spinning reserve, and it is used to make up for losses and imbalances that occur during operations by absorbing reactive power and emitting active power to and from the system. Line flows or bus voltages limits are susceptible to transformer outages, generator outages and transmission line failures. Evaluation of all failures is desired but impractical because each failure could result in the worst violation of the system's operation. Operators generally examine potential faults as frequently as possible [78], [79].

Outages can influence active and reactive power losses on transmission lines. As shown in Equations (4.1-4.2), the active and reactive power losses depend on line currents (I_I). Therefore, any change in line flow will lead to a change in active and reactive power loss in a power system.

Active and reactive transmission line losses are immensely influenced by the outages. Equations 4.1 and 4.2 illustrates the active and reactive power losses concept where the power losses are rather dependent with line currents (I_I). This makes the analysis a bit simpler because any slight active and reactive power loss in a power system will therefore alter as a result of any change in line flow.

$$P_{loss} = \sum_{all\ lines\ 1} R_l I^2{}_l \tag{4.1}$$

$$Q_{loss} = \sum_{all\ lines\ 1} x_l I^2{}_l \tag{4.2}$$

Where R_l and x_l are line l resistance and reactance.

Transmission lines behave a bit different from other structures in a power systems network because they produce reactive power (Q_{gen}) and consume another set of reactive power (Q_l) as illustrated in equations 4.2 and 4.3 respectively. These reactive power losses have huge negative impacts on the transmission line voltage levels, therefore the need control as to achieve more stable networks is essential.

$$Q_{gen} = -\sum_{all\ lines\ 1} \left(B_{capl} V^2{}_{sl} + B_{capl} V^2{}_{rl}\right) \tag{4.3}$$

Where the variables B_{capl}, V_{sl}, V_{rl} represent line susceptance, sending and receiving end voltages, respectively. Contingency analysis defines which transmission line outage or generator outage will lead to a violation in the line flows or bus voltages. Contingency analysis models any single outages and multiple outages to predict system states. The line flows and bus voltages are checked against their limits in the contingency analysis. The convergence speed of contingency analysis is important because the number of contingencies is extremely high in large power systems, and the power system operating condition changes constantly.

The transmission line outages or generator failure that will cause a violation in the line flows or bus voltages are calculated and estimated using contingency analysis. To have a better understanding and forecast system states, contingency analysis models scenarios where a system can have a single or multiple failures for a conclusive analysis. In this state-of-the-art analysis, the line flows and bus voltages are compared to their limitations to check for potential violations and system smooth operations. The number of contingencies in larger power systems is high due to the obvious reasons like size, and the operational condition of the power system is continually changing, therefore the convergence speed of contingency analysis, load demand or locational marginal price forecasting are crucial in their respective criteria.

Since bus voltages are often not a major concern in other systems, contingency analysis utilizing a DC power flow calculates line flow more precisely and quickly than the AC power flow, however that’s not usually the case, other power systems have bus voltage issues therefore a conclusion on which analysis should be used comes to play. This means that in order to forecast the system states following a particular interruption, contingency analysis employing an AC power flow is necessary. It should be noted that not every interruption results in a violation of system restrictions, and that it is impossible to immediately complete an AC power flow analysis for every outage. AC power flow is both superfluous and impracticable for contingency analysis.

A process known as "contingency screening" or "contingency selection" involves choosing the most significant eventualities employing a DC power flow, and therefore review the selected contingencies for specific situations using an AC power flow [80].

4.2 POWER SYSTEM LINEAR SENSITIVITY FACTORS

Power systems have employed sensitivity analysis techniques to extensively prevent having to recalculate the systems power flow. The line outage distribution factors (LODFs) and the power transfer distribution factors (PTDFs) are the metrics employed in these assessments for power flow in transmission networks. The term "PTDFs" refers to changes in line power flows brought on by a change in power injection at a specific bus. According to their definition, LODFs are variations in line power flows brought on by the disconnecting of a specific line [81]. The need for quick online readjustments in contemporary power systems has recently spurred interests in the calculation of these sensitivity factors.

Owing to congestion of transmission lines and human operators' operational consciousness, cascading failures can be defined as a series of component outages that includes at least one triggering component outage and subsequent tripping component outages occurrence [82]. These have been the main problems causing the electrical system's reliability to deteriorate, necessitating action to reverse the power flow on overloaded lines.

Electrical power is then rerouted to adjacent transmission lines when a single line fault or multiple line faults occur in the system. In most cases, this leads to undesirable operating situations when the transmission lines are being overloaded, or transferring power above their intended capacity, leading to cascading faults or entire system blackouts. The congested line should therefore be cleared of the additional load in order to prevent such circumstances. In order for a security analysis to be useful to the operators, it must be completed relatively rapidly. This is the point at which distribution factors like the LODFs and PTDFs must be computed.

These distribution factors provide the system operators with quick critical solutions for systems optimal power flow in terms of power injected and power leaving the network and they are usually based on DC techniques [83].

If a rapid presentation of the results is desired, the challenge of analyzing hundreds of potential outages becomes very challenging to address. Utilizing linear sensitivity factors is one of the quickest ways to provide a swift estimate of potential overloads. These variables, which are obtained from the DC load flow, depict the approximate change in line flows for changes in generation on the network configuration. Power Transfer Distribution Factors (PTDFs) and Line Outage Distribution Factors (LODFs) are the two main types of distribution factors which can be determined in a variety of ways.

4.2.1 Power Transfer Distribution Factors (PTDFs)

PTDFs best describe the how the active power flow when the power is transferred from bus i to j on a single line (line 1). Equation 4.4 shows illustrates the concept.

$$PTDF_{i,j,l} = \frac{\Delta f_l}{\Delta P} \tag{4.4}$$

where:

i = bus where power is being injected

j = bus where power is being drawn or taken out

l = line index

Δf_l = line l active power flow change in MW

ΔP = power transferred from bus i to bus j

The new active power flow for each of the lines of the system can be calculated by using predetermined PTDFs, as shown in Equation (4.5),

$$f_l^{\wedge} = f_l^0 + PTDF_{i,j,l}\, \Delta P \tag{4.5}$$

Where-by:

$f_l^{\wedge}$ = flow on the line after the transfer of the power from bus i to bus j

f_l^0 = flow before the failure

The new flow ($f_l^{\wedge}$) on each line is compared against its limit (f_l^{max}) and the alarm is announced for a violation. The line flow ($f_l^{\wedge}$) should be checked against $-f_l^{max}$ and f_l^{max} because a line flow direction is not considered power flow calculation. The line flow may have reversed due to an outage in the system. The superposition theory is used in the case of simultaneous generator outages since the PTDF factors are linear.

4.2.2 Line Outage Distribution Factors (LODFs)

Equation (4.6) illustrates how line outage distribution factors (LODFs) compute the changes in line active power flow that result from line outages in a power system (4.6). When the line k goes out, the LODFs for the line l are shown in Figure 4.1.

$$LODF_{l,k} = \frac{\Delta f_l}{f_k^0} \tag{4.6}$$

whereby:

$LODF_{l,k}$ = line outage distribution factor of line l after an outage online k

Δf_l = change in MW flow online l

f_k^0 = flow online k before outage

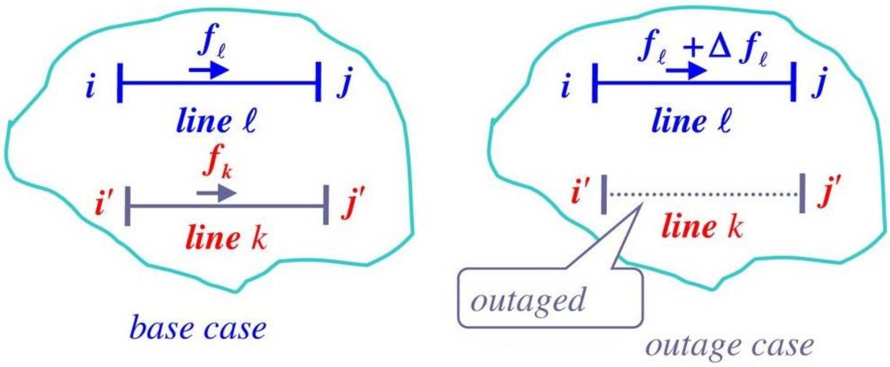


Figure 4.1 Flow change on line *l* due to an outage of line *k*

LODFs are computed and saved in advance and depend on system parameters and structures. Since the pre-contingency flow of line l is known, it can be determined using state estimation techniques or by monitoring the power system, and the post-contingency flow in line l can then be computed using Equation (4.7).

$$f_l^{\wedge} = f_l^0 + LODF_{l,k}\, f_k^0 \tag{4.7}$$

whereby:

f_l^0, f_k^0 = flow online l and line k before outage, respectively

$f_l^{\wedge}$ = flow online l when the line k fails

The operational conditions of the power system have no influence on the PTDFs and LODFs. They have to do with network architecture and transmission network properties. In the event of a lines or generation failure, it is consequently possible to immediately assess the line active power flows against their limits by precalculating such parameters. The preceding steps are involved in the contingency analysis approach employing sensitivity factors:

- Transmission line parameters calculated based on LODFs and LODFs
- Pre-contingency operation evaluation on power systems
- Active power line flow calculations using equation (4.5) from injection to load consumption (from bus a to bus b)

- Active power line flow calculations using equation (4.7) for remaining active line after system failure.
- Design and install an alarm system to be triggered when line constraints have been violated.

4.3 PTDFS AND LODFS FORMULATION

4.3.1 PTDFs Formulation

In power transfer distribution factors, the active power (ΔP) is transferred from the sending bus (bus s), where the power was injected to the receiving bus (bus r) that's the load or the other bus to a different route, as shown in Figure 4.2. Equations (4.8, 4.9 and 4.10) demonstrates that PTDFs provides a portion of the transferred power flowing on a line *l*.

$$PTDF_{l,s,r} = \frac{\Delta f_l}{\Delta P_{s\ to\ r}} \Rightarrow f_l^{\wedge} = f_l^0 + PTDF_{l,s,r}\, \Delta P_{s\ to\ r} \tag{4.8}$$

$$PTDF_{l,s,r} = -PTDF_{l,s,r}\ \ [4.9] \tag{4.9}$$

$$-1 \leq PTDF_{l,s,r}\ \leq 1\ [4.10] \tag{4.10}$$

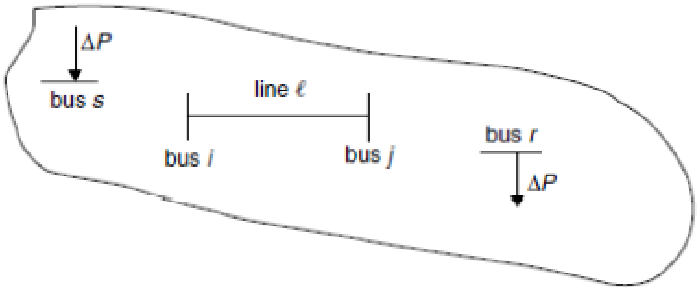


Figure 4.2 Line flow change of line l due to a power transfer from bus r to s

Modelling of power systems using DC techniques, it should be known that bus or node angles represent the system conditions. When modeling the system using DC power flow, the bus angles represent the system states. The voltage magnitude is calculated as one per unit, and the system's active power conservation determines the voltage angle. The voltage angle changes for a one MW power transfer from bus s to bus r, are explained by equation (4.11).

$$\Delta\theta = [X]\,\Delta P_{s\ to\ r} \Rightarrow \begin{bmatrix} \Delta\theta_1 \\ \Delta\theta_2 \\ \cdots \\ \Delta\theta_i \\ \cdots \\ \Delta\theta_j \\ \cdots \\ \Delta\theta_n \end{bmatrix} = \begin{bmatrix} X_{11} & X_{12} & X_{11} & X_{1n} \\ X_{21} & X_{22} & X_{11} & X_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ X_{i1} & X_{i2} & X_{11} & X_{in} \\ \cdots & \cdots & \cdots & \cdots \\ X_{j1} & X_{j2} & X_{11} & X_{jn} \\ \cdots & \cdots & \cdots & \cdots \\ X_{n1} & X_{n2} & X_{11} & X_{nn} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ +1(s) \\ \cdots \\ -1(r) \\ \cdots \\ 0 \\ 0 \end{bmatrix} \tag{4.11}$$

$$\begin{cases} \Delta\theta_i = X_{is} - X_{ir} \\ \Delta\theta_j = X_{js} - X_{jr} \end{cases} \tag{4.12}$$

$$\Delta f_l = \frac{1}{x_l}\left(\Delta\theta_i - \Delta\theta_j\right) = \frac{1}{x_l}\Big((X_{is} - X_{ir}) - \left(X_{js} - X_{jr}\right)\Big) \tag{4.13}$$

$$PTDF_{l,s,r} = \frac{1}{x_l}\Big((X_{is} - X_{ir}) - \left(X_{js} - X_{jr}\right)\Big) \tag{4.14}$$

As shown in Equation (4.14), PTDFs depend on the system parameters, and they are independent of the system operating condition. The reference bus is not considered in Equation (4.11), so the reactance between the slack bus and the other buses should be considered zero.

Equation (4.14) demonstrates that PTDFs are dependent on the system properties but unrelated to overall system operational state. The reactance involving the slack bus and the other buses should be taken to be zero since the reference bus is not contemplated in Equation (4.11).

4.3.2 The formation of LODFs

Whenever a line failure occurs in the system, a change in the flow of line active power can be identified, thus interrupting the overall steady state operation of the power system. Figure 4.3 illustrates how LODFs calculate the active power of line *l* in the event that line *k* fails [2].

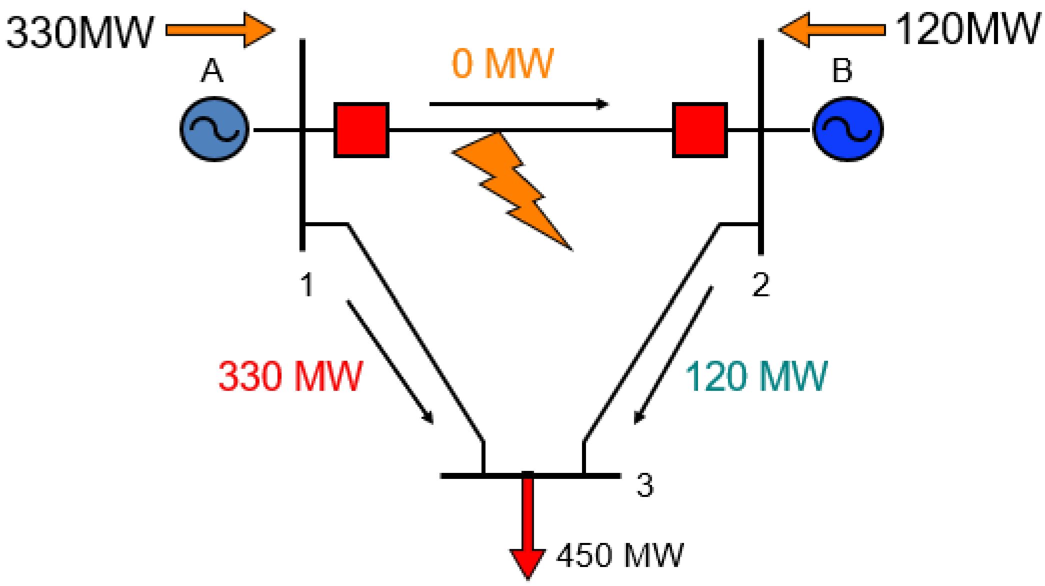


Figure 4.3 Flow change on the line *1-3 and 2-3* when the line *1-2* goes offline.

The formulation of LODFs, is a result of PTDFs analysis. According to Figure 4.5, the specific line outages are simulated as a power change at one of the receiving and sending line [2].

