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Performance of Wavelet Neural Network and ANFIS Algorithms for Short-Term Prediction of Solar Radiation and Wind Velocities

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Abstract: Prediction of wind and solar energy is deemed one of the most important contributory factors towards sustainability. Along the same lines, to harvest energy and guarantee the safety of a place, accurate information about the future of the region is needed. To attain this goal, this paper predicts solar irradiation and wind velocity time series by two robust artificial intelligence algorithms which are called wavelet neural network and ANFIS (Adaptive Network Fuzzy Inference System). The data used for the predictor system are obtained from a meteorological station in Tehran, Iran. The results show that robustness of both algorithms for prediction of wind velocities and solar irradiation and superior strength of wavelet neural network (WNN) to ANFIS for prediction of solar irradiation and wind velocities.

Keywords: Wavelet neural network, ANFIS, Solar radiation, Wind velocity, Iran, Artificial Intelligence

1. Introduction

Wind and solar energy are the most attractable energy resources which have applied in many areas and are paid attention by high level decision makers in terms of energy[1]. Using the combination of wind and solar energy leads to a supportive distribution system for the areas in which developing of the grid is a formidable task. In addition, these resource lead to sustainable energy supply and play key roles in terms of micro-grids for smart grids. Moreover, using these resources as distributer generations results in a decrease in power losses and improvement of voltage profile for grid. In other words, applying on-grid hybrid renewable energy deals with the problems which are created by the stochastic nature of renewable energy [2-4]. For instance, varied seasons, climatic conditions and the other factors lead this process more uncertain. Based on the aforementioned reasons, making a prediction of this energy plays an important role in areas of energy market for experts to make logical decisions for reducing the risk of their investment and policy makers for planning and allocating resources with dispatch. In addition, this system gives information for maintenance, repair and placement of related power plants to meet the most considerable needs and electricity production[5].

For prediction of complicated behavior of wind velocity and solar irradiation different methods and approaches are applied toward reaching the efficient and optimum energy production. For sizing and developing of wind systems as well as integration and placement of wind turbines into power systems, the short-term and long-term prediction of wind velocity have been deemed valuable indicators[6]. Having utilized the mean hourly wind velocity, Cadenas and Rivera assessed the function of Artificial Neural Network (ANN) and Autoregressive Integrated Moving Average (ARIMA) algorithms which are compared with single ARIMA and ANN for wind speed time series. The results prove that using hybrid algorithms for wind velocity give a better performance than single algorithms. Another research done by Torres et al.[7] discussed the performance of a persistence model and ARMA to estimate the data of 1 hour and 10 hour time horizons. The results depict that the persistence model has a more reliable for 1 hour and ARMA outperforms for 10 hour data. In Another research, Arima's derivative and F-Arima is utilized for forecasting wind speed for next day[8]. A generalized feed-forward algorithm is employed by Celik and Kolhe [9] for forecation of wind energy by the measured wind speed data. Moreover, three different ANNs to forecast velocity are applied by Li and Shi[10]. Another research compared ARIMA- ANN with Arima-Kalman for predection of wind velocity[11] . Jian et al[12] alapplied Beysian strutural break model for prediction of wind speed. Vafaeipour et al.[13] applied ANN for wind velocity time-series, Potter et al.[14] used an ANFIS method which combines FL systems with ANN for short term prediction, Zhu et al.[15] used fuzzy clustering ANFIS for two hours forecasting, Guo et al.[16] utilized a hybrid PSO-ANFIS method Support vector machines[17], Taylor Kriging method[18], Salcedo-Sanz employed a GFS–MM5–ANN Model[19].

For prediction of solar irridiation Paoli et al.[20] has applied ANN for daily radiation datasets time series. Voyant et al.[21] used Mediterranean climatic data and applied a hybrid method based on ARMA and ANN for prediction of solar irradiation. Azeez[22] has utilized feed forward BP neural network to predict monthly solar average irradiation for Gusau, Nigeria. Mishra et al. [23] applied

RBFN and MLP for prediction of direct solar irradiation related to eight parts. Another research used LM feed forward to model global solar irradiation and the structure was BP[24]. Senkal et al. applied regression neural network for prediction of solar irradiation based on longitude, latitude, altitude and the average temperature of the surface[25]. Rahoma applied ANFIS for estimation of solar irradiation based on the data of 10 years which are daily[26]. Mehleri et al.[27] applied RFBN for estimation of solar irradiation, and the inputs are tilt angle and orientation.

Behavior of wind velocity during a day is more complicated than forecasting short horizons of solar irradiation. It is more valuable to predict solar irradiation in long-term than short term because this kind of forecasting considers stochastic situations. For example, there are factors in short-term prediction which are obvious such as cloudiness and the status of the sun.

