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Wind Power Prediction Models- Case Study with Artificial neural network for prediction

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ABSTRACT

Research into the viability of renewable energy sources has expanded as a result of the rising prices and unfavorable environmental effects of conventional, nonrenewable energy sources. Since the 1990s, wind energy has had the world's fastest rate of growth in terms of electricity production. Wind is also a renewable energy source that is both more ecologically benign than conventional energy sources and happens naturally. One of the key challenges restricting the use of wind energy as a source of energy in the renewable energy market is reliability. The concepts of wind speed and wind power are interrelated and subject to location- and time-specific variations. Aside from that, there is currently no viable method to store the output of a wind turbine, thus it must be incorporated right away into the electrical grid. Since utility companies must disclose the amount of energy they will produce in the future in order to satisfy expected energy demands, knowing future wind power is essential for wind energy to be economically viable. As more wind power is introduced to the electricity markets, the ability to accurately estimate wind power becomes increasingly important, as a 1% error in estimating wind parameters can result in an estimated loss of $1,200,000 for a 100 MW wind farm over the life cycle of the farm. Hence the importance of this paper by addressing the different sections related to wind energy forecasting in three comprehensive groups. The first section presents the different forecasting methods for wind energy, while the second section presents a case study for building a neural network model to predict wind power using global climate data. The third section refers to using the results of the second section to predict wind energy in Egypt according to Egyptian weather data.

Keywords: wind power data analysis, forecasting models, physical forecasting, statistical wind forecasting, artificial neural network, wind speed.

1. Introduction

More than ever, the entire globe must cooperate to address the climate crisis by developing renewable energy options. Since 2015, all UN members have pledged to make sure that by 2030, everyone will have access to affordable, dependable, sustainable, and modern clean energy. Clean energy comes from renewable sources such as geothermal energy, the sun, wind, tides, and waves (WEA, 2001)

Wind energy is considered one of the most important sources of renewable energy, as it is considered the largest resource for generating electric power, and it is also considered the least expensive for energy production. Thus, an increasing number of countries are realizing that wind energy provides a wonderful possibility to generate electricity in the future, but with intermittent wind speed, which in turn leads to intermittent wind energy, which reduces the optimal use of it, especially with the rise in the economic aspects of energy storage, it has become important to improve the tool For forecasting Wind speed and wind energy scheduling to improve system performance and get the most benefit from environmentally friendly renewable energies, figure(1) Classification of deterministic wind speed and energy forecasting.

Wind energy is one of the RES with the largest resource and the cheapest cost of producing electricity. As a result, more and more countries are realizing how great a prospect wind power offers

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for producing electricity in the future. Forecasting techniques can enhance wind position byaddressing the intermittent nature of wind. Wind energy cannot currently be dispatched, but if it can be scheduled using accurate wind predictions, the financial implications of wind can be considerably reduced. Therefore, increasing the output of wind energy and creating a tool for forecasting wind power have significant technical and economic effects on the wind energy system. Figure (1) provides a classification of wind speed and power prediction.

