International Journal of Multidisciplinary and Current Research

Research Article

ISSN: 2321-3124
Available at: http://ijmcr.com

Short and Mid-Term Wind Power Forecasting with ANN-PSO

Hossein Lotfi[1],Mohammadbaghernaghibi[1], Toktam Lotfi[1] and Sadegh Hesari[1]

Department of Electrical Engineering, bojnourd branch, Islamic university, bojnourd, Iran

Accepted 20 Oct 2014, Available online 27 Oct 2014, **Vol.2 (Sept/Oct 2014 issue)**

Abstract

Wind energy as a source of renewable energy and with the low pollution had a significant growth in recent years. One of the main problems in the use of wind turbines , is rapid changes in output power of these turbines. The wind power depends on the wind speed, which is a random variable and irregular, For efficient operation of wind power units accurate short-term forecasts are essential. The knowledge of future power generation frome wind turbines is useful for schedulers, transmission operators and energy traders. This paper presents a wind power prediction model based on Elman neural network -Particles swarm optimization algorithm. The Data have been used For two sites stanford and chester in the USA in 2008 and 2009. These data include: wind speed, temperature, output power.

Keywords: *Artificial Neural Network(ANN), Particles Swarm Optimization(Pso), Wind power plant, Foreasting*

1. Introduction

Using of wind plant s production energy in power network is growing all around the world. Due to limited Fossil resources and importance of environmental problems , the use of renewable energy sourses is considered. In the wind farm, the power generated by a wind turbine generator varies randomly with time due to the variability of wind speed. Uncertainty of the wind power and wind power penetration increasing will affect system stability and run the risk of blackouts.Therefore, a new operational strategy based on precise wind power forecasts is necessary, and it is important for the power industry to have the capability to estimate power variations[1]. The methods of the wind power generation prediction can be divided into two mean category: time-series analysis and Measurement Model. Measurement Model is a method which utilizes the relationship between the unknown variable and known variable to get the unknown variable. Many study works have been done in the area of the short-term wind speed prediction based on the wind speed measurement data. Mean methods are persistence[2], timeseries[3]. Conventional statistical models are identical to the direct random time-series model, including auto regressive (AR), and auto regressive integrated moving average (ARIMA) [4] models. The persistence models are considered as the simplest time-series models. They can surpass many other models in very short-term prediction. In the recent years, some new methods are catching researcher's attention, namely methods based on artificial intelligence like artificial neural network (ANN) [5], fuzzy logic and neuro-fuzzy [6,7], evolutionary algorithms [8], and some hybrid methods [9]. The accurate comparison of all the methods is quite difficult because these methods depend on different situations, and the data collection is a formidable task. However, there are some comparison and the approximate results, which proved that the artificial-based models outperformed others in short-term prediction.

In this paper we aim, estimate the wind power of chester wind plant by Elman Neural Network in short term, middle-term and long-term periods.

Network inputs are (temperature and wind speed). Networks output is (wind turbin output power). The used algorithm For neural network training is particles swarm optimization(Pso). The aim of training a neural network, find the weights and biases so that to minimizes training error. Result of training and testing network with Pso algorithm compared with levenberg-marquardt algorithm. For training process, the stanford wind unit data used, and for testing the chester wind unit data is employed.

2. Artificial neural networks in wind power plants

The short-term and mid-term forecasting of wind power is needed nowadays. Wind uncertainty will lead to fluctuations in output power. Meanwhile, it is important to forecast the wind speed and wind direction [10]. The first step is collecting good data for making Artificial neural networks (ANN) then some actual data are compared with output of ANN after testing and validating network. Due to negligible error the ANN will be able to forecast outputs

3. Recurrent neural networks

Recurrent networks is a topic of considerable interest. This chapter covers two recurrent networks: Elman, and

Hopfield networks. Elman networks are two-layer backpropagation networks, with the addition of a feedback connection from the output of the hidden layer to its input. This feedback path allows Elman networks to learn to recognize and generate temporal patterns, as well as spatial patterns[11].

The Hopfield network is used to store one or more stable target vectors. These stable vectors can be viewed as memories that the network recalls when provided with similar vectors that act as a cue to the network memory[12].

3.1 Elman nural network

The Elman network commonly is a two-layer network with feedback from the first-layer output to the first layer input. This recurrent connection allows the Elman network to both detect and generate ti me-varying patterns. A two-layer Elman network is shown in figure1.

