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# Prediction of Wind Power Generation Through Combining Particle Swarm Optimization and Elman Neural Network (El-PSO)

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***Abstract –*** In recent years, rapid advances in wind energy production in many countries have made the prediction of wind power very important. In addition, wind power is a complicated signal for modeling and prediction. According to previous studies in this field, wind power prediction requires an efficient method. In the current survey, a method which is a combination of two intelligent methods of Elman neural network and Particle Swarm Algorithm is proposed to predict wind power. The efficiency of the proposed prediction method is shown for predicting of wind power output of wind farms. Results of El-PSO suggested method and El-GA method were compared and evaluated by analysis of variance method (ANOVA). All the results indicate efficient performance of the proposed method (El-PSO).

***Keywords –*** ANOVA, El-GA method, El-PSO method, Elman neural network and wind power.

## 1. INTRODUCTION

Wind energy is transformed into useful kinds of energy such as electrical energy or mechanical energy. Nowadays, wind power has an annual production capacity of 430 TWh, which is 2.5% of the total global electricity consumption [1]. Wind energy is generated in great amounts in wind farms and is linked to the electrical network. A low number of turbines are used to provide electricity in remote regions. Production power of wind turbines is continuously variable due to changes in wind speed and direction and meteorological parameters, such as temperature-pressure, pressure, density, and air humidity. Therefore, it is critical for the wind-electricity industry to predict electricity generation for next minutes or hours. In the recent years, the increase in the proportion of wind plants in total electricity production of major networks has led in a consideration in load distribution economical calculations related to wind energy and its production power [2],[3]. Prediction is an important issue in future decision making. Prediction of wind power and velocity has an important role in future energy life of a country. In the recent years, several studies have been conducted to investigate the prediction of wind power and speed. In these researches, different methods have been employed. Salcedo-Sanz *et al*. [4] investigated wind speed prediction in a Spanish wind farm using SVM. In order to enhance classic SVM performance, two combination methods EP-SVM and PSO-SVM were proposed. Their results showed satisfactory performance of both methods. Liu *et al*. [5] investigated TK model performance in wind speed prediction; the results show better performance of TK as compared to ARIMA. In their survey, Shi *et al*. [6] compared ARIMA, ANN, and SVM for short-term prediction of wind speed. Results showed that performance of a combination of ARIMA-ANN and a combination of ARIMA-SVM is better than ARIMA, ANN, and SVM single models. Amjady *et al.* [7] proposed a model for prediction of short-term wind power, which performed better than previous models. Amjady *et al*. [8] presented a novel HIFM model to predict wind speed, based on the mutual effect of wind temperature and wind speed. Prediction based on actual results of Iran and Spain shows effective performance of the HIFM model. Taylor *et al*. [9] converted all wind speed density predictions into wind power density forecasts in order to evaluate their relative worth. The resultant point forecasts were comfortably superior to those generated by the time series models and those based on traditional high resolution wind speed point forecasts from an atmospheric model. Khosravi *et al*. [10] provided the application of two approaches for the construction of PIs for wind farm power generation. Feed-forward NN models are developed and used for forecasting aggregated power generation in wind farms. The results obtained in this paper can be used in both theoretical and practical studies of wind power generation. From a scientific point of view, other statistical models, such as support vector machines or neuro-fuzzy systems, can be employed for producing quality prediction intervals and uncertainty quantification. Khosravi and Nahavandi [11] provided an enhanced version of the nonparametric LUBE method. The results of their method introduce the proposed nonparametric method as a practically efficient method for quantification of uncertainties associated with wind power point forecasts. Wan, *et al*. [12] proposed a novel HIA approach combining extreme learning machine and particle swarm optimization which is developed and successfully applied for interval forecasting of wind power without the prior knowledge of forecasting errors. A novel objective function accounting for PIs coverage probability and overall skill is constructed to obtain optimal PIs at multiple confidence levels simultaneously through one single

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performance-oriented optimization process to ensure both reliability and sharpness.

In the current study, in order to predict wind power, a combination of Elman neural network and Particle Swarm Algorithm (PSO) is used. Afterwards, the results were compared to a combination of Elman neural network and genetic algorithm and also other previous methods. The results also show excellent performance. This (El-PSO) method can be used as an intelligent remedy in many problems.

The motivations of the proposed method include:

- Based on the excellent performance of the proposed method (El-PSO), not only we have used the method to solve this (prediction of wind power) problem, but also we have used to solve different prediction problems easily.
- Adjusting the parameters of this model is very simple. The calculation speed of the proposed method is a lot higher than other methods.
- Since there is too much dispersion of data in this problem, our method can solve this problem with minimum error.

