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Smart Metering for Smart Electricity Consumption

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ABSTRACT

In recent years, the demand for electricity has increased in households with the use of different appliances. This raises a concern to many developed and developing nations with the demand in immediate increase of electricity. There is a need for consumers or people to track their daily power usage in houses. In Sweden, scarcity of energy resources is faced during the day. So, the responsibility of human to save and control these resources is also important. This research work focuses on a Smart Metering data for distributing the electricity smartly and efficiently to the consumers. The main drawback of previously used traditional meters is that they do not provide information to the consumers, which is accomplished with the help of Smart Meter. A Smart Meter helps consumer to know the information of consumption of electricity for appliances in their respective houses. The aim of this research work is to measure and analyze power consumption using Smart Meter data by conducting case study on various households. In addition of saving electricity, Smart Meter data illustrates the behaviour of consumers in using devices. As power consumption is increasing day by day there should be more focus on understanding consumption patterns i.e. measurement and analysis of consumption over time is required. In case of developing nations, the technology of employing smart electricity meters is still unaware to many common people and electricity utilities. So, there is a large necessity for saving energy by installing these meters. Lowering the energy expenditure by understanding the behavior of consumers and its correlation with electricity spot prices motivated to perform this research. The methodology followed to analyze the outcome of this study is exhibited with the help of a case analysis, ARIMA model using XLSTAT tool and a flattening technique. Based on price evaluation results provided in the research, hypothesis is attained to change the behavior of consumers when they have better control on their habits. This research contributes in measuring the Smart Meter power consumption data in various households and interpretation of the data for hourly measurement could cause consumers to switch consumption to off-peak periods. With the results provided in this research, users can change their behavior when they have better control on their habits. As a result, power consumption patterns of Smart electricity distribution are studied and analyzed, thereby leading to an innovative idea for saving the limited resource of electrical energy.

Keywords: Advanced Meter Infrastructure, Power consumption patterns, Smart Meters, Smart Metering, ARIMA models.

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LIST OF ABBREVIATIONS

AC	Alternate Current
ACF	Autocorrelation Function
AIC	Akaike Information Criterion
AICC	Akaike Information Criterion Corrected
AMI	Advanced Meter Infrastructure
AMR	Advanced Meter Reading
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
ARMAX	Autoregressive Moving Average with Exogenous Inputs
CMCC	China Mobile Communication Corporation
CPP	Critical Peak Pricing
DAP	Day Ahead Pricing
FPE	Final Prediction Error
GARCH	Generalized Autoregressive Conditional Heteroscedastic
HEMS	Home Energy Management System
HAN	Home Area Network
IHD	In-Home Display
MAPE	Mean Absolute Percentage Error
MaxAE	Maximum Absolute Error
MaxAPE	Maximum Absolute Percentage Error
MSE	Mean Square Error
NRMSE	Normalized Root Mean Square Error
OLTP	Online Transaction Processing Systems
PNNL	Pacific Northwest National Laboratory
PACF	Partial Autocorrelation Function
RTP	Real Time Pricing
SBC	Schwarz criterion
SCADA	Supervisory Control and Data Acquisition System
SEMS	Smart Energy Management System
SSE	Sum of Squared Errors of Prediction
TAM	Technology Acceptance Model
TOUP	Time of Use Pricing
WIMAX	Worldwide Interoperability for Microwave Access
WN variance	White Noise variance
XML	Extensible Markup Language

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1 INTRODUCTION

In the early phase of household technology, delivery of electricity is completely depended on traditional energy meters. These meters play a key role in measuring the consumption of electrical energy in individual households. The usage of these meters has been slowly declining with the advancement in technology as rapid changes has been made to encounter the problems occurred by the traditional meters. The major problem arises when habitants are unaware of their daily behavior. Monthly feedback given to the consumers is not sufficient as the consumers will not have knowledge on how much energy does the individual appliances consume. To overcome the problems of traditional electricity meters, Smart Meters have been upgraded and developed. With the use of Smart Meter data, energy alerts will be provided to the consumers based on hourly utilization of energy. The primary objective of the Smart Meters is to reduce the energy consumption in the households. Our thesis utilizes real time Smart Meter data sets obtained from a Swedish electricity company. A case study is performed on hourly measurement data of 16 households to determine consumption patterns.

With its growing attention in the market the behavior of the consumers can be studied and analyzed. The energy consumption patterns can be facilitated in improving the behavior of users. The electricity market can be restructured with the installation of these meters, as it not only preserves the energy, but also reduces carbon dioxide emissions [4]. Trust and credibility of these meters is established only when the consumers have positive quality of experience. Timely consumption of consumers can be reduced as Smart Meters are connected to online billing [2].

1.1 Motivation

Energy expenditures will be lowered by increasing the possibility of reduced consumption using analyzed Smart Meter data motivated to perform this research work. During the usage of traditional meters, there is involvement of wastage of much energy to man power. As the electricity consumption of the household is known on monthly basis by conventional meters, there is an overall demand for the electricity utilities to explore a new development for benefit of the consumers as well as themselves. However, the study determines to make attempts to replace electricity meter in respective households by minimizing the drawbacks occurred by consumer. The daily electrical usages change with respect to habits and it is mostly dependent on behavior of consumers. By using traditional meters, usages are not flattened as consumers are not aware of the knowledge about how much consumption has been made in an hour or any particular interval of time in a day. The uncertain perception of the consumers can also be falsified as most of the consumers have very low knowledge regarding the Smart Meter and its installation. Lastly, to enable change and read concerns in the market also motivated to perform this study.

1.2 Scope of the Thesis

This thesis work deals with hourly energy consumption values acquired from the energy provider. These standard values help energy utilities and consumers to know their energy consumption which is reported on an hourly basis. In fact, behavior of the consumers can be studied and results obtained can help the consumers in changing their behavior, in particular when correlated with a potentially varying price. This work explains a gap between the consumers and energy utilities so that they can communicate more efficiently through the implementation of conservation strategies. The consumers need to be educated with broader knowledge regarding the meter so that wrong perceptions can be altered. A case study is conducted on the standard data obtained for sixteen sets of households. The variation in change of the usage has been well understood and determined. The research work can also help users to think intelligently when using their power. Moreover, daily patterns for the complete day on hourly basis are examined. Future savings which consists in determining when to use which appliance can be done by using prediction models and flattening techniques.

1.3 Study Prerequisites

The important prerequisites contributed in our research work are as follows:

- The analysis of hourly measurement data of 16 households is necessitated while employing data.
- Statistical modeling knowledge is essential to determine the relation between price, cost, consumption, cumulative consumption and cumulative cost on which statistics are calculated such as lag1 autocorrelation, price-cost correlation, price-consumption correlation, cost-consumption correlation, average, standard deviation and coefficient of variation.
- Efficient knowledge on a calculation tool such as "Microsoft Excel" is required to execute statistical calculations while evaluating the graphs.

The importance and evolution of Smart Meters has been studied in research papers and articles. This further contributed in improving the knowledge from traditional meters to advanced meters.

1.4 Structure of Thesis

The flow of the thesis is organized as follows. The first chapter includes a general description of introduction and its segments such as scope of the thesis, motivation and study prerequisites. The second chapter presents background work consisting of evolution of meters from past, traditional meters. It discusses the motions of Smart Grid, Smart Meter, power consumption, people's behavior, ARIMA models and ends with a literature survey. Chapter 3 explains aims and objectives, research questions and the methodology to find the answer to research questions. In chapter 4, a case study is performed on Smart Meter data readings and this is followed with an explanation of results in chapter 5. In chapter 6, results are analyzed with a discussion provided to emphasize the consumption patterns. Finally, conclusions are drawn with explanation of future areas of research in chapter 7.

2 BACKGROUND AND RELATED WORK

2.1 Evolution of Electricity Meters from the Past

In early years, electricity is available only to a specific section of affluent society. The advancement in technology over time encouraged meeting the demands of common people in all parts of the world. The history of electricity meter is well connected involving researchers from past. The general usage of electricity in the early 1870's is only confined to telegraphs and arc lamps. With the invention of the electric bulb by Thomas Elva Edison, the power energy market became widely opened to the public in the year 1879. Oliver B. Shallenberger introduced his AC ampere hour meter in the year 1888. Eventually, the progressive development in metering technology leads in enlightening the lives of many common people [33].

2.1.1 Traditional Electricity Meters and its types

The electrical devices that can detect and display energy in the form of readings are termed as electricity meter. Traditional meters are used since the late 19th century [28]. They exchange data between electronic devices in a computerized environment for both electricity production and distribution. In most of the traditional electricity meter aluminum discs are used to find the usage of power [28]. Today's electricity meter is digitally operated but still has some limitations. A simple 1 Phase 2 Wire electricity meter is shown in the below figure 2.1.

Figure 2.1 Traditional meter [18]

Some of the limitations faced by the traditional electricity meter [28] are as follows:

- Meters are unreliable in nature as consumer has to anticipate for the monthly electricity bill.
- The process of measurement is supported by a specific mechanical structure and hence they are called as electromechanical meters.
- In order to perform meter readings, a great number of inspectors have to be employed.
- Payment processing is expensive and time consuming.
- New type of tariffs on hourly basis cannot be introduced with the corresponding meters for encouraging the consumer.
- Development of meter software applications and supportive network infrastructure is complicated.

Besides the above mentioned limitations, there are also several other elements creating a huge gap between the consumer and distributor because of installation of traditional meters.

Meters are of distinct types. Even though timely development of electricity meters helps the consumer to gain knowledge with respect to electricity consumption, statistics of the consumption couldn't be changed. Some of the basic types of electricity meters are explained as follows:

Different Types	**Outline**
Electrolytic Meter	The whole current passes through the electrolyte. The major drawback is mechanical considerations and adoption by limited localities.
Commutator Meter	Brush-shifting device is used to vary the current load and commutator's of small diameter facilitates in insulation attention. The major drawbacks are inadequate load characteristics, maintenance cost and lack of proper insulation.
Mercury Motor Meter	There is a satisfactory performance with the introduction of this meter. The adoption of rotor made a prominent role in supplying the calibration. The momentary short circuit is reduced or even prevented.
D.C Watt Hour Meter	This meter model is developed for heavy current circuits where the temperature coefficient is high. For indication of demand purposes a separate time switch is used. Also, it is a clock-type meter in which voltage variations is less with the reduced shunt loss.
Single Phase Induction Meter	Magnetic conditions are better improved to control the energy consumption and a considerable improvement in performance is also done. Meter inspection is easily assessed as the construction of this model has accessibility of simplifying assembly.
Poly-Phase Watt Hour Meter	Lagging power factors in the meter reflects the characteristics of the current transformer. Attempts for improving high degree of accuracy have been built to avoid troublesome corrections. Interaction effects, calibration and increase in the effects of shunt loss are the greatest drawback of this model.

Table 1 Various electricity meters [32]

2.2 Smart Grid

Smart Grid is the modern development in electricity grid. Recent electrical grids are becoming weak with respect to the electrical load variation of appliances inside the home. The increase in population is also the indication of electrical grids becoming more fragile. The higher the population, the more load on the grid.

Improving the efficiency of grid by remotely controlling and increasing reliability, measuring the consumptions in a communication that is supported by delivering data (real-time) to consumers, supplier and vice versa is termed as Smart Grid [31]. Automated sensors are used in Smart Grids. These sensors are responsible in sending back the measured data to utilities and have the capability to relocate power failures and avoid heating of power lines. It employs the feature of self-healing operation. Literally, the concept of Smart Meter is commenced from the idea of Smart Grid. A carbon emission reduction of 5% is expected by 2030, annually by its installations and it can show a greater impact on environmental changes [31]. For a sustainable development and establishment of new grid infrastructure, Smart Grids are recommended for many countries.

2.3 Smart Meter

Smart Meter is an environmentally friendly energy meter that is used for measuring the electrical energy in terms of KWh (Kilowatt - hours). It is simply a device that affords a direct benefit to the consumers who want to save money on their electricity bill. They belong to a division of Advanced Meter Infrastructure and are responsible for sending meter readings automatically to the energy supplier. A simple picture of a Smart Meter is shown below.

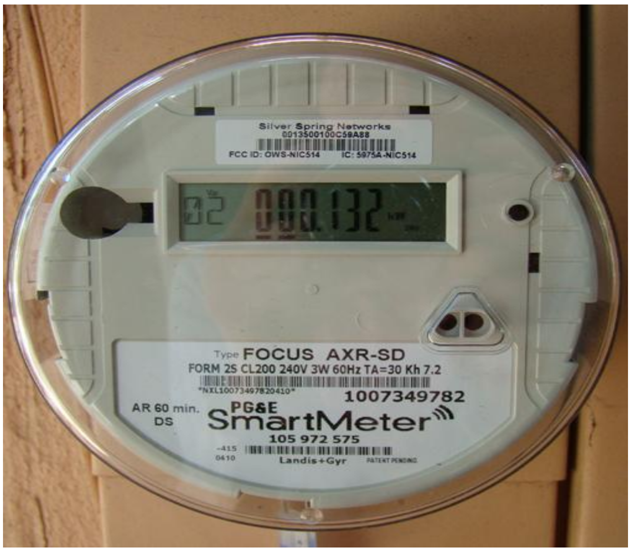


Figure 2.2 Smart Meter [20]

Accurate meter reading will be provided with the inclusion of firm benefits from the Smart Meter. They record the consumption on the basis of hourly or less than hourly intervals. A Smart Meter has non-volatile data storage, remote connect or disconnect capability, tamper detection and two-way communication facilities. They perform remote reporting of the collected data to the central meter. This central meter monitors the functionality of the Smart Meter. From an operational perspective, use of Smart Metering allows an improved management and control over the electricity grid [6]. Some of the benefits of Smart Meters are as follows:

- Low operational cost.
- Time saving to the consumers and utility companies for reporting the meter reading back to the energy providers.
- Online electricity bill payment is allowed.
- Power consumption can be greatly reduced during the high peaks with an intimation policy.
- Has a feature of automatically terminating the appliances off when they are not in use [39].

Smart Meter senses all the consumption generated inside the residents. Meter readings give a broader understanding to the energy utilities so that overall energy usage customs of the habitants can be altered. Finally, all the information that is generated by Smart Meter will increase help in noble generation.

2.4 Power Consumption

The total amount of power consumed in an individual household is referred as power consumption. The consumption of power is an important aspect of electricity supply. People should be aware of preserving energy for future use. With daily usage of electricity, the energy patterns have been slowly varying. This variation of consumption patterns can be caused by weather conditions or unnecessary utilization of power by inhabitants such as increase of appliances in respective households and careless attitude in utilization for example not switching OFF the lights or television when not watching it. These factors may show greater impacts on end user. As the power supplied by energy companies is vast, most of the people are neglecting energy and its savings. The importance of consumption is declining in the mindset of utilities. The energy utilities should play a major role in advancing the Smart Meter technology and should make people participate in reducing energy consequences by creating awareness about the impact of their current level of consumption.

2.5 Study of People’s Behavior

People’s behaviour is termed as behaviour of consumer on appliance consumption in a household. If the consumption of the customer is high then we can empathize that their usage of devices is also high, which means cost is directly proportional to the product of number of uses and the corresponding durations. It is important for energy companies in reaching the anticipation of the customer. In-fact most of the consumers rely on monthly bill they expect for. They usually do not know which appliances are consuming more energy and how they can manage their consumption better. These factors play an important role in influencing the behaviour of the customer. The better understanding of the people’s behaviour is only achieved through analyzing how they use their energy. The consumers should be influenced in a smart way while accessing their appliances [2]. An illustration of a Smart Meter installed in a household while measuring the appliances is shown in figure 2.3.

Figure 2.3 Smart Meter measuring electrical appliances in a household [19]

The above figure expresses the daily activities of household appliances measured by a Smart Meter in a home. Smart Meter is installed outside the house and its hourly consumption data is measured for lowering consumer electricity bills. This measurement facility converts simple home to a smart home.

2.6 ARIMA model

The acronym of ARIMA stands for Autoregressive Integrated Moving Average. ARIMA model is a standard linear time series model that accepts the present values and predicts the future values in the series. It is represented as ARIMA (p, d, q) where parameter p is referred as the order for auto-regression, parameter d is the order for non-seasonal difference and q is the order for the moving average. The ARIMA model accepts time series data as input (combination of past values) and predicts future values as output. Predicting the future values guides in applying many applications such as demand estimations, stock prices estimation, economic estimations and sales representations [23].

There are two types of ARIMA processes, seasonal and non-seasonal ones, which are discussed in detail below.

Seasonal ARIMA model: Seasonality is a regular pattern of changes that repeats over s time periods. A seasonal ARIMA model is expressed as ARIMA (p, d, q) (P, D, Q)$_s$ where P is the order of seasonal auto regressive part, D is the order of seasonal differencing part, Q is the order of seasonal moving average part and s is the number of time periods of seasonal cycle [30].

Different seasonal ARIMA models are:

ARIMA (1, 0, 0) (0, 1, 0)$_{12}$: First-order autoregressive term in non-seasonal part and seasonal differencing of order 1.

$$Y(t) = \mu + y(t-12) + \phi(y(t-1) - y(t-13)) \qquad [30]$$

where μ is constant and

$\phi(y(t-1) - y(t-13))$ is the seasonal difference term

ARIMA (1, 0, 1) (0, 1, 1)$_{12}$: First-order autoregressive term and moving average term in the non-seasonal part and first-order moving average term in the seasonal part with seasonal differencing of order 1.

$$Y(t) = \mu + y(t-12) + \phi(y(t-1) - y(t-13)) - \theta e(t-1) - \Theta e(t-12) + \theta\Theta e(t-13) \quad [30]$$

where μ is the constant

Θ is Seasonal Moving Average(1) coefficient

$\phi(y(t-1) - y(t-13))$ is seasonal difference term

θ is the Moving Average(1) coefficient

ARIMA (0, 1, 1) (0, 1, 1)$_{12}$: First-order moving average term, differencing term in the non seasonal part and first-order moving average term with seasonal differencing.

$$Y(t) = y(t-12) + (y(t-1) - y(t-13)) - \theta e(t-1) - \Theta e(t-12) + \theta\Theta e(t-13) \quad [30]$$

where Θ is SMA(1) coefficient

θ is MA(1) coefficient

ARIMA (2, 0, 1) (2, 1, 0)$_{12}$: Second-order autoregressive term, first-order moving average term in non seasonal part and second-order autoregressive term in seasonal term with seasonal differencing of order 1.

$$Y(t) = \mu + y(t-12) + y(t-24) + \phi(y(t-1) - y(t-13)) - \theta e(t-1)$$

where μ is constant

$\phi(y(t-1) - y(t-13))$ is seasonal difference term

θ is the MA(1) coefficient

It is not recommended to use more than one order of seasonal differencing or more than two orders of total differencing [30].

Seasonal ARIMA present the series in terms of its past values at lag equal to the length of the period (s), while the non-seasonal ARIMA does it in terms of its past values at lag 1 [34].

Non-Seasonal ARIMA model: A non-seasonal ARIMA model is represented as ARIMA (*p*, *d*, *q*) model where *p* is number of autoregressive terms, *d* is number of non seasonal differences and *q* is moving average term [23].

Different non-seasonal ARIMA models are:

ARIMA (2, 1, 1): An ARIMA model with autoregressive term of order 2 and moving average term of order 1 with differencing of order 1.

$$Y(t) = d + a(1).\, y(t-1) + a(2).\, y(t-2) - e(t) - c(1).\, e(t-1)$$

where d is the differencing term

$a(1)$ is first order autoregressive coefficient

$a(2)$ is second order autoregressive coefficient

$c(1)$ is first order moving average coefficient

$y(t-1)$, $y(t-2)$ are series in previous values

$e(t)$ and $e(t-1)$ are residuals at period t and $(t-1)$

ARIMA (1, 1, 1): A mixed model of autoregressive and moving average terms of order 1 with differencing of order 1.

$Y(t) = d + a(1).\, y(t-1) - e(t) - c(1).\, e(t-1)$

where $a(1)$ is first order autoregressive coefficient
d is differencing term
$c(1)$ is first order moving average coefficient
$y(t-1)$ is series in previous values
e(t) and $e(t-1)$ are residuals at period t and $t-1$

ARIMA (1, 1, 0): First order autoregressive term with non seasonal differencing of order 1.

$Y(t) = d + a(1).\, y(t-1)$

where $a(1)$ is first order autoregressive coefficient
d is differencing term
$y(t-1)$ is series in previous values

ARIMA (0, 1, 1): First order moving average term with non seasonal differencing of order 1.

$Y(t) = d - e(t) - c(1).\, e(t-1)$

where $c(1)$ is first order moving average coefficient
d is differencing term
e(t) and $e(t-1)$ are residuals at period t and $t-1$

2.7 Survey of Related Work

The survey is split into four parts, namely socio-economical issues, technological issues, cases and prediction. As we started with literature survey in the initial stage of research, the division of cases is chosen to answer research questions in an organized manner.

Socio-economical issues:

The value of customer satisfaction in communication market is trusted with the services provided by service provider. In [2], the author explains people’s behavior towards the Smart Metering system and states the services such as viewing electric consumption in real time, viewing the effect of turning electrical appliances on and off, making estimation of the next bill, or receiving messages directly from the grid operator. The consumption patterns during night and weekends are projected in the paper.

