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SMART GRID ENERGY MANAGEMENT SYSTEM FOR INDUSTRIAL APPLICATIONS

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DECLARATION

This Project Report is my original work and has not been presented for a Degree in this or any other University:

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DEDICATION

I dedicate this project report to my parents, Mr. and Mrs. Omondi and my brother for their unwavering support and motivation throughout my academic journey.

ACKNOWLEDGEMENT

To begin with, I thank God for the special gift of life and for giving me the capacity, strength, knowledge and opportunity to undertake this research project to completion.

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LIST OF ABBREVIATIONS

ARIMA	Autoregressive Integrated Moving Average
BEMS	Building Energy Management System
BPPT	Back Propagation Through Time
BIP	Binary Integer Programming
CEMS	Community Energy Management System
CBA	Cost Benefit Analysis
DEMS	Data Centre Energy Management System
DER	Distributed Energy Resource
DR	Demand Response
DSM	Demand Side Management
DTOUC	Disaggregation and Time of Use Calculator
EGS	Energy Generation System
EMMS	Energy Monitoring and Management System
EMS	Energy Management System
ESS	Energy Storage System
FTT	Fixed Time Tariff
FIS	Fuzzy Inference System
GUIOS	Graphical User Interface and Operation Scheduler
HAN	Home Area Network
HEMS	Home Energy Management System

ICT	Information Communication Technology
IEEE	Institute of Electrical and Electronic Engineering
IMD	In-operation Machine Detection
LSTM	Long Short Term Memory
MILP	Mixed Integer Linear Programming
MCS	Monte Carlo Simulation
NICLCE	National Institute of Clean and Low Carbon Energy
OpenADR	Open Automated Demand Response
PBP	Payback Period
RERs	Renewable Energy Resources
RNN	Recurrent Neural Network
ROI	Return on Investment
RTP	Real Time Pricing
ST	Schedulable Task
STN	State Task Network

ABSTRACT

Over the years, energy needs have become complicated due to rapid industrialization, population growth and enforcement of stringent measures to reduce the carbon footprint globally. Industries being amongst the largest consumers of electricity generated worldwide, can realize huge savings in energy cost by implementing energy management programs. This research incorporates the aspects of a smart grid in designing an energy management system (EMS) where demand side management (DSM) is utilized to enable industrial users minimize their energy costs. A forecasting model for electricity prices and demand is developed using Long Short Term Memory (LSTM) - Recurrent Neural Network (RNN) technique. The predicted prices are used in load scheduling to realize potential energy cost savings. The non-priority loads are scheduled to leverage on low electricity prices during off peak times. The effectiveness of the designed energy management strategy is tested using an IEEE 30 bus system. A suitable operation schedule with committed units for each hour is given for one sample day. Using the test system with 20 loads yielded an annual energy cost saving of \$2,961,169.20, a payback period (PBP) of 4 years 5 months, and a return on investment (ROI) of 22.78%. The ROI can be improved by considering savings from future years of having the EMS in place. Overall, industries can maintain a competitive edge by investing in an effective EMS that will enable them minimize their electrical energy costs which forms one of the top operating expenses.

Keywords: Smart Grid, Energy Management System, Long Short Term Memory, Recurrent Neural Network, Demand Side Management, Demand Response, Time of Use

CHAPTER 1: INTRODUCTION

1.1 Background

This chapter has introduced the topic of investigation by explaining the major changes in energy demand over the years leading to the shift towards smart grids. It has explained the meaning of a smart grid, its components, and benefits to both consumers and utilities. It has further discussed the concept of energy management and types of EMSs used in different areas. The objectives of the research have also been highlighted and the scope of the work defined. The last section of the chapter has outlined the organization of the rest of the report.

The current energy infrastructure was conceived decades ago when energy needs were quite simple such as powering radios and light bulbs. Electricity generation was centralized and done from non-renewable sources like fossil fuels. The power system was limited to one-way interaction between the utility companies and the consumers who were billed monthly. However, in the 21st century, there are complex energy needs that call for modernizing of the grid as the old power system model is incapable of readily responding to the changes. The adoption of a smart grid is one form of modernizing the energy infrastructure to create a resilient, sustainable, reliable, and secure grid. The smart grid consists of a network of communication and computer processing tools, control systems, automation, and innovative technologies to make the grid respond digitally to the rapidly changing demand. A smart grid allows for a two-way dialogue between the utility companies and consumers, as well as between consumers, where electricity and information is easily exchanged. The components of a smart grid include, smart substations, smart relays, smart meters, smart appliances, automated feeder switches, wireless sensors, synchro phasors and storage devices [1]. Additionally, a smart grid promotes the utilization of renewable energy resources to better manage the electricity needs thereby creating energy independence from the utility grid. Figure 1.1 represents a smart grid with wind and solar Distributed Energy Resources (DERs), transmission lines as well as residential, commercial, and industrial units.



Figure 1.1: Smart Grid

A smart grid improves customer engagement in power management through energy demand management programs. Active consumer engagement enables individuals to control their own energy consumption hence achieve energy savings. Not only does the adoption of a smart grid benefit the consumers but also the utilities by reducing the peak loads and operational cost, as well as improving the power system security and increasing the integration of renewable resources. Energy management is crucial in ensuring that energy is used judiciously to minimize costs and reduce environmental impacts. There are two approaches to energy management that is considering the supplier side or the consumer side. Both approaches are significant in ensuring a balance between demand and supply to improve the network's reliability. An energy management system consists of tools for data collection, analysis, and visual display for effective energy management. A smart energy management system enables the conversion of power network data into useful information for decision support to optimize power system operation. The EMS helps in the effective control, conservation, and monitoring of energy use to minimize consumption hence yield energy savings. Different types of energy management systems are used within different setups such as micro-grids, households, industries, and communities [2].

1.2 Problem Statement

Smart grids offer numerous opportunities for both consumers and utilities in regards to improved reliability, remote control, integration of renewables, and power management. With the increased adoption of smart grids in recent years, industrial consumers have to devise effective ways of promoting their interaction with utility companies. Industries can leverage on the capabilities of a smart grid to design effective energy management schemes to better position themselves in their

various sectors of operation. For instance, the use of smart metering tools and actively engaging machine operators in power management can aid in the development of an operational EMS that can greatly reduce the peak load during unexpected periods hence benefitting not only the industries but also the utilities.

Energy management is a competitive strategy that industries can use to maximize their profits while minimizing on costs. Previous research works have focused on specific applications of EMSs including smart homes, data centers, buildings, communities, a coal mining plant, and a vehicle testing facility. Despite addressing the effective use of energy with an aim of reducing energy costs and maximizing efficiency, past researches have not fully leveraged aspects of the smart grid in designing energy management schemes. Very few researchers have given a specific algorithm for demand side management as most prefer to discuss them theoretically without providing any practical solution. A good number of past research works addressing demand and price forecasting use conventional time series modelling techniques such as ARIMA which are preferable when dealing with linear time series data.

This research has recommended the use of proper load scheduling as a demand side management technique to minimize energy cost in industries. The EMS has enabled the end users to understand their energy usage and variation of electricity prices with demand hence informing the choice to schedule the loads. Load scheduling was done in a manner that reduced the total energy costs while distributing the load ensuring peak demand was experienced at off-peak hours with low electricity prices. The developed EMS has enabled both the consumers and utilities to realize the full benefits of the smart grid by optimizing the use of energy data for power system planning and industrial operations.

1.3 Objectives

1.3.1 Main Objective

To design a general Energy Management System (EMS) that provides recommendations on suitable Time of Use (TOU) for industrial loads based on the predicted electricity prices to minimize energy cost.

1.3.2 Sub-Objectives

- i) To develop a prediction model for electricity prices and demand.

- ii) To devise a technique for load scheduling using the forecasted electricity prices.
- iii) To generate a suitable operating schedule effective in minimizing energy cost.TOU
- iv) To determine the economic viability of implementing an industrial energy management system.

1.4 Research Questions

- i) Which methods are suitable for time series modelling and forecasting?
- ii) What are the crucial factors that need to be considered when performing load scheduling to ensure energy cost reduction?
- iii) How does variation in electricity prices and demand affect load scheduling?
- iv) What tools of economic analysis adequately assess the feasibility of investing in an industrial EMS?

1.5 Scope of Work

This research has developed a generalized EMS to enable the users optimize their energy consumption with ease. Demand Side Management (DSM) technique was employed in controlling energy use with an aim of saving on cost and improving energy efficiency. The process involved optimizing the consumption patterns with respect to the predicted electricity prices prior to selecting a suitable loads' schedule. Python programming was used to analyze the collected data on demand and electricity prices before performing load and price forecasting. LSTM-RNN which is a machine learning algorithm was used in the forecasting. The predicted prices were used in advising the consumer on preferred TOU to reduce the energy cost. The effectiveness of the developed model in minimizing energy cost was tested using an IEEE 30 Bus system.

1.6 Justification

In the 4th industrial revolution, reducing electrical energy cost is crucial in boosting the competitiveness of a manufacturer. The adoption of a solid energy management scheme would significantly reduce the operational expenditure in an industry as well as the associated environmental impacts. Industries have a huge potential of leveraging energy consumption data obtained from a smart grid EMS to improve energy efficiency and achieve savings. Such an EMS enables the industrial consumer to take advantage of lower electricity prices during off-peak times and avoid creating another peak after load shifting by considering each load's needs individually.

The EMS ensures there is peak load management thus maintaining the power system's reliability. An EMS that utilizes the capabilities of smart grids to effectively minimize energy consumption would help industries maximize on their profits hence this research work has provided a feasible solution for large energy consumers.

1.7 Contribution

This research has developed a generalized EMS that recommends suitable TOU for industrial loads based on the predicted electricity prices. The EMS has taken advantage of the opportunity offered by smart grids to process data, make informed decisions, and actively engage consumers in controlling their energy consumption. Load scheduling which is a form of demand side management has been utilized to ensure the attainment of optimum energy cost. The effectiveness of the proposed tool has been tested using an IEEE 30 bus system having 20 loads and 6 generators. The EMS has enabled the industrial users to make decisions on when to operate the energy intensive loads. In this research project, LSTM-RNN has been used in developing a forecasting model to determine the hourly electricity prices before performing load scheduling while taking advantage of low demand times. A recommended schedule with the committed load units has been generated to advise the consumer on how to shift usage to more effective time periods where energy cost is minimum.

1.8 Project Report Organization

The rest of the report has been organized in chapters as follows: Chapter 2 has reviewed related works to identify the existing gaps to help in problem formulation. Chapter 3 has discussed the methods used in previous works as well as the method used in this research. Chapter 4 has discussed and analyzed the simulation results while chapter 5 has described the conclusions arrived at and recommended some topics for future research.

CHAPTER 2: LITERATURE REVIEW

This chapter has reviewed nine past research works in the area of smart grids and energy management in homes and industries. The contributions made in each of the reviewed works and the methods used have been highlighted. The existing gaps have been identified to inform the formulation of a problem for the research. A comparison has also been made between the existing model of EMS and the proposed one.

2.1 Literature Review

Y. Nozaki et al [2] proposed a Data Center Energy Management System (DEMS) that jointly optimized energy usage of all the available equipment in the facility including air-conditioning, power feeding, and ICT systems. Power balance for all devices across different data centers was ensured by combining the DEMS with cutting edge technologies such as cloud computing and virtualization technology. The authors also discussed other energy management systems including a Home Energy Management System (HEMS), a Building Energy Management System, (BEMS), and a Community Energy Management System (CEMS). Tests run on each of these systems yielded either a reduction in carbon dioxide emission or a considerable saving in energy. Two standardization approaches to reduce EMS costs were demonstrated. With shared use of the communication system, the energy cost was minimized whereas the International standardization activities integrated various tasks to achieve the advantages of a smart grid. Experimental analysis was done on a large scale micro grid and the test bed for network integration control system used.

The smart grid technologies discussed by Samad and Kiliccote included the use of micro grids, direct load control, storage, cogeneration, and energy efficiency functionalities [3]. These authors addressed in in-depth automated demand response (DR) as the standardization for communication to achieve maximum production and energy efficiency. Both major production loads and support loads were considered in determining the total industrial energy consumption that needed to be optimized. The authors acknowledged the major role that consumers play in energy management in homes, industries, and buildings following the increased integration of renewable energy resources. It was established that an understanding of the rate structures in the electricity market was crucial in peak load scheduling and management. Additionally, it was proven that automation enabled a faster demand response where loads were used to maintain the grid's balance in real time. The use of a standard information model such as open automated demand response

(openADR) was recommended to support demand side management activities. When designing the automated DR system, only electrical loads were considered. However, in practical industrial facilities there are several demand management opportunities that revolve around energy generation and storage.

Collins et al. [4] came up with an energy monitoring and management system (EMMS) suitable for improving energy efficiency, cost savings, and ecological profile in industries. The system had several modules for in-operation machine detection (IMD), disaggregation and time of use calculator (DTC), and a graphical user interface and operation scheduler (GUIOS). The designed EMMS was best suited for the scheduling of operations to moderate energy consumption. The DTC and GUIOS worked together to provide feedback after the taking of measurements from a single reference point in the system. The GUIOS generated feedback to the operator through the fuzzy inference system to ensure energy and cost savings. The size of a machine's consumption determined the potential cost saving. It was recommended to shift the time of use of the machines to a more effective time period. Using the proposed system for a long time in energy intensive industries resulted in significant savings in consumed energy and costs. A case study of a vehicle testing facility was undertaken and the power disaggregation model simulated. The GUI scheduler was used to schedule machine operations assuming that all processes are schedulable. In reality, some production processes cannot be scheduled and have to be executed as the need arises.

Ogwumike et al. [5] performed scheduling and optimization of various residential loads considering dynamic electricity prices. A day-ahead variable pricing technique was used to ensure that minimum energy bill was attained. The operation of the smart appliances was subject to the machine's operational constraints and the consumer's specific constraints. The scheduling of the home appliances involved mathematical formulation of a constrained linear programming problem solved using Mixed Integer Linear Programming (MILP) optimization technique simulated in MATLAB/SIMULINK. The simulation model representing the residential loads had an intelligent energy controller that monitored the appliances' status and power consumption before optimization. Considering, RTP and FTT, it was noted that optimal scheduling of appliances can yield huge savings in energy. The proposed model mentioned the need to incorporate renewable energy, solar, and an energy storage device for load balancing but did not proceed to implement them.

The authors in [6] introduced a generalized energy management scheme based on state task network (STN) and considering DERs in an industrial facility. The optimal scheduling of schedulable tasks (STs) and use of DERs was done based on a day ahead hourly electricity prices. An objective function was formulated to minimize energy cost whereas several linear constraints were encompassed to guarantee the operations of the processes. MILP was used to solve the objective function. The designed system incorporated process, energy storage system (ESS) and energy generation system (EGS) modeling and also gave the industrial facility the ability to sell excess energy. The DR scheme was effective in maintaining a balance between electricity supply and demand, improving the power system reliability, and reducing the energy costs. Additionally, it enabled the consumers to shift their electricity usage from peak periods to off peak periods. The authors assumed that changes in electricity prices and scheduling of STs only occurred at time horizon interval boundaries.

Using the concept of a smart grid, a power management system with energy storage capability suitable for an industry was developed in [7]. A three pronged approach was used, where a smart grid power management system was first established using smart grid concepts. Secondly, a smart EMS suitable for a coal mine was created to boost energy efficiency, increase the utilization of renewable resources, and improve the reliability of the energy supplying system. The outcomes of the prior stages were used to design the green and smart coal mine having an optimized energy structure. Power quality was considered in the design to ensure that the power system was safe and reliable hence guarantee the ultimate mining production. Other factors taken into account in the system simulation included the control of distributed generation, reactive power compensation, emergency power supply, and peak shaving. Systematic design and optimization was done using energy 3R technology from the National Institute of Clean and Low Carbon Energy (NICLCE). Zhou et al. [7] only addressed smart power management system based on hybrid energy storage disregarding other aspects of power system operation including generation, transmission, distribution, and end use on the consumer side.

M. Acone et al [8] developed an EMS for smart houses that optimized energy consumption and electricity cost while ensuring the consumer's comfort. Both the electrical and thermal loads were taken into account in the optimization whereas the consumer's comfort was ensured by maintaining a steady balance between the in-house temperature and the electrical load usage. The

operation of the EMS was also based on the user's priorities and power tariff when shifting loads to an appropriate time. MATLAB, Simulink and Stateflow were used to simulate the EMS model with the outdoor temperature, set-point temperature, people's presence and the windows state as the inputs. Monte Carlo Simulation was used to compare between the normal and economy scenarios. The authors assumed that lights and steady loads had fixed power consumption, shiftable loads absorbed constant active power in a given work cycle and each appliance performed a single work cycle daily. However, these assumptions are not guaranteed in real life scenarios.

The authors in [9] addressed the significance of adopting a smart grid for effective energy demand management to overcome the problems facing the traditional electric grid. Smart home technology was used to illustrate the role played by the smart grid in ensuring seamless integration of renewable energy to satisfy the rapidly increasing energy demand. The smart homes utilized Information and Communication Technology (ICT) to enable intelligent communication between smart home appliances and smart meters via a home area network (HAN) thereby managing the peak electric demand. These appliances communicated with the electric utility through the advanced metering infrastructure of the smart meters and made intelligent decisions to shift loads to off peak hours where the power tariff was lower thereby saving on cost. A case study of a Puducherry single family home having two bedrooms, a hall and a kitchen was considered. Mahmood et al. [9] failed to consider the technical challenges such as voltage regulation, flicker, and harmonic distortion that are introduced into an existing power system following the integration of renewable energy sources.

The idea of energy storage in prosumer based systems for both energy sharing and management was introduced in [10]. The proposed scheme was highly effective for peak load management with an aim of ensuring that the supply satisfies the demand. The efficacy of the model developed after introducing the storage factor was tested by comparing its performance with that of other users who had Renewable Energy Resources (RERs) of different capacities but lacked a storage system. The implementation of the proposed scheme revealed that there was a higher reduction in the shortage of energy for the system with energy storage than that of the one without ESS. The model effectively minimized the demand-supply gap while considering the price of surplus energy. Binary Integer Programming (BIP) was used for solving the objective function and MATLAB for simulating the proposed model. The model was robust in load management but was not

comprehensive since it offered only one tool for Demand Side Management (DSM), that is, the use of the energy storage functionality. Table 2.1 gives a summary of the literature reviewed, their key contributions, approaches used and their weaknesses.

Table 2.1: Summary of Literature Review

Reference	Contribution	Method Used	Weakness
[2]	Proposed a standardization approach with shared use of communication system in EMSs to reduce the overall energy cost	Experimental analysis	Incorporated only one aspect of smart grids, that is, real time communication
[3]	Recommended the use of a standard information model, (openADR), to support demand side management activities	Theoretical analysis	Only electrical loads were considered when designing the automated DR system
[4]	Designed an EMMS for scheduling of operations to moderate energy consumption by shifting times of usage	Fuzzy inference system	All processes in the vehicle testing facility were assumed to be schedulable which isn't true in reality
[5]	Used a day-ahead variable pricing technique to ensure that minimum energy bill was attained in a residential set up	Mixed Integer Linear Programming	The need to incorporate renewable energy, solar, and an energy storage device for load balancing was mentioned but not implemented.
[6]	Proposed a DR scheme based on day ahead hourly prices to balance supply and demand, improve reliability, and reduce cost	Mixed Integer Linear Programming	Changes in electricity prices and scheduling of STs were assumed to only occur at time horizon interval boundaries
[7]	Developed a smart grid power management system with energy storage capability	Case study of a coal mine	The system was only based on hybrid energy storage disregarding other aspects of power system operation including generation, transmission, distribution, and end use
[8]	Designed an EMS for smart houses to optimize energy consumption and cost taking into account the comfort of the user	Monte Carlo Simulation	The assumption that each appliance performed a single work cycle daily is not guaranteed in real life
[9]	Developed a system for energy demand management in smart homes where ICT is integrated to facilitate communication between the smart appliances and smart meters.	Case study	None of the technical challenges that are introduced into an existing power system following the integration of renewable energy sources was addressed
[10]	Introduced the concept of energy storage in prosumer based systems	Binary Integer Programming	Only one tool for DSM, that is, use of energy storage functionality was explored
This Project	Designed a generalized EMS that employs DSM and can be customized for utilization in many industrial set ups.	Long Short Term Memory Recurrent Neural Network	Historical electricity prices and demand were used as inputs to the LSTM network overlooking other factors that would influence electricity prices including information on public holidays and weather patterns.

