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DAY-AHEAD PRICE FORECASTING BASED ON HYBRID FUZZY NEURAL NETWORK AND SUPPORT VECTOR MACHINE

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ABSTRACT
In this paper, a novel hybrid approach is proposed for electricity prices forecasting in a competitive market, considering a time horizon of one week. In this model combination of Fuzzy Neural Network (FNN) and Support Vector Machine (SVM) has been modeled which is optimized by Particle Swarm Optimization (PSO). The proposed approach is based on the combination of particle swarm optimization and adaptive-network based fuzzy inference system. Energy price forecasting is the key information in the economic optimization of the electric power industry. But, these forecasting problems have a complex behavior due to their nonlinearity, non-stationary, and time variance. Obtained results have been calculated over mainland Spain test case. Obtained results demonstrate the validity of proposed model.

KEY WORDS: Price Forecast, Fuzzy Neural Network, PSO, SVM

INTRODUCTION

A reliable and continues supply of electrical energy is essential for the functioning of today's complex societies. Because of the combination of increasing consumption and obstruction of different kinds, and the extension of existing electrical transmission networks and these power systems are operated closer and closer to their constrains. Accordingly, With the introduction of restructuring into the electric power industry, the price of electricity has become the focus of all activities in the power market (Amjadi, 2007; Shafie-Khah *et al*., 2011; Lei and ZR, 2012).. In order to plan efficient operation and economical capital expansion of deregulated electrical markets, the market owner should be able to anticipate to adjust their bidding strategies to achieve the maximum benefit and on the other hand, consumers can derive a plan to maximize their utilities using the electricity purchased from the pool, or use self-production capability to protect themselves against high prices, these information can be provided only by price forecasting, which nowadays is done by neural networks. Because forecasting of load demand data forms an important component in planning generation schedules in a power system. Electricity has distinct characteristics as compared to other commodities; it cannot be stored economically and transmission congestion may prevent a free exchange of power between control areas. So, the electricity price series can exhibit a major volatility and the application of forecasting techniques prevailed in other commodities can pose large errors in electricity price forecasting (Vilar and Anerios, 2012; Amjady, 2006; Li *et al*., 2007).

For the proposed problem, several strategy have been published by researchers in recent years (Rodriguez and Andres, 2004; Aggarwal *et al*., 2009; Fosso *et al*., 1999) Auto regressive (AR) (Garsia *et al*., 2005) which is a simplest model. Auto Regressive Moving Average (ARMA) (Coenjo *et al*., 2003) and the Auto Regressive Integrated Moving Average (ARIMA) (Nogales *et al*., 2002). Considering the moments of a time series as variant where the error term does not have zero mean and constant variance as with an ARIMA process, the Generalized Auto Regressive Conditional Heteroskedastic (GARCH) in (Wang and Ramsay, 1998). A wavelet transforms (Szkuta *et al*., 1999) signal processing technique. And Dynamic Regression (DR) and Transfer Function (TF) models (Zhang and Luh, 2005). Although these approaches are very accurate, most of them are linear and thus cannot capture nonlinear patterns; moreover, their computational cost is very high and requires a lot of information. These techniques are simple, powerful, and flexible tools for forecasting, providing better solutions to model complex nonlinear relationships than the traditional linear models. But, they have weaknesses in the determination of network architecture, network parameters and the capability of modeling the nonlinear input/output mapping functions. However, electricity price is a time variant signal and their functional relationship rapidly varies with time (Kian and Keyhani, 2001). So, derived information or extracted feature of the NN or FNN rapidly loses its value. While it seems that the NN or FNN learns well the training data, they may encounter large prediction errors in the test phase. In this paper, a new strategy has been proposed for prediction of day ahead price in power market. Accordingly, combination of FNN with SVM has been modeled in this paper which is improved by PSO to find the best accuracy in this procedure. The remaining parts of the paper are organized as follows. In the second section, the proposed price forecast strategy is described. Proposed meta-heuristic algorithm has been presented in section three. Section four presents the obtained numerical results. Section five concludes the paper.

