(12) INTERNATIONAL APPLICATION PUBLISHED UNDER THE PATENT COOPERATION TREATY (PCT)

(19) World Intellectual Property Organization
International Bureau

(43) International Publication Date
2 August 2012 (02.08.2012)

WIPO | PCT

(10) International Publication Number
WO 2012/101656 A2

(51) International Patent Classification:
G06Q 10/04 (2012.01)

(21) International Application Number:
PCT/IN2012/000058

(22) International Filing Date:
27 January 2012 (27.01.2012)

(25) Filing Language: English

(26) Publication Language: English

(30) Priority Data:
236/MUM/2011 27 January 2011 (27.01.2011) IN

(71) Applicant *(for all designated States except US)*: **INDIAN INSTITUTE OF TECHNOLOGY, BOMBAY** [IN/IN]; Indian Institute of Technology, Powai, Maharashtra, Mumbai 400076 (IN).

(72) Inventors; and

(75) Inventors/Applicants *(for US only)*: **KHAPARDE, Shrikrishna Anantrao** [IN/IN]; Professor, Department of Electrical Engineering, I.I.T. Bombay, Powai, Mumbai 400076 (IN). **BALIJEPALLI, Venkata Sita Krishna Murthy** [IN/IN]; PhD Research Scholar, Department of Electrical Engineering, I.I.T. Bombay, Powai, Mumbai 400076 (IN).

(74) Agent: **CHAKRAVARTHY, Kalyan**; No.40,1st Floor, 3rd Main Road, JC Industrial Estate, Kanakapura Road, Bangalore 560062 (IN).

(81) Designated States *(unless otherwise indicated, for every kind of national protection available)*: AE, AG, AL, AM, AO, AT, AU, AZ, BA, BB, BG, BH, BR, BW, BY, BZ, CA, CH, CL, CN, CO, CR, CU, CZ, DE, DK, DM, DO, DZ, EC, EE, EG, ES, FI, GB, GD, GE, GH, GM, GT, HN, HR, HU, ID, IL, IN, IS, JP, KE, KG, KM, KN, KP, KR, KZ, LA, LC, LK, LR, LS, LT, LU, LY, MA, MD, ME, MG, MK, MN, MW, MX, MY, MZ, NA, NG, NI, NO, NZ, OM, PE, PG, PH, PL, PT, QA, RO, RS, RU, RW, SC, SD, SE, SG, SK, SL, SM, ST, SV, SY, TH, TJ, TM, TN, TR, TT, TZ, UA, UG, US, UZ, VC, VN, ZA, ZM, ZW.

(84) Designated States *(unless otherwise indicated, for every kind of regional protection available)*: ARIPO (BW, GH, GM, KE, LR, LS, MW, MZ, NA, RW, SD, SL, SZ, TZ, UG, ZM, ZW), Eurasian (AM, AZ, BY, KG, KZ, MD, RU, TJ, TM), European (AL, AT, BE, BG, CH, CY, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HR, HU, IE, IS, IT, LT, LU, LV, MC, MK, MT, NL, NO, PL, PT, RO, RS, SE, SI, SK, SM, TR), OAPI (BF, BJ, CF, CG, CI, CM, GA, GN, GQ, GW, ML, MR, NE, SN, TD, TG).

Declarations under Rule 4.17:

— *as to the identity of the inventor (Rule 4.17(i))*

[Continued on next page]

(54) Title: A SYSTEM AND METHOD FOR ELECTRICITY PRICE FORECASTING

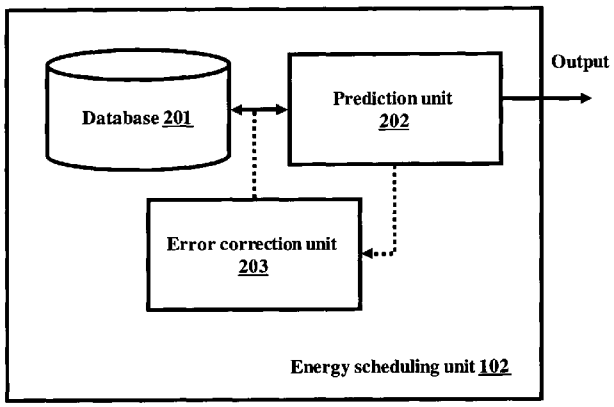


FIG. 2

(57) Abstract: A system and method for electricity price forecasting is disclosed. This invention relates to electricity price forecasting, and particularly to price forecasting by employing error correction techniques. Existing mechanisms do not offer effective error correction mechanisms and hence there are no means to ensure accurate electricity pricing. The method employs a forecasting module that refers to the patterns of energy consumption from the history and accordingly predicts the most likely energy consumption. In addition, the method also employs neural network based mechanisms in order to determine the states of the values. The method compares if there are errors in the prediction. In case there is error, it determines if the error is within the permissible values. Further, if the error is outside the permissible values then a correction factor is applied to the computed values and prediction is updated. FIG. 2

WO 2012/101656 A2

— *of inventorship (Rule 4.17(iv))*

Published:

— *without international search report and to be republished upon receipt of that report (Rule 48.2(g))*

A SYSTEM AND METHOD FOR ELECTRICITY PRICE FORECASTING

FIELD OF INVENTION

[001] This invention relates to electricity price forecasting, and more particularly to price forecasting by employing error correction techniques.

BACKGROUND OF INVENTION

[002] With the increasing competition in power market, electricity price forecasting has become a very vital issue for better operational planning and maximising profits for the service providers. Electricity price forecasting becomes crucial in deregulated environment as electricity demands are more or equal to its generation. Series of prices presents features like high frequency, non-constant mean and variance, an hourly basis, 24 hours a day, 7 days a week basis, calendar effect on weekend and public holidays. There are numerous hard and soft computing techniques to short-term electricity price forecasting based on escalating historical data, least-cost optimization models and taxonomy of price forecasting which consider system loads, power supply and fuel prices.

[003] The hard computing techniques employed today have an exact model built of the system and employ an algorithm to find the solution. For

example, Auto Regression (AR) models, Auto Regression Integrated Moving Average (ARIMA) models and so on. The cited technique can be accurate, but it requires a lot of information, and hence it is complex. In addition, the computational costs involved are very high. In another example, soft computing technique employed do not have a fixed model of the system however, it implements artificial intelligence techniques to map several inputs and the electricity prices appropriately using past behaviour.

[004] In another example, neural network techniques have been widely implemented for load forecasting and electricity price forecasting. Neural network techniques display more accuracy for price forecasting compared to ARIMA models. Neural networks techniques are data driven and simple where it can approximate nonlinear function. These can be powerful and flexible tools for forecasting, if provided with enough data for training, an adequate selection of the input–output samples, an appropriate number of hidden units and enough computational resources available. Generally three-layered feed forward neural networks are implemented for forecasting, implementing nonlinearities and linear functions for the output layer.

[005] All the forecasting techniques rely on the historical data and numerous factors, thus the probability of error in forecast values increases with the increase in number of factors in existing mechanisms. In particular, accuracy in forecasting electricity prices is very critical, since

more accuracy in forecasting reduces the risk of under/over estimating the revenue from the generators for the power companies and provides better risk management. Forecast errors have significant implications for profits, market shares and ultimately shareholder value.

[006] Due to the aforementioned reasons existing forecasting techniques are not very effective. In addition, they do not provide mechanisms in order to perform corrections on the data or eliminate errors over a period of time.

OBJECT OF INVENTION

[007] The principal object of this invention is forecasting electricity prices.

[008] Another object of the invention is employing error correction techniques in order to ensure there are no errors in forecasting.

[009] A further object of the invention is predicting error correction based on artificial neural network techniques.

STATEMENT OF INVENTION

[0010] Accordingly the invention provides a method for predicting forecasts in electricity pricing which is characterized in that for employing error correction techniques to eliminate errors in forecasts.

[0011] There is also provided a method for electricity price forecasting based on energy consumption patterns across market. The method comprising an energy scheduling unit calculating the energy produced and energy consumed for a period of time, the energy scheduling unit estimating electricity price for the period of time, the energy scheduling unit calculating if the energy consumed is more than the energy produced, if the energy consumed is more, then the energy scheduling unit determining the error difference between the estimated electricity price and actual electricity price, the energy scheduling unit applying error correction techniques to the error difference and the energy scheduling unit updating the estimated electricity price as per the error correction.

[0012] These and other aspects of the embodiments herein will be better appreciated and understood when considered in conjunction with the following description and the accompanying drawings. It should be understood, however, that the following descriptions, while indicating preferred embodiments and numerous specific details thereof, are given by way of illustration and not of limitation. Many changes and modifications may be made within the scope of the embodiments herein without departing from the spirit thereof, and the embodiments herein include all such modifications.

BRIEF DESCRIPTION OF FIGURES

[0013] This invention is illustrated in the accompanying drawings, through out which like reference letters indicate corresponding parts in the various figures. The embodiments herein will be better understood from the following description with reference to the drawings, in which:

[0014] FIG. 1 illustrates a system diagram of the forecasting system, according to embodiments as disclosed herein;

[0015] FIG. 2 depicts an energy scheduling unit, according to embodiments as disclosed herein;

[0016] FIG. 3 is a flow diagram depicting the process of energy scheduling, according to embodiments as disclosed herein;

[0017] FIG. 4 depicts neural networks state machine, according to embodiments as disclosed herein;

[0018] FIG. 5 is a graph depicting price data for a period, according to embodiments as disclosed herein;

[0019] FIG. 6 is a graph depicting Market Clearing Price (MCP) over a time period, according to embodiments as disclosed herein;

[0020] FIG. 7 is a graph depicting price and demand standard deviation over a period of days, according to embodiments as disclosed herein;

[0021] FIG. 8 is a graph depicting price standard deviation over a period of hours, according to embodiments as disclosed herein;

[0022] FIG. 9 is a graph depicting the comparison of actual and forecasted values, according to embodiments as disclosed herein;

[0023] FIG. 10 is a graph depicting 11 day MLR values, according to embodiments as disclosed herein;

[0024] FIG. 11 is a graph depicting 30 day MLR values, according to embodiments as disclosed herein;

[0025] FIG. 12 is a graph depicting 30 day MLR values in nn, according to embodiments as disclosed herein;

[0026] FIG. 13 is a graph depicting error probabilities, according to embodiments as disclosed herein;

[0027] FIG. 14 is a graph depicting error probabilities in 30 day nn, according to embodiments as disclosed herein;

[0028] FIG. 15 is a graph depicting error mesh for 30 day MLR, according to embodiments as disclosed herein;

[0029] FIG. 16 is a graph depicting error surf for 30 day nn, according to embodiments as disclosed herein;

[0030] FIG. 17 is a graph depicting comparison of SEC and UEC predicted values, according to embodiments as disclosed herein;

[0031] FIG. 18 is a graph depicting NSW market behavior over a time period, according to embodiments as disclosed herein;

[0032] FIG. 19 is a graph depicting raw data and preprocessing data, according to embodiments as disclosed herein;

[0033] FIG. 20 is a graph depicting price and demand standard deviation day wise, according to embodiments as disclosed herein;

[0034] FIG. 21 is a graph depicting price and demand standard deviation time block wise, according to embodiments as disclosed herein;

[0035] FIG. 22 is a graph depicting price demand and standard deviation for LEX and NSW, according to embodiments as disclosed herein;

[0036] FIG. 23 is a graph depicting normal forecast and SEC forecast values, according to embodiments as disclosed herein;

[0037] FIG. 24 is a graph depicting frequency distribution of error of the day ahead of price forecasts for period of days, according to embodiments as disclosed herein;

[0038] FIG. 25 is a graph depicting error probability, according to embodiments as disclosed herein;

[0039] FIG. 26 is a graph depicting correction factor applied, according to embodiments as disclosed herein; and

[0040] FIG. 27 is a graph depicting a short term forecast, according to embodiments as disclosed herein.

DETAILED DESCRIPTION OF INVENTION

[0041] The embodiments herein and the various features and advantageous details thereof are explained more fully with reference to the non-limiting embodiments that are illustrated in the accompanying drawings and detailed in the following description. Descriptions of well-known components and processing techniques are omitted so as to not unnecessarily obscure the embodiments herein. The examples used herein are intended merely to facilitate an understanding of ways in which the embodiments herein may be practiced and to further enable those of skill in the art to practice the embodiments herein. Accordingly, the examples should not be construed as limiting the scope of the embodiments herein.