This paper is organized as follows: section 1 introduces the problem and mentions a brief review of the literature. Sections 2 and 3 present an explanation of the employed method and the proposed one. Performance results are explained in Section 4. Finally, Section 5 and 6 contain the analysis of results and concluding remarks respectively.

## 2. APPLIED METHODS

### 2.1 Artificial Neural Network

Artificial neural networks are inspired by the neural system of the human brain. In neural networks, results can be generated for different reflections of data. Data distribution and parameter adjustment have significant functions in performance of neural network [13]. In the current paper, Elman neural network, which is one of the most important recurrent neural networks, is used to predict wind power. Structure of Elman neural network is explained in the following section.

### 2.2 Elman Neural Network

Elman networks are a kind of back-propagation multi-layer network that include a feedback from output of the hidden layer to input of the hidden layer. This feedback helps the network to detect transient and time-dependent patterns. These networks use Tansing neurons and Tansing and Purelin functions in their hidden layer and output layer, respectively. In two-layer networks, this sequence is capable of estimating any function, with a limited number of discontinuities. Consequently, the network should own sufficient number of neurons in its hidden layer. The more neurons in this layer are used, the higher matching to the objective function [14]. The neural network structure is made up of a number of layers, containing a number of neurons. These neurons have their own input and output. Each neuron's output is determined based on its input or output, its attachment to other neurons, and external inputs. Among neural network parameters, weights and biases can be mentioned, which can be calculated using the following equations:

$$X = \begin{bmatrix} w \\ b \end{bmatrix} \tag{1}$$

$$X^{new} = X^{old} + e.Z \tag{2}$$

$$X_{(k)} = X_{(k-1)} + Z_{(k-1)} \tag{3}$$

$$\{Z_1, Z_2, \ldots, Z_Q, -Z_1, -Z_2, \ldots, -Z_Q\} \tag{4}$$

Here, $X$, $Z$, $b$, $W$, $Q$, and $K$ are non-adjustable parameters matrix, input data matrix, bias, weight, number of training steps, and number of training samples respectively, $e$ is the correction coefficient (decreasing, increasing, without correction), which indicates whether the weights require correction or not. The following equation can be used for network output:

$$Net = I.W + b \tag{5}$$

Here, *Net* and *I* are the neural network's output and input respectively. Figure 1 illustrates schematic of Elman neural network.

### 2.3 Principles of Genetic Algorithm

Genetic algorithm is a learning method based on biological evolution. John Holland introduced this algorithm in 1970 [15]. Genetic algorithm is initiated from a set of primary random solutions – called initial population; each element of the population is a chromosome, which indicates a solution to the problem. To apply a concept of genetic evolution to an optimization problem in the real word, two points should be taken into account: 1. encoding potential solutions, 2. defining the fitness function (objective function) [16]. In the genetic algorithm, solutions are known as chromosomes and each chromosome consists of several genes. The general structure of the genetic algorithm is summarized as following stages [17]:

<u>First stage</u>: defining the problem solution as a genetic problem.

<u>Second stage</u>: forming an initial population $P(0) = x_1^0, \ldots, x_N^0$ . $Set\ t = 0$.

<u>Third stage:</u> the calculation the mean of fitness $\bar{f}(t) = \sum_i^N f(x_i) / N$ . Allocating fitness value to each person $f(x_i) / \bar{f}(t)$.

<u>Fourth stage</u>: selection operator; in this study, tournament selection operator is employed for selection of parents for the next stage (crossover).

<u>Fifth stage</u>: running the crossover operator with a defined probability for each pair.

<u>Sixth stage</u>: applying mutation operator with a defined probability for each child.

<u>Seventh stage</u>: forming a new population p(t+1) using surviving mechanism.

<u>Eighth stage</u>: setting t=t+1 and returning to the third stage.

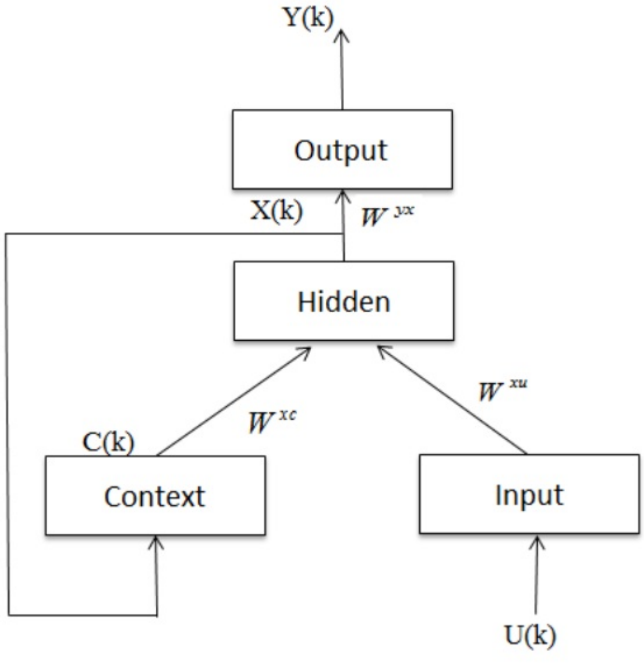


**Fig. 1. Schematic of Elman neural network.**

### *2.4 Particle Swarm Optimization (PSO)*

PSO algorithm is a population-based algorithm, which is inspired by mass motion of natural species, such as birds, fish, etc. In this algorithm, each solution is modeled as a particle that has a value and a fitness value.

