# Forecasting Electricity Price Using Seasonal ARIMA model and Implementing RTP Based Tariff in Smart Grid

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*Abstract:*-A Smart Grid has a two-way digital communication system and it encourages customers to actively participate in different types of Demand Response (DR) programs. In the Smart Grid market, both the supplier and broker agent earn profit while distributing the electrical energy. They have to balance the supply and demand during the distribution of energy. They also participate in energy trading to earn more money. To minimize trading risks, forecasting of wholesale electricity prices is necessary. A Real Time Price (RTP) based power scheduling scheme can be implemented effectively in Smart Grid to match supply and demand. In this scheme, Home Energy Controllers (HEC) and Smart Plugs can be used to shift the operation of schedulable load from peak period to off-peak period. To shift the operation of schedulable load during off-peak period, electricity price should be available in advance. In order to have the electricity price in advance, accurate forecasting is needed. Demand and supply depends on so many factors such as weather condition, cloud cover, wind speed, day of the week and festivals. It is difficult to forecast energy prices in such uncertainty. In this work, the best fitted seasonal ARIMA (Auto Regressive Integrated Moving Average) model is identified and used to forecast the next week's electricity price. This forecasted electricity price helps in deciding the next day's load pattern and minimizing the trading risk. Algorithms for HEC and Smart Plug are presented in this work to identify the optimized time slots and to allow power to the schedulable appliances during those slots.

*Key-Words*: - Smart Grid, Demand Response, Real Time Price, Smart Plug, Home Energy Controller, ARIMA.

## 1. Introduction

Two-way digital communication is used between the supplier and customer in a Smart Grid so that real-time information can be exchanged between them [1]. Smart Grid is a fusion of electrical power engineering and network communications through various types of sensors, smart meters, Home Energy Controllers (HEC) and consumers [2]. Two-way communication can be provided between the smart meter and service provider using GSM (Global System for Mobile) network or WiMAX (Worldwide Interoperability for Microwave Access) [3].Various data such as real power, apparent power, voltage, current, and power factor are required to exchange between the service provider and consumer [4]. If a web portal is made for effective implementation of various Demand Response (DR) programs, customers can receive data either in graphical or tabular form. Due to advancement in Information and Communication Technology (ICT) today, it is very easy to implement such technology. Fig.1 represents such system model. The domestic appliances can be divided into two categories.

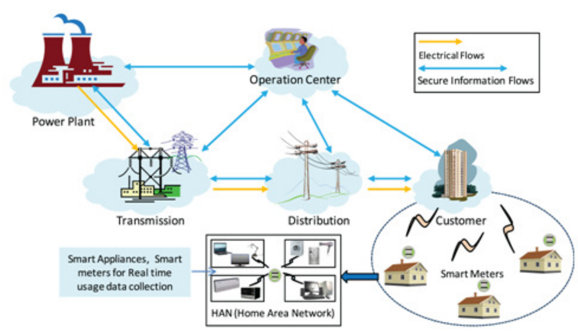



Fig. 1 The Smart Grid infrastructure showing the role of Information and Communication Technology in electrical power system

One is schedulable and another is non-schedulable [5]. Delayed operation of a schedulable load doesn't make a difference for customers. Appliances like PHEV (Plugged in Electric Vehicle), washing machines and dishwashers can be considered as schedulable appliances. The other category of appliances is non-schedulable appliances. Such appliances must get power when switched on. There are various methods presented in different literature about shifting the operation of schedulable appliances to reduce peak demand and PAR (Peak to Average Ratio)[6], [7], [8]. Broker agents buy the electricity from the wholesale market and distribute it to the customers. The supplier and the broker agent implement different types of tariffs while distributing electricity. The Real Time Price method can be considered better than other methods due to its various salient features [9]. In RTP based tariffs, an HEC can be used to decide optimized time slots for the schedulable appliances to reduce cost of energy and PAR [8], [10], [11]. HEC exchanges signals and data with different appliances through ZigBee [12]. Such a network is called the Home Area Network (HAN). Hence HEC, broker agent and supplier need an energy price in advance for effective functioning of the whole system. Forecasting also reduces the trading risk of suppliers and broker agents in the competitive electricity market [13]. Fig.2 shows the architecture of HEC and HAN. In the scheme shown in Fig.2, communication channels are established between users and utility servers through the GSM network [4].