[0042] The embodiments herein achieve a solution for electricity pricing forecast by providing systems and methods thereof. Referring now to the drawings, and more particularly to FIGS. 1 through 27, where similar reference characters denote corresponding features consistently throughout the figures, there are shown preferred embodiments.

[0043] A system and method for forecasting pricing in electricity consumption is determined. The method enables the consumers to determine the pricing forecasts for his consumption patterns. On determining the forecasts the consumer can plan his usage accordingly. The system employs a forecasting module that refers to the patterns of energy consumption from the history and accordingly predicts the most likely

energy consumption. In addition, the method also employs neural network based mechanisms in order to determine the states of the consumption values. The method also compares if there are errors in the prediction. In case there is error, it determines if the error is within the permissible values. In an embodiment, the permissible values may be defined by the supplier earlier. Further, if the error is outside the permissible values then a correction factor is applied to the computed values and prediction is updated. As a result, error control mechanisms help to minimize inaccuracies in the prediction and ensure that the prediction is efficient.

[0044] FIG. 1 illustrates a system diagram of the forecasting system, according to embodiments as disclosed herein. As depicted is the forecasting system in combination with various modules that interact with the forecasting system and are involved in electricity price prediction. The system comprises of a portfolio management unit 101, energy scheduling unit 102, load dispatch center 103, billing system 104, load shedding 105, energy audit 106, energy accounting unit 107 and metering unit 108.

[0045] The portfolio management unit 101 is responsible for handling the entire energy management portfolio. The portfolio management unit 101 receives load and pricing forecasts of the energy consumption from the short term price and load forecast unit that sits within the energy scheduling unit 102. The portfolio management unit 101 determines cost matrix and sends the data to the energy scheduling unit

102. It also sends the cost matrix details for planning schedule of a day's operation.

[0046] The energy scheduling unit 102 is the core component of the system. It is responsible for extracting data on patterns of energy consumption, load, and portfolio in order to determine the schedule for the consumer as per his consumption patterns. The energy scheduling unit 102 also interacts with the metering unit 108 in order to determine how many units of energy have been consumed and the like. The energy scheduling unit 102 further comprises of sub-units such as short term price and load forecast for short time pricing, energy scheduling for a day's operation and so on. It also sends merit order requests to the load dispatch center 103 and accepts the load shed merit order from the load shedding 105. Further, the output from the scheduling unit will be drawl instructions and load shedding advice and the like.

[0047] In an embodiment, the energy scheduling unit 102 at consumer premises in a retail market may be a Smart Meter. The smart meter forecasts the prices received from the utility along with any missing prices and schedules the consumer loads and maximizes the consumer benefits.

[0048] The load dispatch center 103 is responsible for dispatching the load and informing the energy scheduling unit of the load contents and

so on. It also accepts merit order requests from the energy scheduling unit 102.

[0049] The billing system 104 is responsible for performing the billing operations based on the energy consumption patterns. Based on the prediction results obtained the billing system 104 may also provide the approximate costs for the energy patterns required by the consumers. The billing system 104 also provides revenue area priority information to the load shedding 105. Further, the pricing may be in terms of market clearing price, area market clearing price, retail market clearing price and the like.

[0050] The load shedding 105 is responsible for maintaining information of the load shedding at different points of the location which fall within the supplier's areas. The load shedding 105 sends feedback information to the energy scheduling unit 102 based on which the availability of energy is decided and the pricing is estimated.

[0051] The energy audit 106 is responsible for performing energy audit operations. It employs thumb rules in order to compute energy audit parameters.

[0052] The energy accounting unit 107 is responsible for keeping a track of the energy consumption. The energy audit 106 also sends energy account information to the energy thumb rule energy audit unit that performs the actual audit operations.

[0053] The metering unit 108 is responsible for maintaining a record of the energy consumed. The metering unit 108 also comprises an AMR unit, ABT meter and a REC mechanism unit. The units interact with each other in order to keep a track of the energy consumed.

[0054] FIG. 2 depicts an energy scheduling unit, according to embodiments as disclosed herein. The energy scheduling unit 102 is mainly responsible for energy scheduling operations based on the energy consumption patterns of the consumers. The energy scheduling unit comprises within it a database 201, prediction unit 202, and an error correction unit 203.

[0055] The energy scheduling unit 102 fetches the data on the energy consumption patters maintained in the database 201. The database 201 stores history of the energy consumption patters such as energy consumption in a particular locality over a period of days, months, and year or during the day and so on.

[0056] The prediction unit 202 is responsible for predicting the energy pricing for the consumers based on their energy consumption patterns. The prediction unit 202 takes data inputs form the database 201 and obtains pricing prediction. The prediction unit 202 makes a check if there is any error on the computed pricing rates by comparison with the history of the consumption patterns. In case there is an error a check is made if the error is within the permissible limits. The permissible limit is

generally in the range of 60% deviation. If the deviation is more than this range, then the prediction unit 202 sends information to the error correction unit 203.

[0057] The error correction unit 203 fetches data from the prediction unit 202 and performs error corrections. The error correction unit 203 employs different techniques for error corrections that include mean absolute error (MAE), sum of squared error (SSE), root mean squared error (RMSE) and mean absolute percentage error (MAPE). The following are computed as below:

MAE = $\frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i|$.

SSE = 

RMSE = $\sqrt{\frac{\sum(f(x_i)-y_i)^2}{n}}$

MAPE = $\frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_i - F_i}{A_i}\right| * 100$

[0058] In an embodiment, the stochastic error correction techniques are depicted as below:

Let A_n and A_{f_n} be the actual values and predicted values respectively. Error in the forecasted values can be defined as

$$Error(E) = A_n - A_{f_n} \quad (1)$$

Let E=$\{e_1,e_2,e_3,.....,e_m\}$ be the set of error elements and E_1, E_2, E_3,...E_n, be the error blocks and P_p=[0,1].

$$E_{1,2...,n}(P_{p_n}) \geq \zeta \rightarrow A_{f_{1,2...,n}} + E_{1,2...,n} * (\lambda/100)$$

$$E_{1,2...,n}(1 - P_{p_n}) \geq \zeta \rightarrow A_{f_{1,2...,n}} - E_{1,2...,n} * (\lambda/100)$$

Where, ζ - Error probability parameter
λ - parameter for percentage of error addition
P_p - Probability of positive error
n - Number of error blocks

[001] FIG. 3 is a flow diagram depicting the process of energy scheduling, according to embodiments as disclosed herein. At the start of the process, the energy consumption patterns are recorded (301) over a period of time in the database 202. The period of time may be hours, days, months or year. Further, the data consumption patterns are sent (302) from the database 201 to the prediction unit 202. In the prediction unit, the energy pricing is predicted (303) based on the energy consumption patterns stored in the history. A check is made (304) if there is an error in the pricing as compared to the history. This is mainly done by comparing if there is a deviation in the percentage of the difference between the actual value and the predicted value. In case there is error corrections are performed (305) by the error correction unit. The error correction unit

employs various techniques in order to compute the errors such as MAE, SSE, RMSE and MAPE. On performing error corrections the data with newly predicted pricing is sent to the prediction unit 202. Further, the data from the prediction unit is output (306). This data is more accurate as it comprises of error corrected results. The various actions in method 300 may be performed in the order presented, in a different order or simultaneously. Further, in some embodiments, some actions listed in FIG. 3 may be omitted.

[0059] FIG. 4 depicts neural networks state machine, according to embodiments as disclosed herein. The neural networks comprises of first layer of neurons, second layer of neurons and the outputs. The inputs indicate different states of the neural state machine. The input includes factors such as electricity demand, weekly half hour readings in WH, daily half hour readings in WH, electricity price in time t1, electricity price in time t2, electricity price in time t3 and change in demand d(t)- D(t-1). In addition, the inputs may include any other factors. The inputs are fed to every unit of the first layer of neurons. Further, the first layer of neurons is feeding to the second layer of neurons. From the second layer of neurons the data is fed to the output. The output determines the price estimated. In addition, error correction unit 203 is also connected to the output. The error correction unit 203 performs error corrections on the data output from the neural networks.

[0060] FIG. 5 is a graph depicting price data for a period, according to embodiments as disclosed herein. The graph depicts a plot of market clearing price (MCP) against the days for energy consumption. The MCP unit is in terms of power of 10 ^ 4 and days is measured in intervals of 50. Further, the graph is divided into time blocks. For evety time of the day the corresponding energy consumption in terms of MCP is determined from the graph. For example, for a time block of 5, the corresponding days is 50 and the MCP is 0.5x 10 ^ 4. On similar lines, the values for different time period may be computed from the graph.

[0061] FIG. 6 is a graph depicting Market Clearing Price (MCP) over a time period, according to embodiments as disclosed herein. The graph depicts the MCP values in Indian rupee per watt hour against the time period. The time period for which the graph is considered is from July 1, 2009 to September 30, 2010. By employing the graph, for different instances of time it is possible to determine the pricing in rupees for the corresponding energy consumption.

[0062] FIG. 7 is a graph depicting price and demand standard deviation over a period of days, according to embodiments as disclosed herein. The graph depicts the price in rupees per mega watt hour against the time period in days. The days considered is from July 1, 2009 to September 30, 2010. The graph comprises of two plots one for the standard deviation and the other for standard pricing. The standard deviation determines the

demand for energy in mage watt hours. The method employed to determine the standard deviation is as follows: $\sigma = \sqrt{\mathrm{E}[(X-\mu)^2]}$.

[0063] FIG. 8 is a graph depicting price standard deviation over a period of hours, according to embodiments as disclosed herein. The graph depicts standard deviation and standard demand plots of price in rupee for every mega watt hour against time. The demand is in terms of the energy consumed in mega watts per hour. The price standard deviation in time for hour wise is computed as follows: $\sigma = \sqrt{\mathrm{E}[(X-\mu)^2]}$.

[0064] FIG. 9 is a graph depicting the comparison of actual and forecasted values, according to embodiments as disclosed herein. The graph depicts the forecast values for august 31. The graph is split into 24 blocks. Computations are performed employing MLR and MAPE that accounts to 4.21 %. The plots are for pricing against time period. Depicted below is a table corresponding to the graph:

MAPE values for IEX Market- 30 and 10 day period

MAPE (in %)	30day	11day
Normal forecast	12.6572	14.216
UEC	25.3143	28.433
SEC	4.1521	1.919

MAPE for IEX Market- Using MLR and Neural Network (NN)

MAPE (in %)	MLR	NN
Normal forecast	12.657	10.429
UEC	25.314	20.859
SEC	4.152	3.7036

[0065] FIG. 10 is a graph depicting 11 day MLR values, according to embodiments as disclosed herein. The depicted graphs indicate plots of MCP in mega watt per hour against time. The plots indicate actual and predicted value MCP. Plot 1 indicates the 11 day MLR. Plot 2 indicates UEC for 11 day MLR. Plot 3 indicates SEC for 11 day MLR. Further, the plots were for period of 21 august 2010 to 31 august 21.

[0066] FIG. 11 is a graph depicting 30 day MLR values, according to embodiments as disclosed herein. The depicted graphs indicate plots of MCP in mega watt per hour against time. The plots indicate actual and predicted values of MCP. Further, plot 1 indicates 30 day MLR and plot 2 indicates SCE for 30 day MLR.

[0067] FIG. 12 is a graph depicting 30 day MLR values in nn, according to embodiments as disclosed herein. The depicted graphs indicate plots of MCP in mega watt hour against the time period. The plots indicate actual values and predicted values. Plot 1 is for 30 day nn and plot 2 is for SCE 30 day nn.

[0068] FIG. 13 is a graph depicting error probabilities, according to embodiments as disclosed herein. The graph depicts the probabilities of the negative errors. The first plot is for 11 days, the second plot is for 30 days MLR and the third plot is for 30 days NN. By employing the error probability graph it is easy to determine the probabilities of the errors for

different time periods and accordingly the error correction module may act in order to correct the errors in the prediction.