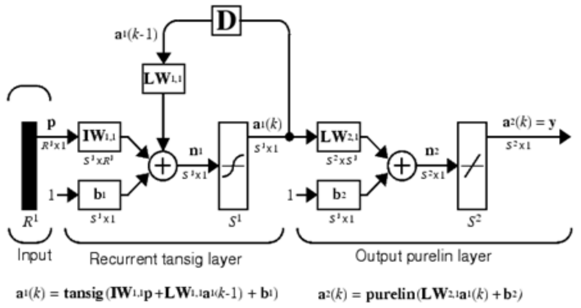

Figure 1 A two-layer Elman network

The Elman network has tansig neurons in its hidden (recurrent) layer, and purelin neurons in its output layer. This combination is special in that two-layer networks with these transfer functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy. The only requirement is that the hidden layer must have enough neurons. More hidden neurons are needed as the function being fit increases in complexity. Note that the Elman network differs from conventional two-layer networks in that the first layer has a recurrent connection. The delay in this connection stores values from the previous time step, which can be used in the current time step. Thus, even if two Elman networks, with the same weights and biases, are given identical inputs at a given time step, their outputs can be different due to different feedback states, Because the network can store information for future reference, it is able to learn temporal patterns as well as spatial patterns. The Elman network can be trained to respond to, and to generate, both kinds of patterns.

4. Model of artificial neural network

Temperature and wind speed are considered as a network inputs,and wind ower output as anetwork output. Figure 2 shows the overall structure of power estimator.

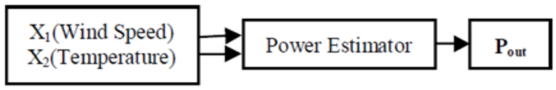

Figure 2 Overall structure of power estimator with ANN

5. Particles swarm optimization

The Pso algorithm is an adaptive algorithm based on the food searhing pattern of birds in the sky. The pso algorithm basically has two parameters for each particle. These are velocity and position components. During each generation, every particle is accelerated towards the previous best position and the global best position of the particles. The next setp is updating of new velocity values using its past veloity, the distance from its previous best position, and distance from the global best position.The new velocity value is then used to calculate the next position of the particle in the search space [13,14]. New velocity and the new position of the particles of equations 1 and 2 are achived.

$$\mathrm{V_i}(t+1) = W.V_i(t) + c.r_1.\left(P_i(t) - X_i(t)\right) + c.r_2.\left(P_g(t) - X_i(t)\right) \quad (1)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (2)$$

6. Traning the neural network with PSO algorithm

Optimization variables in a neural network training include weights and biases relating to the neural network, if Nth layer of assumptive netwok consists of input R and M neuron , then weight (Wn) and bias (Bn) matrix can be gained by 3 and 4 equations .

$$W^n = [w_1^n, w_2^n, \dots, w_M^n]^T \quad (3)$$

$$B^n = [b_1^n, b_2^n, \dots, b_M^n]^T \quad (4)$$

In this equation $\mathrm{W_m^n} = \left[\mathrm{w_{m,1}^n}, \mathrm{w_{m,2}^n}, \dots, \mathrm{w_{M,R}^n}\right]^{\mathrm{T}}$ is weights vector that mth neuron of Mth layer related to the same layer inputs. This layers parameter vector can be shown by 5 equation.

$$\mathrm{X^n} = [\mathrm{w_1^n}, \mathrm{w_M^n};\ \mathrm{b_1^n} \dots, \mathrm{b_M^n}]^{\mathrm{T}} \quad (5)$$

similarly for each layer, there are related parameters vector, bias and weight matrix. Finally for a L-layer network, X variable vector can be obtained from 6 equation .

$$\mathrm{X} = [\mathrm{X^1}, \mathrm{X^2}, \dots, \mathrm{X^L}]^{\mathrm{T}} \quad (6)$$

Process so that the first N vectors Xi (i=1,2,....,n) are randomly generated, that N is the number of group members, the group numbers are selected 4 to 5 time the number of optimization variable. Neural network have been implemented for this vector variables, error for each run as the fitness vector network variables considered to be. The vectors Pi and Pg were calculated according to the fitness achieved, and the N vector new position using the relations (1) and (2) are produced, This process is repeated until the convergence is achieved. The algorithm PSO, the coefficients C1 and C2 are selected equal to 2, W is the inertia factor is equal to 1 initially intended gradually to zero during the iterations.

