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Electricity price forecasting of deregulated market using Elman neural network

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***Abstract*—Price forecasting is one of the main issues faced in deregulated market because of the dynamic behaviour of the electricity prices. In a day-ahead pool market, market participants need forecasted prices to submit their bids to the market operator. Accurate forecast can provide a risk free environment for the producers and consumers to invest into the market. Participants themselves feel that they can have assured return if the forecasted prices are accurate. This paper presents Elman Neural Network to forecast the dynamics in the electricity prices accurately. The proposed method has been tested on Mainland Spain market to forecast the market clearing prices and found to be an efficient method in comparison with many existing methods.**

Keywords—Electricity Price forecasting; Distance correlation; Elman Neural network;

NOMENCLATURE

P_t	Electricity price at hour ‘t’
B	Backlash operator
p	Auto-regressive coefficient
d	Order of differencing
ϕ_t	Coefficient to the price term P_t
Std	Standard deviation of the prices
Std1	Standard deviation of the prices with d=1
Std2	Standard deviation of the prices with d=2
dCov	Distance covariance
dVar	Distance variance
μ_k	Learning rate of iteration ‘k’
E_k	Error in iteration ‘k’
W^k	Weight in iteration ‘k’
a	incremental learning rate
b	detrimental learning rate
Ψ	factor slightly greater than 1
ARIMA	Auto Regressive Integrated Moving Average
ANN	Aritificial Neural Network
FNN	Fuzzy Neural Network
RBFN	Radial Basis Function Neural Network
AWNN	Adaptive Wavelet Neural Network
MAPE	Mean Absolute Percentage Error

I. INTRODUCTION

Electricity prices are highly volatile in nature. One of the main reasons why electricity price forecasting is an important study is the highly dynamic or chaotic nature of the energy market. Even though there always is a risk of volatility in almost every market, the degree of volatility is higher in electricity markets than other markets.

Recalling the fact said above, electricity price forecasting has drawn the attention of different researchers across the globe in the past few decades. Being a new area of interest, a number of price forecasting methods for the electricity market have been proposed recently. In general, these price forecasting tools fall into two main categories [1].

The first approach is the detailed market simulation approach in which a lot of market information is needed. Power utilities and market operators mainly use these simulation-based methods. In these methods the actual market dispatch is imitated by considering initial supply offers, demand bids, and system operating constraints. However, as these methods require full insight into the system operation, they are not practical for market participants. A forecast tool developed using this approach may not be feasible for other markets directly and may also require a lot of changes to be made for making it useful to other markets.

The second category refers to the methods based on mathematical or analysis-based approaches. These approaches forecast future prices using historical operation data.

In a deregulated market, producers and consumers submit their bids for the sale and purchase of electricity respectively.

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Market Operator matches the bids and fixes contracts between them. To submit the bids, market participants require good guess prices in order not to lose their investment. So market participants rely on accurately forecasted prices. Market operator will always require a robust method for forecasting the chaotic behaviour of the electricity prices. In other words, the need of accuracy in forecasting has begun when the electricity industry had undergone drastic changes from monopoly to the competitive market.

In this paper, the Elman recurrent neural network is used to forecast the prices using the historical data. Many authors proposed different approaches for forecasting the electricity prices. Hard computing techniques like ARIMA models [2], Regression techniques [3] and soft computing techniques like ANN approaches, using Fuzzy neural networks [4] and many hybrid networks [5] are used in present day markets.

This paper has been organized into four different sections in addition to the section on Introduction. Section II presents very briefly the methodology of extracting the data from Mainland Spain market, application of the time series modelling on the data, distance correlation plots and the advantage of using Elman neural network over the Hopfield Neural Network for forecasting studies. Section III explores in a lucid manner the price forecasting method using Elman Neural Network. The results and performance evaluation of Elman Neural Network has been reported legibly and Section V presented the findings in the paper as Conclusions.