[0069] FIG. 14 is a graph depicting error probabilities in 30 day nn, according to embodiments as disclosed herein. The first graph depicts error against the time period. By employing the graph it is possible to determine the error values for different time periods.

[0070] The second plot depicts the plot of the probability of error against the error values. The y axis indicates the probability factor and the x axis indicates the error values. Further, both the plots are for 30 days nn.

[0071] FIG. 15 is a graph depicting error mesh for 30 day MLR, according to embodiments as disclosed herein. The depicted graph is for error mesh for 30 day MLR. The plot is for error values against time period and days. From the graph it is easy to determine the error values that could occur over time and for the period of determined days.

[0072] FIG. 16 is a graph depicting error surf for 30 day nn, according to embodiments as disclosed herein. The depicted graph determines the error surf for 30 day in nn. The plot is for MCP error against the time period and for a period of days. From the graph it is easy to surf the error values that could occur over time and for the period of determined days.

[0073] FIG. 17 is a graph depicting comparison of SEC and UEC predicted values, according to embodiments as disclosed herein. Market

clearing price (MCP) forecasting is very essential for both generating companies and consumers to prepare them their bidding strategies and expect to maximize respective benefits with low risks. The prediction of MCP is complex because it depends on various uncertainty values. Hence, SEC-prediction method proposes to solve high complicated nonlinear problems like MCP forecasting by its powerful error correction method. FIG. 17 illustrates Market clearing price (MCP) in Indian Rupees per mega watt hour against time blocks. It displays the actual values of MCP, predicted value of MCP, MCP values generated by SEC and UEC prediction method respectively. Further, it displays that MCP values predicted by UEC-prediction method vary greatly to the actual MCP values whereas; SEC predicted method generates nearest values to the actual values of MCP.

[002] FIG. 18 is a graph depicting NSW market behavior over a time period, according to embodiments as disclosed herein. FIG. 18 displays the values of future forecasting of the Regional Reference Prices (RRP) for the New South Wales (NSW) region of the Australian National Electricity Market (NEM). The graph displays each day RRP values for 48 time blocks providing a price forecast with confidence intervals for each half-hour determined from the actual data over 950 days of NSW RRP from 1 Jan 2008 to August 2010. An extensive examination of the NSW RRP shows that the prices are high from 20^{th} time blocks onwards.

[003] FIG. 19 is a graph depicting raw data and preprocessing data, according to embodiments as disclosed herein. FIG. 19a displays the raw data of Market clearing price (MCP) with respect to 48 time blocks. It illustrates that the MCP values start increasing from 17 time block and it reaches the peak between 26-30 time blocks and then it gradually start decreasing. Prices are low from 39 time block onwards. FIG. 19b displays the pre-processed data of Market clearing price (MCP) with respect to 48 time blocks. It illustrates that the variation in MCP values. Prices are high between 16-42 time blocks.

[004] FIG. 20 is a graph depicting price and demand standard deviation day wise, according to embodiments as disclosed herein. FIG. 20 displays prices and demand standard deviation across each day from 1 Jan 2008 to 31 Aug 2010. It illustrates that there are some spikes in demand over the time but the maximum demand was between 700^{th} -800^{th} day and the prices too had the corresponding spikes with maximum price between 700^{th}-800^{th} day.

[005] FIG. 21 is a graph depicting price and demand standard deviation time block wise, according to embodiments as disclosed herein. FIG. 21a displays price in Indian rupee per mega watt hour against demand in mega watt hour over a period from 1 Jul 2009 to 30 Sep 2010. It illustrates that with increase in demand, the prices also shoots up. But there has been some sharp shoots in the prices whereas the demand had

smooth curves. FIG. 21b displays price in $/MWH against demand in MWH over a period from 1 Jul 2009 to 30 Sep 2010. It illustrates that prices rose with raise in demand.

[006] FIG. 22 is a graph depicting price demand and standard deviation for LEX and NSW, according to embodiments as disclosed herein. FIG. 22a displays price in INR/MWH against demand in MWH over a period from 1 Jul 2009 to 30 Sep 2010 for IEX market. It illustrates that initially demand was high but the price was low. Later, the demand gradually decreased but the prices grew up. FIG. 22b displays price in $/MWH against demand in MWH over a period from 1 Jul 2009 to 30 Sep 2010 for NSW market. It illustrate that prices are directly related to demand, price rises with the increase in demand.

[007] FIG. 23 is a graph depicting normal forecast and SEC forecast values, according to embodiments as disclosed herein. FIG. 23a displays actual and predicted RRP in $/MWH with respect to time block of half an hour for a neural network. It illustrates that the predicted RRP values differ a lot compared to actual RRP values over the time blocks for a normal forecast. FIG. 23b displays actual, predicted and Modeling and Forecasting Electricity Loads and Prices (MFE) RRP in $/MWH with respected to time block of half an hour for a neural network. It illustrates that the predicted RRP values are very close to the actual RRP values over

the time blocks for a SEC-forecast whereas MFE values move along the zero line.

[008] FIG. 24 is a graph depicting frequency distribution of error of the day ahead of price forecasts for period of days, according to embodiments as disclosed herein. FIG. 24a displays NSW-NN-frequency distribution of Error of the day ahead price forecasts for the period of 30 days between 1 Aug 2010 to 30 Aug 2010. It illustrates that the frequency of error is high around zero (0) but it gradually decreases on either side. FIG. 24b displays NSW-NN-cumulative distribution plot of Error of the day ahead price forecasts for the period of 30 days between 1 Aug 2010 to 30 Aug 2010. It illustrates that probability of error value increases logarithmically.

[009] FIG. 25 is a graph depicting error probability, according to embodiments as disclosed herein. FIG. 25 displays NSW- multiple linear regression (*MLR*)-Error probability graph. It displays the variation in probability of negative error with respect to 48 time blocks. It illustrates sea-saw kind of distribution of probability of negative error.

[0010] FIG. 26 is a graph depicting correction factor applied, according to embodiments as disclosed herein. FIG. 26 displays RRP in $/MWH for actual, predicted, SEC-prediction and UEC-prediction respectively with respect to time blocks of half an hour. It illustrates that SEC-predicted values are very close to the actual RRP value but when correction is applied SEC-prediction value overlaps the actual RRP values. Correction was applied at two instant i.e. between 30-35 time blocks and 43-

44 time blocks, and at that instant SEC-prediction generated the actual RRP values. Thus, making the correction method very useful.

[0011] FIG. 27 is a graph depicting a short term forecast, according to embodiments as disclosed herein. FIG. 27 displays grid frequency forecast with respect to time blocks of 15 mins each for Sep 29 and Sep 30. It displays a very short term forecast. It illustrate that the predicted frequency values are close to the actual grid frequency values.

[0012] The embodiment disclosed herein describes a mechanism for error correction and forecasting electricity pricing. Therefore, it is understood that the scope of the protection is extended to such a program and in addition to a computer readable means having a message therein, such computer readable storage means contain program code means for implementation of one or more steps of the method, when the program runs on a server or mobile device or any suitable programmable device. The method is implemented in a preferred embodiment through or together with several software modules being executed on at least one hardware device. The hardware device can be any kind of portable device that can be programmed. The device may also include means which could be e.g. hardware means like e.g. an ASIC, or a combination of hardware and software means, e.g. an ASIC and an FPGA, or at least one microprocessor and at least one memory with software modules located therein. The method embodiments described herein could be implemented partly in

hardware and partly in software. Alternatively, the invention may be implemented on different hardware devices, e.g. using a plurality of CPUs.

[0013] The foregoing description of the specific embodiments will so fully reveal the general nature of the embodiments herein that others can, by applying current knowledge, readily modify and/or adapt for various applications such specific embodiments without departing from the generic concept, and, therefore, such adaptations and modifications should and are intended to be comprehended within the meaning and range of equivalents of the disclosed embodiments. It is to be understood that the phraseology or terminology employed herein is for the purpose of description and not of limitation. Therefore, while the embodiments herein have been described in terms of preferred embodiments, those skilled in the art will recognize that the embodiments herein can be practiced with modification within the spirit and scope of the embodiments as described herein.

WE CLAIM

1. A method for electricity price forecasting based on energy consumption patterns across at least one market, said method comprising:

an energy scheduling unit calculating the energy produced and energy consumed for a period of time;

said energy scheduling unit estimating electricity price for said period of time;

said energy scheduling unit calculating if said energy consumed is more than said energy produced;

if said energy consumed is more, then said energy scheduling unit determining the error difference between said estimated electricity price and actual electricity price;

said energy scheduling unit applying error correction techniques to said error difference; and

said energy scheduling unit updating said estimated electricity price as per said error correction.

2. The method as in claim 1, wherein said period of time is at least one of hours in a day, days, week, months, year.

3. The method as in claim 1, wherein said market is at least one of retail market and wholesale market.

4. The method as in claim 1, wherein said energy scheduling unit calculates energy produced and energy consumed based on inputs obtained from other units comprising of metering unit, billing system, load dispatch center, portfolio management.

5. The method as in claim 1, wherein said error difference is determined from the difference between the energy produced and the energy consumed.

6. The method as in claim 1, wherein said method employs artificial neural networks based techniques for calculating error difference and updating said electricity price.

7. The method as in claim 1, wherein said method further employs stochastic error correction techniques to improve forecast accuracy.

8. The method as in claim 1, wherein said error correction techniques are applied post processing of said estimated electricity price.

9. The method as in claim 1, wherein said error correction techniques take into consideration parameters comprising of electricity price, grid frequency, renewable energy availability, load forecasts.

10. The method as in claim 1, wherein said method further employs different techniques for error correction that include mean absolute error, sum of squared error, root mean squared error and mean absolute percentage error.

11. The method as in claim 1, wherein said method further employs algorithms employing techniques comprising if SVM, MLR in combination with SEC technique to improve the final accuracy of said forecast.

12. The method as in claim 1, wherein said method is further capable of taking real-time inputs and embedding said inputs with other applications using a set of application programming interfaces.

13. An energy scheduling unit for electricity price forecasting based on energy consumption patterns across at least one market, said energy scheduling unit comprising at least one means configured for

calculating the energy produced and energy consumed for a period of time;

estimating electricity price for said period of time;

calculating if said energy consumed is more than said energy produced;

determining the error difference between said estimated electricity price and actual electricity price, if said energy consumed is more;

applying error correction techniques to said error difference; and

updating said estimated electricity price as per said error correction.

14. The energy scheduling unit as in claim 13, wherein said energy scheduling unit is configured for calculating energy produced and energy consumed based on inputs obtained from other units comprising of metering unit, billing system, load dispatch center, portfolio management.

15. The energy scheduling unit as in claim 13, wherein said energy scheduling unit is configured for determining error difference from the difference between the energy produced and the energy consumed.

16. The energy scheduling unit as in claim 13, wherein said energy scheduling unit is configured to use artificial neural networks based

techniques for calculating error difference and updating said electricity price.

17. The energy scheduling unit as in claim 13, wherein said energy scheduling unit is configured for employing stochastic error correction techniques to improve forecast accuracy.

18. The energy scheduling unit as in claim 13, wherein said energy scheduling unit is configured for applying said error correction techniques post processing of said estimated electricity price.

19. The energy scheduling unit as in claim 13, wherein said energy scheduling unit is configured for considering parameters comprising of electricity price, grid frequency, renewable energy availability, load forecasts for error correction.

20. The energy scheduling unit as in claim 13, wherein said energy scheduling unit is configured for employing techniques for error correction comprising of mean absolute error, sum of squared error, root mean squared error and mean absolute percentage error.

21. The energy scheduling unit as in claim 13, wherein said energy scheduling unit further employs algorithms employing techniques

like SVM, MLR in combination with SEC technique to improve the final accuracy of said forecast.

22. The energy scheduling unit as in claim 13, wherein said energy scheduling unit is configured for taking real-time inputs and embedding said inputs with other applications using a set of application programming interfaces.