Particle Swarm Optimization algorithm (PSO) was firstly proposed by Russell Ebechart and James Kennedy, in 1995 [18]. In PSO, vector method is used to search for the solution. This algorithm has been employed in many study fields, including optimization problems, economic problems, and neural network training [19]. PSO is designed to search for the best global solutions, using a swarm of particles and is updated in each stage [20]. Each particle indicates a potential solution in the search space which specifies its velocity and location based on its best experience and location (local best) or the best experience or location of all particles (global best) [21].

Consider an *N* dimensional problem with *i* particle and *t* generation. $X_{i,N}(t)$ and $V_{i,N}(t)$ are location and velocity of the $i^{th}$ particle, respectively. The velocity of the $i^{th}$ particle for the $(t+1)^{th}$ generation can be derived from the following equation [22, 23].

$$\begin{aligned} V_{i,N}(t+1) = {} & \omega(t+1)V_{i,N}(t) \\ & + c_1 r_1\left(X_{pbest,N} - X_{i,d}(t)\right) \\ & + c_2 r_2\left(X_{gbest,N} - X_{i,d}(t)\right) \end{aligned} \tag{6}$$

$$X_{i,N}(t+1) = X_{i,N}(t) + V_{i,N}(t+1) \tag{7}$$

Here $1 \le i \le m$ , $1 \le t \le k$ , c1 and c2 have constant value (c1=c2=2), r1 and r2 are two independent random numbers that follow uniform functions in the [-1 1] interval; ω is the inertia weight that controls the effect of the previous velocity, on the current one.

$$\omega(t) = \omega(1) - \left(\omega(1) - \omega(k)\right) t/k \tag{8}$$

Here, $\omega(1)$ is the initial inertia weight and $\omega(k)$ is inertia weight; the evolved swarm in the final generation of k and t equals the generation maximum repetition and initial repetition of the maximum generation. PSO, as a simple and effective random search algorithm can lead to better results than gradient descent method, penalty function method, or the genetic algorithm in solving some nonlinear optimization problems [24].

## 3. PROPOSED METHOD (EL-PSO)

This section aims to explain the proposed method. In addition, the method of using and combining Elman neural network and particle swarm algorithm will be described.

### *3.1 Training Phase*

Since PSO is an optimization algorithm, it is used in this investigation optimize neural network parameters, such as weights and biases, in the training stage. Firstly, the weights and biases should be defined as an optimization problem and then be optimized by PSO algorithm. In PSO, a particle with a specific vector may test different locations in different repetitions [25]. For neural network training, Sigmund tangent transfer function is used as follows:

$$Tansig\ (\theta) = \frac{2}{(1+\exp(-2\theta))-1} \tag{9}$$

### 3.2 Objective Function

Objective function or the fitness of the proposed El-PSO model in this study is Minimum Mean Squared Errors (MMSE), as follows:

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(X_{ACTi} - X_{FORi})^2 \quad (10)$$

$$MMSE = Min\left(\frac{1}{m}\sum_{i=1}^{m}(X_{ACTi} - X_{FORi})^2\right) \quad (11)$$

Here, *XFOR* is the predicted value, *XACT* is the actual value, and *m* is the number of hour. We aim to minimize the MMSE value, which shows better training of the network and its better preparation to enter the testing stage. In addition, to check correctness of the training stage, Mean Squared Errors (MSE) and Root Mean Square Error (RMSE) are used; RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_{ACTi} - X_{FORi})^2} \quad (12)$$

### 3.3 Testing Phase

In this phase, the trained network should be tested based on error criteria. If the testing error has a small value, it means that the network is trained correctly and acceptable. Otherwise, if still there are high test errors, it should be trained again. Figure 2 shows the flowchart of the proposed method.