2. The Hybrid Forecast Strategy

In this paper, at first the actual data has been interred to SVM based forecast engine as first prediction step. Then, the FNN based forecast engine as the second step. For this purpose we will present the structure of this forecast engine step by step as follows;

A. Support Vector Machine

The following is a brief description on SVR for nonlinear function estimation such as the financial times series. In the primal weight space the model takes the form (Chen *et al*., 2009):

$$f(x) = \omega^T \phi(x) + b$$

With the given training data $\{x_k, y_k\}_{k=1}^N$ and $\varphi(.) : R^n \to R^{nh}$: a mapping to a high dimensional feature space which can be infinite dimensional and is only implicitly defined. Note that in this nonlinear case the vector ω can also become infinite dimensional (Lin and Chang, 2001). The optimization problem in the primal weight space becomes

$$\min_{w,b,\xi,\xi^*} J_p(\omega, \xi, \xi^*) = \frac{1}{2}\omega^T \omega + C\sum_{i=1}^{1}(\xi_i + \xi_i^*)$$

subject to:

$$\omega^T \varphi(x_k) + b - y_k \le \varepsilon + \xi_k^*, k = 1,..., N$$

$$\xi_i, \xi_i^* \ge 0, k = 1,..., N$$

Applying the Lagrangian and conditions for optimality, the following is the dual problem

$$\max_{a,a^*} J_D(a, a^*) = \frac{1}{2}\sum_{k,i=1}^{N}(a_k - a_k^*)(a_1 + a_1^*) + \sum_{k=1}^{N} y_k (a_k + a_k^*)$$

subject to :

$$\sum_{k=1}^{N}(a_k - a_k^*) = 0$$

$$a_k, a_k^* \in [0, c]$$

Here the kernel trick has been applied with $K(x_k, x_l) = \varphi(x_k)^T \varphi(x_1)$ for k, l = 1,...,N. The dual representation of the model becomes;

$$f(x) = \sum_{k=1}^{N}(a_k - a_k^*)K(x, x_k) + b$$

Consider the following Vapnik's ε-insensitive loss function

$$L_\varepsilon(y - f(x)) = \begin{cases} 0, & if\ |y - f(x)| \le \varepsilon \\ L(y - f(x)) - \varepsilon & otherwise \end{cases}$$

where L(.) is convex. Primal problem

$$\min_{w,b,\xi,\xi^*} \frac{1}{2} w^T w + C\sum_{k=1}^{1}(L(\varepsilon_k) + L(\varepsilon_k^*))$$

Where,

$$y_k - w^T \varphi(x_k) - b \le \varepsilon + \varepsilon_k$$

$$w^T \varphi(x_k) + b - y_k \le \varepsilon + \varepsilon_k^*$$

$$\varepsilon_k, \varepsilon_k^* \ge 0$$

Where εk,εk* are slack variables. Here, xk is mapped to a higher dimensional space by the function φ and ξk is the upper training error (ξk* is the lower) subject to the ε–insensitive tube $\left| y_k - w^T \varphi(x_k) - b \right| \le \varepsilon$. The parameters which control the regression quality are the cost of error C, the width of the tube ε, and the mapping function φ (Suykens, 2011).

The constraints imply that we should put most data xkin the tube $\left| y_k - w^T \varphi(x_k) - b \right| \le \varepsilon$. If xk is not in the tube, there is an error ξkor ξk* which we must minimize the objective function SVR to avoid under-fitting or over-fitting the training data by minimizing the training error $C\sum_{k=1}^{1}(L(\varepsilon_k) + L(\varepsilon_k^*))$ as well as the regularization term 1/2wTw.
The Lagrangian for this problem is

$$L(\omega, b, \varepsilon, \varepsilon^*; a, a^*, \eta, \eta^*) = \frac{1}{2}\omega^T \omega + c\sum_{k=1}^{N}(L(\xi_k) + L(\xi_k^*))$$

$$-\sum_{k=1}^{N} a_k(\varepsilon + \varepsilon_k - y_k + \omega^T \varphi(x_k) + b) -$$

$$\sum_{k=1}^{N} a_k^*(\varepsilon + \varepsilon_k^* + y_k - \omega^T \varphi(x_k) - b) - \sum_{k=1}^{N}(\eta_k \xi_k) + \eta_k^* \xi_k^*)$$