A survey is conducted in different countries over different households and user’s feedback is obtained so that people become motivated to be energy-conscious. A socio-technical review to promote sustainable energy consumption using Smart Meters is done. Answers are proposed for a set of research questions such as 1) Is feedback useful for energy saving and behavioral change? 2) What presentation of feedback is good and effective? Scientific advice on energy saving instruments for household energy consumption is provided in [3]. A Smart Metering privacy model is implemented to measure the privacy that a Smart Meter will provide with and without involvement of third parties [4]. The advantages of Smart Metering concept are low metering costs, energy efficiency and easier detection of fraud [7].

A quantitative survey was conducted among various households and results of this survey were presented in paper [9]. The mapping of consumer's perception with household appliances is done. A theoretical framework named TAM is proposed for household perception of Smart Appliances. Mean scores and standard deviations for perceived usefulness, perceived ease of use, attitude and intention to use, safety, control and comfort are tabulated.

Technological Issues:

The connection between meter and the household appliances is carried out in different ways. The connection can be dedicated line, wireless connection, web-based communication and power-line communication between the appliances in home and the meter [1]. The secured scenario can be maintained by connecting the meter to the data centre. When Smart Meters are connected with mobile phones, the actual power consumption of a device when it is switched ON/OFF or plugged in/out is observed [5]. An overview of Smart Metering installations, implementations, and functionality which is installed in the Netherlands is given in [6].

In [8], Smart Metering involves installation of one or several Smart Meters by continuously monitoring and sending feedback of data to the customer. Consumers, by making use of Smart Meters, will get safe, secure and affordable energy, and a reduction of carbon emissions is possible.

In [13], the architecture of Smart Energy Management System was developed to control the transmission capacity and rate generation for the aggregated load conditions of the Smart Appliances. Energy prices, consumption and cost of consumption under different demand conditions i.e. on-peak, mid-peak and off-peak values are tabulated. The energy cost of each appliance is shown in pictorial form.

In [14], the importance of Smart Meter in the market with respect to the customer and business organization has been reviewed. Functionalities and benefits of Smart Meters compared to mechanical meters are explained. The authors are curious to find out the hypothesis to the proposed questions in this particular research paper. To make energy efficient society, the customer must be aware of the energy consumed. So, different feedbacks are proposed in this paper to save energy and improve energy efficiency.

In [38], the monitoring of Smart Meters in Hungary is discussed. The meter has two-way communication capability for tariff based operation and remote control. The communication tools of the meter such as Zigbee, WIMAX and Home Area Network supporting the energy meter is addressed. Energy Management System with high level application possibility has been proposed.

Cases:

In [10], consumption patterns are analyzed in two households and an office in the UK, where real time reporting is done using web. The need for Smart Meters, benefits and how to monitor the power is detailed. Experimental setup is designed in three household premises. The experiment setup contains a section of equipment and software. Graphs are observed on a 24 hour cycle online for weekday, sunday, before and after the change of appliance. The analysis is also done for heating water, turning on central heating and printing from a laser printer. Direct feedback is suggested to identify the appliances of high burn. The aim of influencing consumer habits has been achieved by indicating where the savings are possible.

In [36], a thorough analysis of 15 minute residential meter data of 50 houses were used to derive several target applications such as identifying demand response potentials, abnormal load behaviors and fault diagnosis. In [11], the processing of Smart Meter data with the aid of Supervisory Control and Data Acquisition System, billing and weather data is focused. The data collected by the researchers at Pacific Northwest National Laboratory was used. The load profile of two households with highest and lowest energy consumption over 15 minutes during the month of April is plotted. The impact of temperature on the power consumption of a household is demonstrated.

A Smart Metering development system for a Korean residential environment is explained and system monitoring of other countries is reviewed in [15]. A pilot demonstration with the developed system is conducted in 77 different sized households located in two different cities. The study is focused on verifying the effectiveness of In-Home Display which is an essential component of Korean Smart Metering system. Many ideas such as Advanced Meter Infrastructure, Smart Grid and Smart Metering system have been proposed. The results interpreted convey that people living in small houses are more sensitive to price-related information. The daily power consumption comparison graphs of two cities before and after using In-Home Display are demonstrated. The impact of temperature on daily power consumption is observed.

Prediction:

In [12], price prediction is done on the basis of Home Energy Management System. The experiment evaluated results in saving 22.2% of electricity expenditure daily. Types of pricing models such as Real Time Pricing, Day Ahead Pricing, Time of Use Pricing and Critical Peak Pricing are specified. Client interface data model for the energy consumption is constructed using XML. The graph for actual price and predicted price, maximum power utilization i.e. peak hours are also compared and observed. Test bed is designed to evaluate the Home Energy Management System.

In [21], simulation model presents a generated load profiles for household to construct flat tariffs. The impact of Smart appliances and variable prices on electricity bills of a household is investigated. Field tests are carried out to estimate the bill saving and other cost estimations. The operations of household appliances are shifted so that users can reduce their cost. The load curves for working days, saturday and sunday are demonstrated. Comparison of load curves for flat tariff and time based tariff is shown. The results of the paper show how variable pricing will affect consumer behavior under realistic environment conditions.

In [22], an ARIMA approach to forecast short term electricity prices to improve accuracy by forecasting errors is proposed in the paper. Based on the historical data obtained from California power market, ARIMA model is implemented on daily average prices. Forecasting curves after single and double error adjustments are shown in graphical form. Statistical results such as mean, variance, Mean Square Error, Maximum Absolute Error for forecasting price of California and after twice error adjustments are tabulated.

In [26], spot electricity price forecasting has been done using European Energy Exchange data. ARIMA (3, 0, 3) (1, 1, 1) is founded to be the best fitting model for the experiment. From the results, Maximum Absolute Percentage Error and Mean Absolute Percentage Error of the model are rounded.

In [27], results from Spain and California markets are presented in this paper. The differences of both the market has been observed by applying ARIMA model. Time series analysis is explained with steps from identification to forecasting of the model. The outcome of the Spanish market is 5 hours to predict future prices and 2 hours is needed for California market predictions.

Monthly energy data forecasting approach of Provincial Electricity Authority of Thailand is provided to decompose trend cycles and seasonal patterns. Decomposition technique is used for time series forecasting, while correlation coefficients and mean absolute percentage errors are computed to measure fitting accuracy [36].

In [37], seasonal ARIMA model (2, 0, 1) (2, 1, 0) is used for forecasting the mobile traffic. Analysis is performed based on the real time data obtained from CMCC. NRMSE is calculated for determining and acceptance of forecast errors.

The papers which impacted our research addressed people's behavior towards Smart Metering system [2]; benefits of Smart Meter compared to mechanical meters and feedback to save energy on improving energy efficiency [14]; consumption patterns on a 24 hour cycle are analyzed in two households in the U.K [10]; a Korean residential environment of a Smart Metering system [15]; implementation of ARIMA model on time series analysis [27]; and the use of seasonal ARIMA (2, 0, 1) (2, 1, 0) model which is analyzed with real time data [37].

3 DESIGN AND IMPLEMENTATION

3.1 Aim and Objectives

The main aim of this research is to measure and analyze power consumption using Smart Meter data by conducting a case study on various households. The related objectives are as follows:

Objectives

- To analyze the data on an hourly basis to understand the potential that much line-grained measurements can have on control of electricity consumption.
- To understand how to move demands in time so that the overall power consumption becomes less varying and costly.
- To change people's mind a bit more intelligent during the day for better distribution of energy consumption.
- To select a good prediction model for predicting 24 hour ahead consumption and cost.
- To flatten power distribution graph when abnormal electricity changes occur.

3.2 Research Questions

RQ.1) What are the methods to measure and analyze the power consumption of household applications in a real-time environment?

RQ.2) How can we model the energy consumption of single household and their superposition?

RQ.3) How should power consumption be reduced in household appliances to flatten daily consumption patterns?

The first research question is formulated to retrieve information about methods to measure electricity. More importantly, assumptions and variations with real-time data are accounted and analyzed. The second research question is framed to filter different types of models and select a suitable model for fitting the data. In addition, smart way of superposition of the data is essential to observe behavior of households. The third research question is acquired to find the optimal way to flatten daily consumption patterns.

3.3 Research Methodology

The research methodology involved in our research using case study and stages that are followed for answering the research questions are as below:

1. In the first stage of the research we have to perform a literature review related to Smart Meters. The data which is measured using Smart Meters is obtained from an energy provider. The results which are obtained from data are plotted in the form of graphs and observations are done regarding the consumption, price-cost, cumulative cost of the household and further statistical analysis. Particularly, in this stage the

results are statistically summarized from the arrived data. The flow of research methodology is shown in below figure.

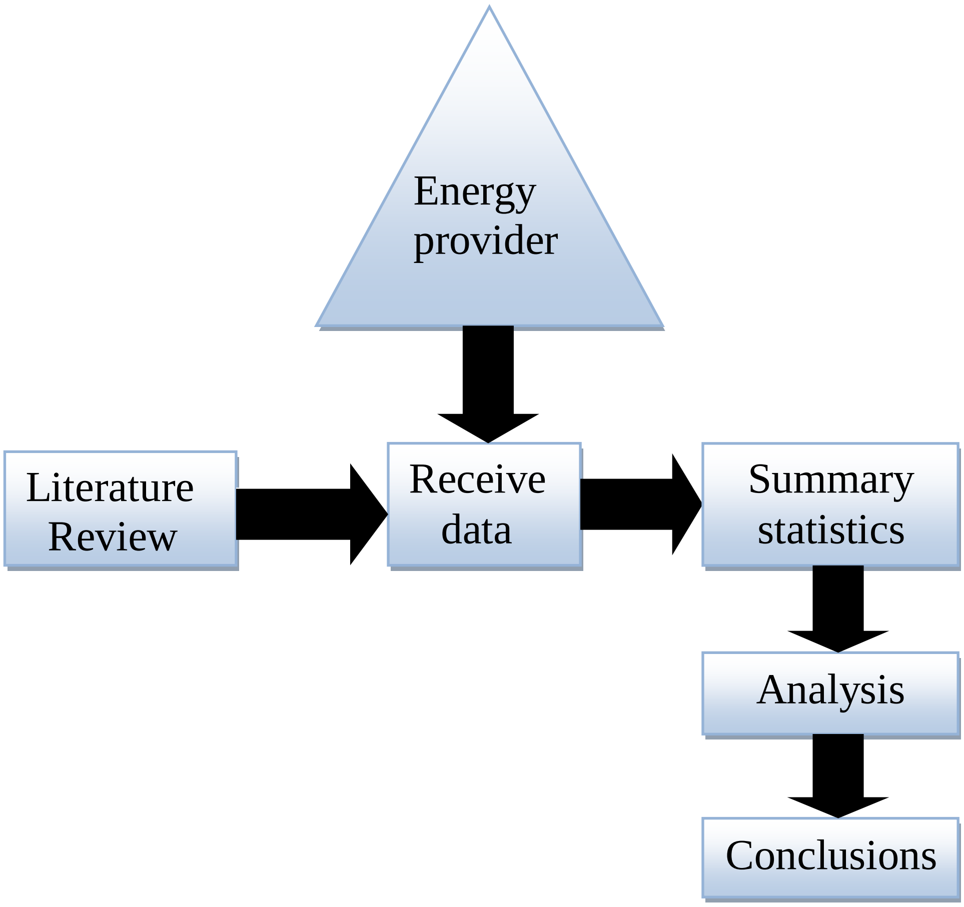


Figure 3.1 Flow of Research Methodology

2. In the second stage of the research, a prediction model is selected. Model matching should be done after model selection, which is followed by validation. Different household energy consumption and cost patterns can be modeled using ARIMA. Various data sets are processed to obtain price-consumption correlations for observing behavior of households using superposition.

3. In the third stage of research, a method of flattening consumption patterns is identified and developed, aiming at flattening daily patterns and attempting to change the attitude of consumers. Finally, conclusions are drawn from the analysis.

4 CASE STUDY

An analysis of data involving a method of research is called case study. Some steps had been followed in the case study of our research. The steps are as follows:

1. In the first step of our study, the Smart Meter data is obtained from a local energy provider that prefers to remain secret. This data was received by our supervisor.
2. This received data is passed to our team by supervisor for evaluating and analysing the results. Smart Meter data is a validated one as it is obtained from an energy utility provider.
3. The received data contains two sets of Microsoft Excel sheets.
   a) The first excel sheet contain price values from days 1 to 30 of the month of April 2012. The name specified for this sheet is “Spotpriser April 2012”. We considered price values of area 4, south of Sweden, which is named as “SE4” in the sheet. The hourly price is varying for each day, i.e. each day has 24 different prices.
   b) The second sheet contains Smart Meter consumption data values of 16 households. The 24 hourly consumption values per day and household are included in the Excel sheet. The data in the sheet ranges from day 30 to day 1 of the month of April. We considered time from 1:00 hour to 23:00 hour of the current day in the sheet as it is, and 00:00 hour of next day which is considered as 24:00 hour of present day. This data is carefully observed and noted in a separate Excel sheet. A careful observation is needed when moving the data from one sheet to another, as skipping of data has a great impact on the results. For reasons of anonymity and privacy, the 16 households are referred by a number from 1 to 16.
4. After reading the data, we need to interpret the real Smart Meter data in a new Excel sheet. In the formulated sheet we arranged time (1:00 to 24:00 hour), price, energy consumption and calculation of cost, cumulative cost, cumulative consumption, lag 1 autocorrelations of price, cost, energy consumption and correlations of price-cost, price-consumption and cost-consumption is determined.
5. Based on the results obtained, graphs are plotted for time versus consumption (KWh), time versus price, time versus cost and time versus cumulative cost. The time is plotted on the x-axis and consumption is plotted on the y-axis for time-consumption graph; time on the x-axis and price on the y-axis for time-price graph; time on the x-axis and cost on the y-axis for time-cost graph; and lastly for time-cumulative cost, time is plotted on the x-axis and cumulative cost is plotted on the y-axis.
6. **Correlation**: It is a statistical measure of how two variables move in relation with each other. It ranges between +1 and -1 [29]. They are of two types.

   Positive correlation: A relationship between two variables which move in the same direction i.e. as one variable decreases, the other variable also decreases and when one variable increases the other variable increases is called positive correlation. In statistics, the maximal value of positive correlation is represented by +1 [29].

   Negative Correlation: A relationship between two variables which move in the opposite direction i.e. as one variable decreases, the other variable increases and as one variable increases, the other variable decreases is called negative correlation. In statistics, the maximal value of negative correlation is represented by -1 [29].

In addition to that computation of price-cost correlation, price-consumption correlation and cost-consumption correlation, average, standard deviation, and coefficient of variation for price, cost and energy consumption is done.

7. The above computed steps are repeated for all days in a month per single household. Similar graphs are generated for all 16 households from the results obtained.
8. The complete analysis can only be achieved with the help of another classified sheet. So, we named those sheets as analysis succeeding with a number representing the household. In this determined sheet, we calculated real cumulative cost, cumulative cost based on average price, difference of real cumulative cost and cumulative cost based on average price. The correlation of price with consumption is done as positive correlation is expected to yield high cumulative cost. A comparison of cumulative based on hourly price with those based on average price is computed because this reveals when hourly prices are disadvantageous/advantageous for consumers. Two graphs are plotted, one with the number of the day on the x-axis and price-consumption correlation on the y-axis represented as correlation graph, another with difference between real cumulative cost and cumulative cost based on average price on the y-axis and the number of the day on the x-axis representing difference graph.
9. The maximum values of data such as price, peak power consumption and cost are documented independently in sheets of "Microsoft PowerPoint" for better understanding. The analysis is performed as a combination of 16 household results and correlation/difference graphs are presented in excel sheets.

   Cross correlation: Cross correlation between consumption and price is a measure to know how effective hourly charging was for the customer. It is a measure for interdependencies.

   +100%: price and consumption follow each other either up/down
   ± 0: price and consumption are approximately independent
   -100%: price up implies consumption down and vice versa

   - For positive correlation, there is a tendency that low prices occur together with high consumption.
   - For negative correlation, there is a tendency that low prices occur together with low cost.

   The mentioned correlations in this research helps the reader with much easier and quicker analysis.
10. A model search has been done, and the XLSTAT tool [40] is found to fit the combination of model selection and prediction. Various ARIMA models are tested by taking consumption data as a reference of one household and comparison of all models is carried to search for the best fitted model.
11. The identification of ARIMA model that fits best is finally chosen and graphed for different cases. The parameters AIC and SBC of the model are quite low and model is fitted on original graph when compared to other models. According to the standard statistics [24], the mentioned parameter values should be low. The model with lowest AIC and SBC has the tendency to exhibit good results. Moreover, different observation characteristics of the model also displayed various impeccable outcomes. As adequacy, efficiency and accuracy strongly reflects the nature of the model motivated us to use this model in our research work.
12. Finally, flattening of the consumption pattern is observed.
13. By performing the above steps, case study is successfully implemented.

5 RESULTS

RQ.1) What are the methods to measure and analyze the power consumption of household applications in a real-time environment?

The research question is split into two complementing directions of research as follows:

Methods to Measure:

There are multiple traditional ways of assessing the meter and its data. The better way of assessing the meter is implemented by using Smart electricity meters rather than opting for traditional meters. The ancient and next generation methods of measuring the energy are explained in background work of this thesis paper. A literature review [2] has been performed to answer the question. The presentation of this part of the research question and its answer is mainly invoking an impressive knowledge for the people of various developed and underdeveloped nations regarding the fundamental changes among electricity market. From the literature survey and final suggestions of research, it was found that Smart Meter is the efficient meter to measure power consumption of household in real-time environment.

Analysis:

We acquired real time hourly power consumption data of 16 households and prices for April month from an electricity provider in the form of excel sheets. Time, price, cost, consumption, cumulative consumption, cumulative cost are tabulated in excel sheet. Lag-1 autocorrelation, price-cost correlation, price-consumption correlation, cost-consumption correlation, average, standard deviation and coefficient of variation of price, cost and consumption are calculated. Each and every factor specified above is tabulated for easy understanding. The data is arranged for all the 16 households and graphs are drawn for consumption, price, cost and cumulative cost. The parameters that are required are defined as follows.

- **Power**: Power is defined as the energy consumed per unit time.

  Power = e/t

  where e is energy consumption in KWh
  t is time

- **Cost (c):** Cost is calculated as the product of price and energy consumption. The unit of measurement is in monetary units.

  c = p.e

  where e is energy consumption in KWh
  p is price in monetary units/KWh

- **Average (m)**: It is defined as sum of different quantities divided by the total number of these quantities. It is formulated as follows:

  $$m = 1/n \cdot \sum_{i=1}^{n} X_i$$

  Where n is total number of terms

X_i is value of each individual element
i = 1, 2, 3, -------- n

- **Standard Deviation (*s*)**: A measure of dispersion of a set of data from its mean is called standard deviation. Standard deviation is calculated as square root of the variance [16]. It is formulated as follows:

$$s = \sqrt{1/(n-1).\sum_{i=1}^{n}(Xi - \overline{X})^{2}}$$

Where n is total number of terms
X_i is value of i^{th} terms
$\overline{X}$ is mean
i = 1, 2, 3, ------- n

- **Autocorrelation**: A mathematical representation of the degree of similarity between a given time series and a lagged version of itself over successive time intervals is termed as autocorrelation [17].

$$r_k = \left(\sum_{i=1}^{n-k}(y_i - \bar{y})(y_{i+k} - \bar{y})\right) / \sum_{i=1}^{n}(y_i - \bar{y})^2$$

where r_k is lag k autocorrelation
i = 1, 2, 3, ------ n
k = 1, 2, 3, ------ n
n is total number of terms
$\bar{y}$ is average of n terms

- **Cumulative consumption (E_i)**: The cumulative consumption is the sum of hourly consumptions during the first *i* hours of the day. The first value of cumulative consumption is taken as it is from consumption.

$$E_i = e_i + E_{i-1}$$

where E_i is cumulative consumption
i = 2, 3, 4, --------- n
e_i is consumption
E_{i-1} is previous cumulative consumption

- **Cumulative cost (C_i)**: The cumulative cost is the sum of hourly costs during the first *i* hours of the day. The first value of cumulative cost is taken as it is from cost.

$$C_i = c_i + C_{i-1}$$

where C_i is cumulative cost at i^{th} hour
i = 2, 3, 4, -------- n
c_i is cost at i^{th} hour
C_{i-1} is previous cumulative cost

- **Coefficient of variation**: The ratio of standard deviation to average is called coefficient of variation. It is formulated as follows:

Coefficient of variation = (Standard deviation / Average)

- The product of average price and larger value of cumulative consumption is called cumulative cost based on average price. It is formulated as follows:

  ACum = $E.\,\overline{p}$

  Where ACum is cumulative cost based on average price

  $$E = \sum_{i=1}^{24} e_i$$

  $$\overline{p} = 1/24 \sum_{i=1}^{24} p_i$$

- The sum of product of consumption and price in a particular hour is called cumulative cost based on hourly price. It is formulated as follows:

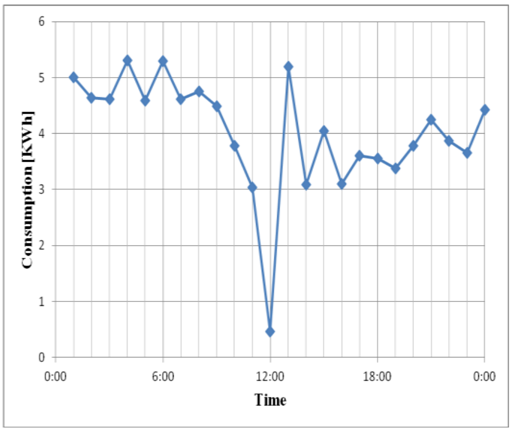
  HCum = $\sum_{i=1}^{24} e_i \,.p_i$

  Where HCum is cumulative cost based on hourly price
  i is hour of the day
  E is sum of consumption of a day
  e_i is consumption of particular hour
  p_i is price on particular hour
  $\overline{p}$ is average price

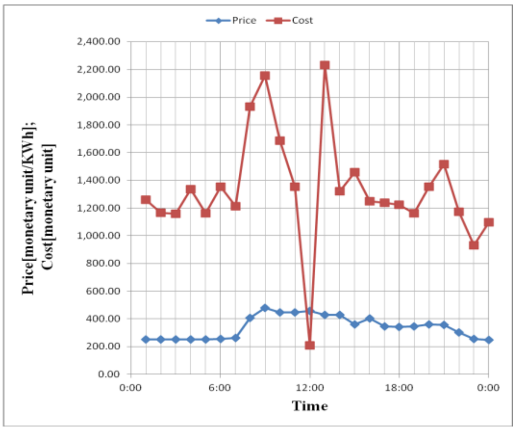
Based on the systematically analyzed data, the graphs are drawn as follows. The selected graphs are displayed in the report as the data is interesting.