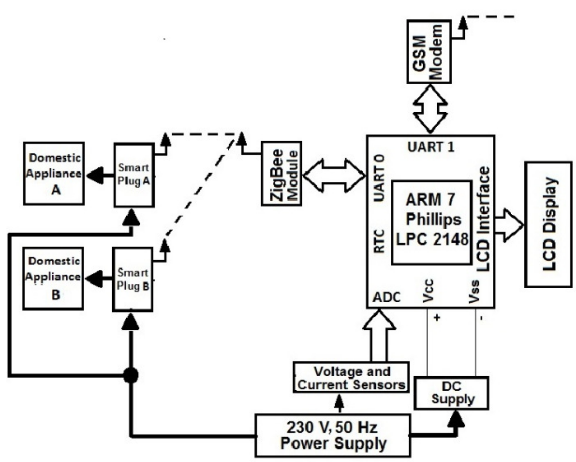



Fig. 2 Architecture showing HEC and HAN. Two schedulable appliances, A and B respectively, which are controlled by smart plugs, are shown in this figure.

Two schedulable appliances A and B are shown in Fig.2. In the future, the domestic appliances based on IPv6 will be available in the market, and they will be able to directly communicate with HEC (or even with the utility). However, presently such appliances are not available in the market, so devices like Smart Plug, which control the power given to the appliances, should be used.

To decide the next-day's load pattern for schedulable appliances using HEC, the energy price must be available in advance. For this purpose past data of electricity price from 1st June 2013 to 31st May 2014 have been collected from Indian Energy Exchange [14]. After analyzing this data, the best fitted seasonal ARIMA model is identified. To implement RTP based tariff effectively, the role of supplier and broker agent should be well defined. To avoid rebound peak [8], HEC must communicate with the supplier and send the current status to it before allowing power to schedulable appliances.

The Smart Grid tariff market domain and the role of the retail distribution grid and broker agents are discussed in section 2. The best fitted seasonal ARIMA model is explained and identified in section 3. Simulation results demonstrating the effectiveness of the proposed method of forecasting is presented in section 4. Algorithms and working of Smart Plug and HEC and their experimental results are presented in section 5. Finally concluding remarks are presented in section 6.

## 2. Smart Grid market domain

Power produced by the centralized power plant transfers to the tariff market through a national grid. Retail energy prices depend on the wholesale market and the auction-based energy market. Physical coupling points regulate the flow of power between the national and regional grid. The regional grid consists of different types of participants like broker agents, producers, consumers and service operators [15]. The wholesale market and auction based market determine the price at which power can be bought from or sold into the national grid. The regional grid consists of different types of participants like broker agents; it interacts with producers and consumers through a specially designed market mechanism. In this mechanism each broker agent acquires a portfolio of producers and consumers by simultaneously publishing prices to buy and sell the power. The broker agent should earn profit while giving this type of service so that they can continue to serve customers and achieve goals of Smart Grid. A tariff market consists of a set of different types of participants like customers, producers and broker agents. At each time slot t, each broker agent publishes two tariffs visible to all agents in the environment.

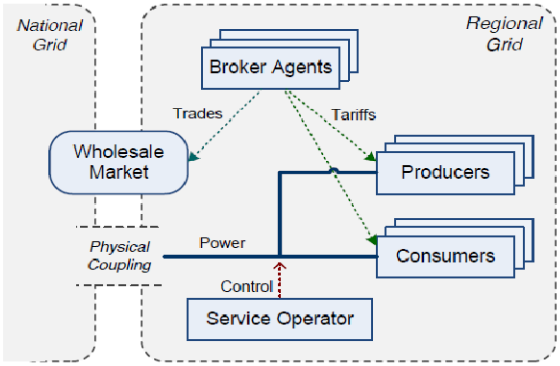



Fig. 3 Smart Grid market domain

Buying from the producers and selling to the customers, both have different tariffs. Broker agent $B_j$ ($j$=1, 2 … N) earns profit $\Omega_t^{B_j}$ (for time slot, t) from this difference, but they may be penalized for supply-demand imbalance. To minimize such penalties and maximize profit, each broker agent should actively participate in trading in the wholesale market. Trading in the market is conducted using a periodic double-auction mechanism that is cleared once every hour. Trading is allowed in the electricity market that is intended to be consumed during the next H hours (normally H=24). Hence the wholesale market conducts H simultaneous auctions to determine the clearing price for each of the H future time slots. Electricity is the most volatile commodity and daily average change of the price can be up to 50% or more [15]. The broker agent should predict the market clearing price in advance under various market scenarios to handle their portfolio effectively. The broker agent will try to maximize its cumulative profit $\sum_H \Omega_t^{B_j}$ by predicting the future market clearing price.

# 3. Time series analysis and forecasting

As discussed in previous sections, to minimize trading risk, maximize the cumulative profit and decide low priced time slots (for schedulable appliances) in advance, the energy price should be forecasted. ARIMA (Auto Regressive Integrated Moving Average) is popularly used to forecast such data. The ARIMA, also popularly known as Box-Jenkis (BJ) Methodology [16], is presented here in short.

