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Electricity point price evaluation using hybrid algorithm

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Abstract: Estimation of price is the most crucial task and the basis for making decisions in competitive bidding strategies. Robustness, reliability and optimal profits for the market players are the main concerns which can be achieved by a point price forecasting module comprising of diminutive prediction errors, less computational time and reduced complexity. Hence in this work, an integrated approach based on Artificial Neural Networks (ANN) trained with Particle Swarm Optimization (PSO) is proposed for short term market clearing prices forecasting in pool based electricity markets. The proposed approach overcomes the difficulties like trapping towards local minima and moderate convergence rates as in existing methods. The work was deliberated on mainland Spain electricity markets and the results obtained are compared with hybrid models presented in the past literature. The response shows decrement in forecasting errors that are identified in price forecasting. The complete research may assist the ISO in finding out the key factors that are fit for prediction with low errors.

Keywords : *Artificial Neural Networks, Particle Swarm Optimization, Market clearing price*

1.0 INTRODUCTION

Introduction of deregulation leads to a customer driven, organized electricity market, which offers opportunities for optimal resource utilization and efficient electricity procurement strategy. The main aim of organized electricity market is to shrink the cost of electricity through competition and maximize the efficient generation and consumption of electricity [1], [2], [3]. The accurate price prediction has become important in the new restructured electricity market [4], as it plays a key role in power system plans, risk assessment and other related decisions [5] and [6]. Because of the dissipate nature of electricity, all the generated electricity must be expended. This initiates the need of accurate price forecasting methodologies for both producers and consumers to establish their own strategies for the benefit or utilities maximization [7]. Popularity of forecasting approaches is based on their accuracy, flexibility, reliability and robustness. Selection of most informative price attributes to address market price behavior and selection of appropriate forecasting model capable of predicting the price using provided data are two main decisions which should be made effectively in forecasting market prices.

The prediction of future price is based on various parameters which include forecasted electricity demand, temperature, sunshine, fuel cost, and precipitation. Presently, many attributes are available for a day-ahead electricity price prediction. Many factors influence the spot prices and can be considered as input features for forecasting the prices. Some of the input features

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may be historical load, system load rate, historical reserves, forecasted load, forecasted reserves and historical prices [8]. Day, time slot, estimated demand, load change and prices of a day before one week before, two weeks before, three weeks before and four weeks before are considered as inputs for price forecasting [9]. The aggregation of load, surplus, historical market clearing prices and oil prices are used as input data set for the price forecasting [10]. The results show that average and maximum day-ahead load and the day-ahead surplus are the most important inputs for forecasting prices.

There are many approaches that can be observed in the electricity price forecasting. The next day electricity prices are evaluated based on time series models like dynamic regression and transfer function models [11]. Non parametric functional methods are proposed to forecast the electricity price and demand series in the market of mainland Spain [12]. In [13], a mid-term electricity price forecasting model using multiple support vector machines (SVMs) is proposed to forecast the hourly electricity price for entire 6 months ahead. In this two SVM modules are used separately for both classifying and forecasting the prices. The work is improved and the SVM module is adjoined with auto regressive moving average with external input (ARMAX), to re-define the error values that obtained from the Least Squares SVM (LSSVM) [14] and [15]. The contribution of wavelet transform is great in hybrid models used for forecasting the electricity prices. The wavelet transforms decomposes and reconstruct the ill-behaved prices into a set of better behaved price series. Hence, these are combined with auto regressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH) to forecast the highly volatile and highly nonlinear electricity prices [7]. The GARCH models are replaced by particle swarm optimized (PSO)-LSSVM forming a new hybrid method based on wavelet-ARIMA-LSSVM to enhance the prediction accuracy for the price forecasting [16]. The wavelet transform with ARIMA model is combined with Radial Basis Function Neural Networks (RBFN) to enhance and overcome the disadvantages in the previous combinations[17]. In [18], a hybrid evolutionary adaptive (HEA) model is developed to forecast the electricity prices in the short term pool based electricity markets. Different methodologies like Wavelet Transform (WT), Evolutionary PSO (EPSO) and Adaptive Neuro Fuzzy Inference Systems (ANFIS) are combined to form HEA. This hybrid model had shown an average MAPE (%) of 4.18%. An integrated model based on WT, LSSVM and chaotic gravitational search algorithm (CGSA) is used for prediction of the electricity prices in Iran's, Ontario's and Spanish electricity markets. The computational time required for this method to produce the results is 27 minutes which is the major disadvantage of the integrated model. Similarly, a hybrid approach constituting of PSO – ANFIS is employed to predict the prices [10]. The hybrid and integrated methodologies have certain advantages and disadvantages. The major challenges faced by these methodologies are consumption of time and complexity in the application.