- Energy consumption graph of some households are shown in the below figures by considering consumption (KWh) on the y-axis and time (24 hours) on the x-axis.
- Price and cost graph of some households are shown in the below figures by considering price, cost on the y-axis and time (24 hours) on the x-axis.
- Cumulative cost graph of some households are shown in the below figures by considering cumulative cost on the y-axis and time (24 hours) on the x-axis.

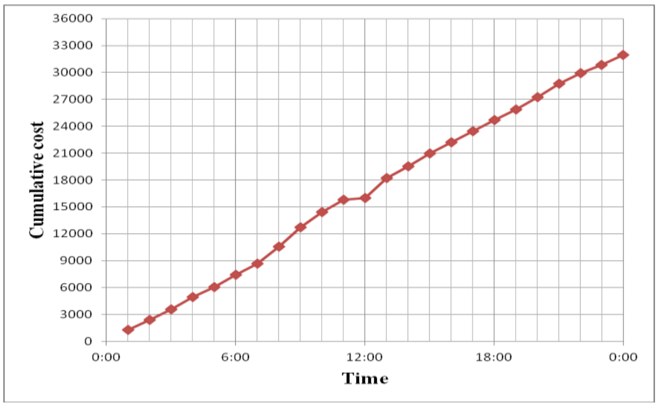
Three graphs for consumption, price-cost and cumulative cost on a particular day of a household, which are interesting for some specific reasons, are shown below. This is the first step of evaluating multiple graphs for further references.



Energy Consumption



Price and Cost

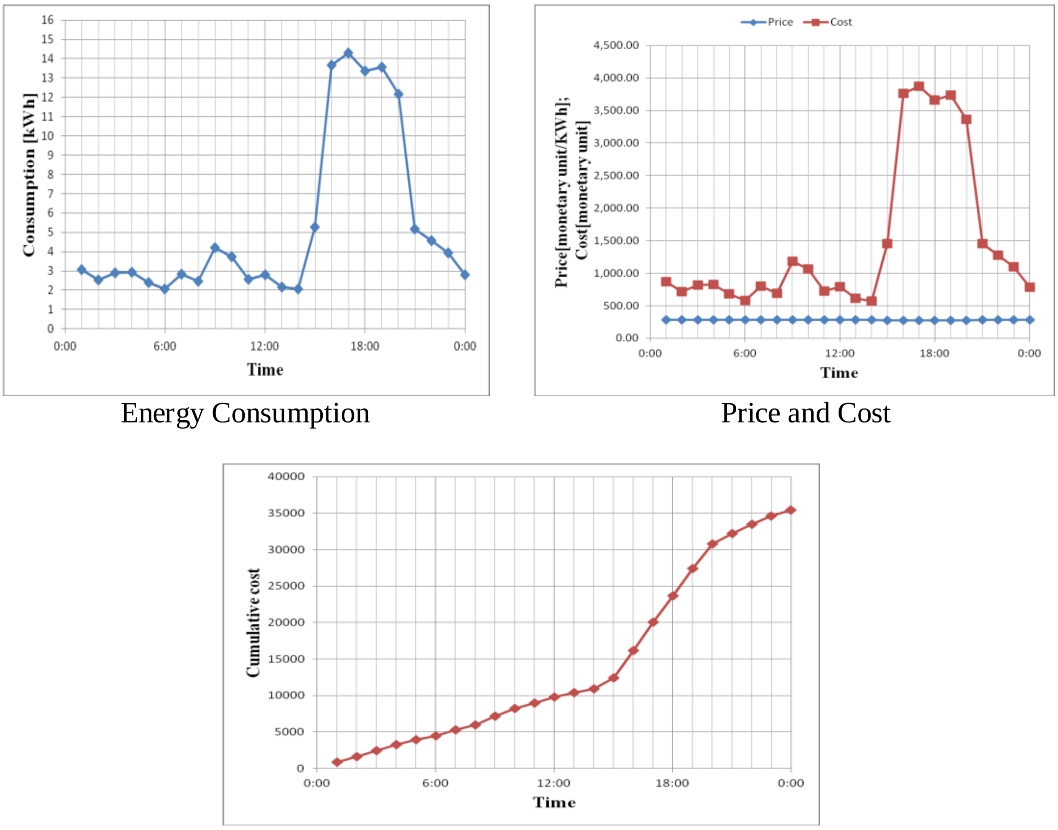


Cumulative cost

Figure 5.1 Energy Consumption, Price, Cost and Cumulative cost of household 3 on April 3

The energy consumption showed in the above figure 5.1 regarding household 3 declines from hour 8:00 to 12:00 and increases sharply from 12:00 to 13:00. Cumulative cost graph is almost linearly increasing from 1:00 to 24:00 hours. The user should be smart enough to play a safer role in utilising energy efficiently by avoiding spikes.

From figure 5.2 regarding household 5, high energy consumption when compared to other households are recorded at 17:00 hour on April 14. The price on April 14 is much less varying. So the price graph is observed as flat. As the user is consuming much energy, the cost factor is high even though the price is low. From the cumulative cost graph, we infer that the curve is not increasing linearly but becomes much steeper at high consumption hours.



Energy Consumption

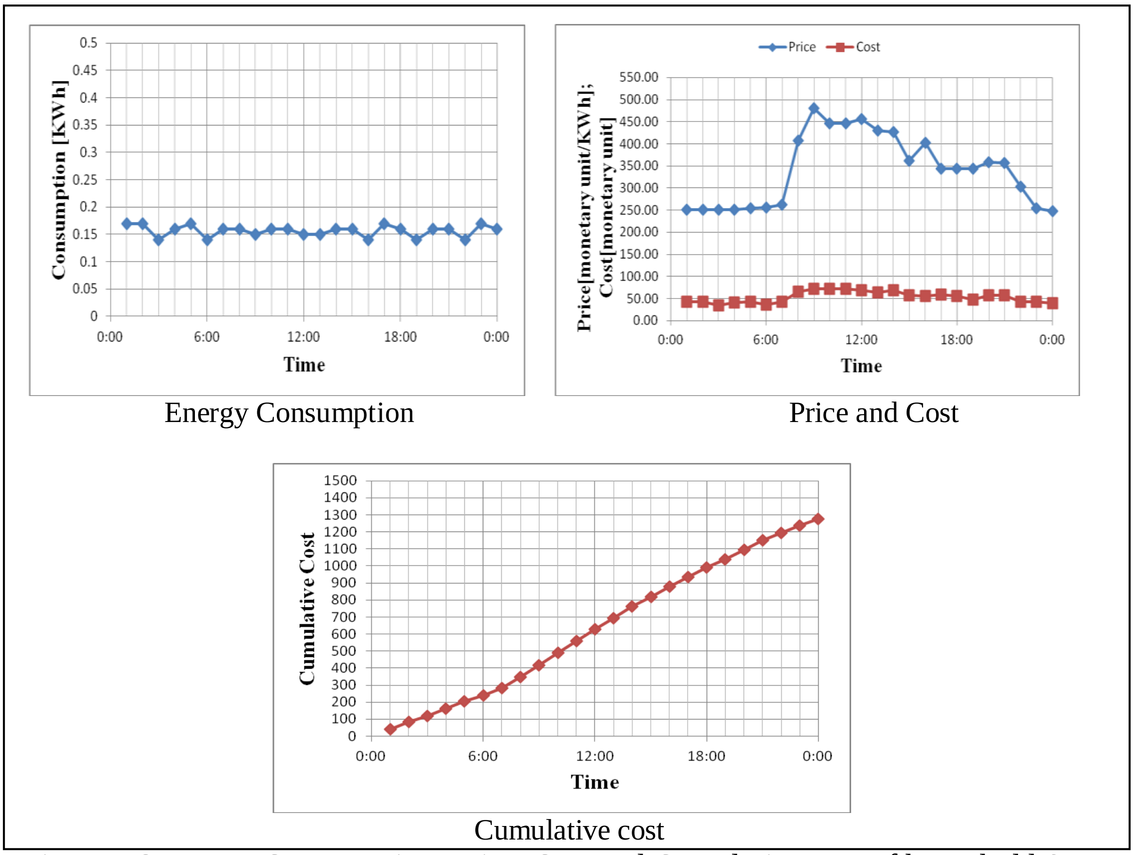
Price and Cost

Cumulative cost

Figure 5.2 Energy Consumption, Price, Cost and Cumulative cost of household 5 on April 14

From the below figure 5.3 regarding household 6, complete flatten energy consumption is observed with very low consumption on April 3. As consumption is very low, cost is low as well, as it is a product of price and consumption. Cumulative cost increases almost linearly from 1:00 to 24:00 hours as the cost is not constant over time.

From the below figure 5.4 regarding household 7, consumption shift between 0 and 1 is observed. This behaviour is different from the remaining households. This unusual behaviour indicates the type of meter that only counts multiples of kw. Here the user is cautioned about the power. The cumulative cost is not increasing linearly but following a stepwise pattern.

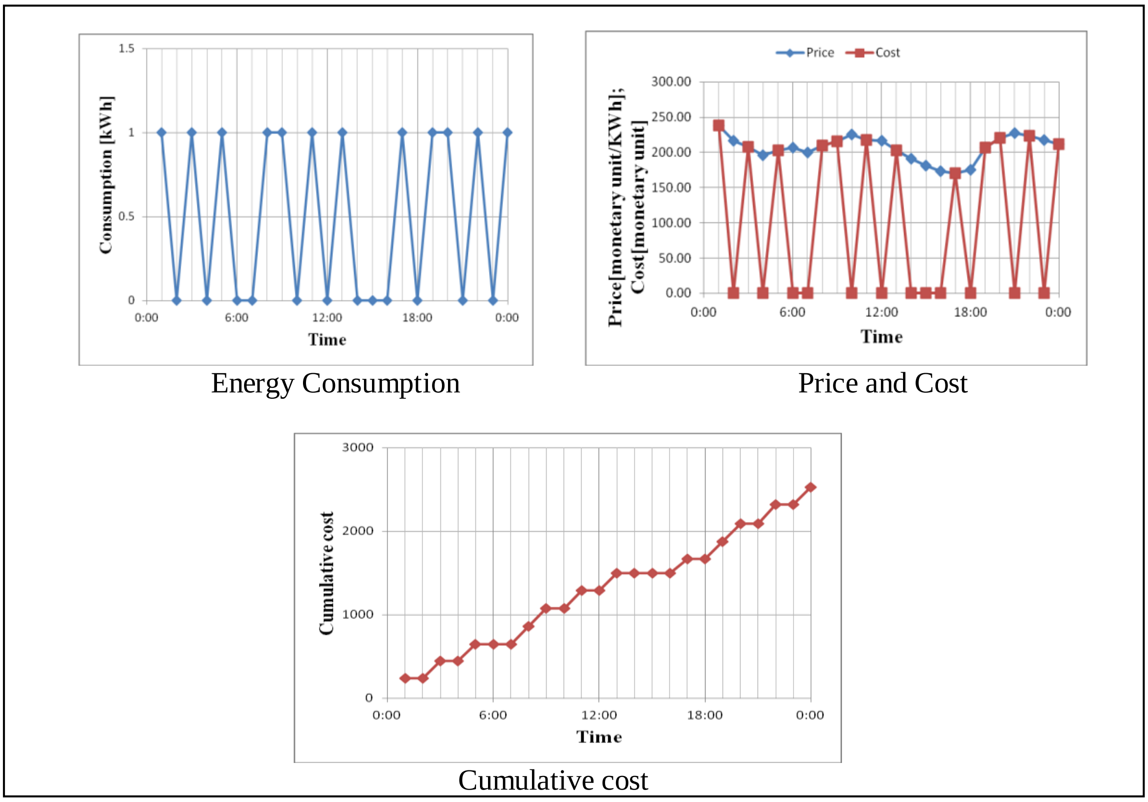


Energy Consumption

Price and Cost

Cumulative cost

Figure 5.3 Energy Consumption, Price, Cost and Cumulative cost of household 6 on April 3



Energy Consumption

Price and Cost

Cumulative cost

Figure 5.4 Energy Consumption, Price, Cost and Cumulative cost of household 7 on April 1

The graphs for energy consumption, price-cost and cumulative cost which are generated above can help the users to study their daily electricity usage. As it is difficult to compare time plots, the necessity of understanding the correlation is evaluated. The parameters obtained in the correlation data sheet is defined in chapter 4. For the convinience of readers, we could only present a specific set of household patterns, revealing somehow interesting behaviours.

After analysis, we found that it would be quite interesting to compare the peak consumption of all households during a particular hour in April 2012 on a single graph.

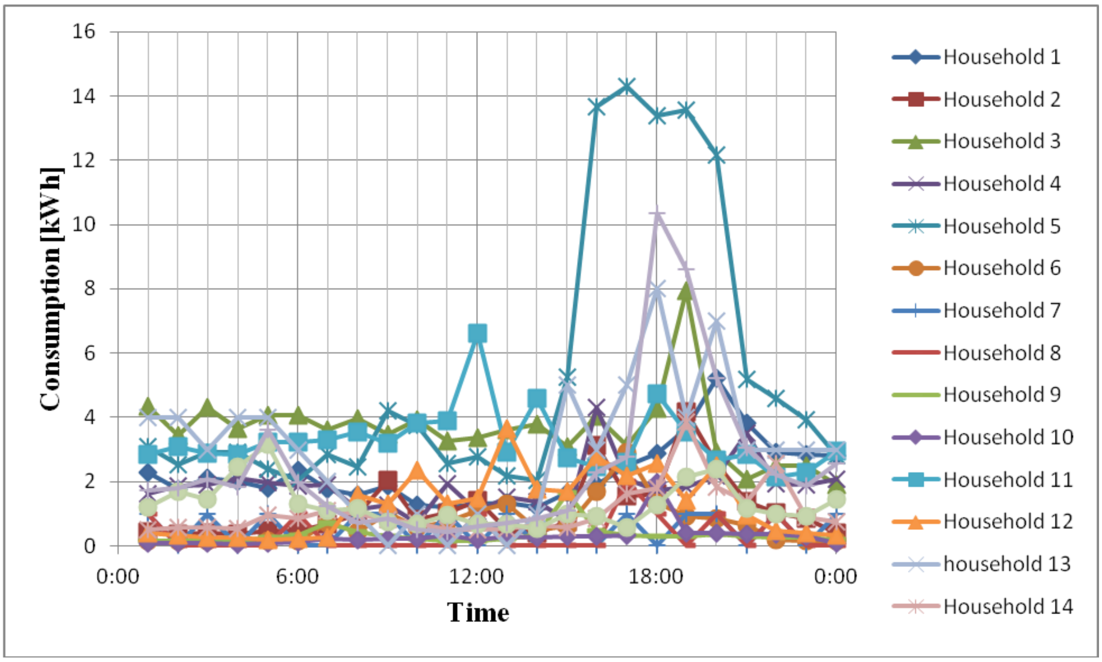


Figure 5.5 Peak energy consumptions of different households

By comparing consumption values of all 30 days in 16 households, high consumption for each household is selected and plotted on a single graph as a reference. From the figure 5.5, household 5 consumed maximum power when compared to other households.

Correlation of 16 Households:

The steps followed to calculate and analyse correlation are as follows:

- The price-consumption correlation, real cumulative cost, cumulative cost based on average price and difference between real cumulative cost and cumulative cost based on average price is calculated for 30 days of all the 16 households.
- Two graphs are generated for each household (correlation and difference graph).
- Correlation graphs are plotted with the correlation on y-axis and number of days on x-axis.
- Difference graphs between real cumulative cost and cumulative cost based on average price on the y-axis and number of days on the x-axis is plotted.
- By analyzing all the graphs and data we came to know that on days during which the correlation between price and consumption is positive, the real cumulative cost is higher than the cumulative cost based on average price, whereas days during which the correlation between price and consumption is negative implies the real cumulative cost is less than the cumulative cost based on average price.
- Real cumulative cost i.e. cumulative cost obtained by hourly price is denoted by HCum and cumulative cost based on average price during the day is denoted by

ACum. A consumer with hourly pricing benefits if HCum is less than ACum and loses if HCum is greater than ACum.

- Depending on the sign of the cross correlation between HCum and ACum, we arrive at the following cases. Bad indicates hourly pricing leads to higher cost than average pricing. Good indicates hourly pricing leads to less cost than average pricing.

Positive $\Leftrightarrow$ HCum $>$ ACum (Bad)
Negative $\Leftrightarrow$ HCum $<$ ACum (Good)
Disappearing $\Leftrightarrow$ HCum $\approx$ ACum (Neutral)

The correlation of 16 households is executed, and some of the most interesting results are displayed below.

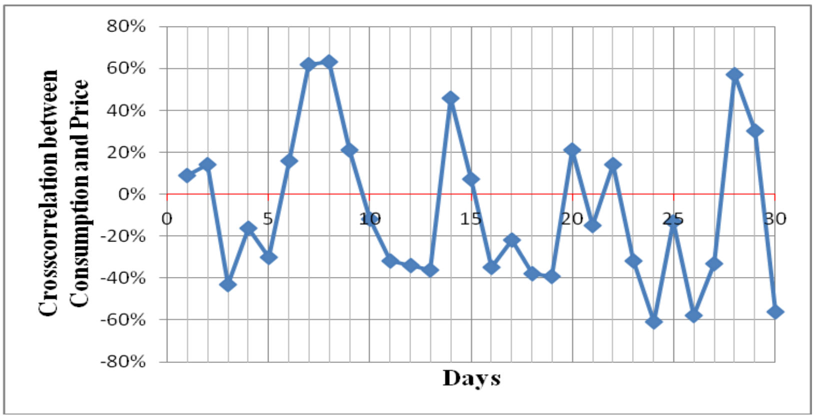


Figure 5.6 Correlation graph for household 1

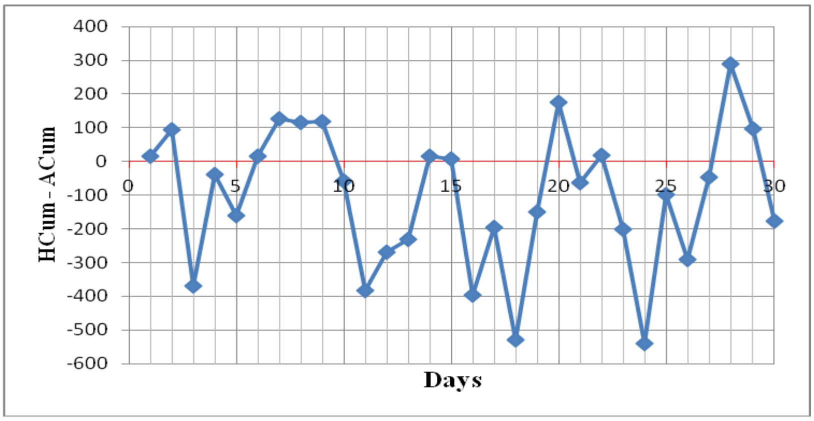


Figure 5.7 Difference graph for household 1

From the figures 5.6 and 5.7 of household 1, we observe that days of negative correlation imply that HCum is less than ACum, which means savings with hourly pricing. For this user, this happens on the majority of days.