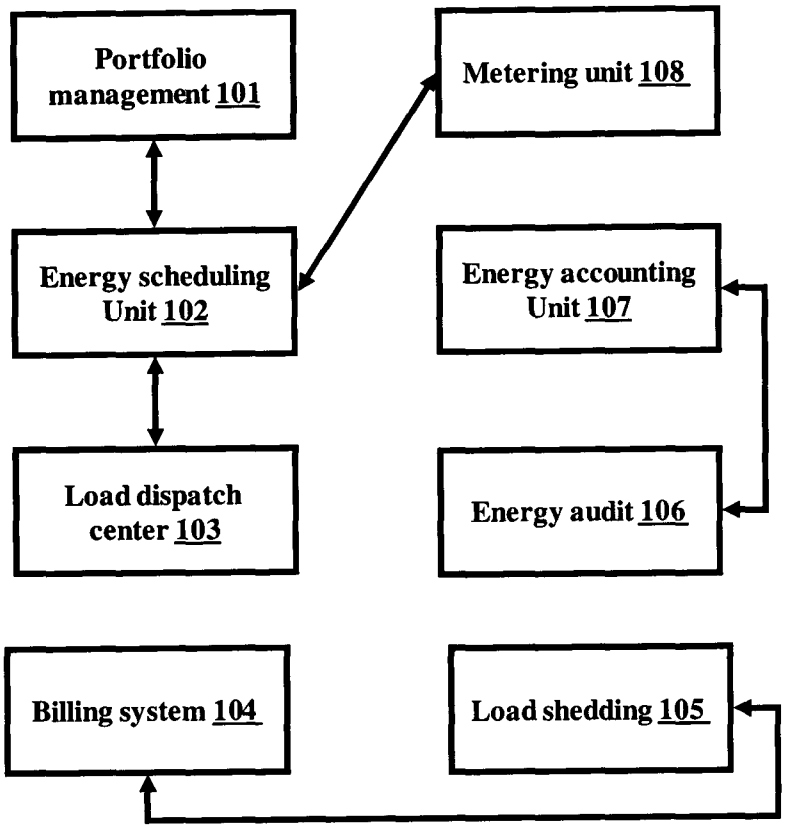

Portfolio management 101
Metering unit 108
Energy scheduling Unit 102
Energy accounting Unit 107
Load dispatch center 103
Energy audit 106
Billing system 104
Load shedding 105

FIG. 1

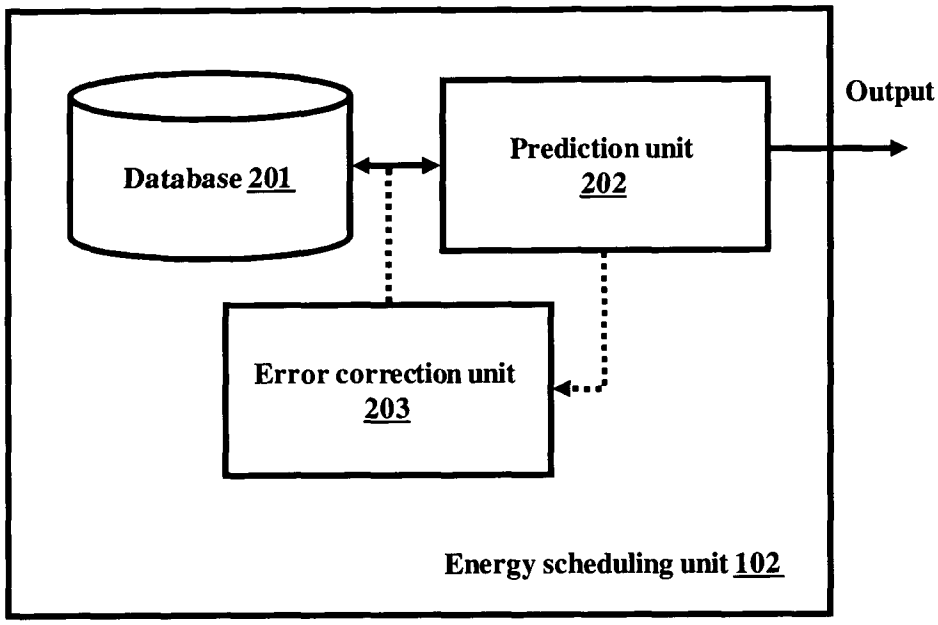

Database 201
Prediction unit
202
Output
Error correction unit
203
Energy scheduling unit 102

FIG. 2

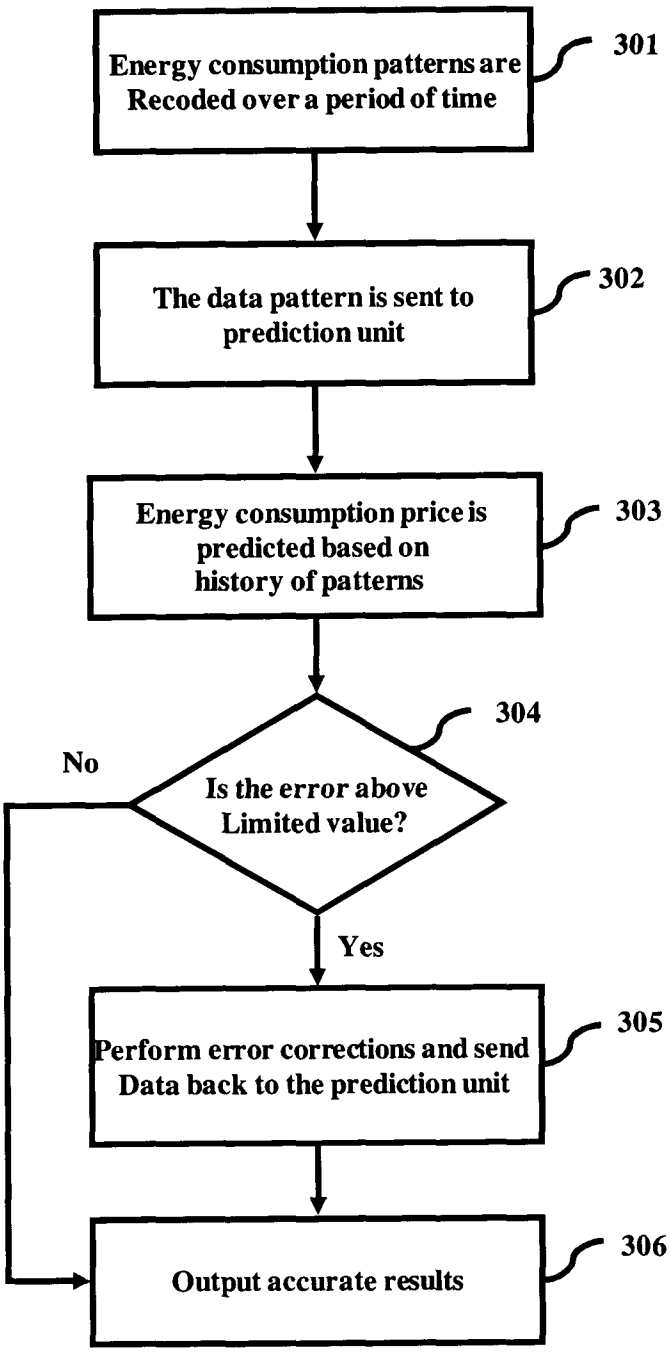

Energy consumption patterns are Recoded over a period of time
301
The data pattern is sent to prediction unit
302
Energy consumption price is predicted based on history of patterns
303
Is the error above Limited value?
304
No
Yes
Perform error corrections and send Data back to the prediction unit
305
Output accurate results
306

FIG. 3

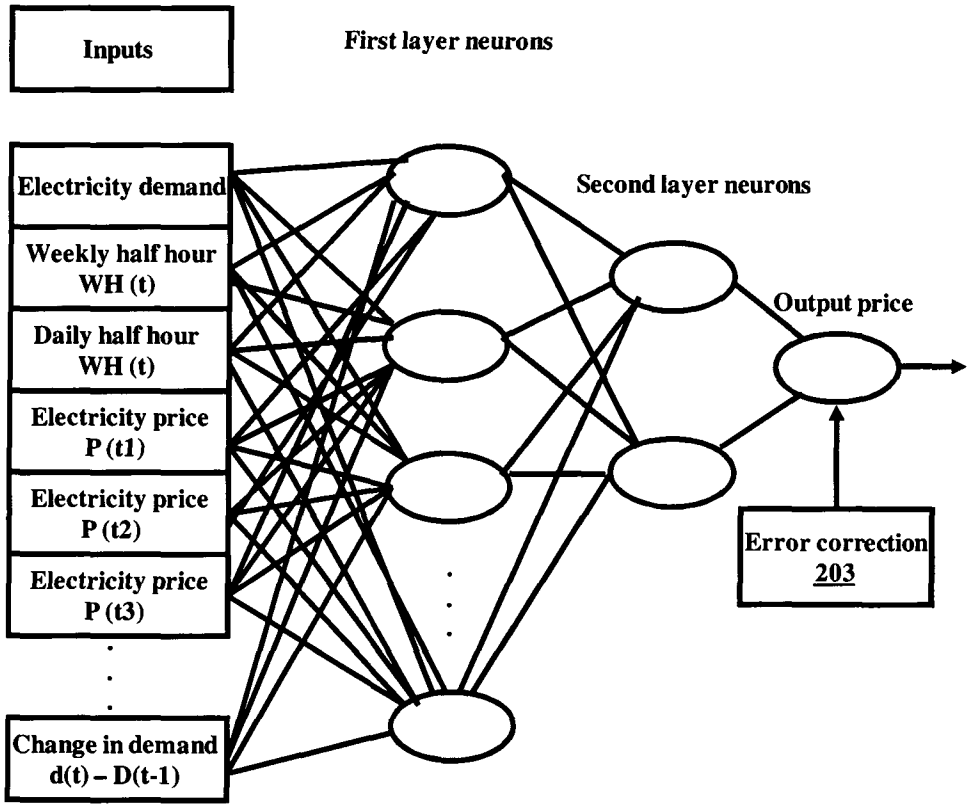

Inputs
First layer neurons
Electricity demand
Weekly half hour WH (t)
Daily half hour WH (t)
Electricity price P (t1)
Electricity price P (t2)
Electricity price P (t3)
Change in demand d(t) – D(t-1)
Second layer neurons
Output price
Error correction 203

FIG. 4

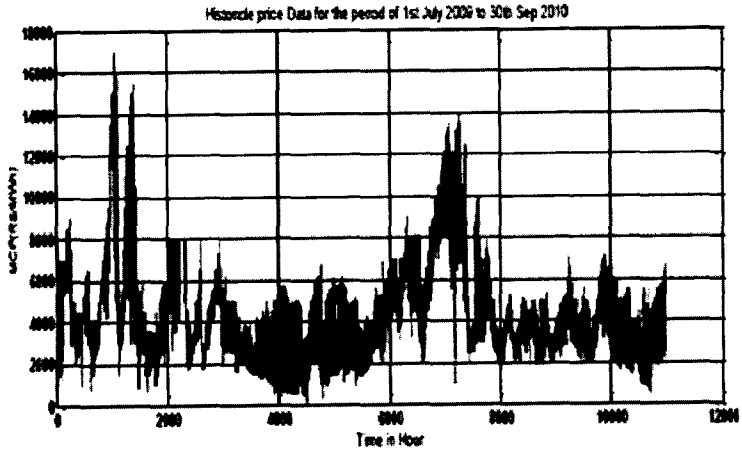

Hisssecle price Data for the period of 1st July 2009 to 30th Sep 2010
0
2000
4000
6000
8000
10000
12000
Time in Hour

FIG. 5

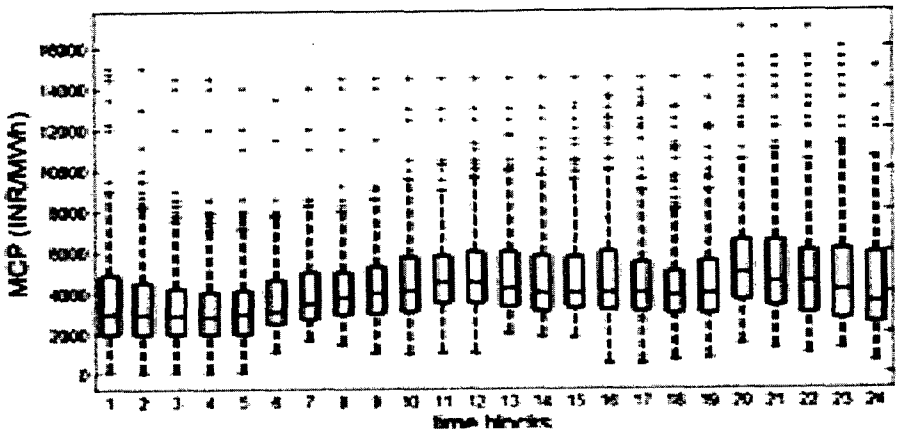

MCP (INR/MWh)
16000
14000
12000
10000
8000
6000
4000
2000
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
time intervals