7. *Assessment of Estimated Results*

7.1 Mse

Mse is the mean of squares summation that are difference between Estimated and Actual power.

7.2 Mae

Mae is difference between Estimated and Actual power.

7.3 Regression

Regression is the relation between actual and predicted output of ANN.

8. Neural network training results

Table 1 shows evaluation Criteria of Elman neural network in wind power prediction for the next five months in stanford unit with Pso and Levenberg-marquardt algorithm.

Table 1 Evaluation Criteria of Elman neural network in wind power prediction for the next five months with both algorithms

Traning stage	Criterion		
	Mse(Mw)	Mae(Mw)	Regression
Pso	0.0375	0.1050	0.99311
Levenberg-marquardt	0.0400	0.1120	0.99290

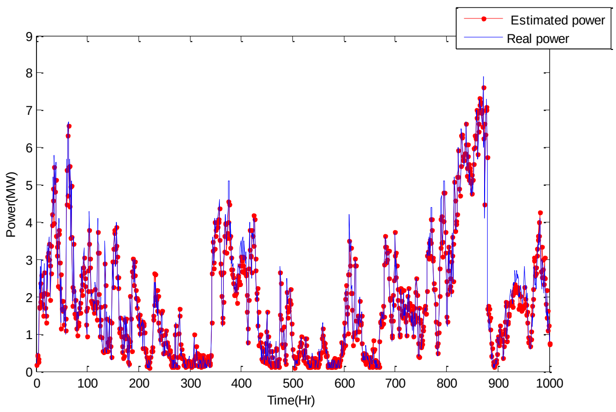

Figure 3 Wind power prediction in small – scale (relating to next seven days) in Stanford unit

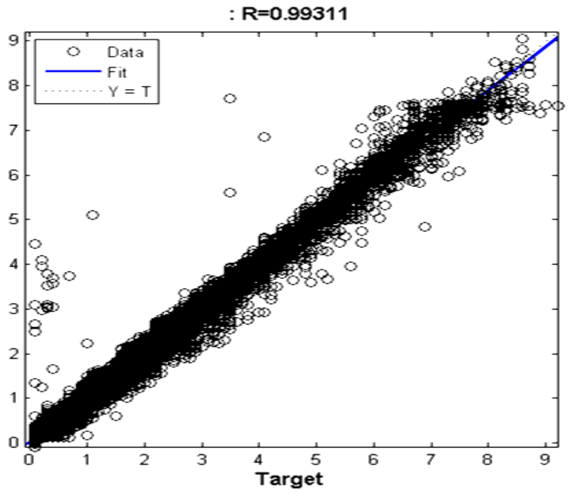

Figure 4 Regression relating to training elman neural network with Pso algorithm

Figure 3 illustrates wind power prediction in small – scale (relating to next seven days) in Stanford wind unit, and figure 4 shows the regression relating to training Elman neural network with Pso algorithm**.** Mse and Mae errors from Pso algorithm respectively are obtained 0.0375 Mw and 0.1050 Mw.

As it is seen in Elman neural network training results by both algorithems , errors of neural network training with Pso algorithm are less than Levenberg-marquardt.

The Mse and Mae errors from Pso algorithm respectively are obtained 0.0375Mw and 0.1050 Mw.

9. Neural Network testing results

Neural network testing results in short-term, medium-term and long-term timescales obtains.

9.1 Wind power prediction for the next one day

Figure 5 and 6 show the wind power prediction for the next one day in chester wind unit by Pso and Levenberg-marquardt algorithm.

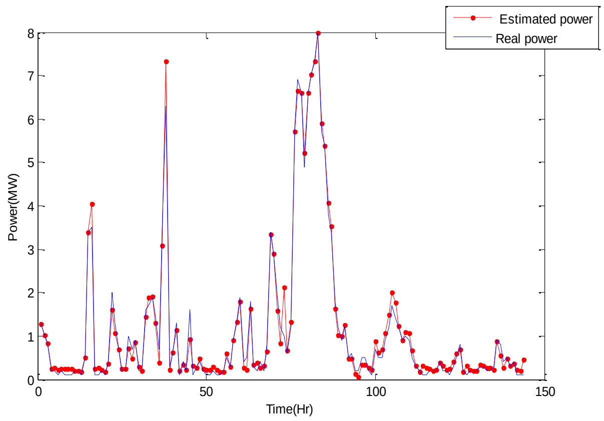

Figure 5 Wind power prediction for the next one day in chester unit by Pso algorithm