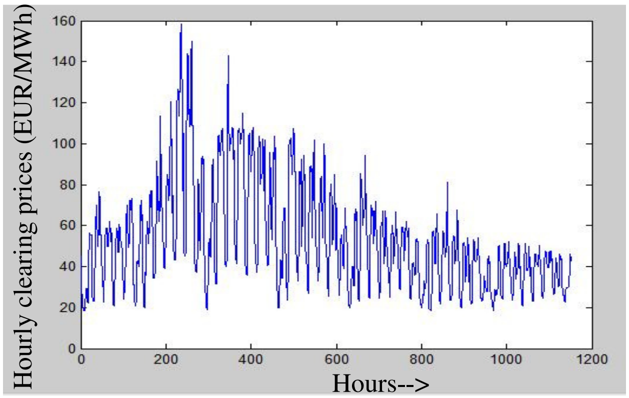

Figure 1 : Data plot of Electricity prices of Spain market

II. METHODOLOGY

A. *Extracting the data*

The Mainland Spain electricity market clearing prices [6] published in monthly basis have been considered for extracting the data. A short span of historical data is sufficient for this method. Market clearing prices from Jan1st, 2002 to Feb 17th, 2002 of Spanish market are considered and plotted in MATLAB as shown in figure1.

B. *Time series modelling*

A simple Autoregressive time series modelling has been applied on the data using the distance correlation technique. The autoregressive coefficient p and order of differencing d should be found for the time series modelling [1].

$$(1-B)^d * P_t = \sum_{l=1}^{p} \Phi_l * P_{t-l} + \in \qquad (1)$$

Where B represents Backlash operator given as

$$B^l * P_t = P_{t-l} \qquad (2)$$

and (1-B) is the stationary inducing operator.

From the figure 1 it is observed that electricity prices show great variations with respect to time. Mathematically speaking, prices show non-constant mean and variance. To stabilize the series, differencing is done. The series after differencing once is shown in figure 2.

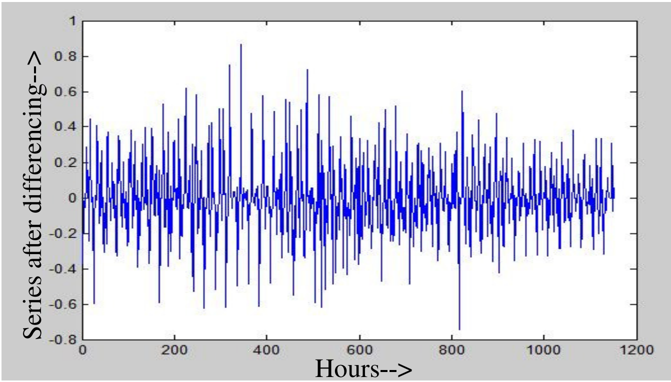

Figure 2 : Plot of data after differencing once (d=1)

Even after the differencing, It is observed from the series that there exists a lot of variance. To reduce the variance, logarithm is applied to the series. The order of differencing is known from the standard deviation values of the series. The standard deviation of the prices after applying logarithm to the series is as follows:

Std = 0.4658

The standard deviation of the series with the order of differencing d=1 is found to be

Std1 = 0.1793

And the standard deviation of the series with the order of differencing d=2 is found to be

Std2 = 0.2112

Here, one can observe that the standard deviation of the series is decreased if the order of differencing is d=1 and is increased if further differencing is done on the series i.e. d=2. As such one can conclude that order of the differencing d=1 is enough for making the series stationary.

C. *Distance correlation*

Autoregressive coefficient and seasonal variations in series can be found from distance correlation plots. Distance correlation is a measure of statistical dependence between two random variables or two random vectors. An important property is that this measure of dependence is zero if and only if the random variables are statistically independent [7]. The distance correlation plot for many lags for the series under consideration is as shown in figure 3.

Distance correlation coefficient at different lags can be found by distance covariance and distance variance.

