Sudan University of Science & Technology

**Sudan University of Science & Technology**

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# Fuzzy Logic Dynamic Electricity Price Forecasting Model for Smart Grid

A Thesis Submitted In Partial Fulfillment of the Requirements for the Degree of Master of Science (M.Sc.) in Electrical Engineering

*(Control and Microprocessor)*

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بسم الله الرحمن الرحيم

**يرفع الله الذين آمنوا منكم والذين أوتوا العلم درجات والله بما تعملون خبير"**

صدق الله العظيم

*المجادلة__آية 11*

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Next to my professors and supervisor, thank you for letting me discover my own way through this big world that is postgraduate life. You let me gain the experience, discipline and knowledge required to complete something of this level in my own time but pushed me in the right direction when I was going astray. Without your gentle prodding I fear I would still be at the beginning!

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# Abstract

Under restructuring of electric power industry, different participants namely generation companies and consumers of electricity need to meet in a marketplace to decide on the electricity price. Electricity price forecasting is an inherently difficult problem due to its special characteristics of dynamicity and nonstationarity. These characteristics can be attributed to the following reasons, which distinguish electricity from other commodities: non-storable nature of electrical energy, the requirement of maintaining constant balance between demand and supply, inelastic nature of demand over short time period, and oligopolistic generation side. In addition to these, market equilibrium is also influenced by both load and generation side uncertainties. Further deployment of the smart grid for power distribution enables a two-way communication between the supplier and the consumer. This enables the supplier to price the energy based on the consumption feedback from the consumer, and the consumer can schedule their consumption behavior to achieve optimal utilization. This thesis presents a solution methodology using fuzzy logic approach and rough set approach for hourly price forecasting, it is implemented on historical weather sensitive data of temperature and historical load data. The datasets used were of Khartoum state for the year 2013 collected in national control centre in Soba, Khartoum by NEC Sudan. The results obtained from the two different approaches were evaluated and compared, the results were satisfactory.

# ملخص البحث

تحت اعادة هيكلة صناعة الطاقة الكهربائية، يجب على مختلف الجهات ذات الصله و هي شركات توليد الكهرباء و المستهلكين الوصول الى نقطة تلاقي من حيث تسعيرة الكهرباء المناسبه لضمان انسياب الكهرباء بصوره مستمره دون تقطعات. التنبؤ بتسعيرة الكهرباء هي مشكله غاية في الصعوبة نظرا لسماتها الخاصه من ديناميكية و عدم الثبات. و يمكن ان يعزى هذه الخصائص للاسباب التاليه، التي تميز الكهرباء من السلع الاخرى : الطابع غير القابل لتخزين الطاقه الكهربائية، و متطلبات الحفاظ على التوازن المستمر بين العرض والطلب، و طبيعة تذبذب الطلب خلال فتره زمنيه قصيره. بالاضافة الى ذلك ، يتاثر توازن السوق ايضا بالعوامل غير المرئيه في الحمل و التوليد. ان الانتقال الى الشبكه الذكيه لتوزيع الطاقة الكهربائية يمكن الاتصال في اتجاهين بين شركات توليد الكهرباء و المستهلك. وهذا يتيح للمورد امكانية تسعير الطاقة الكهربائية على اساس ردود فعل الاستهلاك من المستهلك، ويمكن للمستهلك جدولة السلوك الاستهلاكي لتحقيق الاستخدام الامثل. تقدم هذه الاطروحة منهجية الحل باستخدام نهج المنطق الضبابي للتنبؤ بسعر الكهرباء في كل ساعه. ويتكون الدخل من درجة الحرارة و الحمل الساعه السابقه. والخرج هو تسعيرة الكهرباء للساعه القادمة. مجموعات البيانات المستخدمه هي من ولاية الخرطوم للعام 2013 التي تم جمعها في مركز التحكم القومي بسوبا، الخرطوم من قبل الهيئة القوميه للكهرباء. تم تقييم النتائج التي تم الحصول عليها من المناهج المختلفة و مقارنتها، وكانت النتائج مرضية.

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# List of Abbreviations

| | |
|---|---|
| **AC** | **A**lternating **C**urrent |
| **AFSA** | **F**ish **S**warm **A**lgorithm |
| **AMI** | **A**dvanced **M**eter **I**nfrastructure |
| **ANEM** | **A**ustralian **N**ational **E**lectricity **M**arket |
| **ANFIS** | **A**daptive **N**euro **F**uzzy **I**nference **S**ystem |
| **ANN** | **A**rtificial **N**eural **N**etwork |
| **ARIMA** | **A**uto **R**egressive **I**ntegrated **M**oving **A**verage |
| **BP** | **B**ack **P**ropagation |
| **DR** | **D**emand **R**esponse |
| **DSM** | **D**emand **S**ide **M**anagement |
| **EMS** | **E**nergy **M**anagement **S**ystem |
| **ESI** | **E**nergy **S**ervices **I**nterface |
| **FIN** | **F**uzzy **I**nference **N**et |
| **FIS** | **F**uzzy **I**nference **S**ystem |
| **FSOM** | **F**uzzy **S**elf-**O**rganized **M**ap |
| **HVDC** | **H**igh **v**oltage **D**irect **C**urrent |
| **IEEE** | **I**nstitute of **E**lectrical and **E**lectronics **E**ngineers |
| **KWh** | **K**ilo **W**att **h**our |
| **LTPF** | **L**ong **T**erm **P**rice **F**orecasting |
| **MAPE** | **M**ean **A**bsolute **P**ercentage **E**rror |
| **MTPF** | **M**edium **T**erm **P**rice **F**orecasting |

| | |
|---|---|
| **MWh** | **M**ega **W**att **h**our |
| **NEC** | **N**ational **E**lectricity **C**ompany |
| **NEM** | **N**ational **E**lectricity **M**arket |
| **NIST** | **N**ational **I**nstitute of **S**tandards and **T**echnology |
| **NYISO** | **N**ew **York I**ndependent **S**ystem **O**perator |
| **OED** | **O**rthogonal **E**xperimental **D**esign |
| **OMEL** | **S**panish **E**lectricity **P**rice **M**arket **O**perator |
| **PASA** | **P**rojected **A**ssessment of **S**ystem **A**dequacy |
| **PNN** | **P**robability **N**eural **N**etwork |
| **PSF** | **P**attern **S**equence-based **F**orecasting |
| **RTP** | **R**eal **T**ime **P**ricing |
| **SOM** | **S**elf **O**rganized **M**ap |
| **STPF** | **S**hort **T**erm **P**rice **F**orecasting |
| **SVM** | **S**upport **V**ector **M**achine |
| **TOU** | **T**ime **O**f **U**se |

# CHAPTER ONE

# INTRODUCTION

## 1.1 General Overview

With the growth of power system networks and the increase in their complexity, many factors have become influential in electric power generation, demand or load management. Price forecasting is one of the critical factors for economic operation of power systems. This scenario exists since the usage of electricity will depend on the price per unit at a particular time of day and consumers have access to an electricity pool where they decide what time to buy electricity from the pool. Thus, a cost-conscious consumer will be concerned about the price in the coming hours, days, or even weeks, and will try to optimize their utilization and minimize their total bill through smart use of electricity. With dynamic pricing systems where the consumers would pay based on their time of consumption and the amount of load they consume, it is essential for the consumers to have some price prediction mechanism to assist in scheduling their energy consumption strategy in advance.

Under a fixed pricing scheme in the electricity market, consumption of electricity follows a distinct peak demand curve. This peak demand forces producers to use resources to meet the peak demand. These resources are redundant for the rest of the time. A generator when running at rated load conditions is at its maximum efficiency. During the day the generators are under heavy load conditions and are usually over loaded thus operate at reduced efficiencies. It is also not advisable to invest in more machines to handle a few hours of peak power every day. For instance, in Khartoum state above 1000 MW are required to attend 440 hours of peak consumption for year 2013. Although appliances are designed to operate with high efficiency, peak demands still remain at large. To overcome this inefficiency, the concept of demand management is put forward as a part of the smart grid initiative to achieve load leveling leading to reduced peak consumption. A smart grid utilizes the information about the behaviors of supplier and consumer of electricity and tries to optimize the production and distribution of electricity grid. It uses two-way communication between the consumer and the supplier to exchange information in order to optimizes utilization for the consumer and smooth the demand curve. The general idea of demand management is to design a pricing mechanism which decides the hourly prices that can persuade the consumers to change their usage patterns in order to lower the peak demand, with the expectation that the consumers will respond to it. Another objective of this mechanism is to eliminate fluctuations in the demand beyond a defined threshold. Thus every market player including consumer and retailer are also very concerned about the price in the coming hours, days or may be in the coming month.

## 1.2 Problem Statement

Sudan national grid has taken huge steps toward modernization, such that now it is controlled from central control room. Despite this massive jump, it has been subjected to intermittent power outages and unusual blackouts. For each interruption, the economic loss encountered is high. Currently, the grid operators act as the referees, monitoring activities of the parties and allocating the required power. By its nature, power demand fluctuates highly, and often, there are situations where power demand becomes far more than the system can actually deliver. The system operators have to take special measures to allocate power in those situations. These special measures, in most cases, are not fair because load shading decisions are made on bias basis. Sometimes, handling a sudden increase in demand becomes unmanageable and improper handling of the demand results in system failure. A dynamic - pricing is the answer,  where energy prices could change on an hourly basis with the consumer having the ability to react to the price signal through shifting his electricity usage from expensive hours to other times when possible. The load profile under this scenario would have different characteristics compared to that of the regulated, fixed-price era. This will encourage self - healing characteristics of the grid by maintaining constant balance between demand and supply by triggering demand response, thereby reducing system operator load shedding interference.

## 1.3 Objectives

The main objective of the work is to develop an electricity price forecasting model for generating hour-ahead price forecast by incorporating previous hour load and temperature data. This price forecasting is important to achieve load leveling leading to reduced peak consumption thereby avoiding possible overload or blackout for electrical grid.

## 1.4 Methodology

In this thesis a design of a dynamic electricity price forecasting model is being proposed. The proposed system is to help in optimizing electricity consumption and reducing peak load consumption. The proposed system has been modeled using MATLAB TOOLBOX. Two approaches were attempted to design the model. The first approach was based on mamdani's inference System and the second approach used rough sets. The work presented here is divided into three steps:

i. Collection of data and data analysis.
ii. Development of fuzzy logic model for hourly price forecasting using triangular membership functions for temperature dependent load data.
iii. Development of rough set model for hourly price forecasting.

The proposed model was tested on the datasets of Khartoum state for the year 2013 collected in national control centre in Soba, Khartoum by NEC Sudan. The simulation results were satisfactory for most parts of dataset.

## 1.5 Thesis Layout

This thesis is organized into five chapters. The contents of these chapters are summarized as follows:-

Chapter one includes general overview, problem statement, objectives of the work and a brief summary of methodology is discussed.

Chapter two introduces the concepts of smart grid, demand response, demand side management and rate structure. A literature review of price forecasting techniques and fuzzy inference system structure is also presented.

Chapter three introduces the Datasets for designing and testing the proposed model. A detailed proposed methodology for price forecasting using fuzzy logic and rough set is also presented.

Chapter four compares the results of the two models. It also gives the in-depth evaluation of the performance for all modeled approaches.

In Chapter five, the summary of conclusions and the scope of future work are presented in the recommendations.

# CHAPTER TWO

# BACKGROUND AND RELATED WORKS

## 2.1 Introduction

The current electrical grid which is considered as a greatly modernized engineering achievement is gradually facing challenges due to its limitation. However, it is increasingly out of date and overburdened, leading to costly blackouts and brownouts. Integration of different energy sources to main power grid with almost no losses in energy, maintaining the integrity and security of the grid is biggest challenges of present grid system. There exist a problem in transmission and distribution of electricity which further limit the grid reliability and efficiency. With the introduction of smart grid, real time energy uses monitoring, dynamic pricing scheme, two way communication, greater fault tolerance, better distribution of electricity and better planning of electricity generation will be possible. Centralized electrical supply networks are limited to fossil fuel resources and prone to complete system failures. Decentralized solutions (Micro-Grids) for provision of electricity to every part of the world are gaining popularity especially among the developing countries. These systems can be powered through fossil fuel or renewable and can be linked together to form an electrical network. Small achievement in efficiency will give higher reduction in carbon emission and increase in review generation.

Smart grid offer valuable technology that can be implemented in near future and promise the long-term intelligence which increase the efficiency and reliability in power distribution. It will enable dynamic power distribution and consumption with two way communication between grid and consumer. It will allow the producer to adopt different pricing scheme based on user consumption pastern, source of generation, time of use etc. which help to maintain the production and demand curve.