FIG. 6

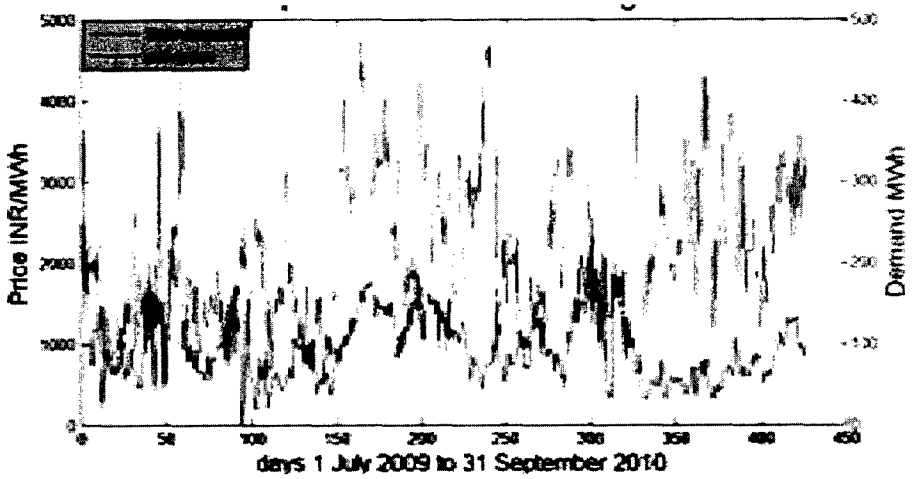

Price INR/MWh
Demand MWh
days 1 July 2009 to 31 September 2010

FIG. 7

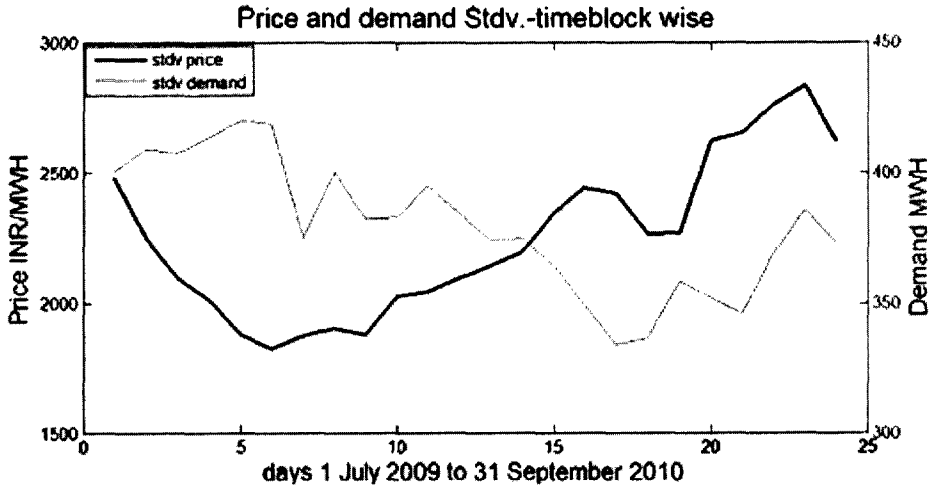

Price and demand Stdv.-timeblock wise
stdv price
stdv demand
Price INR/MWH
Demand MWH
3000
2500
2000
1500
450
400
350
300
0
5
10
15
20
25
days 1 July 2009 to 31 September 2010

FIG. 8

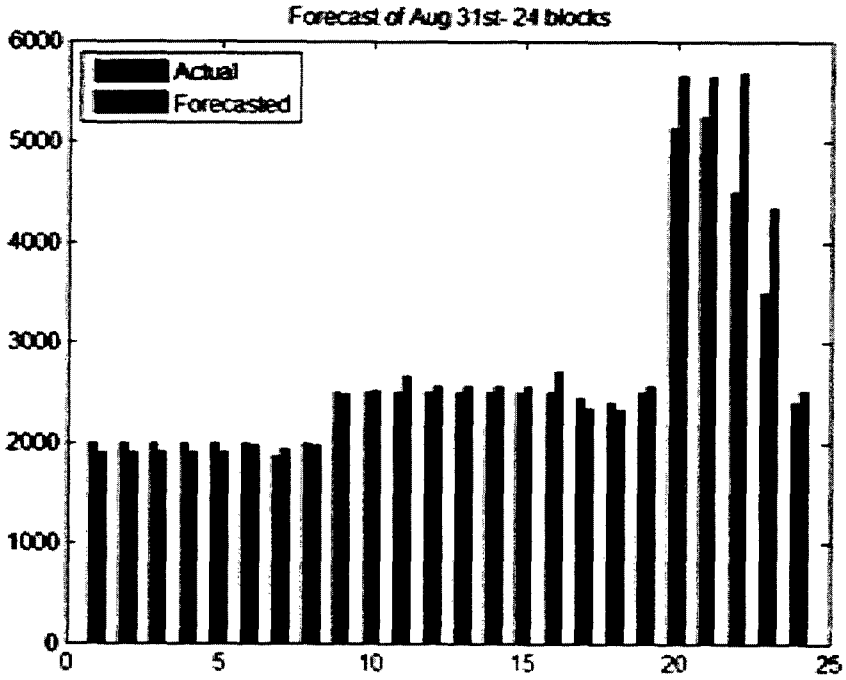

Forecast of Aug 31st- 24 blocks
Actual
Forecasted
6000
5000
4000
3000
2000
1000
0
0
5
10
15
20
25

FIG. 9

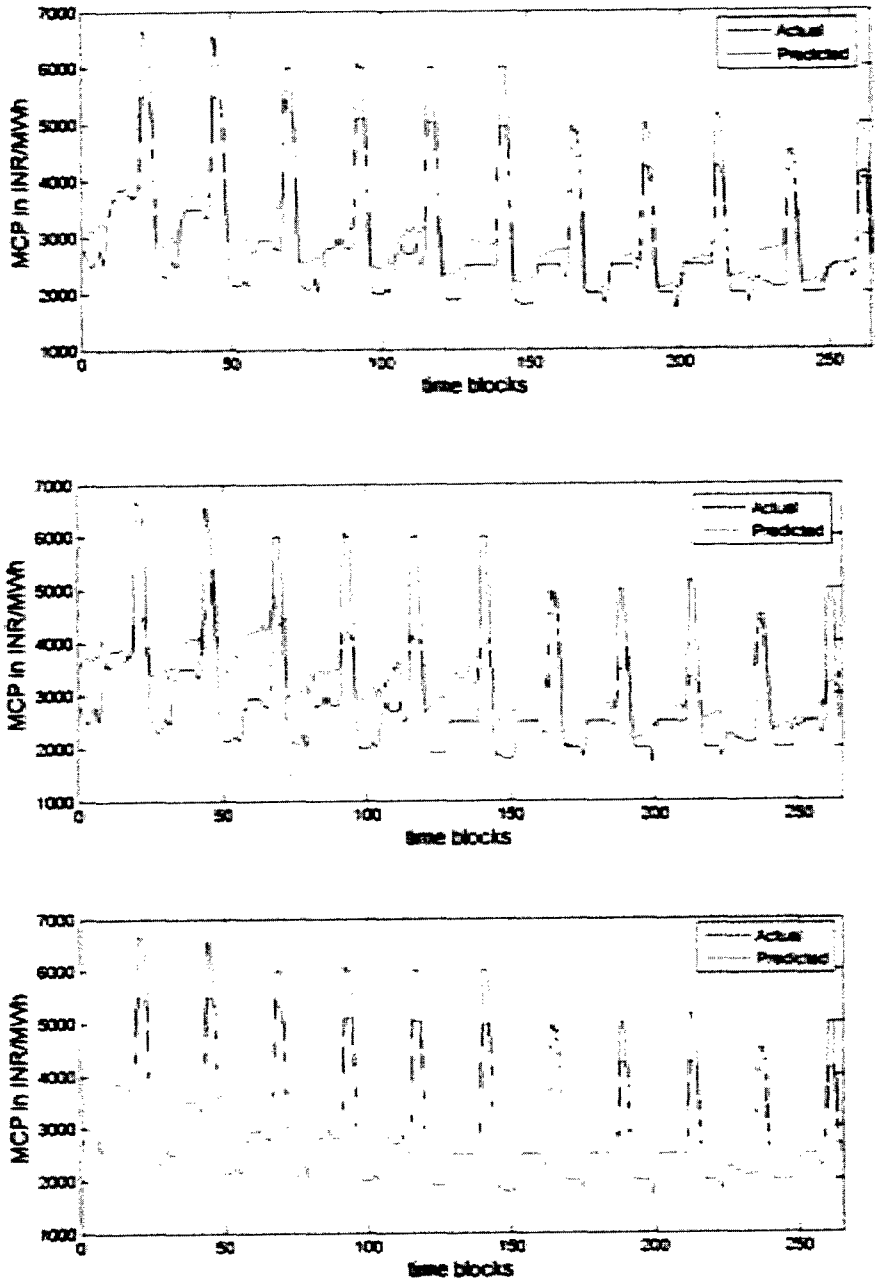
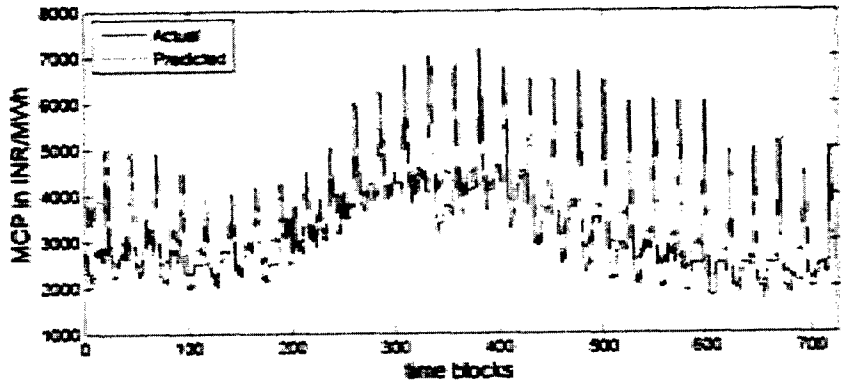

Actual
Predicted
MCP in INR/MWh
time blocks
7000
6000
5000
4000
3000
2000
1000
0
50
100
150
200
250

FIG. 10


Actual
Predicted
MCP in INR/MWh
time blocks

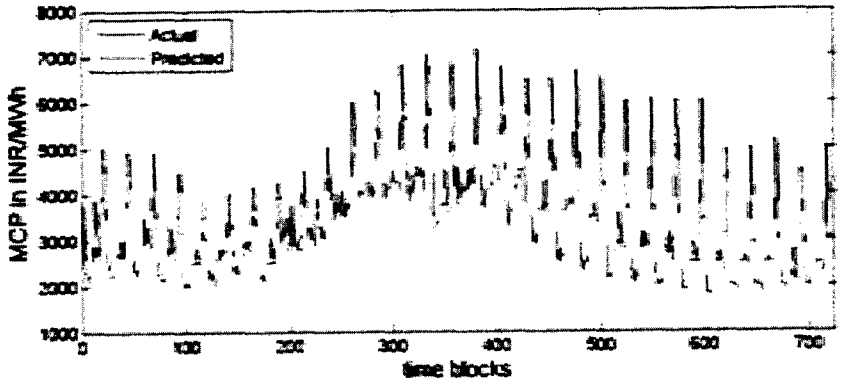
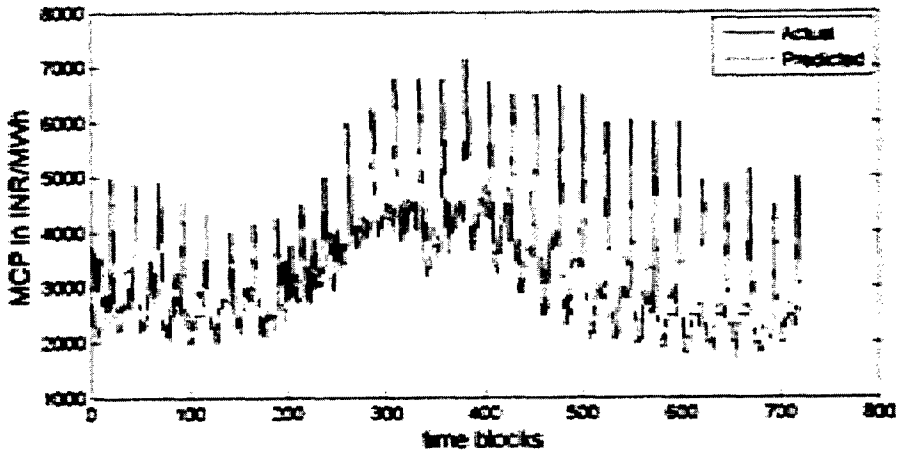