If X_k and Y_k are two random variables where k=1, 2, 3……n

$$a_{j,k}=\|X_j-X_k\| \tag{3}$$

$$b_{j,k}=\|Y_j-Y_k\| \tag{4}$$

where ‖ . ‖ is Euclidean norm.

Compute the n by n distance matrices $(a_{j,k})$ and $(b_{j,k})$. Then take all doubly centred distances

$$A_{j,k}= a_{j,k}-a_{j.}-a_{.k}-a_{..} \tag{5}$$

$$B_{j,k}= b_{j,k} -b_{j.}-b_{.k}-b_{..} \tag{6}$$

Where a_j represents the j-th row mean, a_k represents the k-th column mean, and $a_{..}$ is the grand mean of the distance matrix of the X sample. The notation is similar for the b values. In the matrices of centred distances $(A_{j,k})$ and $(B_{j,k})$ all rows and all columns sum to zero. The squared sample distance covariance is simply the arithmetic average of the products $A_{j,k}\, B_{j,k}$.

The squared sample distance covariance is given by

$$dCov_n^2(X,Y)=\frac{1}{n}\sum_{j,k=1}^{n} A_{j,k}*B_{j,k} \tag{7}$$

And the distance variance is given as

$$dVar_n^2(X)=dCov_n^2(X,X) \tag{8}$$

The distance correlation of two random variables is obtained by dividing their distance covariance by the product of their distance standard deviations. It is a value that lies between 0 and 1. The distance correlation is

$$dCorr(X,Y)=\frac{dCov(X,Y)}{\sqrt{dVar(X)*dVar(Y)}} \tag{9}$$

The distance correlation coefficients of the differenced series we considered for many lags have been plotted is as shown in figure 3.

It is observed that the distance correlation values dropped to very low values after the first 3 lags. Hence, It can be concluded that autoregressive coefficient p=3. Further one can also observe spikes at different instants like 24,48,72,96 etc. in figure 3.

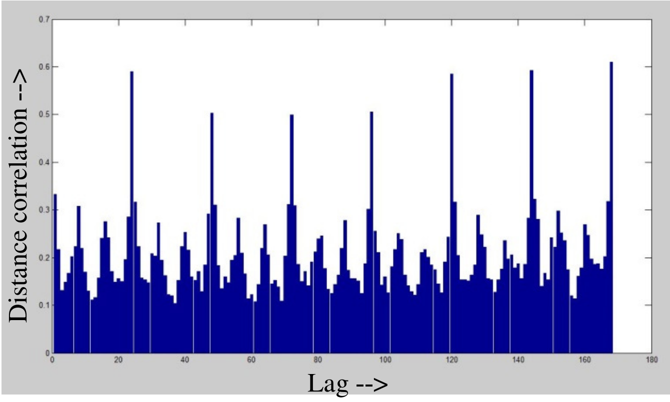

Figure 3 : Distance correlation coefficient of differenced series

Hence one can conclude that the featured prices by distance correlation can be $P_{l\text{-}1}$, $P_{l\text{-}2}$, $P_{l\text{-}3}$, $P_{l\text{-}24}$, $P_{l\text{-}25}$, $P_{l\text{-}48}$, $P_{l\text{-}49}$, $P_{l\text{-}72}$, $P_{l\text{-}73}$, $P_{l\text{-}96}$, $P_{l\text{-}97}$, $P_{l\text{-}120}$, $P_{l\text{-}121}$, $P_{l\text{-}144}$, $P_{l\text{-}145}$, and $P_{l\text{-}168}$. These obtained by distance correlation are same obtained in [2].

D. Elman network

It is a type of recurrent neural network, also known as simple recurrent network, which is capable of storing temporal patterns because of feedback connection. The network structure of Elman neural network is explained in detail in [8].

It consists of self-feedback. The output of every neuron is fed back to its input via a context layer. This topology of Elman network makes it possible to capture ever changing dynamic or chaotic electricity prices.

