Electricity Price Forecasting Using ELM-Tree Approach

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Abstract - ***In power markets there is no regularity in forecasting of electricity price which is the most essential tasks & basis for any decision making. In the competitive electricity markets forecasting of the electricity price is critical for consumers and producers of electricity for planning their operations and also to maintain the risk of electricity. Forecasting also plays a very important role in economic optimization of electricity usage. Artificial intelligence (AI) along with the ELM-Tree Approach has been applied in price forecasting that is, the day ahead usage of the electricity and will also predict the monthly bill of the user as per there electricity usage. For handling the complex interdependencies between the electricity prices, historical load usage and various other factors artificial neural networks are the best method that can be used. This ANN model approach is used to forecast the behaviors of the electricity market based on the various factors such as historical prices, calendar date,occasions and other information to forecast the future prices of electricity and load.***

Key Words: *Artificial Neural Network, Electricity Market, Price Forecasting, Decision Tree, Extreme Learning Machine.*

1. INTRODUCTION

RECENT changes in the electricity industries in several countries have led to the low regulated and more competitive energy markets.In this newly structure, price of the electricity has the key of all the activities in the market. Price forecasting, with dependable accuracy which helps power suppliers for selling up rational offers in the short term.

Generally there are 2 groups of forecasting models, traditional models and advanced techniques viz as ANN, Fuzzy logic [1].

Price forecasting models are thetime series and regression analysis. In the recent years, artificial intelligent(AI) methods are more commonly used for price forecasting. Among these methods, ANN method is the simple and powerful tool used for forecasting. The reason should be the ANN to learn the difficult input-output relationship through a supervised training process with the historical data.

We know that many factors are impacting on the electricity price, in which some of the factors are more important than other are, as practically, we consider only those which are more efficient factors. So, it will be useful to study which factors affect on price and to up to what extent. The factors, which affect the electricity price, are line limit to load pattern, bidding patterns and generator outages factors. In power market, the load pattern is an effective attribute on the bidding behavior of Generating Companies. Therefore we consider the historical price of system and the load as the factors which affect the price.

The performance of the Artificial Neural Network ANN approach is greatly affected by the selection of its inputs. Historical price data and the load have been identified for electricity price forecasting.

1.1 Price Forecasting By ANN

An ANN is a parallel distributed processor made up of the simple processing units called neurons. The neurons have the natural capability for storing experimental knowledge and make it available for use [2].

Every neural network structure has to undergo the training of phase with the available data or patterns. This training / learning phase uses a suitable learning algorithm. The prime objective of the learning algorithm is to modified system data weights of the network is in an orderfashion for attained a desired design objective and to increase the accuracy of the learning stage minimize the error. The working of ANN can be divided in two phases one is training phase and other is recalling phase or testing phase.

In training phase both the input pattern and its corresponding target output is supplied to the network. Input is given to the network at input node; the input layer neuron processed the input by using activation function and gives its output. The output from this layer is given as input to the next level neuron, and so on up to the output node. The links connected between neurons are having some weight. These weights are updated by some learning algorithm in training phase till the error between the network output and actual output for that input data set or pattern is minimized. The level of error depends on the learning algorithm, quality of data and type of network. Once the minimized error is obtained the other inputs are given to trained network to get the output. This is the recall phase or testing phase. The structure of the ANN for training is shown in figure 1.

This describes the modules, which should be considered to design a good neural network model for price forecasting

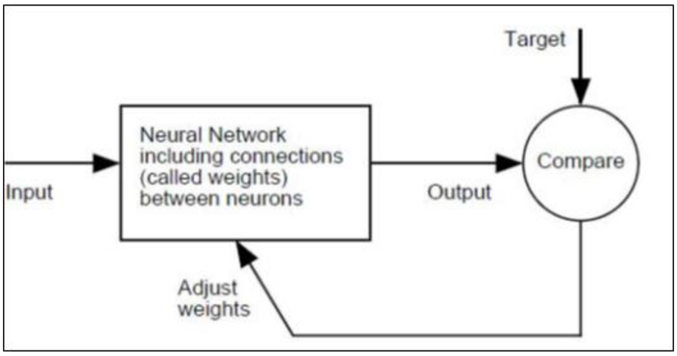

Fig -1: Training of ANN [4].