Actual
Predicted
MCP in INR/MWh
time blocks

FIG. 11


Actual
Predicted
MCP in INR/MWh
time blocks

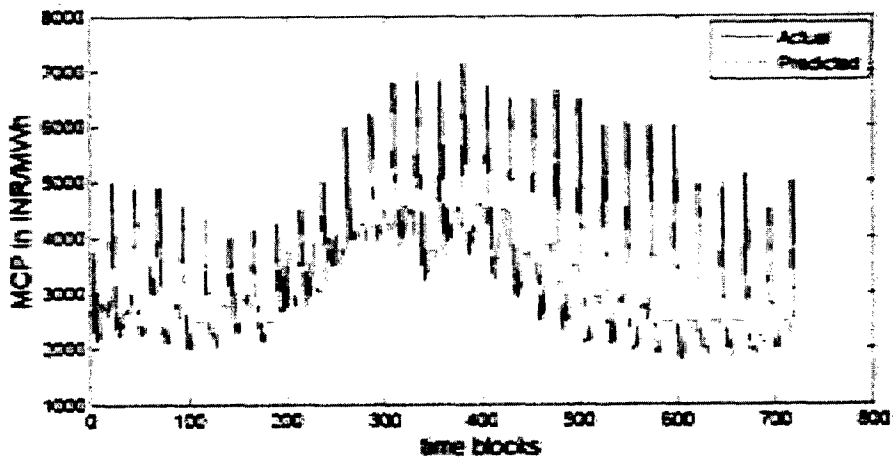

Actual
Predicted
MCP in INR/MWh
time blocks

FIG. 12

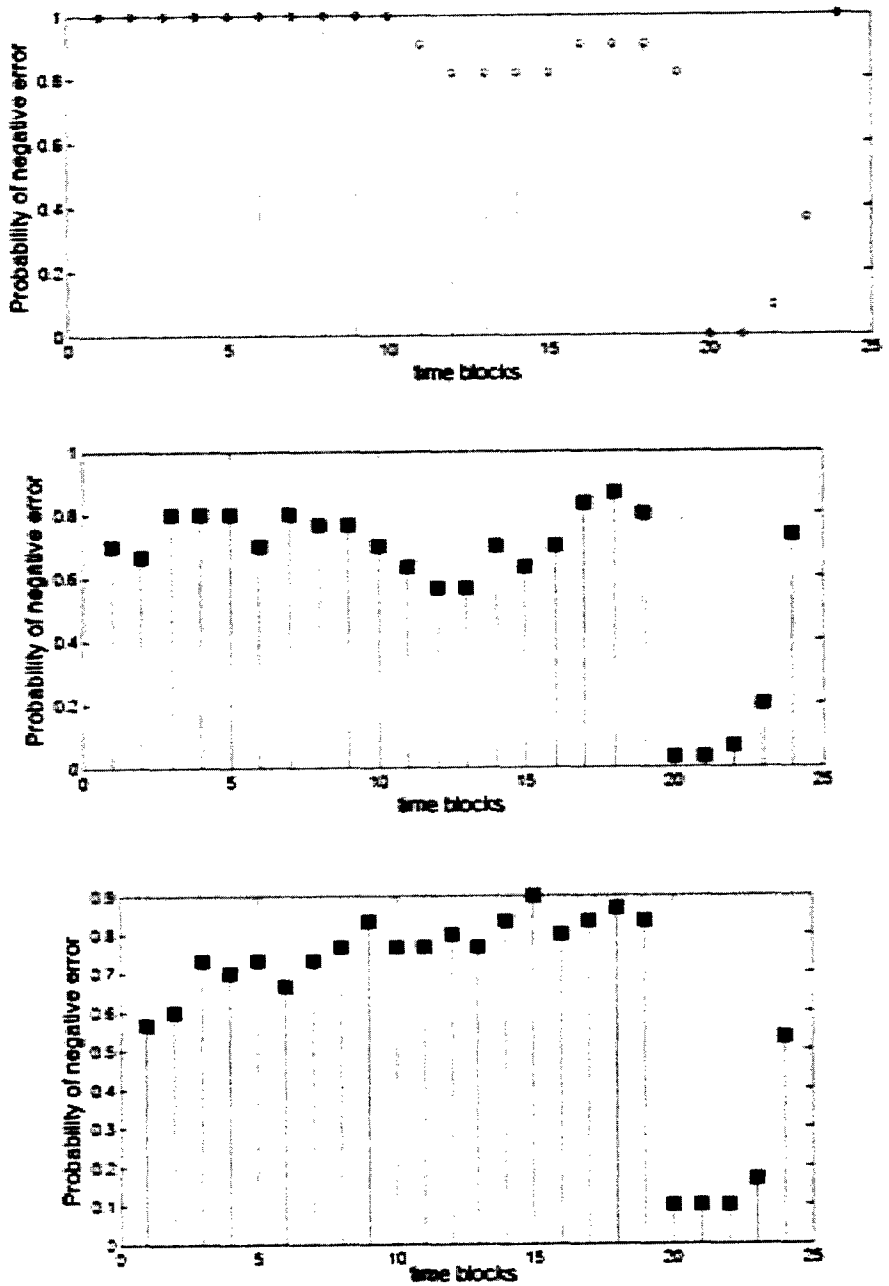

Probability of negative error
time blocks
Probability of negative error
time blocks
Probability of negative error
time blocks

FIG. 13

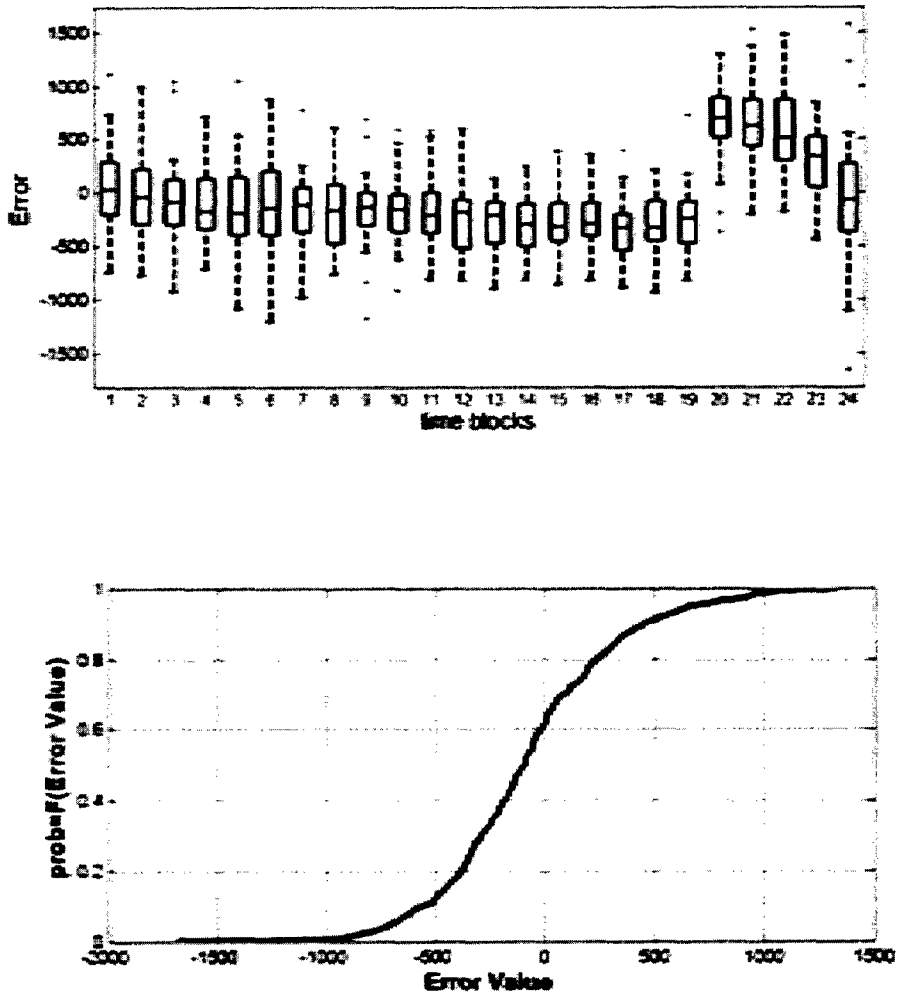


FIG. 14

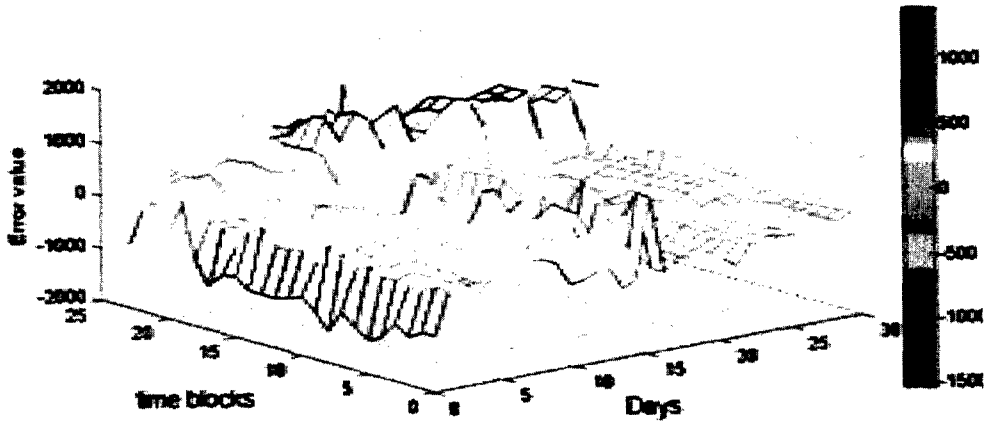

Error value
2000
1000
0
-1000
-2000
time blocks
25
20
15
10
5
0
Days
0
5
10
15
20
25
30
1000
500
0
-500
-1000
-1500

FIG. 15

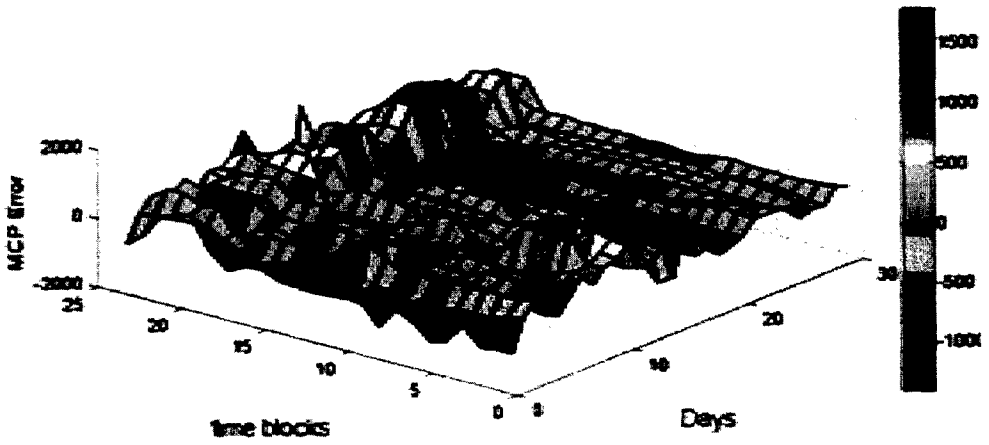

MCP Error
2000
0
-2000
25
20
15
10
5
0
Time blocks
1
10
20
30
Days
1500
1000
500
0
-500
-1000