The performance of artificial intelligence approaches have outperformed in comparison with the classical method in terms of robustness for nonlinear complicated problems. This paper applies two different robust algorithms called wavelet neural network (WNN) and Adaptive Network Fuzzy Inference System (ANFIS). These algorithms are programmed by MATLAB software. The main object of this paper is 1) to forecast received global solar prediction of horizontal surface; 2) to forecast wind velocity time-series; 3) to assess and compare the results of the applied algorithms. To achieve this aim, the datasets of long-term wind velocity with 1 hour intervals (8760 data) and solar irradiation on horizontal surface with 1 hour are used. The size of input samples data for training and testing the system are the 7882 and 876 respectively. The data are obtained from meteorological station in Tehran related to Iran National Meteorological Organization. Solar irradiation and wind velocity datasets in 24 hours during the year are shown in figure 1 and figure 2, respectively. In addition, to validate the performance of algorithms, root mean square error (RMSE) and absolute fraction of variance (R^2) are measured.

Figure 1. Hourly received solar radiation on horizontal surface data, Tehran

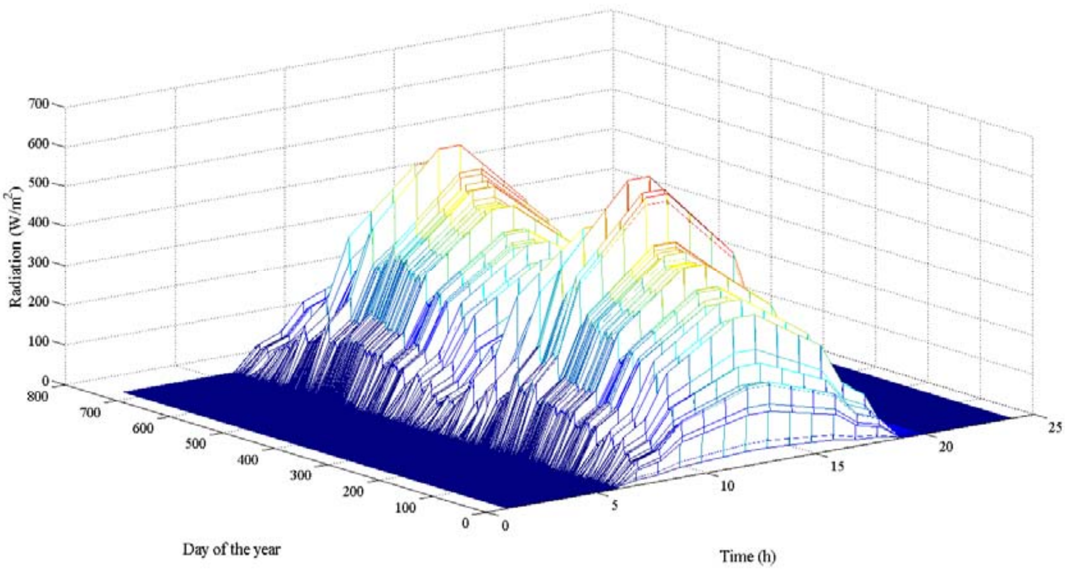
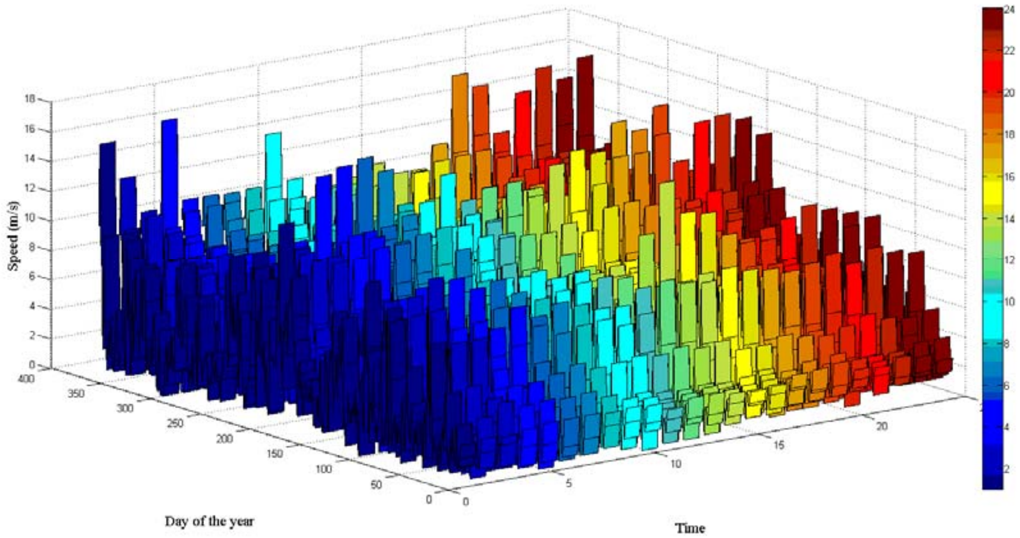


Figure 2. Hourly wind velocity data, Tehran



2. Methodologies

2.1. ANFIS

2.1.1 Fuzzy Inference System

The process of employing fuzzy logic for formulating a non-linear mapping from input to output is called Fuzzy Inference System. This system has three parts a) a rule base containing fuzzy rules which are selected; b) data base which defines membership functions applied for the fuzzy rules; c) a logical system performing the way of inference based on the rules and facts[28-30].