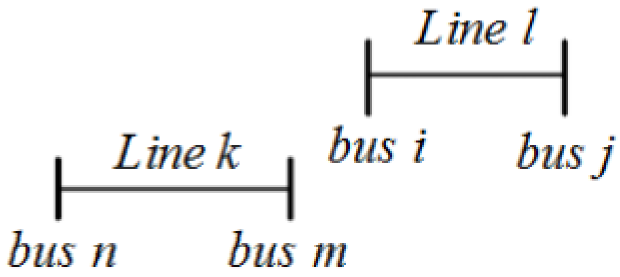


Fig. 4.4 Flow change on the line *l* when the line *k* out

After injecting ΔP_n and ΔP_m into bus *n* and bus *m*, respectively, the active power flow in line *k* switches from P_{nm} to $P^{\sim}{}_{nm}$,. Equation (4.15) can be used to illustrate and simulate line *k* outage scenarios. In this case bus *n* receives all of its injected power through line *k*. One of the safety features installed to mitigate catastrophic incidents was to install circuit breakers that do not allow the power to flow through them, while the line is open.

$$\Delta P_n = P^{\sim}{}_{nm} \ \ and \ \ \Delta P_m = -P^{\sim}{}_{nm} \tag{4.15}$$

Equations (4.16-4.17) use PTDFs to determine the active power flow of line k owing to power injections on buses *n* and *m*.

$$P^{\sim}{}_{nm} = P_{nm} + PTDF_{n,m,k}\,\Delta P_n \tag{4.16}$$

$$\Delta P_n = P^{\sim}{}_{nm} \Rightarrow P^{\sim}{}_{nm} = \left(\frac{1}{1 - PTDF_{n,m,k}}\right) P_{nm} \tag{4.17}$$

Equations (4.18-4.19) describe the power flow variations on line *l* caused by the failure of line *k*.

$$\Delta f_l = PTDF_{n,m,l}\, P^{\sim}{}_{nm} = PTDF_{n,m,l} \left(\frac{1}{1 - PTDF_{n,m,k}}\right) P_{nm} \tag{4.18}$$

The constant in equation (4.18) is equal to the LODFs of line *l* since it connects the flow change on line *l* to the original flow on line *k*.

$$LODF_{l,k} = PTDF_{n,m,l} \left(\frac{1}{1 - PTDF_{n,m,k}}\right) \tag{4.19}$$

$$f_l^{\wedge} = f_l^0 + LODF_{l,k}\, f_k^0 \tag{4.20}$$

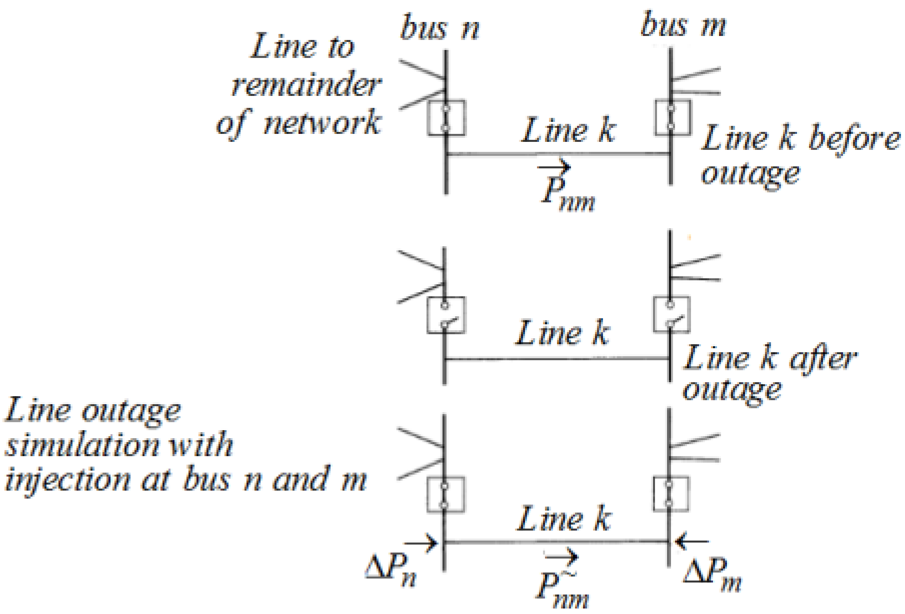


Figure 4.5 Line outage modeled as injections in sending and receiving buses

4.4 COMPENSATED PTDFS

The compensated PTDFs are defined to consider the concurrent line outages (line *k*) and power transfer from one bus (bus *s*) to the other bus (bus *r*) on the power system. Equation (4.20) defines the flow on line *l* as a result of the line *k* outage. Equations (4.21-4.22) are used to compute the new flow of lines *l* and *k* as a result of the power transfer from bus *s* to bus *r*.

$$f_l^{\sim} = f_l^o + PTDF_{s,r,l}\,\Delta P_{s\ to\ r} \tag{4.21}$$

$$f_k^{\sim} = f_k^o + PTDF_{s,r,k}\,\Delta P_{s\ to\ r} \tag{4.22}$$

Equation (4.23) represents the power flow on line *l* as a result of the outage on line *k* and the power transfer from bus *s* to bus *r*. Because these factors are linear, the superposition theory is employed.

$$\begin{aligned} f_l^{\wedge} = {} & \left(f_l^o + LODF_{l,k}\, f_k^o\right) \\ & + \left(PTDF_{s,r,l} + LODF_{l,k} + PTDF_{s,r,k}\right) \Delta P_{s\ to\ r} \end{aligned} \tag{4.23}$$

Equation (4.24) below illustrates the compensated PTDFs:

$$PTDF_{s,r,l} + LODF_{l,k} + PTDF_{s,r,k} \tag{4.24}$$

4.4.1 Contingency selection and ranking

When there is a generator outage or line outage in a functional power system, PTDFs and LODFs can help predict accurately the line active power flows. These variables disregard voltage magnitudes and the system's reactive power flow. An active power flow is not a sufficient signal of line flow overloads in some power systems where reactive power flow has a substantial impact on the system operating condition. Distribution factors are ineffective in these situations for estimating line overloads, necessitating the deployment of an AC power flow.

The main issues with employing an alternating current (AC) power flow analysis for power system contingency assessment are the rapidity of the analysis and, consequently, the number of contingencies that might be considered. Even though analyzing each blackout with an AC power flow analysis provides precise answers for line flow and voltage limit breaches, the process takes too long. Combining the various strategies can resolve the choice between the accurate and slow method, the AC power flow method, and the rapid and approximate method, distributions factor methods. The following tasks are involved in the contingency analysis approach using combination methods:

- Employing distribution factors to choose the contingencies that have a high likelihood of producing overloads.
- Using AC power flow simulation to evaluate the proposed contingency for a precise line flow or bus voltage limit infringement.

Using sensitivity parameters, these outages are ordered in descending order according to performance metrics. A couple of the blackouts are assessed using an AC power flow to determine not only more accurately the line reactive power flows and bus voltages, but also the line active power flows. For contingency rankings, the performance indices (PI) are crucial. They should be selected such that the seriousness of a particular situation is properly underlined.

Based on performance indicators, the final list of critical contingencies for the AC power flow study is created. It is anticipated that performance indexes will include all significant contingencies in this list while excluding minor ones.

The PI can often be divided into two classes. Additionally, a good combination of these two groups is considered.

• Active power-based ranking systems considers changes in line active power flows.

• Methods for ranking security based on reactive power or voltage that consider changes in bus voltage or reactive power flows.

Chapter 5

APPLIED MODELS

In this chapter, the working principles, theory, and governing equations of the applied models will be discussed in a detailed manner. Two models are applied namely, LEAR and DNN-LSTM. For the sake of reproducibility, this thesis only considered publicly available data. In general, when looking at the day ahead forecasting literature, several inputs have been proposed as meaningful explanatory variables, e.g., temperature, gas and coal prices, grid load, available generation, or weather etc.

5.1 The LEAR model

The Lasso Estimated Autoregressive model, which employs L1-regularization and the LASSO, is a parameter-rich ARX configuration [84]. LassoX was the moniker given to it when it was first released by [85].The generic auto - regressive framework specified by Equation (2) in [86], including significant modifications, served as the basis for the so-called full ARX or fARX model, a parameter-rich autoregressive specification including exogenous variables. Although fARX incorporates underpinnings and has a fuller cyclical architecture, it primarily focuses on the most recent weeks of data and therefore does not delve too far into the past data.

The author in [87] employed similar models to the LEAR in two distinct names i.e., $24Lasso_1$ in [88] and $24lasso_{DoW,nl}$ in [87]. The idea was to enhance the model, therefore the area (or inverse) hyperbolic sine variance stabilizing transformation was applied to the data as part of the pre-processing steps and feature selection, empirically validated and advised in [87], [88] and [89]. The data is preprocessed with the area (or inverse) hyperbolic sine variance stabilization transformation.

$$sin^{-1} x = log\left(x + \sqrt{x^2 + 1}\right) \tag{5.1}$$

The equation above signifies the hyperbolic sine variance stabilizing transformation where x can primarily represent the normalized energy demand or LMPs depending on the forecasted variables by taking the in-sample median out of consideration and dividing it by the median absolute deviation, which is then multiplied by a factor for asymptotically normal consistency to the standard deviation. To further understand the concept visit [89] and a have a depth understanding. For clarity and simplicity purposes, long-term seasonal decomposition techniques were entirely left out in this study; in particular, even though they showed prospects of an improved LEAR model, this thesis decided to implement its approaches in future studies.

The model is then calibrated on consistent basis as in [90], throughout the stipulated 4 calibration windows with data ranging from 8 weeks, 12 weeks, 3 years and lastly 4 years to further improve the overall model. Smaller periods of (8-12 weeks) we taken into account as well as longer periods of (3–4 years), because that approach seemed to demonstrate better results over the approach [90].

The LEAR model to forecast hourly day ahead demand $de_{d,h}$, on hour h and day d can be further illustrated by:

$$de_{d,h} = f\left(de_{d-1}, de_{d-2}, de_{d-3}, de_{d-7}, x_d^i, x_{d-1}^i, x_{d-7}^i, \theta_h\right) + \varepsilon_{d,h}$$

$$
\begin{aligned}
&= \sum_{i=1}^{24} \theta_{h,i}\left(de_{d-1,i}\right) + \sum_{i=1}^{24} \theta_{h,24+i}\left(de_{d-2,i}\right) \\
&\quad + \sum_{i=1}^{24} \theta_{h,48+i}\left(de_{d-3,i}\right) \\
&\quad + \sum_{i=1}^{24} \theta_{h,72+i}\left(de_{d-7,i}\right) + \sum_{i=1}^{24} \theta_{h,96+i}\left(x_{d,i}^{1}\right) \\
&\quad + \sum_{i=1}^{24} \theta_{h,120+i}\left(x_{d,i}^{2}\right) + \sum_{i=1}^{24} \theta_{h,144+i}\left(x_{d-1,i}^{1}\right) \\
&\quad + \sum_{i=1}^{24} \theta_{h,168+i}\left(x_{d-1,i}^{2}\right) + \sum_{i=1}^{24} \theta_{h,192+i}\left(x_{d-7,i}^{1}\right) \\
&\quad + \sum_{i=1}^{24} \theta_{h,216+i}\left(x_{d-7,i}^{2}\right) + \sum_{i=1}^{24} \theta_{h,240+i}\left(z_{d,i}\right) \\
&\quad + \varepsilon_{d,h}
\end{aligned} \tag{5.1}
$$

Where $\theta_h = [\theta_{h,1}, \dots \dots, \theta_{h,247}]^T$ are 247 LEAR parameters for a specific hour h. The introduction of Least Absolute Shrinkage and Selection Operator (LASSO) has made the majority of these parameters null characters:

$$\hat{\theta}_h = {}^{argmin}{}_{\theta_h} RSS + \lambda \|\theta_h\|_1 = {}^{argmin}{}_{\theta_h} RSS + \lambda \sum_{i=1}^{247} \left|\theta_{h,i}\right|, \tag{5.2}$$

$$RSS = \sum\nolimits_{d=8}^{N_d} (de_{d,h} - d\hat{e}_{d,h})^2 \tag{5.3}$$

Where RSS is the summation of squared residuals $d\hat{e}_{d,h}$ which is the demand forecast, N_d is the number of days in the training dataset, and $\lambda \geq 0$ is the regularization of the features/ hyperparameters of LASSO. The hyperparameter that controls the L_1 regularization is tuned on every consistent recalibration because estimating with LASSO is computationally fast. In [91], ex-ante cross-validation was used to achieve fast computational timings for estimating LASSO. In this study case, a more effective hybrid strategy to carry out the optimal selection in order to further lower the computing cost was introduced.

5.1.1 Tuned hyperparameters

A hybrid approach for selecting optimal λ was suggested in this section. With constant calibration, an approach to estimate of the hyperparameter with the in-sample Akaike information criterion (AIC) and the Least Angle Regression (LARS) was derived. The LEAR was then recalibrated using the conventional coordinate descent technique, utilizing the optimal result from the LARS method.

This hybrid strategy is being suggested because it offers a decent trade-off between accuracy and computing complexity. It specifically combines the predictability on small calibration windows of the coordinate descent LASSO with the computational efficiency of LARS for ex-ante λ selection. It is crucial to recognize that to have effective and efficient number of methods for selection, researchers have to undergo intense information pre-processing and selection on a number of methods to conclude on a better method. The methods for effective selection involved the below steps.

i. Constant recalibration of per day as minimum, using coordinate descent and Cross Validation (CV).

ii. Least angle regression and cross validation approaches implemented for daily recalibration

iii. An all-inclusive approach of LARS, CV, and AIC on daily recalibration.

The accuracy of the other two methods was poor, and the computational cost of the first technique was excessively high (on par with the cost of the DNN model). In contrast, the suggested method performed way ahead the coordinated descent LASSO utilizing CV, but at a fraction of the computing expense.

5.2 THE DNN-LSTM MODELING

The motivation behind this structure is the ability of LSTM to model chronological sequences and their long term-range dependencies, hence it having the edge to conventional RNNs, therefore the technique can learn and model sequential relations in the time series data as well as a regular layer that can learn relations that depend on non-sequential data. The neural network model applied by the authors in [52], is one of the most accurate deep learning models, that has several parameters as input features and hyper-parameters. These can be tailored and improved for each case study without the need of expertise knowledge in deep learning. In simple terms the DNN is an extension or improved version of a two-layer version of the classic Multilayer Perceptron (MLP) that can be reconstructed depending on the need and expectation of the user. To implement these models, this thesis used Keras, and other python libraries.

5.2.1 Structure

The DL technique was modelled as a deep feedforward neural network containing seven layers of input layers with eighteen different features, 5 hidden layers and a single output layer (EDF or EPF). The Adam optimizer from [92], was used with its hyperparameters and its input features were optimized using the tree Parzen estimator as in [93], i.e. a Bayesian optimization algorithm. The simple DNN structure is shown in figure 5.1.

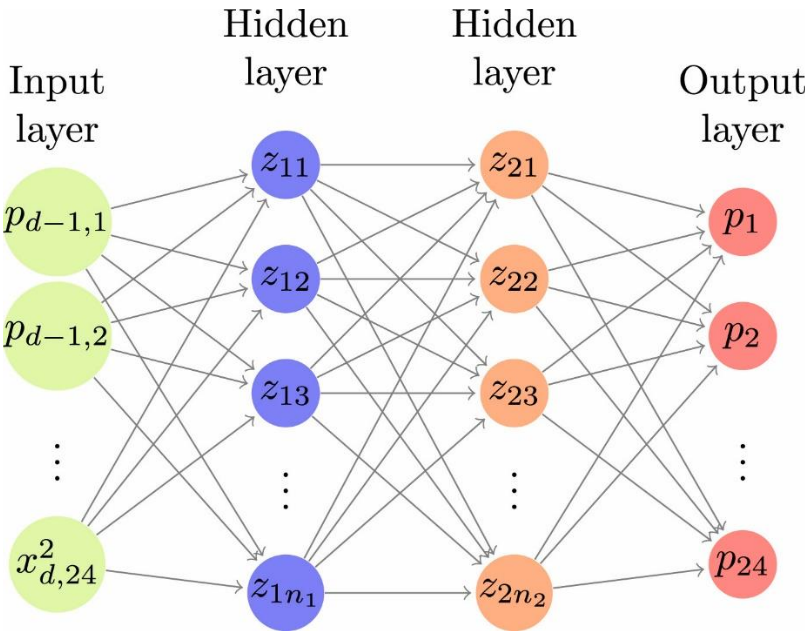


Figure 5.1. Simple DNN model structure

The inputs were divided between those that model sequential time data, e.g. historical electricity demand and those that model regular data, e.g. day of the week or hourly day-ahead forecasting of the system load. This division is necessary because LSTM requires a sequence of time series values as inputs. However, considering all the possible regressors for electricity price forecasting, it is clear that some of them do not have that property.