## 3.1 Different ARIMA processes

### 3.1.1Auto regressive process: ARIMA ($p$, 0, 0)

$$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + e_t \qquad (1)$$

$Y_t$ is the discrete data at time t. In other words, $Y_t$ is an observed time series. Ø is an auto regressive coefficient, and $p$ is the order of autoregressive part. Term $e_t$ is variables or random error terms or white noise.

### 3.1.2 Moving average process: ARIMA (0, 0, $q$)

$$Y_t = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} \qquad (2)$$

In short, a moving average process is simply a linear combination of white noise error terms [16]. Term $q$ shows the number of moving average terms.

### 3.1.3 Integrated process ARIMA (0, $d$, 0)

In random walk process [16], $Y_t = Y_{t-1} + e_t = Y_t - Y_{t-1} = e_t$ so $\Delta Y_t = e_t$ (here $d$=1). In general, $\Delta^d Y_t = e_t$, where $d$ is the order of difference.

While modeling the time series, it is assumed that time series involved are weakly stationary. Many economic time series are non-stationary so they are integrated. In general we have to differentiate a time series $d$ times to make it stationary and then apply the ARMA ($p$, $q$) model to it. So resultant model becomes ARIMA ($p$, $d$, $q$). If we assume $Y' = \Delta Y$, we can write the ARIMA ($p$,1,$q$) process as follows.

$$Y'_t = C + \emptyset_1 Y'_{t-1} + \emptyset_2 Y'_{t-2} + \cdots + \emptyset_p Y'_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} \qquad (3)$$

The equation for the seasonal ARIMA ($p$, $d$, $q$) (P, D, Q)$_s$ model can be written as

$$_p(B^s)\emptyset_p(B)\left(1 - B^d\right)(1 - B^s)^d Y_t = \theta_q(B)\Theta_Q(B^s)a_t \qquad (4)$$

Where $p$ is order of non-seasonal process AR, $q$ is the order of non-seasonal process MA, $d$ is the order of non-seasonal difference, P is the order of seasonal process AR, Q is the seasonal order of process MA, D is the seasonal order of difference, B is back shift operator so $BY_t = Y_{t-1}$. The length of seasonal period is $s$.

$\emptyset_p(B)$ is the auto regressive operator, where$\emptyset_p(B) = 1 - \emptyset_1 \mathrm{B} - \emptyset_2 B^2 - \ldots - \emptyset_p B^p$,

$\theta_q(B)$ is the operator for moving averages, where $\theta_q(B) = 1 - \theta_1 \mathrm{B} - \theta_2 B^2 - \ldots - \theta_q B^q$,

$_p(B^s)$ is the seasonal operator for auto regressive process,
where $_P(B^s) = 1 - {}_1B^s - {}_2B^{2s} - \ldots - {}_pB^{Ps}$,

$\Theta_Q(B^s)$ is seasonal operator for moving averages, where$\Theta_Q(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} \ \ldots \ \Theta_Q B^{Qs}$, and $a_t$ is white noise.

### 3.2 Identification of the best ARIMA model

The following steps are used to identify the best model in the ARIMA process or the Box-Jenkis (BJ) method [16]. Fig.4 represents the process to identify the best ARIMA model.

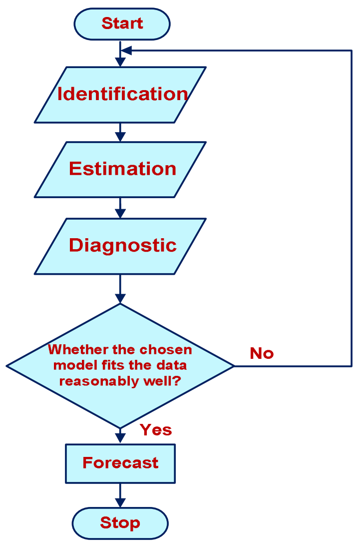



Fig. 4 Process of forecasting

#### 3.2.1 Identification

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are the important tools of this process.

#### 3.2.1.1 Autocorrelation Function (ACF)

It can be represented by the equation

$$\mathrm{ACF}_{(k)} = \sum_{t=1+k} (Y_t - \bar{Y})\,(Y_{t-k} - \bar{Y}) \Big/ \sum_{t=1} (Y_t - \bar{Y})^2 \quad (5)$$

$$= \frac{cov\,(Y_t Y_{t-k})}{var\,(Y_t)}.$$

Hence, it is the ratio of covariance at lag $k$ to the variance of the series. Values of ACF lie between -1 and +1.