The most popular types applied for fuzzy systems are Mamdani, Takagi and Sugeno, and Tskamoto model. The most considerable difference between them is to determine the way of calculation for results. This paper has employed Takagi and Sugeno system.

2.1.2 Structure of ANFIS

ANFIS is a multi-layer structure involved number of nodes connected with each other. ANFIS has manifold capabilities because it has the strong part of neural network for learning and computation, and the ability of using rules of if-then which has its roots in fuzzy systems in comparison with neural networks[31].

To have a better illustration, figure 3 shows an ANFIS with two inputs and one output which are x, y and f, respectively. Takagi and Sugeno was introduced for the first time in 1985[32].

$$\text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } z_1 = p_1 x + q_1 y + r_1 \tag{1}$$

$$\text{If } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } z_2 = p_2 x + q_2 y + r_2 \tag{2}$$

A1, A2, B1, B2 are the membership functions of inputs, and p1, p2, q1, q2, r1, r2 denote the parameters of output function. ANFIS has five layers and each layer involves varied node functions and nodes. Nodes are split into two types: 1) adaptive nodes and fixed nodes. The layers are described as follows:

Layer 1: The nodes in this layer are adaptive nodes.

$$O_{i,1} = \mu A_i(x) \tag{3}$$

$$O_{i,1} = \mu B_i(x) \tag{4}$$

Layer 2: The nodes are fixed and are shown by circle and labeled by $\prod$. The output is calculated based on this formula:

$$O_{2,i} = \omega_i = \mu A_i(y)\mu B_i(y) \ \ with \ \ i = 1,2 \tag{5}$$

ω_i denotes the firing strength of the rule.

Layer 3: all the nodes are fixed and shown by a circle and labeled by N .The name of the output of this layer is normalized firing strength. The output is computed by the i-th firing strength of rule by the summation of all them.

$$O_{3,i} = \varpi_i = \omega_i \big/ (\omega_1 + \omega_2) \ \ with \ \ i = 1,2 \tag{6}$$

Layer 4: the nodes are adaptive nodes and depicted as follows:

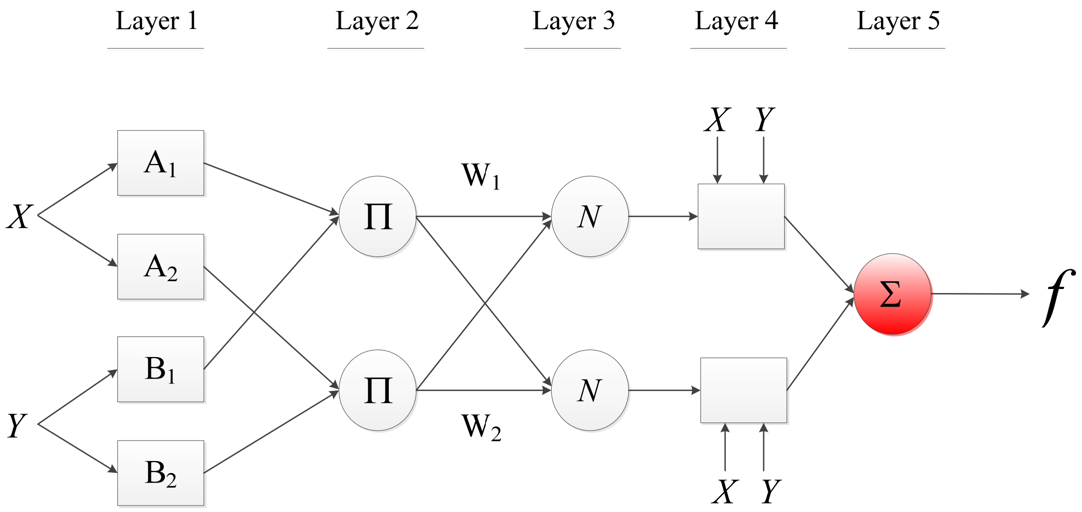
Consequent parameters are p_i, q_i, r_i.

$$O_{4,i} = \varpi_i f_i = \varpi_i (p_i x + q_i y + r_i) \tag{7}$$

Layer 5: The last layer in which the node is single and labeled by Σ and showed by a circle.

$$O_{5,i} = \sum_i \varpi_i f_i = \sum_i \omega_i f_i \Big/ \sum_i \omega_i; \tag{8}$$

Figure 3. A typical ANFIS algorithm



There are three methods used widely to create initial FIS, the grid partition, subtractive clustering and fuzzy c-mean clustering (FCM). FCM extract a set of rules to model the data behavior and needs separate data sets. [33]

2.2 Wavelet

2.2.1 Analysis of wavelet

Wavelet analysis is deemed one of the new branches in mathematic having varied solutions in manifold aspects position of the time frequency plane. This method is a multi-resolution signal creating a robust tool which is suitable for processing and analysis of time non-stationary signal. To have a better clarification, it is a logical idea to describe the algorithm through the translation of primitive function. The concept is shown as follows[34]:

Definition 1: Set $\psi(t)$ is related to function space $L^2(R)$ if

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \tag{9}$$

Definition 2: The expanded and translated form of the mother wavelet $\psi(T)$ creates the basis function of wavelet which is shown as follows:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \tag{10}$$

In which $a > 0$ is considered the scale parameter; $b \in R$ the translation parameter.