2.2 Research Gap

Previous research works have focused on specific applications of energy management systems such as homes, data centers, buildings, and communities. The reviewed research works have not fully leveraged aspects of the smart grid in designing energy management schemes. The approach taken involves installing energy meters on each equipment and doing offline computations as part of the process of load scheduling and energy optimization. Additionally, no specific algorithm for DSM is given. Energy is one of the top operating expenses in an industry but its management is often overlooked. In most developing countries, the energy demand-supply gap continues to widen each day due to population, economic, and industrial growth. A few authors have addressed energy management in specific industries by considering only the electrical loads. There is need for sustainable energy use in industries to ensure minimum energy costs are achieved and environmental ramifications mitigated.

This research work has integrated the ability of smart grids to process and analyze data as well as engage consumers to design an EMS that optimizes energy use in the industry. The collected historical data on electricity prices and demand has been used within the LSTM-RNN forecasting model. The type and number of loads in an industry have been considered when generating a suitable schedule to utilize off peak hours. Unlike other research works that use actual prices to perform the scheduling, a comparison was also made using both actual and predicted prices. The resulting cost saving when predicted prices were used was computed hence making it clear to the consumer the amount that could be saved by adopting the recommended schedule. In summary, the EMS has effectively monitored the details of energy consumption, analyzed the data, and enabled the consumer to make decisions to manage usage, minimize energy cost, and maximize profits. Figures 2.1a) and 2.1b) represent the EMS architectures of the existing and the proposed model respectively.

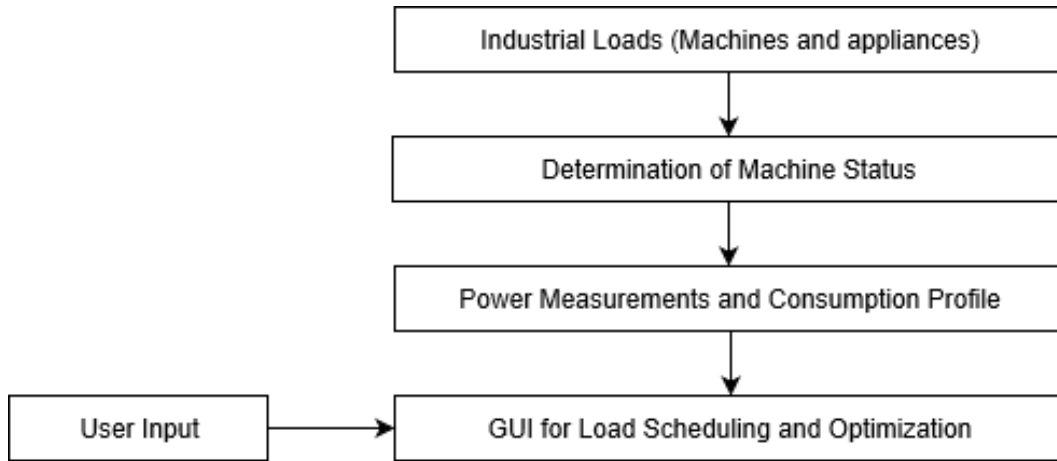


Figure 2.1a: EMS Architecture of Existing Model [4]

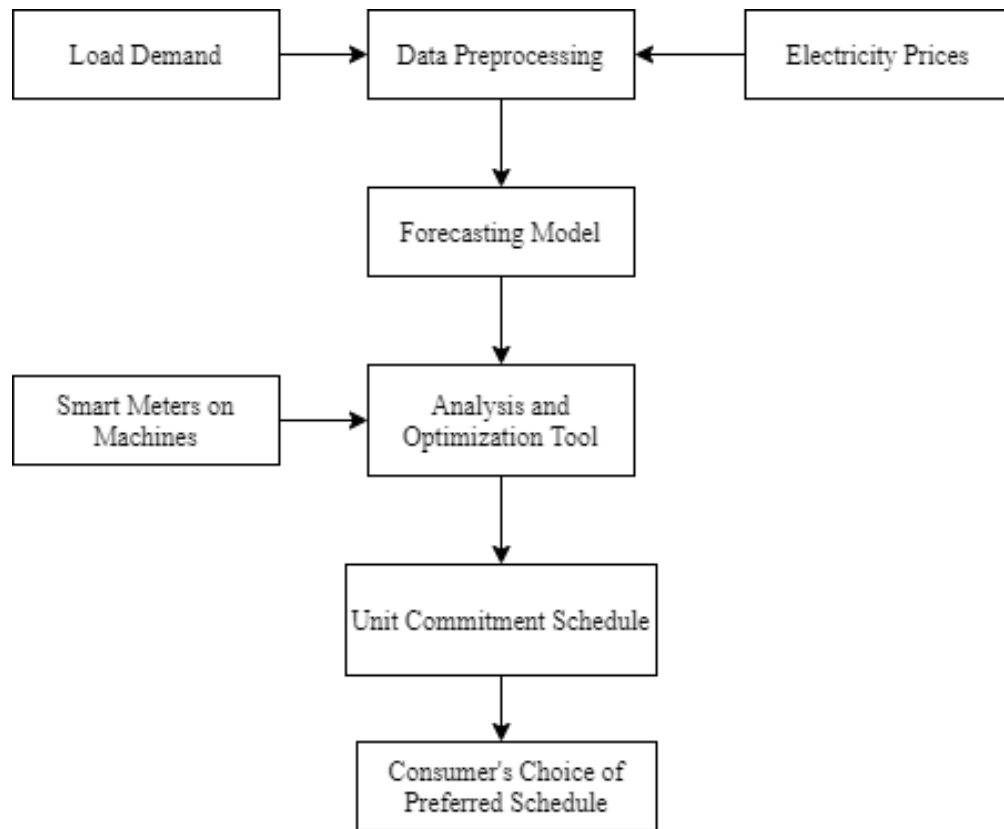


Figure 2.1b: EMS Architecture of Proposed Model

2.3 Problem Formulation

The smart grid DSM programs give consumers the opportunity to manage and control their energy consumption reliably. An example of such a DSM program is load shifting which enables users to reduce their energy usage during peak periods by shifting non-critical loads to off-peak hours. This also reduces grid congestion and the probability of occurrence of power outages by improving the power system's reliability. In this research, a forecasting model has been developed using a machine learning technique. The inputs to the model were historical data on hourly electricity prices and demand. The predicted prices were used to determine suitable load schedules for the industry ensuring that non-shiftable loads were prioritized and the power balance constraint was satisfied. The cost of energy consumed was calculated using both the actual and predicted electricity prices before computing the potential saving. The economic viability of implementing the EMS was also assessed using various economic tools. This research has addressed the energy cost reduction problem from multiple dimensions that is, by minimizing the energy consumption and cost as well as evaluating the economic feasibility of implementing the EMS.

2.3.1 Forecasting and Load Scheduling Model

The collected time series data was refined in preparation for performing demand and price forecasting. RNNs were used to model the time series to ensure that accurate predictions were made. Specifically, LSTM networks were used to learn order dependence in the given sequence. Once accurate forecasting was achieved, the predicted electricity prices were used to perform load scheduling.

The main objective when training the machine learning model was to minimize the loss function. The mean squared error (MSE) loss estimator was chosen due to its suitability in determining the accuracy of the model when dealing with regression problems. MSE was selected over mean absolute error due to its ability to converge even with fixed learning rate and its sensitivity to outliers in the dataset. The magnitude of loss value was directly proportional to the gradient of MSE loss and this gradient reduced as the loss approached zero. A good model should have MSE values closer to zero implying that the probability of the model to make accurate predictions is high. The number of epochs in the LSTM networks was increased until minimum MSE was obtained. The MSE was computed using the formula in equation (2.1):

$$MSE = \frac{1}{n} \sum_{t=1}^n e_t^2 = \frac{1}{n} \sum_{t=1}^n (y_t - f_t)^2 \quad (2.1)$$

Where n is the size of the test set, e_t is the forecast error, y_t is the actual value, and f_t is the forecasted value.

The load scheduling algorithm considered the predicted electricity prices and load type to generate suitable operating times for non-priority loads away from peak periods.

2.3.2 Possible Load Combinations

The number of possible load combinations was determined using a pseudocode written in Python. Given n number of loads, the possible combinations was given by an array of binary groupings with a count from 0 to $2^n - 1$ with n being the total number of loads [4]. The viable load combinations ensured that the supply met the demand at all times and all priority loads were on. A unit commitment schedule was generated showing all the possible machine combinations and the resulting energy cost.

2.3.3 Objective Energy Cost Function

Upon scheduling of the loads, the known power consumption rates and operation times of the active machines were used to determine the energy cost using equation (2.2) which was the overall formulation for computing the energy cost.

$$F(P_i) = \sum_{i=1}^n (C_t \times t \times P_i) \quad (2.2)$$

Where:

$F(P_i)$ = Total cost of electricity consumed by the i^{th} active machine (\$)

C_t = Hourly electricity price (\$/MWh)

t = Running time of each machine (h)

P_i = Power consumed by the i^{th} active machine (MW)

n = Number of machines

2.3.4 Power Balance Constraint

The maximum power consumption for all the machines balanced the power supplied by the generators and/or utility grid at any given instant satisfying the power balance constraint given in equation (2.3a).

$$P_{KS} = (\sum_{i=1}^n P_i) + P_L \quad (2.3a)$$

Where

P_{KS} = Peak power supplied

P_i = Power consumed by the i^{th} active machine (MW)

P_L = Power loss

Considering a region with hundreds of industries that lacked EMSs and shared a distribution grid, the losses in each company would result in a huge power demand hence a significant impact on the grid. However, taking the case of a single industry within this zone, the impact of losses on the grid could be considered negligible. Equation (2.3a) was modified as given in equation (2.3b) for a system with negligible power loss.

$$P_{KS} \geq (\sum_{i=1}^n P_i) \quad (2.3b)$$

The non-priority loads were scheduled to take advantage of lower electricity prices ensuring that the constraint in equation (2.3c) was met.

$$\sum_{j=1}^8 P_{NL} \leq P_{KS} - \sum_{k=1}^{12} P_{PL} \quad (2.3c)$$

Where P_{NL} is the power consumed by each non-priority load and P_{PL} is the power consumed by each priority load.

2.3.5 Economic Viability

The economic feasibility of investing in the industrial EMS was evaluated using CBA. The costs which included the staff time utilized in setting up, implementing and conducting trainings on the use of the system were estimated. Others costs included that of purchasing additional metering tools and hiring experts to actualize the installation and use of the EMS. On the other hand, the

energy and non-energy benefits of the EMS were also determined. The results of the CBA were evaluated using simple payback period (PBP) and return on investment (ROI) computation using equations (2.4) and (2.5) respectively.

$$PBP = \frac{\text{Initial investement cost in the EMS}}{\text{Annual energy cost saving}} \quad (2.4)$$

$$ROI = \frac{1}{PBP} \quad (2.5)$$

2.4 Chapter Conclusion

The reviewed research works addressed energy management in different applications including homes, data centers and specific industries. Various aspects of the smart grid such as remote control, consumer engagement, and data processing ability are not fully utilized in designing the EMS. This project has incorporated these aspects in devising an energy management strategy for shifting usage of loads to more effective TOU. It has also integrated a forecasting and load scheduling model to generate a unit commitment schedule with a huge potential of energy cost saving in energy intensive industries. Both shiftable and non-shiftable loads have been taken into consideration.

CHAPTER 3: METHODOLOGY

This chapter has an overview of the main models of industrial loads in existence and the optimization methods for energy management in smart grids. It has also reviewed the methods used in past researches giving their strengths and weaknesses. A description of LSTM-RNN technique used in this research has been given as well and its key parameters mapped to the forecasting problem. A flowchart has been used to summarize the steps involved in developing the EMS. The simulation and validation tools have also been highlighted in this chapter.

3.1 Scheduling of Industrial Loads

Mathematical modelling is mainly used when scheduling industrial loads. The scheduling acknowledges the machines' interdependencies in various production segments and lines. There are two main types of models for industrial power loads namely:

- i) *Single Objective Model*: In this model, the objective function minimizes the overall cost of energy by employing load rescheduling to satisfy the existing industry constraints such as power balance, production process, energy storage and generation constraints.
- ii) *Multi-Objective Model*: This model has the ability to evaluate problems from multiple dimensions such as lifetime assessment and computation of emission levels. The scheduling approaches used for multi-objective models can be based on optimality theory (single person decision) or game theory (multiple decision makers) [11].

3.2 Optimization Methods for Energy Management in Smart Grids

Optimization is usually done to determine the best possible solution to a problem in a case where there are several contradictory considerations. There exist various optimization techniques that aid in attaining optimal solutions for energy management in smart grids. These methods are broadly classified into three as described in [12]:

- i) *Rule-based techniques*: These methods provide reasonable solutions based on the existing conditions of a system and decision trees are normally used for defining specific cases under investigation.
- ii) *Optimization based techniques*: These techniques utilize mathematical formulations that are either maximized or minimized to obtain the best local or global solutions while satisfying the necessary constraints [12]. Exact mathematical or approximate methods are

- used depending on the complexity of the formulated problem. The exact methods can either be linear or non-linear depending on the nature of the objective function and the constraints.
- iii) *Hybrid techniques*: These methods combine a number of optimization algorithms so that the output is based on the preeminent qualities of the combined techniques. The goal of hybrid techniques is to capitalize on the pros of each algorithm used to improve the quality of the solution while speeding up convergence. Hybrid methods are better placed in dealing with complicated problems since they overcome limitations of other optimization techniques when used solely.

Figure 3.1 summarizes the main techniques for optimizing energy management in smart grids.

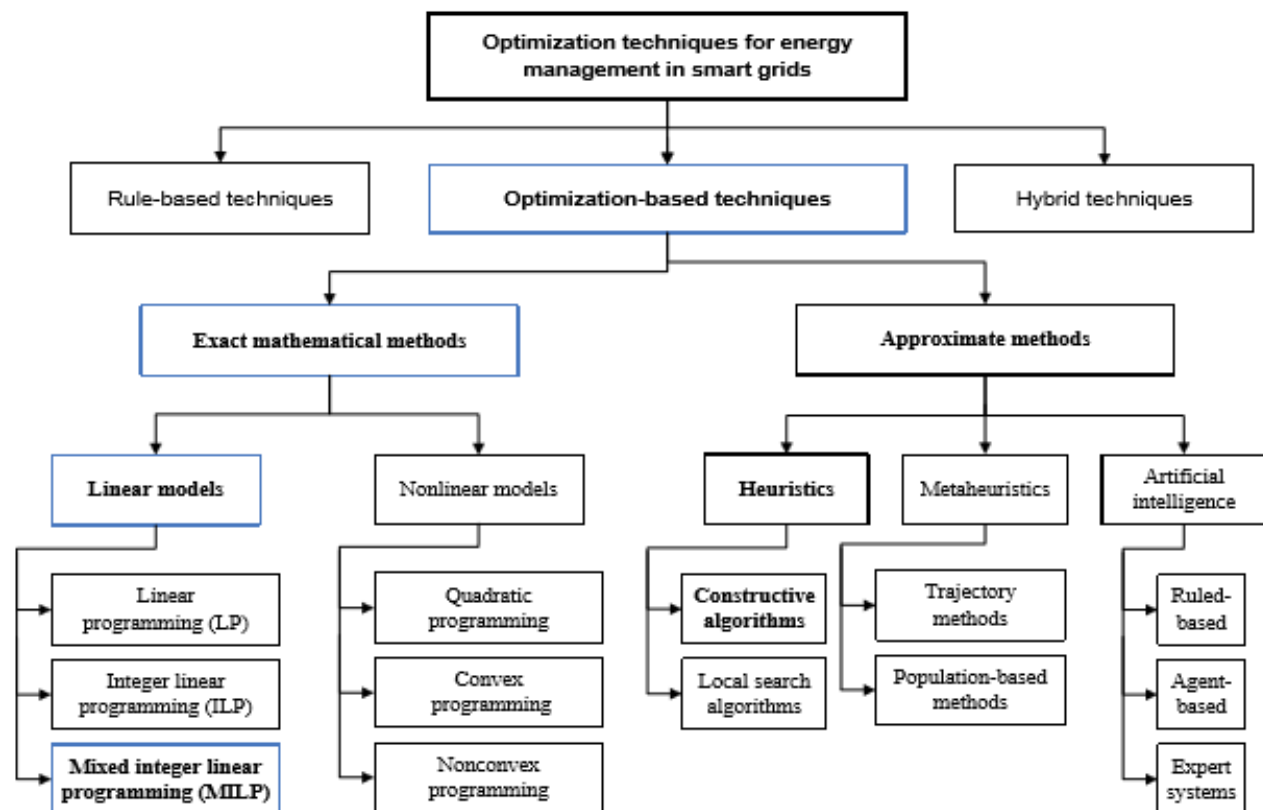


Figure 3.1: Major Techniques for Optimizing Energy Management in Smart Grids [12]

3.3 Review of Previous Methods in EMS

The methods used in the research works reviewed in chapter 2 are fuzzy inference system, Monte Carlo simulation, binary integer programming, and MILP. This section has addressed the uses of these methods, their strengths and weaknesses.

3.3.1 Fuzzy Inference System (FIS)

The fuzzy system has been employed in [4] to compute the optimal scheduling points to reduce consumption in designing an energy management and monitoring system. This intelligent computational method gives outputs based on the given inputs and the fuzzy inference rules. Its working principle is based on fuzzy logic that is similar to human reasoning.

Strengths: Fuzzy logic is simple to use as it only requires a set of input and output variables together with an assortment of fuzzy rules. The method is also quite flexible even when dealing with inaccurate data.

Weakness: There is no much clarity for defining the fuzzy rules hence can lead to inaccurate results if the rules are not sufficiently expressive.

3.3.2 Mixed Integer Linear Programming (MILP)

MILP was used in [5] to schedule and optimize residential loads under a day-ahead variable pricing tool and in [6] to solve the constrained linear programming problem for scheduling of the home appliances involved. MILP is a form of constraint programming with integer or real-valued domains and requiring linear constraints and objective functions. This method is applicable where the decision variables are either discrete or continuous.

Strengths: MILP has excellent performance in solving both single and multi-objective models with bounds and linear constraints. Various mathematical solvers such as XPRESS, MATLAB, CPLEX, and Gurobi exist for use with MILP to optimize objective functions. These mathematical solvers integrate the latest unconventional algorithms and exhibit exceptional performances on optimization. Being a constrained programming technique, it's easy to use and simple to understand. Regardless of the limitation by the constraints, MILP is effective in modeling and solving both theoretical and practical optimization problems.

Weakness: However, MILP as a constrained programming tool is unsuitable in cases with several possibilities that cannot fit into a linear programming formula.

3.3.3 Monte Carlo Simulation (MCS)

This method has been applied in [8] to optimize the energy consumption and cost in smart houses ensuring the comfort of the users. Monte Carlo simulation is a computational algorithm majorly

used in prediction and forecasting models to assess the effects of risks and uncertainties when working with random variables. This technique uses repetitive and random sampling to yield statistical results. The fundamental concept is to use randomness to solve deterministic problems.

Strength: This optimization tool is suitable in solving numerical integration and probability distribution functions. It is highly effective in tackling estimation problems, doing accurate forecasting, and performing risk analysis.

Weakness: Monte Carlo simulation has an overreliance on the inputs hence reasonable assumptions have to be made to obtain quality outputs.

3.3.4 Binary Integer Programming (BIP)

BIP has been used in [10] to solve the objective function for prosumer based energy sharing and management system. This method is preferred in solving binary problems with linear inequalities where each variable can take either the value 0 or 1.