## 2.2 Power Grid Operation

Power grid operation consists of four primary functions namely: power generation, transmission, distribution and control. Power is generated from various sources such as hydro, coal, tidal, wind etc., usually in remote areas due to factors like resource availability, land availability, safety and environmental issues. The power generated at a power station is then pumped to higher voltage of 110kV and above for transmission as high voltage transmission has reduced losses. The transmission system has various configurations and the most popular configuration is three phase AC for long range transmission and high voltage direct current for ultra-long range for distances greater than 600 km. The transmission system connects the generating station to sub stations in different parts of the country. The sub stations steps down to power to operational levels of 11kV for industrial and 230V for domestic appliances in most cases. From the substation onwards, the system becomes a distribution system, distributing power to the individual subscribers. It is necessary to monitor and control the grid for reliable operation. Every time a load is added or removed from the grid, it leads to a change in voltage level, if voltage change goes beyond a certain level, they can be harmful to the devices. Thus a stable value of voltage has to be maintained at all times, between 220 - 230V for safe operation of a device. Thus control of power becomes an important aspect of power system operation. The power industry has a bit of a monopolized status, since a utility company may be completely self-sufficient by attending to power generation, transmission, distribution and control. It does not make sense to invest in equipment and installations to compete with other utilities in the same region as the cost involved is very high. It is better to cooperate with neighbouring grid operators to buy/sell power which benefits both parties and increases their reliability. Since reliability is a major issue in the power grid operation, each power station has certain amount of reserves that come into play in case of a fault or failure. There are basically two types of reserves namely spinning and non-spinning reserves. Spinning reserve can be defined as "the unused capacity which can be activated on decision of the system operator and which is provided by devices which are synchronized to the network and able to affect the active power"

[1]. It can also be defined as "generators online, synchronized to the grid, that can increase output immediately in response to a major outage and can reach full capacity within 10 minutes" [2]. Non-spinning reserves are offline reserves that take more time (30-60mins) to be able to supply the grid. The capacity factor for a power plant is defined as the ratio of the net electricity generated, for the time considered, to the energy that could have been generated at continuous full power operation during the same period. [1] Explains more about spinning reserves and how they are used in frequency control. By reducing the peak or maximum demand, the reserve capacity of a power station can be reduced and the associated costs will eventually reduce. The present grid is struggling to keep up with the growing demand for power. A blackout causes a major inconvenience to the customers and adversely affects the economy by bringing the industries to halt, hospitals and research facilities to a critical condition, leaving people stuck in elevators and stranded elsewhere. The above highlight the need for more efficient, reliable, responsive and secure grid.

## 2.3 Smart Grid Vs Traditional Grid

Smart grid is a very big entity, which encapsulates many technologies into one. The conceptual model of smart grid according to the National Institute of Standards and Technology (NIST) consists of seven domains namely, bulk generation, transmission, distribution, customers, operations, markets and service providers. From the pictorial illustration in Figure 2.1, it is clear that information flow is vital for the operation of smart gird, connecting the various domains and forming the lifeline of the grid. It is this two-way communication that enables the smart grid to be "SMART" and dynamic compared to the traditional grid illustrated in Figure 2.2.

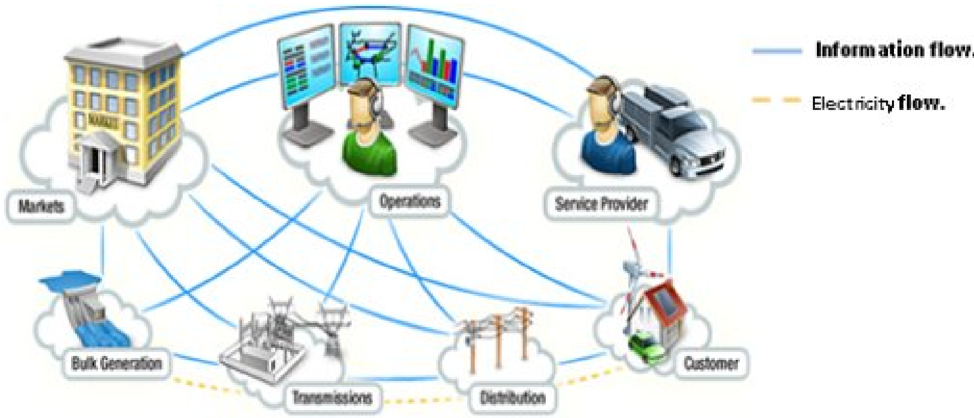


Figure 2.1: NIST smart grid framework

The traditional electricity grid had information flow in only one direction from generation to the customer. The IEEE describes the smart grid as a system of systems and each of the domains of the smart grid described by NIST is a large entity by itself. Brief descriptions of all the domains are provided below.

i. **Bulk Generation:**

   Bulk generation referrers to the generation of electricity from a variety of sources both renewable and non-renewable in bulk quantities used to supply the customers.

ii. **Transmission:**

   The transmission domain handles the transmission of the electricity from distributed bulk generation sources to substations. It takes care of the operational stability of the grid by balancing the supply and demand.

iii. **Distribution:**

   The distribution domain is a bridge between the transmission and customer domains. The distribution network connects all the customers to the grid using the smart meter which forms the information network of the grid. The distribution network connects the distributed generation points of the customers to the grids, thus enabling energy flow from and to the customers from the grid.

iv. **Customers:**

   Customers are the ultimate stakeholders of the grid. The customer has the capability for communication to the utility company through Energy Services Interface (ESI) which is a secure interface for interactions. This

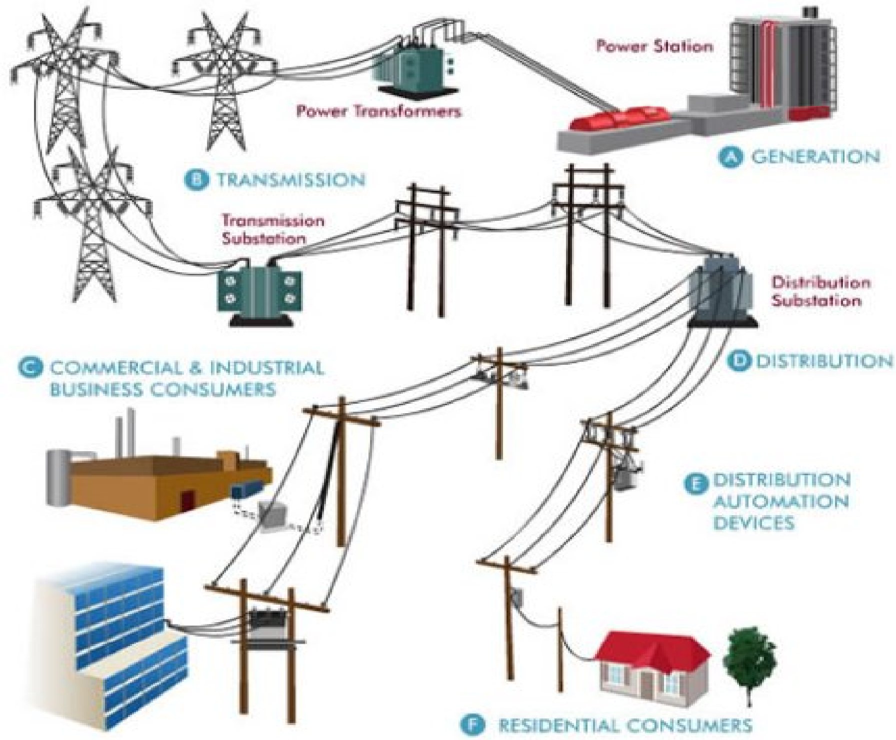


Figure 2.2: Traditional electricity grid

can be used to provide advanced Energy Management Systems (EMS) at the customer end.

v. **Service Provider:**

The service provider domain takes care of the services to support the business process of energy generation, distribution and customers. This involves providing utility services to the customer, billing, customer account management, etc., to providing assistance in home energy generation.

vi. **Operations:**

The operations domain attends to the smooth operation of the grid. Some of the functions of this domain are to monitor, analyse and optimize the grid operations, fault management and grid statistics.

vii. **Markets:**

The market domain is the financial end of the smart grid. It is responsible for market management and operations, retailing, trading, ancillary operations etc.

## 2.4 Demand Response

Demand Response (DR) involves reducing the use of electricity (demand) rather than increasing generation (supply) to meet the needs of the electric power grid. The reduction in demand of common commodities usually leads to reduced price, and in response to the high price, demand side management may be a good price mitigation mechanism for most commodities. The demand of electricity is very inelastic, especially in short term. Electric energy cannot be practically stored in large scale, so supply and demand has to be always balanced in real time. Besides matching of generation and demand, energy market needs to procure several supporting services called Ancillary Services to ensure the uninterrupted operations in cases of outages. Any demand supply imbalance may jeopardize the synchronization, which in turn could lead to system-wide blackout in a few minutes or seconds. In practice, power system operators rely on load forecast to estimate demand, and procure ancillary services from standby generators for any potential contingencies. Demand Response can be primarily classified into two groups namely: Incentive Based DR and Time-Based Rates [3]. Demand side management has thus become of prime importance to a sustainable and energy efficient future.

## 2.5 Demand Side Management

Demand Side Management (DSM) is the planning, implementation and monitoring of those utility activities designed to influence customer use of electricity in ways that will produce desired changes in the utility's load shape, i.e., changes in the time pattern and magnitude of a utility's load. Utility programs falling under the umbrella of demand-side management include load management, new uses, strategic conservation, electrification, customer generation and adjustments in market share [3]. One of the main objectives of DSM is to achieve an optimal flat load curve, and according to the various strategies for load shaping as illustrated in figure 2.3 are: [4].

- **Peak Clipping -** the reduction of utility load primarily during periods of peak demands.

- **Valley-Filling -** the improvement of system load factor by building load in off-peak periods.

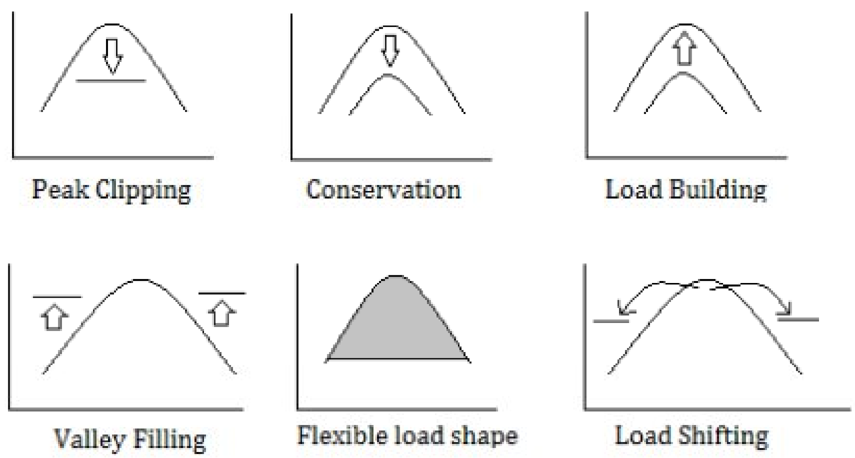


Figure 2.3: Load Shaping Objectives

- **Load Shifting -** the reduction of utility loads during periods of peak demand, while at the same time building load in off-peak periods. Load shifting typically does not substantially alter total electricity sales.
- **Conservation -** the reduction of utility loads, more or less equally, during all or most hours of the day.
- **Load Building -** the increase of utility loads, more or less equally, during all or most hours of the day.
- **Flexible Utility Load Shape -** refers to programs that set up utility options to alter customer energy consumption on an as-needed basis, as in interruptible/ curtailable agreements.

In general, demand-side management embraces the following critical aspects of energy planning [3]:

- Demand side management will influence customer use; thus any program intended to influence the customer's use of energy is considered demand side management.

- Demand side management must achieve selected objectives. To constitute a desired load shape change, the program must further the achievement of selected objectives (i.e., it must result in reductions in average rates, improvements in customer satisfaction, achievement of reliability targets, etc.).
- Demand side management will be evaluated against non demand side management alternatives. The concept also requires the selected demand side management programs advance these objectives to at least as great an extent as non demand side management alternatives, such as generating units, purchased power or supply side storage devices. In other words, it requires that demand-side management alternatives be compared to supply side alternatives. It is at this stage of evaluation that demand side management becomes part of the integrated resource planning process.
- Demand side management identifies how customers will respond. Demand side management is pragmatically oriented. Normative programs ("we ought to do this") do not bring about the desired change; positive efforts ("if we do this; that will happen") are required. Thus, demand side management encompasses a process that identifies how customers will respond, not how they should respond.
- Demand side management value is influenced by load shape. Finally, this definition of demand side management focuses upon the load shape. This implies an evaluation process that examines the value of programs according to how they influence costs and benefits throughout the day, week, month and year.

### 2.5.1 Limitations in current DSM

Current DSM schemes are plagued by the lack of information. One of the most common forms of DSM is load shedding where the supply is cut off for a certain region for a defined period of time on a regular basis as a solution to the increasing demand. This is highly inconvenient to the end user and it is a major problem in developing countries such as Sudan and in developed countries, DSM is usually via pricing strategies. For instance in the Netherlands, the consumers are offer double tariffs, one for the day and the other for the night. This reduced tariff at night is aimed at motivating the consumers to do their high power demand activities at night. The utility providers are coming up with lucrative offers to the customers such as prepaid energy, something adopted from the telecom industry which also aids in load forecasting. The current grid technology doesn't boast a communication channel which is capable of providing real time or near real time data; thus seriously hampering the development of DSM strategies. Real time load data will enable the possibility of real time pricing or more accurate pricing strategies than the existing ones. This communication if two-way can also enable in monitoring the load behaviour at the customer end. Although this may pose certain privacy issues at the customer end, these possibilities are being considered in the design of the smart grid.

### 2.5.2 Role of technology in DSM

The primary bottle neck in the development of smart DSM is the lack of availability of appropriate information at the right time at the right place. Thus technology will enable the data flow and will aid in the development of new, smart and efficient DSM schemes which include automatic load control, automatic pricing and other automated demand response techniques. Technology should address the following short comings for obtaining a reliable and efficient grid;

- The end users do not have an idea about their resources consumption at a given time. The current method in practice is the utility billing system from the utility company which notifies the user about their usage on a monthly basis. Technology should enable more frequent monitoring and reporting service to the customer which would enable them make a smart choice.
- Advanced metering technologies would enable real time pricing strategies
- Distributed generation sources should be connected to the grid which would offer more stability to the grid and also offer financial benefits to the customers.
- Better building Energy Management System (EMS) interconnected to the grid to offer instant demand response.

