Wind Power Forecasting using Artificial Neural Network

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Abstract: - The electric energy generated from wind resources is now one of the most important sources in the electrical power system. Predicting wind speed is difficult because wind characteristics are unpredictable, highly variable, and dependent on many factors. This paper presents the design of an artificial neural network used in wind energy forecasting that has been trained using weather data that influences wind energy generation. Artificial Neural Network (ANN) has gained popularity in recent years due to its superior performance. The main objective of the developed model is to improve the forecasting of energy generated from wind farms. The developed system allows the power system operator to determine the best time to rely on the wind farm to produce power for the electrical system without affecting the stability of the system and reducing the cost of electricity generation due to the traditional method. The analysis is performed by investigating wind potential and collecting data from a highly recommended source. The heatmap, covariance and correlation methods are used to analyze the data, and then the data is used to build an Artificial Neural Network (ANN) in MATLAB 2020. The results show very high accuracy 99.9%.

Key-Words: - Wind power, Artificial Neural Network ANN, Wind Turbine, Feed forward ANN

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1 Introduction

Renewable Energy sources (RES) are very important in the last few years, It occupies a large field of study and development with increasing the fire about global warming, increasing fossil fuels cost, air pollution and worldwide reducing of CO2 are forcing to switch from traditional energy source to Renewable energy source (RES) , such as: wind , solar , hydro ,bio ,and nuclear energy source[1].

Using artificial intelligence is used in many applications recently. It has been used in recent research in electric vehicle charging loads on realistic residential distribution system [2]. Beside this, it has used to make decision regarding selection of wind farms [3]. One of the used techniques is neural networks which has been used in power applications [4] and prediction [5]. Other artificial intelligence techniques such as decision tree has been used in power applications [6]

Increase diversity in energy sources it will be significantly reflected on developing countries, where RES will be the motivation of enhancing business, green economy and creating new qualified jobs [7].
The most type of RES use in Jordan are wind, solar ,hydro and biogas divided in transmission and distribution network in different size from few KW to a few MW, the Jordan government Planning to increase accreditation on RES in the future energy consumption plan ,Jordan's electrical load of about 3500 MW which may reach more than 6200 MW by 2025.Wind energy is one of the strongest possibilities to cover a portion of Jordan's energy demands, as wind availability rates at speeds suited for wind energy applications are deemed adequate and perfect for energy security applications. The wind speed reaching 7-11 m/s which is very applicable for wind energy generation [8-9].

2 Problem Formulation

The generation power from the wind turbine depends on weather conditions included (wind speed, temperature, humidity, pressure and either) this factor will effect of the generation planning. Collecting all type of data that effect on wind power generation and use it in Models that help predict energy output through data, this process will help the operator to know how much energy which will got from the wind farm [10-11].

2.1 Wind Power Equation

The power available from the wind is given by [9]:

$$Pa = (1/2)\ \rho\ A\ V^3 \qquad (2.1)$$

whereas:
Pa is the amount of wind energy available in [W],
ρ is the air density in [Kg/m3],
A is the cross-sectional area in [m],
V is the wind velocity in [m/s]
The air density will change with change the weather condition we can found it by equation (2.2):

$$\rho = P/(R\ T) \qquad (2.2)$$

where: P air pressure in (pa)
R specific gas constant for air in (J/(Kg.C)
T temperate in (C)
The rotor cannot extract all of the power available from the wind stream, and the value of the extracted power is determined by the total efficiency ŋt equation (2.3) shown the final form of wind power equation [9,10]:

$$Pa = (1/2)\ \rho\ A\ V^3\ \eta t \qquad (2.3)$$

From the equation (2.3) showed the variables effecting the wind power which are Pressure, temperate, wind velocity.

2.2 Wind Power Forecasting

The growing importance of wind power raises the issue of understanding its behavior and its impact in electrical sector [11]. Wind power production, being subject to the available wind, can only controlled within the margin of the possible production correspondent to the available wind, thus it has reduced control capacities [12,13]. The extraction of energy from the wind should thus be maximized for economic and environmental reasons. This paper will demonstration that illustrates how to use the proposed Artificial Neural Network (ANN) to estimate wind power based on the input parameters [14-15].