#### 3.2.1.2 Partial Auto Correlation Function (PACF)

It measures the additional correlation between $Y_t$ and $Y_{t-k}$ after adjustments have been made for the intermediate values $Y_{t-1}, \dots\dots, Y_{t-k+1}$. The PACF is closely related to ACF and their values also lie between -1 to +1. The specific computational procedures for PACF are complicated. Using correlogram and partial correlogram the appropriate values of $p$, $d$ and $q$ can be identified.

#### 3.2.2 Estimation

Now a day's several statistical packages are available to handle this task. Using these packages, the final model can be estimated.

#### 3.2.3 Diagnostics

Having chosen a particular ARIMA model and having estimated its parameters, it should be tested using different tests. If the residuals estimated from the chosen model are white noise, the chosen model can be accepted. Suppose the model fails in this test, the process must be repeated. Hence, the BJ methodology is an iterative process.

#### 3.2.4 Forecasting

The ARIMA model obtained in step 3.2.3 is now ready to forecast.

## 4. Simulation results

The SPSS software is used and the expert modeler has been applied to predict next week's electricity prices. Hourly electricity prices from 1st June, 2013 to 31stMay, 2014 have been taken from Indian Energy Exchange [14]. Using these observations, different models are built and forecasting is done for the first week of June, 2014. Data sets with different spans give different models. The best ARIMA model is obtained from the observations of the duration between 1st December, 2013 and 31st May, 2014. It is ARIMA (1, 0, 2) $(1, 1, 1)_{24}$. In this model, the first bracket indicates the non-seasonal part and the second one indicates seasonal part.

Table 1 shows the comparison between different models. In the Table 2, goodness of fit statistics for the data set of six months is given. Mean absolute percentage error (MAPE) is a measure of how much a dependent series varies from its model-predicted level. For the data set of six months between 1st December, 2013 and 31st May, 2014, the value of MAPE is 4.457%. Root Mean Square Error (RMSE) is also a measure of how much a dependent series varies from its model-predicted level, expressed in the same units as the dependent series. Maximum Absolute Percentage Error (MaxAPE) represents the largest forecasted error, expressed as a percentage. Different parameters obtained from the ARIMA (1, 0, 2) $(1, 1, 1)_{24}$ model are listed in Table 3. The result of Ljung-Box test of different models is listed in Table 4.

Fig.5 and Fig.6 represent ACF and PACF respectively for the chosen time series of six months. ACF and PACF are used to identify the stationarity of the time series [16], [17].

Plot of ACF seems like a sine wave variation that indicates that the non-seasonal difference is zero. Plot of PACF clearly shows periodicity of 24. Fig.7 represents PACF by taking the seasonal difference of 1.

Table 1: Comparison of parameters between different models

| Fit Statistics | Twelve month data ARIMA (4,0,8) $(1,1,1)_{24}$ | Nine month data ARIMA (3,0,8) $(1,1,1)_{24}$ | Eight month data ARIMA (2,0,1) $(1,1,1)_{24}$ | Seven month data ARIMA (1,0,2) $(1,1,1)_{24}$ | Six month data ARIMA (1,0,2) $(1,1,1)_{24}$ | Five month data ARIMA (2,0,1) $(1,1,1)_{24}$ | Four month data ARIMA (3,0,0) $(1,1,1)_{24}$ | Three month data ARIMA (3,0,0) $(1,1,1)_{24}$ | Two month data ARIMA (2,0,1) $(1,1,1)_{24}$ | One month data ARIMA (0,1,5) $(0,1,1)_{24}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Stationary R-squared | .707 | .694 | .695 | .692 | .700 | .690 | .694 | .707 | .652 | .313 |
| R-squared | .948 | .937 | .940 | .939 | .944 | .929 | .915 | .892 | .879 | .897 |
| RMSE | 188.73 | 194.205 | 195.003 | 199.242 | 194.526 | 215.347 | 220.491 | 228.585 | 235.850 | 233.891 |
| MAPE | 4.870 | 4.486 | 4.535 | 4.573 | 4.457 | 4.856 | 4.927 | 5.095 | 5.060 | 5.613 |
| MaxAPE | 50.028 | 50.621 | 50.377 | 50.738 | 49.015 | 50.586 | 51.219 | 52.395 | 50.607 | 35.752 |
| MAE | 134.99 | 138.644 | 140.382 | 143.893 | 140.323 | 156.087 | 159.513 | 166.077 | 170.923 | 175.989 |
| MaxAE | 1499.9 | 1518.87 | 1511.53 | 1522.36 | 1435.27 | 1517.82 | 1536.82 | 1572.10 | 1518.46 | 1119.37 |
| Normalized BIC | 10.491 | 10.549 | 10.553 | 10.601 | 10.551 | 10.756 | 10.806 | 10.878 | 10.952 | 10.946 |