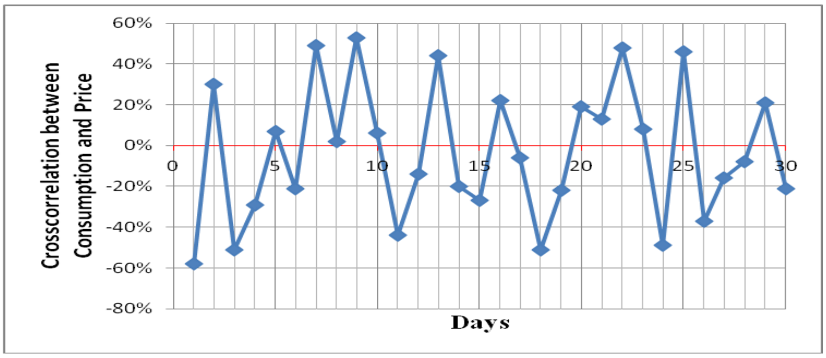


Figure 5.8 Correlation graph for household 3

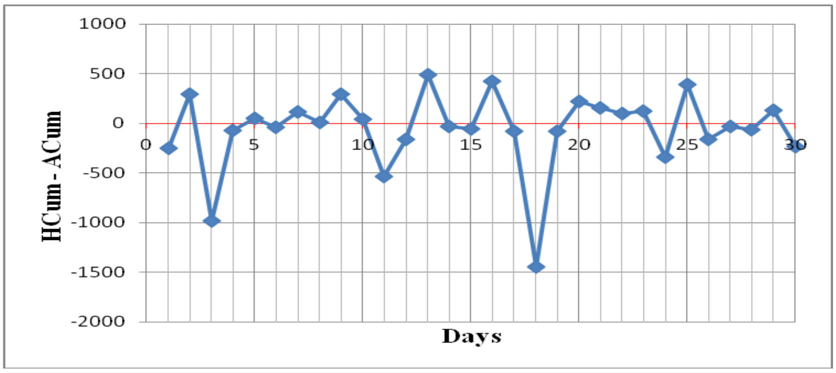


Figure 5.9 Difference graph for household 3

From figures 5.8 and 5.9 of household 3, the consumption of user is partially negative and partially positively correlated with the price. Maximum negative difference is observed on April 18, on which the user experiences a moderate step-down of cost.

From figures 5.10 and 5.11 of household 6, the consumption of user is positively correlated with price. As HCum is greater than ACum results in positive difference, the user mostly loses control over consumption.

From figures 5.12 and 5.13 of household 10, the consumption of user is mostly experiencing positive correlation with price where he can be advised to change his patterns.

From figures 5.14 and 5.15 of household 13, the consumption of user is negatively correlated with price. This results in receiving negative differences. This kind of user is an inspiration to rest of the users in controlling the energy.

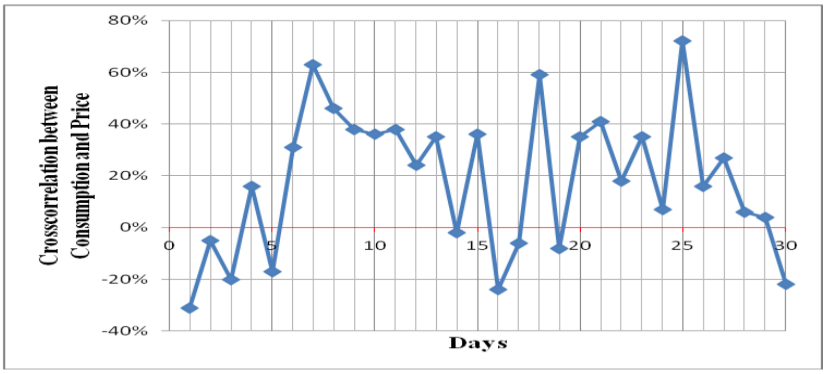


Figure 5.10 Correlation graph for household 6

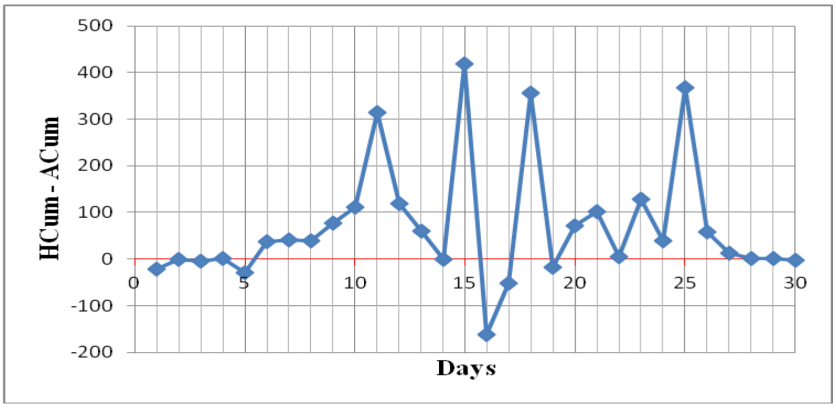


Figure 5.11 Difference graph for household 6

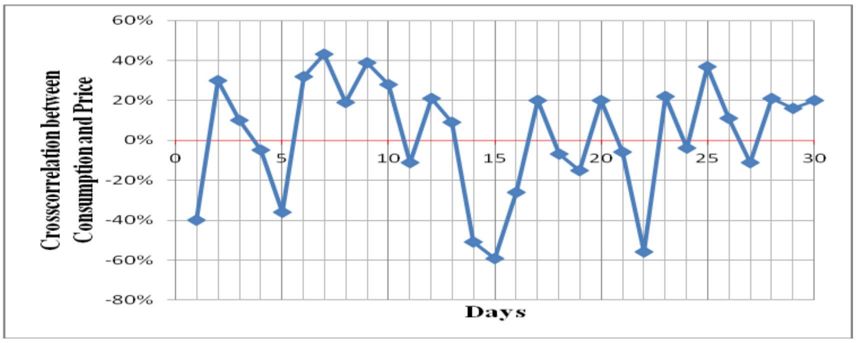


Figure 5.12 Correlation graph for household 10

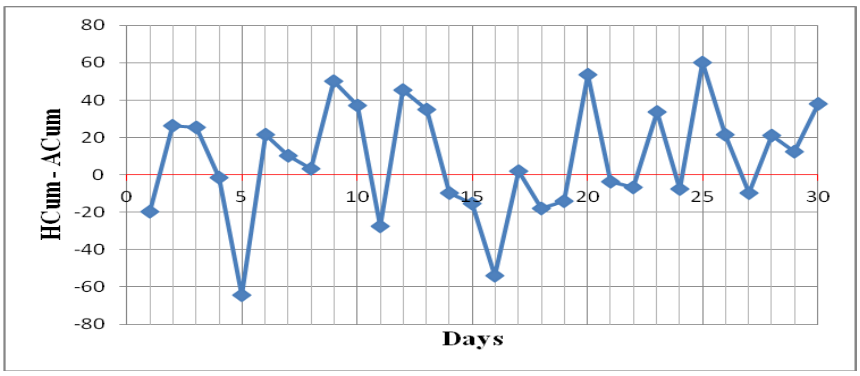


Figure 5.13 Difference graph for household 10

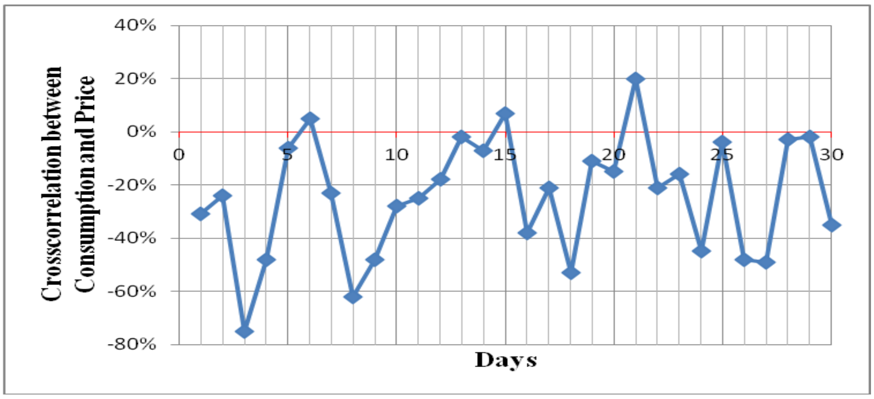


Figure 5.14 Correlation graph for household 13

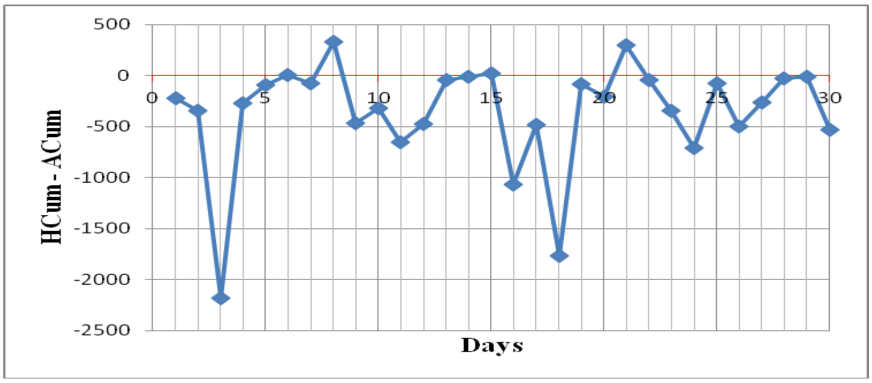


Figure 5.15 Difference graph for household 13

From the correlation part of results we infer that the more negative the correlation, the lower will be the cost based on hourly readings and vice versa. Here the correlation graph results are useful in allowing the users to think about their way of life and corresponding consumption patterns. The user can reduce cost while targeting negative correlation.

RQ.2) How can we model the energy consumption of single households and their superposition?

It was not possible to see any generic daily pattern between the households. To overcome the challenges and conflicts in the electricity market, future predictions are required to distribute energy economically and sufficiently. Hence, finding a suitable prediction model is essential to predict future consumption and cost. The capture of usage patterns through ARIMA models will be investigated, which will also allow the prediction of usage to a certain extent. The energy consumption of households in our research is modeled using a seasonal ARIMA model. Time series collected on hourly, daily and monthly data has seasonal behavior. As our data is related to hourly measurements of one month, seasonal ARIMA model is chosen. This model has the ability to achieve flexibility of data and deliver accuracy results. Modelling of ARIMA can be exercised in the following stages:

1. Identification
2. Estimation
3. Validation
4. Prediction

A flow chart is formulated below for easy understanding of the model.

Flow Chart:

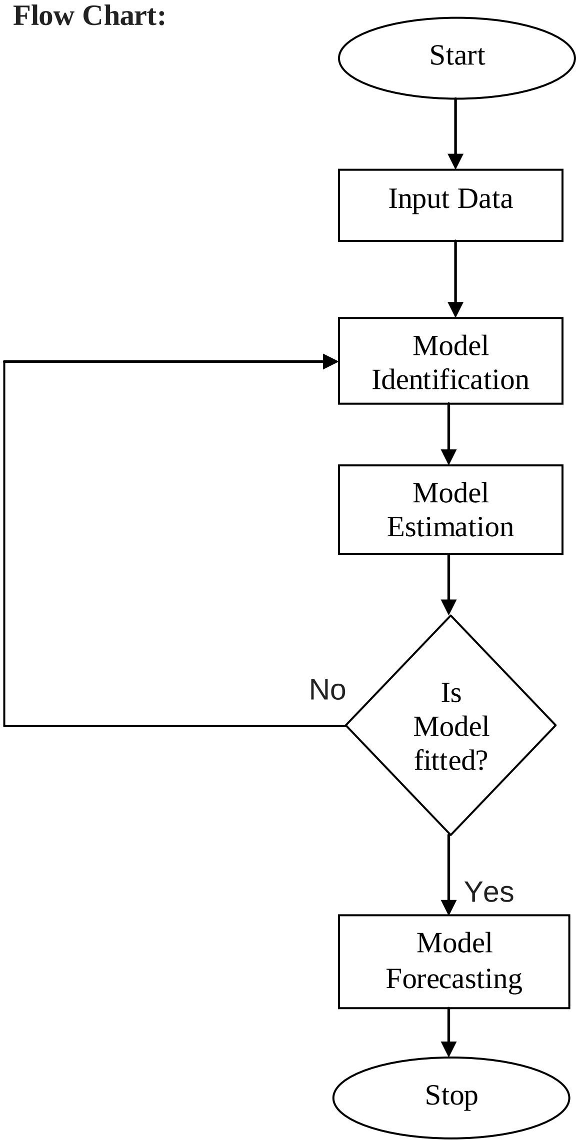


Figure 5.16 Flow chart of ARIMA Modeling

1. **Identification:**

In the identification stage, we need to test different set of models and select a model that fits our data. In this stage, goodness of fit statistics are computed and observed. From complete observations and computations, analysis can be drawn to select one ARIMA model that can fit.

In our thesis we have used AIC to identify the model for goodness of fit. We have tested different ARIMA models like ARIMA (1, 0, 0) $(0, 1, 0)_{12}$, ARIMA (1, 0, 1) $(0, 1, 1)_{12}$, ARIMA (0, 1, 1) $(0, 1, 1)_{12}$, ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ by taking consumption and cost of particular day.

Parameter	ARIMA (1, 0, 0) (0, 1, 0)	ARIMA (1, 0, 1) (0, 1, 1)	ARIMA (0, 1, 1) (0, 1, 1)	ARIMA (2, 0, 1) (2, 1, 0)
AIC	32.565	36.540	34.790	39.897
SBC	33.535	38.480	35.984	42.807
Fitness	Unfit	Unfit	Unfit	Fit

Table 2 Selection of best fit model using XLSTAT tool by considering consumption values

By examining different models, ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ is selected because goodness of fit statistics is best, model is fitted accurately to the original graph, values of AIC and SBC are small when compared to other models. In the above table even if order of the model ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ is double, the values are nearer to the remaining models which indicates model has smaller AIC and SBC values.

The parameters are described as follows:

Sum of Squared Errors of Prediction: Sum of squares of residuals is called sum of squared errors. The formula for SSE is described as follows:

$$\text{SSE} = \sum_{i=1}^{n} (X_i - \overline{X})^2$$

where n is number of observations
$i = 1, 2, 3, \text{- - - - - - -} n$
$\overline{X}$ is the predicted value
X_i is the data

Mean Absolute Percentage Error: A measure of how much a dependent series varies from its model predicted level is called mean absolute percentage error [23]. The formula for MAPE is described as follows:

$$\text{MAPE} = 1/\text{n}. \sum_{i=1}^{n} ((X_i - \overline{X})/X_i)$$

where n is number of observations
$i = 1, 2, 3, \text{- - - - - -} n$
X_i is the data
$\overline{X}$ is predicted value

Final Prediction Error: Final prediction error provides a measure of the quality of model. Different models can be compared using this criterion. The smaller the FPE, the more accurate will be the model [24]. The formula for FPE is described as follows:

FPE= (white noise variance)**.** $((n+p+q) / (n-p-q))$ [35]

where n is number of observations
p is order of autoregressive term
q is order of moving average term

Akaike Information Criterion: Akaike Information Criterion provides the measure of quality of model. Different models can be compared using this criterion. The smaller the AIC, more accurate is the model [24]. The formula for AIC is described as follows:

AIC = -2**.** Log(likelihood) + 2**.**K [35]

$K = p+q+1$
where K is number of parameters in the model
p is order of autoregressive component
q is order of moving average component

Akaike Information Corrected Criterion: AIC corrected for sample size is called Akaike Information Corrected Criterion [25]. The formula for AICC is described as follows:

AICC = AIC + $(2.n\ (p+q+1))/(n-(p+q)-2)$ [35]

where n is number of observations
p is order of autoregressive component
q is order of moving average component

Schwarz criterion: It is a model selection criterion for selecting a model among various models. The formula for SBC is described as follows:

SBC = AIC + 2.909

2. **Estimation:** All the parameters identified in the above stage can be estimated in this stage. The objective of estimation is to reduce sum of squares of errors. The smaller the SSE, the better the model fits the data.

3. **Validation**: Validation is a process of selecting the model that fits original graph. If the model is not fitted to the original graph, then the identification step is done again to select another model. This process is continued until a best fit model is selected. Validation can be done by examining the residuals.

The residuals of the model are examined to check whether the model fits to the original graph or not. Residuals are nothing but the difference between the original values and the predicted values. The smaller the residuals in the graph indicate, the closer is the model. The residuals vary depending on the original graph. If the original graph is below the ARIMA model on same time then the residual show downwards. If the original graph is above the ARIMA model on same time then the residual show upwards. An equation for residual is shown as follows:

Residual = $y_i - \bar{y}_i$

where y_i is the original value

$\bar{y}_i$ is the predicted value

Sometimes more than one model seems to fit for same dataset. In that case the following cases have to be considered in deciding on the model.

- Choose the model with few parameters.
- Compare the models by considering statistics such as SSE, AIC, AICC and SBC. The lower the values of above statistics, the better will be the model. The use of these statistics is explained above.
- Pick the model having lowest standard errors for predicting the future values.

4. **Prediction**:

Finally, a model is used to predict the future values after estimating and validating it. Past values are given as input to predict the future values and this process is known as prediction.

We modelled ARIMA in 'Microsoft Excel' by installing an add-in XLSTAT. By clicking XLSTAT one will see the menu which can be found in Appendix A Figure 0.1.

As we are fitting ARIMA model to a time series, we have to click "Time" menu which can be found in Appendix A Figure 0.2. From those options we have to select "ARIMA". After clicking on "ARIMA" an ARIMA dialog box will appear which can be found in Appendix A Figure 0.3. In the 'time series' column, we select the data for which we have to fit the ARIMA model. In the 'Date data' column, one has to select the hours of the day from 1 to 24. The ARIMA model we have selected is the (2, 0, 1) $(2, 1, 0)_{12}$ model, where autoregressive term is of order 2 and moving average term is of order 1 in a non seasonal model, while autoregressive term is of order 2 in seasonal model with a seasonal difference of order 1. Different cases are tested on the data for 'cost' as well as for 'consumption'.

Seasonal ARIMA model is used in our thesis. (p, d, q) is taken as (2, 0, 1), (P, D, Q) is taken as (2, 1, 0) and S is taken as 12 can be found in dialogue box shown in Appendix A Figure 0.3. By clicking 'predictions' in the 'ARIMA' dialog box we have to give number of predictions to observe in the ARIMA graph which can be found in Appendix A Figure 0.5. As there is a need to know 24 hour prediction, we have given 24 as prediction time steps.

Validation of XLSTAT tool:

Parameter	**XLSTAT tool**	**Manual calculation**
AIC	40.721	40.721
AICC	57.521	57.662
SSE	0.000	0.000
SBC	43.631	43.63

Table 3 Comparison of values of XLSTAT tool and manual calculation

In order to validate the XLSTAT tool, manual calculations are derived for all the parameters based on the formulas. These manually calculated results are compared with automated tool generated values. From the values of table 3, we observe that the results of the manual calculations are approximately equal to tool-generated values.

Prediction Analysis:

A prediction for 24 hours is done for both consumption as well as cost. 500 iterations and 24 observations are performed to the data. Different cases are considered for prediction of cost and consumption. The cases are as follows:

- Consumption of different households on same day (April 18)
- Consumption of the same household on different days
- Cost of different households on same day (April 26)
- Cost of the same household on different days
- Maximum positive correlation between price and consumption
- Maximum negative correlation between price and consumption
- Maximum difference between real cumulative cost and cumulative cost based on average price
- Minimum difference between real cumulative cost and cumulative cost based on average price
- Real cumulative cost is approximately equal to cumulative cost based on average price

Analysis of different cases has been studied to observe transparent nature of customers. These study cases can also improve the real-life context of the consumer from all household data used in the research. The graphs for few cases are shown below. Time is plotted on the x-axis and consumption on the y-axis for ARIMA consumption graph. For ARIMA cost graph, time is plotted on x-axis and cost on y-axis. For the residuals graph, time is plotted on x-axis and residuals are plotted on y-axis for consumption as well as for cost. Residual graph is formed by deducing ARIMA consumption value from original consumption of the household. The equations below are derived to represent average and total cost during the day. They are as follows:

Consumption of household per hour during the day is $E_i\,(d,h)$

Cost of household per hour during the day is $C_i\,(d,h)$

Average cost during the day is $\bar{c}_i\,(d) = 1/24 \sum_{h=1}^{24} C(d,h)$

Total cost during the day $C_i\,(d) = \sum_{h=1}^{24} C_i\,(d,h) \,.\, E_i\,(d,h)$

$$\bar{C}_i\,(d) = \bar{c}_i\,(d) \,.\sum_{h=1}^{24} E_i(d,h)$$

where *d* denotes the day
i denotes the household
h denotes the hour

The outcome of 24 hour prediction generated from the tool is shown below to act intelligently by the user. The results from the ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ model for consumption of different households on same day (April 18) are shown below in Figure 5.17.

The 24 hour prediction is based on 24 hour previous consumption values for ARIMA consumption and 24 hour previous cost values for ARIMA cost.