- **Neural Network Design and Methodology**

A neural network is a machine learning algorithm that mimics the human brain and is inspired by biology. The idea of machine learning refers to a computer's ability to learn from raw data by automatically finding a meaningful pattern [16]. Both supervised and unsupervised learning problems can be addressed by the NN. Supervised learning is used in fitting situations when the input and desired output are known . The NN works with numeric data in these applications, and its goal is to approximate the relationship between the input and output data.
ANNs consist of simple processing units - neurons - subdivided into layers - an input, an output, plus one or more hidden layers - with each connection having a weight factor that varies according to the input and the output [17-19].
There are two types of networks: static and dynamic. Static networks depend only on the current value of inputs, while dynamic networks are governed by differential equations, which show memory [20-23].

During supervised or unsupervised learning, the weights associated with the connections are adjusted based on inputs and outputs that have been presented to the network[24]. The network is given only the inputs in an unsupervised learning process, and it is trained to distinguish different classes of data.

ANNs may also be classified as feed forward and recurrent [25]. Feed forward networks, which are without directed cycles in their topology graph, are typically used to predict wind speed and wind power. Figure 1 shows the typical structure of a multilayer perceptron, which is typically trained by supervised learning and is often used for wind forecasting [26].

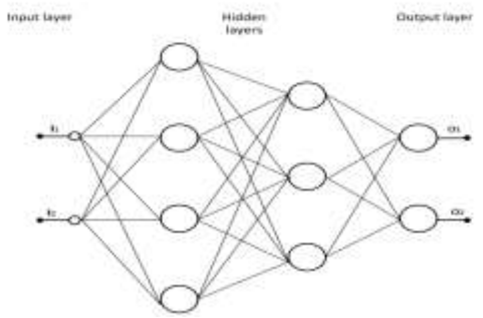


Fig. 1: Structure of a multilayer perceptron network.

- **Feed forward ANN**

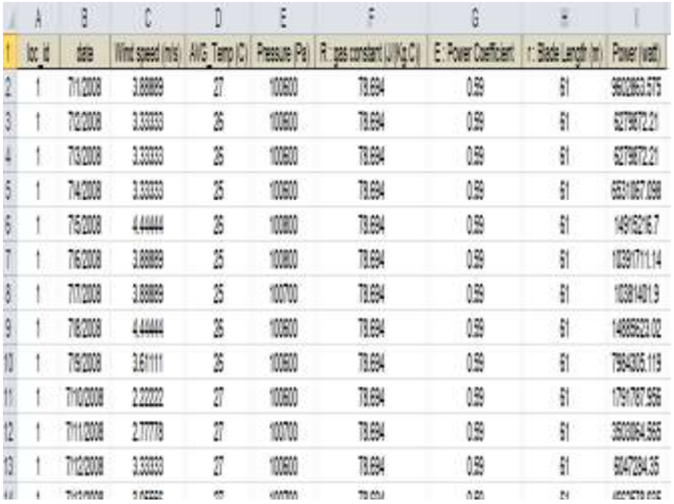
The generic feed forward ANN model consists of numerous layers of neurons, each of which is referred to as a perceptron. It's worth noting that the input layer isn't named a perceptron because it doesn't do any calculations [27-29]. Furthermore, each neuron gets a large number of input signals while only producing a single output signal [30-34]. The weighted sum of the neuron's inputs is computed, and the output is then determined using one of the typically used activation functions, such as sign, step, sigmoid, or linear feature. The sign and step measures are known as hard boundary functions because their values abruptly shift at a specific point, making them ideal for decision-making applications like categorization and pattern recognition [35-38].

- **Recurrent ANN**

Feed forward ANN does not entirely replicate the human brain. As a result, literature has proposed a recurrent ANN with feedback loops from its outputs to the input. The insertion of such loops improved the ANN's learning capabilities. The Hopfield network is a sort of recurrent ANN that works by feeding each network outcome back to all inputs. In order to recover a huge number of essential memory storage, this sort of ANN demands larger storage capacity [39-42].