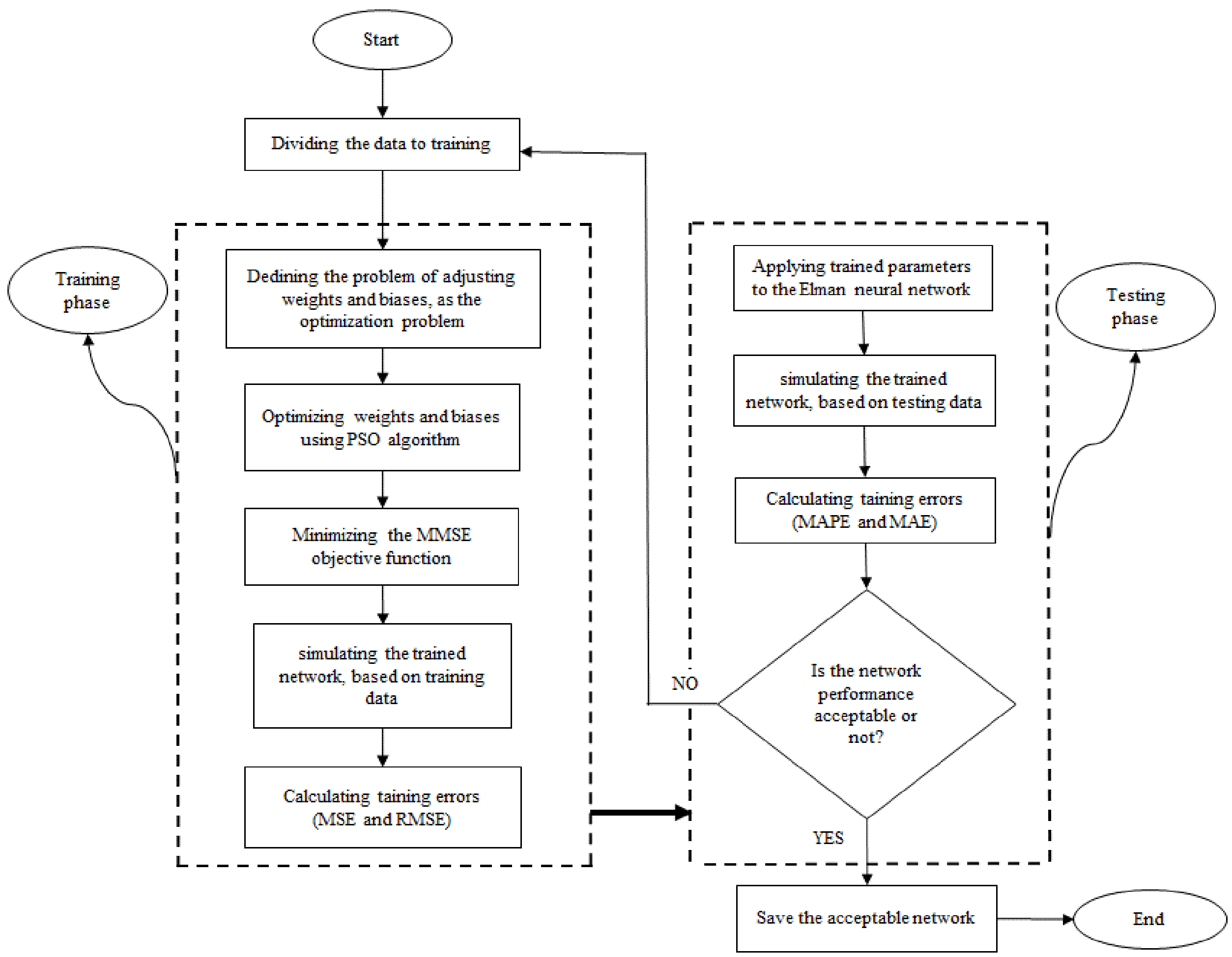


**Fig. 2. Flowchart of the proposed (El-PSO) method.**

In this study, to test the trained network, Mean Absolute Error (MAE), Mean Absolute Percentage of Error (MAPE), and its Modified Version (MMAPE) have been used [7]:

$$MAE = \frac{1}{m}\sum_{i=1}^{m}\left|X_{ACTi} - X_{FORi}\right| \quad (13)$$

$$MAPE = \frac{100}{m}\sum_{i=1}^{m}\left|\frac{X_{ACTi} - X_{FORi}}{X_{ACTi}}\right| \quad (14)$$

$$MMAPE = \frac{100}{m}\sum_{i=1}^{m}\left|\frac{X_{ACTi} - X_{FORi}}{X_{ave-ACTi}}\right| \quad (15)$$

$$X_{ave-ACTi} = \frac{1}{m}\sum_{i=1}^{m}X_{ACTi} \quad (16)$$

*XACT* and *XFOR* are the actual and the predicted values respectively.