Table 2: Goodness of the fit statistics for ARIMA (1, 0, 2)$(1, 1, 1)_{24}$model

| Fit Statistic | Mean | SE | Minimum | Maximum | Percentile | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 5 | 10 | 25 | 50 | 75 | 90 | 95 |
| Stationary R-squared | .700 | . | .700 | .700 | .700 | .700 | .700 | .700 | .700 | .700 | .700 |
| R-squared | .944 | . | .944 | .944 | .944 | .944 | .944 | .944 | .944 | .944 | .944 |
| RMSE | 194.526 | . | 194.526 | 194.526 | 194.526 | 194.526 | 194.526 | 194.526 | 194.526 | 194.526 | 194.526 |
| MAPE | 4.457 | . | 4.457 | 4.457 | 4.457 | 4.457 | 4.457 | 4.457 | 4.457 | 4.457 | 4.457 |
| MaxAPE | 49.015 | . | 49.015 | 49.015 | 49.015 | 49.015 | 49.015 | 49.015 | 49.015 | 49.015 | 49.015 |
| MAE | 140.323 | . | 140.323 | 140.323 | 140.323 | 140.323 | 140.323 | 140.323 | 140.323 | 140.323 | 140.323 |
| MaxAE | 1435.265 | . | 1435.265 | 1435.265 | 1435.265 | 1435.265 | 1435.265 | 1435.265 | 1435.265 | 1435.265 | 1435.265 |
| Normalized BIC | 10.551 | . | 10.551 | 10.551 | 10.551 | 10.551 | 10.551 | 10.551 | 10.551 | 10.551 | 10.551 |

Table 3:ARIMA (1, 0, 2)$(1, 1, 1)_{24}$ Model Parameters

| Model Parameters | | Estimate | | SE | t | Sig. |
|---|---|---|---|---|---|---|
| Energy price model obtained from six month data | AR | Lag 1 | .876 | .011 | 82.413 | .000 |
| | MA | Lag 1 | .166 | .019 | 8.816 | .000 |
| | | Lag 2 | .062 | .018 | 3.503 | .000 |
| | AR, Seasonal | Lag 1 | .346 | .021 | 16.114 | .000 |
| | Seasonal Difference | - | 1 | - | - | - |
| | MA, Seasonal | Lag 1 | .826 | .013 | 63.232 | .000 |

Table 4: Comparison of Ljung-Box Q(18) values of different models

| Ljung-Box Q(18) | Twelve Month | Nine Month | Eight Month | Seven Month | Six Month | Five Month | Four Month | Three Month | Two Month | One Month |
|---|---|---|---|---|---|---|---|---|---|---|
| Statistics | 27.296 | 8.720 | 23.557 | 18.92 | 10.562 | 8.392 | 15.130 | 17.878 | 10.038 | 23.557 |
| DF | 8 | 10 | 14 | 13 | 13 | 13 | 13 | 14 | 13 | 14 |
| Sig. | .001 | .559 | .052 | .126 | .647 | .817 | .299 | .212 | .691 | .052 |