This describes the modules, which should be considered to design a good neural network model for price forecasting

1.2 Input Selection

The aim of the input selection in the case of ANN is finding optimal input parameters. Result of optimal inputs will lead to smaller ANN with more accuracy and speed will also be more. Electricity price affecting parameters can be categorized into:-
Day Type
Historical price data
Amount of Demand.

1.3 Training

The ANN training process requires a set of examples with proper network behavior. During the training of ANN, the weights and biases of the Artificial Neural Networks are repeatedly adjusted to for the purpose of minimizing the network performance function. The training method which is selected for the new ANN models is Levenberg-Marquart back propagation (LMBP), this method updates the weight and bias values according to L-M optimization.

LMBP is an improved version of Gauss-Newton method. To deal with the additive noise in the training samples this method has an extra regularization term. Existing back propagation methods are often too slow for practical problems in comparison to LMBP.

Neurons have nonlinear transfer function known as the “tangent sigmoid" which is present in the hidden and output layers. The inputs received by a tansig node are passed through this function to produce an output. These function generates outputs between -1 and +1.The inputs of these function should also be in same range. That’s why, it is necessary to limit the inputs and target outputs of the artificial neural networks. Both the methods i.e. Mean-standard deviation and min-max normalization methods have been tested and min-max method has been selected.

This normalization method provides the advantage of mapping the target output to the non-saturated sector of tansig function. This process improves the accuracy of the training [3].

1.3 Output and Hidden Layer

The ANN models have the output layer. The output is the hourly price in the model of price forecasting, because of which only one neuron is present in the output layer .

2. Survey of Existing Research Papers

[1] B.R. Szkuta, L.A. Sanabria, T.S. Dillon ,“Electricity Price Short-Term Forecasting Using Artificial Neural Networks”, IEEE Transactions on Power Systems

It presents the System Marginal Price (SMP) short-term forecasting implementation using the Artificial Neural Networks (ANN) computing technique. The described approach uses the three-layered **ANN** paradigm with back propagation. The retrospective SMP real-world data, acquired from the deregulated Victorian power system, was used for training and testing the ANN. The results presented in this paper confirm considerable value of the ANN based approach in forecasting the SMP.

The energy trading levels between market participants, however, is largely dependent on the *short-term* price forecasts. In the Victorian wholesale electricity market, three levels of trading are recognized: bilateral long-term contracts, short term forward trading and spot trading. The bulk of trading is based on a combination of the three. In this paper we limit this influence to two time intervals ahead (time lag). The input data temporal set, used for training the ANN that contains retrospective values of variables is encapsulated in the vector. All input parameters are known for all the time intervals included in the training. The most popular *ANN* architecture is a three-layered, feed-forward system with back-propagation. The success of this configuration dwells in the fact that it can learn from retrospective information in a process called supervised learning. In supervised Learning the network is trained using historical data derived from the system the relationship between input and output is to be determined. The back-propagation learning algorithm, as mentioned earlier, is characterized by two parameters, the training rate and the momentum. These were used by the process of progressive refining weights based on the RMS error minimization. In training, the network learns by adjusting the weights.

[2]Kishan Bhushan Sahay, M. M Tripathi," An Analysis of Short-Term Price Forecasting of Power Market By Using ANN ", International Journal of Science.

A neural network approach for forecasting short-term electricity prices. Almost Until the end of last century, electricity supply was considered a public service and any price forecasting which was undertaken tended to be over the longer term, concerning future fuel prices and technical improvements. Short-term forecasts have become increasingly important since the rise of the competitive electricity markets. In this new competitive framework, short-term price forecasting is required by producers and consumers to derive their bidding strategies to the electricity market. Price forecasting in competitive electricity markets is critical for consumers and producers in planning their Operations and managing their price risk and it also plays a key role in the economic optimization of the electric energy industry. Accurate, short-term price forecasting is an essential instrument which provides crucial information for power producers and consumers to develop accurate bidding strategies in order to maximize their profit.