In general, for the case of electricity load demand and prices, the distinction between these two types of data can be done by considering the time information represented in the data. Specifically, if the data represents a collection of past values, it can normally be modeled as time sequential data and used as an LSTM regressor. By contrast, if the data represents some specific property associated with the day ahead, i.e., it represents direct information of a future event, it cannot be modeled as a time sequence. Examples of the first could be past day-ahead prices or the measured grid load; examples of the second could be the day-ahead forecast of the weather or whether tomorrow (day-ahead) is a holiday.

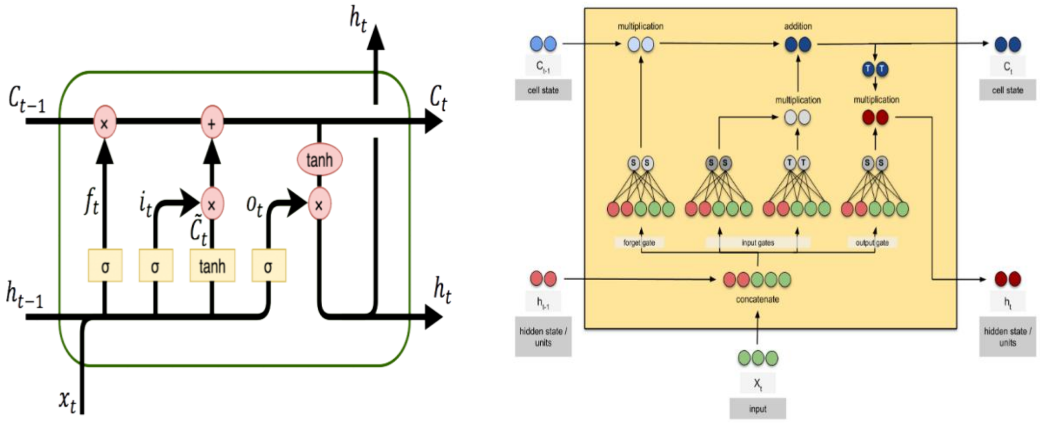


Figure 5.2. Simple LSTM architecture structure and layout.

Where C_{t-1} and C_t are the cell states, h_{t-1} and h_t are the hidden states/units C_{t-1} and x_t are the inputs

The inputs of the model are divided between two groups.

- Input vector $X_F = [x_{F1}, \ldots, x_{FN}]^T \in \mathbb{R}^n$ which represents the feature historical information.
- A collection of $\{x_S^i\}_{i=1}^q$ for q input sequences, where $x_S^i = [x_{S1}^i, \ldots, x_{SN}^i]^T \in \mathbb{R}^n$ is a vector representing past information.

Therefore, using the distinct separation, the model uses DNN to process the inputs X_F and an LSTM to process the time sequence $\{x_S^i\}_{i=1}^q$. Then, the outputs of these two networks are concatenated into one vector and this vector is fed into a regular output layer.

Automatic defining the number of neurons of the model in respect to the layers by n_F^i and n_s^i and then by z_{Fi} and $|z_{Si}, c_{Si}| \top$ the internal state of their neuron i, the structure of the model is shown in Fig. 5.3.

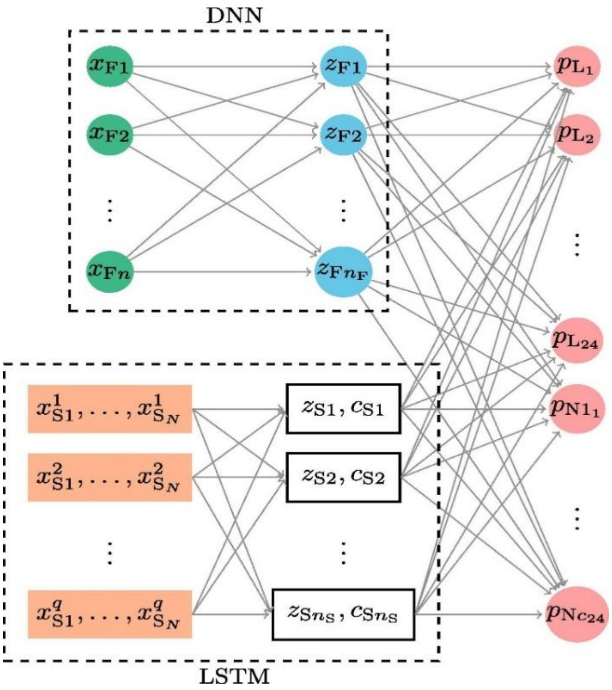


Figure 5.3. DNN-LSTM network to forecast hourly day ahead parameters.

Table 4. Optimal hyperparameters for the DNN-LSTM model

Hyperparameter	***Value***
Activation Function - DNN	ReLU
Activation Function - LSTM	Tanh
Dropout	Automatic Selection
Optimizer	Adam
Estimator	Tree Parzen Estimator (Bayesian Optimization algorithm)
n_{DNN} ***(Number of neurons in DNN)***	Automatic Selection
n_{LSTM}***(Number of neurons in LSTM)***	Automatic Selection

5.2.2 Data

Despite the fact that automatic forecasting models have demonstrated the capability of being more accurate than human forecasters, studies have revealed that many decision-makers have an innate mistrust of them [32]. One way to overcome “algorithm aversion” is to provide the doubters with interpretability [94]. To satisfy such reasoning this thesis will explore an DNN-LSTM as a set candidate for deep learning model that has been demonstrated to be much more reliable forecasting technique within the neural networks scope and also giving a certain amount of interpretability in the machine learning field. To perform the different experiments, we divide the data into three sets.

1. Training set (01.01.2013-30.12.2016): the data used for training and estimating the different models.
2. Validation set (01.12.2016-30.11.2017): a year is used to select the optimal hyperparameters
3. Test set (01.12.2017-30.12.2018): a year of data that us not used at any step during the model estimation process, is employed as the out of sample data to compare the models.

For estimating the hyperparameters, the training dataset is fixed and comprises the two markets datasets of five and seven years prior to the testing period. The datasets have different range because NP doesn’t provide the data for free to the general public anymore, therefore data was acquired from 2013-2018. For evaluating the testing dataset, the DNN is recalibrated on constant basis using a calibration window of five years.

The dataset is separated into a training and a validation datasets in all scenarios, with the latter serving two purposes: early stopping criteria as implemented in [95] to avoid overfitting and enhance hyperparameter optimization.

Table 5. Start and end dates for (out of sample) test dataset

Market	**Test period**
NE-ISO	01.12.2017-30.12.2018
Nord Pool	01.12.2017-30.12.2018

While a training dataset is consistently 156 weeks long, the training and validation datasets are split up in different time frames depending on whether the validation dataset is used for hyperparameter/feature selection or recalibration. Steps are shown below:

- Since the validation dataset is utilized to assist the optimization process, the validation dataset is chosen as the last 52 weeks to estimate the hyper-parameters. This is therefore done to keep the training and validation datasets totally independent henceforth minimizing overfitting, similar to how the dataset is separated into training and test datasets.

- In this study, the validation dataset is only used for early stopping in the testing phase, it is defined by randomly selecting 52 weeks from the total 208 weeks used for training. This is done to ensure that the dataset used to optimize the model parameters contains current data. In the case of hyperparameter optimization, the validation dataset represents the most recent weeks of data, this helps the model to learn the recent market trends giving this model an edge from other conventional neural network techniques that uses data that is over year old. While this isn't a major issue, but still an issue therefore, when implementing the DNN structure, such hyperparameter optimization techniques should be avoided during testing to guarantee that the DNN captures new market effects.

To achieve improved model accuracy and robustness, hyperparameter and feature optimization for DNN model is immensely important in acquiring the most out the model especially in the training and testing period. Therefore, to make sure all procedures were employed for better results, ranges of training datasets were employed starting with the NP and NE-ISO market respectively. Let's take the NE-ISO market data for example, the data ranged from January 1st, 2013, to June 30th, 2022, for which three quarters of the data was used for training and the remaining quarter up to the recent end date was used for validation. To test the DNN models ability for feature selection and learning data trends February 15th, 2017, was selected as the forecasting focal point, the available data from February 20th, 2013, up to February 14th, 2017, were used as testing and validation datasets. Data split for training and validation was classified as 70% of the weeks from the initial date were selected for training and the remaining 30% for validation, thus 166 and 42 weeks respectively.

5.2.2.1 Data processing

In order to obtain time series that are easier to forecast, the data used for the statistical models are processed using Box cox transformation which is a standard preprocessing step in the field of electricity price and demand forecasting. The technique includes the log-transformation as special case. For machine learning and deep learning models the data is respectively normalized to the intervals [0,1] and [-1,1], that is done to ensure these two preprocessing steps help in obtaining more accurate models. These transformations are only applied when estimating the parameters, not when computing metrics or statistical significance.

5.3 ENSEMBLES

Ensembles are forecasting models that can independently predict scenarios and also they can effectively integrate forecasting models from two or more different approaches to create a single robust and more accurate forecast. Ensemble members, or models that contribute to the ensemble, can be of the same kind or different types, and they may or may not have been trained on the same training data [96]. The ensemble members' predictions can be merged using statistics like the mode or mean, or more advanced approaches that learn how much and under what conditions to trust each member.

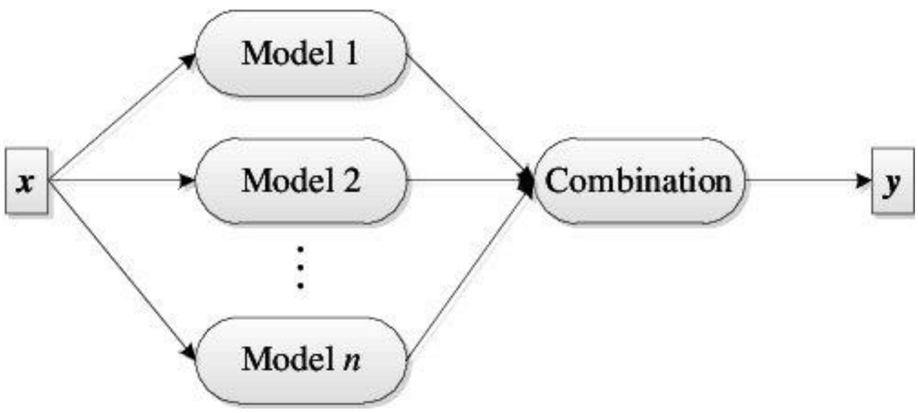


Figure 5.4. Basic ensemble model structure.

There are two primary reasons to utilize an ensemble over a single model, both of which are related:

1. **Performance aspect:** When compared to a single contributing model, an ensemble can generate better forecasts and achieve better results.

2. **Robustness aspect**: The spread or dispersion of the predictions and model performance is reduced by using an ensemble.

Ensemble models are used to improve the prediction performance of a single predictive model on a predictive modeling task [97]. In this study we offer ensembles of LEAR and DNNs as benchmarks of ensemble methods for the models proposed, in order to have benchmark predictions for evaluating ensemble strategies. The ensemble for the LEAR is constructed by taking the arithmetic average of forecasts over four calibration window lengths: eight weeks, twelve weeks, three years, and four years. The ensemble for the DNN is made up of the arithmetic average of four individual DNNs that were estimated four times using the hyperparameter/feature optimization technique approach. The hyperparameter optimization, in particular, is asymptotically deterministic, meaning that the optimal solution is found after an infinite number of iterations.

Each iteration of said approach yields a different sequence of hyperparameters and features, meaning that it is non-deterministic for a finite number of iterations when using a different initial random seed. It is practically impossible to distinguish which of these hyperparameter or feature subsets is better because their relative performance on the validation dataset is essentially equivalent, despite the fact that each of them represents a local minimum. The other positive aspect to why this thesis explored the DNN technique is its extensive adaptability mechanism which allows different architectures and topologies to excel.

CHAPTER 6

CASE STUDIES AND EMPIRICAL DATA

In this chapter we delve into the decision-making process that went into selecting the power markets for this thesis. Important observations and comments will also be made regarding the data used and the actual variables that affected it.

6.1 THE MARKET SELECTION

The methodology implemented when asked what’s the best choice for accurate results when it comes to electricity markets, be it a working vertical market or deregulated market are further elaborated in the sections to follow. Having looked at the different types of market structures this thesis determined that a competitive market would be best suited for the proposed models because it contains a number of dynamics that will contribute to better results if the model operates optimally.

6.1.1 Forecasting techniques

As previously established, applying short-term load forecasting technique came to play due to the need for accurate and more reliable load forecasting techniques therefore with an expectation that the forecast would be more accurate as the time domain for the prediction was very short and few to no external factors can influence the predictions. Due to data availability of newer data in the markets involved a significant conclusion was made to use the day-ahead markets as the basis for the short-term forecasting compared to a week or month to years.

6.1.2 Case study

As mentioned in the previous chapters, the need to have an accurate forecasting technique, data to be used and the market in which the data will be acquired from should be at the very top for every forecaster. EDF on a short-term basis requires strong attention to historical data and how the electricity market operates i.e., if the market is regulated or still operates vertically. Two famous regulated power markets were selected, and data was acquired from as back as 2013-2018 for Nord Pool power market and 2015-2022 for New England ISO market. Nord pool data from 2018-2022 couldn’t be attained because the market now sells the data to the public. A sample data for one of the markets is shown below.