Strengths: Integer programming is suitable for modelling any variable or constraint to be used in a linear program but cannot be input directly in its original form. BIP improves the modelling capability since variables take on integer values that are realistic and flexible.

Weaknesses: BIP has a restrictive parameter set and is not easy to model or solve compared to linear programs hence unsuitable for applications with widely varying conditions.

3.4 Long Short Term Memory Technique

The method used for forecasting the electricity prices and demand is Long Short Term Memory (LSTM) which is a Recurrent Neural Network (RNN) capable of learning long sequences with long time lags [13]. Unlike Feed Forward Networks that do not model memory, RNNs store activations from each time step in the internal state of the network to provide a temporal memory thereby remembering previous inputs. This capability makes RNNs better suited for capturing information from sequences and time series. A simple RNN learns using back propagation through time and experiences the vanishing gradient problem when tackling long term dependencies.

The pioneers of the use of LSTM were Hochreiter and Schmidhuber who devised the method to solve the problem of vanishing gradient by controlling the cell states using various gates [14]. The hidden layers in LSTM have memory blocks with four parts namely:

- i) Input gate which controls the activations that enter the memory cell.
- ii) Forget gate which assists the network in resetting the memory cells by forgetting past inputs.
- iii) Output gate which determines the output to pass on to successive networks and the ones to be filtered.
- iv) Self-connected memory cell

The information at different states is regulated by the inputs and the hidden states generated from the previous steps after sigmoid or tanh activations within the neural network layers. Backpropagation through time (BPPT) is the training algorithm used in LSTM [13]. Equations (3.1) to (3.5) summarize the mathematical functions of the gates which perform the task of limiting the information passing through the memory cell. Figure 3.2 shows the architecture of LSTM memory block.

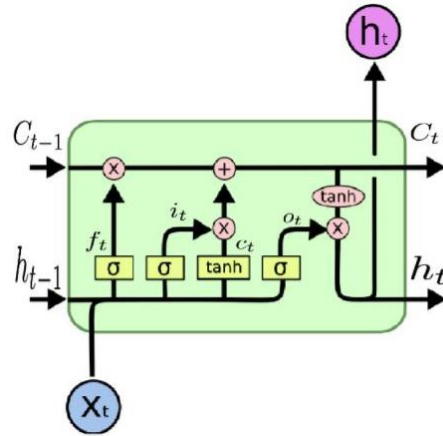


Figure 3.2: Architecture of LSTM memory block [13]

$$i_t = \text{sigmoid}(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \quad (3.1)$$

$$f_t = \text{sigmoid}(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \quad (3.2)$$

$$o_t = \text{sigmoid}(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \quad (3.3)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \text{tanh}(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (3.4)$$

$$h_t = o_t \cdot \text{tanh}(c_t) \quad (3.5)$$

Where i_t is the input gate, f_t is the forget gate, o_t is the output gate, c_t denotes the cell state generated as an additional variable for the cell, x_t is the input, h_{t-1} is the hidden state in the previous step, W is the weight matrix and b is the biases to each layer. The symbol \cdot stands for the operation of element-wise multiplication.

In this research, there were 3 main steps followed in designing the prediction model:

- i) Data preprocessing
- ii) Building the RNN
- iii) Making the prediction and visualization

The LSTM model required that the times series data was within the scale of the network's activation function hence the need to rescale the values to between -1 and 1 using MinMaxScaler in Python. The single input sample data was then reshaped into a 3D array since LSTM requires a three dimensional input with [samples, time steps, features]. Stacked LSTM with four layers was used in this research work where each hidden layer had 50 LSTM units. The model was fit using the efficient Adam version of stochastic gradient descent and optimized using the mean squared error loss function. Once the model was defined, it was fit on the training dataset before being used to make predictions.

3.5 Mapping the Method to the Problem

LSTM was used in this research work to forecast the hourly electricity prices and demand. Some of the keys aspects of the LSTM forecasting model are highlighted:

- Layers – The number of layers influence the learning capacity of the model. It is important to use additional layers and have different numbers of neurons in each to improve hierarchical learning.
- Features and time steps – These define the shape of the input by specifying what the model expects for each sample. The use of lag observations as input features and time steps can improve the predictive capability of the model.
- Batch size – This is the number of training examples used in an iteration. The batch size determines the level of manipulation required for both the training and test datasets.

- Optimization algorithm – There are several optimization algorithms that tend to either accelerate or decelerate the learning process to improve the configuration’s efficiency.
- Weight regularization – This is done to control the rate of learning and reduce overfitting of the networks.
- Dropout – This is a regularization method that slows down learning within the recurrent LSTM networks.
- Loss function - This is an evaluation method for performance of a specific algorithm in modelling the given data. Optimization is done to enable the loss function learn how to reduce the prediction error.

LSTM parameters were mapped to the forecasting problem as summarized in Table 3.1.

Table 3.1: Parameter Mapping for the Forecasting Problem

<i>LSTM Parameter</i>	<i>Mapping to the Forecasting Problem</i>
Input	Historical values of electricity price and demand
Output	Predicted values of electricity price and demand
Bias	Error value being fed back to the input of the forecasting model
Gates	Factors that regulate the variation of electricity price and demand

3.6 Design of the Proposed EMS

The EMS has enabled the industrial consumer to make a suitable selection of the operating hours to ensure optimal energy cost. This has been done taking into consideration the predicted hourly electricity prices. Figure 3.3 shows the key steps involved in designing the proposed EMS.

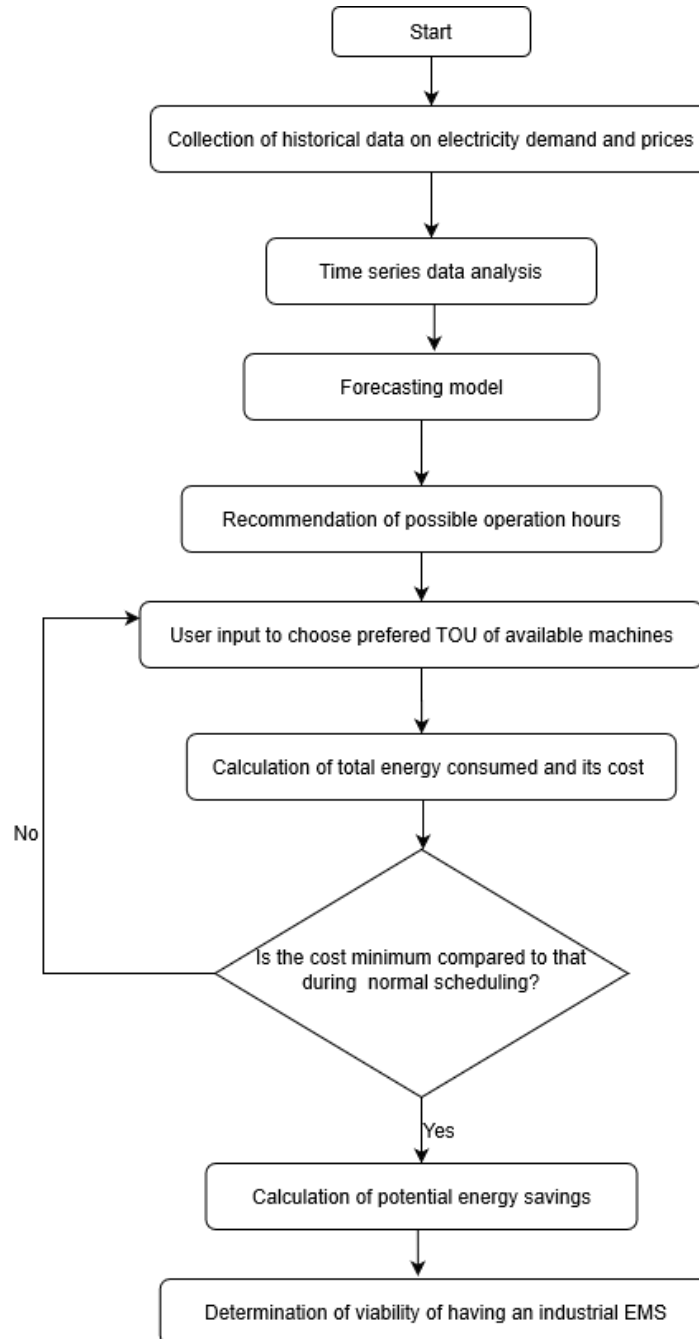


Figure 3.3: Flowchart showing the steps followed in developing the EMS

3.7 Simulation and Validation Tools

The time series forecasting model was built using LSTM-RNN in Python environment. Adam optimization algorithm which is an improved version of stochastic gradient descent was used to update the network weights iterative based in training data within the LSTM model. This optimization technique is easy to implement, has high computational efficiency, and is suitable for

solving complex problems with many parameters. The predicted hourly electricity prices were used to advise the consumer on suitable operation times that would yield minimum energy cost. Based on the consumer’s choice and priority of the loads, a given operation schedule was selected and minimum total energy consumed obtained. The effectiveness of the designed model was tested using an IEEE 6 generator 30 bus system with 20 loads. Figure 3.4 represents the IEEE 30 bus system [15].

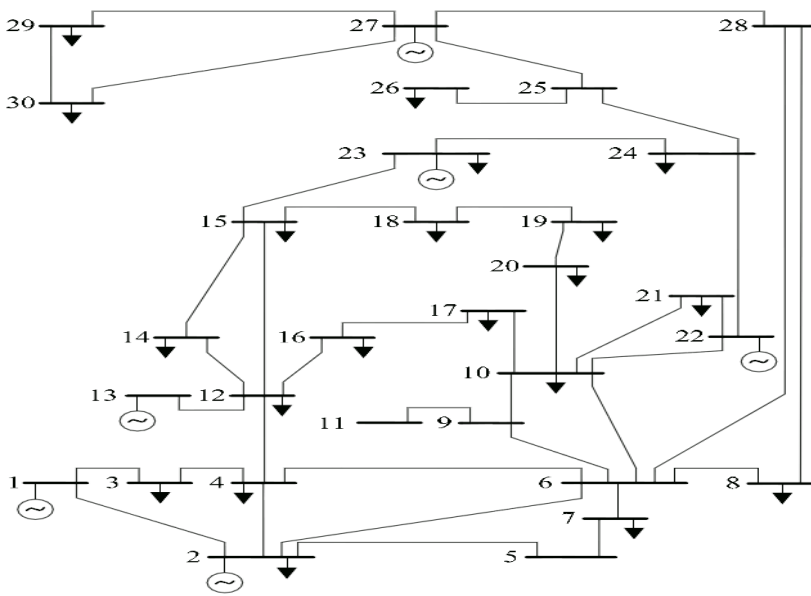


Figure 3.4: IEEE 6 generator 30 bus system

CHAPTER 4: RESULTS, DISCUSSION AND ANALYSIS

This chapter presents the simulation results, discussion, and analysis to inform the conclusions. Graphs were drawn to visualize the gathered data on electricity prices and demand in Texas. Values obtained from the designed forecasting model were compared to the actual data. A unit commitment schedule was generated showing machine combinations during each hour and the potential saving if the recommended schedule was adopted. The economic viability of the EMS was also determined using cost benefit analysis, payback period and return on investment.

Graphs of price variation against time were plotted for each of the zones and attached in Appendix B. The visualizations showed that price variation for each zone was almost similar hence only one zone was selected for further data analysis and modelling. Zone 3, which is Houston was selected because it had the largest population in the state of Texas. Figure 4.1 shows the electricity price variation for zone 3 over the duration of six months.

According to Figure 4.1, it is evident that the electricity prices were extremely higher than normal on a few occasions in the months of August, September, and the beginning of October 2019. In August, which is part of summer, the prices were above \$9,000/MWh for some hours due to the heat wave that was experienced in the state leading to huge energy consumption as most consumers turned on their air conditioners. A state of emergency was declared by the energy regulatory body, the Electric Reliability Council of Texas (ERCOT), requesting consumers to conserve energy and power plants to ramp up for the supply to meet the demand which was over 70,000MW. The process of modelling the load scheduling algorithm was started by visualizing how the average monthly electricity prices and demand varied with time for the 6 months with August being month 0 (Figure 4.2).

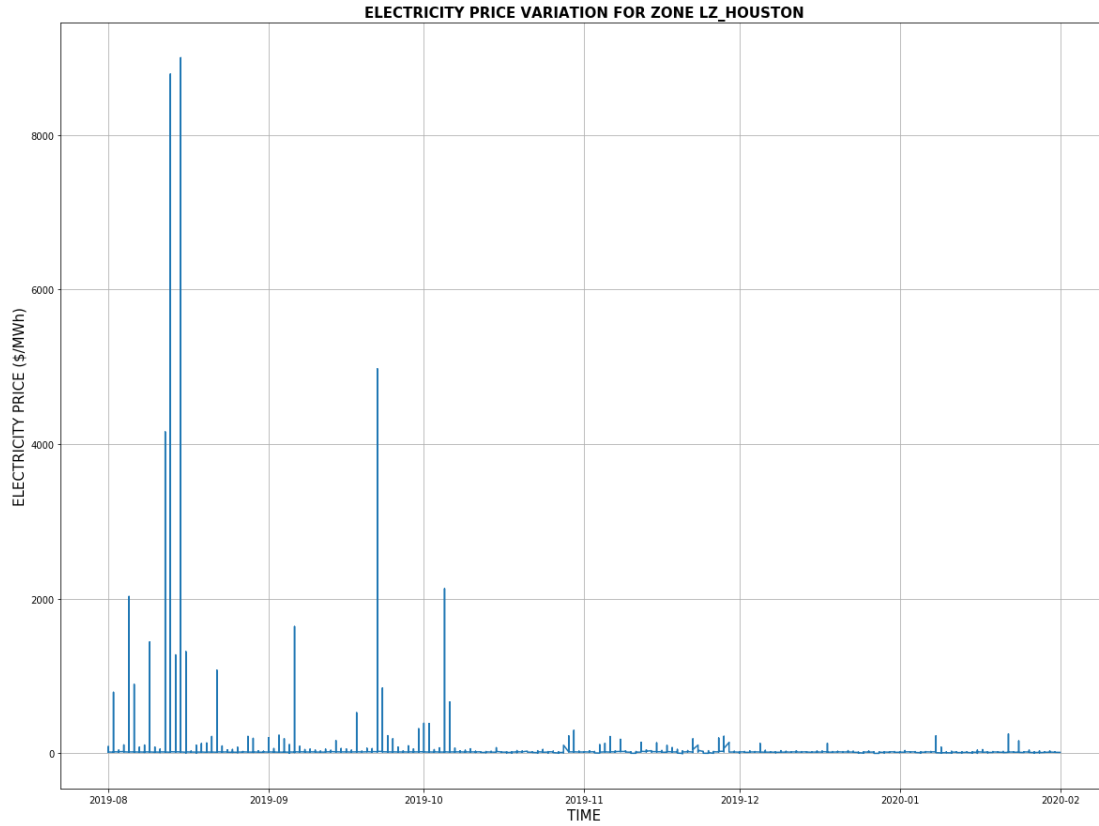


Figure 4.1: Electricity Price Variation for Zone 3

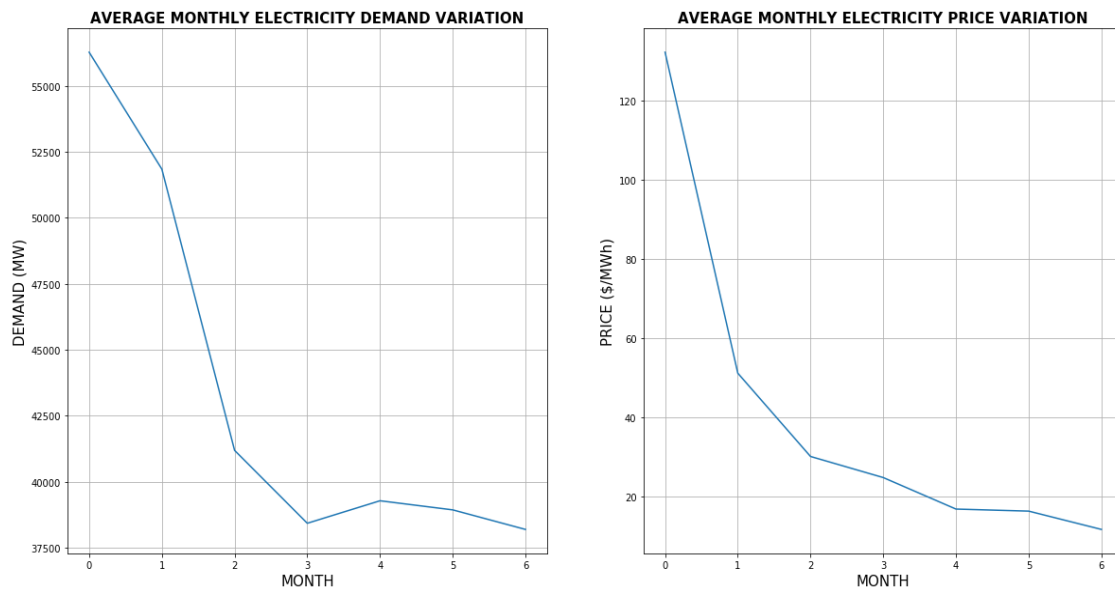


Figure 4.2: Comparison of Average Monthly Electricity Demand and Prices in Zone 3

According to Figure 4.2, demand was directly proportional to price such that at a high demand, the electricity price was also high. For instance, in the month of August 2019 (month 0), demand was over 55,000 MW resulting in the highest average monthly price of over \$120/MWh. Figure 4.2 showed that there existed a positive correlation between the electricity price and power demand hence load scheduling could be done based on any one of the parameters. A forecasting model was developed to predict the electricity prices which were then used to recommend suitable operation schedules.

4.1 LSTM Forecasting Model

Long Short Term Memory (LSTM) networks which are recurrent neural networks that have the capability of learning order dependence were used to model the forecasting algorithm. Data collected from 1st August 2019 to 31st December 2019, formed 80% of the collected data, and was used for training the LSTM model while the remaining 20% (from 1st January to 2nd February 2020) was used to test the model.

Table 4.1 gives the actual and predicted hourly demand and electricity prices for 20th January 2020 which was taken as the sample day. These results showed that the lowest actual demand of 36,990.80MW occurred at 1 a.m. This was mainly because of the few industrial, business, and economic activities that were undertaken at that time. Most people in homes are usually asleep by that time as well. However, there was a notable increase in the actual demand from 38850.34MW to 46996.48MW between 4a.m. and 7a.m. which are the hours where most people wake up and businesses begin to operate again. Overall, demand was higher in the morning hours, up to 10 a.m. compared to the afternoons. Later in the evening, between 5p.m. to 8p.m., the demand increased and could be justified by the increase in activities within residential areas as people get back from work. For the entire sample day, the highest hourly actual electricity cost of 19.10\$/MWh was incurred between 6p.m. and 7p.m. when demand was 42,227.32MW whereas the least price of 15.91 \$/MWh occurred between 11p.m. and midnight when demand was 38637.67MW. The percentage difference between the actual and predicted values was also computed and given in Table 4.1. For the demand, the percentage difference between the actual and forecasted values ranged between 0.06 and 3.08 while for the price, it ranged between 0.89 and 14.01.

The results obtained for the entire test period were used to plot the graph in Figure 4.3 comparing the actual and predicted hourly demand values. According to Figure 4.3, the machine learned the pattern of variation of the demand and predicted values that closely matched the actual demand. This was achieved as the number of epochs in the LSTM model was increased from 50 to 150 when compiling the RNN thereby reducing the mean squared error loss from 9.5936×10^{-4} to 5.4008×10^{-4} .

Figure 4.4 compares the actual and predicted hourly electricity prices. It is evident that the machine learned the pattern in the time series data given in the training set and used that pattern to predict the values in the test set. However, there were negative prices at certain instances implying that the supply was greater than the demand at those times and the utility was actually paying the consumers to use the energy. As the number of epochs was increased, the mean squared error loss reduced from 1.2395×10^{-4} at 50 epochs to 1.0490×10^{-4} at 150 epochs.