FIG. 16

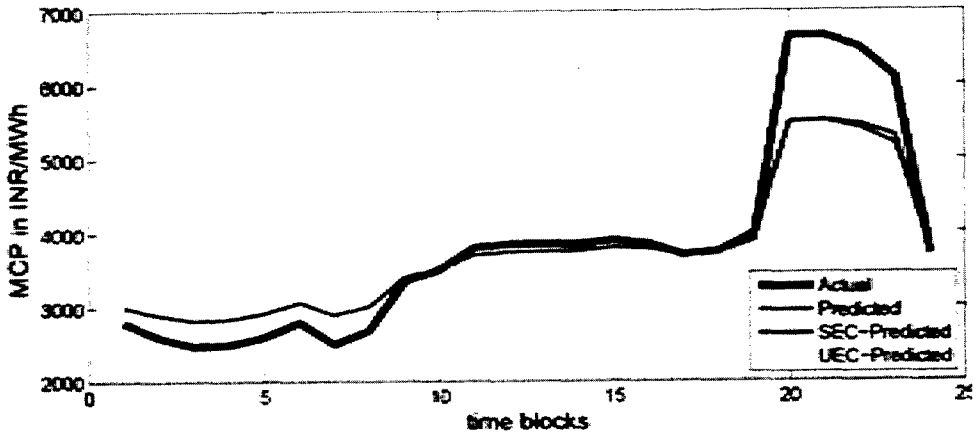

7000
6000
5000
4000
3000
2000
MCP in INR/MWh
0
5
10
15
20
time blocks
Actual
Predicted
SEC-Predicted
UEC-Predicted

FIG. 17



FIG. 18

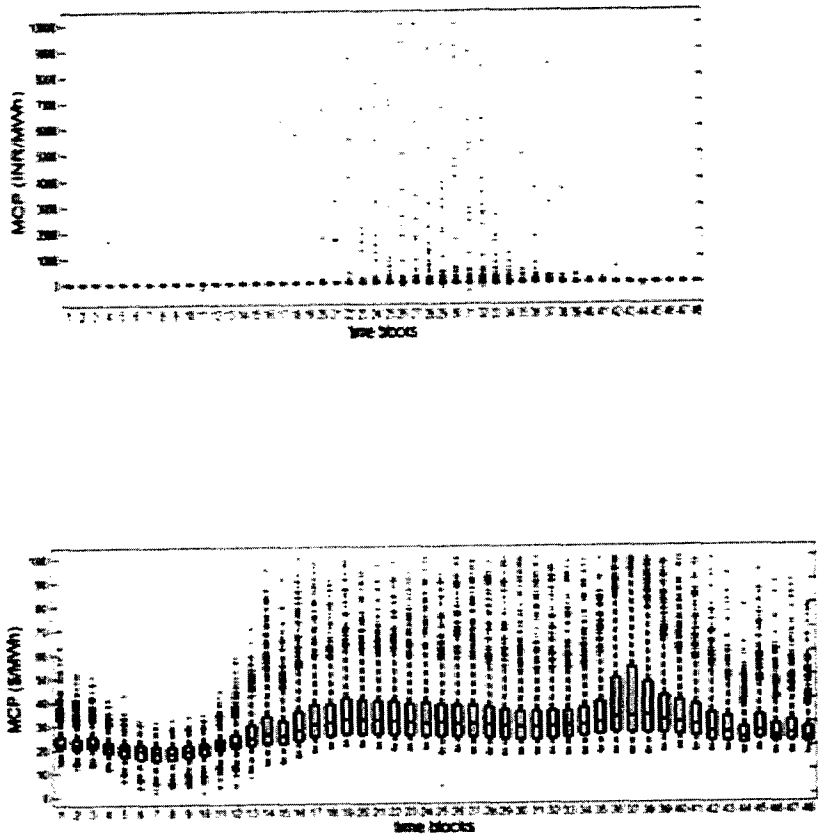


FIG. 19

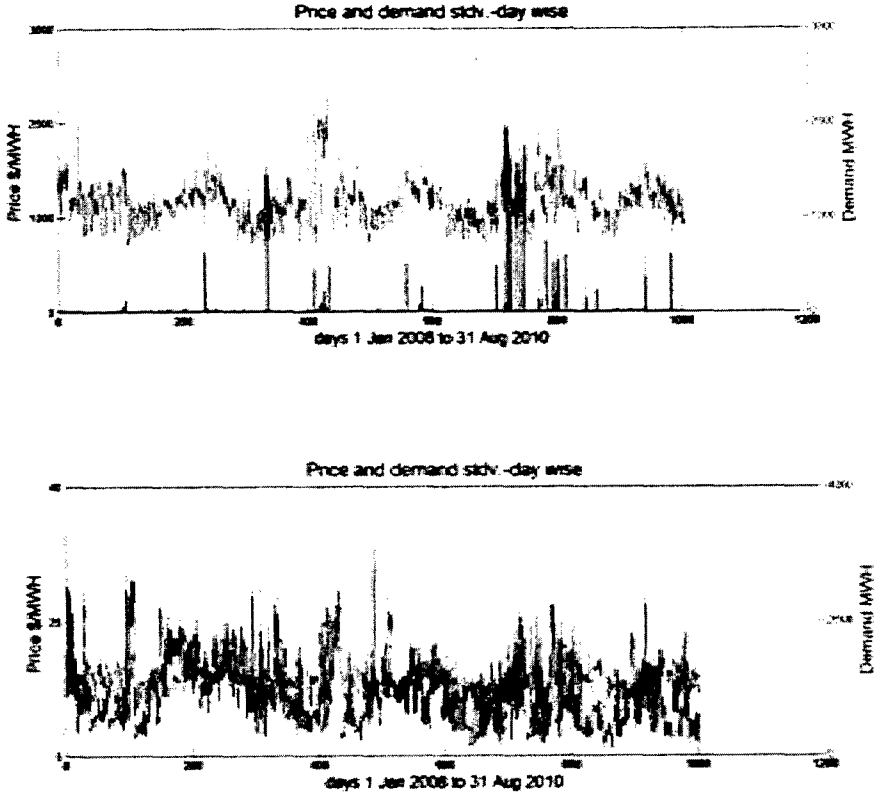

Price and demand stdv.-day wise
Price $/MWH
Demand MWH
days 1 Jan 2008 to 31 Aug 2010
Price and demand stdv.-day wise
Price $/MWH
Demand MWH
days 1 Jan 2008 to 31 Aug 2010

FIG. 20

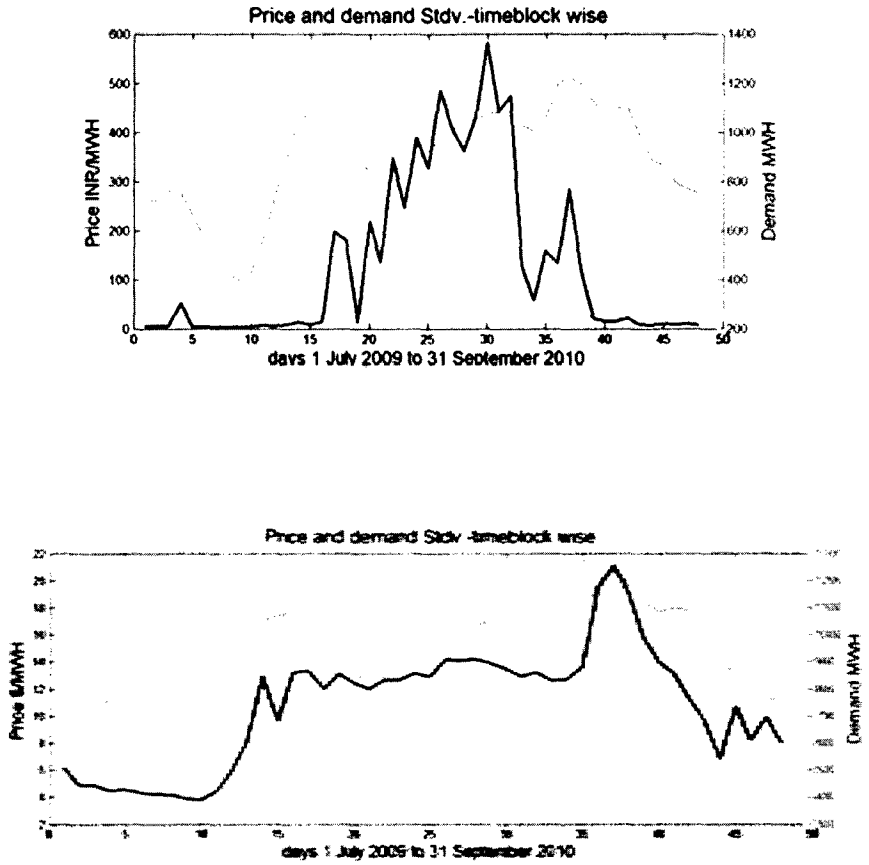

Price and demand Stdv.-timeblock wise
Price INR/MWH
Demand MWH
days 1 July 2009 to 31 September 2010
Price and demand Stdv -timeblock wise
Price $/MWH
Demand MWH
days 1 July 2009 to 31 September 2010

FIG. 21

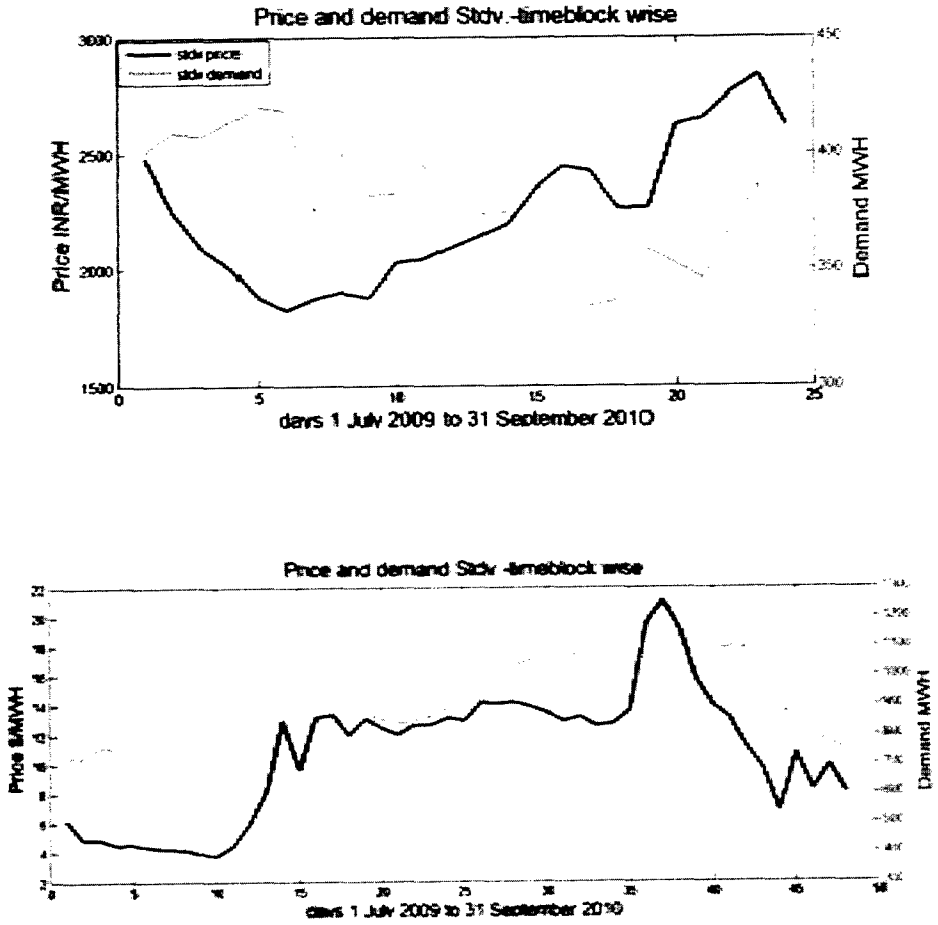

Price and demand Stdv.-timeblock wise
stdv price
stdv demand
Price INR/MWH
Demand MWH
days 1 July 2009 to 31 September 2010
Price and demand Stdv -timeblock wise
Price $/MWH
Demand MWH