2.2.2 Structural design of wavelet neural network

The base of wavelet neural network is back propagation. Having been combined neural networks pros such as forecasting and signal analysis of wavelet, it leads to a reliable forecasted signal for prediction of wind velocities and solar irradiation.

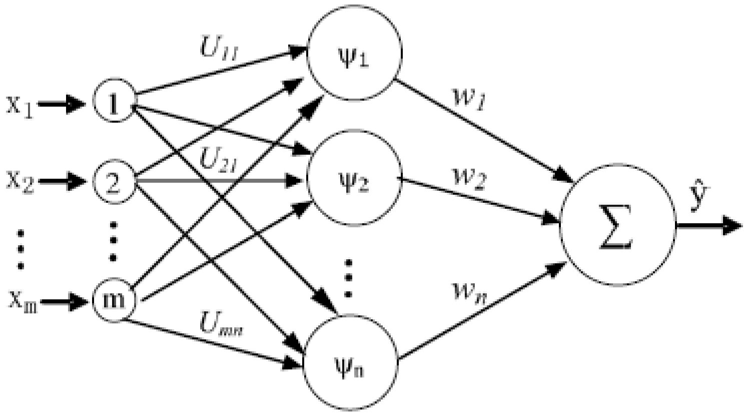
To achieve an accurate prediction, this paper has employed a 3 layer structure the layers are the input layers, hidden layers and output layer with m, n and 1 node, respectively. The structure is shown in Figure 4.

The model is depicted as follows:

$$\hat{y} = \sum_{j=1}^{n} \omega_i \psi_i \left(\sum_{k=1}^{m} \frac{x_k \times U_{kj} - b_j}{a_j} \right) \tag{11}$$

Where, $x = (x_1, x_2, ..., x_m)^T$ denotes the input vector, the predicted output value is $\hat{y}$, U_{kj} denotes the weight of relation between the k_{th} node and j_{th} node of the hidden layer. The hidden layer activation function is denoted by ψ_i . ω_i is considered the layer weight between the j_{th} hidden layer and the output, a_i and b_j are the expansion and translation parameter, respectively.

Figure 4. Diagram of neural network structure



2.2.3 Wavelet neural network training algorithm

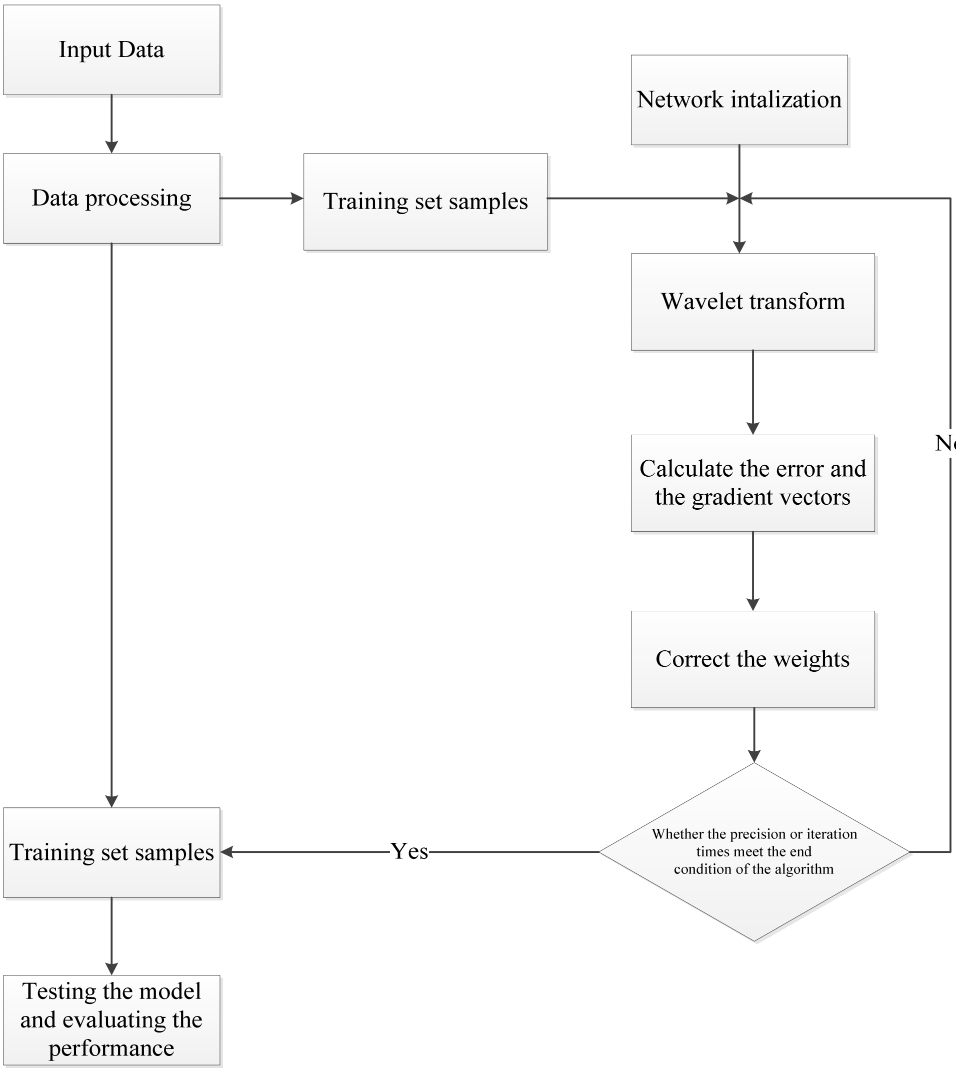
U_{kj} and ω_j are the factors are connection weights to train wavelet neural network model. The optimization process of translation parameters b_j and translation parameters a_j is split into two levels.