1	DT	Energy	Peak_Hour	Peak_DB	Peak_DP	Peak_WTHI	RT_LMP	Avg_DA_LMP	Avg_RT_LMP	OffPk_DA_LMP	OffPk_RT_LMP	NEL	System_Peak_	Peak_Demand	Min_Demand	System_Peak
2	5	310	18	37	24	0	36,36	43,12	30,81	43,12	30,81	315	18	15.727	10.386	0,30768168
3	6	318	18	34	19	0	57,06	39,22	47,39	39,22	47,39	324	18	15.974	10.736	0,3268168
4	7	317	18	38	23	0	39,07	37,01	27,69	37,01	27,69	322	18	16.300	10.781	0,346919038
5	1	369	19	17	2	0	68,91	54,99	30,46	47,92	2,64	375	18	18.881	10.961	0,527908262
6	2	391	18	22	-2	0	80,46	61,15	84,70	61,69	70,91	398	18	18.927	13.208	0,530049737
7	3	374	18	36	1	0	100,23	66,93	70,29	68,68	81,96	380	18	17.960	12.924	0,464562034
8	4	361	19	31	11	0	68,93	47,58	40,39	48,11	37,90	367	19	17.546	12.090	0,434028737
9	5	354	18	37	29	0	29,65	35,98	26,51	36,11	23,20	360	18	17.007	11.863	0,394653219
10	6	320	18	39	35	0	25,74	25,96	17,00	25,96	17,00	325	18	15.713	10.762	0,303260569
11	7	310	18	55	54	0	28,66	18,30	7,62	18,30	7,62	315	18	15.684	10.217	0,303329649
12	1	346	19	27	5	0	87,52	33,74	4,20	12,47	-61,23	352	19	17.873	10.139	0,45689417
13	2	366	18	33	27	0	39,99	37,36	28,69	27,08	18,38	371	18	17.904	12.077	0,459242885
14	3	373	18	23	4	0	43,69	39,58	35,88	23,28	29,41	379	18	18.637	11.817	0,509256701
15	4	375	18	28	12	0	38,32	42,38	35,34	36,35	31,88	381	18	18.169	12.563	0,476651009
16	5	356	18	36	27	0	25,24	28,38	23,33	21,81	26,18	361	18	16.892	12.027	0,385741918
17	6	324	18	38	34	0	47,56	28,60	32,42	28,60	32,42	329	18	15.700	10.812	0,302017132
18	7	323	18	31	19	0	77,55	31,07	32,34	31,07	32,34	329	18	16.447	10.659	0,356037579
19	1	367	18	22	4	0	82,41	41,11	37,79	27,26	5,09	373	18	18.702	11.351	0,515750207
20	2	393	19	21	5	0	68,94	46,79	48,66	30,11	33,29	399	19	19.151	12.913	0,545938104
21	3	379	18	29	7	0	43,00	42,42	44,91	34,79	43,25	385	18	18.314	12.926	0,488601824
22	4	372	19	26	6	0	39,23	46,85	33,85	44,02	36,30	378	19	18.189	12.355	0,48065764
23	5	373	18	27	6	0	49,21	39,43	36,23	34,31	30,38	379	18	17.777	12.714	0,451298701

Figure 6. Sample data for NE-ISO market in its raw format

Figure 6 represents data in its raw format comprising of energy levels peak hours, peak weighted temperature, average LMP prices, peak and min demand and system demand etc. The data is from June 2015- June 2022 a duration of 7 years for the NE-ISO market. The NE-ISO dataset was picked as to illustrate the data, there was no specific reason for the selection. A set of columns for the forecasted output data was made for both the markets to show a basic comparison between the real the demand

and forecasted demand as well the real time Locational marginal pricing (LMP) and forecasted LMP.

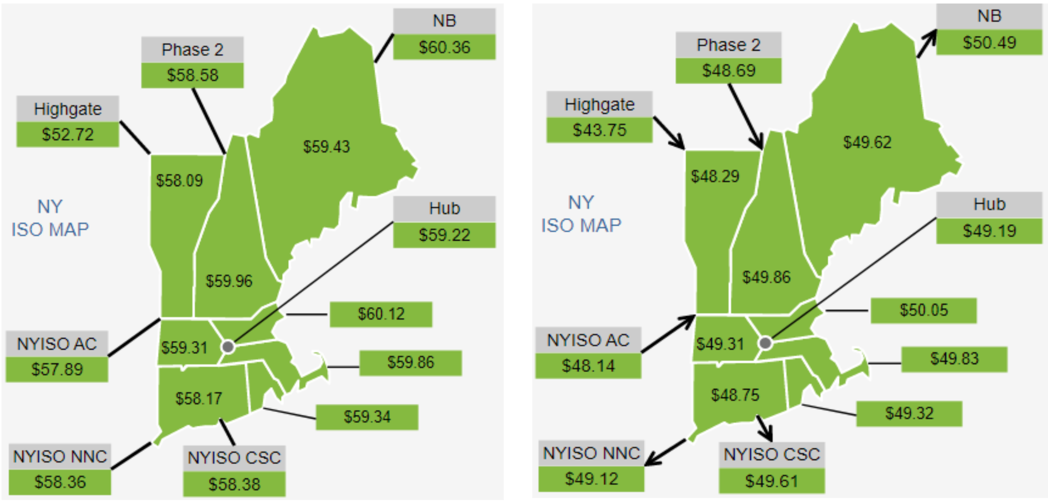


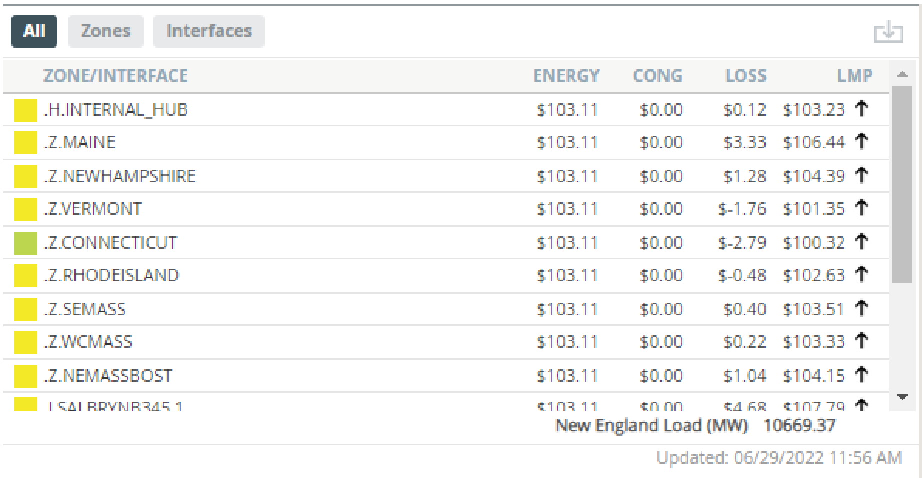
Figure 6.1. Real time and Day ahead LMP maps for NY-ISO.

This thesis proposes a model to reduce the imbalances on hourly forecasted LMPs to real time LMPs and forecasted hourly load demand to real time load demand over a 24-hour period. The amounts of data to be fed into the system will be discussed in detail in the next sections. Since the model will have a test and validation data sets, some of the data will be left out in training so as to validate the model's performance and accuracy.

6.1.3 Input Datasets

Now that we have made arguments on the output dataset i.e., validation dataset, it is imperative to understand and analyze how effective can we determine how input data can and should be acquired for the model. Usually, models are derived on qualitative and quantitative data depending on the architecture, time, and the set goals for the model. The decisions on which types of data feed the model was relatively made easy since the information is already provided on the market websites, unlike in unrealistic situations were researchers have to conduct surveys or questionnaires to understand the consumers’ demand behavior in the electricity markets. It is very impractical to obtain data using quantitative means for such systems given their magnitude and the speeds at which data changes, therefore qualitative data approaches seem feasible.

As noticed in literature, the majority of authors predict load demand or electricity price for countries which is a tad misleading given the fact that countries have different zones which in turn have different temperatures for different geographical locations. If you look at the NE-ISO which is an advanced deregulated market, they focus their predictions based on geographical locations and phases of the entire network. It is very complicated to have a forecasting model that includes different input datasets for temperature and average LMPs and predict the outputs of different locations at the same time. To overcome such a problem five zones were picked from NE-ISO and five cities were also picked from NP and each city has its own set of X variables for input and a benchmark Y data for validation.



All | Zones | Interfaces

ZONE/INTERFACE	ENERGY	CONG	LOSS	LMP
.H.INTERNAL_HUB	$103.11	$0.00	$0.12	$103.23 ↑
.Z.MAINE	$103.11	$0.00	$3.33	$106.44 ↑
.Z.NEWHAMPSHIRE	$103.11	$0.00	$1.28	$104.39 ↑
.Z.VERMONT	$103.11	$0.00	$-1.76	$101.35 ↑
.Z.CONNECTICUT	$103.11	$0.00	$-2.79	$100.32 ↑
.Z.RHODEISLAND	$103.11	$0.00	$-0.48	$102.63 ↑
.Z.SEMASS	$103.11	$0.00	$0.40	$103.51 ↑
.Z.WCMASS	$103.11	$0.00	$0.22	$103.33 ↑
.Z.NEMASSBOST	$103.11	$0.00	$1.04	$104.15 ↑
I.SALBRYNB345 1	$103.11	$0.00	$4.68	$107.79 ↑

New England Load (MW) 10669.37

Updated: 06/29/2022 11:56 AM

Figure 6.2. NE-ISO electricity market zones

Table 4. Area reference and the respective cities from the NP market

Area reference	**City**
NO1	Oslo
NO2	Kristiansand
NO3	Molde, Trondheim
NO4	Tromso
NO5	Bergen

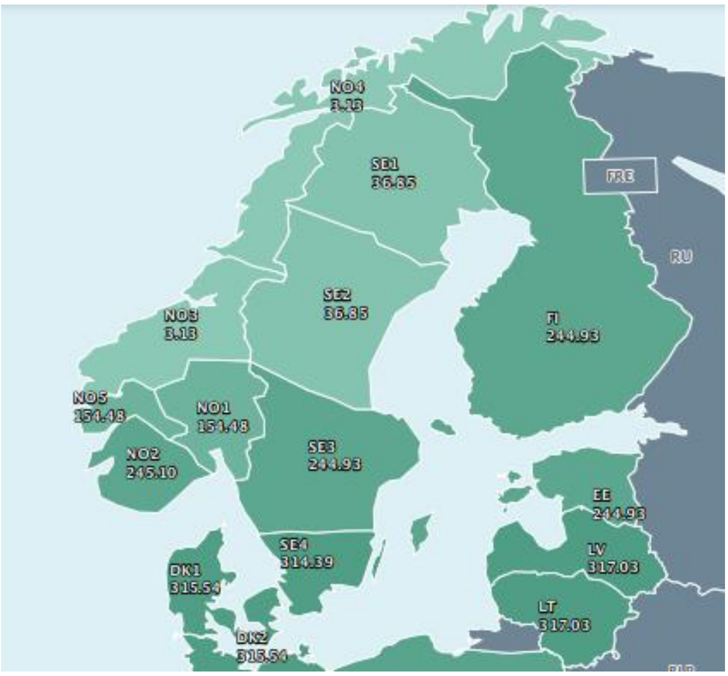


Figure 6.3. Map view of the selected cities in Norway and the table above decodes the geographical area reference.

Different sets of data from weather variables to systems demand can be downloaded from the respective websites when the area reference is decoded. Having made all the necessary selections for the zones and locations to be forecasted in the model, we delve in filtering process and data manipulation to achieve maximum and effective results for the model. The goal of this thesis as mentioned earlier is to forecast the day ahead demand and LMPs for a 24-hour period, therefore we have 10 different zones from two distinct markets, and for simplicity and results justification only two random zones or locations from the pool will be picked.

6.2 JUSTIFICATION ON MODELS

This section will solely be for justification, proofing and reliability stance on the acquired data and the decisions underlying the choice of model to be initiated and the specific markets suggested. The models ability on the validation set and accuracy metrics will also be justified.

6.2.1 Market deregulation

Taking a look at the NE-ISO market and its data, the market is comprised of different types of energy sources that makes the overall chunk of the generation. The carbon emission goals and objectives for a greener environment has pushed generation companies to opt for more sustainable and cleaner energy sources. As shown in figure 6.4, natural gas takes the lead as a primary fuel used in generation electrical energy in the US followed by nuclear power and now renewables have lapsed hydro to be in the top three fuels in the overall ration of fuel mix from NE-ISO.

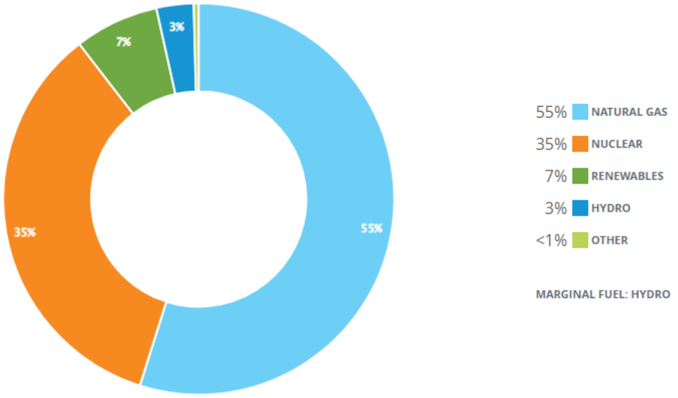


Figure 6.4. Overall ratio of fuel mix chart for NE-ISO as of June 2022.

The need to integrate renewable energy sources to the power grid has huge impacts on the stability of the system and also on the environmental part. A huge chunk of the renewables available in the NE-ISO is coming from refuse 47% and wood 37% with solar and wind ranking 3rd and 5th having 7% and 4% impact on the overall grid as shown in figure 6.5.

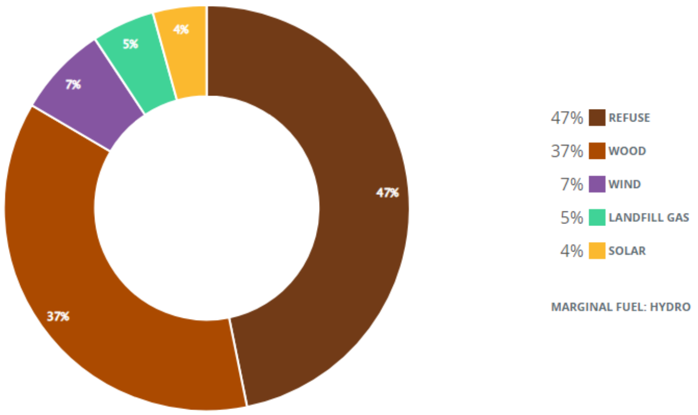


Figure 6.5. Overall ratio for renewable energy fuel mix chart for NE-ISO as of June 2022.

To make significant carbon emission reductions, it is important if market players or generation companies strive to implement greener energy sources but to do so accurate demand forecasting techniques has to live up to the billing. Careful long-term planning can be feasible if accurate forecasts can be made, in investment terms, huge amounts of money have to be poured in to build larger generating systems without disturbing the operation of the existing grid and that can be achieved if and only if there are accurate and reliable forecasting techniques, thus giving room for careful planning.

Date: 06/29/2022

DATE/TIME	FUEL	CO_2 (METRIC TONS)
06/29/2022 07:05	Total	54.49
06/29/2022 07:05	NaturalGas	40.56
06/29/2022 07:05	Refuse	9.2
06/29/2022 07:05	LandfillGas	0.48
06/29/2022 07:05	Wood	4.25
06/29/2022 07:06	Total	51.77

Figure 6.6. Carbon emissions in respect to the fuels.

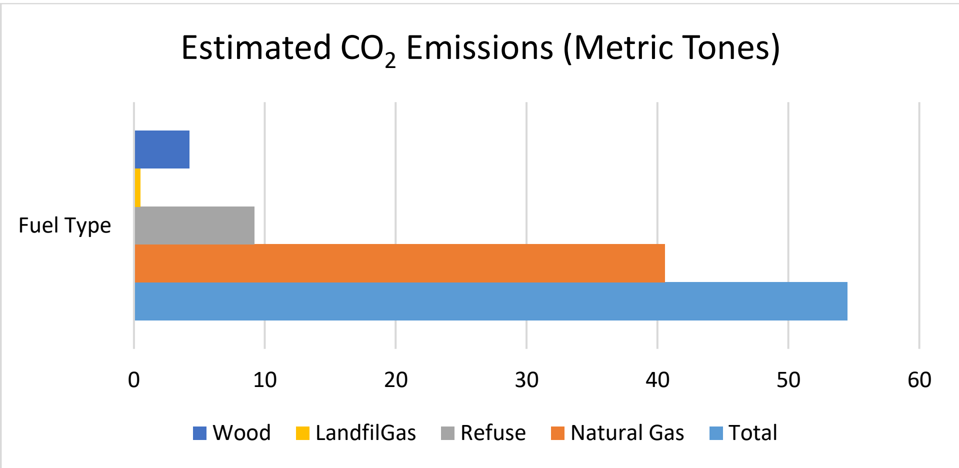


Figure 6.7. Carbon emissions in respect to fuels.

When it comes to greener energy and sustainable aspects of energy production, we still have a long way to go but with the right approaches and implementation of renewable energies into our systems we can reduce the carbon emissions immensely.