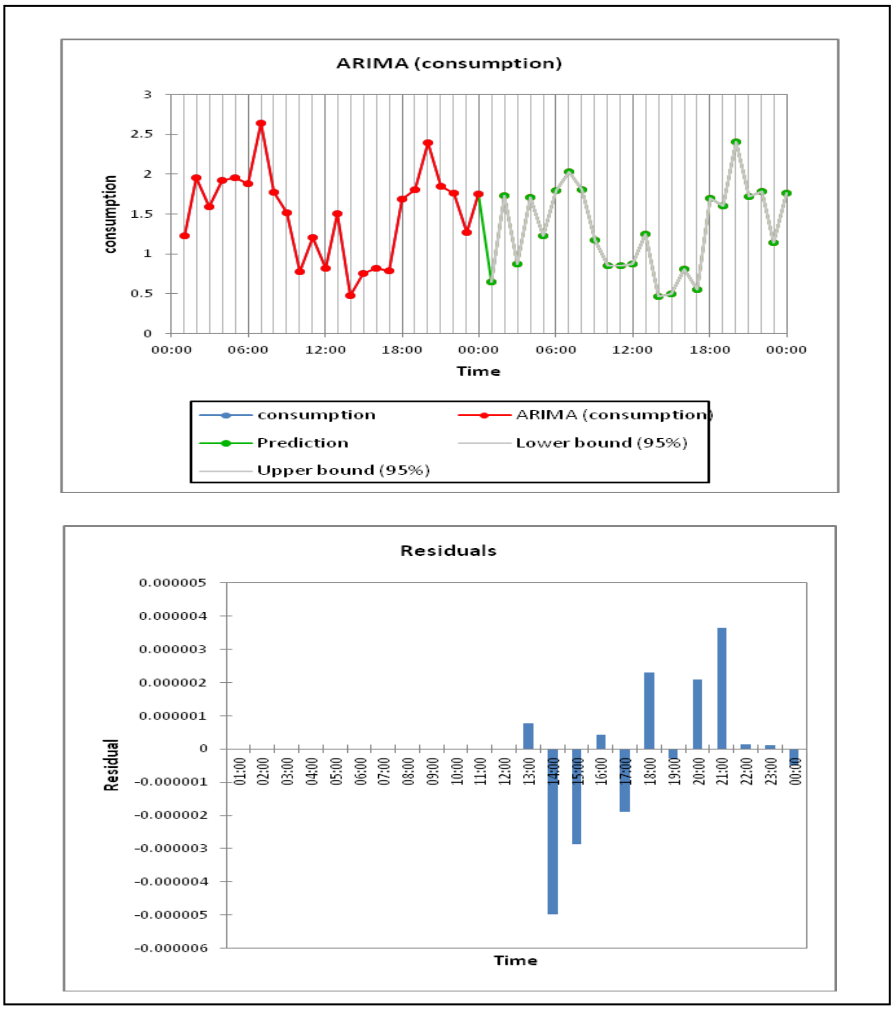


Figure 5.17 Consumption of household 1 on April 18

Parameter	Parameter Value
AR(1)	0.054
AR(2)	0.852
SAR(1)	-0.807
SAR(2)	0.193
MA(1)	0.238

Table 4 Parameter values of household 1 on April 18

The table containing parameter values of ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ of selected households which are generated while predicting the future values are displayed in tables 4, 5, 6, 7, 8, 9, 10, 11.

The consumption graph is in blue, ARIMA (consumption) is in red and prediction is in green. 24 hour prediction of consumption is done on different households by taking a common day (April 18).

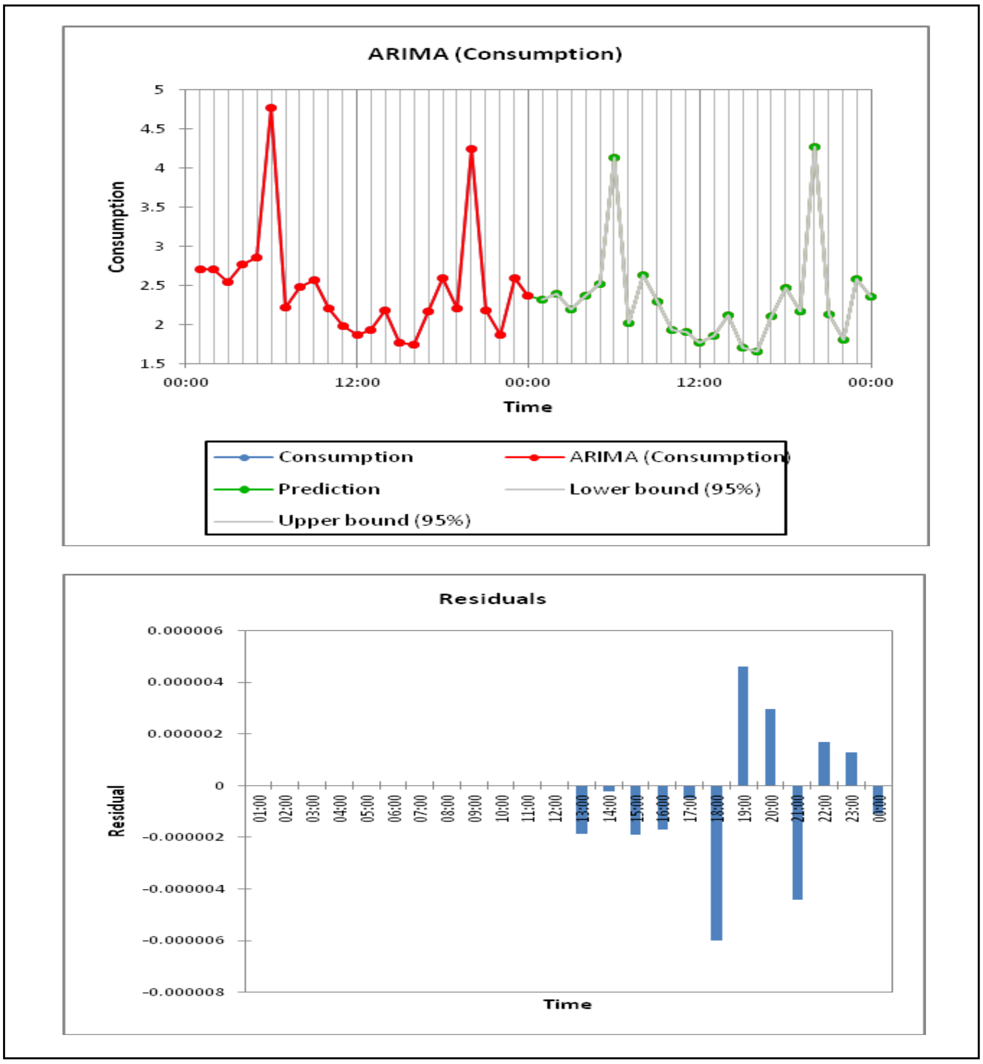


Figure 5.18 Consumption of household 11 on April 18

The 24 hour prediction is obtained by considering previous data. The model is fitted accurately such that the residuals are very small. Obviously, a user can have use of the obtained prediction by knowing the future values.

Parameter	Parameter Value
AR(1)	0.414
AR(2)	-0.121
SAR(1)	-0.800
SAR(2)	0.200
MA(1)	2.828

Table 5 Parameter values of household 11 on April 18

Graphs for 24 hour prediction of ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ model for consumption of same household on different days are shown below.

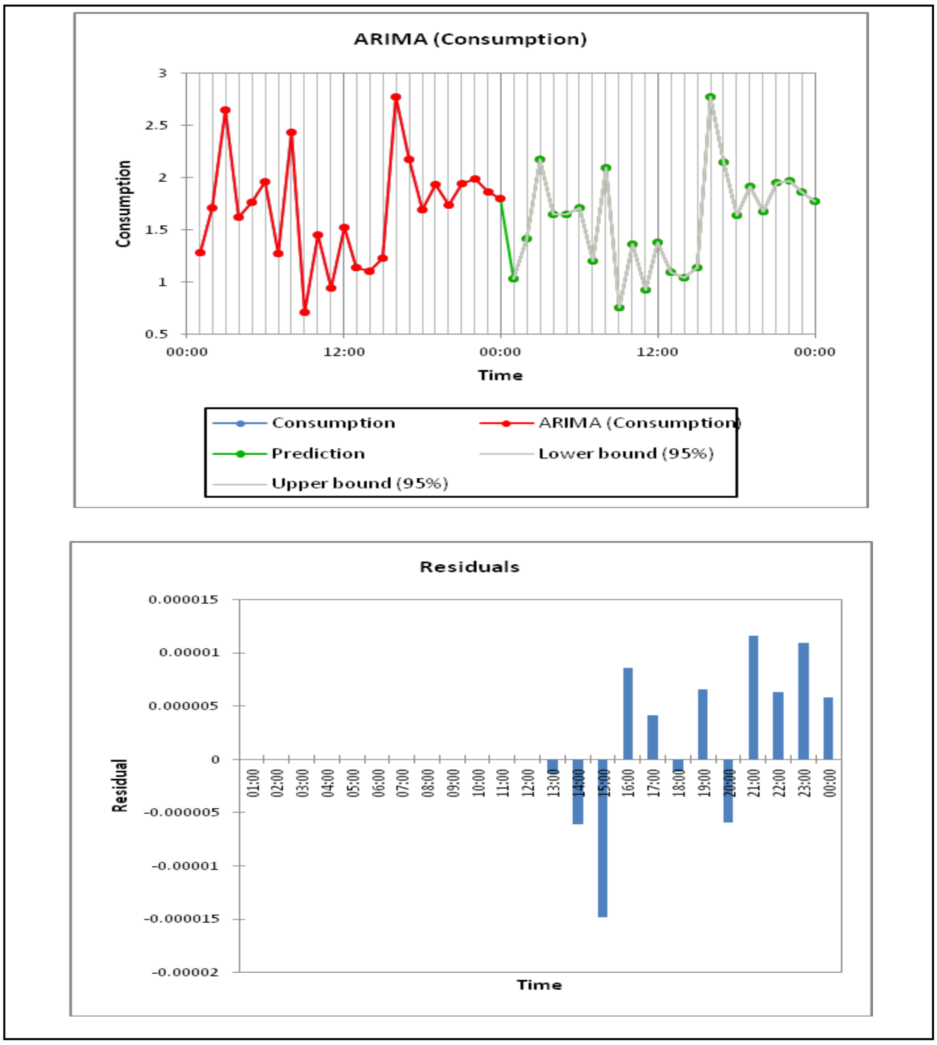


Figure 5.19 Consumption of household 4 on April 22

Parameter	Parameter Value
AR(1)	0.005
AR(2)	-0.076
SAR(1)	-0.801
SAR(2)	0.199
MA(1)	-0.149

Table 6 Parameter values of household 4 on April 22

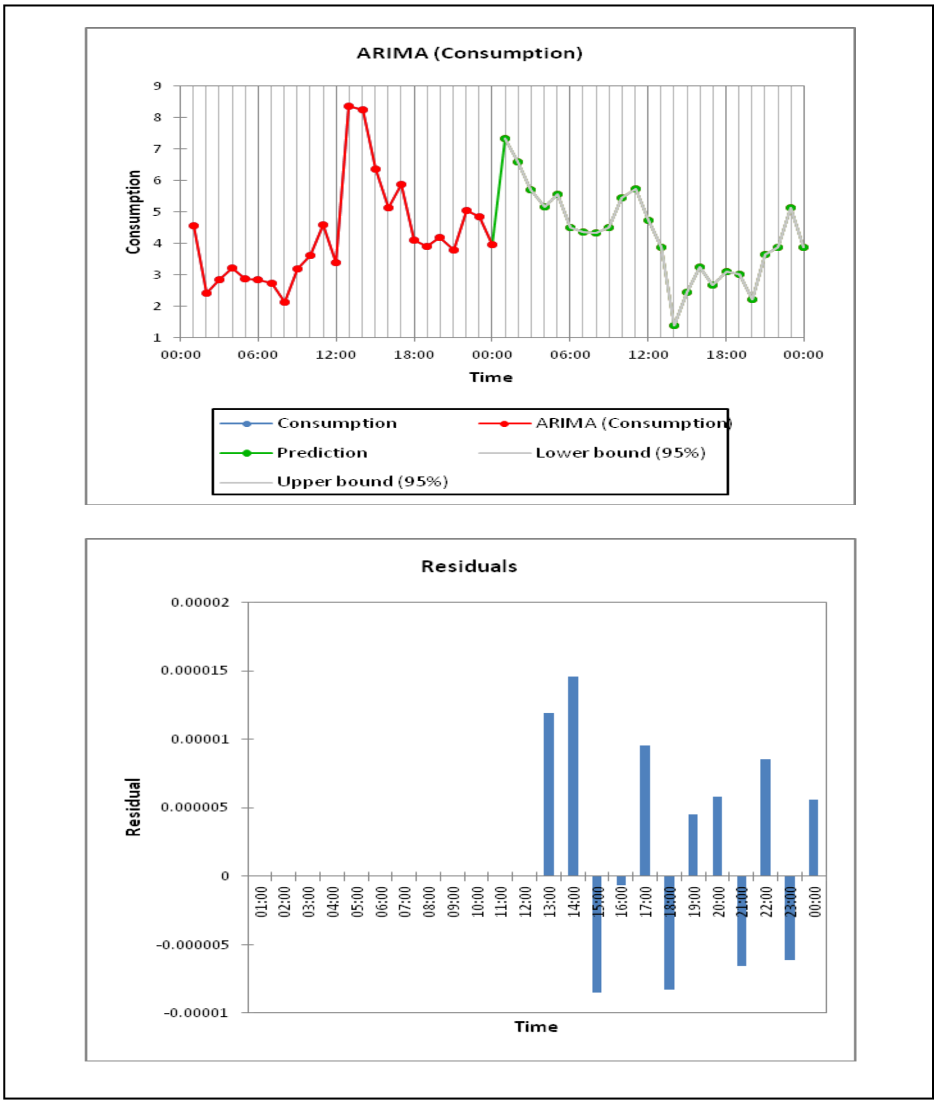


Figure 5.20 Consumption of household 5 on April 7

Parameter	Parameter Value
AR(1)	0.706
AR(2)	0.015
SAR(1)	-0.382
SAR(2)	-1.000
MA(1)	0.350

Table 7 Parameter values of household 5 on April 7

Graphs for 24 hour prediction of ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ model for cost of different households on same day April 26 are shown below.

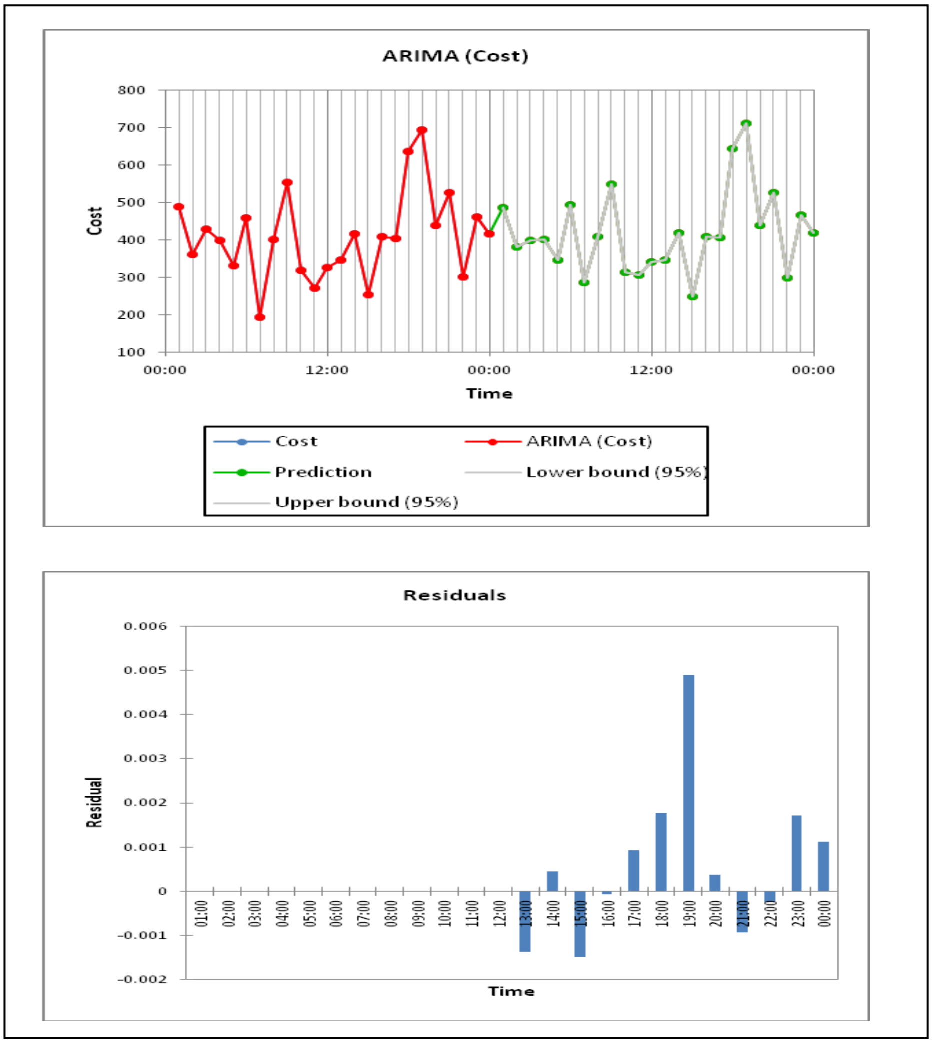


Figure 5.21 Cost of household 1on April 26

Parameter	Parameter Value
AR(1)	-0.017
AR(2)	0.137
SAR(1)	-0.813
SAR(2)	0.187
MA(1)	-0.035

Table 8 Parameter values of household 1 on April 26

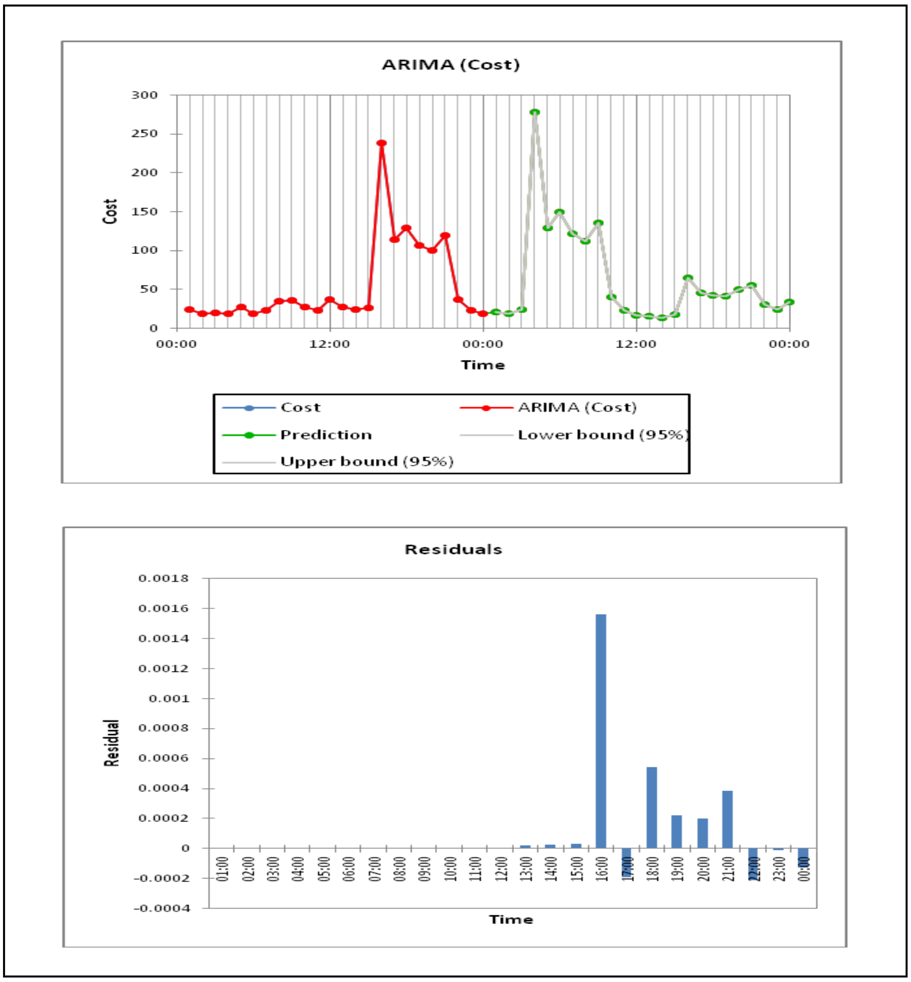


Figure 5.22 Cost of household 10 on April 26

Parameter	Parameter Value
AR(1)	0.467
AR(2)	0.121
SAR(1)	0.185
SAR(2)	-1.000
MA(1)	-0.195

Table 9 Parameter values of household 10 on April 26

Graphs for 24 hour prediction of ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ model for cost of same household on different days are shown below.