2.3 Data Processing

The data for this thesis was obtained for the south of Jordan and included a variety of weather data it was 4735 column and 41 row it was need analyse and filtering. The information was gathered from an internet source (World Weather Online), which provides a wide range of information. The data was collected between July 1, 2008, and June 16, 2021.
The data Contains many factors that have no effect on wind power such as weather Disc, moon phase, moonset, UV index …etc. we began by analysing all of the variables that affect wind energy output, including wind speed, average temperature, humidity, visibility, pressure, dew point, wind gusts, and total precipitation.



	A	B	C	D	E	F	G	H	I
1	loc_id	date	Wind speed (m/s)	AVG_Temp (C)	Pressure (Pa)	R: gas constant (J/Kg.C)	E: Power Coefficient	r: Blade Length (m)	Power (watt)
2	1	7/1/2008	3.88889	27	100600	78.694	0.59	61	9602863.575
3	1	7/2/2008	3.33333	26	100600	78.694	0.59	61	6279872.21
4	1	7/3/2008	3.33333	26	100600	78.694	0.59	61	6279872.21
5	1	7/4/2008	3.33333	25	100600	78.694	0.59	61	6531067.098
6	1	7/5/2008	4.44444	26	100800	78.694	0.59	61	14916216.7
7	1	7/6/2008	3.88889	25	100800	78.694	0.59	61	10391711.14
8	1	7/7/2008	3.88889	25	100700	78.694	0.59	61	10381401.9
9	1	7/8/2008	4.44444	26	100600	78.694	0.59	61	14885623.02
10	1	7/9/2008	3.61111	26	100600	78.694	0.59	61	7964305.119
11	1	7/10/2008	2.22222	27	100600	78.694	0.59	61	1791767.956
12	1	7/11/2008	2.77778	27	100700	78.694	0.59	61	3530864.565
13	1	7/12/2008	3.33333	27	100600	78.694	0.59	61	6047284.35
14	1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Fig. 2: The analyzing Weather data With Power

The data are now ready to be analyzed using two techniques: heat map, correlation matrix, and covariance matrix. A heat map is a data visualization approach that displays the magnitude of a phenomenon as color in two dimensions; through it, we can observe the impact of each element on wind power.

2.4 MATLAB Simulation

In this section, the steps of implementing the ANN for wind power forecasting was illustrated in details:

- Step 1: read the excel sheet with the following parameters: temperature, pressure, Dew point, wind speed, gas constant, power coefficient, and turbine blade length.
- Step 2: Using a Matlab script, code the wind power equation and compute it for all data (from year 2008 - 2021).
- Step 3: Using a Matlab script, code the heat map and compute it for all parameters and observe the relation between them.

- Step 4: Code the normalization method for inputs (recorded parameters) and output (wind power) in a Matlab script and compute it for all data (from year 2008 - 2021)
- Step 5: To prepare the data for training, utilize the nntool box in MATLAB program. Furthermore, choose between two training methods: feed forward back propagation and layer recurrent ANN.

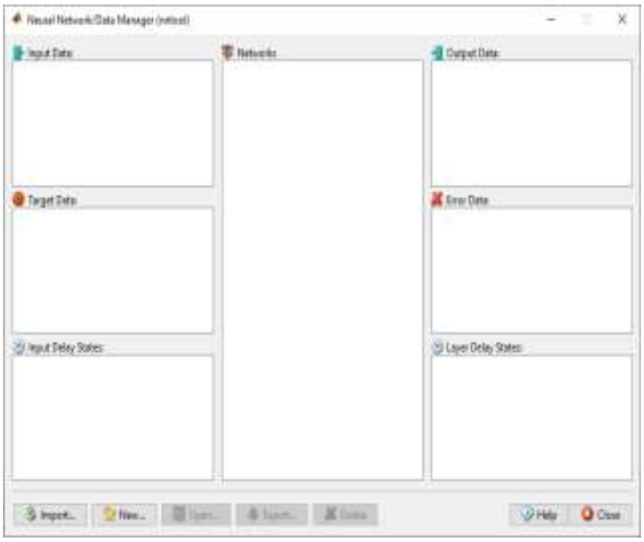


Fig. 3: nntool window of Matlab software

- Step 6: After establishing the layers and neurons counts, train the selected ANN with the needed parameters.