Forward Propagation (FP): The output layer is computed from the input layer based on input samples

Backward Propagation (BP): Weights are computed from the output layer.

Both processes are modified repeatedly to satisfy the tolerance of the model. The steps of the network parameters are shown in figure 5.

Figure 5. The steps of wavelet



To have a better illustration the phases are described as follows:

Phase 1: Network initialization: The related weights between U_{ij} and ω_j are produced randomly. The expansion parameter a_j and translation parameter b_j, network learning rate η, max iteration T and the tolerance ε are set up.

Phase 2: Data Preprocessing. Data are split into training (70%), test data set (15%), validation data (15%). Training data are applied for the training process and the rest of the data for the test process.

Phase 3: Computed error and the gradient vectors. The difference between the calculated data and actual data is computed. The target error formula is:

$$E = \frac{1}{2}\sum_{m}^{m} \hat{y}(k) - y(k)^2 \tag{12}$$

$\hat{y}(k)$ and $y(k)$ denote the estimated and expected output respectively, and the learning rate is η.

The gradient vectors are computed based on the calculated and the tolerance of these equations: $\Delta U_{k,j}(i+1), \Delta\omega_i(i+1), \Delta a_j(i+1),$ and $\Delta b_j(i+1)$ which are described as follows:

$$\Delta U_{k,j}(i+1) = -\eta\left(\frac{\partial E}{\partial \Delta U_{k,j}(i)}\right) \tag{13}$$

$$\Delta\omega_j(i+1) = -\eta\left(\frac{\partial E}{\partial \Delta\omega_j(i)}\right) \tag{14}$$

$$\Delta a_j(i+1) = -\eta\left(\frac{\partial E}{\partial \Delta a_j(i)}\right) \tag{15}$$

$$\Delta b_j(i+1) = -\eta\left(\frac{\partial E}{\partial \Delta b_j(i)}\right) \tag{16}$$

Phase 4: weight correction: The weights and parameters are modified by back propagation, the formulas are:

$$U_{k,j}(i+1) = U_{k,j}^{(i)} + \Delta U_{k,j}(i+1) + \eta(U_{k,j}(i) - U_{k,j}(i-1)) \tag{17}$$

$$\omega_j(i+1) = \omega_j^{(i)} + \Delta\omega_j(i+1) + \eta(\omega_j(i) - \omega_j(i-1)) \tag{18}$$