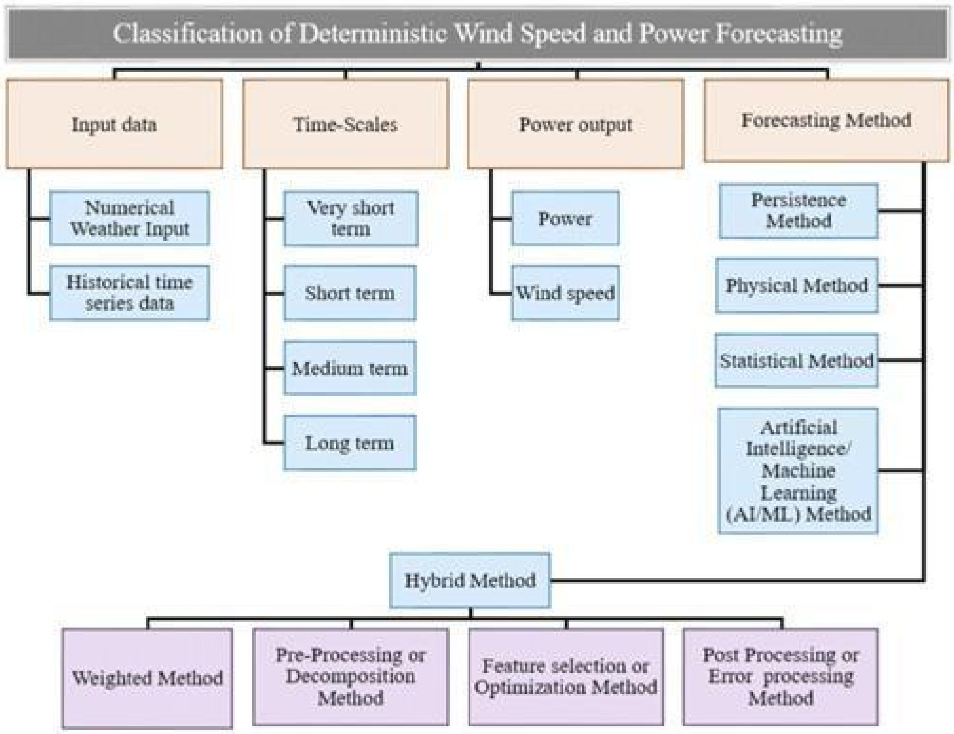

Fig. 1: Wind power and speed forecasting classification

Numerous institutions and businesses with in-depth knowledge of wind energy have devoted a great deal of research to improving wind forecasting methods. In wind farms all throughout the world, models such as Prediktor, WPPT, WPMS, Previento, ARMINES and others have been developed and put into use. Table (1) lists the international wind power software prediction models that were created using physical, statistical, and hybrid approaches.

The prediction of anticipated wind power generation is a crucial step in the assessment of the risk of energy transaction deficits by energy trade enterprises. Energy traders predict energy production on behalf of energy producers using two scenarios:

- Electricity is purchased on the spot market to maintain system operation if there is a shortfall below the forecast (at a cost higher the average energy price).
- With the expectation of generating excess energy from wind farms, energy producers donot compensate for the resulting increase.

In this situation, the financial success of wind farms depends on precise energy output predictions.

Table 1: International prediction models software for wind power

Model name	Developer(s)	Method	Some geographical locations of applications
Prediktor	L. Landberg at Risø, Denmark	Physical	Spain, Denmark, Republic of Ireland, Northern Ireland, France, Germany, USA, Scotland & Japan
WPPT	Eltra/Elsam collaboration with Informatics and Mathematical Modeling at Danmarks Tekniske Universities (DTU), Denmark	Statistical	Denmark, Australia, Canada, Republic of Ireland, Holland, Sweden, Greece & Northern Ireland
Zephyr	Risø & IMM ay DTU, Denmark	Hybrid	Denmark& Australia
Previento	Oldenburg University	Hybrid	Germany, Northern Ireland
e-WindTM	True Wind Inc., USA	Hybrid	USA
Sipreólico	University Carlos III, Madrid, Spain	Statistical	Spain
WPMS	Institute of wind energy technology (ISET), Germany	Statistical	Germany
WEPROG	J. Jorgensen & C. Möhrlen at University College Cork	Hybrid	Ireland, Denmark and Germany
GH Forecaster	Garrad Hassan	Statistical	Greece, Great Britain & USA
AWPPS	École des Mines, Paris	Statistical	Crete, Madeira, Azores & Ireland
LocalPred & RegioPred	M. Perez at center national energy renewable (CENER)	Hybrid	Spain and Ireland
Alea Wind	Aleasoft at the Polytechnic University of Catalonia Spain (UPC)	Statistical	Spain SOWIE Euro wind GmbH, Germany Physical Germany, Austria & Switzerland
EPREV	Institute of Systems and Computer Engineering of Porto (INESC), Institute of Mechanical Engineering and Industrial Management (INEGI) and Center for the Study of Wind Energy and Atmospheric Flows (CESA) in Portugal	Statistical	Portugal
Scirocco	Aeolis Forecasting Services, Netherlands	Hybrid	Netherlands, Germany &

2. Literature review for prediction wind power:

In general, the immediate-short term of minutes to hours to frequently up to one day and the long-term of up to two days are most important in wind forecasting. Over 95% of Germany's area, in 2030 is predicted to have wind generating by WPMS, an example of an immediate-short- term model (Landberg, 2009; Barbounis *et al.,* 2006) represented wind forecasting models for the near future. Additionally, a number of models for forecasting short-term winds have been developed, all of which are based on highly accurate numerical weather prediction (NWP) (Kariniotakis, 2019 With its hybrid approach, Previento can predict wind for up to 24 hours. Additional studies for (Sailor *et al.,* 2018; Landberg, 2001) included long-term wind power forecasting models

Henrik *et al.,* (2007) showed that the forecast inaccuracy lowers when many NWP forecasts are used. Louka *et al.* (2008) also showed that the prediction errors of wind speed forecasts in NWP can be eliminated by Kalman filter.