The shortcomings faced by hybrid and integrated models in the electricity price forecasting can be overcome by a new branch of simplified techniques. ANNs got weighted attention due to its simplicity, accuracy along with a high degree of learning capability in a very short duration of time. Especially, ANNs are getting prominent roles in predicting the electricity prices and demand series. These are successfully applied to forecast the electricity prices by using 13 parameters as inputs [9]. Simple ANNs are applied to forecast the electricity prices of warm and cold days with low, normal and peak loads [19]. A review on electricity price forecasting is presented based on various methodologies used and factors influencing the electricity prices. The various methodologies include game theory models, simulation models and time series models [17]. Neural networks are combined with wavelet transforms and fuzzy logic to predict the signals with hard non linear behavior and time variant functional relationships [20]. Large numbers of the real-world input data samples to train artificial neural networks, normally creates confusion over ANNs during the learning process and thus, degrades their predictive capacity. Hence, discrete cosine transform (DCT) is applied as a preprocessing tool for neural networks (NNs) in the estimation of electricity prices. The time series of prices are transformed into frequency domain using DCT and these are then passed through NN for the prediction [21].

The literature survey on various forecasting models reveals that the forecasting methods follow either time series models or hybrid models or neural networks. The time series models are linear and are hard to predict the non-linear price series. The hybrid models are time consuming and complex in usage. The neural networks combined with DCT and wavelet modules uses repeated normalization of the historical times series which are used as training data set for the ANNs. Slow convergence rate and tendency to become trapped in local minima are the drawbacks of back propagation algorithm (BPA) used in training the NNs. Hence, to overcome the time consuming models, linear models and repeated normalization techniques, trapping and slow convergences ANN training with PSO is proposed in this research work to forecast the next 168 hours of Spanish electricity markets for the weeks in the year 2002. Further, the structure of the paper is as follows: Section 2 provides the research methodology and data required for electricity price forecasting. The proposed research algorithm is depicted in section 3. Numerical results and comparative analysis are explored in section 4 and the concluded milestones of the research work are presented in the section 5.

2.0 METHODOLOGIES

A. Collection of Data

The historical prices from Spanish Electricity market are considered to perform the proposed work. Huge number of factors may influence the electricity price such as, system load of the entire covered area, power import and export, available hydro energy and fuel prices [12]. Out of several parameters proposed by many researches, the historical prices are considered as the most suitable input parameters for the analysis.

Historical Prices

The different price lags are considered as input parameters for the proposed research work. The different price data are taken from daily trading reports of mainland Spain [22]. Different sets of historical prices can be chosen as input features for the prediction of prices. Based on the literature, the historical prices $(p-1)$, (p – 2), (p – 3), (p – 24), (p – 25), (p – 48), (p – 96), (p – 97), (p – 120), (p – 121), (p – 144), (p –145) and (p –168) are considered as input features for each hour of the day for both training and testing data sets.