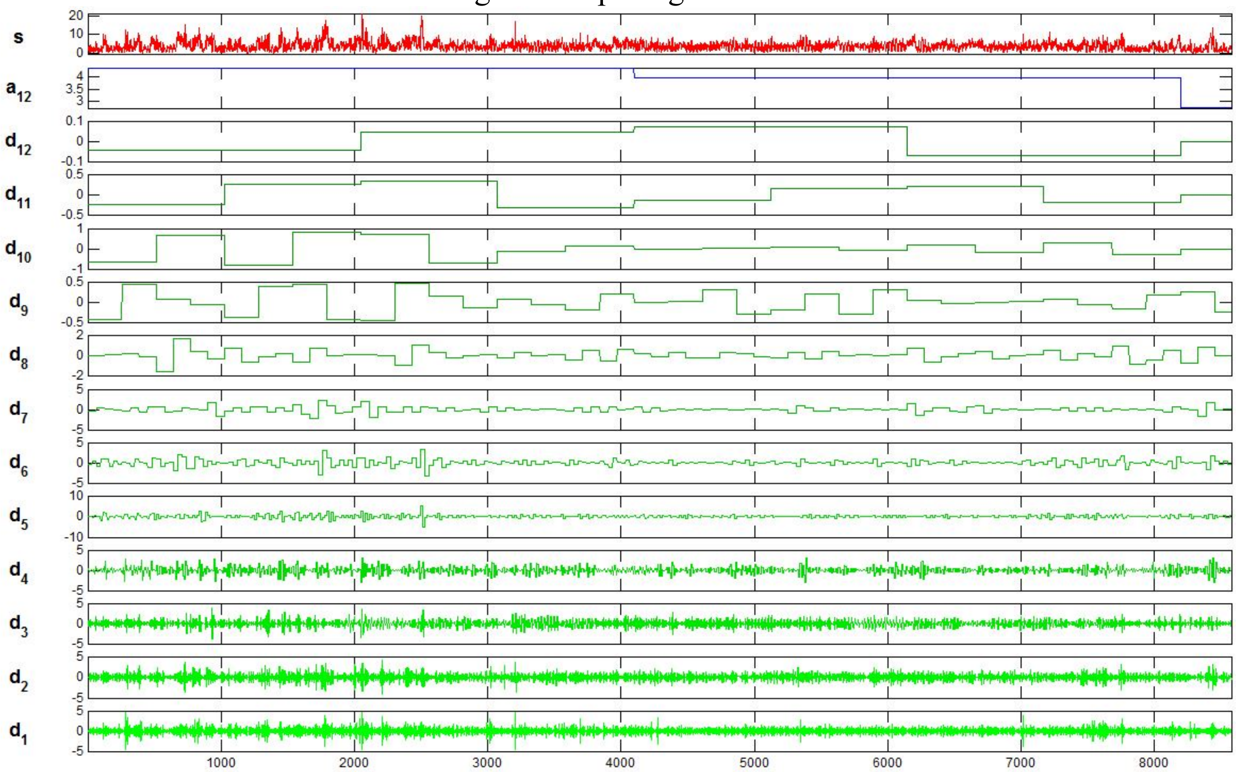
$$a_j(i+1) = a_j(i) + \Delta a_j(i+1) + \eta(a_j(i) - a_j(i-1)) \tag{19}$$

$$bj(i+1) = bj(i) + \Delta b_j(i+1) + \eta(b_j(i) - b_j(i-1)) \tag{20}$$

Phase 5: investigating that the end condition is satisfied or not. The algorithm examine whether the error is less than the expected error (ε). If it does not happen, the algorithm goes back to the third phase.

For a better clarificaiton, the signals of wind velocities as samples are shown as follows in figure 6:

Figure 6. Input signals of wavelet



3. Discussion and result

Having discussed the methodology and the literature, this section tries to discuss ANFIS and wavelet neural network results as predictor systems and compare the results of them with each other. The results show that both algorithm give a great performance in terms of estimation of solar irradiation and wind velocity time series. Figure 7-10 show the estimated output of the applied algorithms. Even though a lot of fluctuations are exist in the nature of wind velocity and solar irradiation time-series, reasonable R^2 and RMSE support the acceptable and robust performance of the utilized algorithms. However, R^2 and RMSE show that solar prediction outperforms the prediction compared to the wind velocities. It is acceptable due to the complicated behavior of wind velocities in comparison with solar irradiation.

Figure 7. Agreement of the actual targets and the predicted outputs for wind velocity data using ANFIS

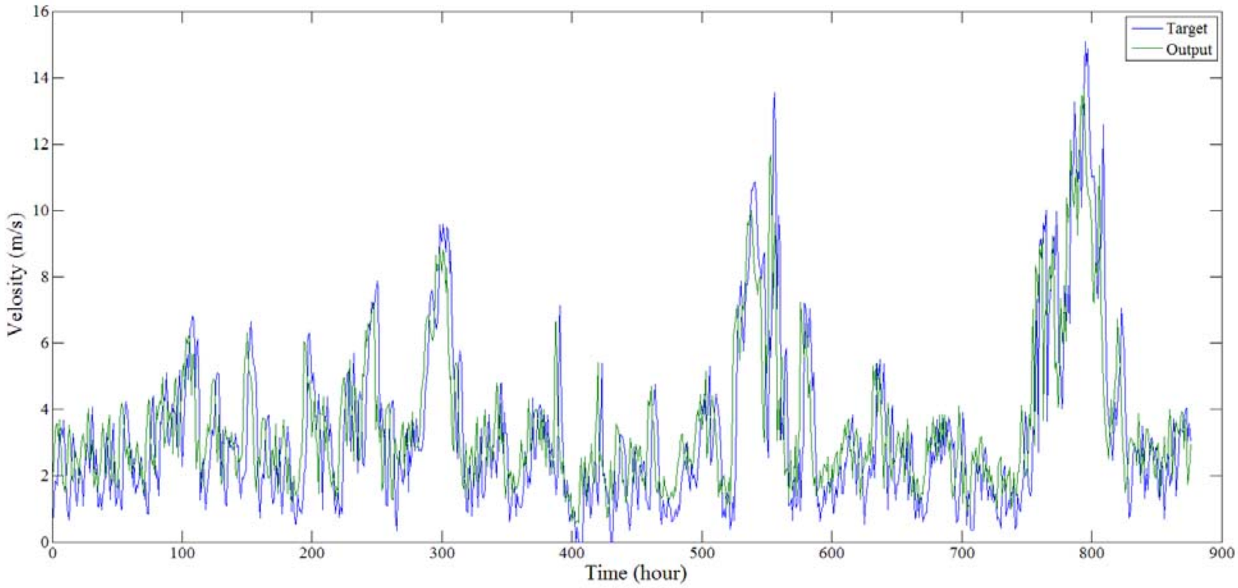


Figure 8. Agreement of the actual targets the predicted outputs for wind velocity data using WNN