Several tools, including WPPT, Predictor, Zephyr, Ewind, WPFS Ver1.0, and AWPPS, have been developed for short-term forecasting. These models have been applied to forecast wind energy in many countries including Denmark, Spain, Germany, France, Ireland, and Greece (Candy *et al.,* 2008)

Two hybrid models, ARIMA-ANN and ARIMA-SVM, have been proposed by (Enas, Khattab, 215; Shi et al., 2012) to predict wind speed and strength. This study conducts a systematic and comprehensive analysis of a case study on wind speed and wind power generation by suggesting hybrid models.

In order to remove seasonal impacts from actual wind speed information, a unique hybrid wind speed forecasting method based on a back propagation neural network and the concept of seasonal exponential adjustment was described in (Guo *et al.,* 2011). In experiments, the suggested method performed better than a single back propagation neural network.

Sfetsos, (2002) suggested a hybrid strategy for short-term wind power prediction in Portugal depended on integration of artificial neural network (ANN). The results of the tests indicate great promise for the suggested hybrid technique to anticipate wind power output.

Chang (2013) proposed combining time series analysis and artificial neural networks to predict mean wind speed data per hour. The proposed methodology can be advantageous for utility companies that employ hourly intervals for operational activities and have a high penetration of wind power generation.

Back propagation neural network-based wind power forecasting methods were covered by We *et al.* (2010); Chang, (2013). the system used to provide energy to a 2400kW (WECS) on the Taichung coast, the model improvement showed good accuracy for short-term of wind power prediction. Chang, (2013) represented the wind forecasting method, back propagation neural networks and recurrent neural networks were both utilized. It has been discovered that neural network forecasting is more accurate than conventional statistical time series analysis.

Utilizing an RBF neural network, (Chang, 2013) presented a technique for forecasting time series of wind power generation. The numerical results show the reliability and accuracy of the suggested prediction methodology, with good matches between realistic values and forecasting values.

According to modified empirical mode decomposition, (Guo *et al.,* 2012) investigated a feed-forward neural network (FNN) wind forecasting method (EMD). Li and Shi (2010) used radial basis function, adaptive linear element, and back propagation as three types of conventional ANNs to predict wind speed.

A novel short-term prediction method based on automated neural network specification and nearest neighbor search using evolutionary optimization algorithms was proposed by Jursa and Rohrig, (2018); Henrik *et al.* (2007). The test results demonstrated that by employing the suggested automated specification method, the wind power forecast error may be decreased.

3. Methodology

The research methodology is divided into two parts, the first section presents the most important models used in forecasting wind energy, while the second section presents the deductive results of a predictive system for wind energy using neural networks. In forecasting wind energy, there are three steps: first, determining the wind speed from a global model; Secondly, the calculation of forecasting or forecasting wind energy output by building a predictive model with neural networks and ensuring the accuracy of the model to be used for use in the third step in regional forecasting, scaling up or downscaling, which can be applied and implemented at different temporal or spatial intervals.

3.1. Methods wind energy prediction:

There are two sorts of wind energy forecasting models. The first is predicated on an analysis of historical wind time series, whereas the second is predicated on expected values from a numerical weather prediction (NWP) model (Taylor, 2009). But to describe wind power forecasts, scientists use physical techniques, conventional statistical or "black box" techniques, and more recently, so-called learning approaches, artificial intelligence, or "grey box" techniques. Hybrid strategies can incorporate any of these.

The first category of models uses a statistical approach to predict mean hourly wind speed or to predict directly the production of electricity, while the second category of models uses explanatory variables (typically hourly mean wind speed and direction) produced by a meteorological model of wind dynamics (Cellura *el al.,* 2009).

3.1.1. Physical approach to wind power forecasting

Several physical models based on weather observations have been developed for wind speed forecasts and wind power calculations (Cellura *et al.,* 2009) Physical models rely on worldwide databases of meteorological data or atmospheric regional climate models, it also need very large computer systems to get correct findings. (Lalas, 1985).