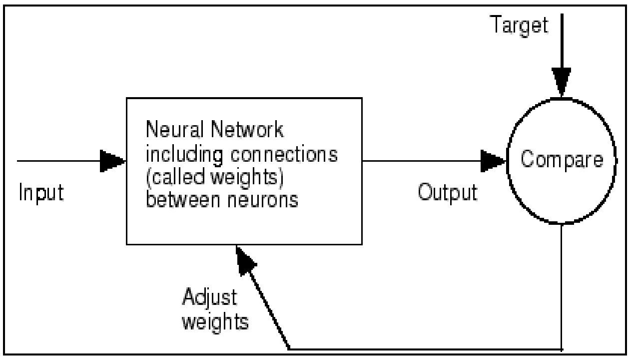

Fig -2: **Neural network weight comparisons.**

In this paper artificial intelligence (AI) had been applied in short-term price forecasting that is, the day ahead hourly forecast of the electricity market price. A new artificial neural network (ANN) has been used to compute the forecasted price in ISO New England market using MATLAB R13. The data used in the forecasting are hourly historical data of the temperature, electricity load and natural gas price of ISO New England market. The simulation results have shown highly accurate day-ahead forecasts with very small error in price forecasting.

[3] Filipe Azevedo, Zita A , "Forecasting Electricity Prices with Historical Statistical Information using Neural Networks and Clustering Techniques" , IEEE Electrical and Power System.

Factors such as uncertainty associated to fuel prices, energy demand and generation availability, are on the basis of the agents major concerns in electricity markets. Facing that reality, price forecasting has an increasing impact in agents' activity. The success on bidding strategies or on price negotiation for bilateral contracts is directly dependent on the accuracy of the price forecast. However, taking decisions based only on a single forecasted value is not a good practice in risk management. Artificial neural networks method is used for finding the market price for a given period, with a certain confidence level. Historical information was used to train the neural networks and the number of neural networks used is dependent of the number of clusters found on that data. K-Means clustering method is used to find clusters. A study case with real data is resented and discussed in detail. At that time, electricity price evolution was directly dependent on the government's social and industrial policy, and price forecasting was mainly focused on the underlying costs namely, fuel prices and technological innovation. Any price forecasting made on that basis was tended to be over the long term. With electricity markets deregulation and opening to competition during 1990s, this changed dramatically.

Ownership on this activity sector become private rather than public or a mixture of both. Competitive markets, like pools or power exchanges, have been introduced for wholesale trading. However, due to the instantaneous nature of the product electricity and uncertainty associated to fuel prices, energy demand, generation availability and technical restrictions, are at the origin of the high volatility that electricity prices exhibit. Also, factors like the structure and the management rules of any specific electricity market may introduce other sources of price volatility. Due to electricity price volatility, generators face price risks because they sell energy at variable pool prices while their fuel and other costs may be fixed. On the other hand, distributors/retailers also face price risks because they supply most of their costumers at an annual fixed tariff but they have to purchase electricity at variable pool price. Facing this reality, electricity price forecast is therefore extremely important for all electricity markets players, namely for risk management.

Several works have been made for price forecast on electricity markets. In those works, we can find a variety of techniques used to achieve that goal. Koreneff *et al.*

Proposed a general use modular time series approach, with detached regression analysis assuming that spot price follows a day, a week- and a year cycle. Stochastic processes were also used to analyse time series and to forecast electricity price. Electricity market players are daily confronted with the necessity to make decisions. Investment decisions are very difficult because they are influenced by investor's cognition, investment behaviour, psychological limitation and even the global economic and political environment

To hedge efficiently it is imperative to have access to good price forecasts in order to develop biddings strategies and negotiation skills. Taking decisions based only on a single forecasted value is not always a good practice on risk management, because there are several factors are on the basis of price formation and some of them are unpredictable.