Both Figures 4.3 and 4.4 prove that the designed model adequately learnt the pattern of the given time series data and suffices in making sequence predictions. The hourly predicted prices were then used to generate a suitable operating schedule for the available loads away from peak periods.

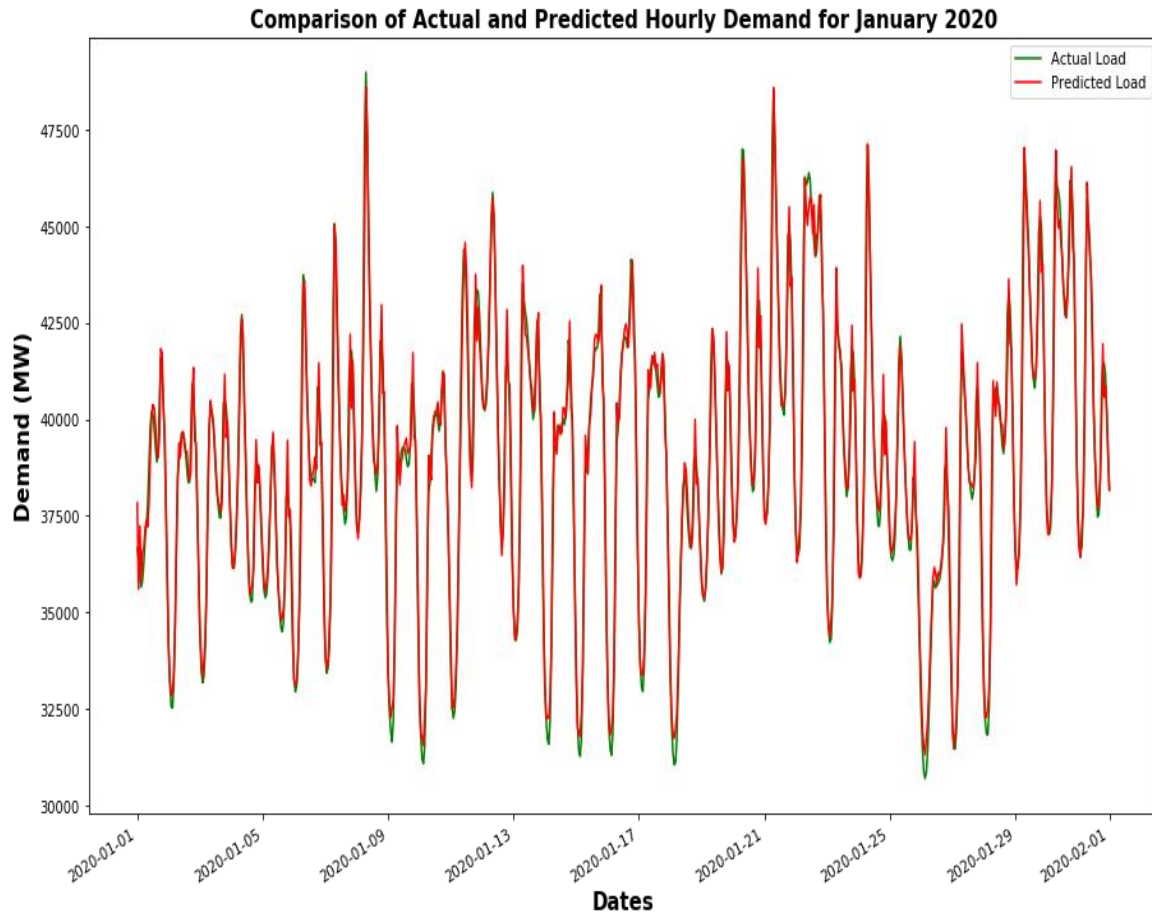


Figure 4.3: Comparison of Actual and Predicted Hourly Demand

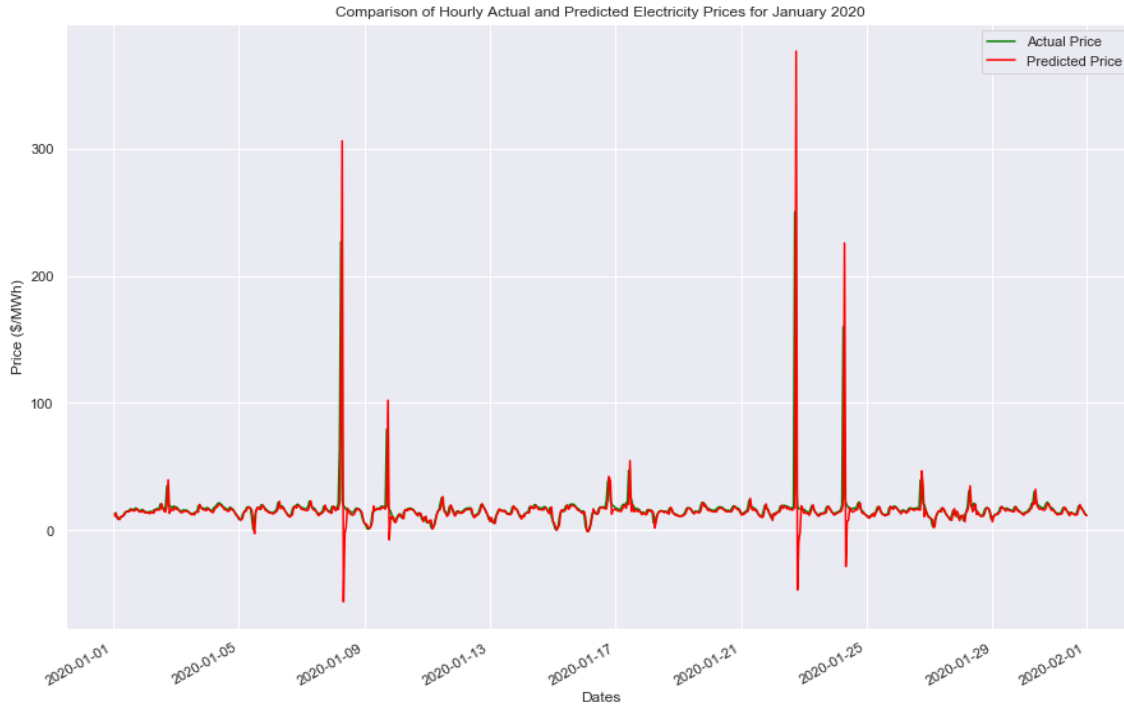


Figure 4.4: Comparison of Hourly Actual and Predicted Electricity Prices

Table 4.1: Comparison of actual and predicted hourly demand and electricity prices for 20th January 2020

Time	Actual Demand (MW)	Predicted Demand (MW)	% Difference in Actual and Predicted Demand	Actual Price (\$/MWh)	Predicted Price (\$/MWh)	% Difference in Actual and Predicted Price
0:00	37376.23	37253.25	0.33	16.27	15.86	2.51
1:00	36990.80	36825.34	0.45	15.83	14.77	6.71
2:00	37096.04	36956.25	0.38	15.45	14.58	5.59
3:00	37627.19	37648.26	0.06	15.63	14.27	8.67
4:00	38850.34	38651.77	0.51	15.22	14.77	2.95
5:00	41348.07	40411.59	2.26	16.51	14.20	14.01
6:00	44660.07	43354.40	2.92	17.45	16.14	7.52
7:00	46996.48	45943.34	2.24	18.29	16.89	7.61
8:00	46965.85	46770.92	0.42	18.02	17.60	2.32
9:00	45644.25	45511.32	0.29	18.10	16.77	7.31
10:00	44143.57	44078.36	0.15	17.35	16.91	2.49
11:00	42273.42	42606.68	0.79	16.27	15.85	2.57
12:00	40709.94	40473.54	0.58	15.65	14.72	5.93
13:00	39559.74	39508.46	0.13	15.61	14.35	8.085
14:00	38635.64	38745.38	0.28	15.47	14.65	5.33
15:00	38132.82	38274.52	0.37	15.20	14.55	4.27
16:00	38199.35	38481.92	0.74	15.60	14.26	8.57
17:00	39388.85	39067.95	0.81	17.31	14.91	13.85
18:00	42227.32	40925.42	3.08	19.10	17.11	10.42
19:00	42960.61	43917.34	2.23	18.66	18.82	0.89
20:00	43075.2	41863.78	2.81	17.84	17.35	2.76
21:00	42206.17	42687.68	1.14	17.27	16.25	5.90
22:00	40406.11	40680.94	0.68	17.12	15.77	7.90
23:00	38637.67	38859.29	0.57	14.11	15.91	12.75

4.2 Load Scheduling Using Predicted Electricity Prices

The hourly predicted prices were used to recommend suitable operating times that would help the consumer reduce energy consumption as well as cost. The decision to use the electricity prices for scheduling was made upon establishing the relationship between the electricity price and demand according to Figure 4.2. As a result, load scheduling was done based on any one parameter either price or demand since the same effect was observed.

A chart was generated showing all the active loads during each hour and the energy cost incurred with and without an EMS using the original schedule as well as the proposed schedule. It was upon the user to decide on whether to adopt the recommended schedule or not. The effectiveness of the operating schedule given was tested on an industrial system modeled based on IEEE 30 bus system. The system had 30 buses, 6 generators, and 20 loads with the supply and demand side parameters summarized in Tables 4.2 and 4.3 respectively.

Table 4.2: Supply Side Parameters

Busbar	Generator (Maximum Power, MW)
1	200
2	80
13	50
22	35
23	30
27	40
Total supply	435

Table 4.3: Demand Side Parameters

Busbar	Unit	Type of Load	Capacity (MW)
2	A	Priority	20
3	B	Non-priority	25
4	C	Priority	36
7	D	Priority	19
8	E	Non-priority	13
10	F	Priority	22
12	G	Priority	14
14	H	Non-priority	37
15	I	Priority	31
16	J	Non-priority	22
17	K	Non-priority	26
18	L	Priority	17
19	M	Priority	12
20	N	Non-priority	30
21	O	Priority	10
23	P	Priority	24
24	Q	Non-priority	28
26	R	Priority	21
29	S	Non-priority	33
30	T	Priority	45
Total Demand			485

The industrial system had 12 priority loads including key production machines and 8 non-priority loads. At every instance, scheduling was done such that all priority loads were on, the power balance constraint was met, and the non-priority loads took advantage of the off-peak hours to minimize the energy cost. Considering the 8 non-priority loads, there were 256 possible combinations (Table in Appendix C) out of which 17 of them led to violation of the power balance constraint. Using the 239 viable load combinations, scheduling was done taking advantage of lower hourly electricity prices to operate non-priority loads that consumed high power. A unit commitment chart was generated to suggest suitable operation times for the consumer to utilize the available loads. Tables 4.4a) and 4.4b) give the original and recommended schedule respectively, with the committed units on the sample day (20th January 2020) as well as the energy cost incurred when using actual and predicted electricity prices.

Table 4.4a): Unit Commitment Original Schedule for 20th January 2020

Time	Unit Commitment - Original Schedule																Consumption of Non-Priority Loads (MW)	Total Consumption by all Loads (MW)	Actual Electricity Price (\$/MWh)	Predicted Electricity Price (\$/MWh)	Hourly Energy Cost using Actual Prices (\$)	Hourly Energy Cost using Predicted Prices			
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P							Q	R	S
12:00:00 AM	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	1	0	1	176	447	16.27	15.86	7273.81	7091.02
1:00:00 AM	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	167	438	15.83	14.77	6932.45	6467.42
2:00:00 AM	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	0	163	434	15.45	14.58	6703.13	6328.10
3:00:00 AM	1	0	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1	162	433	15.63	14.27	6767.79	6180.76
4:00:00 AM	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1	0	161	432	15.22	14.77	6576.12	6381.81
5:00:00 AM	1	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	160	431	16.51	14.20	7115.81	6118.72
6:00:00 AM	1	0	1	1	0	1	1	1	1	0	0	1	1	1	1	1	0	1	0	159	430	17.45	16.14	7503.50	6939.61
7:00:00 AM	1	0	1	1	0	1	1	0	1	0	0	1	1	0	1	1	1	1	0	159	430	18.29	16.89	7862.55	7264.51
8:00:00 AM	1	0	1	1	1	1	1	0	1	0	0	1	1	0	1	1	0	1	0	158	429	18.02	17.60	7730.58	7551.16
9:00:00 AM	1	1	1	1	1	1	1	0	1	0	0	1	1	0	1	1	0	1	0	156	427	18.10	16.77	7726.57	7161.64
10:00:00 AM	1	0	1	1	0	1	1	0	1	0	1	1	1	0	1	1	0	1	0	156	427	17.35	16.91	7406.32	7221.87
11:00:00 AM	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	0	155	426	16.27	15.85	6928.89	6751.11
12:00:00 PM	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	1	1	0	155	426	15.65	14.72	6664.77	6269.73
1:00:00 PM	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	154	425	15.61	14.35	6634.25	6098.32
2:00:00 PM	1	1	1	1	1	1	1	1	1	0	0	1	1	0	1	1	1	1	1	153	424	15.47	14.65	6560.34	6210.79
3:00:00 PM	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	153	424	15.20	14.55	6444.80	6169.42
4:00:00 PM	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	152	423	15.60	14.26	6596.69	6031.47
5:00:00 PM	1	0	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	0	1	151	422	17.31	14.91	7305.88	6293.85
6:00:00 PM	1	1	1	1	0	1	1	0	1	0	0	1	1	0	1	1	0	1	0	151	422	19.10	17.11	8061.26	7221.02
7:00:00 PM	1	0	1	1	0	1	1	0	1	0	0	1	1	0	1	1	0	1	0	151	422	18.66	18.82	7872.41	7942.19
8:00:00 PM	1	0	1	1	0	1	1	0	1	1	0	1	1	0	1	1	0	1	0	150	421	17.84	17.35	7509.59	7302.61
9:00:00 PM	1	0	1	1	0	1	1	0	1	0	1	1	1	1	1	1	0	1	0	149	420	17.27	16.25	7251.30	6823.64
10:00:00 PM	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	0	1	0	149	420	17.12	15.77	7190.40	6622.45
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Total Energy Cost																									
																								170529.17	161106.69

Table 4.4c: Comparison of Total Energy Cost using the Original and Proposed Schedules

	Total Daily Energy Cost Using Actual Prices	Total Daily Energy Cost Using Predicted Prices
Original schedule	170529.17	161106.69
Proposed schedule	142920.77	134695.30
Cost saving achieved using proposed schedule	27608.40	26411.40
% cost saving	16.19	16.39

Table 4.4c shows that the proposed schedule yielded approximately 16% energy cost saving daily whether the actual or predicted hourly electricity prices were used in performing the load scheduling. Based on the analysis in Table 4.4b, adopting the recommended schedule yielded a potential energy cost saving of \$ 8225.47 on that sample day assuming that the industry operated for the entire 24 hours. If each month has 30 working days and each day has a similar energy cost saving, the annual energy cost savings is computed as follows:

$$\text{Annual energy cost saving} = \frac{\$8225.47}{\text{day}} * \frac{30 \text{ days}}{\text{month}} * \frac{12 \text{ months}}{\text{year}} = \$2961169.20 \text{ per annum}$$

The annual energy cost saving is \$2,961,169.20 which is a huge cost that industries can save on if they put in place an industrial EMS.

The load profile for the sample day before and after load scheduling was also plotted in Figure 4.5. It was noted that the scheduling distributed the load in a manner that ensured the peak demand occurred at off-peak hours where electricity prices were minimum. Upon load scheduling, a peak demand of 425 MW was experienced at 3 a.m. when the hourly electricity price was \$14.27/MWh and another peak demand of 434 MW was experienced at 5 a.m. when the price was least, \$14.20/MWh. The low electricity prices during the hours after midnight were attributed to the least cost of generation at that time since consumption was originally low thus disengaging high cost generation such as thermal units.

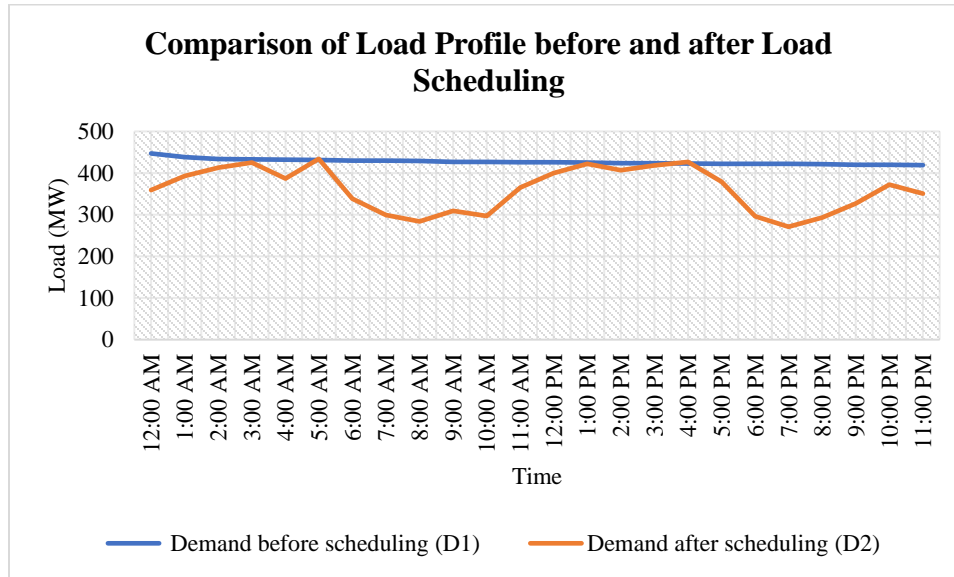


Figure 4.5: Comparison of Load Profile before and after Scheduling

4.3 Economic Viability of an Industrial EMS

The economic analysis of investing in an industrial EMS was done using the cost benefit analysis, payback period, and return on investment.

4.3.1 Cost Benefit Analysis

There were various costs incurred when implementing an EMS. Some of the categories of cost included that of hiring external experts to help in the set up and installation, cost of training the employees on the EMS implementation activities, and the cost of extra energy monitoring equipment. On the other hand, there were energy and non-energy benefits that arose due to the adoption of the EMS. The energy benefits were as a result of improved energy performance yielding energy savings and related cost savings. Typically, some of the non-energy benefits include a reduction in greenhouse gas emissions where dependency on fossil fuels is reduced, improved resources' usage, enhanced equipment lifespan, and improved industry's competitiveness and production. However, in this case, the non-energy benefits were not quantified. The costs and benefits of setting up and implementing an EMS were as outlined in Tables 4.6a and 4.6b respectively.

Table 4.6a: Annual EMS Set Up Cost [16]

Category	Activity	Cost (\$)
Staff time	EMS training	200,000
	EMS set up	900,000
	EMS implementation	400,000
Expert support	International experts	1,000,000
	Local consultants	150,000
Other operational expenses	Extra energy monitoring equipment	10,000,000
	Other low cost expenses	350,000
Total		13,000,000

Table 4.6b: Annual EMS Set Up Benefits

Category	Monetary value (\$)
Energy cost savings	2,961,169.20
Non-energy benefits	N/A

4.3.2 Payback Period

This is the time required to repay the initial capital investment with the operating savings attributed to the investment. PBP helps in quantifying the results of the CBA. The initial cost of investing in the EMS was \$13,000,000 whereas the annual saving was \$ 2,961,169.20 yielding a payback period of 4.39 years.

$$PBP = \frac{\text{Initial investment cost in the EMS}}{\text{Annual energy cost saving}} = \frac{\$13,000,000}{\$2,961,170.476/\text{year}} = 4.39$$

4.3.3 Return on Investment

ROI is a ratio between the net profit and the initial investment cost. The ROI of implementing the designed EMS was obtained to be 0.2278.

$$ROI = \frac{1}{PBP} = \frac{1}{4.39} = 0.2278$$

4.4 Validation of Approach Used in This Project

This research work has developed a generalized EMS model that could be customized for use in various industrial sectors unlike the reviewed papers which focused on specific applications. For instance, [4] narrowed down to an EMMS for a vehicle testing facility whereas [7] developed a power management system for a coal mine. The EMS recommended in this report could be used for various setups provided that the historical data on the electricity prices and demand are available for utilization in the forecasting model to predict values to inform the load scheduling. Additionally, previous research works have not fully leveraged on aspects of the smart grid in designing energy management schemes. In [2], the only smart grid aspect considered was real time communication between the appliances and the EMS. However, this project has incorporated three key aspects of smart grids including:

- i) The ability to process and analyze data
- ii) Real time communication between smart meters and the EMS
- iii) Active consumer engagement in demand management

In [3], an automated DR scheme was proposed to support demand side management activities while in [10], the use of energy storage functionality was explored. The other reviewed works do not recommend any specific technique for DSM. This project has incorporated load scheduling as a DSM technique where non-priority loads of high value have been scheduled for use during off peak hours where electricity prices are lower compared to peak hours. The EMS architectures of the existing and the adopted model in this project were compared in Figures 2.1a) and 2.1b) respectively. It is noted that using this project's approach, the consumer's choice in selecting the preferred schedule was influenced by the potential savings likely to be obtained using the recommended scheme whereas in existing models, a mere observation of the value of power consumption of the loads informed the decision.