6.2.2 Time domain

Since electricity demand and LMPs forecast are of major interests to the power utilities, private investors, and policymakers alike, there is also a great deal of importance when It comes to development professionals. As mentioned in the earlier sections inaccurate forecasts can have immense consequences on the economic and social platforms if they under or overestimate the real time demand or electricity price. Various problems like forced power outages (blackouts), supply shortage that has serious implications on economic growth and overall productivity. On the other hand, overestimating the demand can lead to generation capacity over-investment, higher electricity prices and possibly financial distress. Some authors argued that deep machine learning accuracy of a forecasting model is also tied to the availability of recent and vast amounts of data. Recent data presents current trends that might be present due to areal expansions or generational capacity extensions, or population increase in certain areas [98].

Additionally, the amount of data for certain models depends on the purpose and significance of the project. When it comes to high performing models, minimizing imbalances on the real time demand and forecasted demand is really important, therefore significant amounts of data will need to be used as input variables to increase both the accuracy and performance. That’s why it is crucial to allocate as much data as possible for testing and subtract for validation [99].

Data analysis of the Nord pool and NE-ISO markets for the fourth year (2018) and (2017) respectively, and the scope to narrow down the electricity demand trends against temperature showed that electricity demand forecasts deviations in the summer periods where quite larger compared to other seasons where demand was not at its peak. Authors in [100] and [101] discussed the impacts of weather variables such a temperature to extreme and variability of electricity and gas in England, concluding and supporting the above statement that summer seasons has unforeseen increase in electrify demand. In a nutshell, recent time series models have shifted their focus to summer seasons as to have a better understanding on the model's forecasting accuracy since all-time electricity peak demands are usually recorded in summer. The author in [101] picked the year 2018 for the models application, since it had larger deviations on the real and forecasted demand. The larger the deviations the more the author managed to have a sound conclusion and apply the data trends in the model. The same conclusion can be made for summer seasons in the following figures of forecasted hourly real and day ahead demand. There is a sharp increase in electricity demand from June until early September 2016 in Connecticut zone and the cycle repeats itself until 2021.

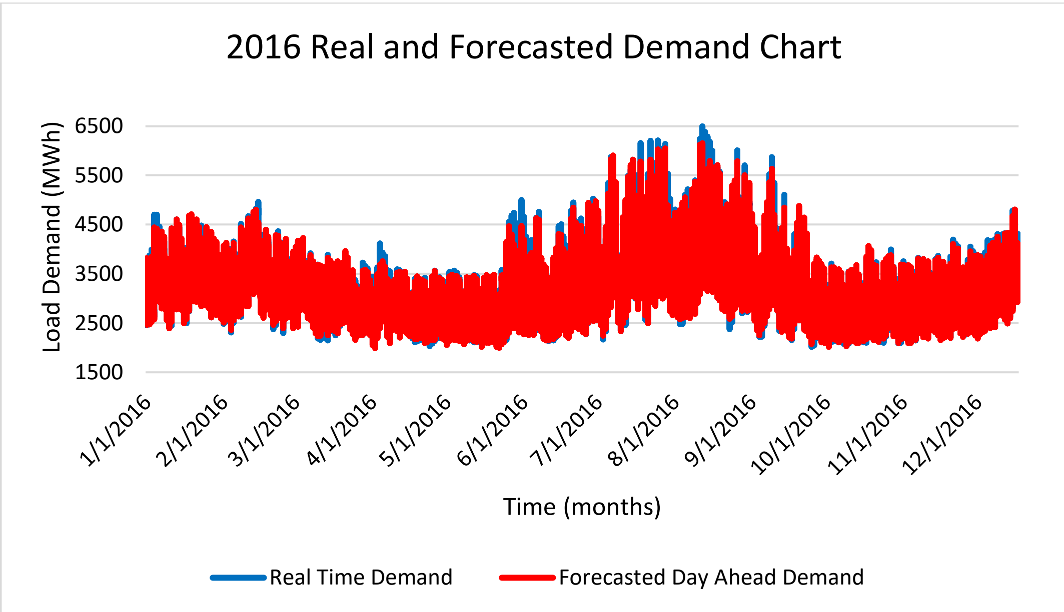


Figure 6.8. Real time and forecasted demand for 2016, Connecticut

As we can see from the graph, a surge in load demand is visible, during summer periods from June to September a rise in demand can be seen due to hotter temperatures therefore consumers opting to use cooling systems and other mechanisms to keep the temperatures down.

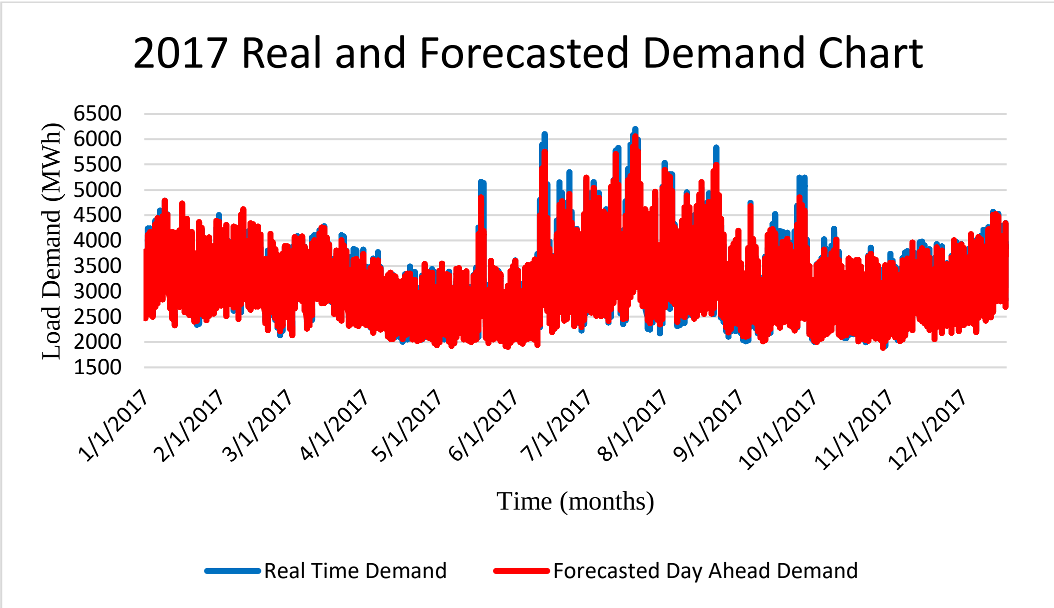


Figure 6.9. Real time and forecasted demand for 2017, Connecticut

As we can see from the graph, a surge in load demand is visible, during summer periods from June to September a rise in demand can be seen due to hotter temperatures therefore consumers opting to use cooling systems and other mechanisms to keep the temperatures down. We can see uneven shifts in load demand due to extreme temperatures. Such occurrences are the reason why we need accurate forecasting techniques because they are costly to the system if the utility fails to meet the demand.

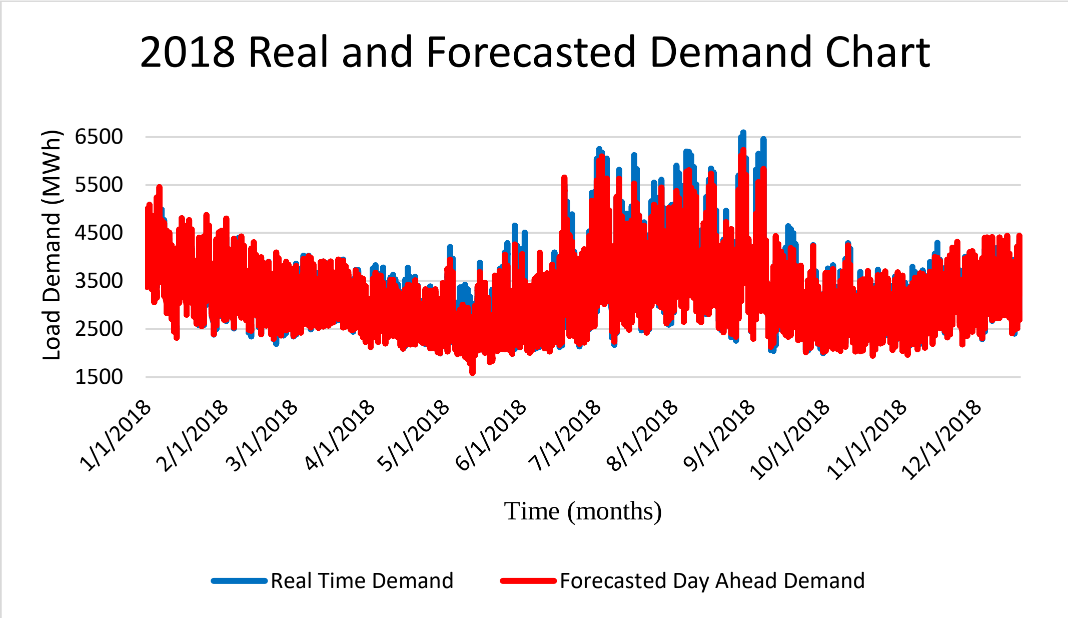


Figure 6.10. Real time and forecasted demand for 2018, Connecticut

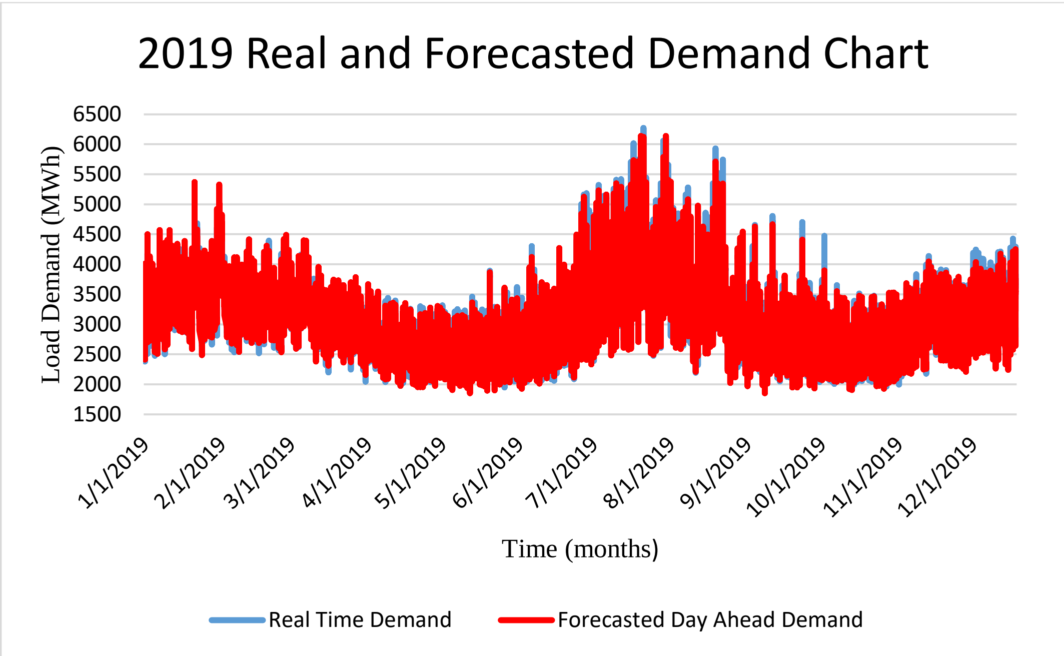


Figure 6.11. Real time and forecasted demand for 2019, Connecticut

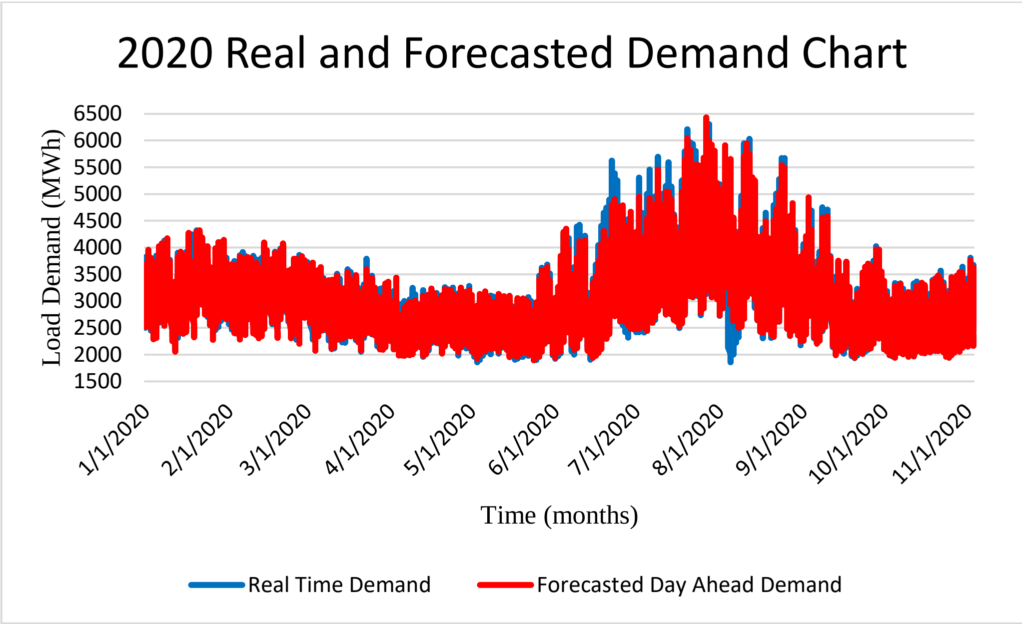


Figure 6.12. Real time and forecasted demand for 2020, Connecticut

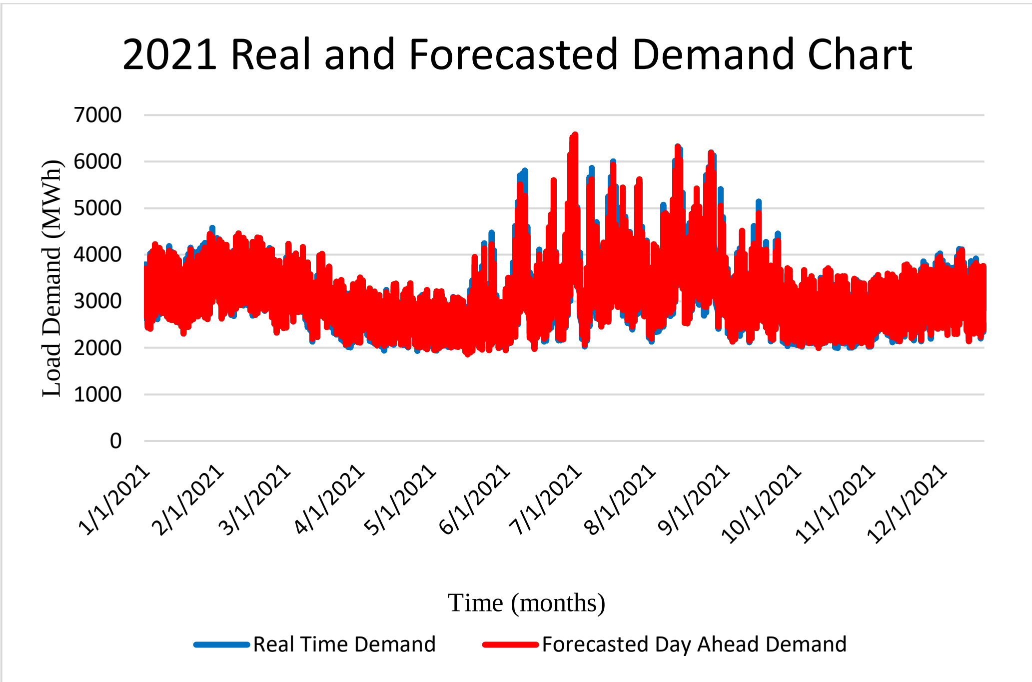


Figure 6.13. Real time and forecasted demand for 2021, Connecticut

CHAPTER 7

EMPIRICAL RESULTS

7.1 PERFORMANCE COMPARISON FOR THE MODELS

This thesis discusses the findings of the proposed models from the experiments carried out on the two markets and divided the results section into two parts for simplicity and clarity. The results parts are structured that one section contains results for the error metrics and the other contains results for the ensemble model comparison of the models employed in this thesis and lastly the graphical representation of the real and forecasted load demand and LMPs for the selected zones and cities.