3. ELM-TREE Approach

3.1 Extreme Learning Machine

Given a training set X that contains N distinct instances with n inputs and m outputs, i.e. X={(**x**i,**y**i)|**x**i=[xi1,...,xin]T∈Rn,**y**i=[yi1,...,yim]T∈Rm,i=1,...,N }, the SLFNs with ˜N hidden nodes and activation function g(**x**) are formulated as where **w**j=[wj1,...,wjn]T is the weight vector connecting the input nodes and the j^{th} hidden node , bj is the bias of the j^{th} hidden node, βj=[βj1,...,βjm] T is the weight connecting the j-th hidden node and the output nodes, and **o** I is the output of **x**i in the network.

The standard SLNFs can approximate the N training instances with zero error, i.e., there exists **w**j, bj, and βj, such that:

. ∑j=1 βj g(**w**j · **x**i +bj) = **y**i, i= 1, . . . , N.
Algorithm1: Extreme Learning Machine–ELM.

Input: Training Set{(**x**i,**y**i)|**x**i∈Rn,**y**i∈Rm,i=1,...,N}; activation function g(**x**);the number of hidden node N.

Output: Input weight **w**j, input bias bj, and output weight β.

Steps:-

1. Randomly assign input weight **w**j and bi as bj where
j=1,...,N.
2. Calculate the hidden layer output matrix **H**;
3. Calculate the output weight β=**H**†**Y** where **H**† is the Moore–Penrose generalized inverse of matrix **H** **[3]**.

3.2 Extreme Learning Machine with uncertainty reduction.

In this section, a new classification model named ELM-Tree is developed to handle the over-partitioning problem. The key difference between ELM-Tree and traditional DT lies in the determination of the leaf nodes. In the ELM-Tree model, ELMs are embedded as the leaf nodes when certain conditions are met. Thus, there are two key steps in the construction of ELM-Tree, i.e., splitting a non-leaf node and determining an ELM leaf node[3].

Input: Node $X=\{(\mathbf{x}_i,y_i)\}^N_{i=1}$,where $\mathbf{x_i} = \{x_{i1},...,x_{in}\} \in R^n$ is the i^{th} instance, $y_i \in \{1,...,m\}$ is the class label of $\mathbf{x}_i$,m is the number of classes, and A_j, j = 1,...,n is the j-th attribute.
Output: Two child nodes X_1 and X_2.

1. For each attribute Aj, sort its values x_1 j,...,x_{nj} in ascending order, and the sorted values are recorded as x_{1j^*} ≤...≤x^*_{Nj};

2. Get all the available cut-points of each A_j, i.e., $cut_{ij} = x*_{ij}+x*_i+1,j/2$, i=1,2,⋯,N−1;

3. Calculate the information gain of each A_j and its cut-point cut_{ij} :

$$Info(X) - \left[\frac{|Xij1|}{|X|} info(Xij1) + \frac{|Xij2|}{|X|} info(Xij2)\right]$$

Where X_{ij1}= {**x**i ∈ X | x_{ij}≤ cut_{ij}} and X_{ij2}∈ {**x**i ∈ X| x_{ij}> cut_{ij} } are the two subsets of X divided by cut_{ij}, |X| is the size of X, and I (cut_{ij}) is the expected information of cut_{ij};

4. For each attribute A_j, select its optimal cut-point $cut_{i(j)j}$ where

$i^{(j)}$=argmax{*Gain*(X,cut_{ij})};

i=1,...,N−1

5. Calculate the split information of the optimal cut-point for each A_j:

Split(X,$cut_{i(j)j}$)=

$$-\left(\frac{|xi\ (j)\ j1|}{|X|}\log 2\frac{|xi\ (j)\ j1|}{|X|} + \frac{|xi\ (j)\ j2|}{|X|} log2\frac{|xi\ (j)\ j2|}{|X|}\right)$$

6. Calculate the gain ratio of A_j:

$$Ratio(X, |A_j) = \frac{Gain(X, cut\ i(i)j}{Split(X, cut\ i(i)j)}$$

7. Select the optimal attribute A_{j*} where

$$j^*=\text{argmax}\ \{Ratio(X,A_j)\};$$

8. Split X into X1 and X2 by A_{j*} and its optimal cut-point $cut_{i(j*)j*}$ where X1={**x**i ∈ X $|x_{ij}*\le cut_{i(j*)j*}$} and X2 ∈ {**x**i ∈ X $|x_{ij*}>cut_{i(j*)j*}$}[3].

