Machine Learning-Based Prediction of Wind Power Using MATLAB

Omar Ratib Khazaleh, Firas Alawneh, Ali Alkhuzaie

Corresponding author: Omar Ratib (Omar.ratib12@gmail.com)

Abstract The increasing pressure to increase the use of renewable energy in the face of climate change has pushed the sustainable energy agenda forward with wind power at the forefront due to the fact that it has a large greenhouse gas emission reduction curve. However, due to the variation in wind speed, its penetration challenges undermine the predictability of power systems, which is essential for integrating volatile renewable energy sources into grids. In this paper, the focus is on the application of machine learning (ML) algorithms in improving the availability of reliable wind power forecasts as applied to wind power management and integration into power systems. In this context, this paper presents the post hoc analysis through different neural network configurations such as feedforward neural networks (FNNs), nonlinear autoregressive networks with external inputs (NARX), back-propagation neural networks, and radial base function (RBF) networks. These models were trained and validated for their ability to predict wind energy using data obtained from the Fujairah wind turbines in Jordan, which were obtained through a SCADA system from November 2013 to August 2024. The accuracy evaluation of the constructed models shows that the proposed FNN model, due to its ease and efficiency in determining the number of layers and neurons, showed the smallest RMSE and MAE compared to other models, thus confirming the FNN model as the most accurate and reliable model for wind energy prediction. On the other hand, the RBF network, which this study observed its ability to resolve nonlinear data, provided less positive results, indicating that the algorithm will require further optimization and further combination with the specific nonlinearity of wind energy data. From this study, we can highlight the importance of machine learning techniques when it comes to wind energy prediction, which is very important for wind energy management and exploitation. The knowledge derived from this research enhances the theoretical understanding of previous work in this area, but also provides compelling recommendations for energy suppliers seeking to enhance the effectiveness of their business operations and integrate more sustainable supply methods.

Index Terms: Machine Learning, Wind Power Prediction, Neural Networks, Renewable Energy, SCADA Systems, Feedforward Neural Networks (FNNs), Nonlinear Autoregressive Networks with External Inputs (NARX), Back-Propagation Neural Networks (BPNN), Radial Basis Function Networks (RBF), and Wind Turbine Performance.

1. INTRODUCTION

Pressures to reduce greenhouse gas emissions and combat climate change have accelerated the shift to clean energy as a form of energy, thereby reducing reliance on fossil fuels – the main cause of carbon dioxide emissions. This shift has given importance to renewable energy sources such as solar, wind, hydropower, biomass and geothermal energy. These alternatives are essentially green approaches to meeting growing energy needs without degrading the environment. Currently, about 18 percent of the global energy mix comes from renewable energy sources, and as technologies are developed and implemented, this proportion is likely to grow significantly [1].

Wind energy, a major renewable energy resource, is seeing significant progress across the world due to countries' desire to reduce their greenhouse gas emissions and promote sustainable energy industries. Wind energy has been a major area that has attracted strong investment among countries, with its installed capacity growing tremendously in the past few years [2], [3], [4]. The favorable wind conditions in Jordan have led to the development of several wind farms, including the Tafilah wind farm, which is the largest in Jordan, and the Fujeij wind turbines, which are the main focus of this paper. Figure 1 shows an example of wind speeds in Jordan as follows: A map of low, medium and high wind speeds at 50 meters above ground level, where the power output is proportional to the cube of the wind speed.