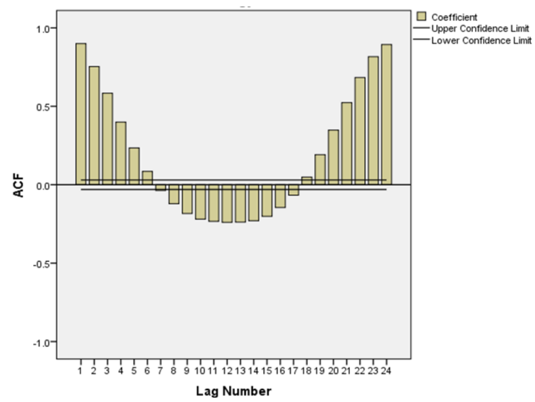



Fig. 5 Auto Correlation for model obtained from six month data

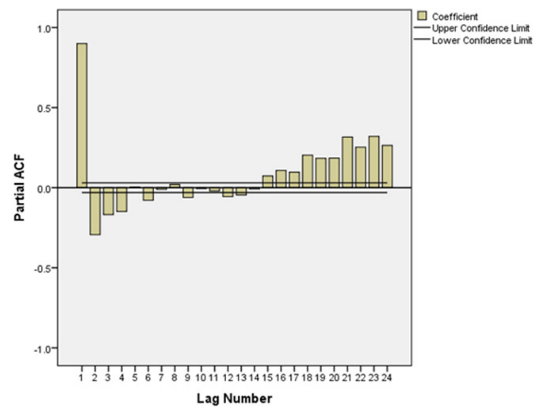



Fig. 6 Partial Auto Correlation for model obtained from six month data

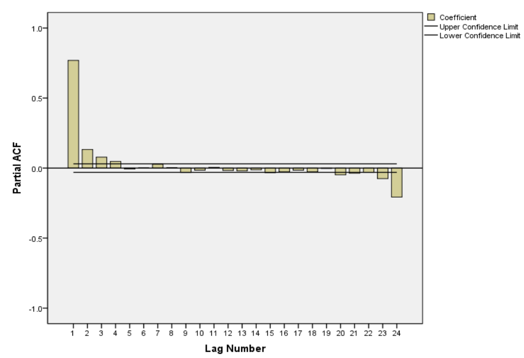



Fig. 7 PACF after taking the seasonal difference 1

Fig.8 presents the residual ACF and PACF. Only one significant spike is observed in this figure, so the model can be used for forecasting. Fig.9 shows the observed, fit and forecasted data using the ARIMA (1, 0, 2) $(1, 1, 1)_{24}$ model. The Ljung-Box test also indicates goodness of model as the significance value is greater than 0.05. Fig.10 shows actual price of first week of June, 2014 compared with forecasted price obtained from ARIMA model calculated using six months' data.

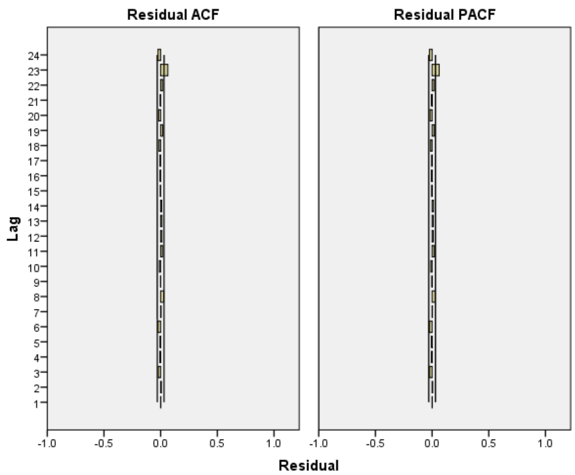



Fig. 8 Residual ACF and PACF obtained from ARIMA (1, 0, 2) (1, 1, 1)$_{24}$ model

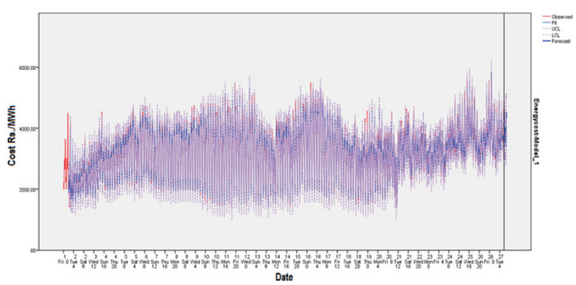



Fig. 9 Observed, fit and forecasted data using the ARIMA (1, 0, 2) (1, 1, 1)$_{24}$ model.

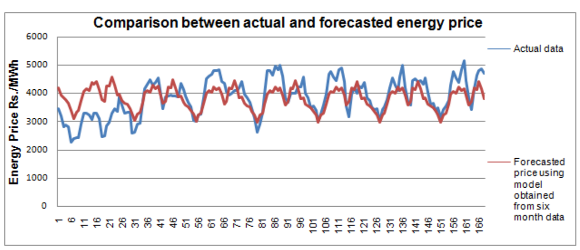



Fig.10 Comparison between forecasted and actual energy prices for the first week of June, 2014 obtained from the ARIMA (1, 0, 2)(1,1,1)$_{24}$ seasonal model (data obtained over six months)

## 5. Smart Plug and Home Energy Controller

For effective implementation of RTP based tariff, use of Smart Plugs and HECs are necessary. After forecasting the next day's electricity price, the supplier sends the forecasted retail energy price to all the HECs of each customer. In this section, algorithms of Smart Plug, HEC and their experimental results are presented.

### 5.1 Smart Plug

Smart Plug is used to allow power to domestic appliance according to the signals sent by HEC. In Fig.11 and 12 operation of Smart Plug is explained. The view of Smart Plug is shown in Fig.13.