### *3.4 Summary*

In the present investigation, a combination of Elman neural network and PSO algorithm is employed to predict wind power. Figure 3 illustrates actual wind power data use in this paper. The proposed method is tested for both wind-power forecast of Sotavento wind farm in Spain and prediction of aggregated wind power of Irish power system using their real data obtained from [26, 27] respectively.

Having uniform distribution, data have been normalized in an interval between [-1 1], using the following normalization formula:

$$X_{norm} = \frac{(X - Min(X))}{(Max(X) - Min(X))} \times 2 - 1 \qquad (17)$$

Here, *Xnorm* is the normalized value; *X* is the non-normalized value, *Min* (*x*) and *Max* (*x*) are minimum and maximum of the non-normal, in a row. In addition, 80% and 20% of the data were used in the training and testing phases of the neural network.

## 4. RESULTS AND DISCUSSIONS

As it was stated in Section 1, wind power is of great importance in generation of different kinds of energy. In addition, it is important to propose a method to predict wind power with negligible error and have a better performance compared with previous methods – which has a very important place in today's decision making and studies. In this study it has been tried to compare the performance of El-PSO method with a combination of Elman neural network and genetic algorithm, for short-term prediction of wind power. Table 1 shows the performance of the El-GA method in neurons and different layers. Four months, from April to July, have been selected, trained, and tested to investigate the performance of the suggested method. Table 2 shows the RMSE and MMAPE results for prediction of aggregated wind power of Irish power system in September and October 2010. Table 3 illustrates the performance of El-PSO method and El-GA method, and other methods from April to July 2010. All the stages of optimization, training, and testing of the proposed method are done in MATLAB 2012 software.

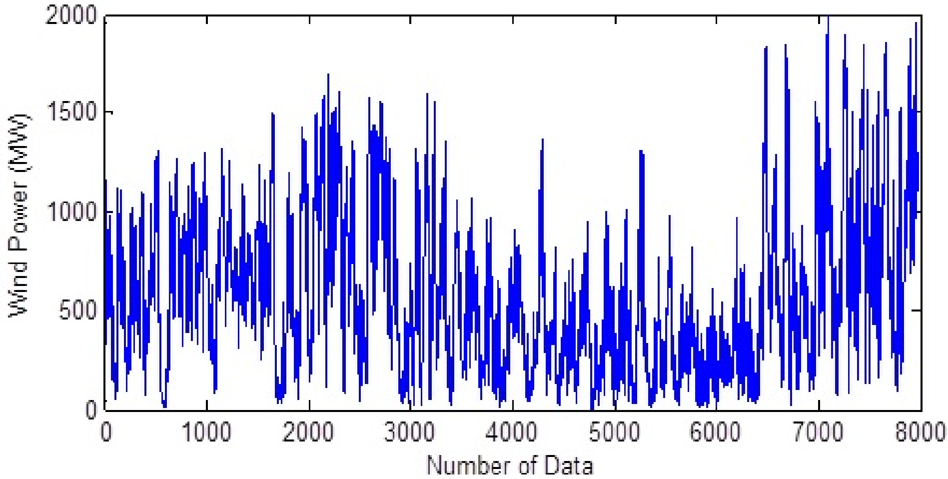


**Fig. 3. Actual wind power data used in this study.**

**Table 1. Different performance of the proposed method and El-GA method, in different layers and neurons.**

| Layers | Neurons | El-GA | | | | Proposed Method (El-PSO) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | MSE | RMSE | MAE | MAPE (%) | MSE | RMSE | MAE | MAPE (%) |
| 2 | 28-1 | 0.161 | 0.401 | 0.332 | 2.827 | 0.156 | 0.395 | 0.326 | 1.943 |
| 3 | 32-2-1 | 0.162 | 0.402 | 0.342 | 10.179 | 0.151 | 0.389 | 0.318 | 2.991 |
| 3 | 30-19-1 | 0.159 | 0.399 | 0.33 | 9.0179 | 0.154 | 0.392 | 0.33 | 5.94 |

**Table 2. RMSE and MMAPE results for prediction of aggregated wind power of Irish power system in September and October 2010.**