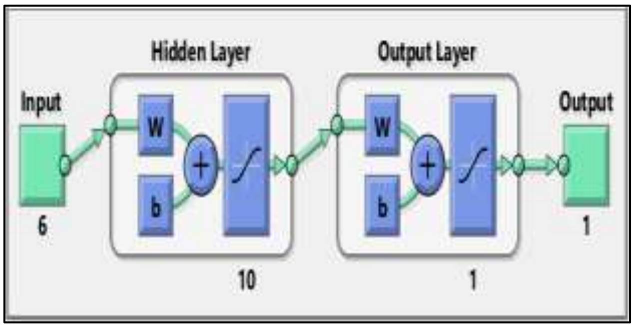


Fig. 4: ANN structure after design process.

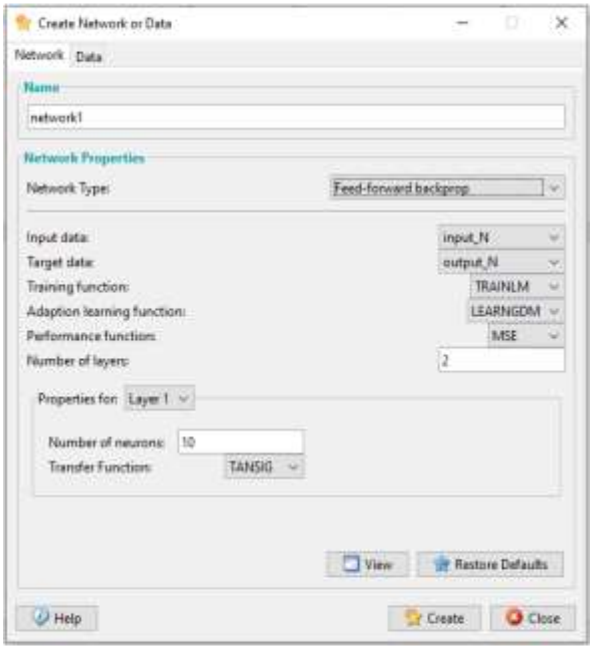


Fig. 5: ANN design process

- Step 7: repeat step 6 for parameters of (temperature, pressure, wind speed, wind gust, humidity and visibility) and neurons for layer recurrent ANN and compare the results with the feed forward method.
- Step 8: repeat step 6 for different number of parameters and neurons for feed forward method. (28 training)
- Step 9: Compare the predicted results with the recorded data for each train to see the training attempts.
- Step 10: In terms of regression and MSE, distinguish between the training trials.

The following is the results of feed forward ANN training for 6 parameters mentioned in step 8:

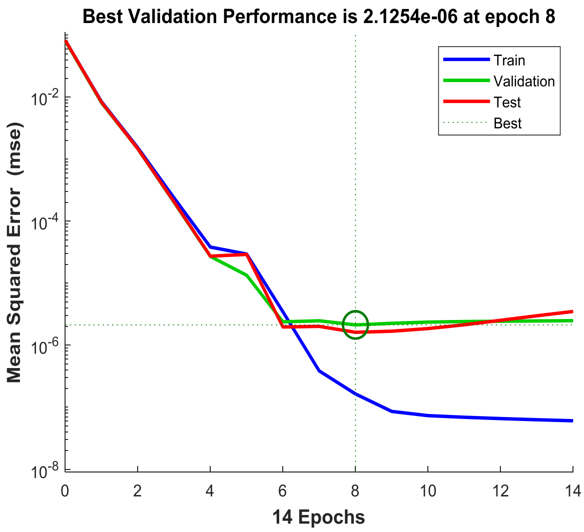


Fig. 6: Regression results of ANN training.