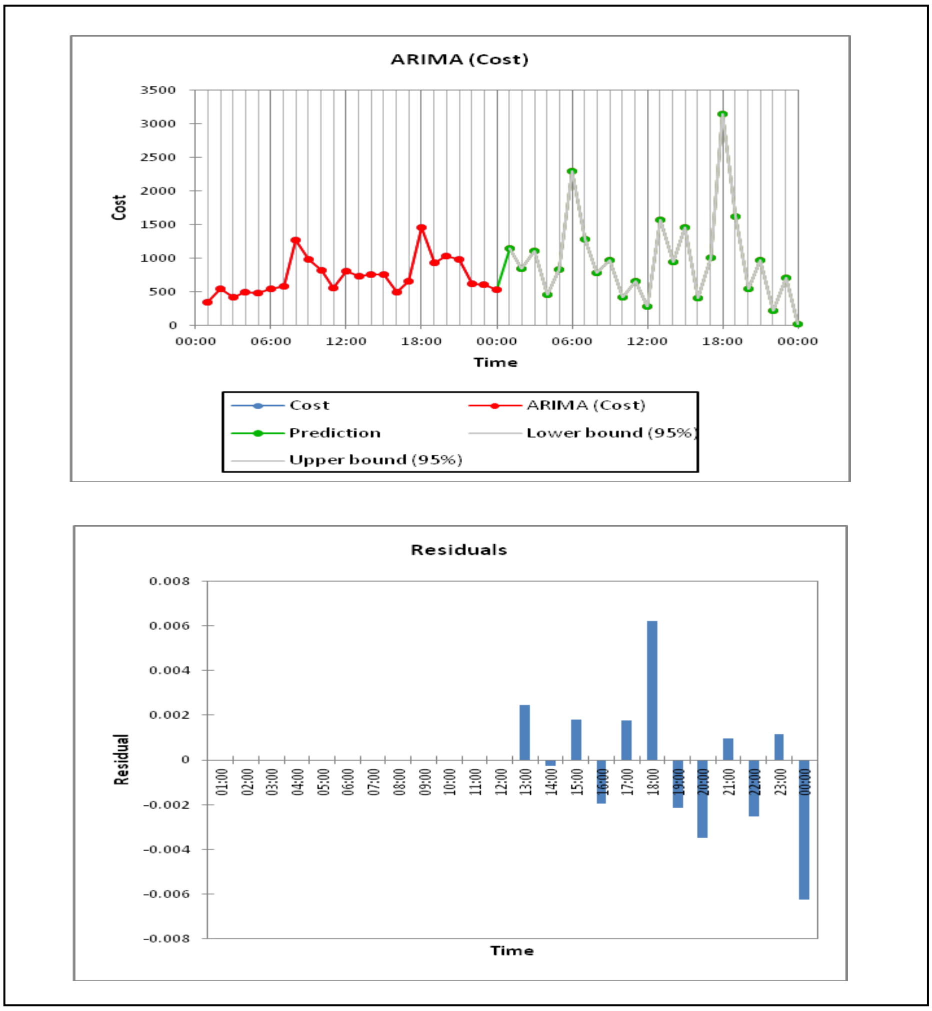


Figure 5.23 Cost of household 1 on April 20

Parameter	Parameter Value
AR(1)	-0.100
AR(2)	0.424
SAR(1)	0.942
SAR(2)	0.058
MA(1)	0.818

Table 10 Parameter values of household 1 on April 20

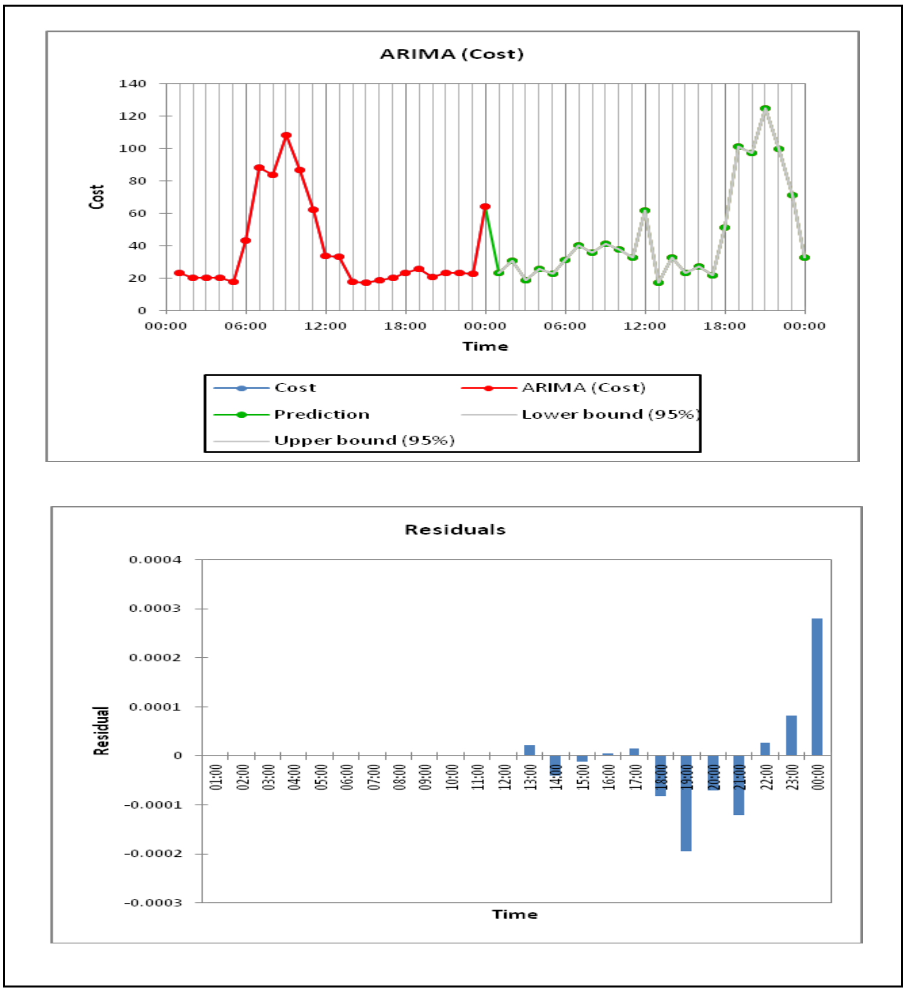


Figure 5.24 Cost of household 10 on April 28

Parameter	**Parameter Value**
AR(1)	0.388
AR(2)	0.501
SAR(1)	-0.176
SAR(2)	-1.000
MA(1)	0.569

Table 11 Parameter values of household 10 on April 28

where AR(1) is autoregressive term of order 1
AR(2) is autoregressive term of order 2
SAR(1) is seasonal autoregressive term of order 1
SAR(2) is seasonal autoregressive term of order 2
MA(1) is moving average term of order 1

Maximum positive correlation between price and consumption:

The day for a particular household displaying maximum positive correlation is selected and ARIMA modeling for consumption and cost is performed. Consumption and cost of household 4 on April 7 are shown in Appendix; see Figure 0.3 and 0.4 for further reference.

Maximum negative correlation between price and consumption:

The day of a particular household displaying maximum negative correlation is selected and ARIMA modeling for consumption and cost is performed. Consumption and cost of household 10 on April 15 are shown in Appendix; see Figure 0.5 and 0.6 for further reference.

Maximum difference between real cumulative cost and cumulative cost based on average price:

The day of a particular household displaying maximum difference between the hourly cumulative cost and cumulative cost based on average price is selected and ARIMA modeling for consumption and cost is done. Consumption and cost of household 4 on April 17 are shown in Appendix; see Figure 0.7 and 0.8 for further reference. The equation for maximum difference is described as follows:

$$max_d \{C_i (d) - \overline{C}_i (d)\}$$

where $C_i (d)$ is hourly cumulative cost

$\overline{C}_i (d)$ is cumulative cost based on average price

Minimum difference between real cumulative cost and cumulative cost based on average price:

The day of a particular household having minimum difference between hourly cumulative cost and cumulative cost based on average price is selected and ARIMA modeling for consumption and cost is done. Consumption and cost of household 4 on April 18 are shown in appendix figure 0.9 and 0.10 for further reference. The equation for minimum difference is described as follows:

$$min_d \{C_i (d) - \overline{C}_i (d)\}$$

where $C_i (d)$ is hourly cumulative cost

$\overline{C}_i (d)$ is cumulative cost based on average price

Real cumulative cost approximately equal to cumulative cost based on average price:

The day of a particular household having hourly cumulative cost and cumulative cost based on average price which are nearly equal is selected and ARIMA modeling for consumption and cost is done. Consumption and cost of household 4 on April 14 are shown in Appendix; see Figure 0.11 and 0.12 for further reference. The equation is described as follows:

$$C_i (d) \approx \overline{C}_i (d)$$

where $C_i (d)$ is hourly cumulative cost

$\overline{C}_i (d)$ is cumulative cost based on average price

With the observation of 24 hour prediction values, users implement the predicted values for greater reduction of cost and consumption. Eventually, this model serves a larger impact in progressive development of both users and utility providers.

Modeling of Superposition:

For the consumer and distributor, correlation is also the main important factor to investigate and concentrate. In order to observe direct performance of data from all the households by consumer and distributor, superposition is derived and conveyed. It would be an inviting aspiration for many users who are eagerly looking forward to view the data comfortably. The designed superposition structure shows in helping users to assess variations and thus the superposition is explained in a tabular fashion. The trend change observations in the table are guided from the price-consumption correlation behavior of the users. Superposition is sum of consumptions of households that we are interested in. We want to see to which extent the households follow similar patterns. For this, we investigate the correlation between consumption and price. Moreover, the figures below are the combination of behavior of households.

Household	April 30	April 29	April 28	April 27	April 26	April 25	April 24	April 23	April 22	April 21	April 20	April 19	April 18	April 17
1	-56%	30%	57%	-33%	-58%	-13%	-61%	-32%	14%	-15%	21%	-39%	-38%	-22%
2	23%	36%	-12%	-23%	-3%	1%	0%	30%	12%	25%	-12%	-13%	-6%	-3%
3	-21%	21%	-8%	-16%	-37%	46%	-49%	8%	48%	13%	19%	-22%	-51%	-6%
4	-55%	5%	29%	-50%	-2%	47%	-50%	-34%	-4%	-7%	14%	-23%	-66%	37%
5	-45%	9%	-25%	-36%	-39%	22%	-26%	-20%	26%	34%	-18%	-35%	-53%	-41%
6	-22%	4%	6%	27%	16%	72%	7%	35%	18%	41%	35%	-8%	59%	-6%
7	-3%	-6%	-16%	-12%	29%	3%	-4%	-5%	17%	13%	-9%	-12%	-13%	15%
8	16%	-2%	-6%	24%	-2%	18%	-8%	21%	-24%	1%	13%	5%	9%	-22%
9	37%	-15%	9%	-18%	41%	14%	27%	8%	-20%	42%	38%	-12%	-15%	9%
10	20%	16%	21%	-11%	11%	37%	-4%	22%	-56%	-6%	20%	-15%	-7%	20%
11	-58%	26%	11%	14%	-46%	6%	-11%	-9%	-9%	7%	-12%	-26%	-32%	-27%
12	3%	28%	43%	-3%	3%	26%	-7%	20%	-16%	52%	54%	7%	-9%	15%
13	-35%	-2%	-3%	-49%	-48%	-4%	-45%	-16%	-21%	20%	-15%	-11%	-53%	-21%
14	-10%	24%	18%	-11%	10%	28%	-18%	22%	1%	76%	70%	4%	15%	14%
15	2%	-7%	15%	-28%	-29%	-3%	-25%	-32%	-9%	-23%	-42%	-33%	-52%	-41%
16	74%	-5%	58%	-38%	-51%	39%	-81%	63%	-11%	-1%	45%	17%	-8%	-15%
min	-58%	-15%	-25%	-50%	-58%	-13%	-81%	-34%	-56%	-23%	-42%	-39%	-66%	-41%
max	74%	36%	58%	27%	41%	72%	27%	63%	48%	76%	70%	17%	59%	37%

Figure 5.25 Correlations, maximum correlation and minimum correlation values of 14 days for 16 households

The Figures 5.25, 5.26 and 5.27 show the diversity between households during one day and for one household between different days. From the observation of figures, behavior of households is changing from day to day. The users are not having any reference day and reference household either to follow. Some correlations of the households in the table are strongly correlated which leads to higher costs. The price of particular day for duration of one month is fixed by the utility company for all the households, but the electricity cost and consumptions are varied respectively depending upon their usages.

The Figures 5.25, 5.26 and 5.27 demonstrate collection of price consumption correlation data of 16 households for a period of 30 days. Minimum and maximum values of a particular household for 30 days is shown horizontally whereas minimum and maximum values of particular day for 16 households is shown vertically.

Household	April 16	April 15	April 14	April 13	April 12	April 11	April 10	April 9	April 8	April 7	April 6	April 5
1	-35%	7%	46%	-36%	-34%	-32%	-12%	21%	63%	62%	16%	-30%
2	-18%	-39%	-24%									
3	22%	-27%	-20%	44%	-14%	-44%	6%	53%	2%	49%	-21%	7%
4	-42%	12%	-2%	25%	13%	-28%	23%	-25%	48%	70%	-16%	1%
5	-50%	-21%	-86%	42%	-27%	-47%	-15%	-16%	12%	27%	36%	-50%
6	-24%	36%	-2%	35%	24%	38%	36%	38%	46%	63%	31%	-17%
7	3%	15%	-4%	-8%	4%	-4%	4%	24%	19%	-6%	-2%	-15%
8	-13%	-10%	0%	3%	13%	-13%	-1%	0%	3%	-3%	9%	-27%
9	49%	-51%	-13%									
10	-26%	-59%	-51%	9%	21%	-11%	28%	39%	19%	43%	32%	-36%
11	-31%	31%	55%	-11%	35%	-19%	-11%	5%	-13%	17%	12%	-7%
12	-29%	-60%	-21%	42%	26%	17%	24%	24%	-20%	-1%	51%	11%
13	-38%	7%	-7%	-2%	-18%	-25%	-28%	-48%	-62%	-23%	5%	-6%
14	17%	-23%	22%	17%	-18%	-47%	28%	15%	25%	4%	10%	53%
15	-55%	16%	-27%									
16	-40%	-16%	-52%									
min	-55%	-60%	-86%	-36%	-34%	-47%	-28%	-48%	-62%	-23%	-21%	-50%
max	49%	36%	55%	44%	35%	38%	36%	53%	63%	70%	51%	53%

Figure 5.26 Correlations, maximum correlation and minimum correlation values of 12 days for 16 households

The correlation in green is ‘negative correlation’, the correlation in red is ‘positive correlation’, and correlation in yellow colour is ‘negligible correlation’.

Household	April 4	April 3	April 2	April 1		min	max
1	-16%	-43%	14%	9%		-61%	63%
2						-39%	36%
3	-29%	-51%	30%	-58%		-58%	53%
4	-27%	-49%	-28%	39%		-66%	70%
5	-27%	-33%	-22%	-42%		-86%	42%
6	16%	-20%	-5%	-31%		-31%	72%
7	1%	-19%	9%	24%		-19%	29%
8	24%	-9%	-2%	-2%		-27%	24%
9						-51%	49%
10	-5%	10%	30%	-40%		-59%	43%
11	-37%	-35%	7%	-3%		-58%	55%
12	-4%	25%	45%	-30%		-60%	54%
13	-48%	-75%	-24%	-31%		-75%	20%
14	25%	4%	32%	-11%		-47%	76%
15						-55%	16%
16						-81%	74%
min	-48%	-75%	-28%	-58%			
max	25%	25%	45%	39%			

Figure 5.27 Correlations, maximum correlation and minimum correlation values of 4 days and maximum correlation, minimum correlation values of 16 households

The computed price-consumption correlation is used in superposition of all 16 households data. Lastly from analysis of data, there is a probability that people can think majorly about individual functions and from super-positioning of data, people can behave more intelligently from the observations. Some households are exhibiting positive correlation on one day and negative correlation on other day. A minimum correlation of -86% and a maximum correlation of +76% are observed from the data. No systematic behaviours are visible as households are changing behaviour from day to day. An overall average cross correlation is very small of value -2% which indicates that if behavioural change is not applied then overall advantage for hourly rate will practically vanish. Based on the results tabulated, we confirm that it is hard to find a typical user and difficult to superpose and predict.

RQ.3) How should power consumption be reduced in household appliances to flatten daily patterns?

The demand for electricity and its usage are constantly rising at a pace. The importance of abnormal variations in consumption has to be studied and necessary steps are followed to adapt the changes in their patterns. For energy consumption, price is a prime factor followed to exhibit the behaviour of consumers. Hence there is necessity of choosing price as a reference to flatten the consumption patterns is investigated. The average of lag1 to lag 6 autocorrelations of price during a month is computed. Through this computation, positive correlation is being observed for 4 hours, which later shifts to negative correlation. Obviously, there is a quite long autocorrelation w.r.t prices. There is an unavoidable delay, i.e. user has to wait for the next hour to see price and consumption. While the price is rising, the user tries to contribute the load. In particular, consumption peaks that occur with price peaks shall be avoided. The graph below is drawn by taking autocorrelation of prices on y-axis and lag on x-axis to illustrate the shift of price autocorrelations.

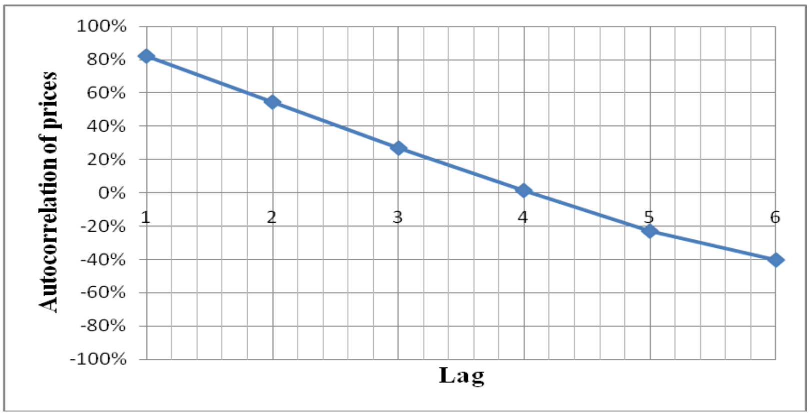


Figure 5.28 Autocorrelation of prices

Consequently based on the above observation, the duration of time over which the consumption curve should be flattened is estimated. This encourages consumers to recognise the significance of hourly duration for flattening the consumption at high prices. From all the choices and observations, we discuss an effective flattening model of consumption in our research. The process to flatten energy consumption patterns can be achieved as follows.

- A period with increasing price for a duration of 4 hours is selected.
- The average of corresponding consumption values for 4 hour duration of increasing price is obtained and the previous values are replaced by this average.
- The procedure is repeated if there is another duration with increasing price through 4 hours duration on the same day for that particular household.
- From calculating average of high price consumption values, any cost reduction in the flattened case can be identified.

Graphical representation of different household patterns are shown below.

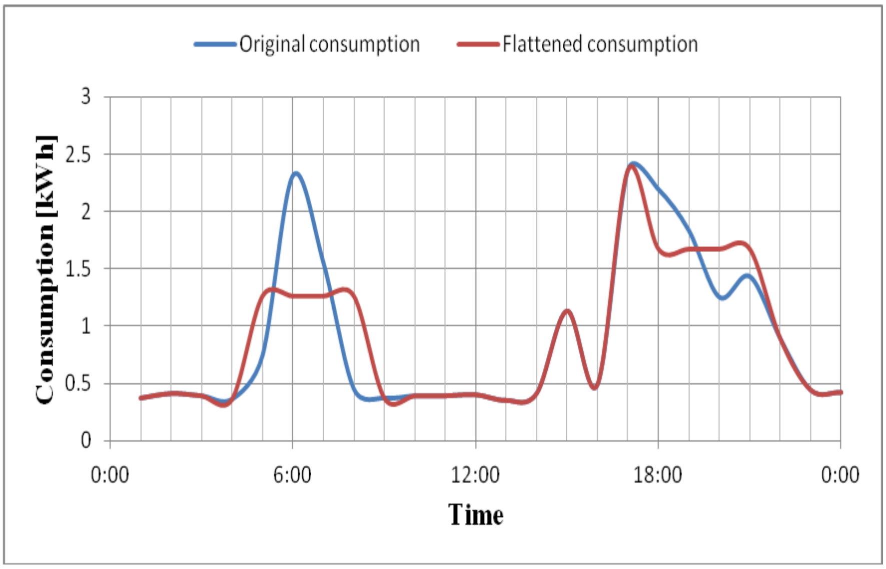


Figure 5.29 Consumption of household 2 on April 27

The graph in blue indicates the original consumption and the graph in red indicates the flattened consumption. From the above consumption graph of household 2 on April 27, consumption is varying at peaks from 5:00 to 8:00 hour and 18:00 to 21:00 hour. So the average of corresponding consumption in 4 hour duration is performed at two instances of time to achieve flatness. Even though there is high consumption at 17:00 hour, because of low price the user will not be affect in terms of cost.

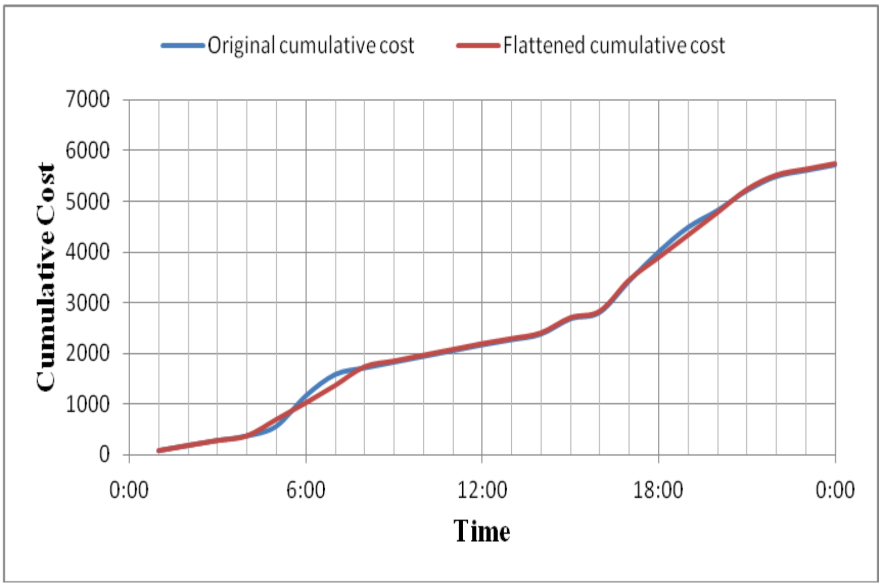


Figure 5.30 Cumulative cost of household 2 on April 27

In order to observe how two cumulative cost functions differ from each other, the above illustration is performed. The effect of consumption flattening is clearly seen on cumulative cost graphs. The cumulative cost graph increases linearly at flattened consumption hours and follows the original cumulative graph in remaining hours.