| Methods | Error Criteria | Test Month (2010) | | |
|---|---|---|---|---|
| | | September | October | Average |
| Persistence method [28-30] | RMSE (MW) | 125.33 | 164.12 | 144.73 |
| | MMAPE (%) | 24.11 | 25.91 | 25.01 |
| Irish EirGrid company [27] | RMSE (MW) | 118.21 | 160.56 | 139.38 |
| | MMAPE (%) | 23.93 | 23.71 | 23.82 |
| SA [7] | RMSE (MW) | 127.91 | 139.64 | 133.77 |
| | MMAPE (%) | 24.22 | 25.61 | 24.91 |
| GA [7] | RMSE (MW) | 118.41 | 119.71 | 119.06 |
| | MMAPE (%) | 21.54 | 22.14 | 21.84 |
| PSO [7] | RMSE (MW) | 111.84 | 110.48 | 111.16 |
| | MMAPE (%) | 19.83 | 19.76 | 19.79 |
| DE [7] | RMSE (MW) | 102.42 | 100.24 | 101.33 |
| | MMAPE (%) | 17.19 | 16.09 | 16.64 |
| NDE [7] | RMSE (MW) | 77.21 | 73.28 | 75.24 |
| | MMAPE (%) | 15.87 | 14.69 | 15.28 |
| El-GA | RMSE (MW) | 64.19 | 65.05 | 64.62 |
| | MMAPE (%) | 11.02 | 9.19 | 10.105 |
| Proposed Method (El-PSO) | RMSE (MW) | 25.83 | 21.48 | 23.655 |
| | MMAPE (%) | 7.82 | 6.23 | 7.025 |

**Table 3. RMSE and MMAPE results for wind power forecast of Sotavento wind farm in April–July 2010.**

| Methods | Error Criteria | Test Month (2010) | | | | |
|---|---|---|---|---|---|---|
| | | April | May | June | July | Average |
| Persistence method [28-30] | RMSE (MW) | 1.12 | 0.85 | 0.78 | 0.83 | 0.90 |
| | MMAPE (%) | 35.91 | 30.84 | 34.33 | 36.84 | 34.48 |
| Multivariate ARIMA [28] | RMSE (MW) | 0.84 | 0.74 | 0.70 | 0.69 | 0.74 |
| | MMAPE (%) | 28.74 | 27.21 | 28.91 | 29.54 | 28.60 |
| RBF [31] | RMSE (MW) | 0.59 | 0.52 | 0.59 | 0.50 | 0.55 |
| | MMAPE (%) | 25.08 | 18.11 | 26.45 | 27.75 | 24.35 |
| MLP [32] | RMSE (MW) | 0.51 | 0.62 | 0.52 | 0.47 | 0.53 |
| | MMAPE (%) | 22.44 | 19.82 | 25.24 | 26.14 | 23.41 |
| NDE [7] | RMSE (MW) | 0.46 | 0.44 | 0.44 | 0.38 | 0.43 |
| | MMAPE (%) | 7.75 | 11.43 | 16.06 | 9.33 | 11.14 |
| El-GA | RMSE (MW) | 0.40 | 0.40 | 0.40 | 0.40 | 0.40 |
| | MMAPE (%) | 12.99 | 7.88 | 8.37 | 8.04 | 9.32 |
| Proposed Method (El-PSO) | RMSE (MW) | 0.38 | 0.38 | 0.37 | 0.39 | 0.38 |
| | MMAPE (%) | 5.65 | 6.98 | 4.87 | 6.53 | 6.01 |

## 5. ANALYSIS OF VARIANCE METHOD

In Table 4, the performance of the proposed method has been depicted in different ahead for short-term prediction of wind power. Since the proposed method has shown different behavior in different ahead, this method is performed in different ahead and the results, which are calculated by MAE, are analyzed using ANOVA. This part is carried out in Minitab software version 16. Figures 4 and 5 illustrate Minitab output for illustration of distribution and mean of different ahead.

Furthermore, Table 5 shows statistical characteristics of the proposed method in different ahead. Based on ANOVA results, this method has the best performance and the least mean error in one hour ahead time interval.

**Table 4. Performance of the proposed method (El-PSO) in different ahead.**

| Time series | MSE | MAE | MAPE (%) |
|---|---|---|---|
| One hour ahead | 0.156 | 0.326 | 1.943 |
| 5 hours ahead | 0.1694 | 0.334 | 2.968 |
| 10 hours ahead | 0.1711 | 0.343 | 8.209 |
| 15 hours ahead | 0.1563 | 0.3262 | 4.8332 |
| 20 hours ahead | 0.1766 | 0.3353 | 10.4374 |
| One day ahead | 0.1712 | 0.338 | 7.9178 |