- Intelligent devices those are capable of responding to pricing and demands messages and taking smart decisions.

## 2.6 Rate Structures

Another strong influence on DR is the changing rate structures of retail electricity. The amount that customers should be charged is a complex problem because of the rapid changes in demand and the concomitant changes in transmission congestion and generation availability. Rate structures have been a topic of debate even back to the first days of commercially available electricity in the late 19th century when the idea of charging more for electricity during high loads of the system was an obvious choice to some engineers and economists. The most popular rate structure through the history of electricity has been a flat rate pricing, which is an average of the capital costs to the providers, as a function of the demand from the consumer. This protects consumers from high fluctuations, but does not reflect the cost of supply at any given time. The next two sections cover some of the emerging rate structures beyond the flat-rate tariff that is still the norm for most consumers. Clearly, time of day rate structures necessitates deployment of an enabling technology such as AMI, and therefore both are expected to evolve together.

### 2.6.1 Real time/ dynamic pricing

Real Time Pricing (RTP) describes a system that charges different retail electricity prices for different hours of the day and for different days. For each hour, say 4-5 p.m. on June 21, the price may differ from the price at any other hour, such as 3-4 p.m. on June 21 or 4-5 p.m. on June 22. In most other industries that have highly volatile wholesale prices, such as fruits, vegetables, fresh fish, gasoline, or computer chips, retail prices adjust very quickly to reflect changes in the wholesale price of the good.

### 2.6.2 Time of use pricing

While RTP has not been widely accepted or implemented, Time of use (TOU) pricing has been used extensively. Under TOU, the retail price varies in a preset way within certain blocks of time. For instance, a typical TOU pricing plan for weekdays during the summer charges 5.62¢ per kilowatt-hour (kWh) from 9:30 p.m. to 8:30 a.m., 10.29¢ per kWh for 8:30 a.m. to noon and 6 p.m. to 9:30 p.m., and 23.26¢ per kWh for noon to 6 p.m. 1 Typically, the weekend and holiday rates are equal to the off-peak weekday rate. The rates for each time block (usually called peak, shoulder, and off-peak) are adjusted infrequently, typically only two or three times per year. As a result, the price is the same at a given time of day (on a weekday) throughout the month or season for which the prices are set. Thus, for instance, the retail price signal is the same on a very hot summer afternoon, when demand may be at its annual peak, as it is on a mild summer afternoon when demand is much lower.

An economic view of real-time and TOU energy pricing has been presented in [5] where it is shown that dynamic pricing is the ideal method to capture the true cost of producing energy . Also, dynamic changes in energy prices provide an incentive for the customer to reduce their energy consumption during peak energy-use hours . Since dynamic energy pricing results in a time shift of consumption from peak time to off peak time, the grid power capacity requirement reduces, which can result in around 10% gain for the whole energy economy [5].

## 2.7 Factors Influencing Electricity Price

An electricity price refers to the clearing price in the deregulated market or the price paid by the consumers per unit of electricity consumed. Electricity price are highly unstable in open market or for consumers, and its instability further increases by deployment of smart grid as it is influenced by many visible and invisible factor. It is unfeasible to engineer all the influencing factor as feature in predicting model but can be analyzed through correlation matrix between price and influencing factor. Factor influencing price may differ based on the prediction time horizon explained in previous section. Short term price depend on current demand, type of energy used for generation, historical price trend, hour of days etc. Medium term and Long term price is influence by factors like energy reserve (oil and gas), expected demand, population growth and various economic factor. Most of the research on price prediction uses this factor as input features for prediction models.

Deployment of smart grid increases the complexity in predicting price with increase in influencing factor. Factor involving human behavior, response for the price from community, dynamicity in price may affect the price in short and long term. Thus predicting model for smart grid should be able to incorporate all this factor along with traditional factors affecting electricity price.

## 2.8 Overview of Price Forecasting Techniques

Electricity price forecasting has become one of the most significant aspects in electricity market for trading and planning. The positive economic consequences have attracted many stake holders to invest time and money for development of new algorithm for precise price prediction. This financial aspect has drawn alarming interest to many researchers, and has produced many significant research and contribution in electricity price forecasting. This research thrust is more deepen with the introduction of smart grid. The concept of dynamic pricing scheme, a component of smart grid has further extended the research interest in electricity price Forecasting. Precise knowledge about the future electricity price will help consumer to plan consumption and supplier to plan the production based on user behavior. This chapter discusses some of the most popular algorithm, technique and research proposed till date in the field of electricity price forecasting.

Generally price forecasting models can be categorized in to two groups: time series and game theory models. Time-series models use a non dynamic approach, where predictions are made based on previously observed values only. The second category involves the dynamic model that recognizes the fact that the price is not only a function of the time of the day, but also depends upon the various factors. This approach tries to model the market participant's strategy and find mathematical solution for predicting the price. In oligopolistic electricity markets, participants shift their bidding curve from their actual marginal cost to maximize their profits these models include mathematical solution for games and price evolution can be considered as the outcome of a power transaction game. Further forecasting can be classified based on planning horizon duration.

### 2.8.1 Short term price forecasting

Short Term Price Forecasting (STPF) is important for quick decision making process, markets can plan their bidding strategy using the foretasted price to maximize their profit in deregulated market . In smart grid consumer can make decision of power consumption based on the current and predicted near future price. Short Term prediction includes next hour price prediction, day ahead price prediction.

### 2.8.2 Medium term price forecasting

Medium Term Price Forecasting (MTPF) includes prediction for next week, next month or up to 1 year. In traditional pricing scheme MTPF is affected by seasonal effect, like rise in electricity price in summer, holidays due to higher demand and decline in winter. In smart grid deployment other factor like type of source, demand from a community, peak time of the day etc might influence electricity price. Medium term foretasted price can be used by supplier to optimize their production cost by planning the resource allocation for generation of electricity.

### 2.8.3 Long term price forecasting

Long Term Price Forecasting (LTPF) time horizon varies from couple of year to decades. Long term price trends are used by policy maker to plan pricing scheme and management of resources. Investor uses it for analyzing recovery of investment in power plant construction, production and transmission. Based on the type of production, price forecast can be used to conserve resources like, nuclear plant can make planning regarding purchase of uranium, hydro plant can consider construction of reservoir and solar/wind farm can make further analysis on construction of new plan based on cost analysis.

## 2.9 Existing Price-forecasting methodologies

Due to the importance of accurate price forecasting in volatile electricity market, a number of approaches have been presented in the literature. These approaches range from traditional time series analysis to machine learning techniques for forecasting future prices. ARIMA and GARCH models are some examples of traditional methods. On the other hand, artificial neural network (ANN) , ARIMA model enhanced with wavelet transform, hidden markov model, fuzzy inferred neural network, and support vector regression are some examples of machine learning techniques. In this section we will analyze few of these methods.

### 2.9.1 ARIMA

In [6], the authors used an ARIMA model based on wavelet transformation for electricity price forecasting. Historical data was first split using the wavelet transform before the application of ARIMA modeling. Then, the forecasted results were obtained by applying inverse wavelet transformation.

An autoregressive integrated moving average (ARIMA) model has been proposed by Jakasa et al. in [7]. They used this model to predict one-day ahead electricity prices from the German market. In the experiment, a method similar to Box and Jenkins [8] model has been used. Experiment runs on data from 2000 to 2011, in which 2557 observations were used to train the model and 1279 observations used to test the model.

### 2.9.2 Artificial Neural Network

As presented in [9], ANN is a well-known approach for short term forecasting, thus ANN can be used for forecasting price in the next hour using the input data with specially designed features. The ANN promise to give very accurate results provided that the ANN trained with the correct set of input features and enough input data points.

In [10], the authors presented the ANN model for price prediction using history and other estimated factors in the future to fit and extrapolate the prices and quantities. They implemented three-layer back propagation (BP) network using historical market clearing price, system load and fuel price as input variable.

In [11], the authors present combination model including probability neural network and orthogonal experimental design for electricity price prediction. He implemented PNN as classifier which has advantage of a fast learning process as it requires a single -pass network training stage for adjusting weight. Orthogonal Experimental Design (OED) was used to find the optimal smoothing parameter which help to increase prediction accuracy.

### 2.9.3 Support vector machine

In [12], authors proposed a Support Vector Machine (SVM) model for price forecasting using historical price, demand data and Projected Assessment of System Adequacy (PASA) data as input variables. They performed their experiment using Australian National Electricity Market (NEM), New South Wales regional data over the year 2002.

In [13], the authors proposed model for time series prediction using Fish Swarm Algorithm (AFSA) for choosing the parameter of SVM. This model used Optimized support vector machine for electricity price forecasting.

### 2.9.4 Fuzzy Inference

Neural network and Fuzzy inference log based hybrid model was proposed in [14]. In their model, a feed forward network is proposed with three layers, input, hidden and output layer. In the hidden layer, it performs the fuzzification.

In [15], the authors proposed fuzzy inference net (FIN) method for price forecasting. Proposed method uses FIN to extract fuzzy rules with FSOM to evaluate the probability of unknown data for the predetermined cluster. This technique is used in groups the users determine freely to evaluate the attribute. FIN has an advantage of not necessarily containing similar group so the grouping can be freely as desired.

### 2.9.5 Self organized map

In [16], presents a method for short term price forecasting using self organized map (SOM). They used two-stage method, SOM network is used in the first stage and a support vector machine which used to fit the output from SOM to each subset in the second stage in a supervised manner. Having removed the anomalies from the training set they obtained mean absolute percentage error (MAPE) as 10.24% in hybrid network approach for the ISO New England market. A neural network based on similar days method has been explored in [17] by Mandal et al. for daily and weekly electricity price forecasting. In the experiment they select similar price days corresponding to forecasted day using Euclidean Norm. In order to forecast the price in a single day they use 45 days prior to forecasting day as well as 45 days prior and 45 days after the same day in last year data as input values to the ANN model. Using their model they obtained MAPE 6.93% for daily forecasting in PJM market data in year 2006. Pattern Sequence Similarity In [18], Mart´ınez-A´ lvarez et. al presented a method which was based on pattern sequence similarity. In this approach, a clustering technique was first used on the data before application of the Pattern Sequence-based Forecasting (PSF) algorithm to produce one step ahead forecasts of the electricity prices. In the experiment, k-means clustering was used to cluster the training data. The training is performed using data collected from 3 different electricity markets, namely New York (NYISO), Australia (ANEM) and Spain (OMEL), for the years 2004–2005, while testing is carried out for using data from 2006. The authors perform a detailed analysis using these three different datasets, and compared their results to those obtained using other methods. As this work is quite recent and the three datasets used are publicly available, we use the results described in this paper as benchmarks in order to evaluate our proposed method.

## 2.10 Fuzzy Inference System

Fuzzy Inference System (FIS) is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves all of the pieces that are described in the previous sections: membership functions, fuzzy logic operators, and if-then rules. Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani-type inference expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. It's possible, and in many cases much more efficient, to use a single spike as the output membership functions rather than a distributed fuzzy set. This is sometimes known as a *singleton* output membership function, and it can be thought of as a predefuzzified fuzzy set. It enhances the efficiency of the defuzzification process because it greatly simplifies the computation required by the more general Mamdani method, which finds the centroid of a two-dimensional function. Rather than integrating across the two-dimensional function to find the centroid, we use the weighted average of a few data points. Mamdani type Fuzzy Controller has four components namely fuzzifier, knowledge base, inference engine and defuzzifier. These are described in the following four sections. Figure 2.4 shows the fuzzy model creation stages.

### 2.10.1 Fuzzifier

The fuzzifier performs measurements of the input variables (input signals). All the monitored input variables are scaled, and the crisp input quantities that have numerical values are transformed into fuzzy quantities (which are also referred to as linguistic variables in the literature). This transformation is performed using membership functions. The classic set, it is known from set theory to be a crisp set which has a concrete definition of its boundary. For example, if set A can consist of real numbers greater than 10, then it can be expressed as,

$$A = \{x | x \geq 10\} \tag{2.1}$$

Here, a clear and precise boundary is defined as no number greater than 10 can be a member of the set. The decision is precise in its term because it can tell that a particular number is either a member or not a member of the set. In real life, it may not be able to define everything so precisely as of ”yes” or ”no.” If it is to be considered in the context of human concepts and thoughts, many situations will be


Figure 2.4. Fuzzy model creation stages.

found where human thoughts tend to be abstract and imprecise. There may not be a clear boundary for decision-making. As an example, consider a sensor for controlling room temperature. If the sensor is to be configured, it have to be set to a precise value, such as 70 degrees F, to be the criterion of the high temperature. If the room temperature reaches 69.5 degrees, the sensor will interpret that it is not hot, i.e., cold. If it is considered in the context of human beings, then there will not be any difference between the 69.5-degree and 70 degree temperatures. To capture this degree of abstractness, the fuzzy Set, which does not have a crisp boundary, has been formed. In fuzzy sets the decision is made with the membership functions. A Fuzzy set A in x is defined as a set of ordered pairs as follows:

$$A = \{(x, \mu A(x)) | x \in X\} \tag{2.2}$$

where $\mu A$ is called the membership function for the fuzzy set A. The value of A varies from 0 to 1. X is referred to as the universe of disclosure, which is basically the collection object. The universe may consist of continuous or discrete (ordered or unordered) objects. If the universe of discourse X is a continuous space, they may be segmented into several fuzzy sets and referenced according to our daily linguistic terms, such as ”large,” ”medium, ” or ”low.” These values are called linguistic values or linguistic labels. The membership function of a fuzzy set is used to determine the degree of truth for a user input value against the fuzzy sets member variables. Membership functions can come in triangular, trapezoidal, gaussian, bell shaped and sigmoidal form. In a model, more than one of such functions can be used to construct a single membership. In this smart grid model, the triangular membership function is used along with the trapezoidal membership function.