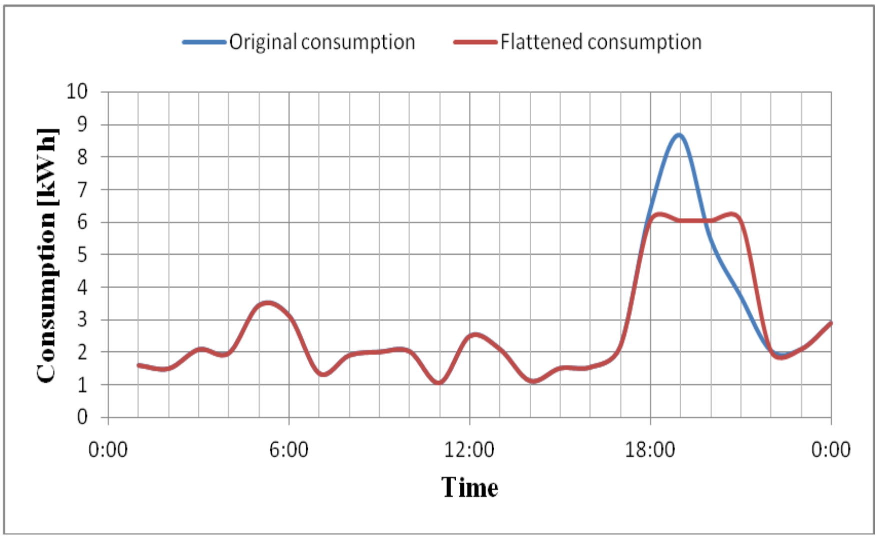


Figure 5.31 Consumption of household 5 on April 25

From the above consumption graph of household 5 on April 25, consumption is increasing from 18:00 to 21:00 hour. The average of corresponding consumption from 18:00 to 21:00 hour duration is performed to obtain flatness.

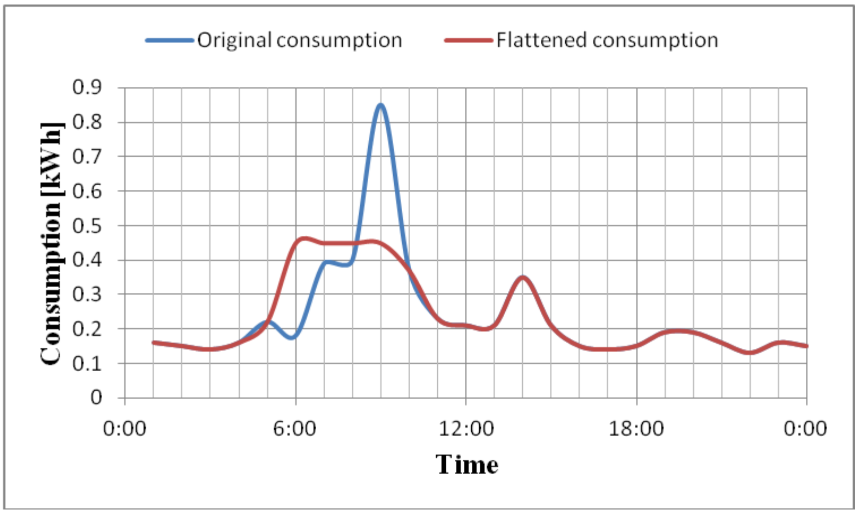


Figure 5.32 Consumption of household 6 on April 20

From the above consumption graph of household 6 on April 20, consumption is increasing from 6:00 to 9:00 hour. The average of corresponding consumption from 6:00 to 9:00 hour duration is performed to achieve flatness. The important aspect of flatness is less peaky consumption is better and may lead to less peaky price.

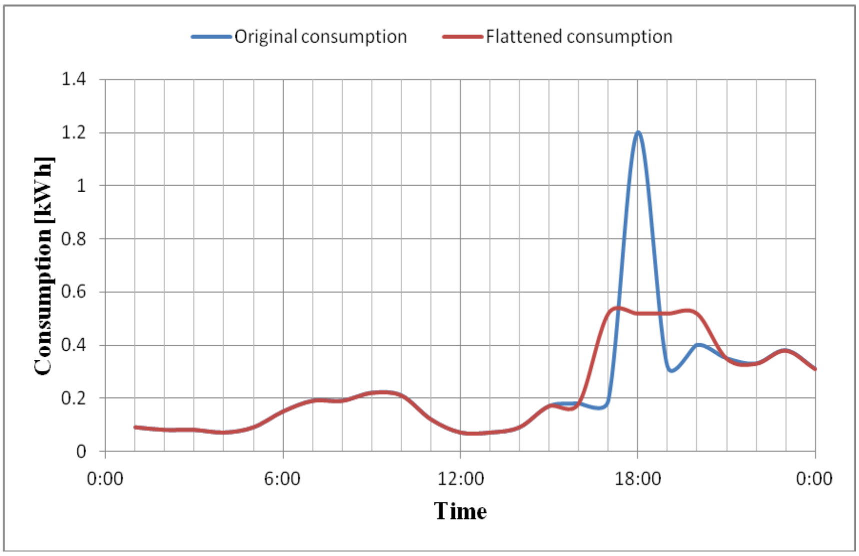


Figure 5.33 Consumption of household 10 on April 14

From the above consumption graph of household 10 on April 14, consumption is increasing from 17:00 to 20:00 hour. The average of corresponding consumption from 17:00 to 20:00 hour duration is performed to achieve flatness.

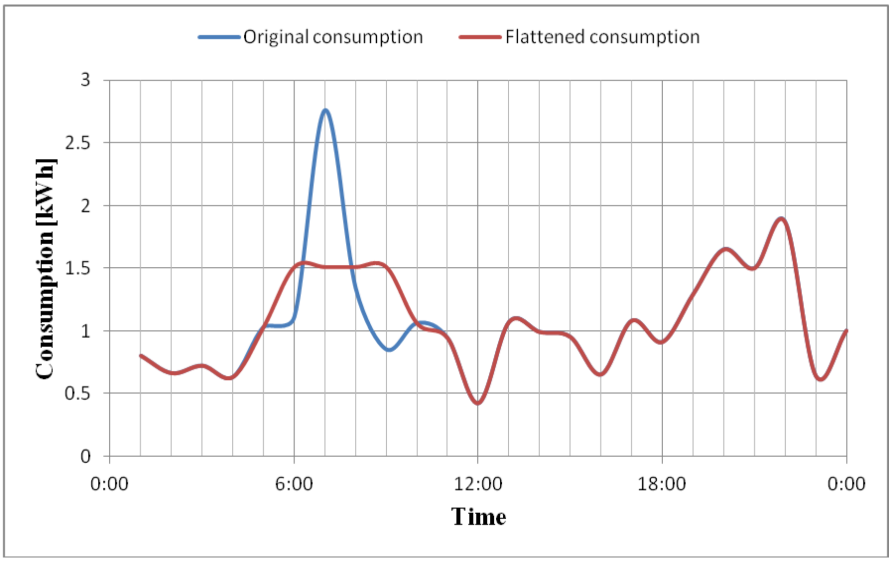


Figure 5.34 Consumption of household 14 on April 19

From the above consumption graph of household 14 on April 19, consumption is increasing from 6:00 to 9:00 hour. The average of corresponding consumption from 6:00 to 9:00 hour duration is performed to achieve flatness.

From the results obtained, we found that as most of the users are uninformed with prices, the graphical patterns of their consumption shows most of the households consume high energy peaks at high prices and varied consumption during low prices. Therefore, the outcome of flattening attempts to play a significant role aiming to distribute energy effectively. The flattening technique considered in the research is in response to the concerns in the electricity market determining the consumers to save money. A single comparison graph for cumulative cost is drawn for one household and remaining households are projected in the form of table 12.

The table below shows the cumulative cost computed for original and flattened values of household 5, household 6, household 10, and household 14. The values in the table are relatively compared to demonstrate evidence of bringing when hourly prices are advantageous or disadvantageous for consumer. From the below cumulative cost table, the values denoted in red corresponds to peak price hours obtained from the household. Lastly, the improved variations help consumers to gain knowledge and encourage them to achieve immediate savings with benefits.

Household 5 April 25		**Household 6 April 20**		**Household 10 April 14**		**Household 14 April 19**	
Cum cost	Flatten cum cost	Cum cost	Flatten cum cost	Cum cost	Flatten cum cost	Cum cost	Flatten cum cost
435.04	435.04	43.42	43.42	25.35	25.35	225	225
836.51	836.51	83.87	83.87	47.96	47.96	408.8	408.8
1392.7	1392.7	121.5	121.5	70.49	70.49	605.3	605.3
1923.5	1923.5	164.5	164.5	90.21	90.21	776.4	776.4
2865.3	2865.3	224.8	224.8	115.6	115.6	1065.1	1065.1
3733.6	3733.6	275.5	351.7	158	158	1382.4	1496.8
4167.3	4167.3	390.6	484.5	211.7	211.7	2246.2	1969.4
4941.2	4941.2	538.5	650.8	264.9	264.9	2742.3	2528.4
5832.7	5832.7	887.1	835.3	326.7	326.7	3067.3	3105.6
6686.8	6686.8	1043.6	991.9	386.3	386.3	3459.3	3497.7
7148.2	7148.2	1141	1089.3	420.6	420.6	3805.3	3843.6
8196.9	8196.9	1229.9	1178.3	440.5	440.5	3958.5	3996.9
8965.7	8965.7	1313.9	1262.2	460.3	460.3	4333.9	4372.3
9371.5	9371.5	1447.3	1395.6	485.4	485.4	4663.4	4701.8
9924.2	9924.2	1531.1	1479.5	532.5	532.5	4977.4	5015.8
10485	10485	1586.6	1535	582	582	5180.7	5219.1
11274	11274	1638.5	1586.8	633.5	722.9	5513	5551.4
13700	13574	1694	1642.4	961.8	865.2	5795.6	5834
17212	16031	1764.3	1712.6	1050	1008.5	6193.6	6231.9
19576	18645	1834	1782.3	1160.7	1152.5	6708.4	6746.7
21255	21383	1892.5	1840.9	1258.5	1250.3	7180.2	7218.6
22089	22217	1940.1	1888.4	1350.8	1342.5	7762.2	7800.6
22675	22803	1990.1	1938.4	1457.3	1449	7953.7	7992
23461	23589	2031.9	1980.3	1544.1	1535.8	8231.6	8270

Table 12 Flattened and non-flattened cumulative cost of households 5, 6, 10 and 14

6 DISCUSSION

With all the obtained data from the statistical analysis, the following results are implied:

- A close inspection is done from the obtained data and results confirms that the usage of electricity by most of the households is high during the beginning, middle of the month and low during the ending of the month. Nevertheless, this strongly reflects the real characteristics of people's attitude towards electricity.

- Graphs are generated to state the performance and analysis of 16 households for consumption, price-cost and cumulative cost. The patterns of graphical analysis suggest consumers to serve a competitive nature among them. With the computation of price-consumption correlation results, we can observe that more negative the correlation, the lower will be the cost while as more the positive correlation higher will be the cost if hourly pricing was applied.

- Several models were observed and a precise selection is done on the basis of goodness of fit statistics. An idea and a methodology of using seasonal ARIMA for predicting future electricity prices and cost have been proposed. Resource utilization can be effectively improved with the observation of distributed statistics. The unstable behaviour of users is noticed and compared from the prediction analysis. Best fitting graphs are shown in the analysis. The graphs generated for this analysis can bring people to adopt changes requested in the paper.

- The correlations in the superposition can make people to imitate and defend to control their future statistics. As it is hard to find a typical user, it is also difficult to predict a typical user's behaviour.

- Therefore to study the patterns of households a flattening technique is proposed to save the cost of the consumer.

7 CONCLUSION AND FUTURE WORK

In this thesis work, we analysed and interpreted different sets of consumption data of various households and their daily behaviour patterns are graphed. We suggested their subjected patterns should be altered with respect to the forecasting techniques discussed in this paper. The proposed models and the study in this research can also encourage users to shift their consumption and optimize the cost constraint. The answers obtained from the research questions are given in this section. They are as follows:

RQ1: What are the methods to measure and analyze the power consumption of household applications in real-time environment?

From the literature review in the background of the research, we can conclude that effective measurement of electricity consumption can be performed by using Smart Meters. In-case of analysis, various computations of data such as correlation, autocorrelation, standard deviation, price average's of the day is done on excel sheets. The role of the cross correlation is an ability to produce potential savings through hour-wise billing to some extent. The derived relations in a novel statistical display can emphasize readers with simple structure examination.

RQ2: How can we model the energy consumption of single households and their superposition?

From the discussed ARIMA model in the results section, we can conclude that ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ is complacent model for goodness of fit. It accounts to a degree of predicting future price developments. To estimate the next day performance, 24 hour prediction is helpful. The developed model explores distinct ways of restructuring the market competition. The effectiveness of utility and customer playing a role in flattening consumption and thus prices for the electricity market can be improved with the usefulness of good forecasting models.

RQ3: How should power consumption be reduced in household appliances to flatten daily consumption patterns?

A method to flatten the consumption curve thereby reducing cost is demonstrated. From the analysis of the flattening technique in the results section, we can conclude that consumers can be encouraged by adding beneficiary modifications adjusting the consumption timings. The flattened graphs allow competitors to formulate negotiation strategies and this developed technique accounts a significant role for both consumers and sellers.

Ultimately we would like to conclude that, there is an equal responsibility of every human to preserve and protect our energy resources. Thus, the collective investigated results in this paper can attribute in preservation for its future use.

FUTURE WORK:

Future case studies can be conducted on Artificial Neural Network, Generalized Autoregressive Conditional Heteroscedastic model and Autoregressive Moving Average with Exogenous Inputs for predicting different data sets. The major advantage of these models when compared to other models are determining complex nonlinear relationships between dependent and independent variables, modeling of volatility distribution, flexibility and improving the future forecasts using previous forecast errors. Besides, this work can also be extended with evolution of several other real time data obtained from gas and water meters probably with a further developed flattening technique.

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APPENDIX A

Figure 0.1 Menu of XLSTAT

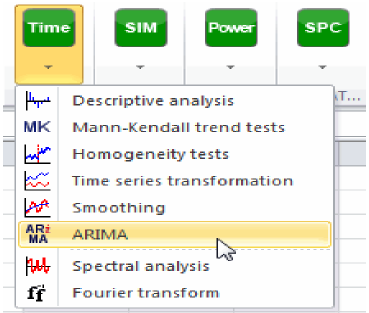

Figure 0.2 Drop down menu in Time series function

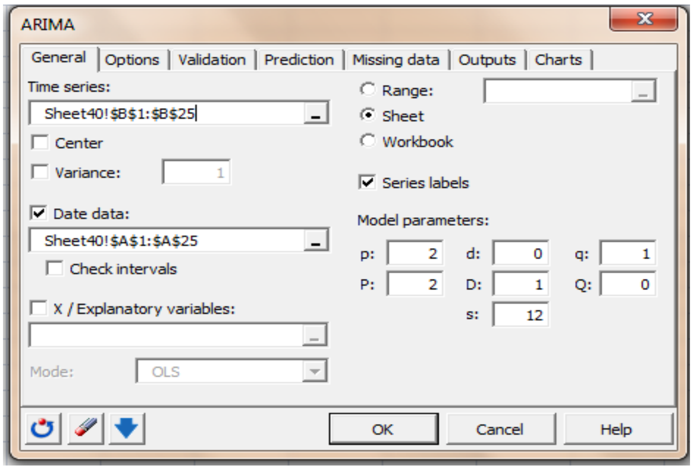

Figure 0.3 ARIMA command window

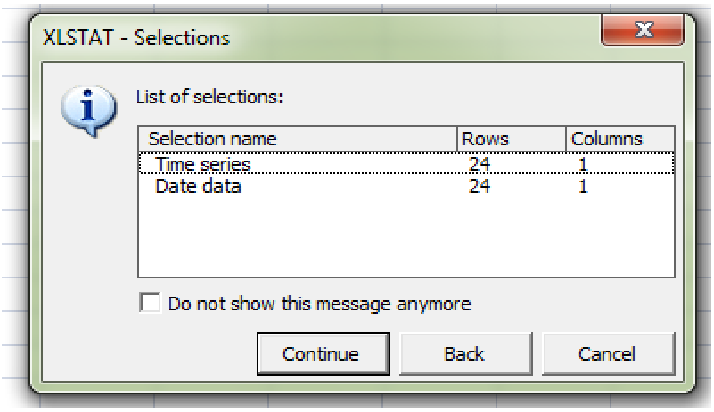

Figure 0.4 XLSTAT selections

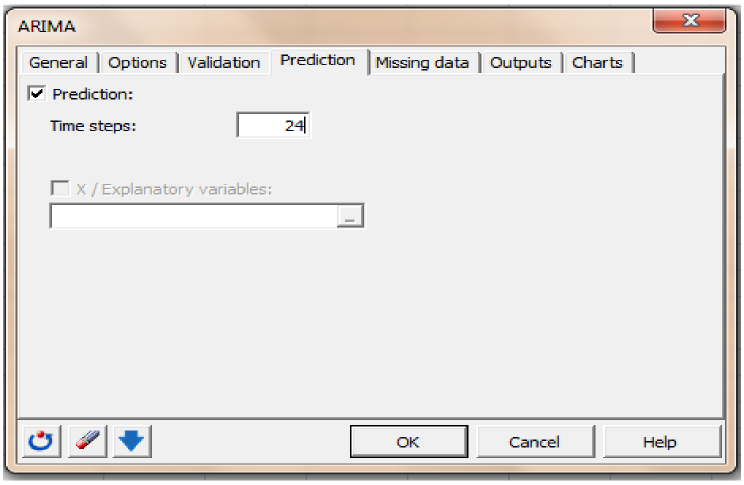

Figure 0.5 XLSTAT Prediction time steps

Time	**SE4**	Cost	Consumption	cum.consumption	cum.cost
1:00	238.45	531.7435	2.23	2.23	531.7435
2:00	216.39	486.8775	2.25	4.48	1018.621
3:00	207.75	452.895	2.18	6.66	1471.516
4:00	196.37	447.7236	2.28	8.94	1919.2396
5:00	203.07	452.8461	2.23	11.17	2372.0857
6:00	207.04	459.6288	2.22	13.39	2831.7145
7:00	199.54	474.9052	2.38	15.77	3306.6197
8:00	210.22	336.352	1.6	17.37	3642.9717
9:00	215.77	412.1207	1.91	19.28	4055.0924
10:00	225.21	358.0839	1.59	20.87	4413.1763
11:00	217.71	317.8566	1.46	22.33	4731.0329
12:00	216.48	346.368	1.6	23.93	5077.4009
13:00	203.25	359.7525	1.77	25.7	5437.1534
14:00	191.60	346.796	1.81	27.51	5783.9494
15:00	181.02	302.3034	1.67	29.18	6086.2528
16:00	173.52	249.8688	1.44	30.62	6336.1216
17:00	170.25	316.665	1.86	32.48	6652.7866
18:00	175.55	475.7405	2.71	35.19	7128.5271
19:00	206.86	562.6592	2.72	37.91	7691.1863
20:00	220.18	660.54	3	40.91	8351.7263
21:00	227.51	445.9196	1.96	42.87	8797.6459
22:00	224.07	540.0087	2.41	45.28	9337.6546
23:00	217.36	376.0328	1.73	47.01	9713.6874
0:00	211.89	457.6824	2.16	49.17	10171.3698
	Correl	Correl	Correl		
	0.788	0.579	0.513		
price-cost	45%				
price-consumption		9%			
cost-consumption			93%		
				avg price *cum consumption	cum cost-(avg* cum consumption)
average	206.54	423.81	2.05	10155.77668	15.593125
std-dev.	17.80	96.25	0.42		
coeff. of var.	9%	23%	20%		

Figure 0.6 Data sheet of household 1 on April 1

APPENDIX B

XLSTAT 2012.6.03 - ARIMA - on 07-12-2012 at 22:06:23
Time series: Workbook = april 18 consumption.xlsx / Sheet = Hsld 1 Apr18 / Range = 'Hsld 1 Apr18'!$C$1:$C$25 / 24 rows and 1 column
Date data: Workbook = april 18 consumption.xlsx / Sheet = Hsld 1 Apr18 / Range = 'Hsld 1 Apr18'!$A$1:$A$25 / 24 rows and 1 column
Confidence intervals (%): 95
Center: No
Model parameters: p = 2 / d = 0 / q = 1 / P = 2 / D = 1 / Q = 0 / s = 12
Optimize: Least Squares (Convergence = 0.00001 / Iterations = 500)
Prediction: 24
Confidence intervals (%): 95
Seed (random numbers): 123456789