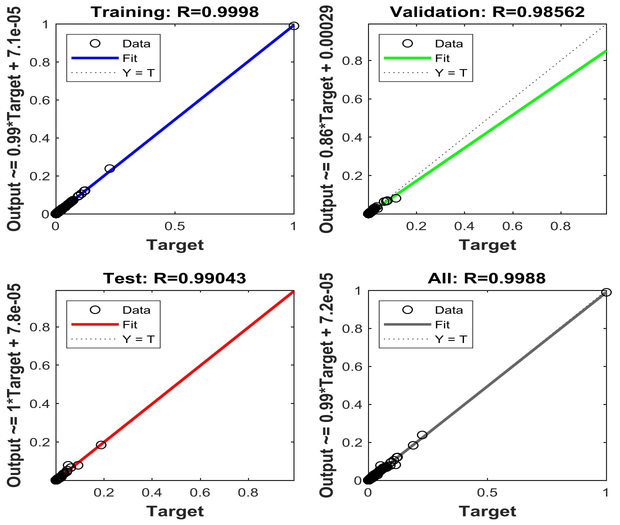


Fig. 7: ANN training performance

Figures 6 show that the tool box had four regression plots, the first of which used 70% of the data and indicated that the training procedure was excellent. The second figure shows how to validate the Forecasting findings, and the third plot shows how to test the regression with new data. The last graph depicts the overall regression.
Figures 7 shows that the validation and testing processes have a low mean squared error, demonstrating the training's effectiveness.

3 Results and Discussions

In this section, the obtained results from the covariance and correlation matrices, as well as the ANN training of feed forward and layer Recurrent methods that estimate the produced power from six parameters, were presented and analyzed. Furthermore, we discussed the impact of ANN training on a number of parameters in order to determine which was the most beneficial.

Table 1. Covariance matrix of the estimated parameters

	Avg. Temp.	Wind speed	Visibility	Pressure	Dew Point	Wind Gust	Total precip	Wind power
Avg. Temp.	0.071710	0.001545	0.54898	0.007671	0.0408226	0.018231	0.000697	0.003427
Wind speed	0.001545	0.022253	0.003967	-0.00546	-0.006607	0.002960	0.023844	0.004637
Visibility	0.054898	0.003967	0.059135	-0.0078	0.028523	0.005316	0.002635	0.004299
Pressure	0.007671	-0.00596	-0.00978	0.013924	-0.00241	-0.00053	-0.05504	-0.0049
Dew Point	0.040826	-0.00607	0.028523	-0.00246	0.034730	-0.1494	-0.00969	-0.00734
Wind Gust	0.018231	0.002960	0.005316	- 0.000583	-0.014940	0.030538	0.003708	0.000735
Total precip	0.000697	0.023844	0.002635	-0.00554	-0.007969	0.003708	0.026731	0.004414
Wind power	0.003427	0.004637	0.004299	-0.00490	-0.000734	0.000735	0.004414	0.005278

3.1 Covariance and Correlation Matrices

Covariance is a measure of the relationship between two random variables, and statistics principles can help investors monitor it. The statistic measures how much – and how far – the variables change in tandem. To put it another way, it's a measure of the variance between two variables.
matrix of covariance Determines the nature of relationship between the variables, with a negative value indicating an inverse relation and a positive value indicating a direct relationship between the two variables being investigated. Except for pressure (-0.004900) and dew point(-0.000734), all parameters in Table 1 exhibit a positive relationship with wind power. Also the Pressure have negative relationship with wind speed (-0.005496), Visibility (-0.009578) , Dew point (-0.002461), wind gust (-0.000583) and total Precip (-0.005504). Another

factor have negative relationship with the other factor which is the Dew point like (-0.014940) with wind gust and (-0.007969) with total Precip.