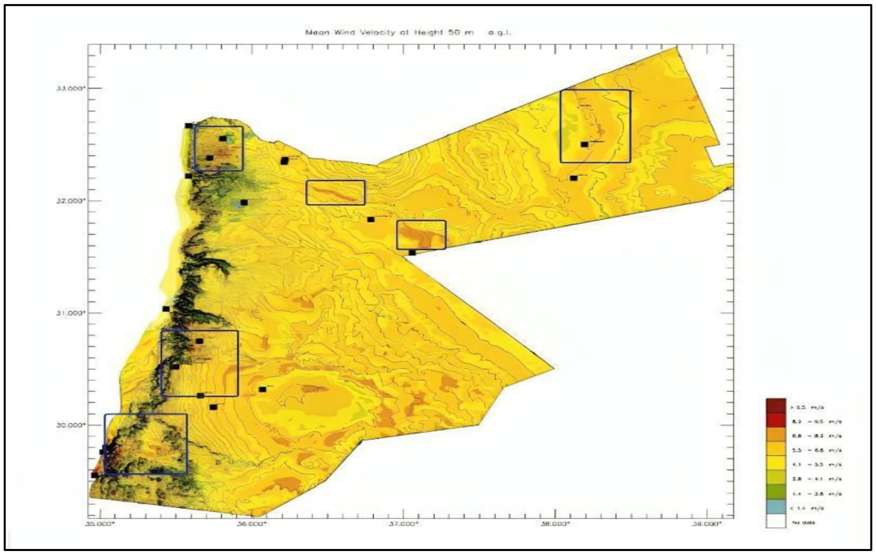

Figure 1: Wind speed map of Jordan [5].

One of the main drawbacks of wind power is its randomness, as wind flows cannot be predicted based on the weather conditions in the area where the wind turbine is located. Overcoming these challenges requires highly complex grid management, practical backup systems, and advances in energy storage. Among the approaches worth considering are the development of new forecasting techniques, flexible management and policy to ensure grid efficiency, and the invention of more efficient storage technologies to enhance grid stability [6].

For smooth integration into the power system and balancing electricity supply and demand, wind energy forecasting is of utmost importance. This improves the stability of the power grid and also helps in efficient use of power generation and transmission resources and infrastructure. This may also contribute to lower operating costs and reduce dependence on other forms of power supply [7]. This may result in efficiency benefits of the system operation and decrease in the electricity cost. This paper focuses on the use of wind power as a source of electrical energy and more especially the use of wind turbines in power forecast. A number of literature reviews have been reviewed to look into the various methods and approaches that are adopted in wind turbine powerforecasting. The text mining technique has been employed to extract the pattern of publications in the wind power research field while the word segmentation has been used to determine the direction of future research in wind power. Other methods in wind power forecasting included in the literature review are neural and deep learning networks; other classifications of the deep learning technique involve [8].

The purpose of this paper is to improve the accuracy of wind energy forecasting using intelligent models and control models to integrate wind energy into power systems. With the increasing concern about climate change and the general process of transitioning to renewable energy sources, wind energy forms a framework. This type of energy is unpredictable because weather conditions play a major role in determining the amount of energy that can be produced and this type of energy poses many challenges in power grid management as well as the requirements of energy forecasting methods that can enhance the reliability of supply. The research uses the power of machine learning algorithms to forecast wind energy in order to improve the performance of the grid and reduce dependence on traditional electricity supply. Therefore, improving the accuracy of forecasting is not only a goal of the project that aims to increase the level of wind farm operation efficiency but also serves the great purpose of developing efficient and sustainable energy resources.

2. AL FUJAIJ WIND TURBINE

The "Capacity Building in Wind and Concentrated Solar Power (WECSP)" project was launched in 2011 after the signing of the project agreement (No. Europe Aid/129543/C/SER/JO) between the European Delegation in Oman, the Ministry of Planning and International Cooperation as well as the National Center for Research and Development, on 17 November 2010. The main objectives are development, analysis, installation, capacity building and piloting in the fields of wind and concentrated solar power. With financial support from the European Union, the main objectives of the WECSP project are to improve the capacity of the National Center for Research and Development, train staff in the fields of wind and concentrated solar power as well as educate university students. This work follows the technical support with the initial phase of the WECSP project from 2011 to 2014 Technical Support.

A. Objective of the Project

The main objective of the WECSP project is to implement the efficient and adequate use of other energy sources including renewable energy in Jordan. In particular, the project assists the National Energy Research Center (NERC) in guiding and coordinating the development and promotion of the strategic objective of the Government of Jordan on the use of renewable energy sources within the scope of the Jordan Renewable Energy Strategy 2007- 2020.

B. WECSP Project Site Location

The pilot wind and CSP plants, along with the test facility, are located at the Fujayj site in Shobak at an elevation of 1,270 meters above sea level, at coordinates 30.5720°N and 35.6240°E (WGS 84). This site is located approximately two hundred and twenty-five kilometers south of Amman, the capital of Jordan, and approximately one hundred and eighty kilometers north of the Sea of Aqaba.