3.3. Construct an ELM-Tree

The induction of ELM-Tree is described in Algorithm 3. There are two important parameters in Algorithm 3,i.e.,the truth level threshold $\theta \in [0,1]$, and the uncertainty coefficient
$\varepsilon \in [0,1]$. For implementation, we further modify the uncertainty coefficient as $\varepsilon \times \log2(m)$ for entropy-based ELM-Tree and $\varepsilon \times \ln(m)$ for ambiguity-based ELM-Tree, where m is the number of classes in X.

Input: A training set with N instances, n attributes and m classes; truth level threshold $\theta \in [0,1]$; uncertainty coefficient $\varepsilon \in [0,1]$;
and integer parameter $N^* \in \{1,...,N\}$.

Output: An ELM-Tree.

Steps:-

Ω is initialized as an empty set;
Consider the original training set as the root-node, and add it to Ω;
while *Ω is not empty* **do**
Select one node from Ω, denoted by X;
if $\max\{p_i\}^m_{i=1} > \theta$ *or* $|X| < N^*$ **then**
Assign X a label, i.e., $\text{argmax}_i\ \{p_i\}^m_{i=1}$,and remove it from Ω;
else
if $I(cut_{ij}) < \varepsilon$ *for* i=1,...,N−1,j=1,...,n **then**
Train an ELM for X and remove it from Ω;
else
Split X into two child nodes X1 and X2 by Algorithm2;
Remove X from Ω, add X1 and X2 to Ω;
end
end
end [3].

4. PROPOSED SYSTEM

To forecast (predict) future power need, the electric power production may be planned. This is called power load adaption. To reduces the cost of electricity bill and also to provide estimated usage of the load an accurate load forecasting is very important. It can be divided into long-term load forecasting, mid-term forecasting, short-term forecasting. Midterm and long-term forecasting mainly used in power factory to help them to forecast the electricity load usage by their users, and the time ranges of long term is from six months to twelve months and midterm forecasting is from one month to six months respectively. The short-term forecasting can be used in generators macroeconomic control, power exchange plan and so on. And the prediction is from one day to seven days in the future, or a little longer time [1].

Factors influencing System Load usage : The Four major categories of factors that influence system load are:-

1. Economic Factors: The economic environment in which the utility operates has a clear effect on the electric demand consumption patterns
2. Weather factors: Significant changes in load pattern are due to metrological factors as most of the utilities have large components of weather sensitive load such as space heating, air conditioning and agricultural irrigation
3. Random disturbances: These include loads such as steel mills, wind tunnels whose operations can cause large variations in electricity usage.
4. Time factor: The principal of time viz. seasonal effects, weekly – daily cycle legal and religious holidays play an important role in influencing load patterns[3].