Summary statistics:

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
consumption	24	0	24	0.470	2.640	1.503	0.555

Results after optimization (consumption):

Goodness of fit statistics:

Observations	24.000
SSE	0.000
MAPE(Diff)	0.000
MAPE	0.000
WN Variance	0.000
WN Variance	0.000
-2Log(Like.)	28.721
FPE	
AIC	40.721
AICC	57.521
SBC	43.631

Model parameters:

Parameter	Value	Hessian standard error	Lower bound (95%)	Upper bound (95%)	Asympt. standard error	Lower bound (95%)	Upper bound (95%)
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Parameter	Value	Hessian standard error	Lower bound (95%)	Upper bound (95%)	Asympt. standard error	Lower bound (95%)	Upper bound (95%)
AR(1)	0.054				1.769	-3.414	3.522
AR(2)	0.852				0.589	-0.302	2.006
SAR(1)	-0.807				0.372	-1.537	-0.077
SAR(2)	0.193				0.372	-0.537	0.923
MA(1)	0.238	0.231	-0.214	0.689	1.792	-3.275	3.751

Predictions and residuals:

Observations	consumption	ARIMA(consumption)	Residuals	Standardized residuals	Standard error	Lower bound (95%)	Upper bound (95%)
1:00	1.230	1.230	0.000	0.000			
2:00	1.960	1.960	0.000	0.000			
3:00	1.590	1.590	0.000	0.000			
4:00	1.920	1.920	0.000	0.000			
5:00	1.950	1.950	0.000	0.000			
6:00	1.880	1.880	0.000	0.000			
7:00	2.640	2.640	0.000	0.000			
8:00	1.770	1.770	0.000	0.000			
9:00	1.510	1.510	0.000	0.000			
10:00	0.770	0.770	0.000	0.000			
11:00	1.200	1.200	0.000	0.000			
12:00	0.820	0.820	0.000	0.000			
13:00	1.500	1.500	0.000	0.241			
14:00	0.470	0.470	0.000	-1.569			
15:00	0.750	0.750	0.000	-0.900			
16:00	0.820	0.820	0.000	0.136			
17:00	0.790	0.790	0.000	-0.594			
18:00	1.690	1.690	0.000	0.722			
19:00	1.800	1.800	0.000	-0.091			
20:00	2.390	2.390	0.000	0.653			
21:00	1.850	1.850	0.000	1.147			
22:00	1.760	1.760	0.000	0.040			
23:00	1.270	1.270	0.000	0.032			
0:00	1.750	1.750	0.000	-0.160			
1:00		0.643			0.000	0.643	0.643
2:00		1.724			0.000	1.724	1.724
3:00		0.868			0.000	0.868	0.868
4:00		1.703			0.000	1.703	1.703
5:00		1.231			0.000	1.231	1.231
6:00		1.795			0.000	1.795	1.795
7:00		2.035			0.000	2.035	2.035
8:00		1.806			0.000	1.806	1.806
9:00		1.176			0.000	1.176	1.176
10:00		0.850			0.000	0.850	0.850
11:00		0.849			0.000	0.849	0.849
12:00		0.867			0.000	0.867	0.867
13:00		1.244			0.000	1.244	1.244
14:00		0.468			0.000	0.468	0.468
15:00		0.491			0.000	0.491	0.491
16:00		0.809			0.000	0.809	0.809
17:00		0.551			0.000	0.551	0.551
18:00		1.695			0.000	1.694	1.695
19:00		1.599			0.000	1.599	1.599
20:00		2.410			0.000	2.410	2.410
21:00		1.714			0.000	1.714	1.714
22:00		1.783			0.000	1.783	1.783
23:00		1.142			0.000	1.142	1.142
0:00		1.762			0.000	1.762	1.762

Figure 0.1 ARIMA data sheet of household 1 on April 18

APPENDIX C

Graphs for 24 hour prediction of ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ model for maximum positive correlation between price and consumption are shown below.

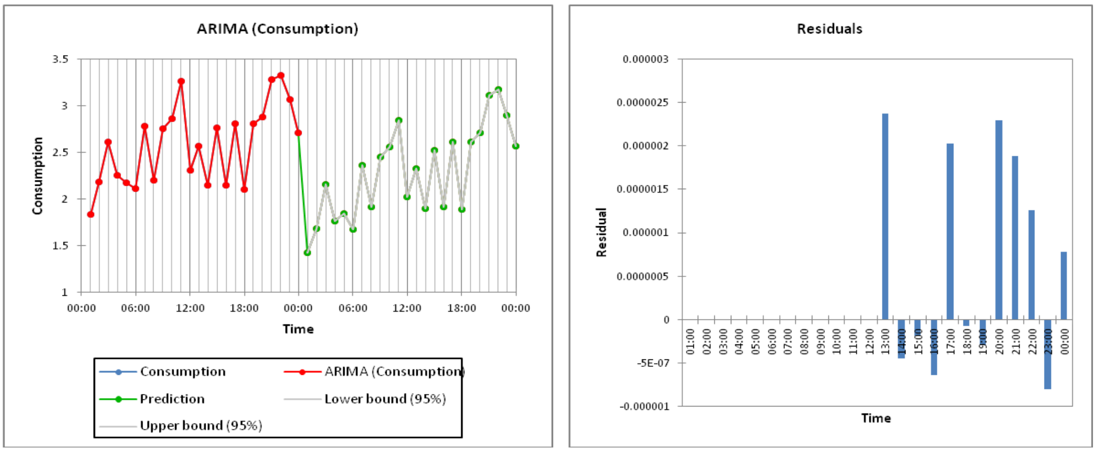

Figure 0.1 Consumption of household 4 on April 7

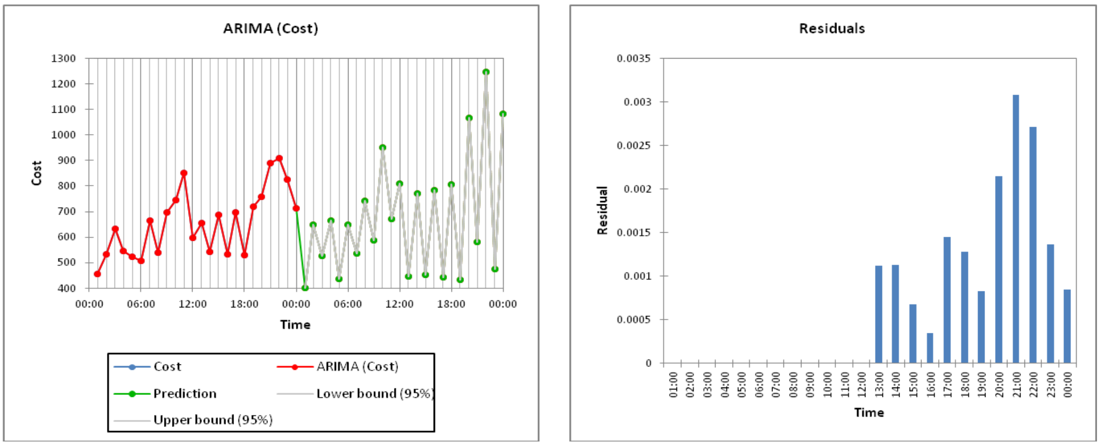

Figure 0.2 Cost of household 4 on April 7

Graphs for 24 hour prediction of ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ model for maximum negative correlation between price and consumption are shown below.

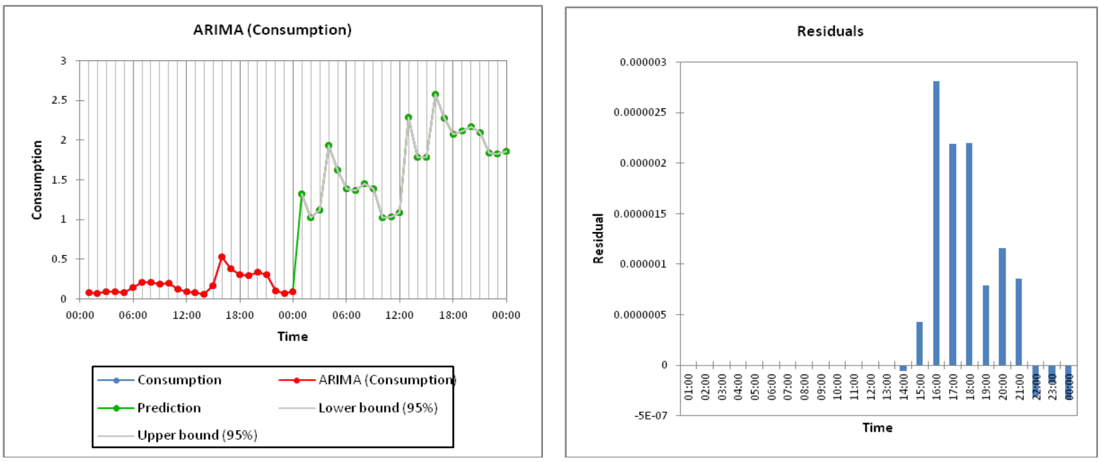

Figure 0.3 Maximum negative correlation consumption of household 10 on April 15

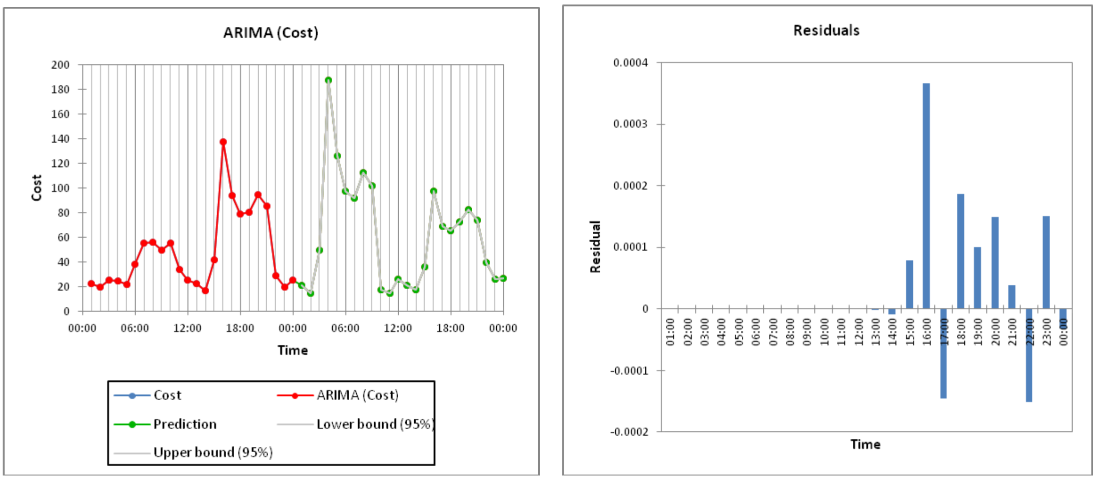

Figure 0.4 Maximum negative correlation cost of household 10 on April 15

Graphs for 24 hour prediction of ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ model for maximum difference between hourly cumulative cost and cumulative cost based on average price are shown below.

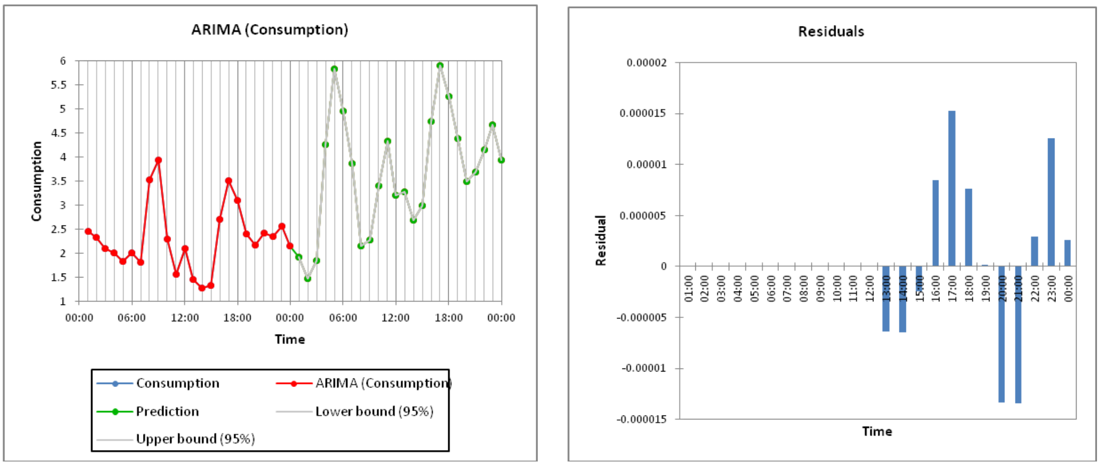

Figure 0.5 Consumption of household 4 on April 17

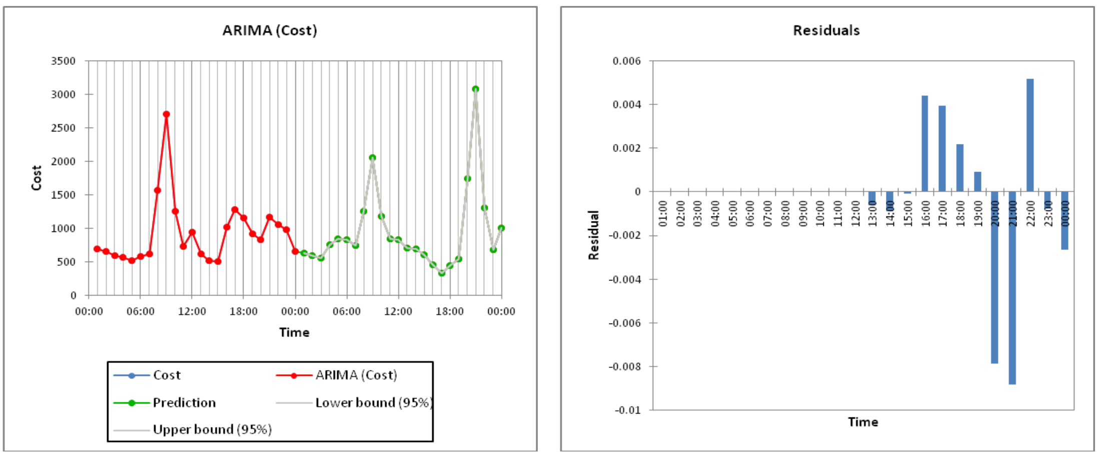

Figure 0.6 Cost of household 4 on April 17

Graphs for 24 hour prediction of ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ model for minimum difference between hourly cumulative cost and cumulative cost based on average price are shown below.

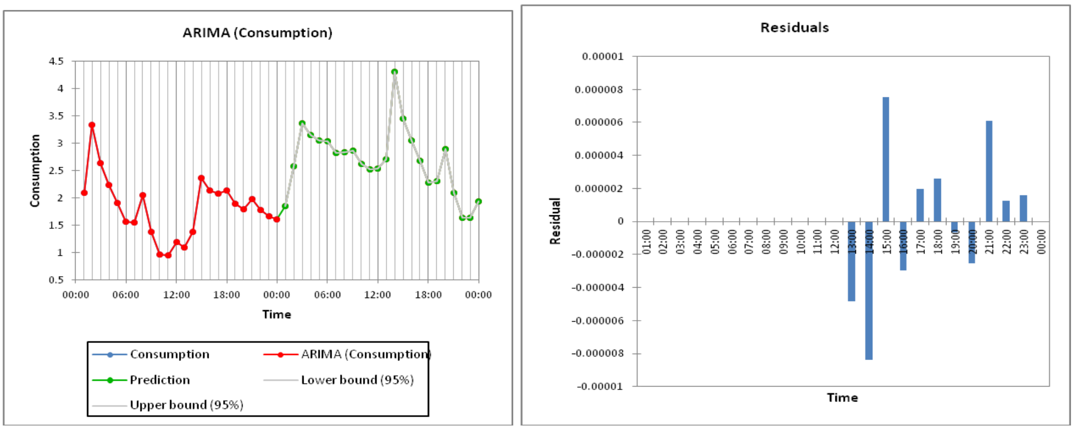

Figure 0.7 Consumption of household 4 on April 18

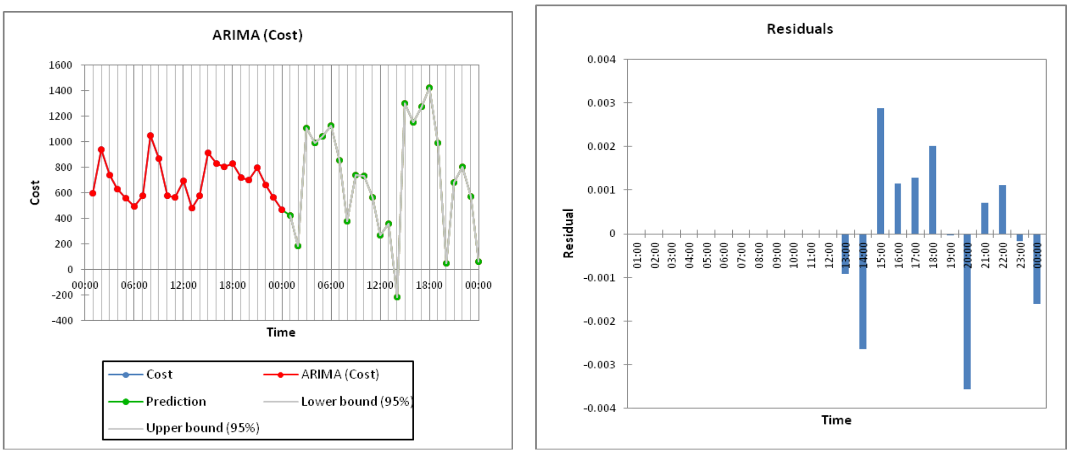

Figure 0.8 Cost of household 4 on April 18

Graphs for 24 hour prediction of ARIMA (2, 0, 1) $(2, 1, 0)_{12}$ model for hourly cumulative cost approximately equal to cumulative cost based on average price are shown below.

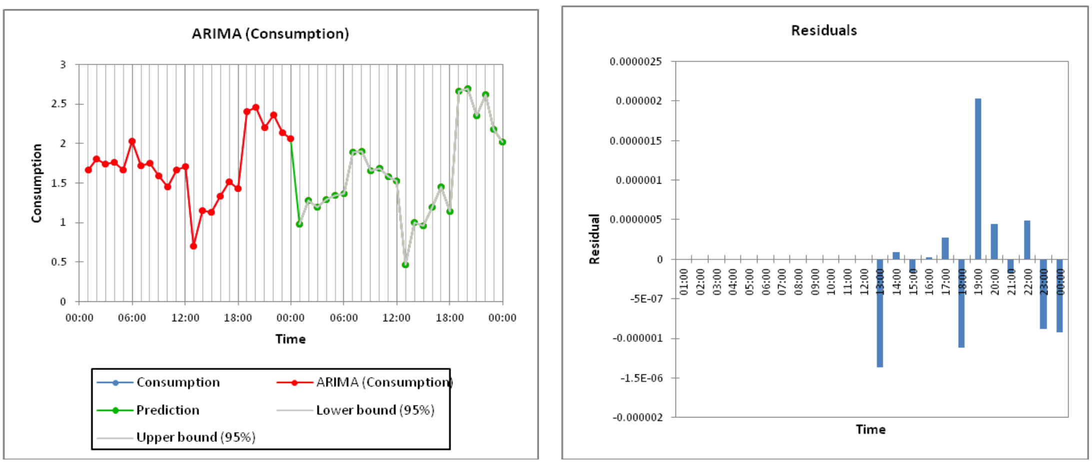

Figure 0.9 Consumption of household 4 on April 14

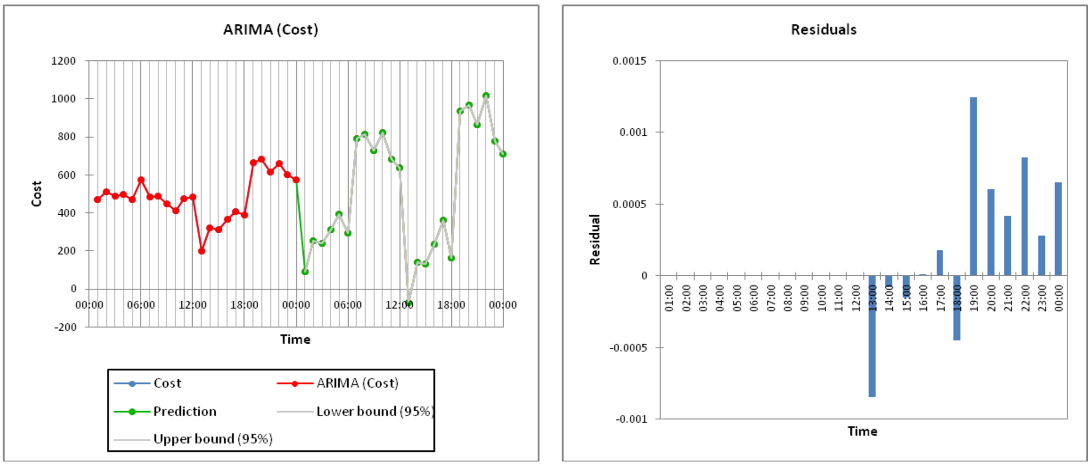

Figure 0.10 Cost of household 4 on April 14