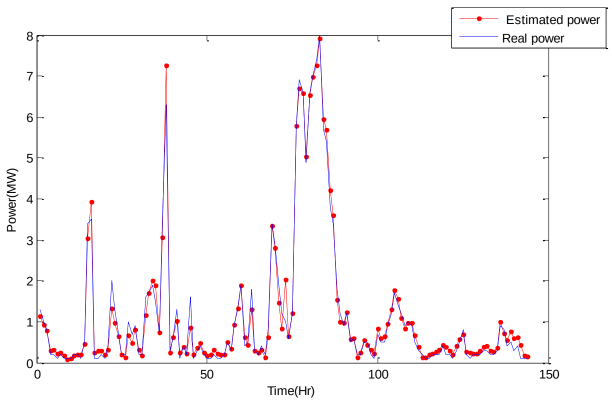

Figure 6 Wind power prediction for the next one day in chester unit by Levenberg-marquardt algorithm

Table 2 shows evaluation Criteria of neural network in wind power prediction for the next one day with both algorithms. Mse and Mae errors from Pso algorithm respectively are obtained 0.0415 Mw and 0.1192 Mw

Table 2 Evaluation Criteria of neural network in wind power prediction for the next one day with both algorithm

Next one day	Criterion		
	Mse(mw)	Mae(mw)	Regression
Pso	0.0415	0.1192	0.99282
Levenberg-marquardt	0.0450	0.1235	0.99258

9.2 Wind power prediction for the next three days

Figure 7 and 8 show the wind power prediction for the next three days in chester wind unit by Pso and Levenberg-marquard algorithm. Table 3 shows evaluation Criteria of neural network in wind power prediction for the next three days with both algorithms. Mse and Mae errors from Pso algorithm respectively are obtained 0.0245 Mw and 0.1042 Mw.

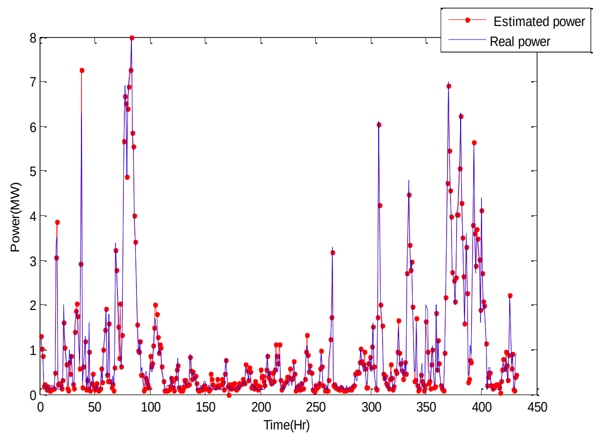

Figure 7 Wind power prediction for the next three days in chester unit by Pso algorithm

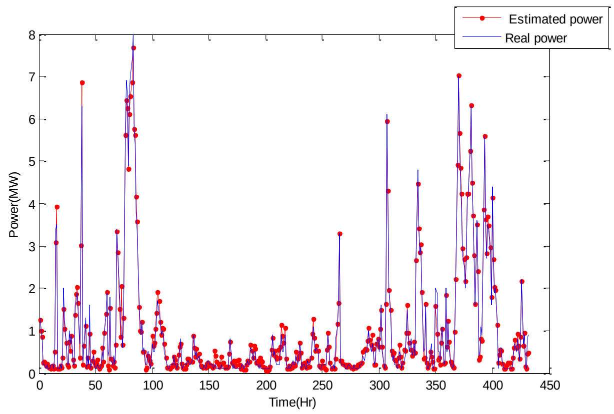

Figure 8 Wind power prediction for the next three days in chester unit by Levenberg-marquardt algorithm

Table 3 Evaluation Criteria of neural network in wind power prediction for the next three days with both algorithms

Next three days	Criterion		
	Mse(mw)	Mae(mw)	Regression
Pso	0.0245	0.1042	0.99396
Levenberg- marquardt	0.0272	0.1067	0.99365

9.3 Wind power prediction for the next five days

Figure 9 and 10 show the wind power prediction for the next five days in chester wind unit by Pso and Levenberg-marquardt algorithm. Table 4 shows evaluation Criteria of neural network in wind power prediction for the next five days with both algorithms. Mse and Mae errors from Pso algorithm respectively are obtained 0.0224 Mw and 0.1026 Mw.