3.1.2. Statistical approach to wind power forecasting:

The statistical approach relies solely on historical data, disregarding weather factors. It typically utilized time series analysis techniques and artificial intelligence (neural networks, neuron-fuzzy networks) (Torres *et al.,* 2005; He, 1999). Statistical frameworks the collection of models includes dynamic forecasting models that describe the dynamics of wind power and any changes in the weather, a semi-parametric power curve model for wind farms that accounts for wind speed and direction, etc.

Statistical models include both linear and nonlinear models, as well as structural and black-box models. Black-box models are created from data in a fairly mechanical way with little knowledge of the subject matter, in contrast to structural models that depend on the analyst's understanding of the phenomenon of interest (Damousis and Dokopoulos, 2001).

These models make it possible to directly calculate wind power from input parameters in a single step. The majority of data mining-based models, including time series analysis techniques and fuzzy models and model trees, can be employed as output models (e.g. ARIMA, fractional ARIMA).

In contrast to physical methods, statistical methods only need to convert input variables into power output once. The Box-Jenkins method, the Kalman filter, and the use of autoregressive (AR), moving average(MA), autoregressive moving average model (ARMA), and autoregressiveintegrated moving average model are additional statistical techniques that were used.

Modeling a statistical link between data points using traditional time series analysis isn't the only option, there are other methods for modeling a statistical relationship between data points than traditional time series analysis. The most widely used soft computing (or machine learning) techniques are artificial neural networks (ANN) and fuzzy systems; however other models like grey predictors and support vector machines (SVM) have also been used. Learning approaches are sometimes known as artificial intelligence (AI) approaches. They are referred to as learning approaches because they use historical time series to discover the connection between anticipatedwind and anticipated power output. In recent years, they have been referred to as "grey box" strategies.

3.1.3. Artificial Intelligence Methods

As artificial intelligence has advanced, numerous unique AI wind speed and power forecast algorithms have lately been created (AI). Among the recently established procedures are artificial neural networks (ANN), fuzzy logic methods, support vector machines (SVM), neuro- fuzzy networks, and evolutionary optimization algorithms.

ANN models can extract the dependency between variables and express complicated nonlinear relationships through training (Zeng, Qiao, 2011) Examples of ANN-based techniques include back propagation neural networks, recurrent neural networks, ridgelet neural networks, radial basis function (RBF) neural networks, and adaptive linear element neural networks.

Artificial neural network (ANN) might handle non-linear and complex scenarios in terms of categorization or forecasting. ANN models can depict a complex nonlinear relationship and extract the link between variables through the training phase (Zhao, Zhu2011). ANN-based technique plays important role for the problem of wind power forecasting. Examples of ANN- based techniques include back propagation neural networks, recurrent neural networks, radial basis function (RBF) neural networks, adaptive linear element neural networks and ridgelet neural networks.

3.1.4. Hybrid approach energy power forecasting:

Weather forecasts and time series analysis are used in the hybrid method, which blends physical techniques with statistical techniques, or more specifically, short- and medium-term models (Zeng and Qiao, 2011)

Hybrid models seek to combine the benefits of each model in order to generate the most accurate forecasting outcomes. Due to the limited information offered by individual forecasting techniques, a hybrid approach can make use of the data already in existence, combine data from many models, and optimise the advantages of numerous forecasting techniques, increasing prediction accuracy (Zhao *et al.,* 2011; Barbounis and Theocharis, 2007)

3.2. Wind power prediction using artificial neural network (ANN):

3.2.1. Data transformation

The study was based on the use of global data on wind speed and wind energy estimated at this speed to build a predictive model for wind power generation using artificial neural networks, andafter obtaining the artificial networks model with high predictive accuracy, the model was used to build a predictive system for the future of wind power generation according to Egyptian data for wind speed.

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To obtain the goal of the paper in predicting the Egyptian wind power at different wind speeds. The global wind forecast data collected two variables, wind power and wind speed, the paper prepared the data for use in an artificial neural network (ANN). Figure (2) shows the data preprocessing.