In [4], a rule based technique was used in solving the energy optimization problem while [5], [6] and [10] used mathematical based methods, that is, MILP and BIP. The rule based method is just like human reasoning hence not very reliable whereas the mathematical approaches are suitable where there exist few appliances. The mathematical techniques tend to have a large convergence time thus metaheuristic algorithms such as genetic algorithm are preferred for cost and energy

consumption minimization. Time series modelling is mainly done using statistical forecasting methods like ARIMA. However, in this research, a machine learning technique based on neural networks was used in the forecasting model. LSTM-RNN being a machine learning algorithm has high computational efficiency in handling large data sets compared to traditional statistical time series models.

Just like the EMSs in past research works, the developed Industrial EMS in this project yielded a considerable energy cost saving. In [4], the usage of 20 machines for heating and cooling in a vehicle testing facility was shifted from time period 1 (8a.m to 4p.m.) to time period 2 (1a.m. to 9 a.m.) resulting in an annual cost saving of \$6491.4. Similarly, in this project, a daily energy cost saving of \$8225.47 was achieved using an industrial test system with 20 high consumption loads in a 24 hour operations industry. It is noted that the value of the energy cost saving depended on the size of an industry based on its scale and hours of operations. The energy cost savings accumulate over time with continued use of the industrial EMS resulting in a significant value of saving.

4.5 Chapter Conclusion

The historical data on electricity prices and demand were successfully used in developing a time series forecasting model based on LSTM RNN. The accuracy of the prediction model was monitored using the MSE loss which reduced as the number of epochs increased in the LSTM networks. The forecasted price influenced the scheduling of the non-priority loads in order to take advantage of off peak times when electricity prices were lower. The results obtained using the forecasted prices were compared with those obtained with actual prices. This is different from the approach used in other research works where either the actual or predicted prices are used in the load scheduling and not both. Using predicted prices in the scheduling is suitable for future planning once a good forecasting model is developed.

A unit commitment chart was generated showing possible machine combinations for one sample day and the potential energy cost saving that would be achieved using the original and proposed schedules with actual and predicted electricity prices. The proposed load schedule yielded a 16.19% saving using actual prices and 16.39% saving with the predicted prices compared to the original schedule. The annual energy saving obtained upon adopting the recommended schedule

and using the predicted prices, was \$2,961,169.20 yielding a PBP of 4.39 years with an initial capital cost of \$13,000,000. The PBP indicated the results of the CBA implying that the initial investment cost would be paid back in less than five years. Typically, there is a huge investment cost in an industrial EMS and a PBP of 5 years is considered economically profitable when both the energy and non-energy benefits are taken into account. In this research, a challenge was encountered when quantifying the non-energy benefits hence these were overlooked. In practice, the monetary value of these benefits need to be considered to be able to realize a reasonable cost to benefit ratio as well as ROI.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

This chapter has given a detailed conclusion from the research and suggested focus areas for future studies.

5.1 Conclusions

This research was aimed at designing a general EMS that utilized DSM to minimize energy cost. The DSM technique used is load scheduling whereby suitable operation times were suggested to the consumer based on the predicted hourly electricity prices. It is noted that whenever demand was high exceeding the supply, the electricity price was also high hence the need to shift time of use of machines to off peak periods. A unit commitment schedule was generated to enable the consumer to easily make a choice on shiftable loads which were not of priority. This operation schedule ensured that all priority loads were on at all times and the power balance constraint was always satisfied. Using the recommended operation schedule resulted in potential energy cost savings since the time of use of non-priority loads was shifted to a more effective time period.

The LSTM –RNN is effective in time series forecasting especially when dealing with non-stationary and non-linear data compared to conventional techniques such as ARIMA. The use of a mean squared loss function made it possible to track the error value and ensure that it was minimum by increasing the number of epochs. During demand forecasting, increasing epochs from 50 to 150 reduced the MSE loss from 9.5936×10^{-4} to 5.4008×10^{-4} . The predicted hourly electricity prices were used to schedule the available loads on one sample day. All the priority loads were on for 24 hours during the sample day while the non-priority ones were scheduled to take advantage off-peak periods with lower electricity prices. A unit commitment chart was generated showing a possible schedule for available loads and the resulting energy saving if the predicted prices were effectively used in shifting the TOU. Testing the effectiveness of the designed model using an IEEE 30 bus system with 20 loads yielded an annual energy cost saving of \$2,961,169.20. Long term use of an industrial EMS is likely to yield huge energy and cost savings.

In conclusion, the designed industrial energy management model enabled users to actively manage their energy consumption by shifting the use of non-priority loads to off peak durations. The system generated automated unit commitment schedules daily based on the hourly predicted prices thereby improving energy performance and saving on cost. Taking into consideration the non-

energy benefits of implementing an EMS as well as the future savings to be yielded by the EMS would help in obtaining a shorter PBP and a higher ROI to justify the investment.

This research has used a better forecasting model based on machine learning rather than the conventional time series modelling and analysis methods. It has also utilized the predicted price values in recommending the suitable load schedules rather than solely using the actual prices thus could be used in future system planning. Additionally, both the priority and non-priority loads were considered in the scheduling. Overall, it can be concluded that a well implemented EMS can help an industry realize significant energy saving and energy related cost savings which can be used in generating new business opportunities and maintaining competitiveness.

5.2 Recommendations for Further Work

Further research should be done in the following areas to improve on the findings of this work:

- i) Use of other inputs that affect parameters in the LSTM network when developing the forecasting model. This project only considered historical data on electricity prices and demand. Other inputs to the LSTM network would include information on holidays, specific day of the week or specific week of the year and weather patterns.
- ii) Considering other DSM techniques when developing the EMS. This project only incorporated proper load scheduling to reduce energy cost whereas there exist other techniques such as valley filling and peak clipping which modify the load profile for dynamic energy management.
- iii) Designing an EMS that integrates the management of other forms of energy rather than electrical energy. Energy is a top operating expense in industries. Other than electrical energy, other forms of energy that need to be monitored in industries include natural gas, water, compressed air and steam.
- iv) Exploring the integration of an industrial EMS with resource planning systems taking into account all factors of production such as the availability of raw materials, capital, power supply, and labor.

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**SMART GRID ENERGY MANAGEMENT
SYSTEM FOR INDUSTRIAL APPLICATIONS**

HERINE ALIENO OMONDI
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This report submitted for the partial fulfillment of the requirement for the award of the Degree of Masters of Science in Energy Management in the Department of Mechanical and Manufacturing Engineering in the University of Nairobi.

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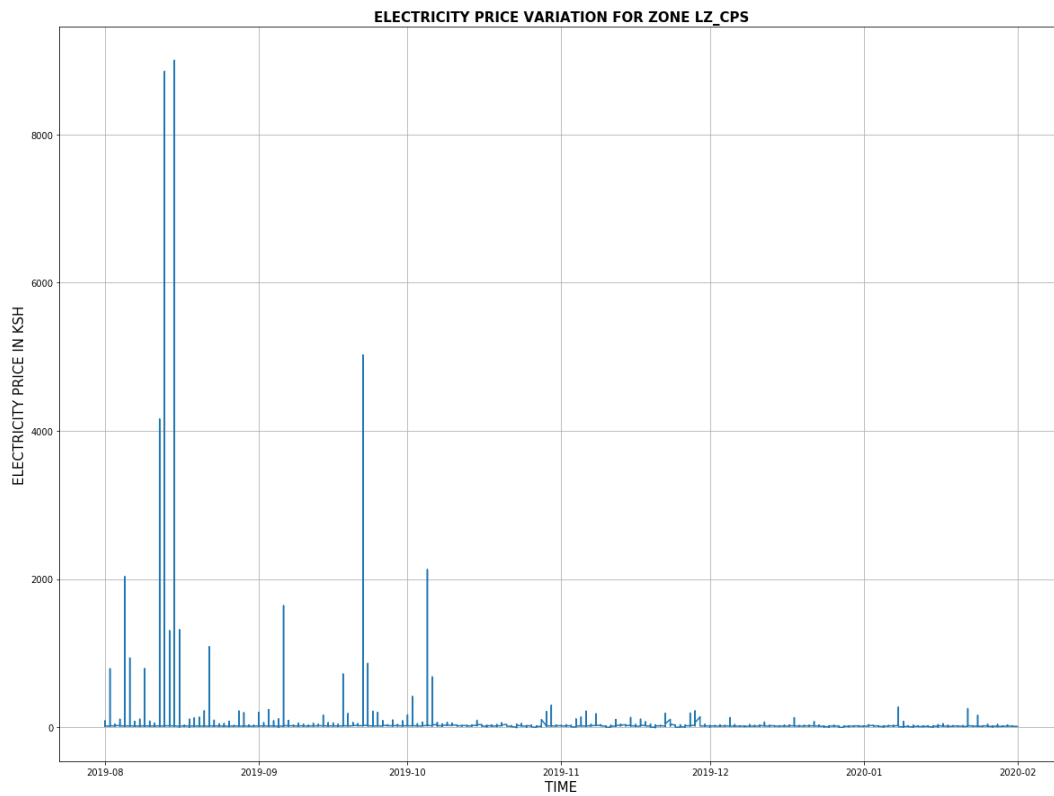
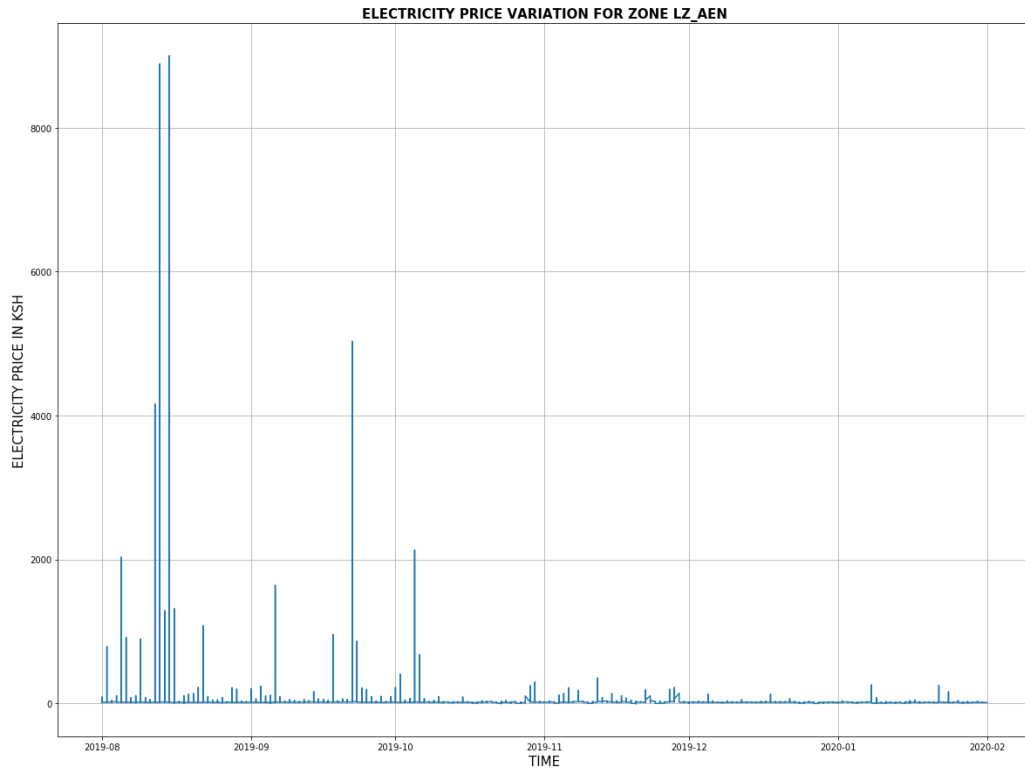
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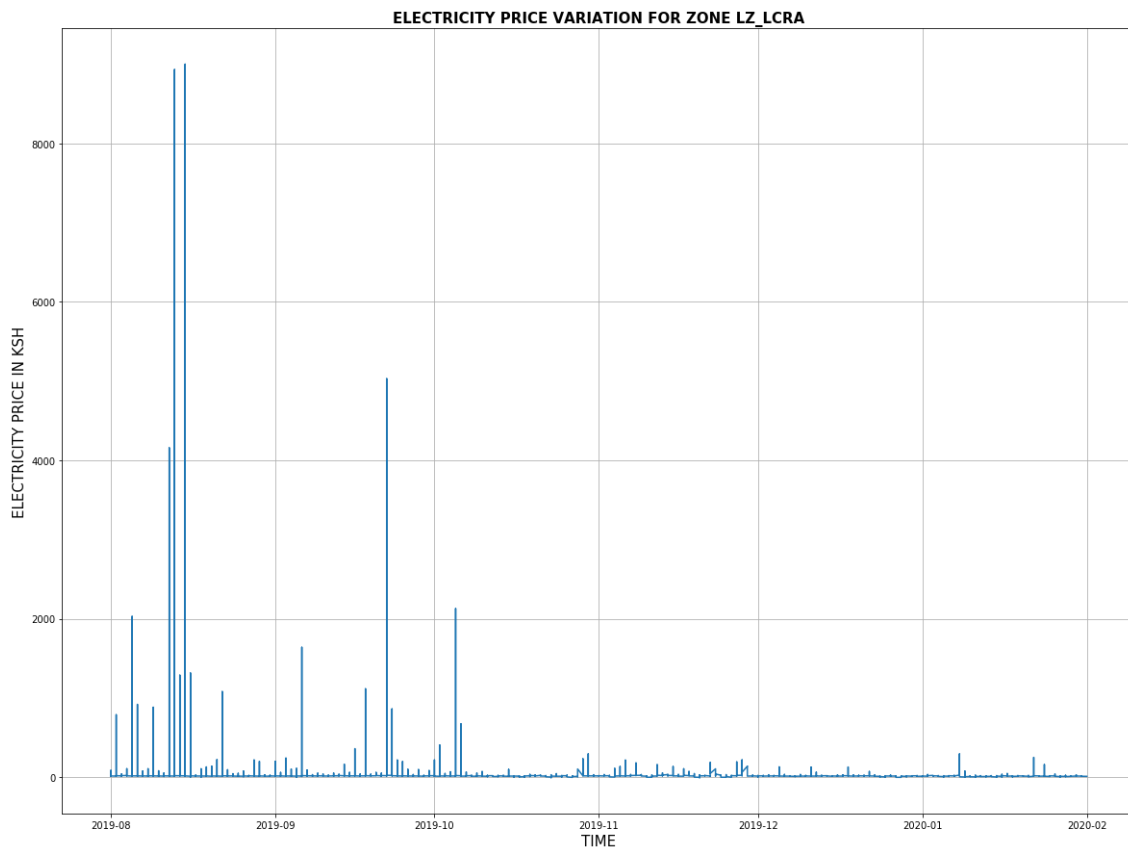
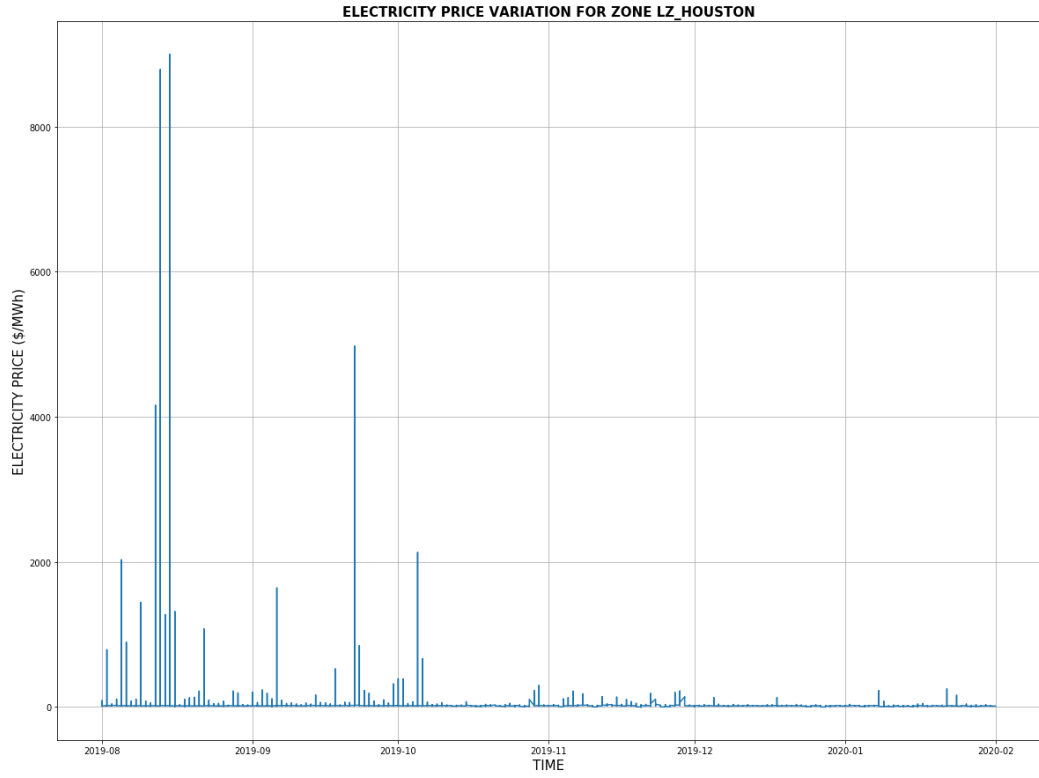
Appendix B