B. Forecasting Electricity Prices Using Integrated Approach

Artificial Neural Networks have been greatly utilized in broad areas of research like pattern recognition, classification, function approximation, optimization and prediction. In general a Multi Layered Perceptron (MLP) network consists of 3 layers; namely are input, hidden and output layers [9] and [23]. The basic step in accurate approximation of any nonlinear mapping can be accomplished by sound training of the neural network. Generally the ANN is trained based on the statistical parameters, which are preprocessed. The output of the neurons can be determined as shown below.

$$X_i = f\left(\sum_{l=1}^{N} w_{il} a_l\right) \quad (1)$$

In general, the ANNs learn through updating weights and biases based on BPA by minimized mean squared error between actual and targeted outputs. In this study, a three layered model of ANN is utilized to get good accuracy of the proposed scheme by training with PSO algorithm. A large testing data set is presented to check the solution. The set of completely unknown test data was applied for validation and testing.

C. PSO Algorithm

PSO is an evolutionary approach proposed by Kennedy and Eberhart in the year 1995 [24]. It is inspired based on the biological and sociological behavior of birds searching for their food. In searching the path for the food, best solution is also captured. It initiates by placing the particles randomly in problem hyperspace. Consider a D variable problem with N particle in a swarm. The vectors x and v of a particle denotes the position and velocity respectively. The position of particles were updated based on current position, current velocity, distance from $P_{best,i}$ and g_{best}. The updating of velocity and position vector are done based on the following rules:

$$v_i^{t+1} = wv_i^t + c_1 \times rand \times \left(p_{best,i} - x_i^t\right) + c_2 \times rand \times \left(g_{best} - x_i^t\right) \quad (2)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (3)$$

Where,

v_i^t Velocity of particle i at iteration t
w Weighting factor
c_j Acceleration coefficient
rand Random number between 0 and 1
x_i^t Position of particle i at iteration t
$p_{best,i}$ Local best of swarm i at iteration *t*
Best solution so far

In (2) wv_i^t, $c_1 \times$ rand $\times$ ($p_{best,i} - x_i^t$) and $c_2 \times$ rand$\times$ ($g_{best} - x_i^t$)provides exploration ability, individual effort and group effort of particles respectively. In each of the iteration t, calculated velocities are employed to find the next position of the particles. This will continue until the stop criterion is met [30]. In the present work maximum number of iterations and least MAPE (%) or whichever is the first is used as stopping criteria for the PSO algorithm.

3.0. RESULTS AND DISCUSSIONS

The proposed PSO trained ANN approach is validated on Spanish Electricity Markets for the year 2002. It is utilized by many of the researchers as a standard point of references. Hence, prices in the year 2002 is used as test case in the present work. A case study for the month of February resembling winter season is considered for the forecasting. The training data set constitutes of hourly prices of 6 weeks past to the day, whose prices are to be estimated. In the present scenario, the training and testing data sets for the Spanish electricity markets are shown in the table 1.

The estimated and the actual price values in the Spanish electricity market for the winter week is shown in Figure 1. The figure reveals the closeness between the actual and predicted values. The figure also reveals that the estimated value follows the actual even at the peaks and off peaks. The empirical results obtained for the Spanish electricity markets are compared with the previous researches using the statistical indicators. The Mean Absolute Percentage Error (MAPE(%)) is taken as a statistical indicator to assess the prediction capacity of the proposed approach.

TABLE 1
THE VARIOUS DATA SET USED FOR TRAINING AND TESTING PURPOSE

	Training Data	Testing Data
Winter week	January 7 to February 17, 2002	February 18 to 24, 2002