The large dimension and dimension units difference between the measured data, will seriously affect the prediction performance. Data normalization is essential to eliminate the dimensional influence among the wind power prediction indices to increase accuracy and efficiency, the normalization equation is expressed as:

$$X_{\text{caled}} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where mean represents the mean of the training samples, std. means the standard deviation of the training samples. The normalized data is distributed in a reasonable range, which is beneficial for further processing and analysis

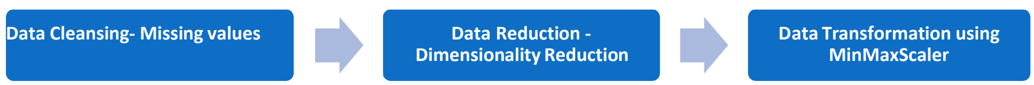

Fig. 2: Data Preprocessing

4.3. Data Splitting

The data were randomly assigned to training (58.4%), testing (25.4%), and holdout (16.2%) subsets, table (2). Before training, all covariates were normalized using the formula (x−min)/(max−min)

Table 2: Artificial Neural Network (ANN) Processing Summary

		N	Percent
Sample	Training	28018	58.4%
	Testing	12194	25.4%
	Holdout	7795	16.2%
Valid		48007	100.0%
Total		48007	

3-2-1. Architecture of multilayer perceptron neural network

The aim of this study was also to examine whether an artificial neural network (ANN) can help correctly predict wind energy by analyzing the data obtained from global weather data, Figure (4) shows the number of neurons in each layer of inputs and outputs. The architecture of the ANN model defined 3 nodes for the hidden layer, while the output layer has 1 node for the windpower variable generated.

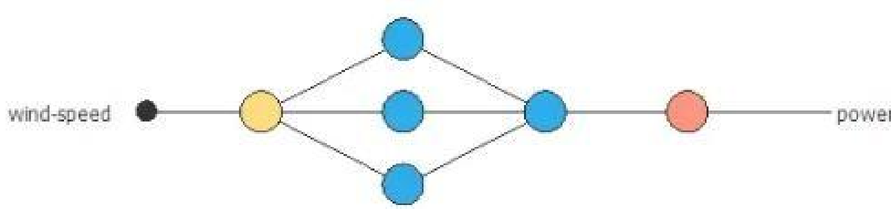

Fig. 4: Archetcture Nural Network (ANN)

Table 3: Parameter Estimates for architecture neural network

	Predictor	Predicted: Hidden Layer 1 H(1:1)	H(1:2)	H(1:3)	Output Layer power
Input Layer	(Bias)	.369	.204	.484	
	Wind speed	.193	1.120	-1.250-	
Hidden Layer 1	(Bias)				.642
	H(1:1)				.783
	H(1:2)				-.837-
	H(1:3)				-.828-

The outcome supports the testing sample's function in preventing overtraining. The table (4) shows that the rate of inaccurate predictions based on the training and testing samples is, respectively, 0.007 and 0.008, while the rate in the holdout data set drops to 0.007. The learning process was carried out until the testing sample reached 20 consecutive steps without a decrease in the error function, figure (5). shows the optimal network architecture for wind power prediction.

$$y = \sum_{i=0}^{n} (W_i * x_i) + B$$

3.2.2. Training Strategy for wind power generated prediction (Loss function):

Neural network's learning will be determined by the loss index. It is made up of a regularization term and an error term. When using neural networks, the loss index is crucial. It outlines the goalthat the neural network must do and offers a gauge of the caliber of the representation that is necessary for learning. To determine the ideal number of hidden nodes in the effectiveness of theArtificial Neural Network prediction models is evaluated in comparison to well-known Persistence (P) prediction models in the literature using Root-Mean-Square Error (RMSE) and Mean Absolute Error (MAE), (appendix).

Table 4: (ANN) Model summary

Training	Sum of Squares Error	104.678
	Relative Error	.007
	Stopping Rule Used	Maximum number of epochs (20) exceeded
	Training Time	0:00:00.75
Testing	Sum of Squares Error	46.032
	Relative Error	.008
Holdout	Relative Error	.007

3.2.4. Training strategy neural network analysis for wind power prediction:

The normalized squared error is the specified error term. It divides the squared error between the neural network's outputs and the data set's targets by the normalization coefficient. A number of zero indicates a perfect prediction of the data, while a value of 1 indicates a prediction of the data"in the mean" by the neural network. There are no configurable parameters for this error phrase. Finding the neural network settings that reduce the loss index is the responsibility of the optimization algorithm. As an optimization algorithm, we choose the quasi-Newton.