With Lagrange multipliers $a_k, a_k^*, \eta_k, \eta_k^* \ge 0$ for k=1,…,N. Dual problem, where;

$$\textit{subject to } \sum_{k=1}^{N}(a_k - a_k^*)$$

$$cL'(\varepsilon_k) - a_k - \eta_k = 0, k = 1, ..., N$$

$$cL'(\varepsilon_k^*) - a_k^* - \eta_k^* = 0, k = 1, ..., N$$

$$a_k, a_k^*, \eta_k, \eta_k^* \ge 0, \ \ k = 1, ..., N$$

So, SVR estimation function combined with the loss function is the foundation of the SVR. Support Vector Machine (SVM) is used in many machine learning tasks such as pattern recognition, object classification, and with regression analysis in time series prediction in Support Vector Regression, or SVR, a methodology in which a function is estimated using observed data which in turn is used to train the SVM (Zhang and Shen, 2013).

B. Fuzzy Neural Network
Neuro-Fuzzy is a combination of two systems of fuzzy logic and neural network. Neuro-fuzzy systems based on fuzzy inference system are trained using a learning algorithm derived from neural network system. Thus, the neuro-fuzzy system has all the advantages possessed by a fuzzy inference system and neural network systems (Ages, 2013)
Techniques neuro-fuzzy system can learn the behavior of the data is quite large and can be set automatically fuzzy rules and fuzzy-set to the highest level of accuracy (Aldas *et al.*, 2013) The proposed ANFIS structure has been presented in Fig. 1.

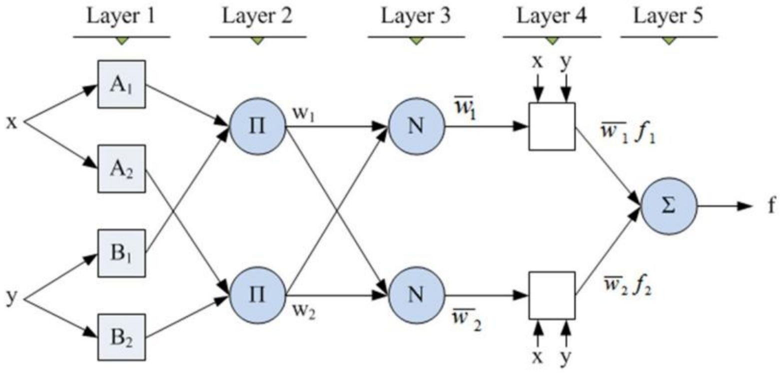

Figure 1 ANFIS structure with 2 Inputs

At first, the network propagates from the input layer to the output layer. Outputdari neuron / node-to-i in layer l is denoted as O_ (l, i), as follows (Arimbawa *et al*., 2013):

Layers 1

Every node i in this layer is an adaptive node with node activation function as follows:

$$O_{l,i} = \mu_{Ai}(x) \quad for\ i = 1,2\ or$$

$$O_{l,i} = \mu_{Ai-2}(y) \quad for\ i = 3,4$$

With x and y are input at node i, and Aiadalah linguistic labels such as good, bad, etc.. Ol In other words, i is the membership function of Aidan specifies the degree of membership of x and y with respect to Ai. Keanggotaaμ_Ai function (x) based on the equation bell with a maximum value of 1 and a minimum value of 0.

$$\mu Ai(x) = bell(x; a, b, c) = \frac{1}{\left(1 + \left|\frac{(x-c)}{a}\right|^{2b}\right)}$$

Where {a, b, c} is the set of parameters. Ci and ai parameters can be set to change the value of the center and width of the bell curve, while bidigunakan to adjust the slope of the curve and must be positive so that the curve is not inverted. If the values of these parameters change, the bell curve function will also change. This means it will form various linguistic membership function for the set Ai, ..., Isesuai Sugeno fuzzy model. Parameters in this layer are called premise parameters.

Layers 2

Each node in this layer is nonadaptif node. Its output is the product of all the inputs that go on this layer.

$$O_{2,i} = w_i = \mu_{Ai-2}(y), \quad i = 1,2, \ldots, n$$

Each output node degree of activation states (firing strength) of each fuzzy rule. The number of nodes in this layer shows the number of rules were established.