C. WECSP Project Facilities and Plants

The following bullet points list the Facilities and Plants associated with this investigational project:

- Building: The facility was built with the support of the Ministry of Planning and International Cooperation to accommodate laboratories, classrooms and offices.
- The pilot wind farm: The EU-funded wind turbine system currently has a capacity of 1.0 MW and feeds the national electricity grid (medium voltage). This system consists of a 71-meter high wind mast, wind speed and direction measuring devices mounted on the top of the mast, and a medium voltage substation with an integrated control and braking system.
- The tenders for these facilities were completed by early 2013, and the supply contracts were awarded by NERC/NCRD. The final step involved in the overall program is almost complete in harnessing wind energy.

D. Installation and Operation of Reference Mast at Al Fujaij

As part of the project activities implemented by the Royal Scientific Society (RSS) and NERC under the WECSP project, a reference mast was constructed at the Fujeij site in the southern part of Jordan. This installation complies with the IEC 61400-12-1 standard of 2005.

A 1.65 MW wind turbine, part of the TWT-1.65 wind turbine family from the Spanish company MTOI, was installed at the Fujeij site. The two operating turbines have active step force control, variable rotor speed, and a multi- pole variable speed synchronous generator connected to the grid using an inverter, producing an active power of 1650 kW. The turbine also has the ability to produce reactive power with cos Phi = 0.9 and capacitive as well as inductive. The generator is connected directly to the main shaft of the rotor without the need for a gearbox. The threeblade turbine rotor is located facing the wind (in front of the tower) and has an auxiliary deflection system in the structure to keep the rotor facing the wind. Furthermore, the rotor blades are equipped with tilt control systems in order to control the output power at rated levels above the rated wind speed. All functions are managed and controlled by the turbine control system and the turbine is 71 meters high and is made of tubular steel. The following Figure 2 shows the wind turbine in Al-Fujaij on site:

Figure 2: Al Fujaij Wind Turbine [9].

3. METHODOLOGY

This section provides a detailed description of the implemented procedure towards achieving the aim starting by highlighting the data description, explanation for the wind power forecasting using neural network, stating the how the model performance will be evaluated based on forecast accuracy:

A. Data description

Measurements taken at the Al Fujaij Wind Turbine have been obtained from the SCADA system in intervals of ten minutes. This data collection was initiated in November 2013 and up to August 2024 and this will be approximately 360,000 readings. The SCADA system constantly monitors different operational parameters and records them and hence offers a good opportunity to analyze wind turbine performance over this long period. The dataset is organized into the following columns:

- Year: The year of the measurement.
- Day: The day of the month.
- Month: The month of the year.
- Hour: The hour of the day.
- Minute: The minute within the hour.
- AF01WindSpd1: Wind speed measurement in meters per second (m/s).
- AF01AtPwr: Power output in kilowatts (kW).

Since the principal goal here is modeling, we proceed to randomly select 10,000 samples from our dataset for our cases. The data is then transformed to make it in the manner required by the neural network training, namely input and output. On the basis of the given attributes, it is attempted to forecast the wind power using neural network.

B. Wind Power Forecasting using Neural Network Artificial Neural Network is a model, and the main idea of construction of it is the imitation of the brain activity, which allows for making calculations significantly faster than possible by other means. ANNs are highly flexible tools as can be used in tasks such as clustering, classifying and even making predictions. In training process, the network uses already known patterns related with some problems in order to improve its performance and its ability to approximate. Generalization means the extent to which the network can be able to deal with new patterns that it has not been trained on. A specialized class of algorithms called the gradient descent is used in order to minimize errors and maximize the accuracy of predictions where necessary. Learning in ANNs is classified into supervised learning in which the training data is provided with labels which are used during learning and unsupervised learning system in which no labels are used.

Data Handling

The data was then imported and, in the beginning, this was done using the MATLAB built-in function, readable as shown below: The dataset was structured into two key variables:

- **inputData**: Includes the features Year, Day, Month, Hour, Minute, and Wind Speed.
- **outputData**: Comprises the target variable, Power Output.

Scalability issues associated with computational resources were also addressed by filtering the dataset down to the first 10 000 rows only. This subset is aimed at preventing the overloading of the training process while at the same time creating a big enough data set for training. The extracted data was then restructured to conform with the input layer of the neural network where by every row represented a feature and vice versa represented a sample.