7.1.1 Accuracy metrics

The thesis started by presenting the results of the deep neural model and LEAR model respectively in terms of their accuracy metrics and graphically represent their findings to support the argument made in the sections to follow on which metrics to use in EDF and EPF. In the electricity demand and price forecasting, majority of metrics utilized to measure the accuracy of forecasts are the (MAE), (RMSE), (MAPE), (MASE) as shown by the equations below,

$$MAE = \frac{1}{24N_d}\sum_{d=1}^{N_d}\sum_{h=1}^{24}\left|de_{d,h} - de^{*}{}_{d,h}\right|, \tag{5.1}$$

$$RMSE = \sqrt{\frac{1}{24N_d}\sum_{d=1}^{N_d}\sum_{h=1}^{24}\left(de_{d,h} - {de^*}_{d,h}\right)^2}, \tag{5.2}$$

$$MAPE = \frac{1}{24N_d}\sum_{d=1}^{N_d}\sum_{h=1}^{24}\frac{\left|de_{d,h} - {de^*}_{d,h}\right|}{de_{d,h}}, \tag{5.3}$$

$$MASE = \frac{1}{N}\sum_{k=1}^{N}\frac{\left|de_{d,h} - {de^*}_{d,h}\right|}{\frac{1}{n-1}\sum_{i=2}^{n}\left|{de_i}^{in} - {de_{i-1}}^{in}\right|}, \tag{5.4}$$

where, $de_{d,h}$ and ${de^*}_{d,h}$ (can be altered for EDF and EPF) respectively represent the real and forecasted demand on an hour h and day d, de – demand, pe – price and N_d is the number of days in the out-of-sample test period, i.e., in the test dataset.

The MAE and RMSE are not immensely useful because absolute errors are difficult to assess between different datasets and markets. Furthermore, electricity costs and profits are generally directly related to power prices, therefore measures based on quadratic errors, such as the Root Mean Square Error (RMSE), are difficult to interpret and do not accurately capture the fundamental problem of most forecasting users. Most energy trade applications, in particular, have underlying risk, rewards, and costs that are linearly related to the demand and it's forecasting mistakes. As a result, linear measures describe the underlying hazards of predicting errors better than quadratic metrics.

Conversely, since MAPE values can get very big with demand values that are near to zero, especially when there are blackouts (independent of real absolute mistakes), the MAPE is frequently dominated by low-price periods and is therefore not very instructive. In [102], the symmetric Mean Absolute Percentage Error (sMAPE) was defined as:

$$sMAPE = \frac{1}{24N_d}\sum_{d=1}^{N_d}\sum_{h=1}^{24} 2\frac{\left|de_{d,h} - de^*{}_{d,h}\right|}{\left|de_{d,h}\right| + \left|de^*{}_{d,h}\right|}, \tag{5.5}$$

While scaled errors do indeed solve the issues of more traditional metrics, they have other associated problems that make them unsuitable in the context of EDF and EPF;

I. As MASE depends on the in-sample dataset, forecasting methods with different calibration windows will naturally have to consider different in-sample datasets. As a result, the MASE of each model will be based on a different scaling factor and comparisons between models cannot be drawn.

II. The same argument applies to models with and without rolling windows. The latter will use a different in-sample dataset at every time point while the former will keep the in-sample dataset constant.

III. In ensembles of models with different calibration windows, the MASE cannot be defined as the calibration window of the ensemble is undefined.

IV. Drawing comparisons across different time series is problematic as electricity prices are not stationary. For example, an in-sample dataset with spikes and an out-of-sample dataset without spikes will lead to a smaller MASE than if we consider the same market but with the in-sample/out-sample datasets reversed.

The rMAE accuracy metric solves some of these issues, it has (as any metric based on percentage errors) a statistical distribution with undefined mean and infinite variance [103], [104]. Similar to MASE, it normalizes the error by the MAE of a naive forecast. However, instead of considering the in-sample dataset, the naive forecast is built based on the out-of-sample dataset. For day-ahead electricity prices of hourly frequency, rMAE is defined as:

$$rMAE = \frac{\frac{1}{24N_d}\sum_{d=1}^{N_d}\sum_{h=1}^{24}\left|de_{d,h} - de_{d,h}\right|}{\frac{1}{24N_d}\sum_{d=1}^{N_d}\sum_{h=1}^{24}\left|de_{d,h} - de^{*naive}{}_{d,h}\right|}, \tag{5.6}$$

Where the $\frac{1}{24N_d}$ factor cancels out in the numerator and the denominator. There are three natural choices for the naive forecasts:

- $de^{*naive,1}{}_{d,h} = de_{d-1,h}$,
- $de^{*naive,2}{}_{d,h} = de_{d-7,h}$,
- $de^{*naive,3}{}_{d,h} = \begin{cases} de_{d-1,h}, & \text{if d is Tue, Wed, Thur or Frid,} \\ \mathrm{de}_{\mathrm{d-7,h}} & \text{if d Sat, Sund, or Mond.} \end{cases}$

In the context of EPF, rMAE using $\mathrm{de}^{*\mathrm{naive,2}}{}_{\mathrm{d,h}} = \mathrm{de}_{\mathrm{d-7,h}}$ is arguably the best choice for two reasons:

i. it is easier to compute than the one based on $\mathrm{de}^{*\mathrm{naive,3}}{}_{\mathrm{d,h}}$ and, unlike the rMAE based on $\mathrm{de}^{\mathrm{naive*,1}}{}_{\mathrm{d,h}}$, it captures weekly effects,

ii. Given a set of forecasting models, the relative ranking of the accuracy of the models is independent from the naive benchmark used. Hence, in the remainder of the article we will use rMAE to explicitly refer to the rMAE based on $\mathrm{de}^{*\mathrm{naive,2}}{}_{\mathrm{d,h}}$. It is important to note that, similar to rMAE, one could also define the relative RMSE (rRMSE) by dividing the RMSE of each forecast by the RMSE of a naive forecast.

Since the in-sample dataset is no longer required, utilizing a rolling window is no longer a concern because the out-of-sample dataset remains unchanged. Models with differing calibrating periods can also be assessed, and the rMAE of ensembles can be specified accurately. Furthermore, the challenge of establishing conclusions in quasi time - series data is alleviated because the metric is standardized by the MAE of a conventional forecast for much the same sample. rMAE should always be utilized to assess innovative approaches in EDF because of its superior properties. Whereas other metrics can be used in tandem with rMAE, it is critical to incorporate and implement rMAE in order to gain more equitable perceptions and evaluations.

7.2 INDIVIDUAL MODELS

In terms of rMAE, MAE, MAPE, SMAPE, and RMSE, Table 5 compares the performance of the two separate models and their modifications. The LEAR model is shown for four distinct calibration windows that represent 182, 728, 1824, and 2554 days, or 8 weeks, 12 weeks, 3 years, and 4 years, respectively. The four DNNs were also acquired by running the feature/hyperparameter optimization technique four times and picking the appropriate feature/hyperparameter classification out of each trial, as seen in the preceding section which included ensembles and hyperparameters. There were several discoveries formed:

- The MAPE appears to be an ineffective indicator because it contradicts the other three linear indicators as well as the quadratic metric. While the rMAE, MAE, and sMAPE all concur on which model is the best in every circumstance, the MAPE virtually seldom complies. The German market exemplifies this unreliability: whereas the MAPE and sMAPE measurements are normally of similar order of magnitude, the MAPE in the German market is roughly ten times bigger. This effect can be attributed to negative and extremely closer to zero pricing in Germany, resulting in very large absolute percentage errors that distort the MAPE. The German market was utilized to substantiate the argument made on MAPE indicators but not included in this thesis.

- It appears that the DNN models are much more precise over state of the art statistical LEAR model. In respect to linear metrics, a DNN is the best model across the two marketplaces. Furthermore, the majority of DNN models outperformed all four LEAR models in all the markets examined

- Even though the RMSE yields significantly distinct findings, which is should be made to understand given that the metric is based on quadratic rather than linear errors. Nevertheless, it however demonstrates overall dominance of the DNN model:

the DNN is better in both datasets, despite the fact that it is evaluated by decreasing absolute errors (versus LEAR). Additionally, while the DNN appears to be poorer in two markets based on RMSE indicators, the RMSE indicator doesn't quite accurately reflect the fundamental dilemma, and it might be argued that it is not the optimal metric for evaluating the efficiency and the overall performance for electricity demand and price forecasting models.

Table 7. DNN model accuracy metrics, NP market.

		DNN_1	DNN_2	DNN_3	DNN_4
NP	rMAE	0.324	0.401	0.303	0.344
	MAE	1.586	1.91	1.607	1.504
	MAPE	5.527	6.313	5.373	5.603
	sMAPE	4.956	5.772	4.759	5.156
	RSME	3.263	3.648	3.249	3.149

Table 8. LEAR model accuracy metrics, NP market.

		$LEAR_{182}$	$LEAR_{728}$	$LEAR_{1824}$	$LEAR_{2554}$
NP	rMAE	0.364	0.361	0.371	0.370
	MAE	1.741	1.739	1.786	1.779
	MAPE	6.125	6.146	5.888	5.933
	sMAPE	5.445	5.408	5.430	5.447
	RSME	3.460	3.453	3.394	3.393

Table 7 and 8 results, shows the DNN and LEAR models accuracy metrics for LMPs from the Nord Pool (NP) market in terms of the different metrics (rMAE, MAPE, MAE, RMSE, and sMAPE). To attain higher accuracy metrics, the thesis employed four different sets of configurations and the best-case scenarios is highlighted for a specific model in respect to the metric.

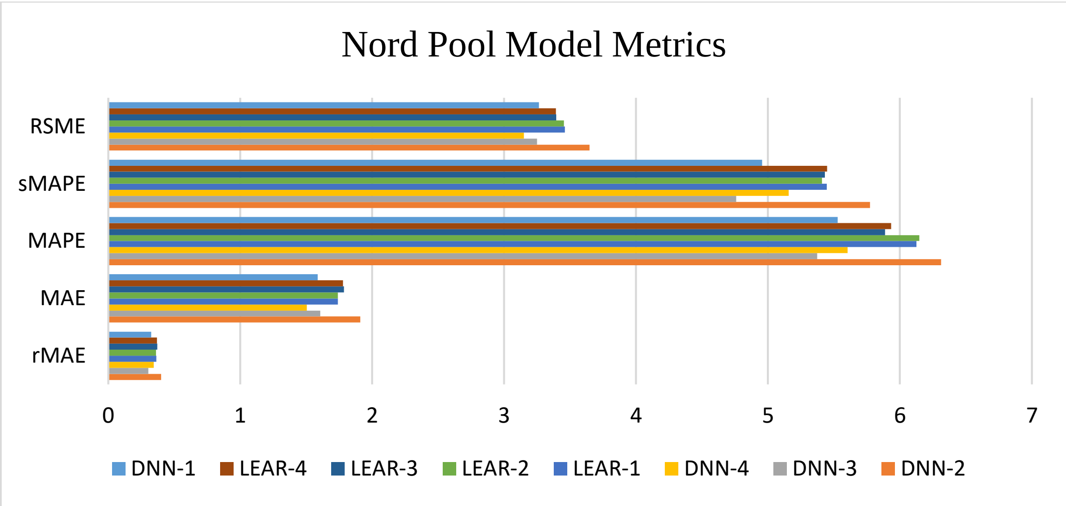


Figure 7. LMPs accuracy metrics comparison

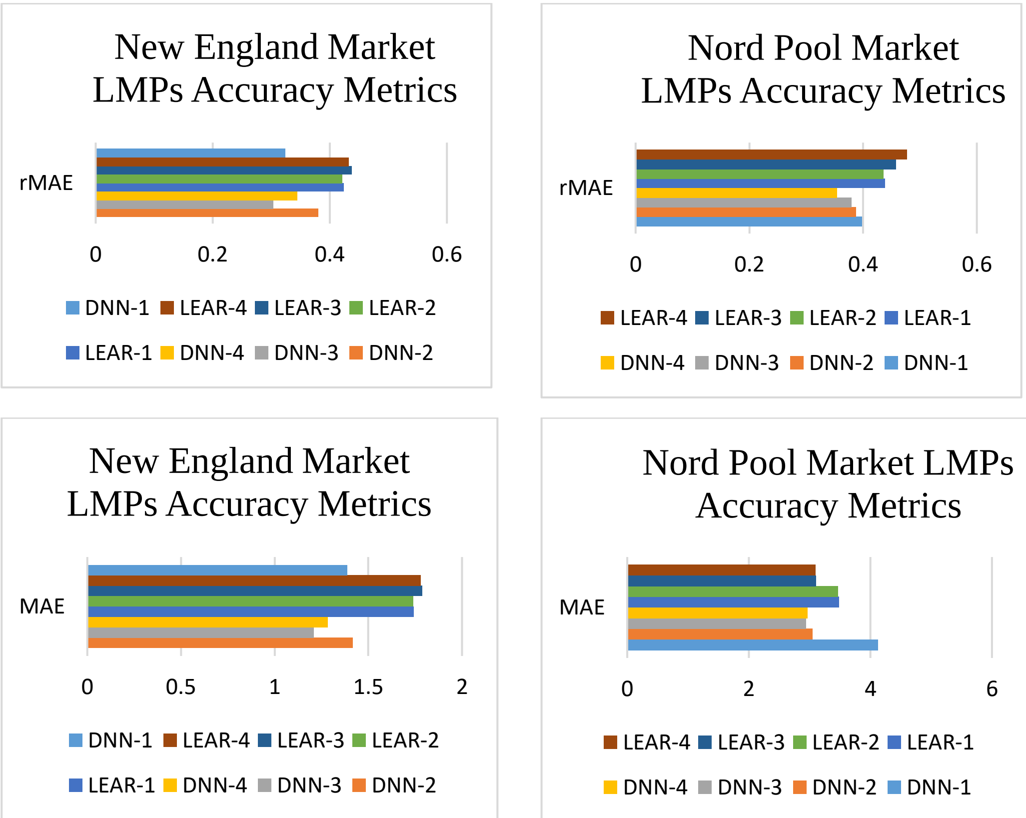


Figure 7.1 Accuracy metrics comparison

To better understand the distinction on model performance, two metrics are selected for comparison, the rMAE and MAE, to validate that the deep learning models performs better than the statistical models. The figures 7 and 7.1 clearly shows the deep learning models are much more accurate in all the five-accuracy metrics employed.

Table 9. DNN accuracy metrics, NE-ISO market

		DNN_1	DNN_2	DNN_3	DNN_4
NE-ISO	rMAE	0.398	0.387	0.379	0.354
	MAE	4.122	3.045	2.944	2.963
	MAPE	10.21	9.78	9.182	9.334
	sMAPE	7.52	7.21	7.274	7.013
	RSME	4.236	4.763	3.102	3.298

Table 10. LEAR accuracy metrics, NE-ISO market

		$LEAR_{182}$	$LEAR_{728}$	$LEAR_{1824}$	$LEAR_{2554}$
NE-ISO	rMAE	0.438	0.436	0.378	0.377
	MAE	3.477	3.467	3.098	3.095
	MAPE	10.84	10.78	10.09	10.08
	sMAPE	8.68	8.84	7.45	7.43
	RSME	3.715	3.704	3.246	3.124

Table 9 and 10 results, shows the DNN and LEAR models accuracy metrics for load demand from the New England ISO (NE-ISO) market in terms of the different metrics (rMAE, MAPE, MAE, RMSE, and sMAPE). To attain higher accuracy levels, the thesis employed four different sets of configurations and the best-case scenarios is highlighted in purple for a specific model in respect to the metric.