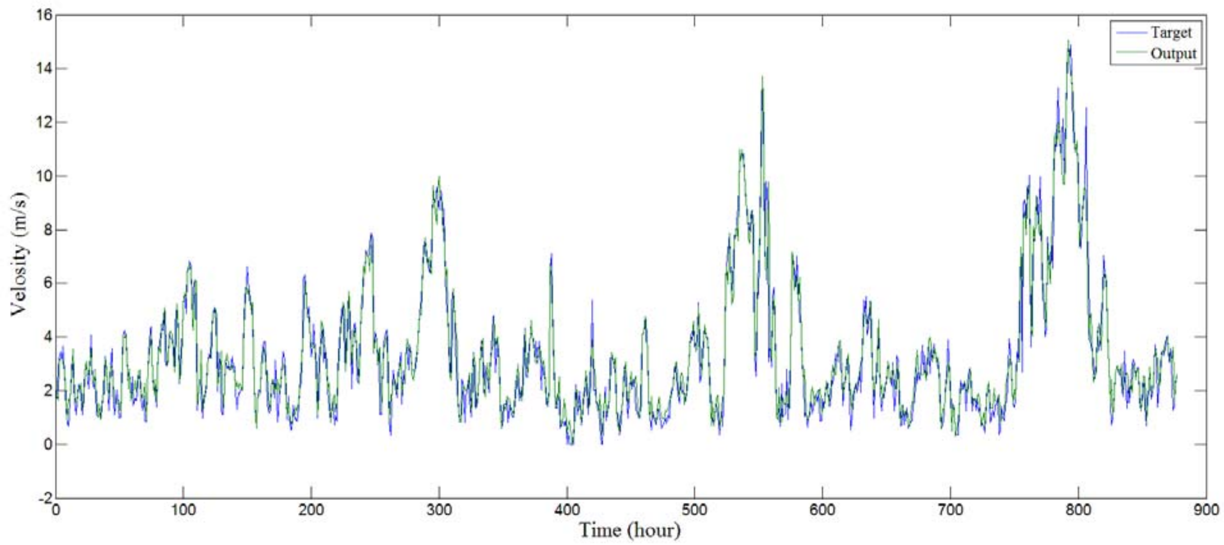


Figure 9. Agreement of the actual targets and the predicted outputs for solar irradiation data using ANFIS