C. Feedforward Neural Network

Feedforward Neural Networks (FNNs) are computational models defined in layered architecture. Such networks contain a large number of neurons placed in layers with connection between neurons via synaptic links (weights). Forward connection among neurons in a layer is done where each neuron receives interconnection from each of the neurons in the previous layer inclusive of the bias node that is considered as extra neuron. Neuron function entails transforming information received through connection weights The function of a neuron entails converting the information received by means of connection weights. Mathematically, the output yi of a neuron i is calculated as follows [10]:

$$yi = \emptyset i(\sum w^i z^i + b^i) \tag{1}$$

where n^i is the total incoming connections, z^i is the input,
w^i is the weight, b^i is the bias, and $\emptyset i$ is the activation function at the i-th node to limits the amplitude of the output the node into a certain range.

The underlying concept of design in an FNN is a function f(x,w) where x is a p-dimensional vector that is the input and w is an n-dimensional vector of weights thus representing a solution to a problem hence; the architecture of this FNN and weight vector must be learned during problem solving. Called the activation function, number of nodes, number of layers, and node topology are examples of the optimization process. The following Figure 3 represents the schematic diagram of FNN [10]:

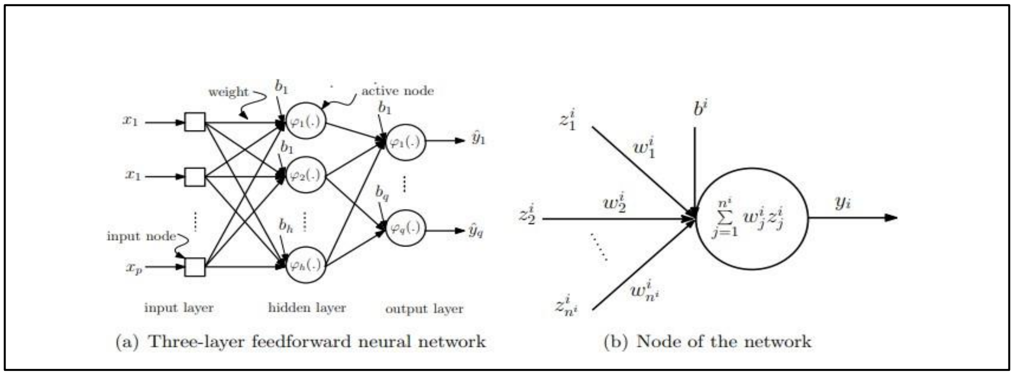

Figure 3: Schematic diagram of FNN.

D. NARX Network

The given structure of the NARX network consists of two parts of inputs. It supports high-speed network and has good generalization features and can be trained either in The so-called Nonlinear Autoregressive Network with xogenous Inputs or NARX model is very effective in the prediction of chaotic time series and therefore very suitable for the forecast of wind power. Implemented in real-valued signals rather than binary signals, this network uses delayed inputs and recurrent outputs, as well as dynamic and nonlinear components which make them learnable from trivial tasks beyond the applications of linear, or time invariant ones. NARX is implemented as a feedback recurrent dynamic neural network with multiple layers. Compared to other neural networks, its ability to learn time series data is more efficient because of improvements made to its gradient descent approach – making it more reactive series-parallel or parallel. Distinction between the modes: In series-parallel mode, an original output is directly reused as an input whereas in parallel mode only feedback output is used as input. For instance, let w(t) be the external input and s(t) be its output at any time instant t with the term 'ni' as the time delay in the external input. The network's output, s(t), is influenced by both the current and previous inputs w(t-i) and the prior outputs s(t-i), as illustrated in the formula [11]:

$$s(t) = f(s(t-1), s\ (t-2),.\ \ldots, s(t-n\_0), w(t-2), \ldots, w(t-n\_i)) \tag{2}$$

This makes it possible for the NARX network to self-adjust depending on both the input and output data making it more suitable in real life situations.

a. Back-Propagation Network

The back-propagation method is most important and commonly practiced in the field of Artificial Neural Networks (ANNs) especially for training in several areas. This method employs feed-forward network that consists of input layer, hidden layers, and output layer. The following is a simplified breakdown of the training process
[12] and [11]:

1. Forward Propagation:

- Inputs are provided to the operations of the network.
- Every hidden node determines the net inputs for the node through the addition of the weighted sum of the inputs and a bias,
  $z_{netj} = v_{oj} + \sum x_i\, v_{ij}$.
- Hidden nodes produce z_j in the form of applying an activation function most commonly the sigmoid function
  $z_j =$
  $f(z_{netj})$.

2. Output Calculation:

- Each output node calculates net input as the weighted sum of elements of the hidden layer plus a bias, $y_{netk} = w_{ok} + \sum z_j w_{jk}$.
- The final output y_k is derived by applying the activation function to y_{netk}.