Table 2. Correlation matrix of the estimated parameters

	Avg. Temp.	Wind speed	Visibility	Pressure	Dew Point	Wind Gust	Total precip	Wind power
Avg. Temp.	1	-0.03867	-0.84303	0.242753	-0.81807	0.389576	0.015919	-0.17614
Wind speed	-0.03867	1	0.109352	-0.31224	-0.23765	0.113546	0.977632	0.427899
Visibility	-0.84303	0.109352	1	-0.33379	0.629387	0.125094	0.066278	0.243315
Pressure	0.242753	-0.31224	-0.33379	1	-0.1119	-0.02829	-0.28528	-0.57161
Dew Point	-0.81807	-0.23765	0.629387	-0.1119	1	-0.45876	-0.26154	-0.0542
Wind Gust	0.389576	0.113546	0.125094	-0.02829	-0.45876	1	0.129784	0.057869
Total precip	0.015919	0.977632	0.066278	-0.28528	-0.26154	0.129784	1	0.371586
wind power	-0.17614	0.427899	0.243315	-0.57161	-0.0542	0.057869	0.371586	1

A totally negative linear correlation between two variables is shown by a -1 value in the table 3. A score of 0 shows that there is no linear association between two variables. Moreover, a value of 1 denotes a perfect positive linear correlation between two variables.

3.2 ANN Training with Different Methods

Table 3 ANN training methods

Number of inputs = 6					
ANN Method		Feed forward back-prop		Layer Recurrent	
N in layer (1)	N in layer (2)	SSE	MSE	SSE	MSE
10	1	5.101E-03	1.080E-06	2.365E-01	5.008E-05
20	1	4.867E-02	1.031E-05	2.831E-01	5.995E-05
30	1	1.573E-03	3.332E-07	3.316E-01	7.022E-05
40	1	1.441E-03	3.051E-07	2.664E-02	5.641E-06
50	5	3.838E-03	8.128E-07	2.224E-01	4.710E-05
50	10	1.421E-03	3.010E-07	2.791E-02	5.911E-06

Table 3 presented two approaches for training neural networks, with the feed forward method outperforming the second strategy in terms of SSE and MSE. To get the lowest possible error in training, the ANN should include two layers, each with 50 and 10 neurons.

Table 2 showed that the high degree of correlation is between wind speed (-0.427899) and wind power (strong proportional relation), whereas the poorest relationship with power is Dew point (-0.0542) parameter (weak inverse relation).

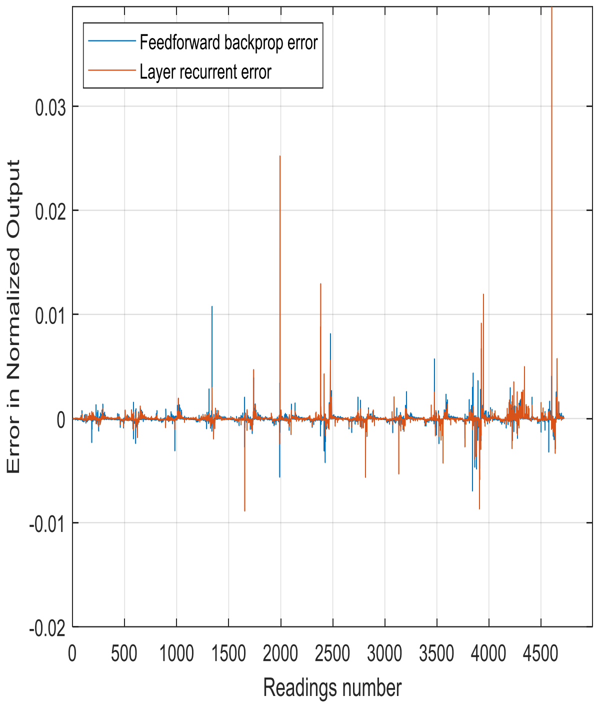


Fig. 8: Comparison between the two ANN approaches in terms of error.

3.3 Feed Forward Back-Propagation Training for 6 Inputs with Different Number of Layers and Neurons

Table 4 shows the Feed forward back-prop technique training results for six parameters Avg. Temp, Wind speed, Visibility, Pressure , Dew Point and Total precip, (which gave better outcomes in the comparison). The number of neurons in each layer was changed started with 10 neurons in layer1 and 1 neurons in layer2. First we started changed the number of neurons in layer1 and keep the neurons constant in layer2 , after that we keep neurons in layer1 and changed neurons in layer2 in three step 5, 10 and 15, and each training's regression results were recorded. The best regression results (0.9995) were obtained with 50 neurons in the first layer and 10 neurons in the second.