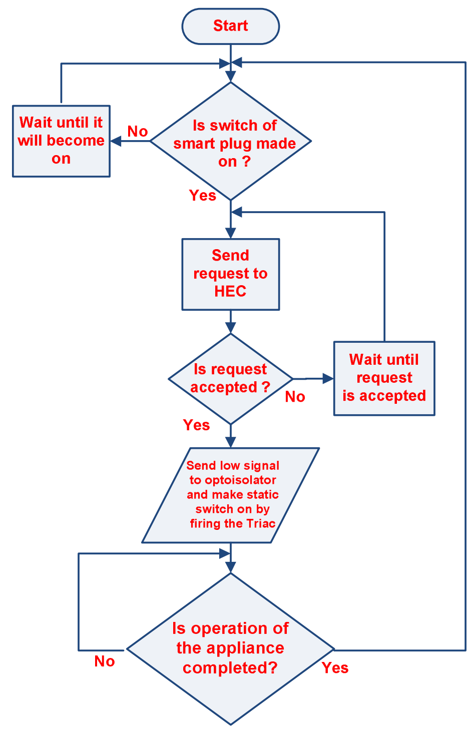



Fig.11 Flowchart for operation of Smart Plug

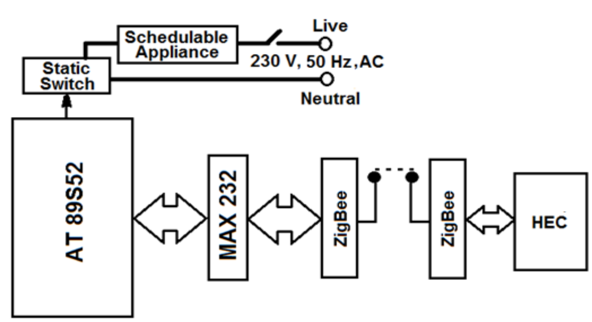



Fig.12 Functional block diagram showing communication between Smart Plug

Above figure shows how smart plug communicates with HEC.


Fig. 13 Actual view of Smart Plug

## 5.2 Home Energy Controller

The working of HEC is shown in Fig.14. The architecture of HEC cum smart meter and HAN is shown in Fig.2. 32 bit, LPC 2148, ARM 7 controller board is used for HEC. Two schedulable appliances A and B are shown in this figure exchanging signals with HEC. Power is given to the schedulable appliances through Smsrt Plugs.

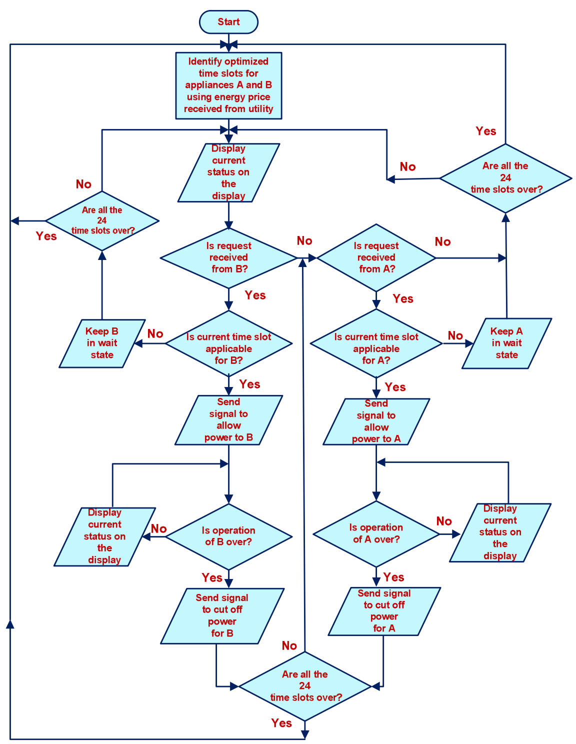



Fig.14 Working of HEC

Program is made to identify the successive minimum priced time slots for schedulable loads A and B. Fig. 15 shows the view of HEC. Signal is sent to Smart Plug through UART 0 to control the schedulable load. The LCD display shows different types of information during the working of HEC. This is shown in Fig. 18. In the first line, current consumption P in Watts and the total cost of energy consumed (in Rs., till the time of a day) is displayed. In the second line, the current status of schedulable appliances A and B is shown. In second part of second line of the LCD display, status of a current time slot is shown. A number '24' indicates current time slot (between 23:00 PM to 00:00 AM) and '4.19' indicates the value of electricity of current time slot in Rs. To decide the next day's load pattern, the energy prices of the next 24 hours are sent every day to the HEC at 12:00 AM.