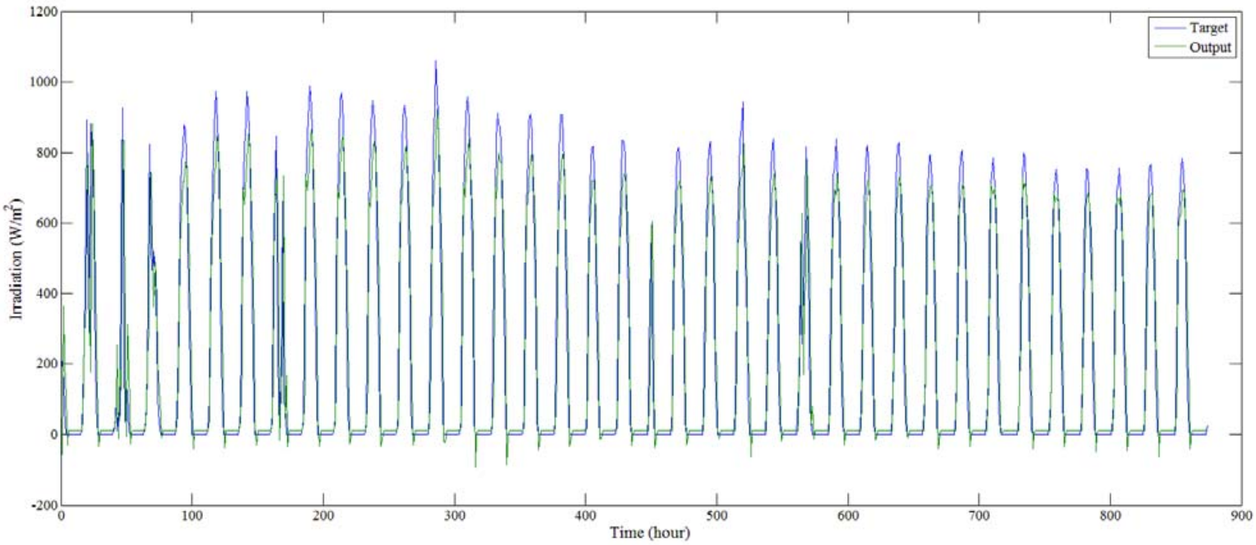
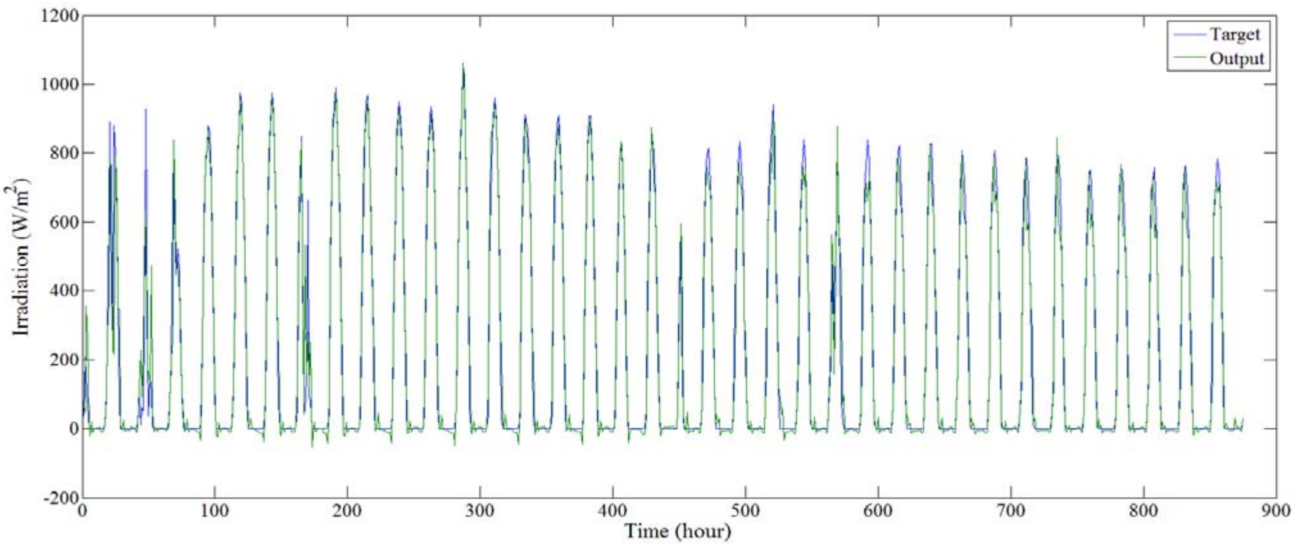


Figure 10.. Agreement of the actual and the predicted test outputs for solar irradiation data using WNN



For validation of the applied approaches for forecasting, statistical indicators are used such as root mean square error (RMSE) and absolute fraction of variance (R^2). These indicators are the most popular in previous studies. A good model should have a small RMSE. In other words, the smaller RMSE the model has, the more reliable results are gained. In contrast with RMSE, a reliable fit happens, when R^2 is near 1[35]. R^2 shows the robustness of the correlation between estimated and actual data. The aforementioned statistical indicators and their related equations are shown as follows.

$$RMSE = \left[(1/n) \sum_{i=1}^{n} \left(f_{out_i} - t_i \right)^2 \right]^{0.5} \tag{21}$$

$$R^2 = 1 - \left(\sum_{i=1}^{n} (fout_i - t_i)^2 \Big/ \sum_{i=1}^{n} fout_i^2 \right) \tag{22}$$

Table 1 shows the results of RMSE and R^2 as follows:

Table 1: The results of indicators for valiation

	Solar irradiation (W/m²) forecast		**Wind velocity (m/s) forecast**	
	WNN	ANFIS	WNN	ANFIS
RMSE	68	103	0.6533	0.8
R^2	0.9845	0.9461	0.9674	0.9083

In this paper, the type of FIS is sugeno, the number of clusters is 10, and the accepted radius which is 0.5. The structure of the wavelet neural is 16-15-1 and the max iteration is 500. Although performance of both algorithms for forecasting the time series is outstanding, R^2 and RMSE resulted by using WNN outperform for forecasting of solar irradiation and wind velocities.

4. Conclusion

Prediction of the solar irradiation and wind velocities is considerable information for high level policy makers, energy managers and all the individuals who deal with trading electricity, maintenance, repair and scheduling of solar projects and wind farms. To overcome the complicated behavior of wind and uncertain nature of renewable resources, strong and effective algorithms are needed to forecast the future behavior of them for a special region. The data used for solar irradiation and wind velocity are obtained from a meteorological station in Tehran with 1 hour intervals. The algorithms which are used to forecast are ANFIS and wavelet neural network and they are validated by popular statistical indicators based on actual data. Although both algorithms results are logical in terms of prediction of wind velocities and solar irradiation, WNN gives a superior performance to ANFIS for wind velocity time series and solar irradiation. Because this issue is so applicable for many sections of energy, it merits further researches. So hybrid algorithms such as ICA-WNN and MCDM-ANFIS might have better results and they deserve investigation. In addition, these results for designing and placement of wind farms and solar plants can be utilized.

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