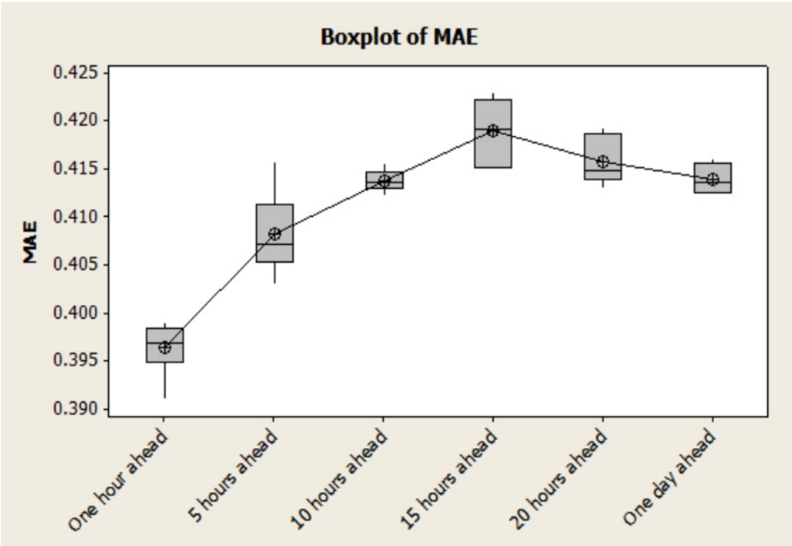


**Fig. 4. Mean resulted from different ahead.**

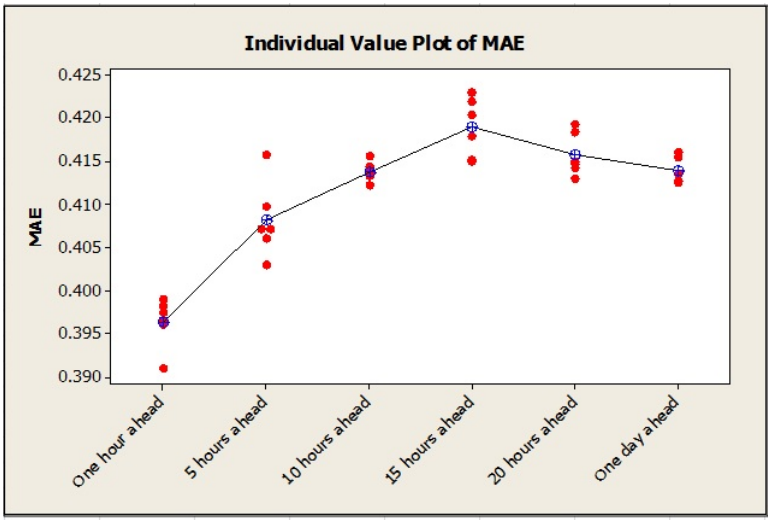


**Fig. 5. Distribution resulted from different ahead.**

**Table 5. Statistical characteristics of the proposed method (El-PSO) in different ahead.**

| Variable | Mean | Standard deviation | Median | Variance |
|---|---|---|---|---|
| One hour ahead | 0.39643 | 0.00281 | 0.39699 | 0.00001 |
| 5 hours ahead | 0.40821 | 0.00432 | 0.40719 | 0.00002 |
| 10 hours ahead | 0.41384 | 0.00114 | 0.4137 | 0.000001 |
| 15 hours ahead | 0.41898 | 0.00343 | 0.41922 | 0.00001 |
| 20 hours ahead | 0.41579 | 0.00249 | 0.41485 | 0.00001 |
| One day ahead | 0.41402 | 0.00151 | 0.41358 | 0.000002 |

## 6. CONCLUSION

Wind power is a multivariate nonlinear function that has a non-uniform and unique space. The wind-power data which have been used in this paper have a relatively broad distribution; consequently, the more the data distribution, the weaker the performance of the neural network. In this survey, wind power prediction is performed using a novel and highly efficient method. Elman neural network requires an intelligent method for parameters optimization. Particle Swarm Algorithm is used to optimize weights and biases. El-PSO method has a better performance as compared to previous methods and El-GA method.

## REFERENCES


[1] World Wind Energy Association WWEA 2011 Date of publication: April.

[2] Burton N.J. and E. Bossanyi. 2001. Wind Energy Handbook. Wiley.

[3] Watson S.J., Landberg L. and Halliday J.A., 1994. Application of wind speed forecasting to the integration of wind energy into a large scale power system. *IEE Proceeding of Generation, Transmission and Distribution* 141: 357-362.

[4] Salcedo-Sanz S., Ortiz-Garcia E.G., Pérez-Bellido A.M., Portilla-Figueras A. and Prieto L., 2011. Short term wind speed prediction based on evolutionary support vector regression algorithms. *Expert System Application* 38: 4052–4057.

[5] Liu H.P., Shi J. and Erdem E., 2010. Prediction of wind speed time series using modified Taylor Kriging method. *Energy* 35: 4870–4879.

[6] Shi J., Guo J.M. and Zheng S.T., 2012. Evaluation of hybrid forecasting approaches for wind speed and power generation time series. *Renewable and Sustainable Energy Review*16: 3471–3480.

[7] Amjady A., Keynia F. and Zareipour H., 2011. Short-term wind power forecasting using ridgelet neural network. *Electric Power Systems Research* 81: 2099– 2107.