### 2.10.2 Knowledge base

The Fuzzy reasoning process involves data and linguistic control rules or if then rules, this is called a knowledge base. After getting a particular input from the user, the Fuzzy Controller interacts with the data and the rules simultaneously to determine the output. The data provide the information for the linguistic control rules, and the rule base (expert rules) specifies the control goals. The rule base contains a set of if-then rules. The rules are generated in many ways, depending upon the problem domain. Rules can be formed in a combination of user experience, expert’s domain knowledge, modeling the action of the operator, process observation, and gradual learning, etc.

### 2.10.3 Fuzzy inference

The inference engine (reasoning mechanism) is the kernel of the fuzzy controller. It works with the linguistic variable to obtain the result. The linguistic variables come in the form of words used in day-to-day language expression. The inputs to the fuzzy system such as ”power capacity,” ”displacement,” ”velocity,” etc. may be considered as linguistic variables. To quantify the values the linguistic values can be expressed in the form of “low,” ”moderate,” ”high,” etc. The values can be further divided in to ”very low,” ”moderately high,” etc. Once the linguistic variables and their values are defined, the rules map the fuzzy inputs to fuzzy outputs through the inference engine. The Inference Engine triggers the if then rules based on user input. A fuzzy if-then rule (also known as Fuzzy rule) assumes the following form: If x is A, then y is B, where A and B are linguistic values defined by fuzzy sets on X and Y, respectively. ”x is A” is the antecedent, or premise, while”y is B” is the consequent, or conclusion. In this way, all input variables are converted into linguistic variables, and inference engine evaluates the value within the set of if-then rules. Then, a result is obtained with the linguistic variables in fuzzified form.

### 2.10.4 Defuzzification

The result obtained from the inference engine needs to be converted back into a crisp value. This process is known as defuzzification. The defuzzification may consist of scale mapping factors similar to the ones used in the inference engine rule-generation process. However, this time, the output comes in the real-world decision context. The deffuzzifier may also use membership functions to generate real world output. There are several defuzzification techniques, such as the center of area, bisector, the mean-max method, the first of maxima method, the last of maxima method etc. In the current controller the bisector method is used for defuzzification.

# CHAPTER THREE

# METHODOLOGY AND IMPLEMENTATION

## 3.1 Explanation of Datasets

There are two factors that can be used to forecast next hour electricity price, which are temperature and load. Temperature is important because demand of load depends on temperature of the day. Normally when temperature is high, the demand will also be high. The hourly temperature (°C) and load (MWh) are datasets of Khartoum state for the year 2013 collected in national control centre in Soba, Khartoum by NEC Sudan.

The data are the hourly load demand data and temperature of Khartoum state taken for the whole year of 2013. These two factors were used to forecast the next hour electricity price. In this study, load data of January/6/2013 and July/7/2013 was used for testing the model as they represent normal Sunday working days. The January dates represent a cool day and the July date represent a hot day. Figure 3.1 is a sample captured from the datasets collection. The first column shows the date and hour of the day at which the sample data is recorded. The second column shows electricity load of Khartoum state in MWh at that specific hour and date shown in column one. The third column shows the temperature of Khartoum state in degrees Celsius at the specific hour and date shown in column one in the same row. The dataset is available for 8760 hours which represents the 365 days.

## 3.2. Fuzzy Model

Figure 3-2 shows Mamdani's Fuzzy based model in FIS Editor. Inputs are grid loads and temperature. Output is forecasted price. "And method" is set to be min. "Or method" is set to be max. "Implication" is set to be min. "Aggregation" is set to be max. "Defuzzification function" is set to be bisector.

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| Time | KHARTOUM_AREA Load(MW) | Tempreature© |
|---|---|---|
| 1/1/2013 0:00 | 456.455 | 22.305 |
| 1/1/2013 1:00 | 408.991 | 21.463 |
| 1/1/2013 2:00 | 378.402 | 20.584 |
| 1/1/2013 3:00 | 360.299 | 20.002 |
| 1/1/2013 4:00 | 347.838 | 19.636 |
| 1/1/2013 5:00 | 334.336 | 18.904 |
| 1/1/2013 6:00 | 338.042 | 17.915 |
| 1/1/2013 7:00 | 346.259 | 17.402 |
| 1/1/2013 8:00 | 348.163 | 17.732 |
| 1/1/2013 9:00 | 384.024 | 19.673 |
| 1/1/2013 10:00 | 414.975 | 22.488 |
| 1/1/2013 11:00 | 448.158 | 24.942 |
| 1/1/2013 12:00 | 460.755 | 27.469 |
| 1/1/2013 13:00 | 464.276 | 29.446 |
| 1/1/2013 14:00 | 473.943 | 30.655 |
| 1/1/2013 15:00 | 480.146 | 31.57 |
| 1/1/2013 16:00 | 465.5 | 31.9 |
| 1/1/2013 17:00 | 461.912 | 31.973 |
| 1/1/2013 18:00 | 456.564 | 30.728 |
| 1/1/2013 19:00 | 550.805 | 29.336 |
| 1/1/2013 20:00 | 570.176 | 28.055 |

Figure 3.1: Datasets sample collected from NEC Sudan

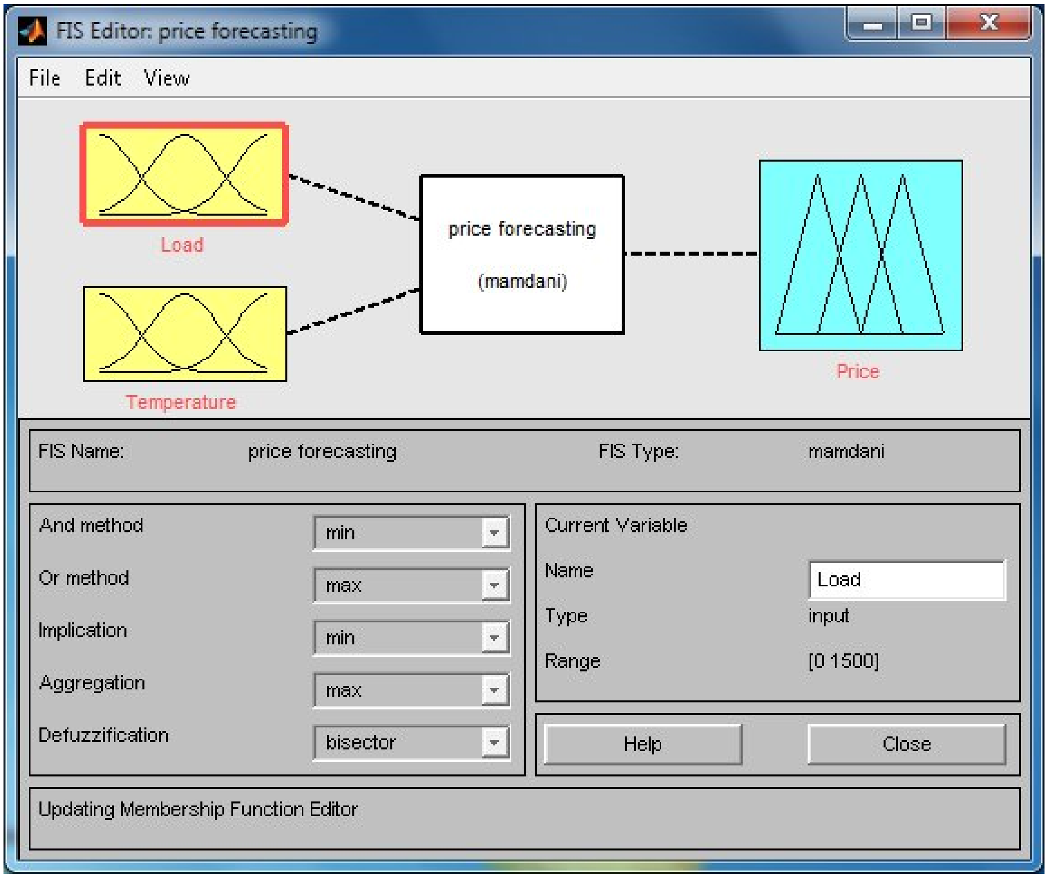


Figure 3.2: Mamdani's fuzzy based model

Using simple statistical analysis approach on the load data and temperature for the year 2013 the membership function was identified. The statistics used for load data and temperature were the minimum load, quartile 1, quartile 2 (median), quartile 3 and maximum load. The statistics used for temperature data were the minimum temperature, median and maximum temperature. The formula percentages of data for quartile as in Equations (3.1), (3.2) and (3.3).

Total data (n sample size) = 8760

$$\text{Quartile1} = \frac{n+1}{4} \tag{3.1}$$

$$\text{Quartile2} = \frac{2n+1}{4} \tag{3.2}$$

$$\text{Quartile3} = \frac{3n+1}{4} \tag{3.3}$$

### 3.2.1 Load membership function

Min = 185, Q1 = 554.6, Q2 = 688.8, Q3 = 823.7 and Max = 1218.4. The load data are then classified into five different classes, namely the Very High, High, Medium, Low and Very Low.

$$\text{Very Low} = (*, \text{Min}, (\tfrac{Min+Q1}{2})) = (100, 185, 369.8)$$

$$\text{Low} = (\text{Min}, \text{Q1}, (\tfrac{Q1+Q2}{2})) = (185, 554.6, 621.7)$$

$$\text{Medium} = (\text{Q1}, \text{Q2}, (\tfrac{Q2+Q3}{2})) = (554.6, 688.8, 756.3)$$

$$\text{High} = (\text{Q2}, \text{Q3}, (\tfrac{Q3+Max}{2})) = (688.8, 823.7, 1021.1)$$

$$\text{Very High} = (\text{Q3}, \text{Max}, *) = (823.7, 1218, 1500)$$

Figure 3.3 shows membership functions of load in Membership function editor. There are five membership functions for load: very low, low, medium, high and very high. All five membership functions are set to be triangle type.

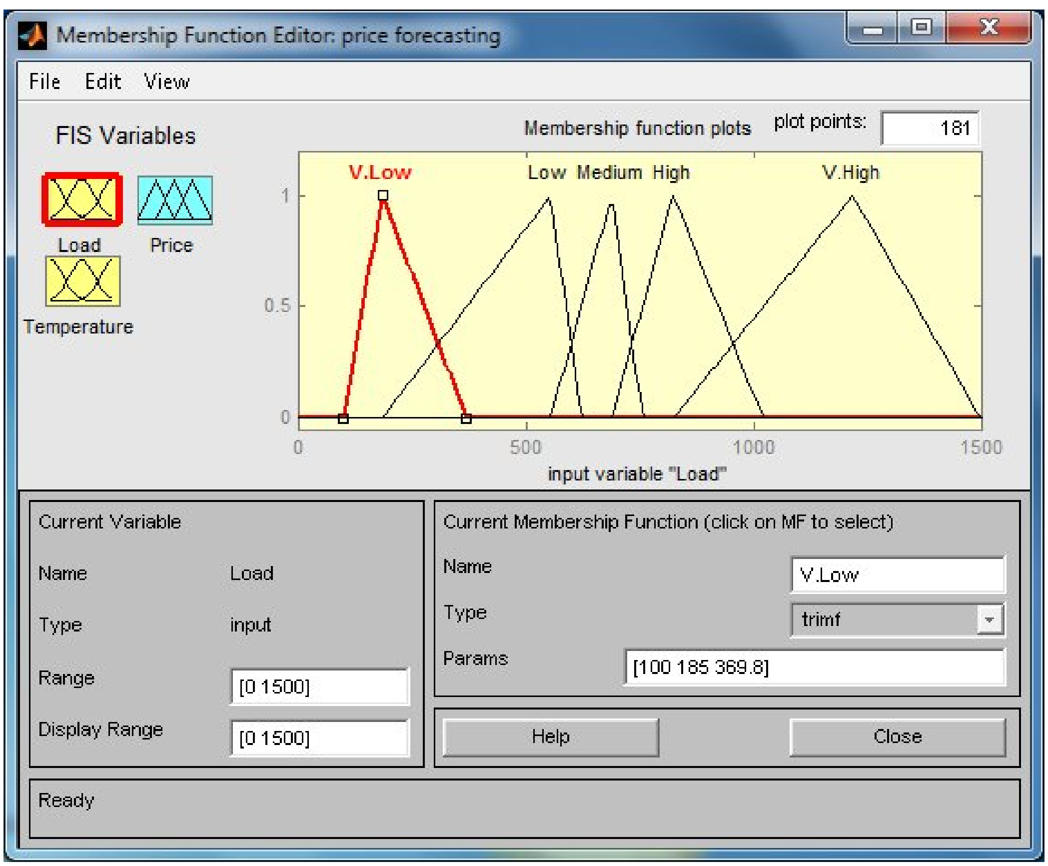


Figure 3-3: Membership functions of load

### 3.2.2 Temperature membership function

Min = 11.5, Median = 31.2 and Max = 45.2. The temperature data are then classified into three different classes, namely Hot, Medium and Cool.

$$\text{Cool} = (*, \text{Min}, (\frac{Min+Med}{2})) = (5, 11.5, 21.35)$$

$$\text{Medium} = (\text{Min, Med}, (\frac{Med+Max}{2})) = (11.5, 31.2, 38.2)$$

$$\text{Hot} = (\text{Med, Max}, *) = (31.2, 45.2, 50)$$

Figure 3-4 shows membership functions of temperature in Membership function editor. There are five membership functions for temperature: very cool, cool, medium, hot and very hot. All five membership functions are set to be triangle type.