Layers 3

Each node in this layer is nonadaptif node that displays the degree of activation functions ternomalisasi (normalized firing strength) is the ratio of the i-th output node in the previous layer to the entire output of the previous layer, the shape function of node :

$$O_{3,i} = \overline{w} = \frac{w_i}{w_1 + w_2}, \quad i = 1,2$$

Layers 4

Each node in this layer is an adaptive node with a node function:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i)$$

With $\overline{w_i}$ is the normalized degree of activation to layer 3 and {pi, qi, ri} states consequent adaptive parameters.

Layers 5

In this layer there is only one fixed node whose function is to add up all the entries.

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

Adaptive network with five layers is equivalent degan Sugeno fuzzy inference system.

Learning Process with Parameter Consequent upon RLSE for Phase Forward

Based on ANFIS architecture in Figure 1, note that if the value of the parameter premise remains the overall output can be expressed by a linear combination of the consequent parameters.

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2$$
$$= \bar{w}_1(p_1 x_1 + q_1 x_2 + r_1) + \bar{w}_2(p_2 x_1 + q_2 x_2 + r_2)$$
$$= (\bar{w}_1 x_1)p_1 + (\bar{w}_1 x_2)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x_1)p_2 + (\bar{w}_2 x_2)q_2 + (\bar{w}_1)r_2 \quad (8)$$

If the number N of data learning applied to equation (9), the importance of the

$$(\bar{w}_1 x)_1 p_1 + (\bar{w}_1 y)_1 q_1 + (\bar{w}_1)_1 r_1 + (\bar{w}_2 x)_1 p_2 + (\bar{w}_2 y)_1 q_2 + (\bar{w}_2)_1 r_2 = u_1$$
$$(\bar{w}_1 x)_p p_1 + (\bar{w}_1 y)_p q_1 + (\bar{w}_1)_p r_1 + (\bar{w}_2 x)_p p_2 + (\bar{w}_2 y)_p q_2 + (\bar{w}_2)_p r_2 = u_p \quad (9)$$

If equation (10) is expressed by the matrix equation, in the form of:

$$AX = B \quad (10)$$

With the dimensions of each matrixA, X and B is PxM, Mxl, and Pxl. Where P is the number of training data pairs and M is the number of consequent parameters. The best solution is to maminimumkan ||AXB||2. With theoretical solution obtained LSE X*, LSE from X, is to use the pseudo-inverse of X:

$$X^* = (A^T A)^{-1} A^T B \quad (11)$$

$$\left.\begin{aligned} X_{i+1} &= X_i + S_{i+1} a_{i+1}(b_{i+1}^T - a_{i+1}^T X_i) \\ S_{i+1} &= S_i \frac{S_i a_{i+1} a_{i+1}^T S_i}{1 + a_{i+1}^T S_i a_{i+1}}, \quad i = 0,1,\ldots,P-1 \end{aligned}\right\} \quad (12)$$

With a_i^T is a row vector of the matrix A, b_i^T is the ith component of the matrix B, and Si is the covariance matrix. Initial conditions of X0 is 0 and S0 is γI, where γ is a large positive number and I is the identity matrix with size MxM. The weights of this proposed ANFIS forecast engine have been optimized by PSO. The proposed structure of proposed method has been presented in Fig. 2. Also, the selected input for price prediction has been presented in Table 1. These parameters have been selected by trial and error. In the following description of this algorithm has been presented as;