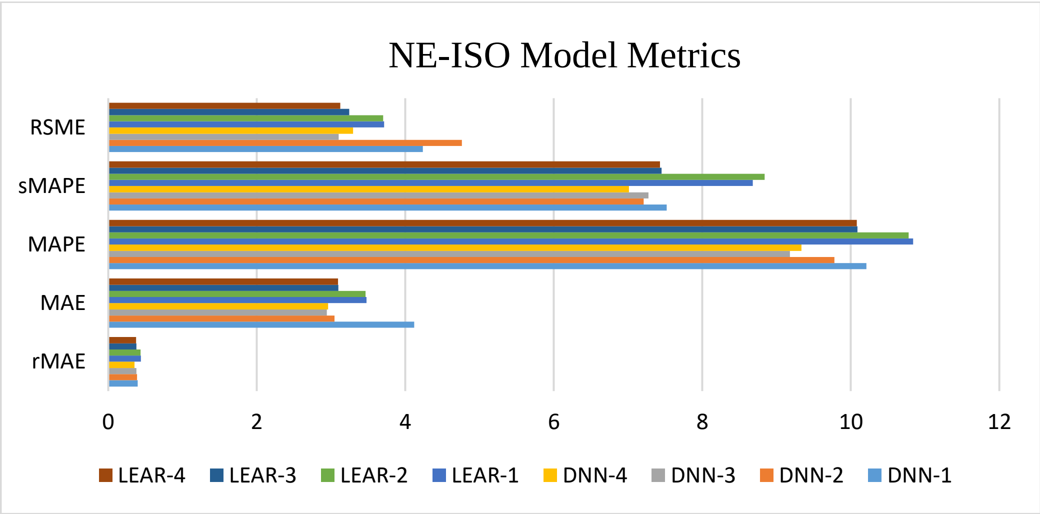
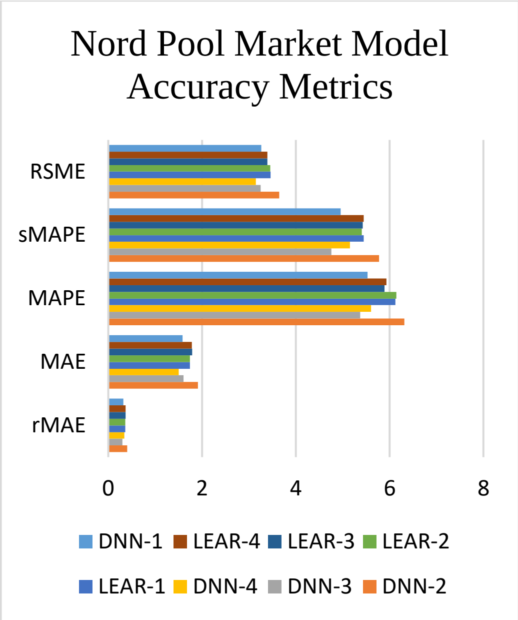


Figure 7.2. LMPs accuracy metrics comparison, NE-ISO electricity market

Figure 7.2 Shows the graphical representation on the comparison of the DNN and the LEAR models for New England ISO market in terms of rMAE, MAE, MAPE, sMAPE and RMSE. The results complement the basic principles suggested and analyzed in the section earlier in terms of accuracy metrics: studies in energy load demand forecasting must eschew MAPE and instead utilize metrics like sMAPE or rMAE. The preceding hypotheses are substantiated by the below claims:

1. MAE would be just as solid as rMAE. Furthermore, since the errors really aren't absolute, there is no way to compare datasets, therefore rMAE is preferable.
2. sMAPE is far more accurate and reliable over MAPE, and it accords with MAE/rMAE. However, it suffers from an undefined mean and unlimited variance. As a result, it's much less reliable than the proposed rMAE.
3. MAPE is not really a reliable indicator since it prioritizes sets of data near zero. As a result, MAPE can produce deceptive outcomes and inaccurate findings.
4. Although RMSE is somewhat dependable than MAPE, it does not entirely accurately reflect the core potential risks connected with EPF. As a consequence, it must never be employed to objectively assess forecasting models on its account.



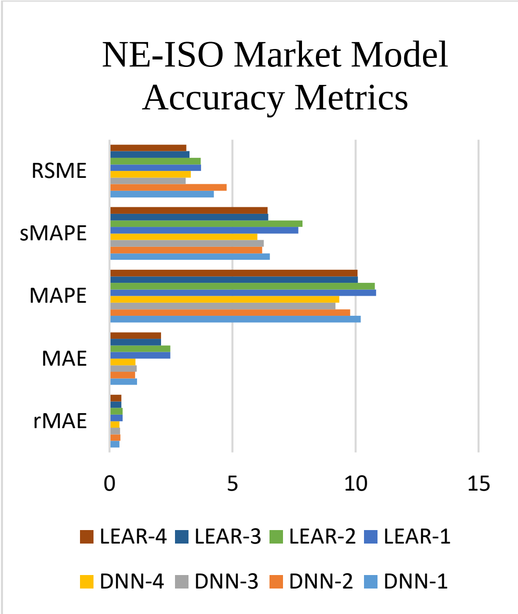


Figure 7.3. Load demand accuracy metrics

7.2.1 Ensembles

Table 11 compares the performances of the two ensemble models with the best DNN and LEAR models in respect of the rMAE metric, which really is undoubtedly the most reliable statistic. Numerous insights can be derived from the table 7 below:

i. In particular, for two markets and all verifiable indicators, the ensemble of DNNs outperforms the best individual DNN model. Similarly, for the two markets and dependable indicators, the ensemble of LEAR models outperforms the best individual LEAR model. The MAPE and RMSE measurements are the outliers to this criterion, although as previously stated, MAPE is a problematic indicator, and RMSE doesn't accurately depict the fundamental issue of EDF.

ii. Like before, the ensemble of DNNs is the most accurate model in terms of rMAE throughout all the electricity markets experimented, suggesting that DNN models are much more efficient than LEAR models.

Table 11. Ensemble model accuracy metrics: New England ISO Market

		LEAR Model	*DNN Model*	*Best LEAR*	*Best DNN*
NE-ISO	rMAE	0.364	0.342	0.357	0.354
	MAE	2.013	1.862	2.095	2.075
	MAPE	10.045	9.159	10.079	9.325
	sMAPE	6.985	6.345	7.538	7.012
	RMSE	3.271	3.145	3.421	3.289

Table 11 clearly shows the comparison between then ensembles of the proposed DNN model and the benchmark LEAR model for the New England ISO market in terms of the relative accuracy metrics employed (RMAE, MAE, MAPE, sMAPE and RMSE). The comparative analysis also involves the best-case scenario of the performing model in terms of MAE, and rMAE, which are the two most reliable metrics and all the accuracy metrics, therefore the best-case scenario for every metric is highlighted in purple. It can be seen that the DNN model outperformed the state-of-the-art statical model in all accuracy metrics for the NE-ISO market case study.

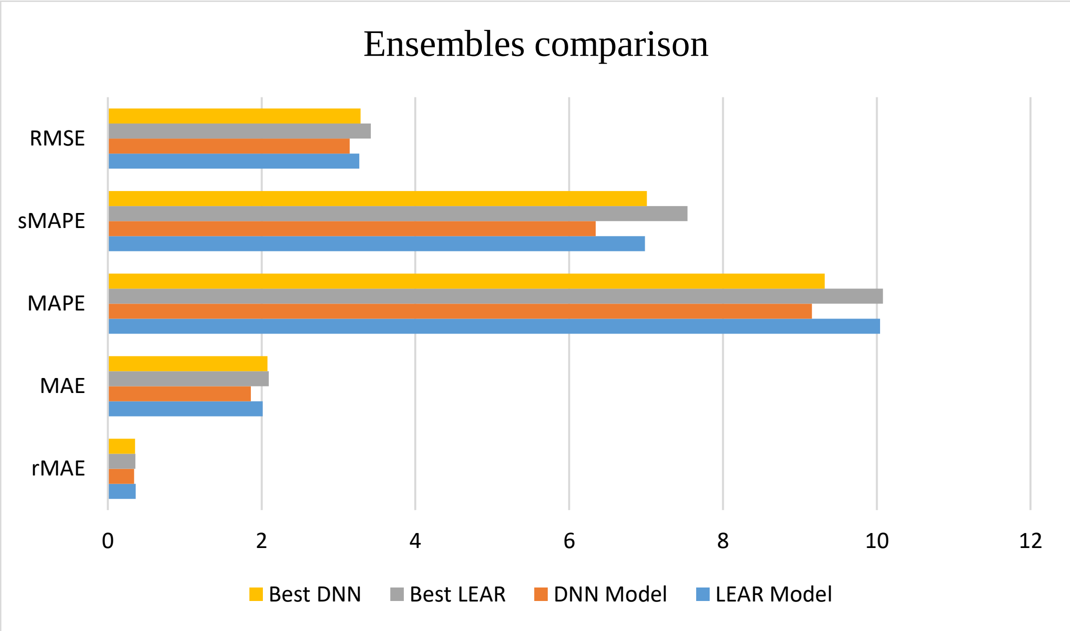


Figure 7.4. Comparative analysis of the best ensemble case scenario

In detail figure 7.4 shows the comparative analysis also involving the best ensemble case scenario of the performing model in terms of MAE, and rMAE, which are the two most reliable metrics and the best case per model.

Table 12. Ensemble model accuracy metrics: Nord Pool Market

		LEAR Model	*DNN Model*	*Best LEAR*	*Best DNN*
	rMAE	0.208	0.197	0.265	0.202
	MAE	1.327	1.272	1.541	1.306
NP	MAPE	4.022	3.873	4.846	4.073
	sMAPE	3.498	3.369	4.105	3.459
	RMSE	1.851	1.808	2.153	1.849

Table 12 clearly shows the comparison between then ensembles of the proposed DNN model and the benchmark LEAR model for the Nord Pool market in terms of the relative accuracy metrics employed (RMAE, MAE, MAPE, sMAPE and RMSE). The comparative analysis also involves the best-case scenario of the performing model in terms of MAE, and rMAE, which are the two most reliable metrics and all the accuracy metrics, therefore the best-case scenario for every metric is highlighted. It can be seen that the DNN model outperformed the state-of-the-art statical model in all accuracy metrics for the NP and NE-ISO market case study.

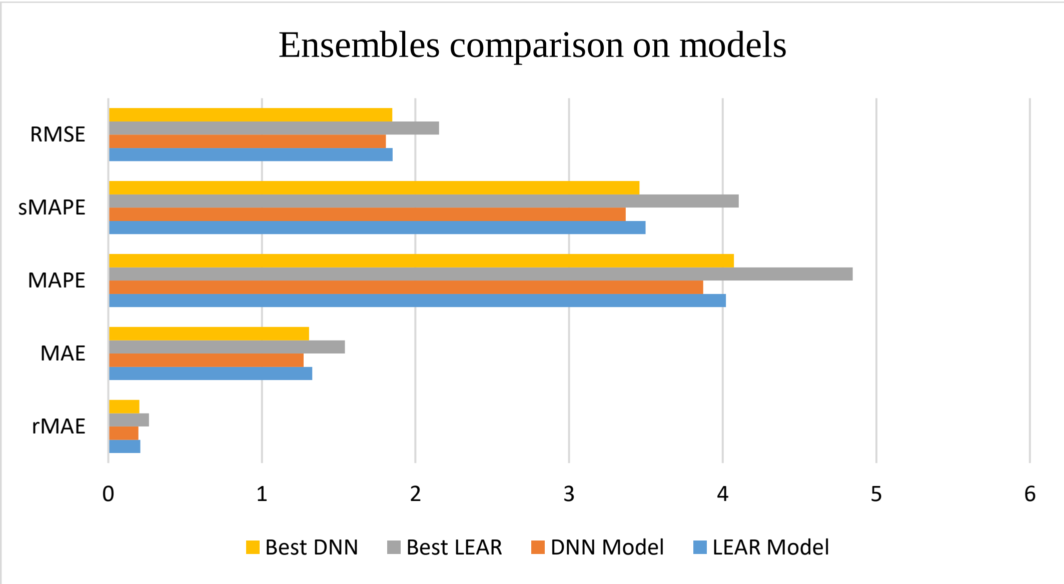


Figure 7.5. Ensemble accuracy comparison of DNN and LEAR models

Figure above graphically illustrates the comparison between then ensembles of the proposed DNN model and the LEAR model for two markets in terms of RMAE, MAE, MAPE, sMAPE and RMSE.

7.2.2 Computation time

In addition to just comparing the models' prediction accuracy, it is also mandated to assess the computational times of these forecasting approaches, as discussed in the preceding section. Table 11 shows a comparative information of the computational time taken to estimate the models under study, i.e., the time necessary to recalibrate each model on regular routines. The computational time is presented as a range because it is non-deterministic. These results were obtained with a standard i5-6920HQ laptop with a quad-core processor.

Even though the LEAR model achieves significantly worse accuracy than the DNN model, its computational time is 30 to 100 times faster; specifically, the LEAR model is 50 times faster when comparing the maximum computing time of both approaches.

Table 13. Computation time for the proposed forecasting models.

MODEL	TIME
LEAR	10–25 s
LEAR ENSEMBLE	25–45 s
DNN	2–4 min
DNN ENSEMBLE	5–15 min

7.3 DISCUSSION AND REMARKS

This thesis can conclude with some last notes on the motivations for the accuracy metrics used, a quick analysis of the impact of the various metrics studied, and a discussion of comparing new models in the coming sections and the graphical real and forecasted parameters for better understanding.

7.3.1 Squared vs Absolute errors

The thesis mostly explored accuracy metrics based on absolute errors throughout the research, that is, metrics that measure the accuracy of forecasting the distribution's median. One could argue that a test based on squared errors should be selected since the LEAR model is estimated by reducing squared errors, which leads to relatively mean forecasts [105]. While there are some merits to the argument, this thesis opted for absolute metrics for three main reasons stated below:

1. The metric for assessing accuracy must be the one that accurately suits the fundamental problems in EDF and EPF. Since the demand of electricity is continuous in the case of EDF, linear indicators are highly probable and the finest approach to assess the risks with forecasting errors.
2. While the RMSE data were supplied, they are not qualitatively identical to the MAE/rMAE values. Due to capacity limitations, the RMSE results were hardly investigated in depth because absolute errors better describe the fundamental problem of EDF, and the results are not identical.
3. Although the LEAR model is evaluated utilizing squared errors, this is largely due to the fact that the techniques for efficiently estimating the LASSO, such as coordinate descent, employ squared errors. The LEAR model has a computational advantage over the DNN as a result of this. Regularized quantile regression [106] is an alternative, nevertheless it adds to the computational overhead while providing minimal gain in terms of MAE/rMAE accuracy.

7.3.2 Performance of the LSTM-DNN and LEAR models

The models based in deep learning proved to be more accurate and efficient and hence outperformed those based on conventional neural networks and statistical approaches, according to the detailed comparison of accuracy metrics and computational time. This is particularly true in the context of DL ensemble models, where the ensemble of DNNs produces substantially outstanding results than just about any other model present in the literature at the moment.

While DNNs surpassed LEAR models in terms of low complexity and computational time, the latter remain the state-of-the-art in terms of low complexity and computational time. Their performance is slightly behind to that of DNN; however, they have an advantage for less computation time when compared to the contemporary DNN model. In brief, depending on the decision time available, new models for electrical energy load demand forecasting and locational marginal pricing should be compared to LEAR models or DNNs. To be regarded more accurate than state-of-the-art approaches, a method must either outperform the DNN model or outperform LEAR while requiring equivalent or fewer computational resources.