Hopfield neural network is also a recurrent neural network. It does not have self-feedback. But Hopfield neural network is not used for forecasting studies because the energy function we define while training the network will search for a minimum energy point which usually lands in a local minima. Generally Hopfield networks are used in optimization problems. Hence Elman neural network prove its mettle in forecasting studies.

III. Price Forecasting Using Elman Neural Network

The featured prices obtained in section II are used as inputs to the Elman neural network for training the Elman neural network.

Training of the Elman neural network is done using MATLAB toolbox. Normalization of the inputs to the neural network is done by min-max method as mentioned in [8]. All the features inputs are linearly normalized between {1, -1}. Gradient descent back propagation with adaptive learning rate is used as leaning algorithm for stabilization of weights.

In the concept of adaptive leaning rate, there are parameters to be modified during the learning phase to obtain the better result. The weight stabilization equation in adaptive learning rate method [9] is

$$W^{k+1}=W^k-\mu_k.\Delta E(W^k) \tag{10}$$

$$\mu_{k+1}=\begin{cases} a*\mu_k & if\ \dfrac{E_k}{E_{k+1}}\le\psi \\ b*\mu_k & otherwise \end{cases} \tag{11}$$

Where a, b, ψ are parameters to be selected by trial and error method for more accuracy in the forecast. Parameters ‘a’ is called incremental learning rate, ‘b’ is called detrimental learning rate and ψ is a factor which is slightly greater than 1. The step by step procedure for activating the Elman neural network utilizing MATLAB neural network toolbox is as follows:

[Step 1] Type ‘nntool’ in Command Window

[Step 2] Create a new network with required number of neurons by selecting ‘Elmanbackprop’ under ‘network type’ section

[Step 3] Select ‘TRAINGDA’ adaptive learning method under ‘training function’ section

[Step 4] Train the created network with required learning parameters

[Step 5] After the completion of training, Save the trained network as ‘network_name’

[Step 6] Use the trained network by loading it to some variable using ‘load’ function Variable = load(‘network_name’)

[Step 7] Give the test patterns as Output=’variable.network(test_pattern)’

IV. RESULTS AND PERFORMANCE EVALUATION

A. *Training the neural network*

Elman neural network with 16 featured prices and 10 neurons as input and one output node is formed using neural network toolbox in MATLAB. The number of nodes is selected randomly by trial and error method. Network is trained by 1008 (42 days * 24 hours) patterns. Each training pattern consists of a target hour and 16 past lagged influential prices.

The values of a, b, ψ are adjusted as 1.02, 0.9, 1.04 which gave the best forecast results.

B. *Performance evaluation*

The robustness of the method proposed is proved by comparing the results obtained with the existing methods. Comparing the mean absolute percentage errors (MAPE) obtained by different methods can prove the ability of the proposed method. The computation of MAPE is explained legibly in [8].

C. *Presentation of Results*

The forecasted prices and actual prices of the Spanish market for the week from February 18, 2002 to February 24, 2002 also named as winter week are shown in figure 4. The historical data used for forecast of winter week is January 07, 2002 to February 17, 2002.