Table 4 Evaluation Criteria of neural network in wind power prediction for the next five days with both algorithms

Next five days	Criterion		
	Mse(mw)	Mae(mw)	Regression
Pso	0.0224	0.1026	0.99465
Levenberg-marquardt	0.0245	0.1048	0.99433

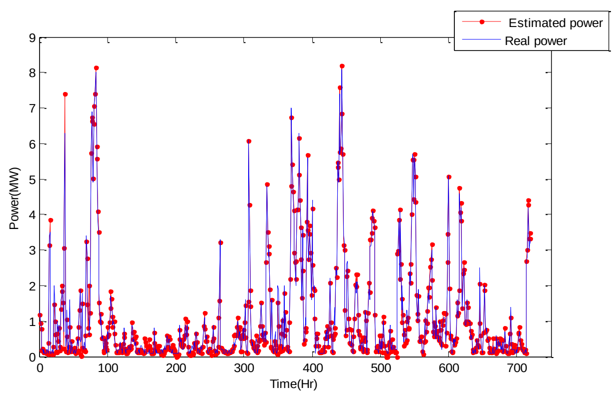

Figure 9 Wind power prediction for the next five days in chester unit by Pso algorithm

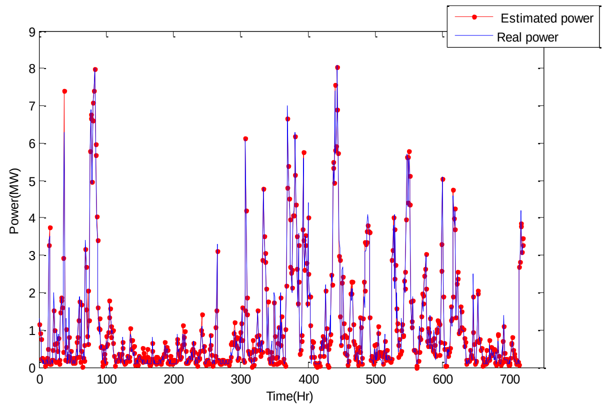

Figure 10 Wind power prediction for the next five days in chester unit by Levenberg-marquardt algorithm

9.4Wind power prediction for the next seven days

Figure 11 and 12 show the wind power prediction for the next seven days in chester wind unit by Pso and Levenberg-marquardt algorithm. table 5 shows evaluation Criteria of neural network in wind power prediction for the next seven days with both algorithms**.** Mse and Mae errors from Pso algorithm respectively are obtained 0.0205 Mw and 0.0935 Mw.

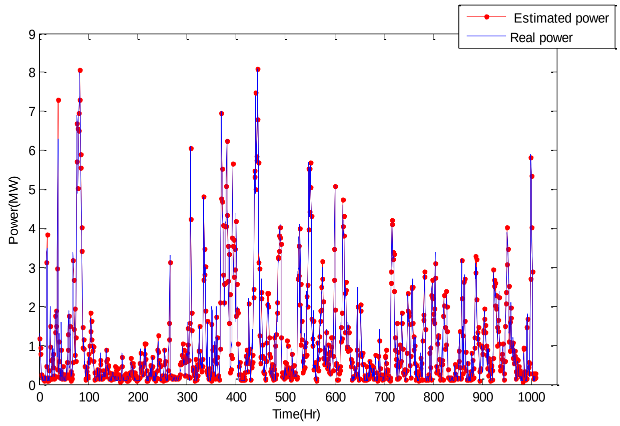

Figure 11 Wind power prediction for the next seven days in chester unit by Pso algorithm

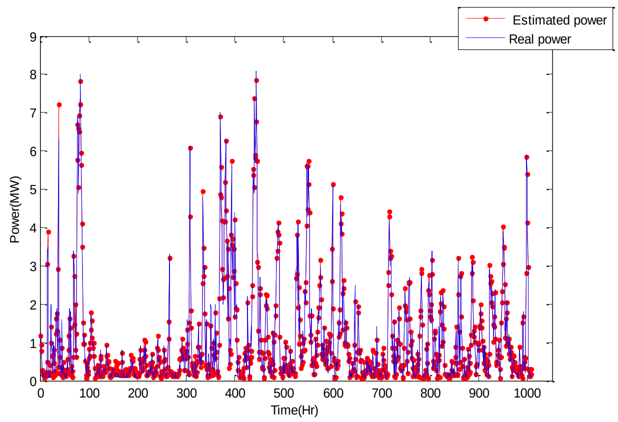

Figure 12 Wind power prediction for the next seven days in chester unit by Levenberg-marquardt algorithm