Table 4. Feed forward back-propagation training for 6 inputs

N in layer (1)	N in layer (2)	Regression
10	1	0.9983
15	1	0.9254
20	1	0.9927
25	1	0.9767
30	1	0.9992
35	1	0.9679
40	1	0.9995
50	5	0.9987
50	**10**	**0.9995**
50	15	0.9427
100	5	0.9430
100	10	0.9721
100	15	0.9288
200	5	0.5952
200	10	0.9669
200	15	0.8797

3.4 ANN Training with Different Parameters and Neurons

Many training sessions employing the Feed forward back-prop method were held in this part. Each training contains a different amount of variables as well as neuron count. These completed trainings assist us in illustrating the optimal variable to use in the wind power generation forecast procedure. The best training was trial 27, which included Temperature, Humidity, Visibility, and Pressure as training variables with 40 neurons, as shown in Table 5.

Table 5. ANN training results for different variables and different neurons

Trial	Training inputs	Neurons number	Regression	MSE
1	Temperature	10	0.48827	0.0022
2	Temperature	40	0.48356	0.0018

3	Temperature	50	0.48030	0.0022
4	Humidity	10	0.28159	0.0031
5	Humidity	40	0.31025	0.0030
7	Humidity	50	0.30274	0.0026
8	Visibility	10	0.30888	0.0029
9	Visibility	40	0.31531	0.0031
10	Visibility	50	0.30758	0.0028
11	Pressure	10	0.31442	0.0028
12	Pressure	40	0.28790	0.0025
13	Pressure	50	0.27470	0.0030
14	Temperature & Pressure	10	0.64869	0.0019
15	Temperature & Pressure	40	0.63456	0.0020
16	Temperature & Pressure	50	0.67036	0.0013
17	Temperature & Visibility	10	0.51451	0.0021
18	Temperature & Visibility	40	0.55484	0.0020
19	Temperature & Visibility	50	0.51416	0.0022
20	Temperature & Humidity & Visibility	10	0.55793	0.0020
21	Temperature & Humidity & Visibility	40	0.57050	0.0019
22	Temperature & Humidity & Visibility	50	0.57870	0.0016
23	Temperature & Humidity & Pressure	10	0.66780	0.0016
24	Temperature & Humidity & Pressure	40	0.65606	0.0014
25	Temperature & Humidity & Pressure	50	0.67130	0.0016
26	Temperature & Humidity & Visibility & Pressure	10	0.66030	0.0014
27	Temperature & Humidity & Visibility & Pressure	40	0.68860	0.0014
28	Temperature & Humidity & Visibility & Pressure	50	0.62560	0.0017.

- **Training using one variable**

Predicting quality of wind power using one variables have the best regression and MSE when training using the temperature with 10 neurons the regression was (0.48827) and the MSE was (0.00226) as showed in the figure 9 , All the other variables have low regression and MSE.

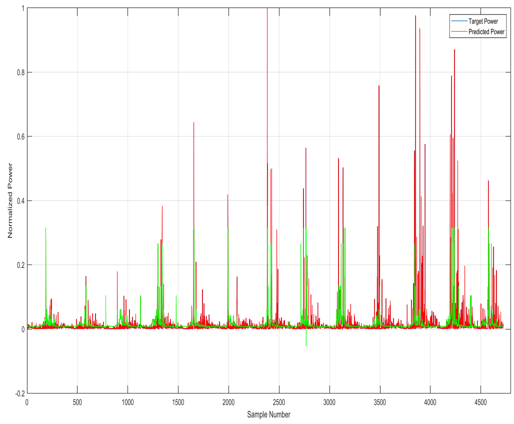


Fig. 9: Power Forecasting using temperature with 10 neurons

- **Training using two variables**

As shown in Table (5) the training using two variables has the best regression and MSE when used the Temperature & Pressure with 50 neurons with (0.67036) regression and (0.00132) MSE, showed in figure10.