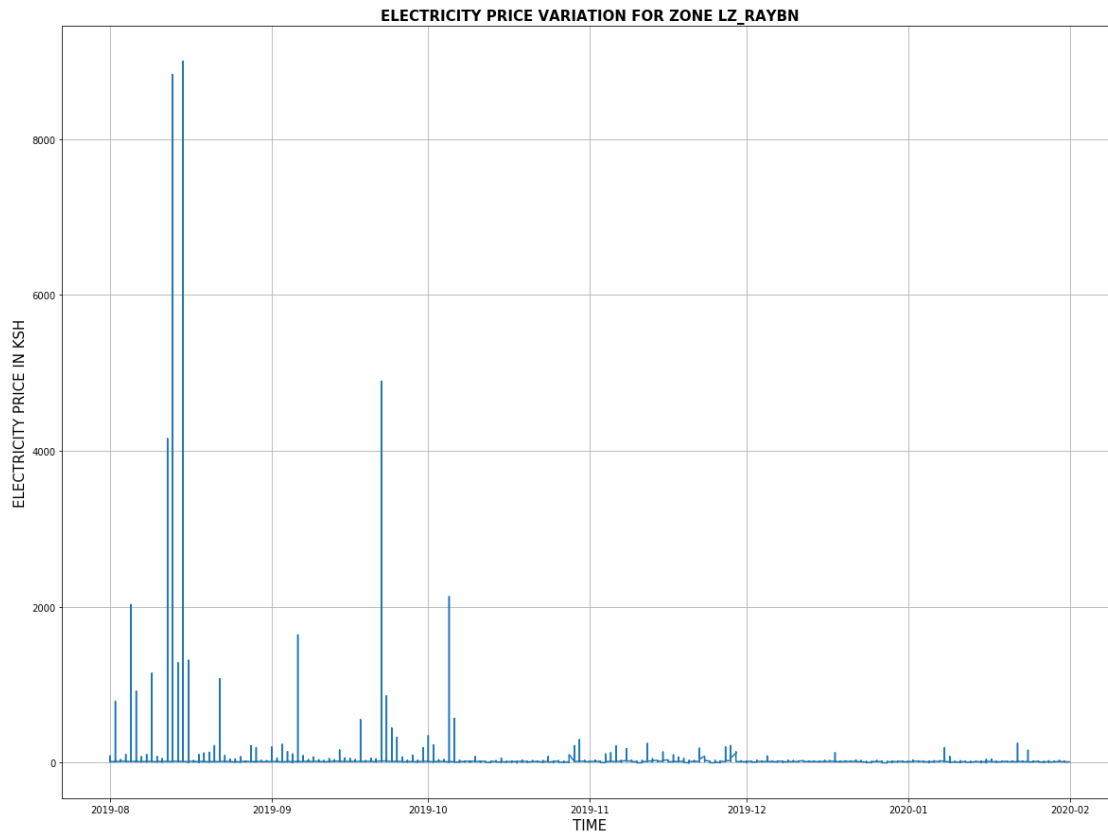
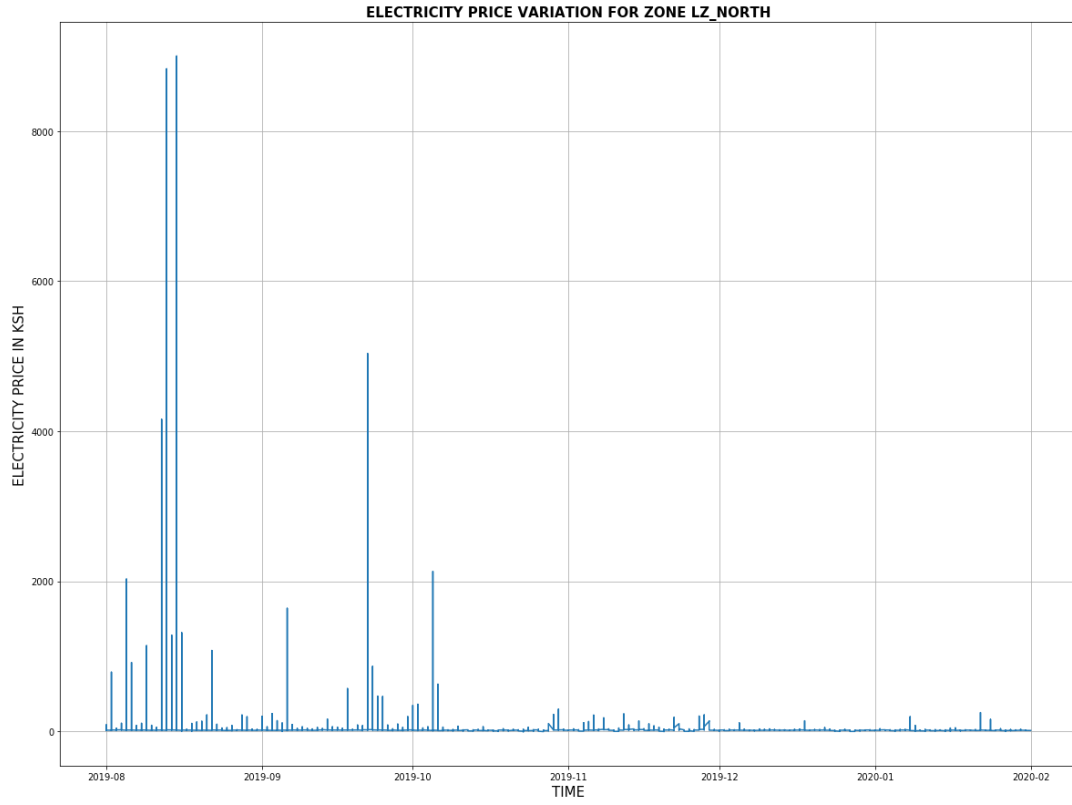
A sample of the electricity prices' and demand' data obtained from ERCOT's website

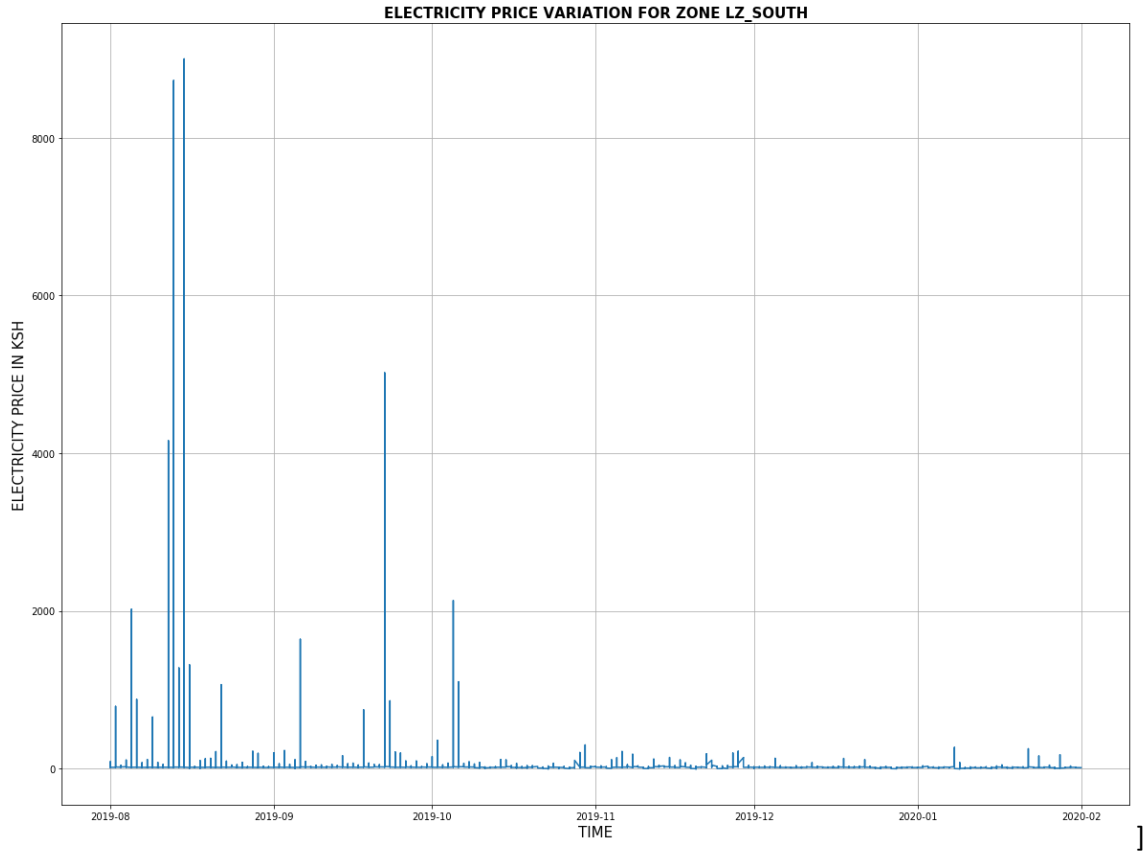
Date	Price	Zone	Date	Load
8/1/2019 0:00	14.9725	LZ_AEN	8/1/2019 0:00	48790.98
8/1/2019 0:00	15.4175	LZ_CPS	8/1/2019 1:00	45795.72
8/1/2019 0:00	14.8525	LZ_HOUSTON	8/1/2019 2:00	43642.73
8/1/2019 0:00	14.9875	LZ_LCRA	8/1/2019 3:00	42269.95
8/1/2019 0:00	14.4225	LZ_NORTH	8/1/2019 4:00	41738.05
8/1/2019 0:00	14.405	LZ_RAYBN	8/1/2019 5:00	42466.69
8/1/2019 0:00	15.835	LZ_SOUTH	8/1/2019 6:00	43963.8
8/1/2019 0:00	13.7675	LZ_WEST	8/1/2019 7:00	44750.44
8/1/2019 1:00	13.77	LZ_AEN	8/1/2019 8:00	47032.88
8/1/2019 1:00	14.6375	LZ_CPS	8/1/2019 9:00	50543.7
8/1/2019 1:00	13.6375	LZ_HOUSTON	8/1/2019 10:00	54552.66
8/1/2019 1:00	13.79	LZ_LCRA	8/1/2019 11:00	58606.93
8/1/2019 1:00	12.7575	LZ_NORTH	8/1/2019 12:00	62142.24
8/1/2019 1:00	12.7225	LZ_RAYBN	8/1/2019 13:00	65502.1
8/1/2019 1:00	15.6425	LZ_SOUTH	8/1/2019 14:00	67930.12
8/1/2019 1:00	11.015	LZ_WEST	8/1/2019 15:00	69064.36
8/1/2019 2:00	13.1275	LZ_AEN	8/1/2019 16:00	69423.25
8/1/2019 2:00	13.8	LZ_CPS	8/1/2019 17:00	68873.78
8/1/2019 2:00	13	LZ_HOUSTON	8/1/2019 18:00	67408.39
8/1/2019 2:00	13.0975	LZ_LCRA	8/1/2019 19:00	65187.94
8/1/2019 2:00	12.325	LZ_NORTH	8/1/2019 20:00	62743.85
8/1/2019 2:00	12.3025	LZ_RAYBN	8/1/2019 21:00	60401
8/1/2019 2:00	14.5575	LZ_SOUTH	8/1/2019 22:00	56392.16
8/1/2019 2:00	11.0875	LZ_WEST	8/1/2019 23:00	52189.19
8/1/2019 3:00	12.4725	LZ_AEN	8/2/2019 0:00	48586.96
8/1/2019 3:00	13.3325	LZ_CPS	8/2/2019 1:00	45676.93
8/1/2019 3:00	12.3475	LZ_HOUSTON	8/2/2019 2:00	43704.77
8/1/2019 3:00	12.5025	LZ_LCRA	8/2/2019 3:00	42372.65
8/1/2019 3:00	11.475	LZ_NORTH	8/2/2019 4:00	41991.95
8/1/2019 3:00	11.4425	LZ_RAYBN	8/2/2019 5:00	42776.25
8/1/2019 3:00	14.3775	LZ_SOUTH	8/2/2019 6:00	44159.82
8/1/2019 3:00	9.7275	LZ_WEST		
8/1/2019 4:00	12.79	LZ_AEN		
8/1/2019 4:00	13.6225	LZ_CPS		
8/1/2019 4:00	12.675	LZ_HOUSTON		
8/1/2019 4:00	12.6775	LZ_LCRA		
8/1/2019 4:00	11.845	LZ_NORTH		
8/1/2019 4:00	11.8075	LZ_RAYBN		
8/1/2019 4:00	14.6475	LZ_SOUTH		
8/1/2019 4:00	10.205	LZ_WEST		

Graphs Showing Electricity Price Variation for all Zones









Appendix C

Project Code

Visualizing the variation in price and demand with time for the 8 zones in Texas

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os

os.listdir('data')

# reading project data
data=pd.read_csv('./data/ElectricityPrices.csv',sep=',', parse_dates=['Date'])
data=data.iloc[:,0:14]
print('population size= %d'%len(data))
print(data.dtypes)
data.head()

raw=pd.read_csv('./data/ElectricityPrices.csv',sep=',', parse_dates=['Date'])
raw
raw.min()

#data reprocessing and cleaning
data.isna().sum() # total number of entries which are not a number (NaN)
price_data=pd.DataFrame()
price_data['Date']=data['Date'].dt.date
price_data['Time']=data['Date'].dt.time
price_data['Price']=data['Price']
price_data['Zone']=data['Zone']
price_data.head()

def unique_zone():
    zones=[]

    for Zone, data in price_data.groupby('Zone'):
        zones.append(Zone)
```

```
    return zones

def zoneCode_gen():
    _z= unique_zone()

    zone_code=[]

    count=1

    while count<=len(_z):
        zone_code.append(count)

        count+=1

    Area_Code=pd.DataFrame()

    Area_Code['Code_No.']=zone_code

    Area_Code['Zone']= _z

    return Area_Code

def loc_zone(code):

    areas=zoneCode_gen()

    zone=list(areas.Zone[areas['Code_No.']==code])

    #print(zone[0])

    return zone[0]

def req_zone(code):

    req_zone=loc_zone(code)

    Area_Code=zoneCode_gen()

    elec_price = price_data.merge(Area_Code, on=['Zone'])

    req_data=elec_price[elec_price['Code_No.']==code]

    cols_drop=['Code_No.']

    req_data=req_data.drop(cols_drop, axis=1)

    req_data.Date=pd.to_datetime(req_data['Date'])

    #req_data=req_data.set_index('Date')

    return req_data

def plot_price_var(code):

    wk_data=req_zone(code)
```

```
wk_data=wk_data.set_index('Date')
reg=loc_zone(code)
plt.figure(figsize=(20,15))
plt.plot(wk_data.Price)
plt.xlabel('TIME',fontsize=15,weight=100)
plt.ylabel('ELECTRICITY PRICE ($/MWh)',fontsize=15,weight=100)
plt.title('ELECTRICITY PRICE VARIATION FOR ZONE %s' %reg,fontsize=15,weight=1000)
plt.grid(True)
plt.show()
def daily_d(code,month):
    w=req_zone(code)
    wk=w.reset_index()
    daily=pd.DataFrame()
    daily['Date']=wk.Date
    daily['Price']=wk.Price
    daily = daily[daily['Date'].dt.month==month]
    return daily
def monthly_data(month,city_code):
    _ddata=pd.DataFrame()
    _ddata=daily_data(city_code)
    _ddata['Month']=_ddata['Date'].dt.month
    monthly_data=_ddata[_ddata['Month']==month]
    monthly_data=monthly_data.set_index('Date')
    return monthly_data
def annual_var(zone_code):
    req=pd.DataFrame()
    req=req_zone(zone_code)
    req=req.reset_index()
    req['Month']=req.Date.dt.month
    req=req.groupby('Month').mean()
```

```
return req
zones=[i for i in range(1,8)]
for zone in zones:
    plot_price_var(zone)
# SAMPLE DATA FOR ANALYSIS
#From the visualizations above it is noted that price variation for each zone is almost similar to each and every other
zone
#Hence one zone to use for further data analysis and modelling.
# sample zone LZ_Houston of zone code 3
sample_data=req_zone(3)#TRY WITH DIFFERENT ZONE CODE
sample_zone=str(sample_data['Zone'].unique())
sample_data=sample_data.drop('Zone',axis=1)
print('population size= %d'%len(sample_data))
sample_data.head()
os.listdir('data')
# reading regional demand data for LZ_Houston
demand_data=pd.read_csv('./data/DemanData.csv',parse_dates=['Date'])
demand_data=demand_data.iloc[:,0:14]
print('population size= %d'%len(demand_data))
print(demand_data.dtypes)
demand_data.head()
# data cleaning and feature engineering
demand_data.dropna(axis=1, how='all', inplace=True)
demand_data.dropna(axis=0, how='all', inplace=True)
data.isna().sum()
print('population size= %d'%len(demand_data))
demand_data=demand_data.drop_duplicates(keep= 'first')
print('population size= %d'%len(demand_data))
_data=pd.DataFrame()
_data['Date']=demand_data['Date'].dt.date
```

```
_data['Time']=demand_data['Date'].dt.time
_data.Date=pd.to_datetime(_data['Date'])
#_data.Time=pd.to_datetime.time(_data['Time'])
_data['Load']=demand_data['Load']
# merged demand data and price data
price_demand = sample_data.merge(_data, how='outer')
price_demand.isna().sum()
price_demand.dropna(axis=0, how='all', inplace=True)
price_demand.head()
price_demand.dtypes
price_demand=price_demand.set_index('Date')
weekly_data = price_demand.resample('W').mean()
monthly_data= price_demand.resample('m').mean()
monthly_data.head
monthly_data=monthly_data.reset_index()
monthly_data.head
daily_data = price_demand.resample('d').mean()
daily_data.head(10)
# PERFORMING COMPARISON ANALYSIS
A comparison is made between the trend at which the demand profile and price is varying
#using average monthly data of demand and price
plt.figure(1)
plt.figure(figsize=(20,10))
ax=plt.subplot(121)
monthly_data['Load'].plot(ax=ax)
plt.title('AVERAGE MONTHLY ELECTRICITY DEMAND VARIATION',fontsize=15,weight=1000)
plt.ylabel('DEMAND (MW)',fontsize=15,weight=100)
plt.xlabel('MONTH',fontsize=15,weight=100)
plt.grid(True)
ax=plt.subplot(122)
```



```

monthly_data['Price'].plot(ax=ax)

plt.title('AVERAGE MONTHLY ELECTRICITY PRICE VARIATION', fontsize=15,weight=1000)

plt.ylabel('PRICE ($/MWh)',fontsize=15,weight=100)

plt.xlabel('MONTH',fontsize=15,weight=100)

plt.grid(True)

plt.show()

```

Demand Forecasting

```

import numpy as np

import matplotlib.pyplot as plt

pd.plotting.deregister_matplotlib_converters()

import seaborn as sns

import pprint

%matplotlib inline

Step 1: Importing files after importing the necessary libraries

df = pd.read_csv("ModifiedDemanData.csv")

print("="*50)

print("First Five Rows ", "\n")

print(df.head(2), "\n")

print("="*50)

print("Information About Dataset", "\n")

print(df.info(), "\n")

print("="*50)

print("Describe the Dataset ", "\n")

print(df.describe(), "\n")

print("="*50)

print("Null Values t ", "\n")

print(df.isnull().sum(), "\n")

Step 2 - Reformat the datetime columns

# Extract all Data Like Year Month Date Time etc

demand = df

```

```

demand["Month"] = pd.to_datetime(df["Datetime"]).dt.month_name()
demand["Year"] = pd.to_datetime(df["Datetime"]).dt.year
demand["Date"] = pd.to_datetime(df["Datetime"]).dt.date
demand["Time"] = pd.to_datetime(df["Datetime"]).dt.time
demand["Week"] = pd.to_datetime(df["Datetime"]).dt.week
demand["Day"] = pd.to_datetime(df["Datetime"]).dt.day_name()
demand = df.set_index("Datetime")
demand.index = pd.to_datetime(demand.index)
demand.head(10)

Step 3
TestData = demand.tail(745)
Training_Set = demand.iloc[:,0:1] #All rows column 0(index which is the datetime) and 1
Training_Set = Training_Set[:-745] #Exclude the last 745 rows
print("Training Set Shape ", Training_Set.shape)
print("Test Set Shape ", TestData.shape)
from sklearn.preprocessing import MinMaxScaler
Training_Set = Training_Set.values
sc = MinMaxScaler(feature_range=(0, 1)) #transform each value in the column proportionally within the range [0,1]
#preserves the shape of the dataset, use a scaler after the train_test_split to avoid data leakage
Train = sc.fit_transform(Training_Set)
X_Train = []
Y_Train = []
# Range should be from 745 Values to END
for i in range(745, Train.shape[0]):
    # X_Train 0-745
    X_Train.append(Train[i-745:i])
    # Y Would be 745 th Value based on past 745 Values
    Y_Train.append(Train[i])
# Convert into Numpy Array
X_Train = np.array(X_Train)

```

```
Y_Train = np.array(Y_Train)
print(X_Train.shape)
print(Y_Train.shape)

# Shape should be Number of [Datapoints , Steps , 1 )
# we convert into 3-d Vector or #rd Dimesnsion
X_Train = np.reshape(X_Train, newshape=(X_Train.shape[0], X_Train.shape[1], 1))
X_Train.shape

Step 4: Modelling

from tensorflow import keras
from tensorflow.keras import layers
from keras.layers.core import Dense, Activation, Dropout
from keras.layers.recurrent import LSTM
from keras.models import Sequential

regressor = Sequential()

# Adding the first LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True, input_shape = (X_Train.shape[1], 1)))
regressor.add(Dropout(0.2))