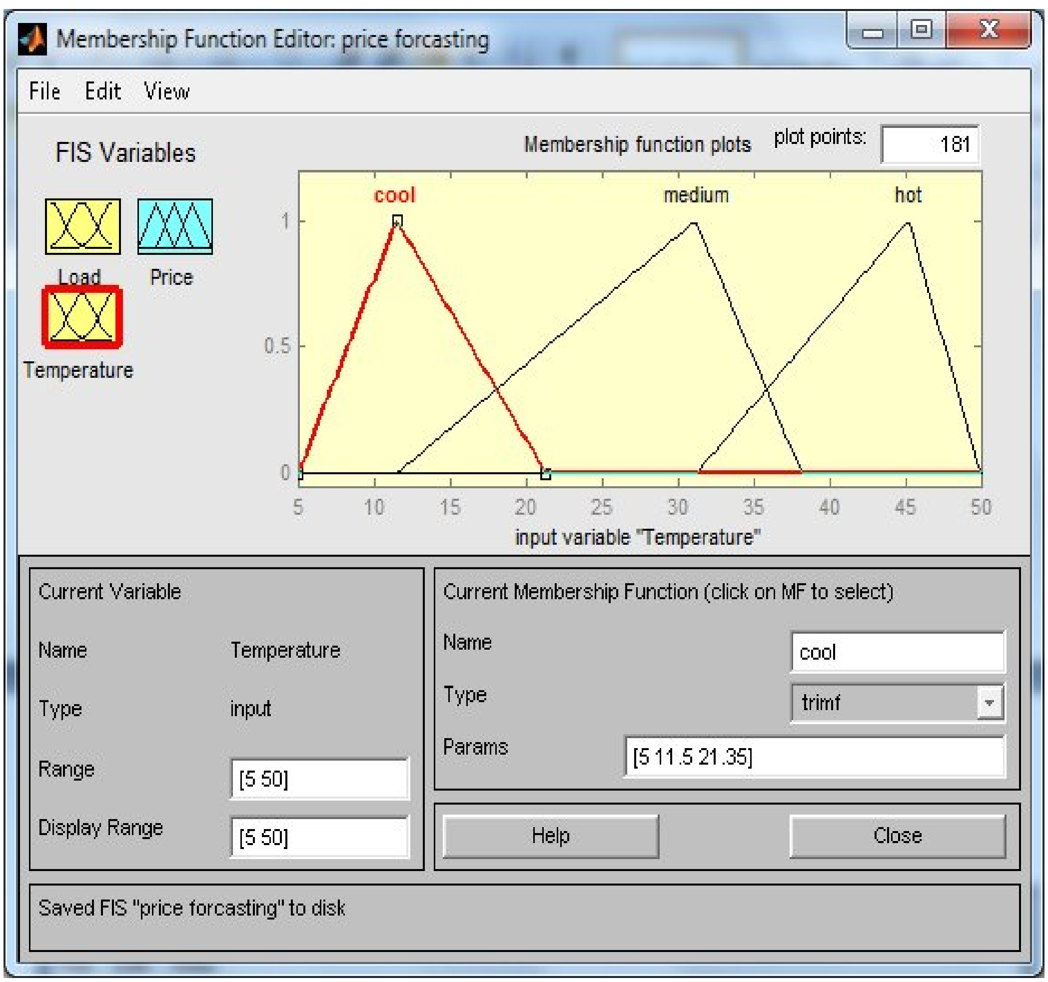


Figure 3.4: Membership functions of temperature

### 3.2.3 Price membership function

Since NEC has a fixed price policy, it is needed to design dynamic price parameters with an overall year cost that fulfill the current pricing structure. To achieve this the current international price through which we import electricity from Ethiopia is chosen as a reference price, that is five cents per kilowatts hour. This price happens to coincide with the price at which NEC supplies business and governmental institutions. For simulation purposes we consider it as 0.34 SDG/kWh.

To obtain the price membership function we then need to classify the 2013 year load into five range classes as shown in the Table 3.1.

Table 3.1: Price classes based on 2013 year load

| **Load Range (MWh)** | **Load (MWh)** | **Load Percentage (%)** | **Price (SDG/kWh)** |
|---|---|---|---|
| 0 -- 400 | 156725 | 2.585 | 0 |
| 400 – 600 | 1245382 | 20.540 | 0.1 |
| 600 - 800 | 2336914 | 38.544 | 0.25 |
| 800 - 1000 | 1857665 | 30.639 | 0.5 |
| 1000 - | 466309 | 7.691 | 1 |
| **Total** | **6062995** | | |

It is needed to verify that the chosen price parameters for the load classes will be equal the standard price chosen. To achieve this a multiplication of the load percentage class by its price class and obtain their summation.

Simulation price= 0.2585x0 + 0.20540x0.1 + 0.38544x0.25 + 0.30639x 0.5 + 0.07691x1 = 0.347 SDG/kWh

The price classes gave a simulation price of 0.347SDG/kWh which has an acceptable margin of error of 2%.

The membership function of price is obtained using price data from Table 3.1.

Min = 0, Q1 = 0.1, Q2 = 0.25, Q3 = 0.5 and Max = 1. The price data are then classified into five different classes, namely the Very High, High, Medium, Low and Very Low.

Very Low $= (*, \text{Min}, (\frac{Min+Q1}{2})) = (0, 0, 0.05)$

Low $= (\text{Min}, \text{Q1}, (\frac{Q1+Q2}{2})) = (0, 0.1, 0.175)$

Medium $= (\text{Q1}, \text{Q2}, (\frac{Q2+Q3}{2})) = (0.1, 0.25, 0.375)$

High $= (\text{Q2}, \text{Q3}, (\frac{Q3+Max}{2})) = (0.25, 0.5, 0.75)$

Very High $= (\text{Q3}, \text{Max}, *) = (0.5, 1, 1)$

Figure 3.5 shows membership functions of price in Membership Function Editor. There are five membership functions for price: very low, low, medium, high and very high. All membership functions are set to be triangle type.

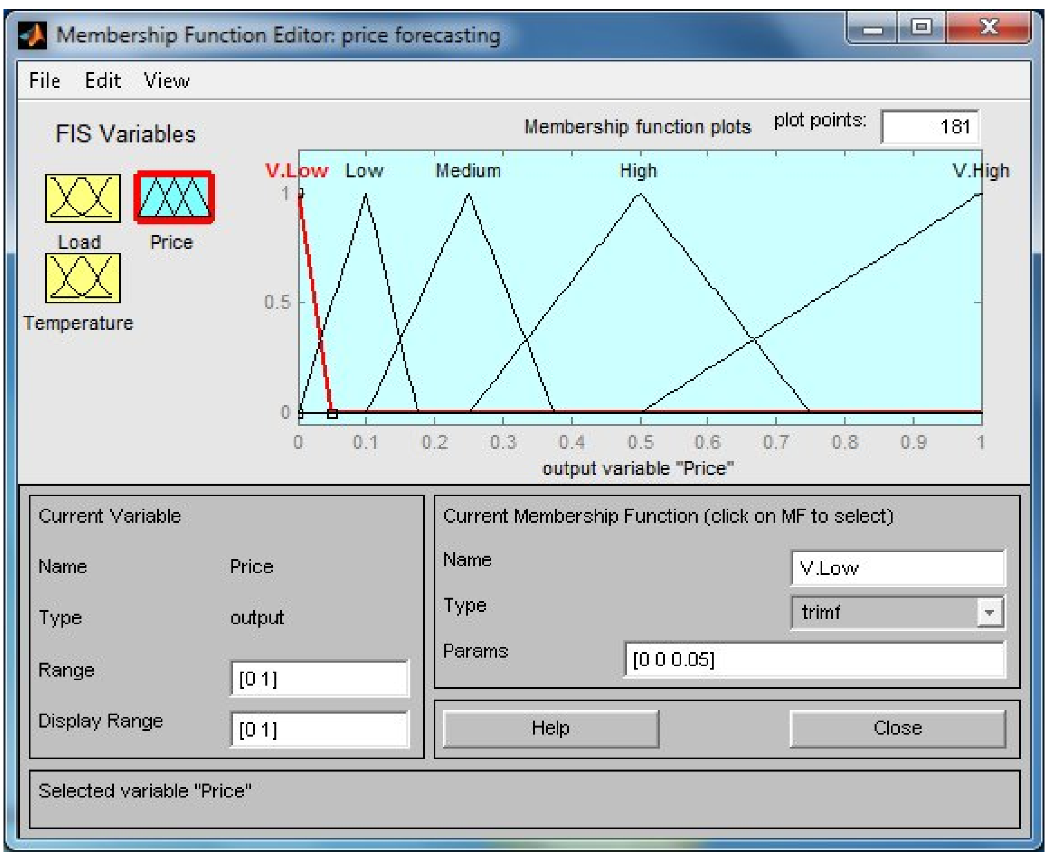


Figure 3.5: Membership functions of price

Table 3.2 shows the 15 rules that determine how the model works. The rules are based on the Load, Temperature and Price membership function discussed above.

Figure 3.6 shows fifteen rules in Rule Editor of the proposed fuzzy model. Figure 3.7 shows a snapshot of the rules which fire for a given input of Load 681 MWh and Temperature of 30.6 °C. The output computed after defuzzification is 0.24 SDG/kWh for the proposed fuzzy model. Figure 3.8 shows the proposed fuzzy model in surface viewer.

Table 3.2 : Rules of the fuzzy model

| ***Load*** / ***Temp*** | *V.Low* | *Low* | *Medium* | *High* | *V.High* |
|---|---|---|---|---|---|
| *Cool* | V.Low | Low | Medium | Hot | High |
| *Medium* | V.Low | Low | Medium | Hot | V.High |
| *Hot* | Low | Medium | Hmedium | Hot | V.High |