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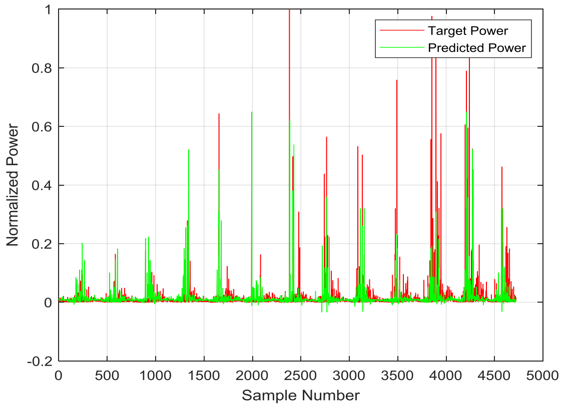

Fig. 10: Power Forecasting using temperature and pressure with 50 neurons.

- **Training using three variables**

As shown in Table (5) it can be seen that the best three variables can use for training are Temperature & Humidity & Pressure with 50 neurons the regression was (0.67130) and the MSE was (0.00161), the result showed in figure.11.

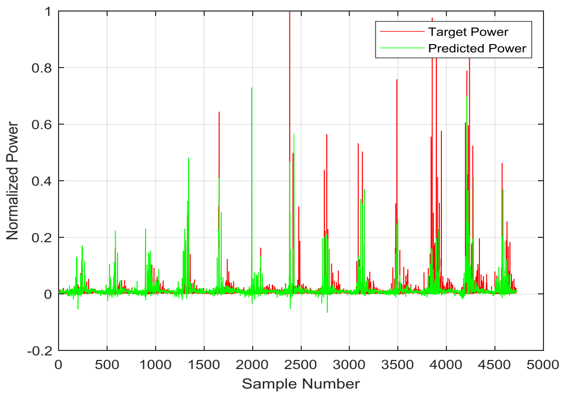

Fig. 11: Power Forecastingusing temperature, humidity and pressure with 50 neurons.

- **Training using Four variables**

The best Forecasting of all training is the forecast of wind power using the combination of four specified parameters (temperature, humidity, visibility, and pressure), and as shown in figure 12, increasing the number of neurons up to 40 had a favorable influence on the quality of the forecasting. However, in terms of amplitudes and frequency of calculated wind speeds, the combined parameters Forecastingsurpasses the other techniques in terms of regression and MSE.

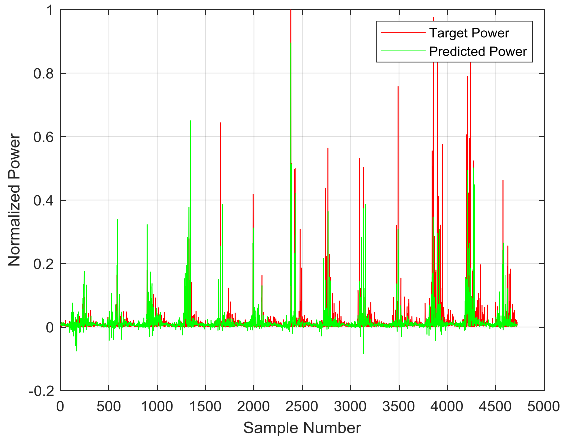

Fig. 12: Power Forecasting using temperature, humidity, visibility and Pressure with 40 neurons.

4 Conclusions

In this paper, a model of ANN with Weather conduction was built via MATLAB-SIMULINK as a real case study. A covariance and correlation matrices are proposed to study the covariance between each pair of components and the correlation between variables of the data used. All parameters, temperature, humidity, visibility, and pressure exhibit a positive relationship with wind power. Feed forward back-prop technique and Layer Recurrent ANN are used. The performance of the proposed approach was assessed and validated by the Regression, SSE and MSE. The best regression results were obtained with 50 neurons in the first layer and 10 neurons in the second using feed forward technique. For Different variables it can be seen that, the best training was the trial 27, which included temperature, humidity, visibility, and pressure as training variables with 40 neurons. The accuracy of the proposed system reaches 99.9%.

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