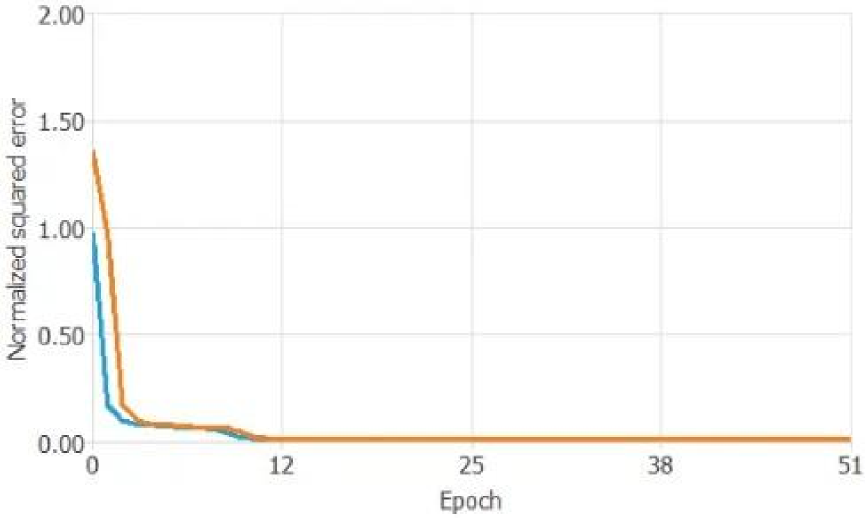

Fig. 5: Qausi-Network methods error history

The following figure (6) shows how the training (blue) and selection (orange) errors decrease with the epochs during the training process. The final values are training error = 0.007 NSE and selection error = 0.008 NSE, respectively.

$$normalized\_squared\_error = \frac{\sum (outputs - targets)^2}{normalization\_coefficient}$$

3.2.5. Testing model of neural network analysis for wind power prediction:

The purpose of the testing analysis is to validate the generalization capabilities of the neural network. Using the testing data set, which have never been used before to build the ANN architecture. The correlation coefficient R^2 would be 1. As we have R^2 = 0.996, the neural network is predicting the testing data by optimal way as showed in figure (7).

$$\mathbf{R} = \frac{\sum_{i=1}^{n}(\mathbf{x}_{o,i} - \bar{\mathbf{x}}_{o,i})\mathbf{X}(\mathbf{x}_{p,i} - \mathbf{x}_{p,i})}{\sqrt{\sum_{i=1}^{n}(\mathbf{x}_{o,i} - \bar{\mathbf{x}}_{o,i})^2 \mathbf{X} \sum_{i=1}^{n}(\mathbf{x}_{p,i} - \bar{\mathbf{x}}_{p,i})^2}}$$

4. Result and discuss for prediction wind power using the model of ANN analysis:

After building a model of neural artificial networks to predict the generation of wind energy and ensuring the accuracy of the model, the model was provided with climatic data for wind speed in Egypt to predict wind energy.