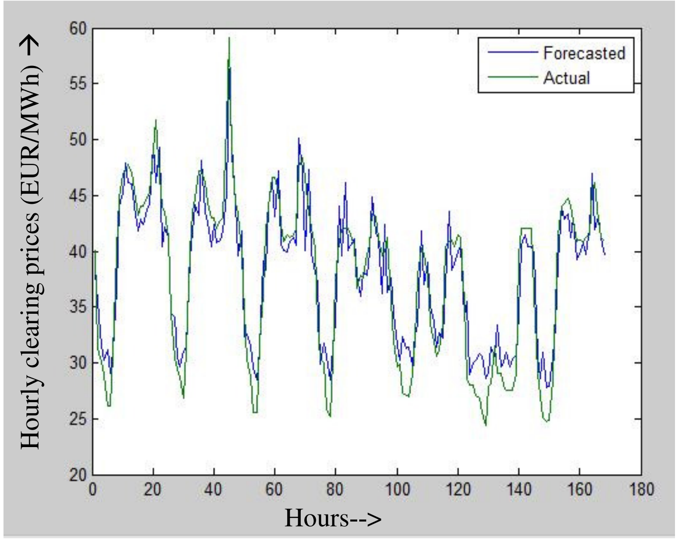

Figure 4 : Forecasted clearing prices of winter week of 2002

Similar procedure is followed for forecast of summer week from July 20, 2000 to July 26, 2000 as shown in figure 5 by training the neural network with clearing prices from June 08, 2000 to July 19, 2000.

To prove the effectiveness of the proposed method, two seasons of different years are considered.

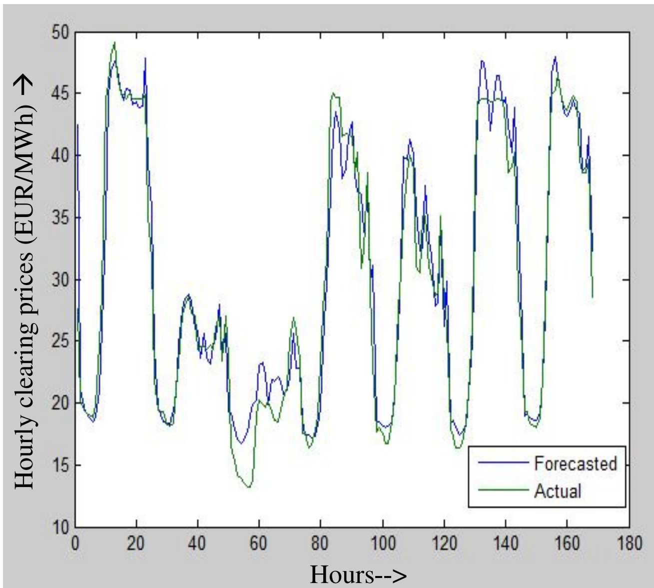

Figure 5 : Forecasted clearing prices of summer week of 2000

D. *Comparison with other methods*

The effectiveness of this method is proved by comparing the MAPE values of the forecast results by different methods.

Table 1: MAPE comparison of different methods for winter week

S.No.	Method	MAPE
1	ARIMA [2]	13.39
2	Wavelet-ARIMA [10]	10.70
3	FNN [4]	9.84
4	Wavelet-ARIMA-RBFN [11]	6.76
5	AWNN [5]	9.64
6	Elman Neural Network	5.43

The forecasted errors for both the winter week and summer week by proposed method were compared with errors reported by various researchers on the same Mainland Spain Market data utilizing ARIMA[2], Wavelet-ARIMA [10], FNN [4], Wavelet-ARIMA-RBFN [11] and AWNN [5] methods. It was found that the proposed method got the lowest forecasted error and the Elman Neural Network can be employed for forecasting the electricity prices accurately in deregulated electricity markets. The MAPE comparison of different methods for winter week and summer week were presented in Table 1 and Table 2 respectively.

Table 2: MAPE comparison of many methods for summer week

S.No.	Method	MAPE
1	ARIMA [2]	6.32
2	Wavelet-ARIMA [10]	4.78
3	FNN [4]	4.62
4	Wavelet-ARIMA-RBFN [11]	4.27
5	AWNN [5]	3.43
6	Elman Neural Network	3.00

V. CONCLUSION

The proposed Elman Neural Network forecasted the Electricity prices more accurately with lowest mean absolute percentage error in comparison with widely used existing methods. The proposed method has been tested for robustness on the Mainland Spain Market data sample captured during winter week and summer weeks. The Elman neural network is capable of capturing high dynamic variations in price and hence can be applied for forecasting the electricity prices accurately in a deregulated environment.

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BIOGRAPHIES

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