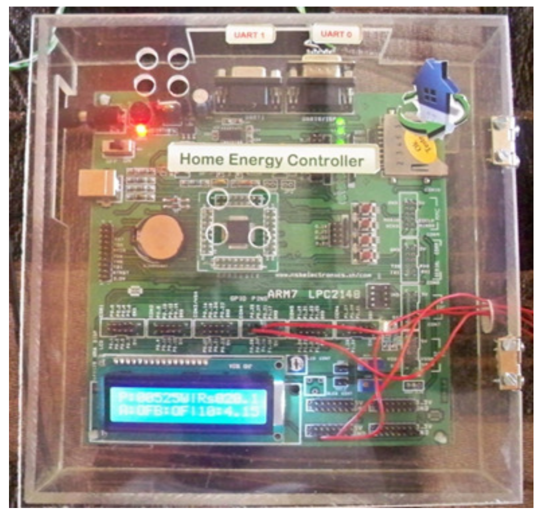



Fig.15 View of Home Energy Controller

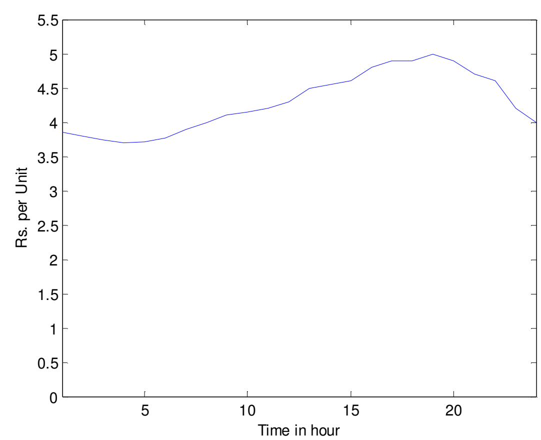


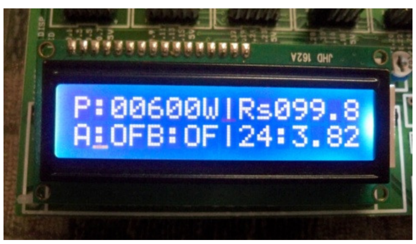

Fig.16 Hourly energy price sent by utility

After receiving these values, HEC calculates optimized time slots for device A and B and accordingly it turns on and off these devices to reduce the daily cost and Peak to Average Ratio

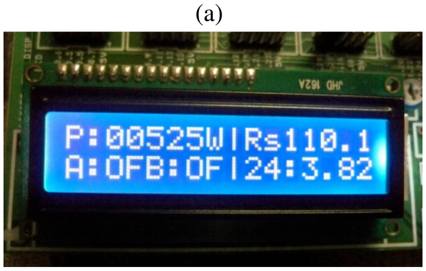
(PAR) [8]. This hourly energy price (used in this work) is shown in Fig.16.

To save the time during testing, one minute is considered as one hour. During low-priced night hours (having off-peak time slots) schedulable appliances having higher consumption (like PHEV) are allowed to run. The complete test set-up is shown in Fig.17.

Fig. 17 Test set up showing HEC, Smart Plugs and Smart Grid distribution board




(a)




(b)

Fig.18 (a) First phase of testing: Appliances are run during optimized time slots. (b) Second phase of testing: Appliances are run during non-optimized time slots.

In the first phase of testing, HEC turns on and off washing machine (A) and PHEV (B) (through Smart Plugs) as per the optimized time slots calculated in the starting of the operation. At the end of 24th hour (24th minute in the experiment) the cost of consumption is Rs.99.80. This is shown in Fig. 18(a). In the second phase, appliances are run during the non-optimized time slots (without the help of HEC). In this case total cost of energy consumed is Rs. 110.10. From this test it can be concluded that by shifting the operation of schedulable appliances towards optimized time slots, 10.3% of money is saved. This incentive is given to the customer to use such schedulable appliances during off-peak hours to reduce peak load and Peak to Average Ratio (PAR) during the day.

# 6. Conclusions

In this analysis the best fitted seasonal ARIMA model to forecast electricity price is identified. The data set of hourly prices of twelve months is used to identify the best model. The best fitted model is ARIMA (1, 0, 2) $(1, 1, 1)_{24}$ obtained from six month's data between 1st December, 2013 to 31st May, 2014. Hence data of six months is enough to forecast the electricity price for the first week of June, 2014. The actual electricity price varies from the forecasted one due to the uncertainty of demand, weather, day of the week, week of the month, month of year, festivals etc. If the RTP-based tariff is implemented, some amount of load will shift towards the lower priced time slots and the resultant demand curve will be altered. Thus, it may result into further changes in the actual electricity price. So the forecasted electricity price would vary from the real electricity price, however if RTP based tariff is implemented regularly, this variation will be very small. Although there is an existence of such variation, forecasting is very helpful to decide the next day's load pattern for HEC and manage the trading risk of the supplier and broker agent. The function of Smart Plug and HEC in minimization of energy cost (and reducing peak demand) is explained in this work. A considerable amount of money can be saved using the presented strategy.

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