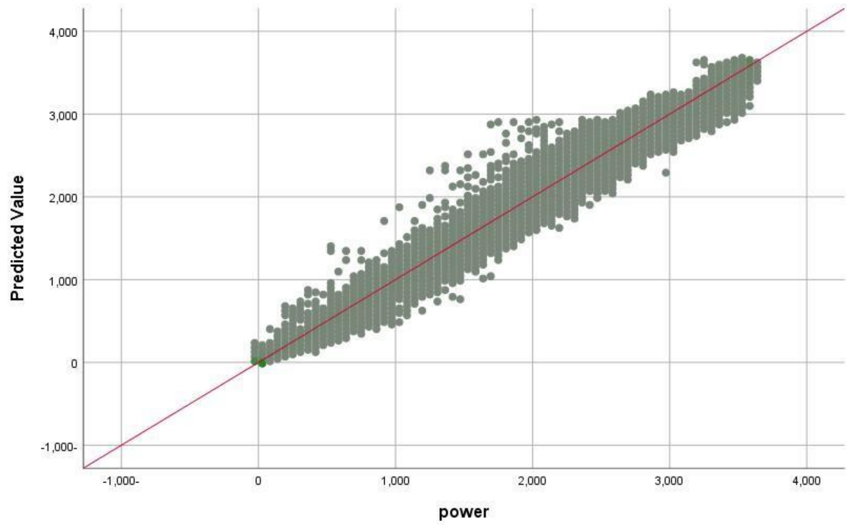

Fig. 6: Wind power liner regression chart

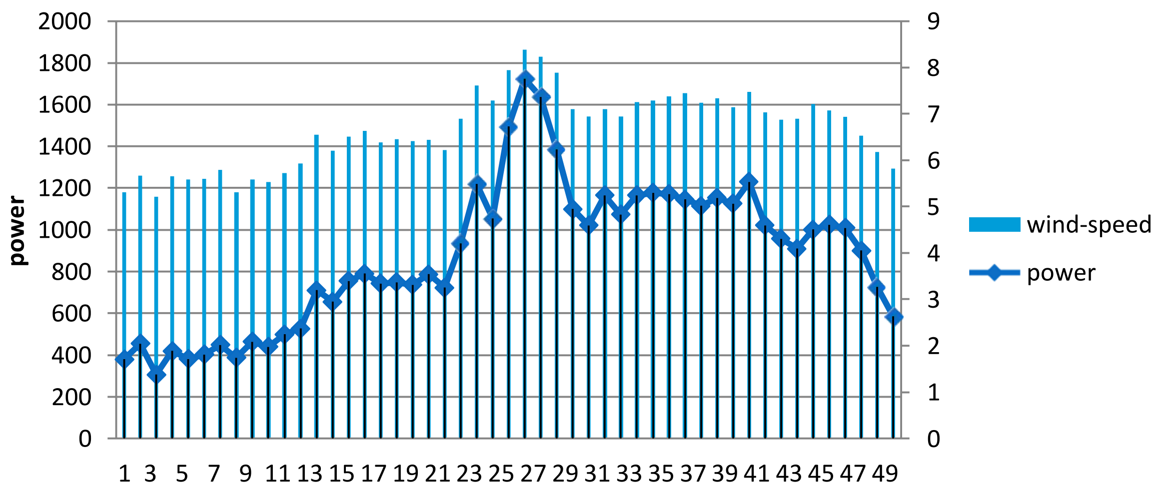

Fig. 7: Egypt Wind power speed output

Neural network calculate the wind power as outputs for a Egypt wind speed data set of inputs. When wind-speed is 8.764104 meters per second, the power is 1885.861 kilowatts. Figure (7) shows the outputs plot for neural network through some resulting wind power points.

5. Conclusion and future advances for wind power prediction:

The aim of this research was to determine the effectiveness of artificial neural networks in forecasting wind power generated from different weather data in Egypt, using global data of wind speed and generated power.

The predicted accuracy of wind energy forecasting systems is becoming more important as the amount of wind energy used in the electricity grid increases. Many researchers have discussed wind energy forecasts and improved forecast accuracy, and according to studies, it is necessaryto conduct more research on hybrid methods to combine different methods, such as combining physical and statistical methods, to achieve results closer to reality,

An important factor is the focus on developing better training algorithms for ANN prediction models to achieve higher accuracy of the predictive wind power model.

Expanding studies on used of wind data, to create a more accurate assessment process and to establish a standard for evaluating the effectiveness of wind energy forecasting approaches

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7. Appendix

- **Root Mean Square Error (RMSE):**

Root Mean Square Error (RMSE) is a measurement of the discrepancy between actual and predicted power productions as determined by an ANN model. The ANN model effectively captures the hidden mathematical relationship between the input (independent) and output (dependent) variables, as well as vice versa, because small RMSE values result in more accurate predictions as the following equation.

$$\boldsymbol{RMSE = \sqrt{\sum_{i=1}^{n} \frac{(x_{p,i} - x_{o,i})^2}{n}}}$$

- **Mean Absolute Error (MAE):**

The mean absolute error (MAE) is the average difference between the predicted and actual power productions as determined by the ANN model. As small MAE values imply more accurate predictions, comparable to the RMSE performance metric, the ANN model is successfully capable of capturing the hidden mathematical relationship between the input (independent) and the output (dependent) variables, and vice versa, as the following equation.

$$\mathbf{MAE = \frac{1}{n} \sum_{i=1}^{n} |x_{p,i} - x_{o,i}|}$$