3. Error Backpropagation:

- The error at each output node is determined by comparing the actual output $y_k$to the target output t_k, and computing the error.
- All weights and the biases are updated in an attempt at reducing the entire error with modifications made during the backpropagation stage.

By adjusting weights and biases randomly at the start and repeatedly through the calculation of the error a network is programmed to approximate the desired output for inputs given in the hope that the error will reduce through successive iteration.

b. Radial Basis Function (RBF) Network

Like most other models of neural networks, Radial Basis Function Neural Networks (RBFNNs) are based on the principles of function approximation. For these networks, the distance between the point where the evaluation is done and the center of each neuron defines the function of the radical base function that can be a kernel function or a Gaussian function. RBFs works out as localized receptors as their output is determined by how close the input is to a stored vector center.

In particular, at the surface, if the distance between the vector $x\rightarrow$ and the center $c\rightarrow$ of an RBF ϕj , denoted as ‖
$x\rightarrow - c\rightarrow i$ ‖, is equal to zero, the neuron activity is maximal
(1). As the distance rises, the impact lessens to zero, as characterized by the negative slope [13].

An RBF network is structured in three layers: an input layer, a hidden layer also called the feature extraction layer and an output layer also called the summation layer. The input layer could also incorporate several predictor variables, in which different variable is connected to one neuron. It transmits the input vectors to the hidden layer that consists of several RBF units – each with Gaussian kernels, and biases. The transformation performed by the j-th neuron in the hidden layer is non-linear, described by [14]:

derivative, $\delta_k = (t_k - y_k)f'(y_{netk})$.

- This error is then utilized to modify the weights from the hidden to the output layer, $hj(x) = exp(-\frac{\| x\rightarrow - c\rightarrow i \|^2}{2\sigma_j^2})$
$\Delta w_{jk} = \alpha\delta_k z_j$, and the biases, $\Delta w_{ok} = \alpha\delta_k$.

4. Error Propagation to Hidden Layer:

- The error term for each of the hidden node is determined by the weighted error, $\delta_{netj} = \sum\delta_k w_{jk}$.
where σj denotes the standard deviation of Gaussian
function located at $c\rightarrow$. In the output layer, the function
$yk(x)$ for the k-th output unit is calculated by summing the contributions of all the hidden neurons, weighted by their respective connections to the output neuron:

- Specific weights and threshold are updated using, $\Delta v_{ij} = \alpha\delta_j x_i$ and $\Delta v_{oj} = \alpha\delta_j$.

5. Weight Updates:

$$yi = \sum_{j=1}^{n_h} w_{kj}\, h_j(x) + b_k \quad (3)$$

where w_{kj} is the weight of the link between the j-th hidden unit and the k-th output unit and b_k is the bias. It, therefore, sums up and weighs the action potentials from the hidden layer before undertaking the final transformation to give the output of the network. Hence these biases are multiplied by their weights w and then summed so as to incorporate them into this summation to alter the final outcome.

c. ***Performance Evaluation of Forecast Accuracy*** The reliability of wind power output increases in those situations where decision makers can accurately forecast the levels of wind power. The forecasting model is based on the past data and the model is checked for its efficiency on the basis of test data. Actual observed values are used to compare with the forecasted values so as to determine the accuracy of the prediction. Commonly used metrics to evaluate forecast accuracy include the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE), defined as [15]: preprocessed and transformed into sequences with the help of preparets. This step is useful for modelling time-series data in NARX networks as needed Analysis of a given time series data is done through a time-delayed neural network.

The NARX network is then trained with these sequences in preparing the sequences, data normalization is employed as a pre-processing technique without which the network would not learn responses to inputs within the anticipated range. After training the network, the network is evaluated and the output matrix is transformed into cell format. In order to measure the accuracy of the model, MSE and RMSE are obtained. The RMSE value is shown and after completion of the training the actual outputs as well as predicted outputs for NARX network are shown graphically.