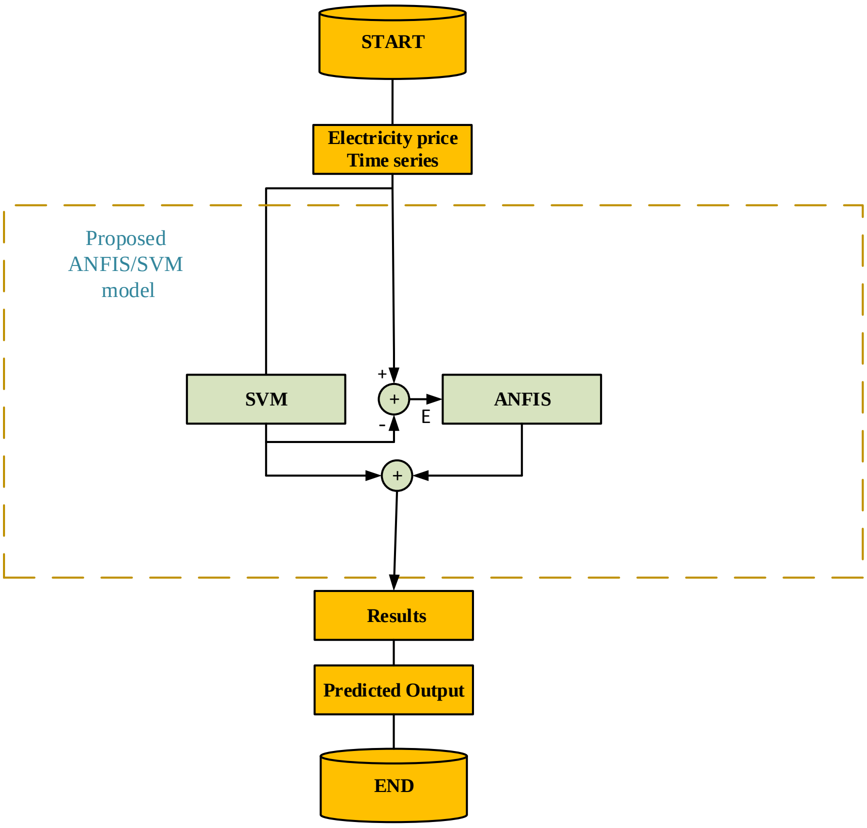

Fig. 2. Proposed forecasting structure model

Table 1. System input for ANFIS system

Input	Horizon
P_{t-24}	Price of 24 hours
P_{t-48}	Price of 48 hours
P_{t-72}	Price of 72 hours
P_{t-96}	Price of 96 hours
P_{t-120}	Price of 120 hours
P_{t-144}	Price of 144 hours
P_{t-168}	Price of 168 hours

3. Particle Swarm Optimization

PSO is one of the optimization techniques and a kind of evolutionary computation technique which is launched by Aberhart Rasel. The method has been found to be robust in solving problems featuring nonlinearity and non-differentiability, multiple optima, and high dimensionality through adaptation, which is derived from the social-psychological theory. The features of the method are as follows (Shayanfar *et al*., 2014):

1. The method is developed from research on swarm such as fish schooling and bird flocking.

2. It is based on a simple concept. Therefore, the computation time is short and requires few memories (Abedinya *et al*., 2009):

3. It was originally developed for nonlinear optimization problems with continuous variables. It is easily expanded to treat a problem with discrete variables. According to the research results for birds flocking are finding food by flocking.PSO is basically developed through simulation of bird flocking in two-dimension space. The position of each agent is represented by XY axis position and also the velocity is expressed by VX (the velocity of X axis) and VY (the

velocity of Y axis). Modification of the agent position is realized by the position and velocity information (Abedinya *et al*., 2009) Bird flocking optimizes a certain objective function. Each agent knows its best value so far (pbest) and its XY position. This information is analogy of personal experiences of each agent. Moreover, each agent knows the best value so far in the group (gbest) among pbest. This information is analogy of knowledge of how the other agents around them have performed. Namely, each agent tries to modify its position using the following information (Abedinya *et al*., 2012; Bipirayeh *et al*., 2013):

– The current positions (x, y),
– The current velocities (VX, VY),
– The distance between the current position and pbest
– The distance between the current position and gbest

This modification can be represented by the concept of velocity and the place of that. Velocity of each agent can be modified by the following equation:

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

$$V_i(t+1) = \omega v_i(t) + c_1 r_1(t)[pbest_i(t) - x_i(t)] + c_2 r_2(t)[leader_i(t) - x_i(t)] \quad (4)$$

Where
xi: position of agent i at iteration k
vi: velocity of agent i at iteration k
w: inertia weighting
c1,2: tilt coefficient
r1,2: rand random number between 0 and 1
leader: archive of unconquerable particles
pbesti: pbest of agent i
gbest: gbest of the group

Convergence of PSO strongly is depended of w, c1, c2. While c1,2 are between 1.5 till 2, however the best choice to these factors is 2.05. Also, 0≤w<1 whereas this value is really important factor to system convergence and this is better that this factor define dynamically. While it should be between 0.2 and 0.9 and it should decrease linear through evolution process of population. Being extra value of w at first, provides appropriate answers and small value of that help the algorithm to convergence at the end (Bipirayeh *et al*., 2013) Fig.3 shows a flow chart of searching point by PSO.