# Adding a second LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a third LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a fourth LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50))
regressor.add(Dropout(0.2))

# Adding the output layer
regressor.add(Dense(units = 1))

# Compiling the RNN
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')
```

```
regressor.fit(X_Train, Y_Train, epochs = 150, batch_size = 32)
Df_Total = pd.concat((demand[["Load"]], TestData[["Load"]]), axis=0)
inputs = Df_Total[len(Df_Total) - len(TestData) - 745:].values
inputs.shape
inputs = Df_Total[len(Df_Total) - len(TestData) - 745:].values
# We need to Reshape
inputs = inputs.reshape(-1,1)
# Normalize the Dataset
inputs = sc.transform(inputs)
X_test = []
for i in range(745, 1490):
    X_test.append(inputs[i-745:i])
# Convert into Numpy Array
X_test = np.array(X_test)
# Reshape before Passing to Network
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
# Pass to Model
predicted_stock_price = regressor.predict(X_test)
# Do inverse Transformation to get Values
predicted_stock_price = sc.inverse_transform(predicted_stock_price)
True_Price = TestData["Load"].to_list()
Predicted_Price = predicted_stock_price
dates = TestData.index.to_list()
Machine_Df = pd.DataFrame(data={
    "Date":dates,
    "TrueLoad": True_Price,
    "PredictedLoad":[x[0] for x in Predicted_Price ]
})
True_Price = TestData["Load"].to_list()
Predicted_Price = [x[0] for x in Predicted_Price ]
```

```

dates = TestData.index.to_list()

#Machine Learned the Pattern Predicting Future Values

fig = plt.figure(figsize=(15,10))

ax1= fig.add_subplot(111)

x = dates

y = True_Price

y1 = Predicted_Price

pd.plotting.register_matplotlib_converters() #to handle the error float argument must be a string or no. not a timestamp

plt.plot(x,y, color="green", label="Actual Load")

plt.plot(x,y1, color="red", label="Predicted Load")

# beautify the x-labels

plt.gcf().autofmt_xdate()

plt.xlabel('Dates',weight=1000,fontsize=15)

plt.ylabel("Demand (MW)",weight=1000,fontsize=15)

plt.title("Comparison of Actual and Predicted Hourly Demand for January 2020",weight=1000,fontsize=15)

plt.legend()

```

Price Forecasting

```

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

pd.plotting.deregister_matplotlib_converters()

import seaborn as sns

import pprint

%matplotlib inline

Step 1: Importing files after importing the necessary libraries

df = pd.read_csv("ModifiedElectricityPrices.csv")

print("="*50)

print("First Five Rows ", "\n")

print(df.head(2), "\n")

print("="*50)

```

```
print("Information About Dataset","\n")
```

```
print(df.info(),"\n")
```

```
print("="*50)
```

```
print("Describe the Dataset ", "\n")
```

```
print(df.describe(), "\n")
```

```
print("="*50)
```

```
print("Null Values t ", "\n")
```

```
print(df.isnull().sum(), "\n")
```

Step 2: Reformatting the datetime columns

```
# Extract all Data Like Year Month Date Time etc
```

```
dataset = df
```

```
dataset["Month"] = pd.to_datetime(df["Datetime"]).dt.month_name()
```

```
dataset["Year"] = pd.to_datetime(df["Datetime"]).dt.year
```

```
dataset["Date"] = pd.to_datetime(df["Datetime"]).dt.date
```

```
dataset["Time"] = pd.to_datetime(df["Datetime"]).dt.time
```

```
dataset["Week"] = pd.to_datetime(df["Datetime"]).dt.week
```

```
dataset["Day"] = pd.to_datetime(df["Datetime"]).dt.day_name()
```

```
dataset = df.set_index("Datetime") #set datetime as the index
```

```
dataset.index = pd.to_datetime(dataset.index)
```

```
dataset.head(10)
```

Step 3: Unique months

```
# How many Unique Months do we Have in the Dataset
```

```
print(df.Month.unique(), "\n")
```

```
print("Total Number of Unique Months", df.Month.nunique(), "\n")
```

Step 4: Modelling

```
TestData = dataset.tail(744)
```

```
Training_Set = dataset.iloc[:,0:1] #All rows column 0(index which is the datetime) and 1 which is the price
```

```
Training_Set = Training_Set[:-744] #Exclude the last 744 rows
```

```
from sklearn.preprocessing import MinMaxScaler
```

```
Training_Set = Training_Set.values
```

```
sc = MinMaxScaler(feature_range=(0, 1)) #transform each value in the column proportionally within the range [0,1]
#preserves the shape of the dataset, use a scaler after the train_test_split to avoid data leakage
Train = sc.fit_transform(Training_Set)
X_Train = []
Y_Train = []
# Range should be from 744 Values to END
for i in range(744, Train.shape[0]):
    # X_Train 0-744
    X_Train.append(Train[i-744:i])
    # Y Would be 744 th Value based on past 744 Values
    Y_Train.append(Train[i])
# Convert into Numpy Array
X_Train = np.array(X_Train)
Y_Train = np.array(Y_Train)

print(X_Train.shape)
print(Y_Train.shape)
# Shape should be Number of [Datapoints , Steps , 1 )
# we convert into 3-d Vector or #rd Dimesnsion
X_Train = np.reshape(X_Train, newshape=(X_Train.shape[0], X_Train.shape[1], 1))
X_Train.shape
#LSTM RNN
from tensorflow import keras
from tensorflow.keras import layers
from keras.layers.core import Dense, Activation, Dropout
from keras.layers.recurrent import LSTM
from keras.models import Sequential
regressor = Sequential()
# Adding the first LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True, input_shape = (X_Train.shape[1], 1)))
```

```
regressor.add(Dropout(0.2))

# Adding a second LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))

regressor.add(Dropout(0.2))

# Adding a third LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))

regressor.add(Dropout(0.2))

# Adding a fourth LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50))

regressor.add(Dropout(0.2))

# Adding the output layer
regressor.add(Dense(units = 1))

# Compiling the RNN
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')

regressor.fit(X_Train, Y_Train, epochs = 150, batch_size = 32)

Df_Total = pd.concat((dataset[["Price"]], TestData[["Price"]]), axis=0)

inputs = Df_Total[len(Df_Total) - len(TestData) - 744:].values #Values of the test data twice

inputs.shape

inputs = Df_Total[len(Df_Total) - len(TestData) - 744:].values

# We need to Reshape
inputs = inputs.reshape(-1,1)

# Normalize the Dataset
inputs = sc.transform(inputs)

X_test = []

for i in range(744, 1488):

    X_test.append(inputs[i-744:i])

# Convert into Numpy Array
X_test = np.array(X_test)

# Reshape before Passing to Network
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
```



```
# Pass to Model
predicted_stock_price = regressor.predict(X_test)

# Do inverse Transformation to get Values
predicted_stock_price = sc.inverse_transform(predicted_stock_price)

True_Price = TestData["Price"].to_list()
Predicted_Price = predicted_stock_price
dates = TestData.index.to_list()

Machine_Df = pd.DataFrame(data={
    "Date":dates,
    "TruePrice": True_Price,
    "PredictedPrice":[x[0] for x in Predicted_Price ]
})

True_Price = TestData["Price"].to_list()
Predicted_Price = [x[0] for x in Predicted_Price ]
dates = TestData.index.to_list()

#Machine Learned the Pattern Predicting Future Values
fig = plt.figure(figsize=(15,10))
ax1= fig.add_subplot(111)
x = dates
y = True_Price
y1 = Predicted_Price

pd.plotting.register_matplotlib_converters() #to handle the error float argument must be a string or no. not a timestamp
plt.plot(x,y, color="green", label="Actual Price")
plt.plot(x,y1, color="red", label="Predicted Price")

# beautify the x-labels
plt.gcf().autofmt_xdate()#to format the x axis nicely if it has dates
plt.xlabel('Dates')
plt.ylabel("Price ($/MWh)")
plt.title("Comparison of Hourly Actual and Predicted Electricity Prices for January 2020")
plt.legend()
```

Load Combinations

```
#Possible non-priority load combinations
```

```
import numpy as np
```

```
def dec2bin(num):
```

```
    if num>0:
```

```
        dec2bin(int(num//2))
```

```
        print(num%2,end="")
```

```
N_loads=8 #Total number of non-priority loads
```

```
CombN=2**N_loads #Possible combinations
```

```
print("possible combinations =",+ CombN)
```

```
LoadState=np.zeros((CombN, N_loads))
```

```
LoadState
```

```
for i in range(0,CombN):
```

```
    LoadState= bin(i)
```

```
    print (LoadState)
```

```
#Possible combinations of loads where 0 means OFF and 1 means ON (256 by 8 matrix)
```