J. Back-Propagation Neural Network

$$RMSE = \sqrt{\sum_{i=1}^{N} (y_i - \hat{y})^2 / n} \tag{4}$$

A Back-Propagation Neural Network is developed through feed forward neural network design function feedforwardnet() with a training function of ‘trainlm’ representing Levenberg-Marquardt optimization. The work uses a network with 10 neurons in the hidden layer and other parameters of training which include epochs,

where $y(t)$ denotes the actual values, $y'(t)$ the forecasted values, and N the total number of forecasts used for the evaluation.

d. Feedforward Neural Network

In the following section, the feed forward neural network is developed which is a part of MATLAB’s neural network tool-box and created by feed forward net () function. It defines hiddenLayerSize, which sets the number of neurons in the hidden layer to a number of 10 and has one hidden layer only.

The training of network occurs on the prepared inputData and the outputData using the train function. Finally, during the testing phase, the actual output data is compared with the predicted outputs or results which in this case is referred as the predictedOutput. To calculate the MSE, the perform function is used when the RMSE is obtained from the obtained MSE. The value of RMSE is shown to measure the exactness of the network. Further, a plot is created to display the actual and predicted power output where the actual is marked as blue and the predicted as red color.

e. NARX Neural Network

The code then trains a Nonlinear Autoregressive Network with Exogenous Inputs (NARX) with the narxnet function. This network also contains delay of input delay and feedback delay which are denoted as inputDelays and feedbackDelays. There is a network brought in with ten neurons in the hidden layers. In training data is error goal and learning rate among others. The network is trained with the use of train function with the inputData and outputData. After the training process, estimation values are produced and then the results can be compared with the real values. Following the model construction, the MSE and RMSE are generated for analysis. Then, the RMSE shows the difference of inputs and the accurate outputs, and a plot for actual and predict results is drawn.

K. Radial Basis Function (RBF) Network

Last of all, a Radial Basis Function (RBF) Network is designed using the newrb function. The RBF network is constructed with spread parameter set to be equal to 10. This is based on the value of zero for the second term of width of the radial basis functions, which is desirable to achieve a value of 0. 0 as the level of mean square error we want to achieve, and maximum of fifty neurons in the hidden layer. When the above mentioned inputData and outputData are used, the network is trained and tested with the selfsame data. The predictions are as a result assessed via the MSE and the RMSE. Finally, the RMSE of the model is shown and there is a plot to visualize the actual and predicted values of the RBF network.

E. Results

This work aims to compare and contrast different neural network architectures that aim to predict wind power output based on historical data. The models discussed here are feedforward neural network (FNN), nonlinear regression neural network with external inputs (NARX), back propagation network (BPNN), and radial basis function (RBF) network. The performance of these models is evaluated based on two evaluation metrics: root mean square error (RMSE) and mean absolute error (MAE). Below, as shown in Figure 4 to Figure 7, we explain the results and significance of each model.

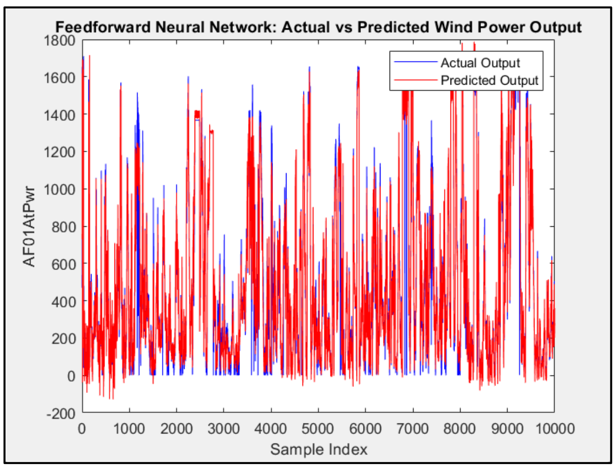

Figure 4: Feedforward neural network: Actual vs predicted wind power output.

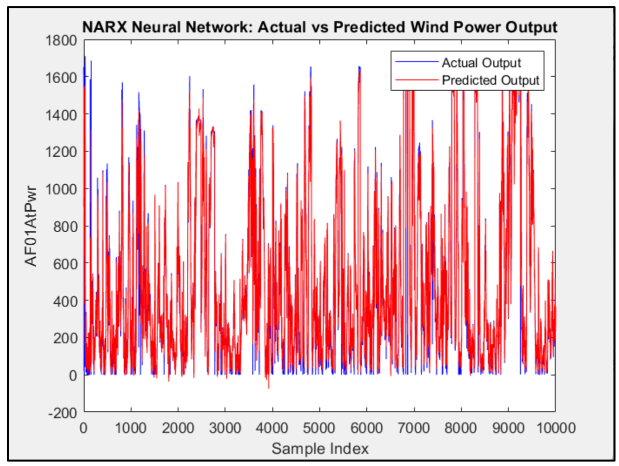

Figure 5: NARX network: Actual vs predicted wind power output.