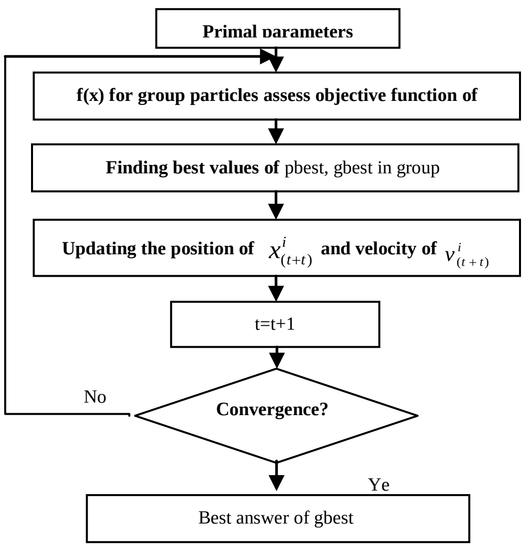

Fig.3. Flow chart of PSO algorithm

4. Numerical Results

For the Spanish electricity market, three weeks have been selected to forecast and validate the performance of the proposed model. The first one corresponds to the last week of May 2002 (from May 25th to 31st). The second one corresponds to the last week of August 2002 (from August 25st to 31th), which is typically a low demand week. The third one corresponds to the third week of November 2000 (from November 13th to 19th), which is typically a high demand week. The hourly data used to forecast the first week are from January 1st to May 24th, 2002. The hourly data used to forecast the second week are from June 1st to August 24th, 2002. The hourly data used to forecast the third week are from September 1st to November 12th, 2002. In this paper, Mean Absolute Percentage Error (MAPE) is considered as a types of accuracy measures (Amjady, 2012):

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|P_i^{true} - P_i^{forecast}\right|}{\bar{P}_i^{true,N}} * 100\% \qquad (20)$$

where N=24 for daily forecasts, N=168 for the weekly forecasts, and $\bar{P}_i^{true,N}$ is the average true price for the Nth hour. The obtained results for proposed model has been presented in Fig. 4 to 7.

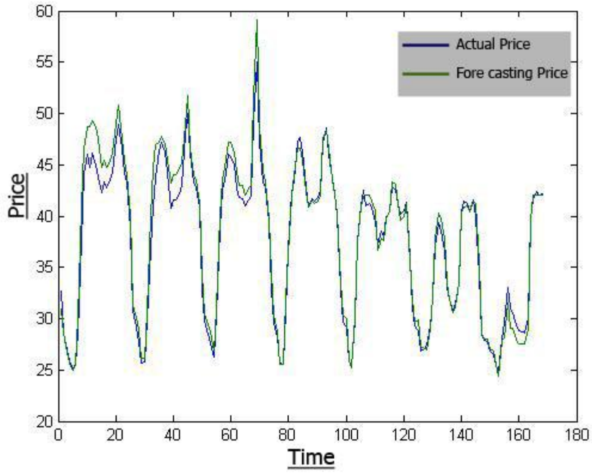

Fig. 4. Forecasting the price of test case in Winter season based on porposed method

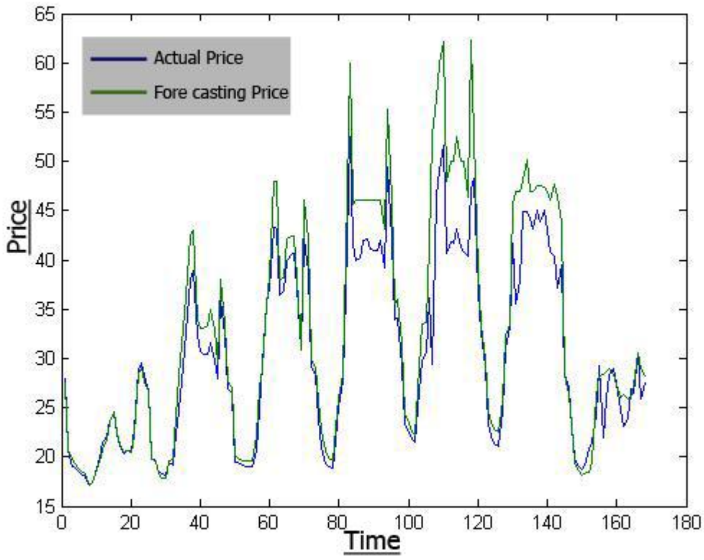

Fig. 5. Forecasting the price of test case in Summer season based on porposed method