```
X = np.array([LoadState])
```

```
#Power consumed by the non-priority loads (8 by 1 matrix)
```

```
Y = np.array([25,13,37,22,26,30,28,33])
```

```
Total_PowerConsumed = np.dot(X,Y)
```

```
Total_PowerConsumed
```

```
import pandas as pd
```

```
#convert array into a dataframe
```

```
df = pd.DataFrame (Total_PowerConsumed)
```

```
#save to csv file
```

```
filepath = 'TotalConsumptionforNonPriorityLoads.csv'
```

```
df.to_csv(filepath,index=False)
```

```
df2 = pd.DataFrame (X)
```

```
#save to csv file
```

```
filepath = 'Combinations.csv'
```

df2.to_csv(filepath,index=False)

Table Showing the Possible Non-priority Load Combinations (Total Priority Loads = 271MW)

	B	E	H	J	K	N	Q	S	Total Non-Priority Load (MW)	Possibility of Combination
1	1	0	0	1	1	1	1	1	164	Impossible
2	1	0	1	0	1	1	1	1	179	Impossible
3	1	0	1	1	0	1	1	1	175	Impossible
4	1	0	1	1	1	0	1	1	171	Impossible
5	1	0	1	1	1	1	0	1	173	Impossible
6	1	0	1	1	1	1	1	0	168	Impossible
7	1	0	1	1	1	1	1	1	201	Impossible
8	1	1	0	1	1	1	1	1	177	Impossible
9	1	1	1	0	0	1	1	1	166	Impossible
10	1	1	1	0	1	1	0	1	164	Impossible
11	1	1	1	0	1	1	1	1	192	Impossible
12	1	1	1	1	0	1	1	1	188	Impossible
13	1	1	1	1	1	0	1	1	184	Impossible
14	1	1	1	1	1	1	0	1	186	Impossible
15	1	1	1	1	1	1	1	0	181	Impossible
16	1	1	1	1	1	1	1	1	214	Impossible
17	0	1	1	1	1	1	1	1	189	Impossible
18	0	0	1	1	1	1	1	1	176	Possible
19	0	1	1	0	1	1	1	1	167	Possible
20	0	1	1	1	0	1	1	1	163	Possible
21	1	1	1	0	1	0	1	1	162	Possible
22	0	1	1	1	1	1	0	1	161	Possible
23	1	1	1	1	0	1	0	1	160	Possible
24	0	1	1	1	1	0	1	1	159	Possible
25	1	1	1	0	1	1	1	0	159	Possible
26	1	1	1	1	0	0	1	1	158	Possible
27	0	1	1	1	1	1	1	0	156	Possible
28	1	1	1	1	1	0	0	1	156	Possible
29	1	1	0	0	1	1	1	1	155	Possible
30	1	1	1	1	0	1	1	0	155	Possible
31	0	0	1	0	1	1	1	1	154	Possible
32	1	0	1	0	0	1	1	1	153	Possible
33	1	1	1	1	1	1	0	0	153	Possible
34	0	1	0	1	1	1	1	1	152	Possible
35	1	0	1	0	1	1	0	1	151	Possible
36	1	1	0	1	0	1	1	1	151	Possible
37	1	1	1	1	1	0	1	0	151	Possible
38	0	0	1	1	0	1	1	1	150	Possible
39	1	0	1	0	1	0	1	1	149	Possible
40	1	1	0	1	1	1	0	1	149	Possible
41	0	0	1	1	1	1	0	1	148	Possible
42	1	0	1	1	0	1	0	1	147	Possible

43	1	1	0	1	1	0	1	1	147	Possible
44	0	0	1	1	1	0	1	1	146	Possible
45	1	0	1	0	1	1	1	0	146	Possible
46	1	0	1	1	0	0	1	1	145	Possible
47	1	1	0	1	1	1	1	0	144	Possible
48	0	0	1	1	1	1	1	0	143	Possible
49	1	0	1	1	1	0	0	1	143	Possible
50	1	0	0	0	1	1	1	1	142	Possible
51	1	0	1	1	0	1	1	0	142	Possible
52	0	1	1	0	0	1	1	1	141	Possible
53	1	0	1	1	1	1	0	0	140	Possible
54	0	0	0	1	1	1	1	1	139	Possible
55	0	1	1	0	1	1	0	1	139	Possible
56	1	0	0	1	0	1	1	1	138	Possible
57	1	0	1	1	1	0	1	0	138	Possible
58	1	1	1	0	0	1	0	1	138	Possible
59	0	1	1	0	1	0	1	1	137	Possible
60	1	0	0	1	1	1	0	1	136	Possible
61	1	1	1	0	0	0	1	1	136	Possible
62	0	1	1	1	0	1	0	1	135	Possible
63	0	1	1	0	1	1	1	0	134	Possible
64	1	0	0	1	1	0	1	1	134	Possible
65	1	1	1	0	1	0	0	1	134	Possible
66	0	1	1	1	0	0	1	1	133	Possible
67	1	1	1	0	0	1	1	0	133	Possible
68	0	1	1	1	1	0	0	1	131	Possible
69	1	0	0	1	1	1	1	0	131	Possible
70	1	1	1	0	1	1	0	0	131	Possible
71	0	1	0	0	1	1	1	1	130	Possible
72	0	1	1	1	0	1	1	0	130	Possible
73	1	1	1	1	0	0	0	1	130	Possible
74	1	1	0	0	0	1	1	1	129	Possible
75	1	1	1	0	1	0	1	0	129	Possible
76	0	0	1	0	0	1	1	1	128	Possible
77	0	1	1	1	1	1	0	0	128	Possible
78	1	1	0	0	1	1	0	1	127	Possible
79	1	1	1	1	0	1	0	0	127	Possible
80	0	0	1	0	1	1	0	1	126	Possible
81	0	1	0	1	0	1	1	1	126	Possible
82	0	1	1	1	1	0	1	0	126	Possible
83	1	0	1	0	0	1	0	1	125	Possible
84	1	1	0	0	1	0	1	1	125	Possible
85	1	1	1	1	0	0	1	0	125	Possible
86	0	0	1	0	1	0	1	1	124	Possible
87	0	1	0	1	1	1	0	1	124	Possible
88	1	0	1	0	0	0	1	1	123	Possible
89	1	1	0	1	0	1	0	1	123	Possible
90	1	1	1	1	1	0	0	0	123	Possible

91	0	0	1	1	0	1	0	1	122	Possible
92	0	1	0	1	1	0	1	1	122	Possible
93	1	1	0	0	1	1	1	0	122	Possible
94	0	0	1	0	1	1	1	0	121	Possible
95	1	0	1	0	1	0	0	1	121	Possible
96	1	1	0	1	0	0	1	1	121	Possible
97	0	0	1	1	0	0	1	1	120	Possible
98	1	0	1	0	0	1	1	0	120	Possible
99	0	1	0	1	1	1	1	0	119	Possible
100	1	1	0	1	1	0	0	1	119	Possible
101	0	0	1	1	1	0	0	1	118	Possible
102	1	0	1	0	1	1	0	0	118	Possible
103	1	1	0	1	0	1	1	0	118	Possible
104	0	0	0	0	1	1	1	1	117	Possible
105	0	0	1	1	0	1	1	0	117	Possible
106	1	0	1	1	0	0	0	1	117	Possible
107	1	0	0	0	0	1	1	1	116	Possible
108	1	0	1	0	1	0	1	0	116	Possible
109	1	1	0	1	1	1	0	0	116	Possible
110	0	0	1	1	1	1	0	0	115	Possible
111	1	0	0	0	1	1	0	1	114	Possible
112	1	0	1	1	0	1	0	0	114	Possible
113	1	1	0	1	1	0	1	0	114	Possible
114	0	0	0	1	0	1	1	1	113	Possible
115	0	0	1	1	1	0	1	0	113	Possible
116	0	1	1	0	0	1	0	1	113	Possible
117	1	0	0	0	1	0	1	1	112	Possible
118	1	0	1	1	0	0	1	0	112	Possible
119	0	0	0	1	1	1	0	1	111	Possible
120	0	1	1	0	0	0	1	1	111	Possible
121	1	0	0	1	0	1	0	1	110	Possible
122	1	0	1	1	1	0	0	0	110	Possible
123	0	0	0	1	1	0	1	1	109	Possible
124	0	1	1	0	1	0	0	1	109	Possible
125	1	0	0	0	1	1	1	0	109	Possible
126	0	1	1	0	0	1	1	0	108	Possible
127	1	0	0	1	0	0	1	1	108	Possible
128	1	1	1	0	0	0	0	1	108	Possible
129	0	0	0	1	1	1	1	0	106	Possible
130	0	1	1	0	1	1	0	0	106	Possible
131	1	0	0	1	1	0	0	1	106	Possible
132	0	1	1	1	0	0	0	1	105	Possible
133	1	0	0	1	0	1	1	0	105	Possible
134	1	1	1	0	0	1	0	0	105	Possible
135	0	1	0	0	0	1	1	1	104	Possible
136	0	1	1	0	1	0	1	0	104	Possible
137	1	0	0	1	1	1	0	0	103	Possible
138	1	1	1	0	0	0	1	0	103	Possible

139	0	1	0	0	1	1	0	1	102	Possible
140	0	1	1	1	0	1	0	0	102	Possible
141	1	0	0	1	1	0	1	0	101	Possible
142	1	1	0	0	0	1	0	1	101	Possible
143	1	1	1	0	1	0	0	0	101	Possible
144	0	0	1	0	0	1	0	1	100	Possible
145	0	1	0	0	1	0	1	1	100	Possible
146	0	1	1	1	0	0	1	0	100	Possible
147	1	1	0	0	0	0	1	1	99	Possible
148	0	0	1	0	0	0	1	1	98	Possible
149	0	1	0	1	0	1	0	1	98	Possible
150	0	1	1	1	1	0	0	0	98	Possible
151	0	1	0	0	1	1	1	0	97	Possible
152	1	1	0	0	1	0	0	1	97	Possible
153	1	1	1	1	0	0	0	0	97	Possible
154	0	0	1	0	1	0	0	1	96	Possible
155	0	1	0	1	0	0	1	1	96	Possible
156	1	1	0	0	0	1	1	0	96	Possible
157	0	0	1	0	0	1	1	0	95	Possible
158	1	0	1	0	0	0	0	1	95	Possible
159	0	1	0	1	1	0	0	1	94	Possible
160	1	1	0	0	1	1	0	0	94	Possible
161	0	0	1	0	1	1	0	0	93	Possible
162	0	1	0	1	0	1	1	0	93	Possible
163	1	1	0	1	0	0	0	1	93	Possible
164	0	0	1	1	0	0	0	1	92	Possible
165	1	0	1	0	0	1	0	0	92	Possible
166	1	1	0	0	1	0	1	0	92	Possible
167	0	0	0	0	0	1	1	1	91	Possible
168	0	0	1	0	1	0	1	0	91	Possible
169	0	1	0	1	1	1	0	0	91	Possible
170	1	0	1	0	0	0	1	0	90	Possible
171	1	1	0	1	0	1	0	0	90	Possible
172	0	0	0	0	1	1	0	1	89	Possible
173	0	0	1	1	0	1	0	0	89	Possible
174	0	1	0	1	1	0	1	0	89	Possible
175	1	0	0	0	0	1	0	1	88	Possible
176	1	0	1	0	1	0	0	0	88	Possible
177	1	1	0	1	0	0	1	0	88	Possible
178	0	0	0	0	1	0	1	1	87	Possible
179	0	0	1	1	0	0	1	0	87	Possible
180	1	0	0	0	0	0	1	1	86	Possible
181	1	1	0	1	1	0	0	0	86	Possible
182	0	0	0	1	0	1	0	1	85	Possible
183	0	0	1	1	1	0	0	0	85	Possible
184	0	0	0	0	1	1	1	0	84	Possible
185	1	0	0	0	1	0	0	1	84	Possible
186	1	0	1	1	0	0	0	0	84	Possible

187	0	0	0	1	0	0	1	1	83	Possible
188	0	1	1	0	0	0	0	1	83	Possible
189	1	0	0	0	0	1	1	0	83	Possible
190	0	0	0	1	1	0	0	1	81	Possible
191	1	0	0	0	1	1	0	0	81	Possible
192	0	0	0	1	0	1	1	0	80	Possible
193	0	1	1	0	0	1	0	0	80	Possible
194	1	0	0	1	0	0	0	1	80	Possible
195	1	0	0	0	1	0	1	0	79	Possible
196	0	0	0	1	1	1	0	0	78	Possible
197	0	1	1	0	0	0	1	0	78	Possible
198	1	0	0	1	0	1	0	0	77	Possible
199	0	0	0	1	1	0	1	0	76	Possible
200	0	1	0	0	0	1	0	1	76	Possible
201	0	1	1	0	1	0	0	0	76	Possible
202	1	0	0	1	0	0	1	0	75	Possible
203	1	1	1	0	0	0	0	0	75	Possible
204	0	1	0	0	0	0	1	1	74	Possible
205	1	0	0	1	1	0	0	0	73	Possible
206	0	1	0	0	1	0	0	1	72	Possible
207	0	1	1	1	0	0	0	0	72	Possible
208	0	1	0	0	0	1	1	0	71	Possible
209	1	1	0	0	0	0	0	1	71	Possible
210	0	0	1	0	0	0	0	1	70	Possible
211	0	1	0	0	1	1	0	0	69	Possible
212	0	1	0	1	0	0	0	1	68	Possible
213	1	1	0	0	0	1	0	0	68	Possible
214	0	0	1	0	0	1	0	0	67	Possible
215	0	1	0	0	1	0	1	0	67	Possible
216	1	1	0	0	0	0	1	0	66	Possible
217	0	0	1	0	0	0	1	0	65	Possible
218	0	1	0	1	0	1	0	0	65	Possible
219	1	1	0	0	1	0	0	0	64	Possible
220	0	0	0	0	0	1	0	1	63	Possible
221	0	0	1	0	1	0	0	0	63	Possible
222	0	1	0	1	0	0	1	0	63	Possible
223	1	0	1	0	0	0	0	0	62	Possible
224	0	0	0	0	0	0	1	1	61	Possible
225	0	1	0	1	1	0	0	0	61	Possible
226	1	1	0	1	0	0	0	0	60	Possible
227	0	0	0	0	1	0	0	1	59	Possible
228	0	0	1	1	0	0	0	0	59	Possible
229	0	0	0	0	0	1	1	0	58	Possible
230	1	0	0	0	0	0	0	1	58	Possible
231	0	0	0	0	1	1	0	0	56	Possible
232	0	0	0	1	0	0	0	1	55	Possible
233	1	0	0	0	0	1	0	0	55	Possible
234	0	0	0	0	1	0	1	0	54	Possible

235	1	0	0	0	0	0	1	0	53	Possible
236	0	0	0	1	0	1	0	0	52	Possible
237	1	0	0	0	1	0	0	0	51	Possible
238	0	0	0	1	0	0	1	0	50	Possible
239	0	1	1	0	0	0	0	0	50	Possible
240	0	0	0	1	1	0	0	0	48	Possible
241	1	0	0	1	0	0	0	0	47	Possible
242	0	1	0	0	0	0	0	1	46	Possible
243	0	1	0	0	0	1	0	0	43	Possible
244	0	1	0	0	0	0	1	0	41	Possible
245	0	1	0	0	1	0	0	0	39	Possible
246	1	1	0	0	0	0	0	0	38	Possible
247	0	0	1	0	0	0	0	0	37	Possible
248	0	1	0	1	0	0	0	0	35	Possible
249	0	0	0	0	0	0	0	1	33	Possible
250	0	0	0	0	0	1	0	0	30	Possible
251	0	0	0	0	0	0	1	0	28	Possible
252	0	0	0	0	1	0	0	0	26	Possible
253	1	0	0	0	0	0	0	0	25	Possible
254	0	0	0	1	0	0	0	0	22	Possible
255	0	1	0	0	0	0	0	0	13	Possible
256	0	0	0	0	0	0	0	0	0	Possible

Appendix D

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Smart Grid Energy Management System for Industrial Applications

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Abstract— Energy is one of the top operating expenses in industries. Following the increased adoption of smart grids in recent years, industries can leverage on its capabilities to design effective energy management schemes for competitive advantage. This paper addresses the challenge of energy management in industries by incorporating the aspects of a smart grid in designing an energy management system (EMS) where demand side management (DSM) is utilized to enable users control their energy usage and minimize costs. A forecasting model for electricity prices and demand is developed using Long Short Term Memory (LSTM) - Recurrent Neural Network (RNN). The predicted prices are used in load scheduling to realize potential energy cost savings. The non-priority loads are scheduled to leverage on low electricity prices during off peak times. The effectiveness of the designed energy management strategy is tested using an IEEE 30 bus system. A suitable operation schedule with committed units for each hour is given for one sample day. Using the test system with 20 loads yielded an annual energy cost saving of \$2,961,169.20 and a payback period (PIB) of 4.29 years. Quantifying both the energy and non-energy benefits of investing in an EMS justifies its high investment cost. Long term use of an industrial EMS is likely to yield huge energy and cost savings.

Keywords— Smart grid, Energy Management System, Long Short Term Memory, Recurrent Neural Network, Demand Side Management, Demand Response, Time of Use

I. INTRODUCTION

Various research works have explored energy management from different perspectives. Y. Nozaki et al. discussed EMSs for homes, buildings, communities, and data centers where energy is optimized jointly [1]. Tests run on each of these systems yielded either a reduction in carbon dioxide emission or a considerable saving in energy. Energy cost was minimized with shared use of the communication system. Automated demand response (DR), the role of consumers in energy management, and various smart grid technologies such as direct load control, storage, and cogeneration were explored by Samad and Kilicote [2]. The importance of understanding the rate structures when performing peak scheduling was emphasized. The use of a standard information model that supports DSM activities was recommended. Collins et al. [3] came up with an energy monitoring and management system (EMMS) suitable for improving energy efficiency, cost savings, and ecological profile in industries. The model had a graphical user interface and operation scheduler (GUIOS) that generated feedback to the operator through the fuzzy inference system to ensure energy and cost savings. The scheduler was used to schedule

machine operations assuming that all processes are schedulable.

According to Ogunmike et al. [4], scheduling of residential loads is done using dynamic prices determined from a day ahead variable pricing technique. A constrained linear programming problem for scheduling the appliances is solved using Mixed Integer Linear Programming optimization. It was noted that optimal scheduling of appliances can yield huge savings in energy. A generalized energy management scheme based on static task network was proposed in [5]. The scheduling of tasks and distributed energy resources was done based on the day-ahead hourly prices. The DR scheme enabled the users to shift electricity usage to off peak periods thus balancing the supply and demand, improving power reliability, and reducing the energy cost. In [6], a smart power management system based on hybrid energy storage is proposed. The authors created a smart EMS for a coal mine to boost energy efficiency, increase the utilization of renewable resources, and improve the reliability of the energy supplying system taking into consideration power quality aspects.

M. Accone et al [7] designed an EMS for smart houses that optimized energy consumption and electricity cost while ensuring the consumer's comfort. MATLAB, Simulink and Stateflow were used to simulate the EMS model whereas Monte Carlo Simulation was used to compare between the normal and economy scenarios. The importance of a smart grid in energy demand management was addressed in [8]. The authors introduced the smart home concept where smart appliances communicate with the smart meters using a Home Area Network to inform electricity usage decisions. Lastly, the idea of energy storage in prosumer based systems for both energy sharing and management was brought forth in [9]. The model was suitable in peak load management. Binary Integer Programming (BIP) was used for solving the objective function. This paper will therefore incorporate aspects of a smart grid in designing an EMS that will recommend suitable time of use (TOU) for industrial loads based on the predicted electricity prices.

A. Contribution

The capabilities of smart grids to process data, make informed decisions, and actively engage consumers in controlling their energy consumption are used in designing the EMS. LSTM machine learning technique is used in developing the prediction model. Load scheduling is performed based on the forecasted hourly electricity prices. A

suitable operating schedule with committed units is generated to inform the user on effective ways of minimizing energy cost.

B. Paper Organization

The rest of the paper is organized as follows: Section II is the problem formulation, Section III is the proposed methodology, Section IV is a presentation of simulated results, while Section V is the work's conclusion and suggestions for further research. Lastly, the references used are listed.

II. PROBLEM FORMULATION

A multi-objective problem of not only seeking to minimize the energy consumption and cost but also to assess the economic viability of implementing an EMS is addressed. A forecasting model is developed using a machine learning technique rather than conventional time series modelling methods like Autoregressive Integrated Moving Average Model (ARIMA). Unlike other researchers that use actual hourly electricity prices to do scheduling, predicted prices are used. This approach is highly recommended for long term planning in order to defer unnecessary energy costs. The economic viability of implementing the EMS is assessed using various economic tools.

A. Forecasting and Load Scheduling Model

The forecasting model is developed using LSTM RNN machine learning technique. The inputs to the model are historical data on hourly electricity prices and demand. LSTM networks are used to learn order dependence in the given sequence for accurate prediction. The main objective when training a machine learning model is to minimize the loss function. The mean squared error (MSE) loss estimator is chosen due to its suitability in determining the accuracy of the model when dealing with regression problems. MSE is selected over mean absolute error due to its ability to converge even with fixed learning rate and its sensitivity to outliers in the dataset. The magnitude of loss value is directly proportional to the gradient of MSE loss and this gradient reduces as the loss tends to zero. A good model should have MSE values closer to zero implying that the probability of the model to make accurate predictions is high. The number of epochs in the LSTM networks is increased until minimum MSE is obtained. The MSE is computed using the formula in equation 1:

$$MSE = \frac{1}{n} \sum_{t=1}^n e_t^2 = \frac{1}{n} \sum_{t=1}^n (y_t - f_t)^2 \quad (1)$$

Where n is the size of the test set, e_t is the forecast error, y_t is the actual price, and f_t is the forecasted price. The predicted prices are used to determine suitable load schedules.

B. Possible Load Combinations

Given n number of loads, the possible combinations is given by an array of binary groupings with a count from 0 to 2^n-1 [3]. The viable load combinations must ensure that the supply meets the demand at all times and all priority loads are on. A unit commitment schedule is generated showing all the possible machine combinations and the resulting energy cost.

C. Objective Energy Cost Function

Upon scheduling of the loads, the known power consumption rates and operation times of the active machines are used to determine the energy cost using equation 2.

$$F(P_i) = \sum_{t=1}^T (C_t \times t \times P_i) \quad (2)$$

Where $F(P_i)$ is the total cost of electricity consumed by the i^{th} active machine (\$), C_t is the hourly electricity price (\$/MWh), t is the running time of each machine (h), P_i is the power consumed by the i^{th} active machine (MW), and n is the number of machines.

D. Power Balance Constraint

The maximum power consumption for all the machines need to balance the power supplied by the generators and/or utility grid at any given instant. Considering a region with hundreds of industries that lack EMSs and share a distribution grid, the losses in each company will result in a huge power demand hence a significant impact on the grid. However, taking the case of a single industry within this zone, the impact of losses on the grid can be considered negligible. Equation 3a gives the power balance constraint assuming such an industrial set up.

$$P_{ext} \geq (\sum_{i=1}^n P_i) \quad (3a)$$

Where P_{ext} is the peak power supplied and P_i is the power consumed by the i^{th} active machine (MW).

The non-priority loads are scheduled to take advantage of lower electricity prices ensuring that the constraint in equation 3b is met.

$$\sum_{i=1}^n P_{n1} \leq P_{ext} - \sum_{i=1}^n P_{p1} \quad (3b)$$

Where P_{n1} is the power consumed by each non-priority load and P_{p1} is the power consumed by each priority load.

E. Economic Viability

The economic feasibility of investing in the industrial EMS is evaluated using cost benefit analysis (CBA). The costs which include the staff time utilized in setting up, implementing and conducting trainings on the use of the system are estimated. Others costs include that of purchasing additional metering tools and hiring experts to actualize the installation and use of the EMS. On the other hand, the energy and non-energy benefits of the EMS are also determined. The results of the CBA are evaluated using simple PBP and return on investment (ROI) computation using equations 4 and 5 respectively.

$$PBP = \frac{\text{Initial investment cost in the EMS}}{\text{Annual energy cost saving}} \quad (4)$$

$$ROI = \frac{1}{PBP} \quad (5)$$

III. LSTM-RNN TECHNIQUE

LSTM-RNN is proposed for forecasting the electricity prices and demand. The method is capable of learning long sequences with long time lags [10]. Unlike Feed Forward Networks that do not model memory, RNNs store activations from each time step in the internal state of the network to provide a temporal memory thereby remembering previous inputs. This capability makes RNNs better suited for capturing information from sequences and time series. A simple RNN learns using back propagation through time and experiences the vanishing gradient problem when tackling long term dependencies.

The pioneers of the use of LSTM were Hochreiter and Schmidhuber who devised the method to solve the problem of vanishing gradient by controlling the cell states using various gates [11]. The hidden layers in LSTM have memory blocks with four parts namely:

- (i) Input gate which controls the activations that enter the memory cell.
- (ii) Forget gate which assists the network in resetting the memory cells by forgetting past inputs.
- (iii) Output gate which determines the output to pass on to successive networks and the ones to be filtered.
- (iv) Self-connected memory cell.

The information at different states is regulated by the inputs and the hidden states generated from the previous steps after sigmoid or tanh activations within the neural network layers. Backpropagation through time (BPPT) is the training algorithm used in LSTM [10]. Equations 6 to 10 summarize the mathematical functions of the gates which perform the task of limiting the information passing through the memory cell.

$$i_t = \text{sigmoid}(W_{i1}x_t + W_{i2}h_{t-1} + b_i) \tag{6}$$

$$f_t = \text{sigmoid}(W_{f1}x_t + W_{f2}h_{t-1} + b_f) \tag{7}$$

$$o_t = \text{sigmoid}(W_{o1}x_t + W_{o2}h_{t-1} + b_o) \tag{8}$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \text{tanh}(W_{c1}x_t + W_{c2}h_{t-1} + b_c) \tag{9}$$

$$h_t = o_t \cdot \text{tanh}(c_t) \tag{10}$$

Where i_t is the input gate, f_t is the forget gate, o_t is the output gate, c_t denotes the cell state generated as an additional variable for the cell, x_t is the input, h_{t-1} is the hidden state in the previous step, W is the weight matrix and b is the biases in each layer. The symbol \odot stands for the operation of element-wise multiplication. Figure 1 shows the architecture of LSTM memory block.

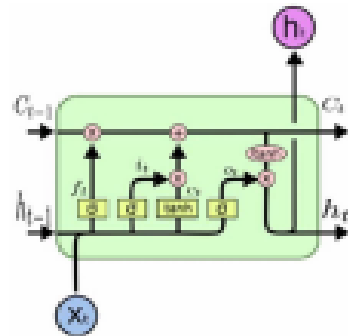


Figure 1: Architecture of LSTM memory block

Stacked LSTM with four layers is used in this paper where each hidden layer has 50 LSTM units. The model is fit using the efficient Adam version of stochastic gradient descent and optimized using the mean squared error loss function. Once the model is defined, it is fit on the training dataset before being used to make predictions. The key aspects of the LSTM forecasting model are highlighted below:

Layers: The number of layers influence the learning capacity of the model. It is important to use additional layers and have different numbers of neurons in each to improve hierarchical learning.

Features and time steps: These define the shape of the input by specifying what the model expects for each sample.

The use of lag observations as input features and time steps can improve the predictive capability of the model.

Batch size: This is the number of training examples used in an iteration. The batch size determines the level of manipulation required for both the training and test datasets.

Optimization algorithm: There are several optimization algorithms that tend to either accelerate or decelerate the learning process to improve the configuration’s efficiency.

Weight regularization: This is done to control the rate of learning and reduce overfitting of the networks.

Dropout: This is a regularization method that slows down learning within the recurrent LSTM networks.

Loss function: This is an evaluation method for performance of a specific algorithm in modelling the given data. Optimization is done to enable the loss function learn how to reduce the prediction error.

A summary of LSTM parameters mapping for the forecasting problem is given in Table 1.

Table 1: Parameter Mapping for the Forecasting Problem

LSTM Parameter	Mapping to the Forecasting Problem
Input	Historical values of electricity price and demand
Output	Predicted values of electricity price and demand
Bias	Error value being fed back to the input of the forecasting model
Gates	Factors that regulate the variation of electricity price and demand

The key steps involved in designing the EMS are:

- (i) Analysis of historical data on electricity prices and demand.
- (ii) Building a forecasting model.
- (iii) Recommendation of possible operation hours.
- (iv) User input to choose preferred TOU of available machines.
- (v) Calculation of total energy consumed and energy cost.
- (vi) Calculation of potential energy savings if the cost obtained in the previous step is less than that incurred during normal scheduling.
- (vii) Determining viability of having an industrial EMS.

The effectiveness of the designed model is tested using an IEEE 6 generator 30 bus system with 20 loads. Figure 2 represents the IEEE 30 bus system.

system generates automated unit commitment schedules daily based on the hourly predicted prices thereby improving energy performance and saving on cost. Taking into consideration the non-energy benefits of implementing an EMS as well as the future savings to be yielded by the EMS would help in obtaining a shorter PBP and a higher ROI to justify the investment.

Further research can consider other inputs that affect demand in the LSTM network when developing the forecasting model. Moreover, other DSM techniques can be taken into account when developing the EMS. It would be beneficial to also design an EMS that integrates the management of other forms of energy rather than electrical energy.

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Appendix E**Table of Corrections**

No.	Concern Raised	Correction Made
1	Clarification of statement given in page 1 paragraph 2 line 2 concerning centralized generation	The statement has been rephrased to illustrate that several decades ago electricity generation was centralized and from non-renewable sources
2	Missing explanation for the smart grid diagram in Figure 1.1	The components in Figure 1.1 have been stated to include wind and solar Distributed Energy Resources (DERs), transmission lines as well as residential, commercial, and industrial units
3	Lack of evidence of how the load scheduling technique used smooths the load profile as was stated in the last paragraph of Section 1.2	The statement in the last paragraph of Section 1.2 has been rephrased to show that the load scheduling done, distributed the load ensuring peak demand was experienced at off-peak hours with low electricity prices. This is further supported by the graph plotted in Figure 4.5 to compare the load profile for the sample day before and after scheduling
4	Use of EMS and TOU abbreviations in the statement of the main objective	The full forms of EMS and TOU have been used to state the main objective
5	Clarification on the running time, t of each machine as given in Equation 2.2	An assumption was made of a case where all machines had an equal runtime of 1 hour at their rated power
6	How the total load demand depicted in Table 4.3 was met by the available supply given in Table 4.2	All the priority loads were ON each hour as they were the key production loads whereas the non-priority loads with high consumption were rescheduled for use during hours with low electricity prices ensuring that the power balance constraint given in Equation 2.3c was met at all times
7	Lack of a reference that guided the computation of the EMS initial investment cost as given in Table 4.6a	Reference [16] has been included
8	How the validation of results was achieved	A comparison was made between the energy cost savings achieved in this project and that in reference [4] as explained in the last paragraph of Section 4.4
9	Clarification on level of accuracy achieved by the forecasting model	The MSE loss values obtained upon increasing the number of epochs in the RNN have been included in paragraph 3 and 4 of Section 4.1
10	Contradictory statement given in recommendation iv) of Section 5.2 compared to what was stated in Section 2.2	Recommendation iv) has been rephrased to illustrate that further research should integrate EMSs with other resource planning systems taking into account all factors of production within an industry