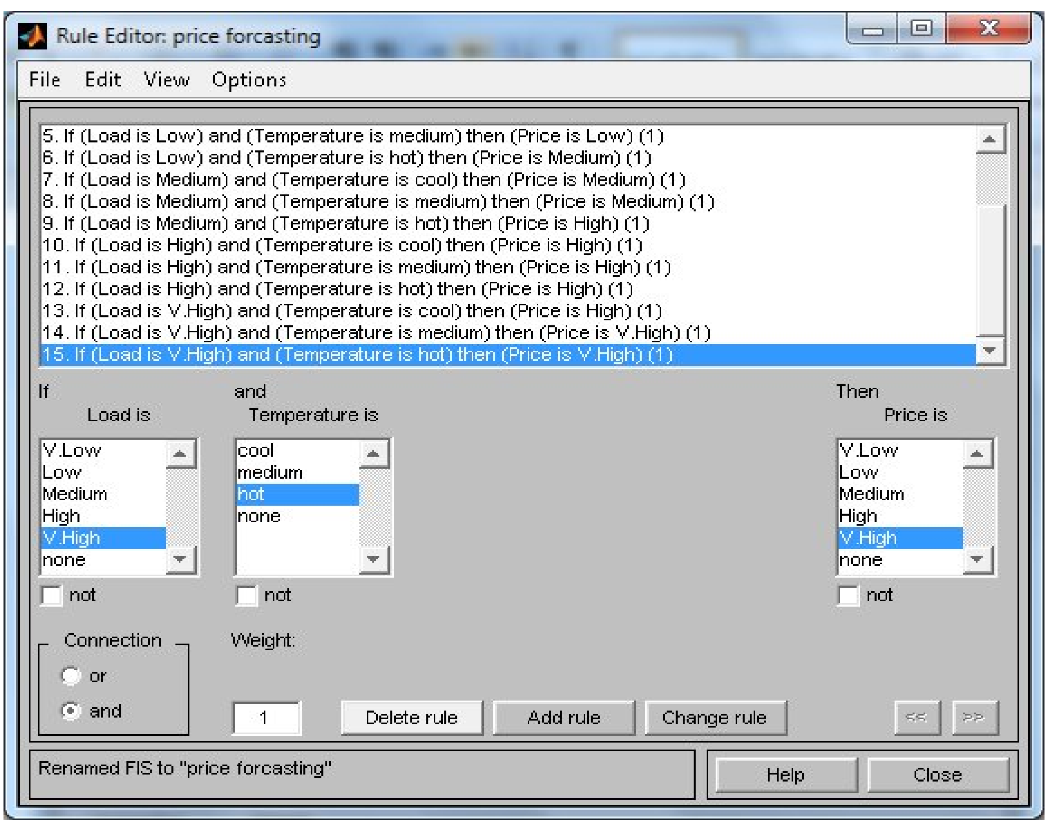


Figure 3.6: Rule editor for proposed fuzzy model

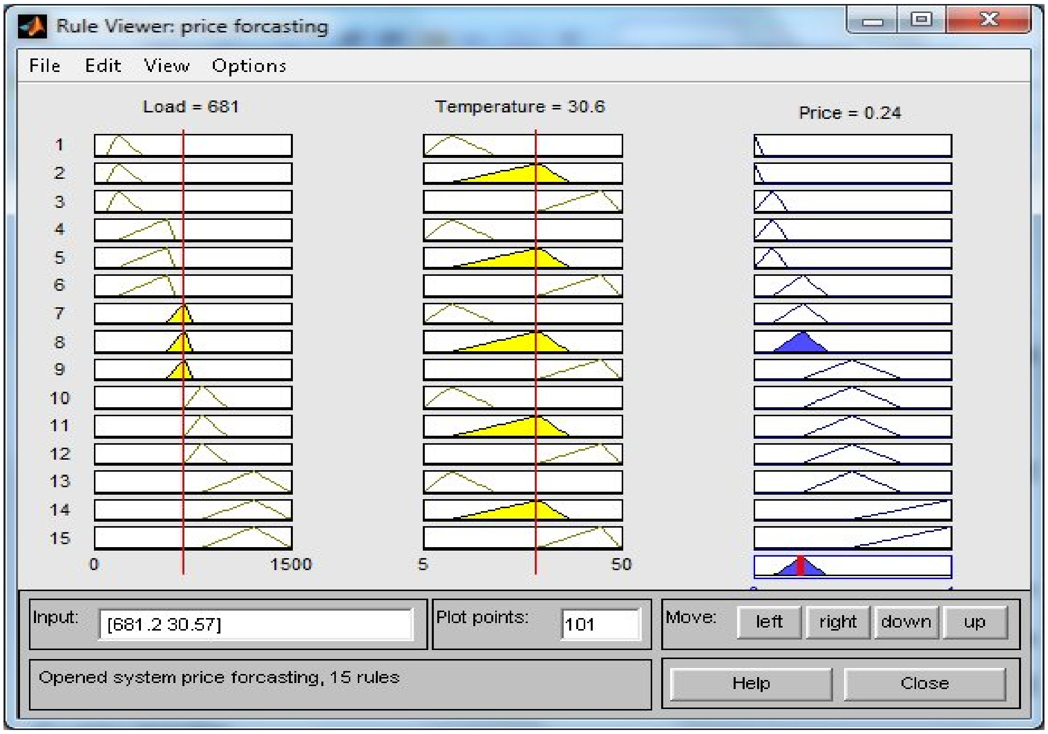


Figure 3.7: Rule viewer for proposed fuzzy model

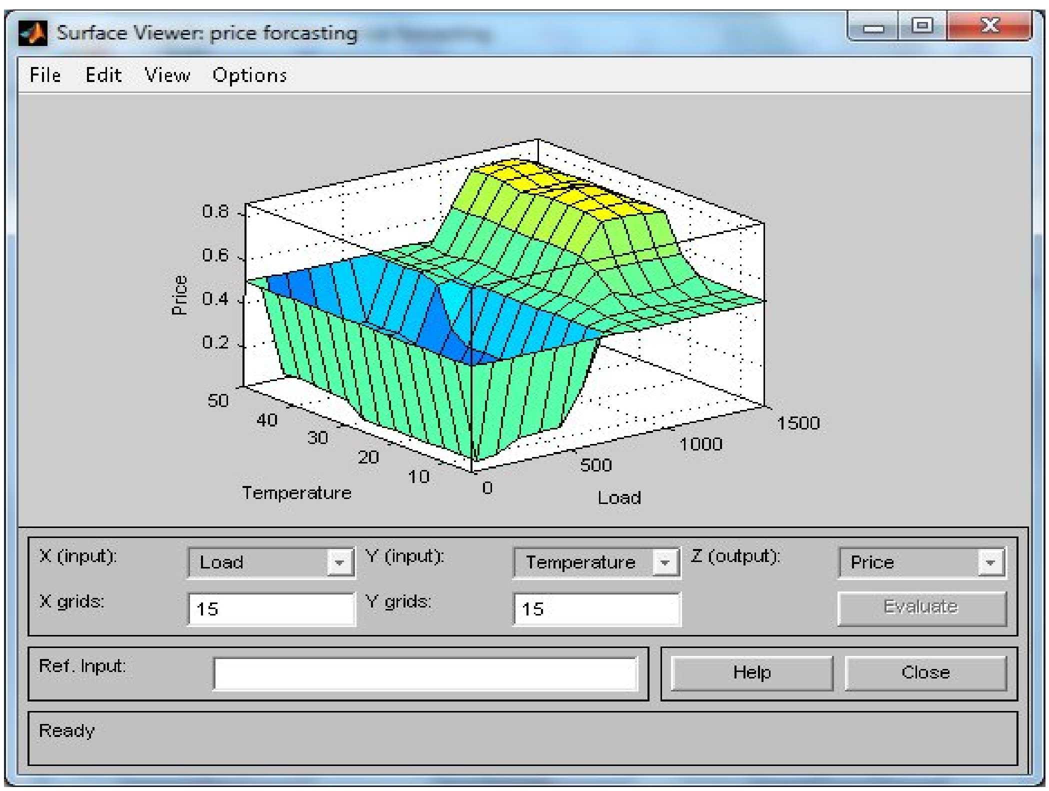


Figure 3.8: Surface viewer for proposed fuzzy model

## 3.3. Rough Set

An alternative decision making model is created based on the Rough Set approximation. The rough Set based decision model is more concrete in terms of the boundaries defined for a particular set; hence it is less granular in nature. The current model is built for the purpose of comparing the fuzzy price output. The results from both the models gave a detailed insight about outputs of each model. Because the rough set model is primarily built to compare fuzzy results, the basic construction of the rough set model is very similar to the fuzzy model. The same rule base and inference engine have been used to construct the rough set model. Similar to the fuzzy model, the input parameters are kept the same. Grid load and temperature are the input parameters used for forecasting a price. fuzzy Logic does not provide any specific boundary. However, in Rough Set, the idea of the membership function does not exist, so it is needed to define a more concrete boundary. The values for each member variables have been changed. For grid load and temperature the terminal values that are used to define the boundary between classes are presented in Table 3.3

Table 3.3: Variables class boundaries of Rough set model

| **Class** / **Variable** | *V.Low* | *Low* | *Medium* | *High* | *V.High* |
|---|---|---|---|---|---|
| *Load(MWh)* | 100-369.8 | 369.9-621.7 | 621.8-756.3 | 756.4-1021 | 1021.1-1500 |
| *Price(SDG/kwh)* | 0 | 0.1 | 0.25 | 0.5 | 1 |
| *Temp (°C)* | Cool | Medium | Hot | | |
| | 5 - 21.35 | 21.36 –38.3 | 38.3 - 50 | | |

From Table 3.3, it can be seen that the difference in the level of the inputs. Once the values are obtained from the input set, the rules are fired based on the decision table (Table 3.2) created for the fuzzy Logic. As the rule base is kept identical, the model will produce similar results as of the fuzzy model. The fuzzy model has fifteen different rules in the rule base.

The rough set model gets user input values of grid load and temperature. Based on the input, divide the values for grid load into very low, low, medium, high and very high boundaries, or for temperature into Cool, Medium and Hot boundaries. Then, check the necessary rules to decide the output price.

# CHAPTER FOUR

# RESULTS COMPARISON AND PERFORMANCE EVALUATION

In this Chapter, comparison of results and performance evaluation will be discussed. In Section 4.1, statistics of grid load and fixed price strategy are presented. In Section 4.2, performance of power price for Fuzzy method is presented. Section 4.3 details the performance of power price for Rough Set method. Section 4.4 compare and analyze the performance of the two methods. All the results in this chapter were based on the simulation of 365 days of the year of 2013. To be more specific, 8760 hours simulation results were obtained for the year 2013.

## 4.1 Power Price Using Fixed Rate

Figure 4.1 shows hourly power price curve of a typical day. It is clear that the price is constant throughout the day and it is fixed like that of the whole year. This is the method the NEC uses now. Figure 4.2 shows hourly grid load curve of two normal working Sunday days, this are 6$^{th}$ January, 2013 and 7$^{th}$ July, 2013. Since January month is winter and July month is summer, this two dates will give a clear indication of how the grid load is affected by temperature. Figure 4.2 shows the highest grid load occurred at 15:00 pm on the July date. Hourly price were not affected by the hourly grid load because it is constant value. Figure 4.3 shows the hourly cost of power consumption curve of the two dates. Equation 4.1 shows the connection among cost, price and load.

$$\text{Cost} = \text{Price} * \text{Load} \tag{4.1}$$

Figure 4.3, the graph pattern is similar to that of figure 4.2, because the price is fixed. The lowest hourly cost was at 4:00, when temperature is relatively lower. The highest hourly cost was at 15:00, when temperature is relatively higher. This pattern occurs on both dates of January and July and it can be observed throughout the year with very minor fluctuations from the above pattern.

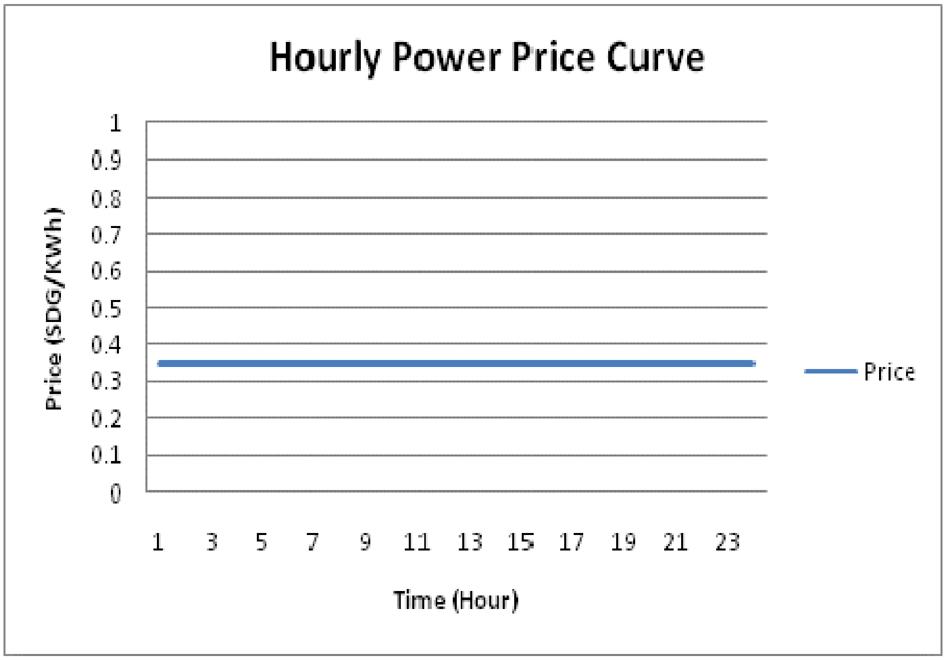


Figure 4.1: Fixed power price curve

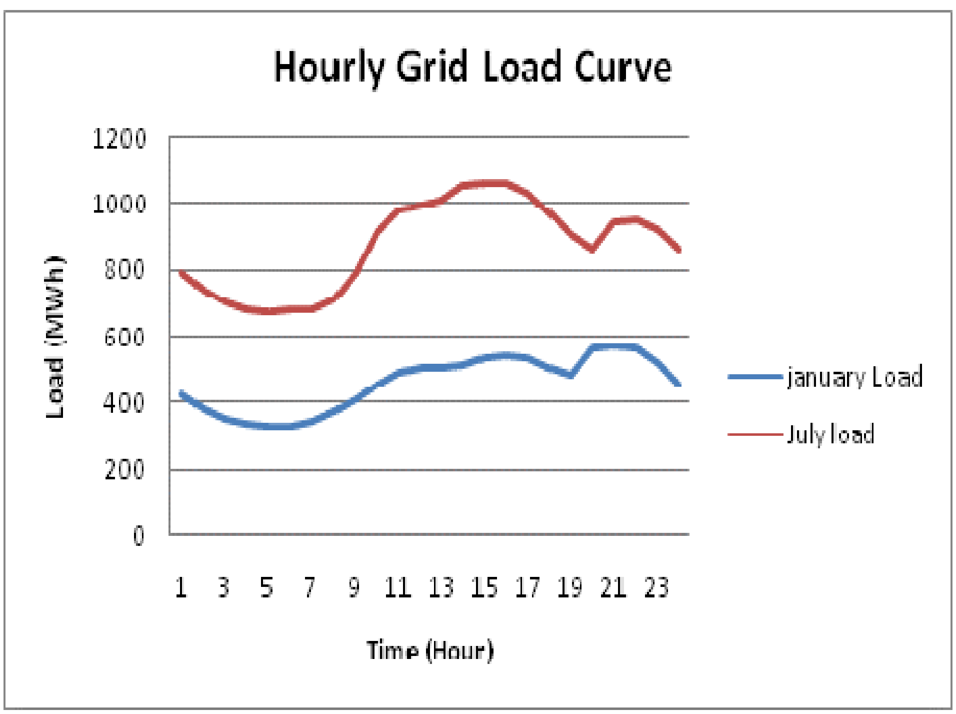


Figure 4.2: Grid load curve on Jan/6/2013 and Jul/7/2013

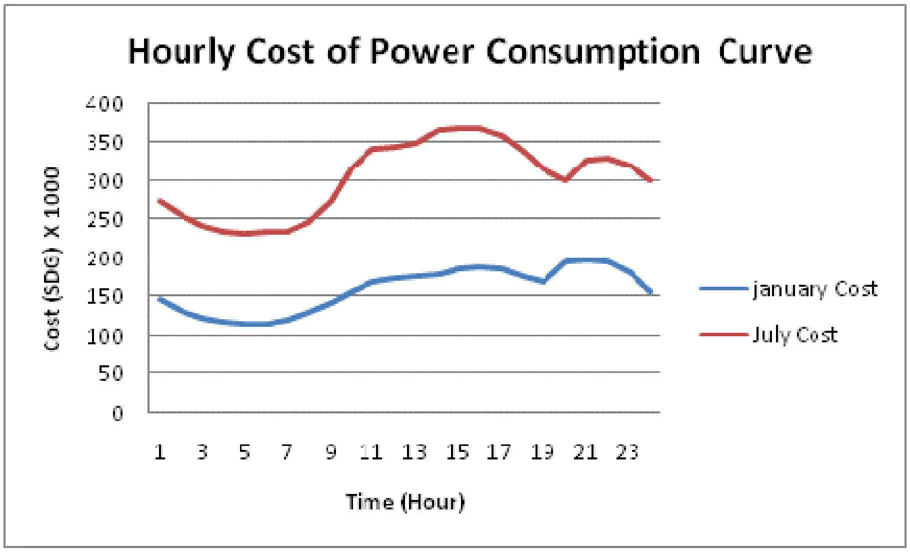


Figure 4.3: Cost of power consumption curve on Jan/6/2013 and Jul/7/2013

Figure 4-4 shows monthly grid load of year 2013. The highest monthly load was in July when people have strong cooling needs. The lowest monthly load occurred in January, when the climate is cool and very few cooling needs are required.