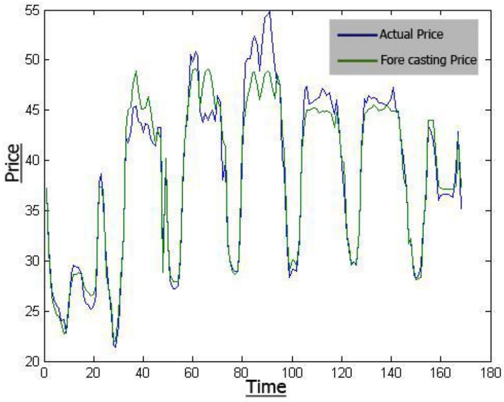

Fig. 6. Forecasting the price of test case in Spring season based on porposed method

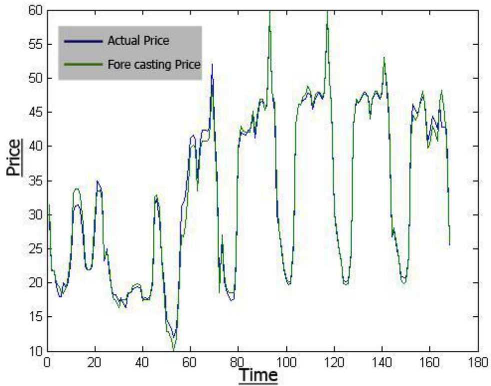

Fig. 7. Forecasting the price of test case in Fall season based on porposed method

Also, obtained numerical results of the proposed method in comparison with other techniques have been resented in Table. 2.

Table. 2. Obtained numerical results for MAPE in comparison with other techniques.

	Winter	Spring	Summer	Fall	Average
ARIMA (Tang *et al.*, 1991)	6.32	6.36	13.39	13.78	**9.96**
Mixed-model (Fleten and Pettersen, 2005)	6.15	4.46	14.90	11.68	**9.30**
NN	5.23	5.36	11.40	13.65	**8.91**
Wavelet-ARIMA (Amjady and Keynia, 2009)	4.78	5.69	10.70	11.27	**8.11**
WNN (Anbazhagan and Kumarappan, 2012)	5.15	4.34	10.89	11.83	**8.05**
FNN (Aggarwal *et a*l., 2009)	4.62	5.30	9.84	10.32	**7.52**
HIS (Areekul *et a*l., 2010)	6.06	7.07	7.47	7.30	**6.97**
AWNN (Coelho *et a*l., 2011)	3.43	4.67	9.64	9.29	**6.75**
NNWT (Yamin and Shahidehpour, 2004)	3.61	4.22	9.50	9.28	**6.65**
CNEA (Niimura, 2006)	4.88	4.65	5.79	5.96	**5.32**
HPA(Catal *er a*l., 2011)	3.65	4.19	6.76	6.53	**5.28**
Proposed	2.53	2.63	3.46	2.8	**3.40**

Regarding to the achieved numerical results, it can be claimed that the proposed method has good forecasting in thus market in comparison with other methods. In table 2, the proposed method could provide good results in all of seasons. So, it can be said that the proposed strategy could provide the best results in comparison with other techniques.

CONCLUSION

Energy price forecasting is the key information in the economic optimization of the electric power industry. But, this forecasting problem has a complex behavior due to their nonlinearity, nonstationarity, and time variancy. In this paper, a novel hybrid approach is proposed for electricity prices forecasting in a competitive market. In this strategy two stage forecast engine has been considered. In the first step the SVM forecaster has been presented and in the second step the FNN based forecast engine predict the price. Also, for improving the FNN capabilities this forecast engine has been improved by PSO. The proposed technique is tested over Spanish electricity market through comparison with other new recent price forecast techniques. Obtained results demonstrate the validity of proposed model in this problem.

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