[8] Amjady N., Keynia F. and Zareipour H., 2011. A new hybrid iterative method for short term wind speed forecasting. *European Transactions on Electrical Power* 21: 581–595.

[9] Taylor J.W., McSharry P.E. and Buizza R., 2009. Wind power density forecasting using ensemble predictions and time series models. *IEEE Transactions on Energy Conversion* 24: 775-782.

[10] Khosravi A., Nahavandi S. and Creighton D., 2013. Prediction intervals for short-term wind farm power generation forecasts. *IEEE Transactions on Sustainable Energy* 4(3).

[11] Khosravi A. and S. Nahavandi. 2013. Combined nonparametric prediction intervals for wind power generation. *IEEE Transactions on Sustainable Energy* 4:849-856.

[12] Wan C., Xu Z., Pinson P., Yang Dong Z. and Wong K.P., 2014. Optimal prediction intervals of wind power generation. *IEEE Transactions Power System* 29(3), May.

[13] Kutsurelis J.E., 1998. *Forecasting Financial Markets Using Neural Networks: An Analysis of Methods and Accuracy*. Master of Science Thesis, US Naval Academy.

[14] Hagan M.T., Demuth H.B. and Beale M.H., 2002. Neural Network Design. Colorado ISBN-13: 978 0971732100: University of Colorado.

[15] Kusiak A., Vanelli A. and Kumar K.R., 1986. Clustering analysis: models and algorithms. *Control and Cybernetics* 15: 139–153.

[16] Hsu C.M., Chen K.Y. and Chen M.C., 2005. Batching orders in warehouses by minimizing travel distance with genetic algorithms. *Computers in Industry* 56: 169–178.

[17] Mu¨hlenbein H., 1997. Genetic Algorithms. in: E. Aarts, J.K. Lenstra (Eds.), Local Search in Combinatorial Optimization, Wiley, New York, pp. 137–171.

[18] Kenedy J. and R. Eberhart. 1995. Particle swarm optimization. Proceedings of IEEE International Conference on Neural Networks, 1942-1948.

[19] Onwunalu E. and J. Durlofsky. 2010. Application of a particle swarm optimization algorithm for determining optimum well location and type. *Computers & Geosciences* 14: 183–198.

[20] Zhou C., Ding L.Y. and He R., 2013. PSO-based Elman neural network model for predictive control of air chamber pressure in slurry shield tunneling under Yangtze River. *Automation in Construction* 56: 208–217.

[21] Zhang H., Li X., Li H. and Huang F., 2005. Particle swarm optimization-based schemes for resource-constrained project scheduling. *Automation in Construction* 14: 393–404.

[22] Chen J.H., Yang L.R. and Su M.C., 2009. Comparison of SOM-based optimization and particle swarm optimization for minimizing the construction time of a secant pile wall. *Automation in Construction* 18: 844–848.

[23] Lu M., Lam H.C. and Dai F., 2008. Resource-constrained critical path analysis based on discrete event simulation and particle swarm optimization. *Automation in Construction* 17: 670–681.

[24] Yu C., Teo K.L., Zhang L.S. and Bai Y.Q., 2010. A new exact penalty function method for continuous inequality constrained optimization problems. *Journal of Industrial and Management Optimization* 6: 895–910.

[25] Kennedy J. and R.C. Eberhart. 1997. A discrete binary version of the particle swarm algorithm. In *Proceedings of the World MultiConference on Systemics, Cybernetics and Informatics*, Piscataway, New Jersey: 4104–4108.

[26] Sotavento wind farm data http://www.sotaventogalicia.com/tiempo real. english/instantaneos.php.

[27] Ireland wind power data http://www.eirgrid.com/operations/ system performance data.

[28] Kavasseri R.G. and K. Seetharaman. 2009. Day-ahead wind speed forecasting using f- ARIMA models. *Renewable Energy* 34(5): 1388–1393.

[29] Fan S., Liao J.R., Yokoyama R., Chen L. and Lee W.J., 2009. Forecasting the wind generation using a two-stage network based on meteorological information. *IEEE Transactions Energy Conversion* 24(2): 474–482.

[30] Damousis L.G., Alexiadis M.C., Theocharis J.B. and Dokopoulos P.S., 2004. A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation. *IEEE Transactions of Energy Conversion* 19(2): 352–361.

[31] Sideratos G. and N. Hatziargyriou. 2007. Using radial basis neural networks to estimate wind power production. *IEEE Power Engineering Society General Meeting*, doi:10.1109/PES. 385812.

[32] Costa A., Crespo A., Navarro J., Lizcano G., Madsen, H. and Feitosa E., 2008. A review on the young history of the wind power short-term prediction. R*enewable and Sustainable Energy Reviews* 12(6): 1725–1744.