Figure 4-5 shows monthly cost of power consumption of year 2013. It is very clear that the trend indicated by monthly cost curve is the same compared with monthly grid load curve. The highest cost occurred in July, while the lowest cost occurred in January.

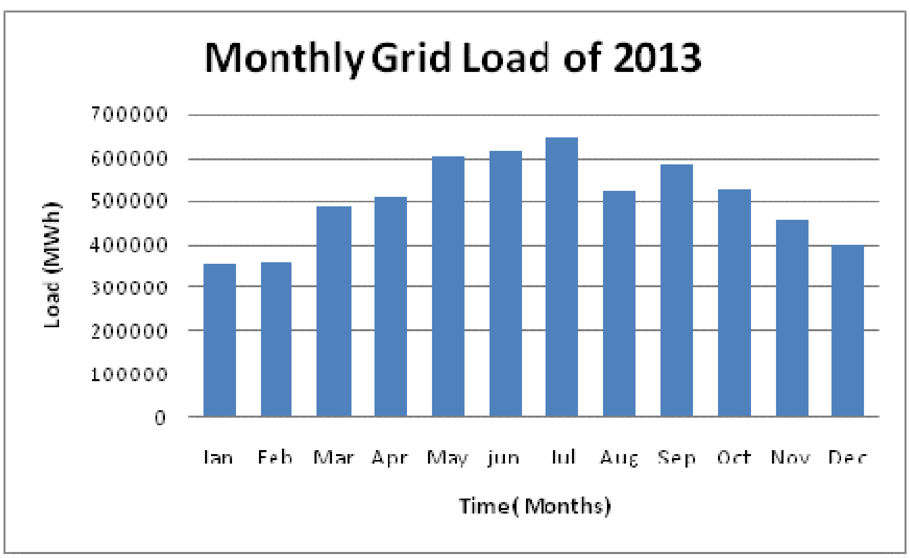


Figure 4.4: Monthly grid load of Year 2013

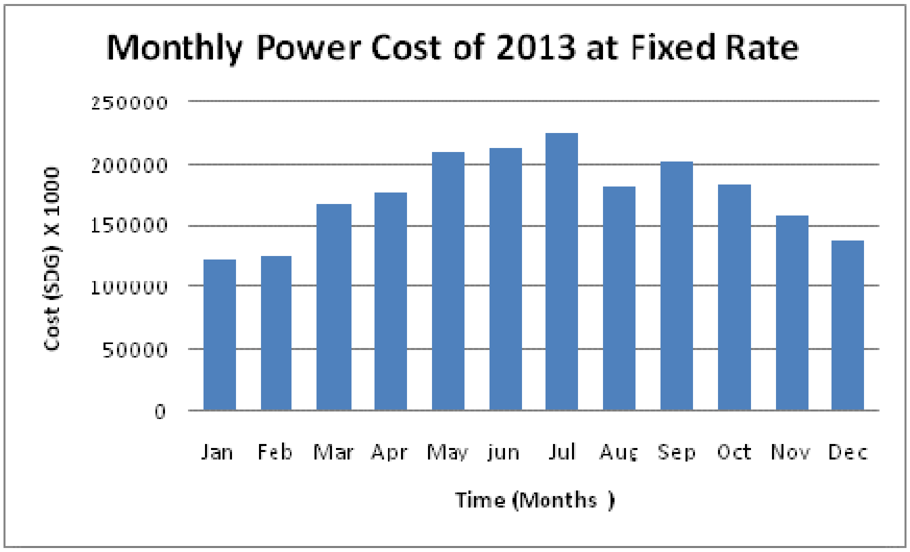


Figure 4.5: Monthly cost of power consumption of Year 2013

## 4.2 Power Price Using Fuzzy Method

Figure 4.6 shows hourly price curve of fuzzy method at Jan/6/2013 and Jul/7/2013. The grid load curve used to obtain the price curve is shown on Figure 4.2. It is clear from the graph that the price curve follows the trend of the grid load curve of Figure 4.2. That is as the grid load increases during the hot hours of the day, the price/kWh increases and vice versa. Figure 4.6 shows hourly cost of power consumption of the fuzzy method. It is curve pattern resembles the price curve of Figure 4.5 more than that of load curve of Figure 4.2. Figure 4.8 shows a monthly cost of power consumption using fuzzy method and fixed rate. It is clear from the chart that during the cool months from November to March the fuzzy method cost of power consumption is less than that of fixed rate. During the hot months from April to September the fuzzy method cost of power consumption is higher than that of fixed rate. It starts to increase slowly from April until it reaches it is maximum at July, which is a Ramadan month, then starts to decrease. Month of august is an exception in the above pattern due to decreased grid load as a result of coincidence with Eid Alfitir and flooding that occurred in this month which ended up in electricity cutoff from many parts of the city.

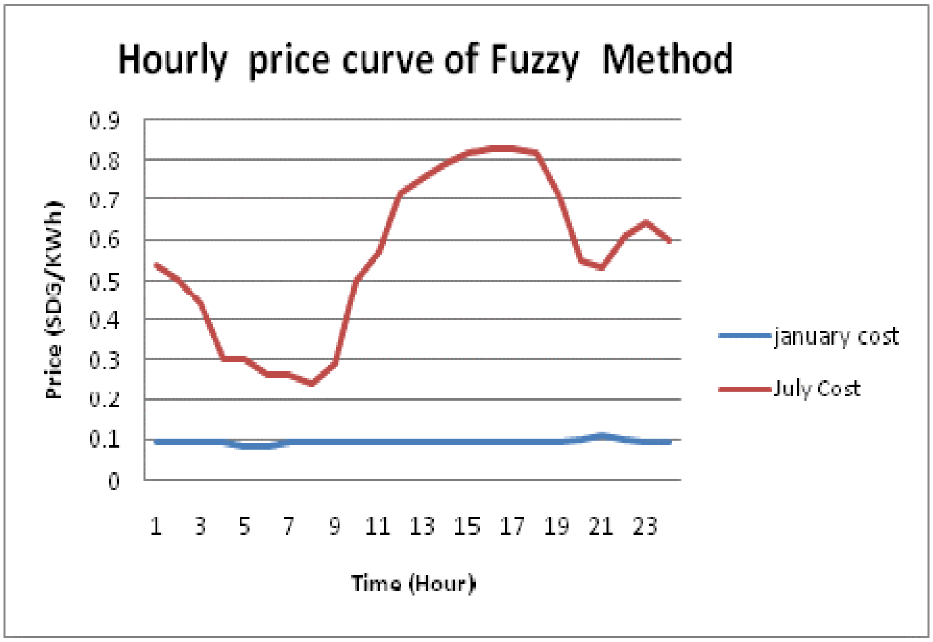


Figure 4.6: Price curve on Jan/6/2013 and Jul/7/2013 using fuzzy method

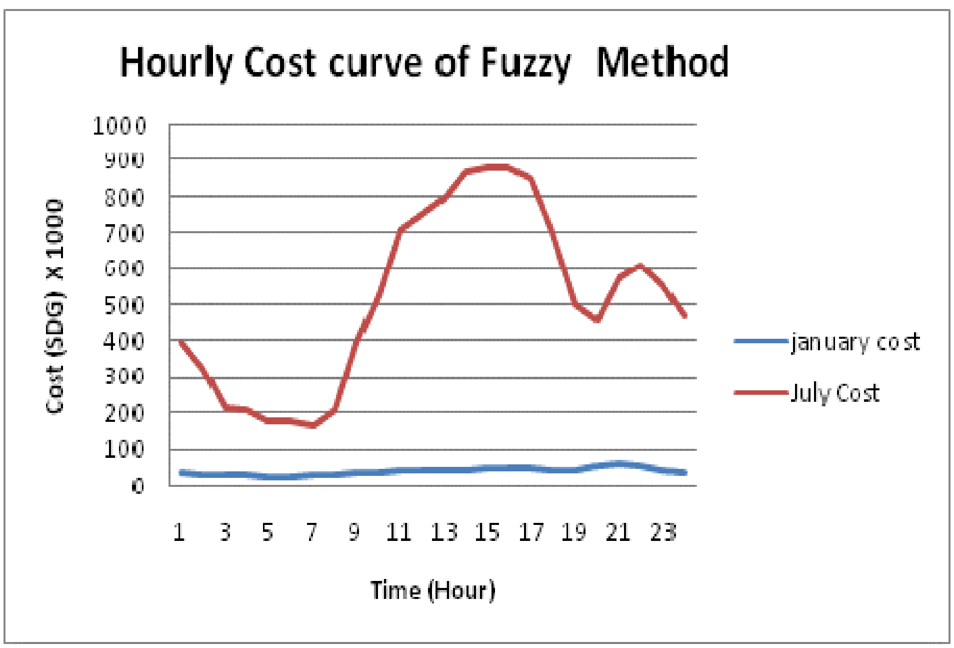


Figure 4.7: Cost of power consumption curve on Jan/6/2013 and Jul/7/2013 using fuzzy method

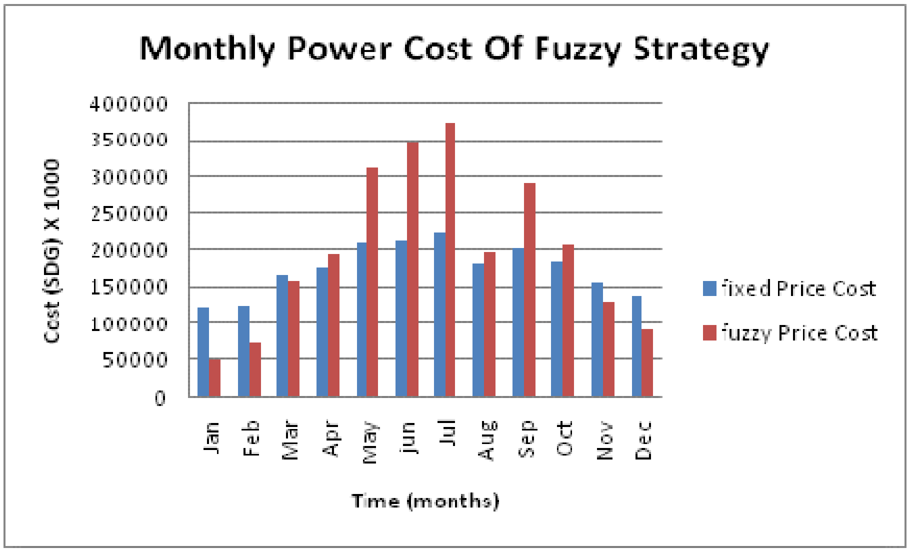


Figure 4.8: Monthly cost of power consumption of Year 2013 using fuzzy method

Table 4.1 shows the quarterly saving rates of fuzzy method. In the first and last quarters, the saving rate of fuzzy method are +31.8% and+ 9.3% consecutively .The positive sign indicates that the consumer is paying less than the fixed rate and can even consume more power at lesser price. However, in the second and third quarter of 2013 the saving rate of Fuzzy method is -42.8% and -41.4%. The total saving rate of the year 2013 is -15.8%. The negative sign indicates that the consumer is paying more for power than at the fixed rate, this is clear shown in the chart of Figure 4.5, especially the months of May, June, July and September. This is due to peak load hours mostly from 11.00Am to 5.00pm are supplied with higher prices to force power consumers to reduce their consumption. As they reduce their demand the price/kWh will automatically decrease and eventually reduces the cost of power. At this month's the grid load is very high and even sometimes more than what NEC can supply. This may result in frequent electricity cutoff due to load shedding and frequent transformer damage as a result of more load demand than rated kVA of transformer. Therefore, by giving higher prices at this time we reduce demand and also we can encourage the NEC to supply more electricity from thermal power stations without fearing of losses. Figure 7.11 shows quarterly cost of fuzzy method.