FIG. 22

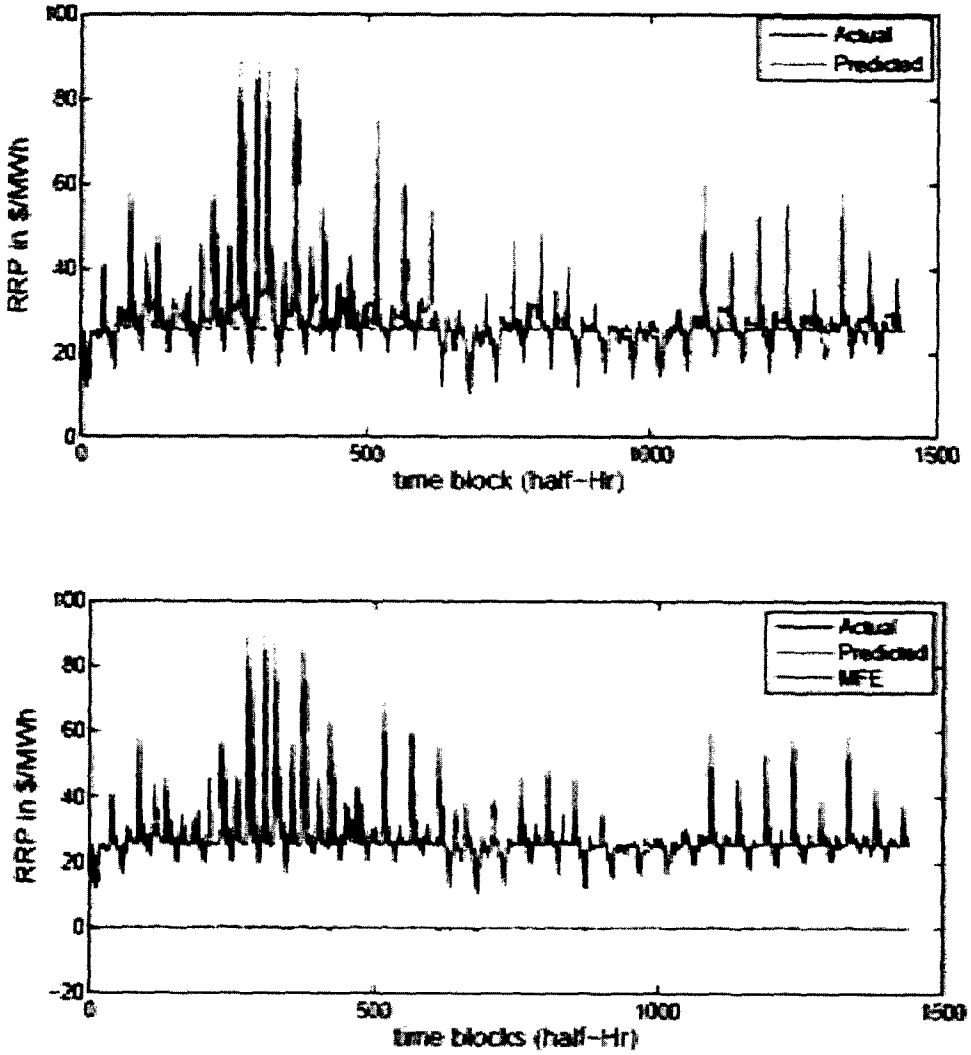

Actual
Predicted
RRP in $/MWh
time block (half-Hr)
Actual
Predicted
MFE
RRP in $/MWh
time blocks (half-Hr)

FIG. 23

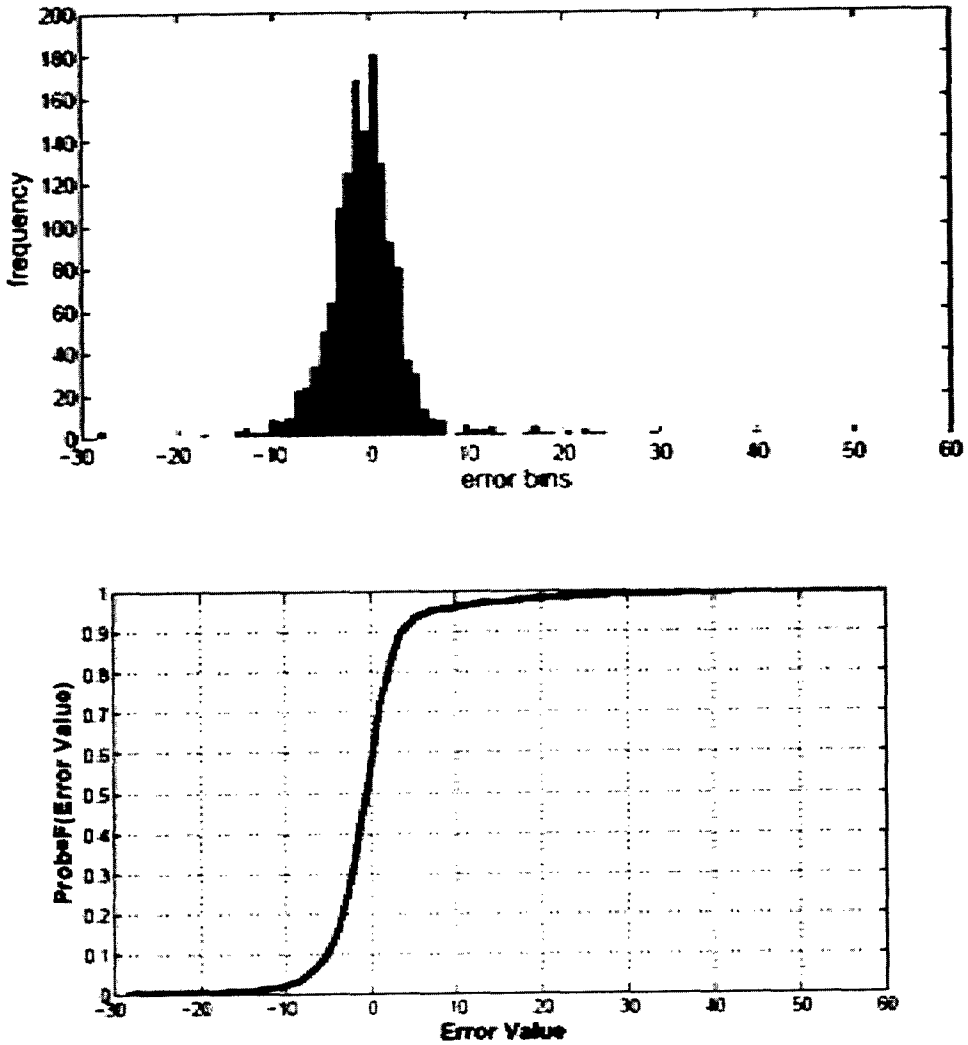


FIG. 24

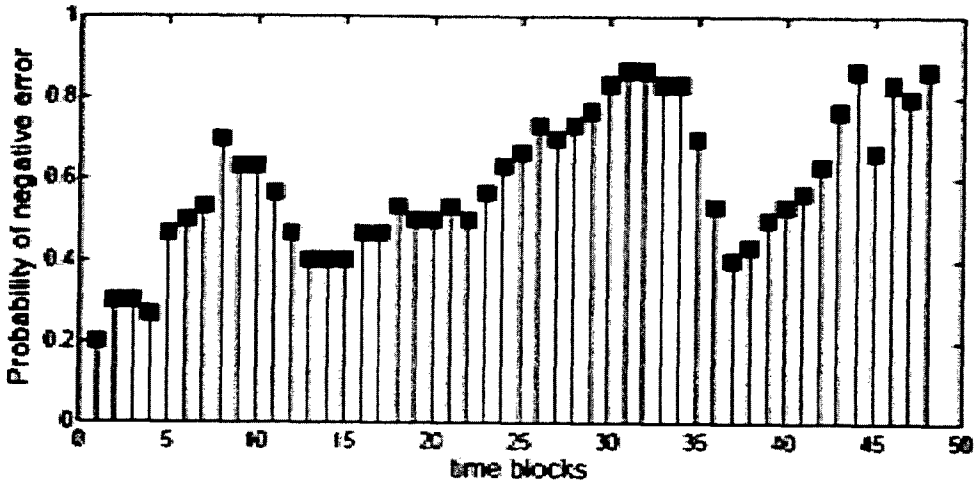

Probability of negative error
time blocks
0
0.2
0.4
0.6
0.8
1
0
5
10
15
20
25
30
35
40
45
50

FIG. 25

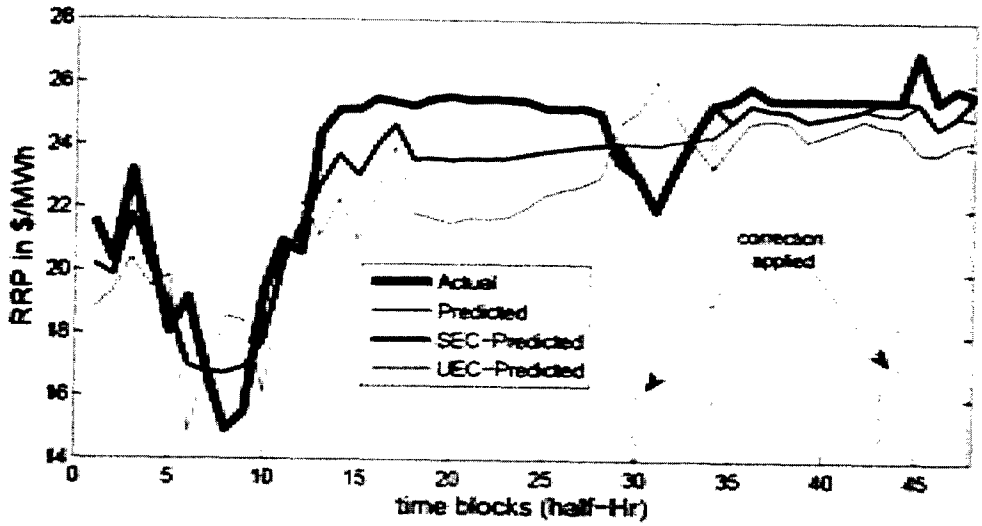

RRP in $/MWh
time blocks (half-Hr)
Actual
Predicted
SEC-Predicted
UEC-Predicted
correction applied

FIG. 26

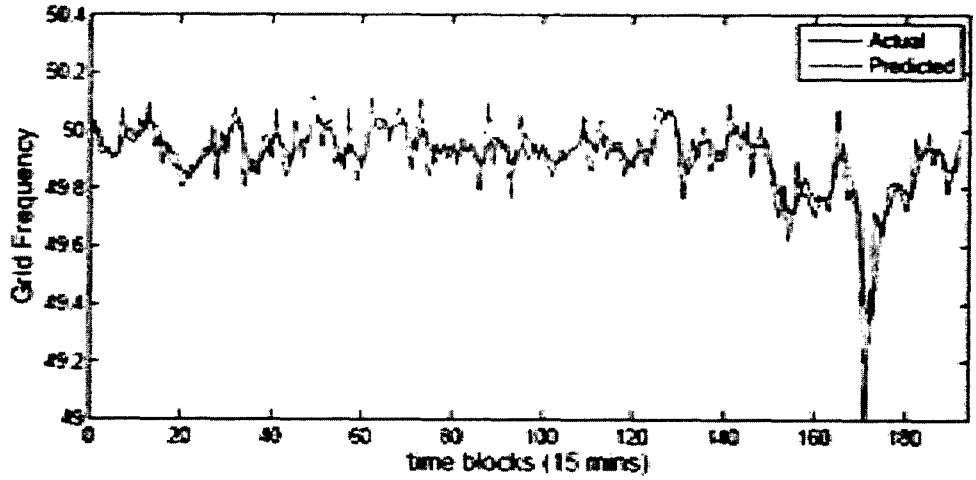


FIG. 27