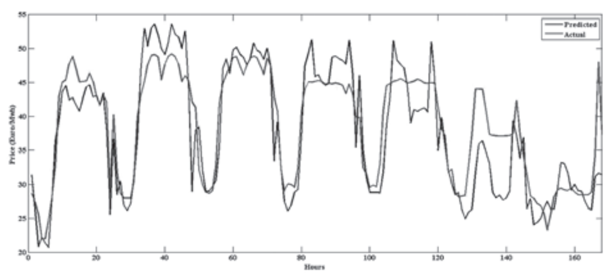

FIG. 1. GRAPH BETWEEN THE ESTIMATED VALUE AND ACTUAL VALUE FOR THE WINTER SEASON IN SPANISH ELECTRICITY MARKETS

the map (%) is expressedas:

$$\text{MAPE}\,(\%) = \frac{100}{N}\sum_{i=1}^{N}\frac{\left|y_{if} - y_{ia}\right|}{y_{ia}} \quad (4)$$

The results of MAPE (%) obtained through proposed approach for the Spanish electricity markets are shown in table 2. It is observed that the iteration count in PSO makes a huge importance in training the neural networks. It is also noticed that the proposed approach predict the prices with an average MAPE (%) of 2.7641% at an iteration count of 500. It could be further reduced by increasing the iterations in the PSO algorithm but it is observed that the PSO will take much time in evaluation of prices. The MAPE (%) results of the test week is obtained through other approaches like wavelet transform+neural networks+fuzzy logic (WNF) [24], wavelet-ARIMA-RBFN [23], wavelet-EPSO-ANFIS [16], CGSA-LSSVM [17] and the proposed approach are shown in table 3. The proposed approach produces the results with better forecasting accuracy over the other approaches. An average value of 6.32% of MAPE (%) has been recently reported DCT-ANN [21]. It can be seen, the performance of the proposed method is best when compared to recently proposed techniques. Although, the model is not made for forecasting the price spikes specifically, it performs satisfactorily in their presence with finer overall results.

TABLE 2

RESULTS OF MAPE (%) THROUGH PROPOSED APPROACH

S. No.	Model	MAPE	Iteration count
1	ANN with PSO training	2.7641	500
2	ANN with PSO training	2.8383	300
3	ANN with PSO training	3.0547	200
4	ANN with PSO training	3.3049	100
5	ANN with LM training	4.2516	200

It is clear from numerical results that the proposed approach can provide a more accurate and effective forecasting which are nearer to real Spanish's electricity market prices. The results through the proposed approach are obtained in fraction of seconds using MATLAB on a personal computer with 2 GB of RAM and 2.0 GHz based processor. The reduced complexity and less computational times are the novelties of the proposed PSO pre-processed ANN approach. The uniqueness of the proposed approach lies in less computational time in evaluating the prices as compared with many other recent techniques. The required computation time for the module recently reported using wavelet, LSSVM and CGSA [25] is about 27 minutes. The approach detailed based on wavelet-EPSO-ANFIS in [18] needs a minimum time of 40 seconds to produce the result. The computational time required by the recently proposed approaches like wavelet-ARIMA-RBFN [17], MI+CNEA [26] and MI+CNN [27] were 5 min, 40 min and 35 min respectively. But, the proposed approach evaluates the price series with a reduced computational time. Hence this causes the novelty of the proposed approach and could be used for real life applications to present the best trade off between prediction accuracy and computation times.

TABLE 3

MAPE (%) COMPARATIVE RESULTS FOR SPANISH ELECTRICITY MARKET WINTER WEEK

Reference	Reference	Winter week
[20]	WNF	3.3800
[17]	Wavelet +ARIMA+RBFN	4.2700
[18]	HEA	3.0400
[25]	CGSA+LSSVM	4.4170
[21]	DCT-ANN	4.0300
Present	PSO trained ANN	2.7641

4.0 CONCLUSION

This paper presents a novel model for day-ahead electricity price forecasting by using the artificial neural networks for Spanish electricity markets. The historical prices for the previous 42 days are considered as the input factors for forecasting the next 7 days. The present work is compared with advanced, hybrid and complex models which are used in the recent researches. The numerical results suggest that the the recent researches. The numerical results suggest that the accuracy is well-heeled and sound in forecasting the electricity prices for the deregulated environments to achieve the efficient frontier for the market players.

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