Table 5 Evaluation Criteria of neural network in wind power prediction for the next seven days with both algorithms

Next seven days	Criterion		
	Mse(mw)	Mae(mw)	Regression
Pso	0.0205	0.0935	0.99586
Levenberg- marquardt	0.0221	0.0964	0.99555

Conclusion

Using of neural network in wind power forecasting is one of economical and simple ways in planing for using wind plant and their availability in electricity competitive market**.** This paper presented in overview of the use of modern forecasting for predicting wind power generation by combination of Particle swarm optimization technique and Neural network.

Neural network training results for wind power prediction in stanford unit with Pso are better than Levenberg-marquardt algorithm. errors of neural network prediction with Pso are less than Levenberg-marquardt algorithm.

Neural network testing results For wind power prediction in chester unit with Pso are better than Levenberg-marquardt algorithm. errors of neural network prediction with Pso in each four time interval are less than Levenberg-marquardt algorithm.

But this paper has some defects, the wind speed data is only from one wind farm and it dose not consider the humidity, density, etc., which affect the wind speed. So a lot of researches should be done in the future.

Refrences

[1] Rui-Lin Xu, Xin Xu, Bo Zhu and Min-you Chen, “The Application of Genetic-Neural Network on Wind Power Prediction” ,Springer-Verlag Berlin Heidelberg, pp. 379–386, 2011.

[2] M.C.Alexiadis, P.S. Demopoulos, H.S.Sahsamanoglou, “Short term forecasting of wind speed and related electrical power” [J]. Solar Energy, 1998,63(1): 61-68

[3] L. Ma, S. Y. Luan, C. W. Jiang, H. L. Liu, and Y. Zhang, "A review on the forecasting of wind speed and generated power," Renew. Sust. Energy Rev., vol. 13, pp. 915-920, May 2009.

[4] R. G. Kavasseri and K. Seetharaman, "Day-ahead wind speed forecasting using f-ARIMA models," *Renew. Energy*, vol. 34, pp. 1388- 1393, May 2009.

[5] I. J. Ramirez-Rosado, L. A. Fernandez-Jimenez, C. Monteiro, J. Sousa, and R. Bessa, "Comparison of two new short-term wind-power forecasting systems," Renew. Energy, vol. 34, pp. 1848-1854, Jul. 2009.

[6] G. Sideratos and N. D. Hatziargyriou, "An advanced statistical method for wind power forecasting," IEEE Trans. Power Syst., vol. 22, pp. 258- 265, Feb. 2007.

[7] C. W. Potter and W. Negnevitsky, "Very short-term wind forecasting for Tasmanian power generation," IEEE Trans. Power Syst., vol. 21, pp. 965-972, May 2006.

[8] R. Jursa, K. Rohrig, "Short-term wind power forecasting using evolutionary algorithms for the automated specification of artificial intelligence models," Int. J. Forecast., vol. 24, pp. 694-709, Oct.-Dec.2008

[9] R. Bessa, V. Miranda, and J. Gama, "Improvement in wind power forecasting based on information entropy-related concepts," presented at the 2008 IEEE Power & Energy Society General Meeting, Pittsburgh, Pennsylvania, Jul. 2008.
[10] Sh. Singh, T. S. Bhatti, D. P. Kothari, "Wind Power Estimation Using Artificial Neural Network," ASCE Journal of Energy Engineering, Vol. 133, Issue 1, 2007.
[11]-Elman, J. L., "Finding structure in time," *Cognitive Science*, vol. 14, 1990, pp. 179-211.
[12]-Li, J., A. N. Michel, and W. Porod, "Analysis and synthesis of a class of neural networks: linear systems operating on a closed hypercube," IEEE Transactions on Circuits and Systems, vol. 36, no. 11, November 1989, pp. 1405-1422.
[13] Clerc, M., Kennedy, J., 2002. The particle swarm-explosion, stability, and convergence in a multidimensional complex space. EEE Transactions on Evolutionary Computation 6 (1), 58–73.
[14] Konstantinos E. Parsopoulos and Michael N. Vrahatis, "On the Computation of All Global Minimizers Through Particle Swarm Optimization", IEEE transactions on evolutionary computation, vol. 8, NO. 3, June 2004.