Table 4.1: Quarterly saving rates using Fuzzy method for year 2013

| **Months** | **Fixed cost (SDG)** | **Fuzzy cost (SDG)** | **Fuzzy saving** |
|---|---|---|---|
| Jan - Mar | 415348200 | 283360500 | +31.8% |
| Apr - Jun | 599253900 | 855800800 | -42.8% |
| Jul - Sep | 610486400 | 863527900 | -41.4% |
| Oct - Dec | 478818200 | 434008000 | +9.3% |
| **Total** | 2103907000 | 2436697000 | -15.8% |

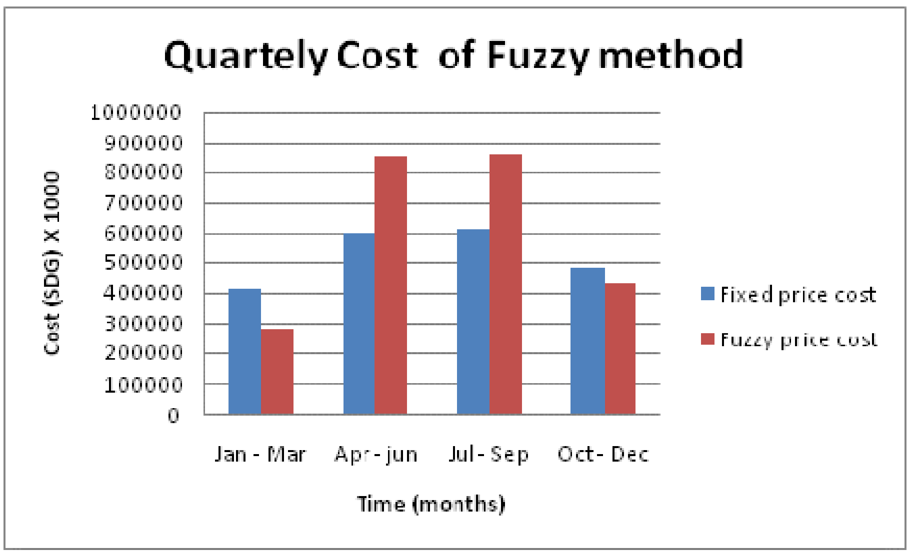


Figure 4.9: Quarterly cost of power consumption of Year 2013 using fuzzy method

## 4.3 Power Price Using Rough Set Method

Figure 4.10 shows price curve that applied Rough set method at Jan/6/2013 and Jul/7/2013. The grid load curve used to obtain the price curve is shown on Figure 4.2. The graph is of rigid form that is it takes considerable time for a variable to change in addition to not changing smoothly. It can be observed that on January date from 3.00 to 5.00 am the price was free and constant at 0.1 SDG/kWh on the remaining of the day. The maximum price occurs on the July date from 15.00 to 17.00 which is 1 SDG/kWh. This time was a peak load hour. Figure 4.11 shows hourly cost of power consumption of the rough set method.

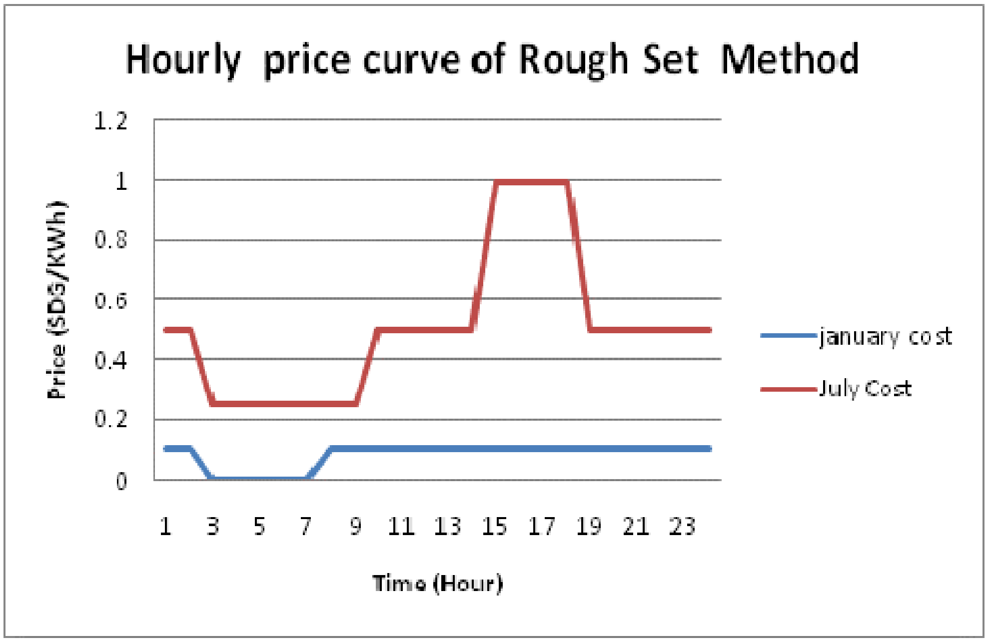


Figure 4.10: Price curve on Jan/6/2013 and Jul/7/2013 using rough set method

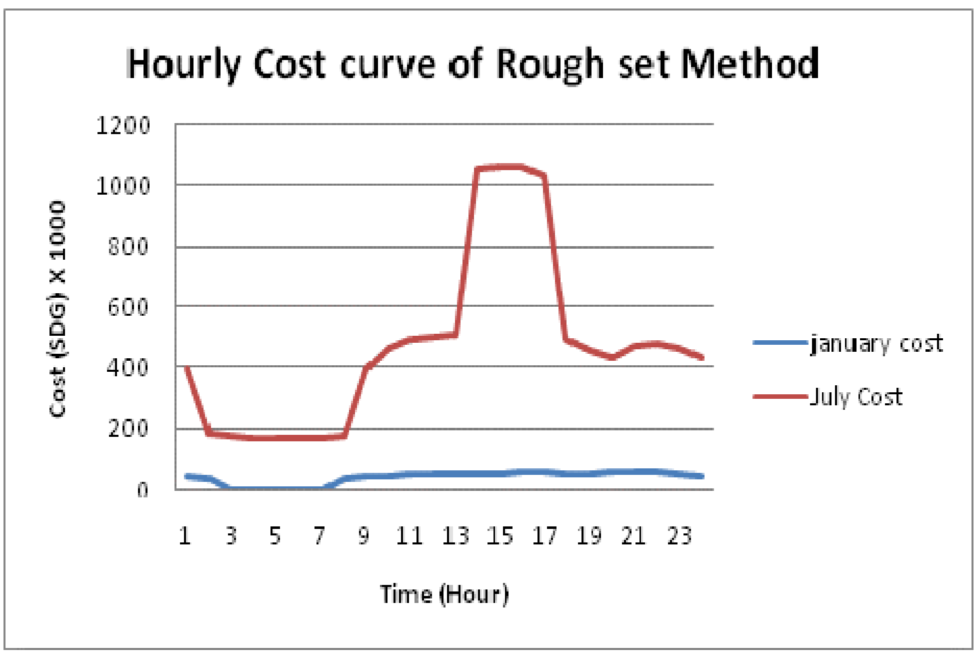


Figure 4.11: Cost of power consumption curve on Jan/6/2013 and Jul/7/2013 using rough set method

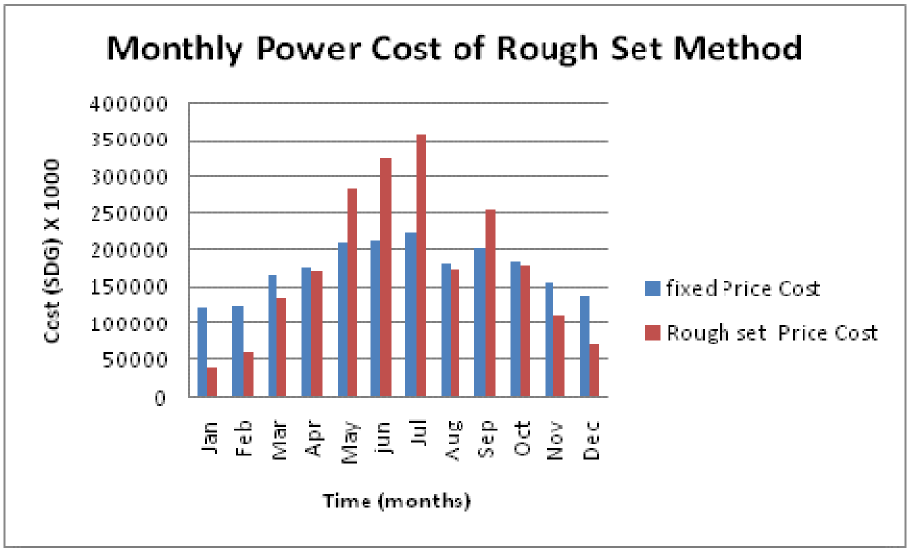


Figure 4.12: Monthly cost of power consumption of Year 2013 using rough set method

Table 4.2 shows the quarterly saving rates of rough set method. In the first and last quarters, the saving rate of rough set method are +43.8% and+ 23.9% consecutively. The positive sign indicates that the cost of power is in favor of the consumer. That is, it is cheaper than fixed price. In the second and third quarters the rough set saving rates are -30.2% and -29.3% consecutively. The negative sign indicates that the cost of power consumption using rough set is higher than fixed price. The total saving rate of year 2013 using rough set is -3.2%.

Table 4.2: Quarterly saving rates using Rough set method for year 2013

| **Months** | **Fixed cost (SDG)** | **Rough set cost (SDG)** | **Rough set saving** |
|---|---|---|---|
| Jan - Mar | 415348200 | 236948900 | +43.8% |
| Apr - Jun | 599253900 | 780415300 | -30.2% |
| Jul - Sep | 610486400 | 789563400 | -29.3% |
| Oct - Dec | 478818200 | 364483500 | +23.9% |
| **Total** | 2436697 | 2171411 | -3.2% |

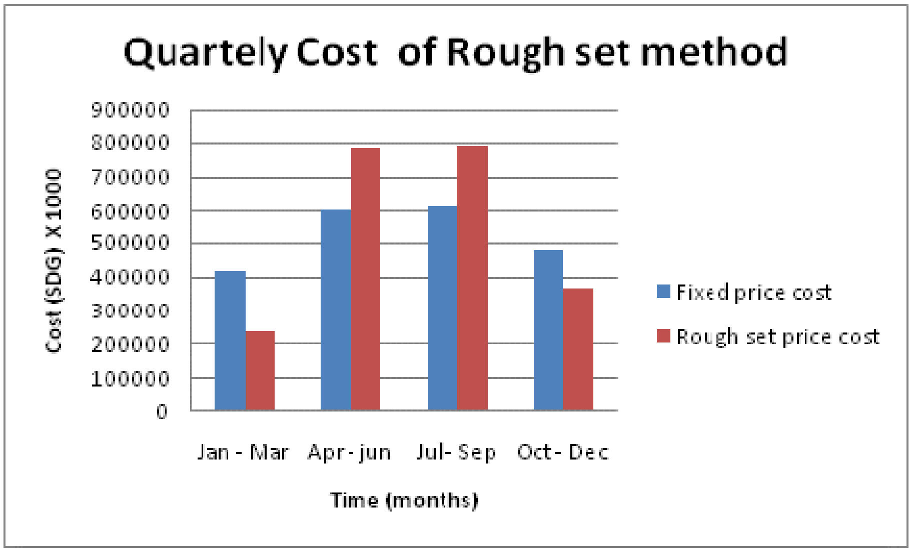


Figure 4.13: Quarterly cost of power consumption of Year 2013 using rough set method

## 4.4 Comparison between the Fuzzy and Rough set methods

The rough set method gave a total power cost saving rate of -3.2% compared to fuzzy method which gave -15.8%. This mean the consumer in rough set method will overall pay more of 3.2% of what he is supposed to pay for electricity in the year of 2013. Using fuzzy method he will pay 15.8% more. Taking it from the cost saving point the rough set method outperformed the fuzzy method. However, the fuzzy method has the ability to reduce the price instantly as the load demand decreases thereby reducing the cost. The rough set method price remains constant most of the time (except at boundary values) despite of load decrease or increase thereby the cost remains almost fixed. The main reason behind developing the model is to avoid peak hour load by providing an interaction environment between the consumer and supplier. The fuzzy method outperformed the rough set method in this characteristic by indicating to the consumer to decrease the load demand before peak hour occur. In return the consumer can observe his action benefit by the decreased price. In rough set this only occur at boundary values, without giving the consumer an indication to reduce his power usage.

# CHAPTER FIVE

# CONCLUSION AND RECOMMENDATION

## 5.1 Conclusion

In this thesis an electricity price forecasting models based on rough sets and fuzzy logic were proposed. The results of fuzzy logic and rough set technique for hourly price forecasting for the Khartoum state are investigated and show that the proposed fuzzy model technique gives a good performance and reasonable response. Its performance reliabilities were evaluated by comparing the monthly power consumption between the fixed price/kWh and predicted proposed model price/kWh. The rough set approach has proved to have better performance in term of total cost of power consumption. Mamdani's' FIS approach shows better performance than rough set in term of varying the price/kWh as the electricity loads varies during the day. This characteristic makes Mamdani's FIS model a better approach for indirectly implementing energy management schemes such that the total and peak energy usage is monitored and maintained at a desired level by raising the user awareness to power usage.

## 5.2 Recommendations

Future work will focus on refining and extending the proposed design, which may lead to best cost saving rates for end consumers and better performance in peak demand response for power suppliers. There are many areas where the current model can be extended.

- The membership functions chosen for the input are triangular functions, other shapes, such as the bell shape, sigmoidal shape, etc., can also be tried to see the overall variation in the price.
- One issue with fuzzy logic is that it cannot incorporate statistical data in a direct fashion. Historical data are incorporated in the form of rules. The power industry is highly statistics driven. There should have been some way to incorporate the new trends of inputs that are based on statistical findings.

Currently, the only way to incorporate changes is to alter the rule base, and the change has to be done manually.

- The other ways to change the fuzzy model is to try with other defuzzification approaches such as the Center of Area. Different approaches for defuzzification may result in a better outcome from the model. Weight factor can also be assigned to each input parameters. Currently, all the load and temperature have similar weight. If we want to prioritize between parameter, load would receive more priority than temperature.
- Learning is another attribute that can be incorporated into the current model. Adaptive Neuro Fuzzy Inference System (ANFIS) is one way that the current model can be extended to. In ANFIS, the learning is done with the incorporation of a neural network. The Fuzzy system is trained over time to become self-adaptive. Once the training is complete, the system is capable of making intelligent changes based on a neural network.
- Automated metering infrastructure research need to be started to enable the deployment of the dynamic pricing model.

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