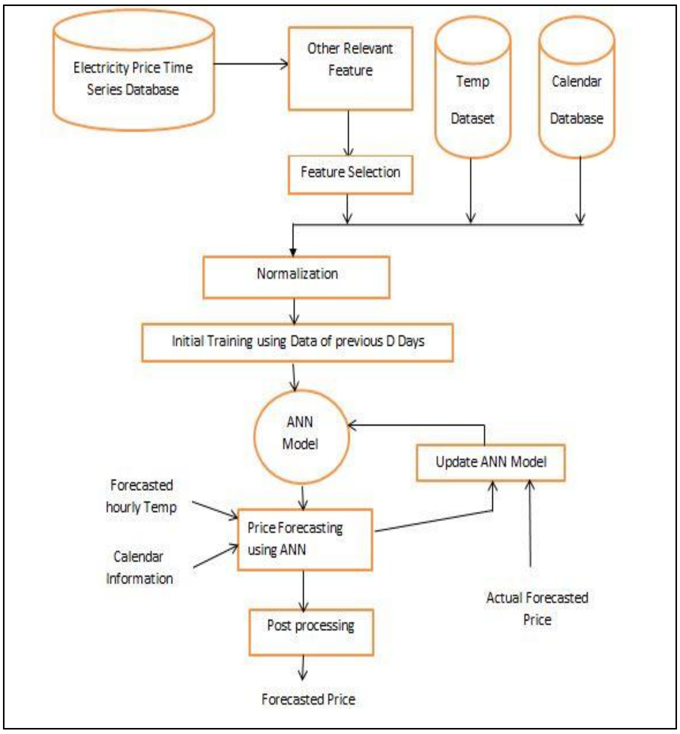

Fig. 3: System Architecture.

4.1 Modules

The system architecture is divided into two modules:-
a. Data Pre-processing Module
b. Constructing ANN-Model Module

4.1.1 Data Preprocessing Module:-

Feature Extraction:-

The electricity market data comes in the form of a time series, and does not provide any specific features for use with ANN. Thus we have to create features from the available past data to be used as inputs to the ANN. For the purpose of the forecasting it is very much necessary to consider both short and long-term forecasting and sometimes seasonal pattern also become mandatory to be consider. Because of seasonal patterns sudden changes might be observed in the price of electricity. So to capture the changes we sought of creating the features which are relevant based on the historical data which can lasts for a longer period. Also other features such as last year same day, same hour, last week same day same hour price fluctuation etc. can be created.

Feature Selection:-

For the purpose of robust forecasting system, feature selection is a very important step.

Using the learning algorithm the estimated accuracy is obtained based on which evaluation of the feature subset is done. Cross validation is used for estimation of accuracy. Unsupervised learning problems can also use cross-validation which results in better clusters by some other target or objective function is used instead of classification accuracy

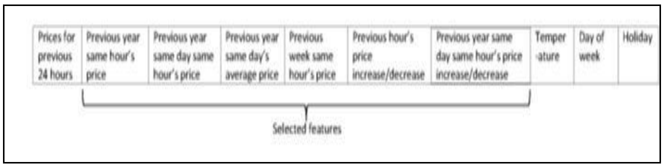

Fig. 4: Features Selection.

Incorporating Other Features:-

Using historical prices, features are generated which gave good forecasting results, but for gaining more better results we have to consider other features which are indirectly associated with price data for electricity. The parameters which can affect the load or price of electricity is also considered.

Normalization

Normalization is compulsory in the ANN where the data input is different from each other and ranging in different measurements and scale. In this approach the defined different input data that has different scales, thus the normalize the data is used to achieve a consistent form. Use map min max function available in Matlab to normalize our input data. Map min max returns a normalized matrix by normalizing the each row to the range of provides minimum and maximum values. In our method we normalize the data into the range of the input (-1, 0, 1).

4.1.2 Constructing ANN Model Module

Many models of the ANN has been proposed for purpose of classification and regression (forecasting) problems in machine learning. Out of all the models, the multilayer perceptron is the best known and most widely used. Typically, a feed forward ANN contains unit arranged in three layers, input, hidden and output. Each layer contains a number of units which contain shared data but these are not connected to each other. Our ANN model we select three layer network with ten nodes in the hidden layer. To perform the forecasting using a neural network, 2 basic steps are requiring training and learning.

In the learning step of the neural network learns how to reconstructing the input and output map by updating the weight of inputs given and biases at the end of each iterator. Back propagation is the most common learning algorithm, in which at the end of iteration output error is propagated back to input adjusting the weight and biase. To overcome from the slow convergence rate of the back propagation algorithm the main two parameters are learning rate and momentum can be adjusted.

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propagation algorithm the main two parameters are learning rate and momentum can be adjusted.

5. CONCLUSIONS

System will have gained high relevance and will represent one of the main sources of information that can bias one common base for system user for bidding in the electricity market. In particular scenarios, such as for generator companies, forecasting of electricity price and consumption level can be used as possible value for finalizing the price level in this competitive market.

The application will provide:

1. Forecasting of Electricity price based on various parameters such as calendar date, temperatures.
2. Report Generation mechanism on daily basis, weekly basis.

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