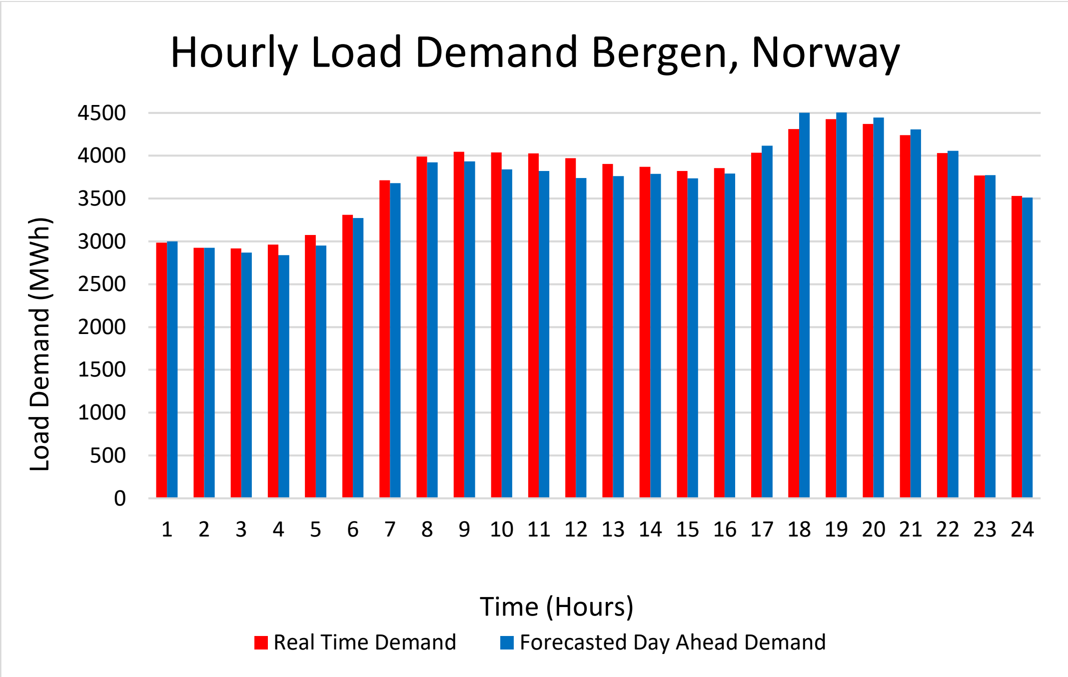


Figure 7.6. Hourly real and forecasted electricity price over a 24 hours' period NP electricity market, Bergen, Norway.

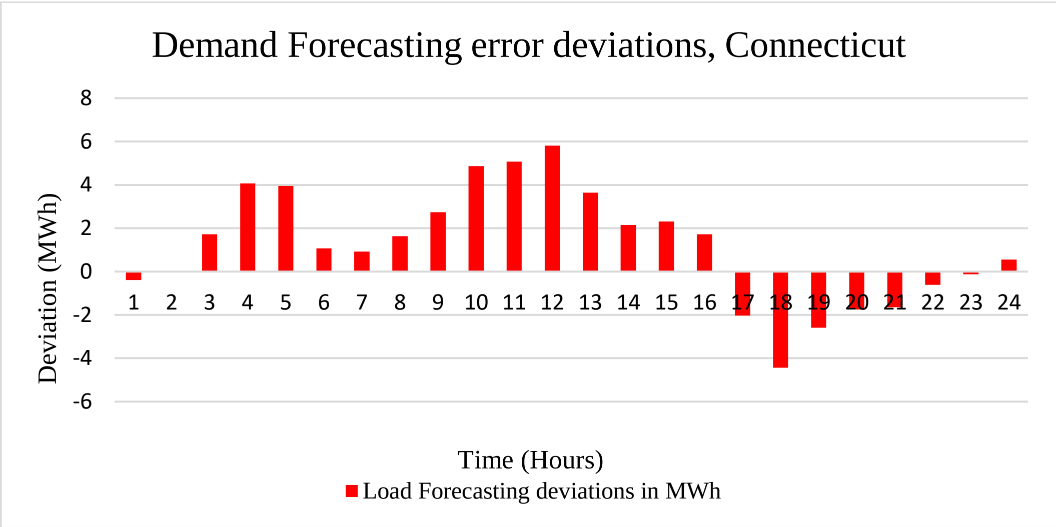


Figure 7.7. Hourly comparative analysis for the real time and forecasted hourly demand over a 24 hours' period NP electricity market, Bergen, Norway.

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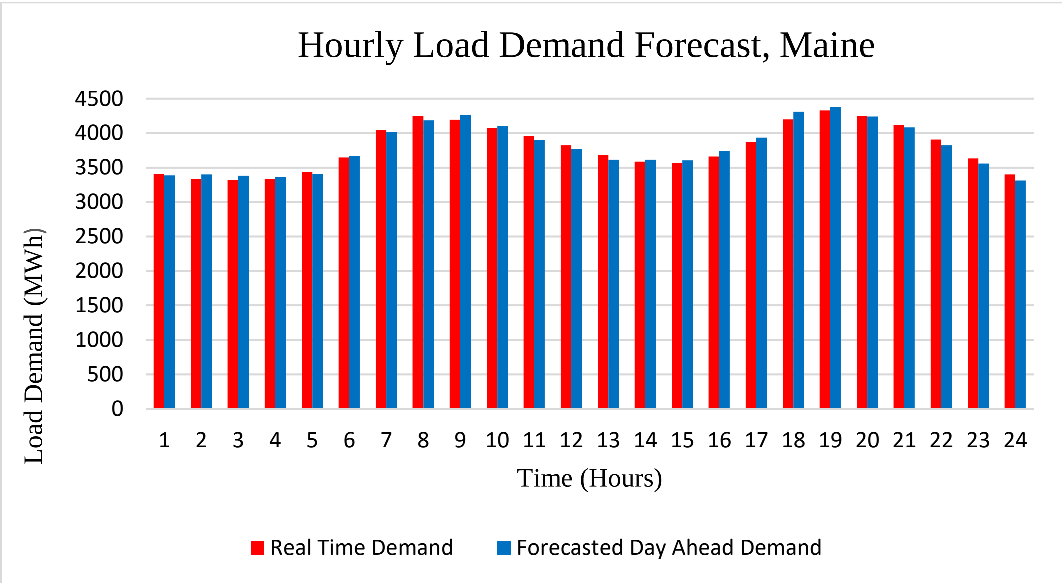

Figure 7.8. Hourly comparative analysis for the real time and forecasted hourly demand over a 24 hours' period NE-ISO electricity market, Maine Zone.

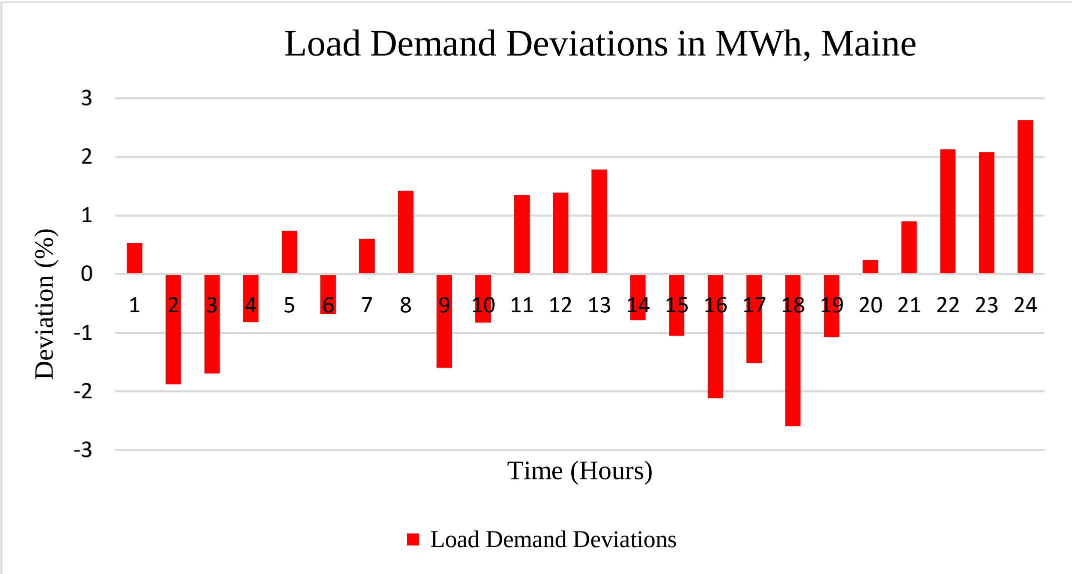

Figure 7.9. Hourly deviations on the real time and forecasted hourly demand over a 24 hours' period for NE-ISO electricity market, Maine.

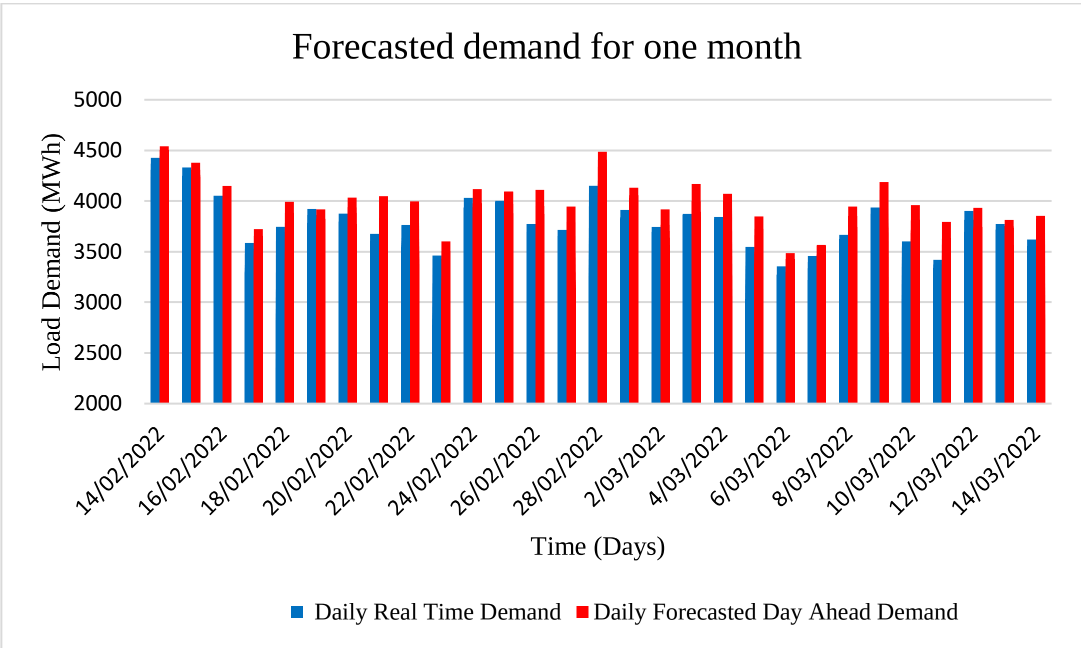

Figure 7.10. Daily real time and forecasted demand for one-month period for NE-ISO electricity market, Maine.

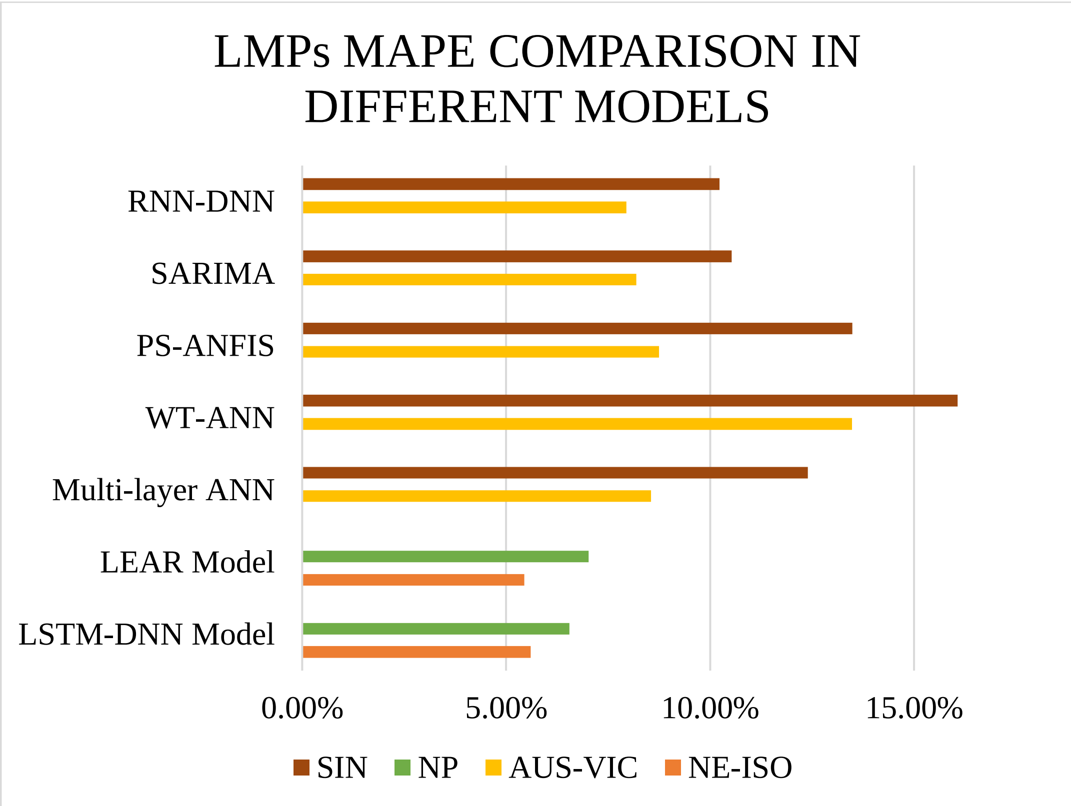

Figure 7.11. LMPs MAPE comparison

The comparison for the proposed models and the contemporary models found in the literature were made to validate the claims that the deep learning models and the state-of-the-art statistical models are quite superior, and they should be he model benchmarks in EDF and EPF context. All the models compared were tested in two different markets to have a sound conclusion on model robustness and adaptability.

8 CONCLUSION

This thesis developed two state-of-the-art models for short time electricity demand and locational electricity price (LMPs) and compared them for accuracy and computational time. The author developed an open access also recommended that open access platform with complete documentation and data for enhanced model accuracy and stability since, thus helping future researchers to carry on from the existing study cases as well have state-of-the-art models for comparison. The author also examined various factors affecting the quality of the research, such as accuracy metrics and dataset size, and a conclusion resulted in suggested solutions to ensure that future research will be reproducible, useful, and adequate, in particular because the field of EDF lacks a rigorous approach to compare and evaluate new forecasting models.

To further elaborate the paragraph above, EPF and EDF do evolve therefore the use of exclusive datasets to which other researchers have limited access is really important and thesis suggested an open-access anaconda notebook and dataset that includes five years and seven years of recent data from five distinct markets. The benchmark dataset's purpose is to give future researchers a similar framework so that novel techniques may be tested under different circumstances and effective comparisons can be made. The python, open-source anaconda notebook module can be found here and its accessible to the public [107].

Since contemporary techniques in EDF and EPF are frequently not evaluated with proven approaches, electricity markets and different zones therefore thesis compared one of the best statistical and deep learning techniques in two distinct markets that has 10 zones for extensive analysis. At the moment the toolbox only supports python programming language but, in the future, the author would like to support more languages and with the help of other scholars, and further extend the impact of the studies.

With the use of these findings, this thesis was able to demonstrate that while LEAR approaches are the best model for applications requiring quick decision times, deep neural networks outperformed them overall. Furthermore, we have demonstrated that ensemble model approaches frequently produce findings that are appreciably superior to those of their solo counterparts. Based on the results presented, it can be concluded that following guidelines and proper methodologies to what constitutes to a good forecasting model has significant implications to how the model will perform.

In a nutshell, three most important recommendations were made from the research,

i. Statistical testing was required to reach significant conclusions,

ii. MAPE is an unreliable metric in electricity demand forecasting, and it should be avoided,

iii. The test dataset should be at least one year long, and the availability of data plays a big role in the accuracy and robustness of an electricity forecasting model.

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