The Feedforward Neural Network also performs the best as manifested by the lowest RMSE and MAE values among the models used in this study, thus showing that the model is accurate in predicting wind power output. The RMSE of 92.27 suggests that, on average, the forecasts deviate from the actual values by around 92.27 units, which is about 5.6 percent of the total range of the data, which range from 0 to 1650. The MAE of 45.10 implies that the average absolute error covers approximately 2.7% of the data range. This indicate that the FNN model is best suited for the wind power forecasting since it is able to describe the patterns in the data set better that the other models considered in this paper.

This work has utilized a NARX network where past outputs are used as feedbacks for future predictions and the results demonstrate a higher RMSE and MAE compared with FNN. The RMSE of 117.08 and MAE of 66.10 indicate that the NARX model can capture some dynamics in wind power output, but it is less accurate than the FNN. The higher error values may suggest that the feedback mechanism brings additional complexity that the model is unable to completely manage, resulting in increased prediction mistakes.

Back-Propagation Neural Network performs slightly worse than FNN but better than NARX and RBF models. With an RMSE of 94.12 and an MAE of 49.35, the BPNN's prediction accuracy is equivalent to the FNN's, albeit with slightly greater error margins. This shows that while the BPNN is excellent at capturing underlying patterns in the data, it may not generalize as well as an FNN. While theback-propagation technique is effective, it may have limitations when dealing with wind power data that is nonlinear and complex.

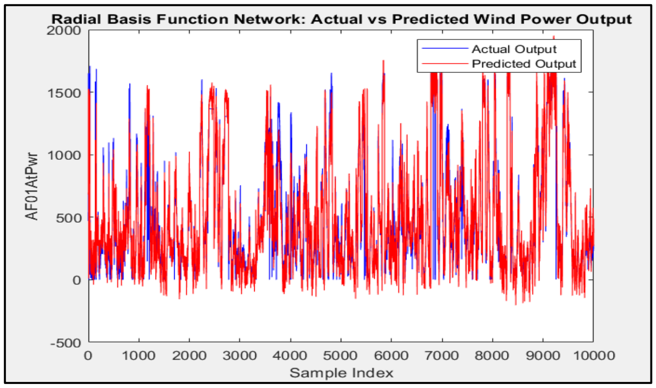

Figure 6: Back-Propagation Neural Network: Actual vs predicted wind power output.

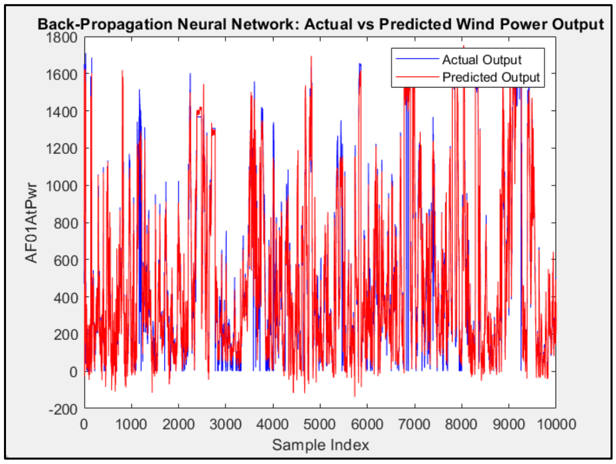

Figure 7: RBF network: Actual vs predicted wind power output.

Of all the models used when dealing with non-linear data through radial basis function, the RBF network exhibits highest error rates with the RMSE of 115. 74 and the MAE is 71. 85. These values reveals that the RBF network performed poorly in the sense that it did not accurately estimate wind power output which is unlike the other models.

a. Comparison and Best Model Selection

Looking at the results in the evaluation of RMSE and MAE, Feedforward Neural Network performs more efficiently than the other two models for all the intervals. It is the simplest of all the architecture types, and because of that, and thanks to the ability that shows it can model the input features and the wind power output accurately, is the most appropriate model for the job. The Back-Propagation Neural Network too gives a good performance, but the FNN has better performance than the B-PNN. As stated earlier, since NARX network is capable of modeling dynamic systems, the use of feedback networks does not lead to enhanced accuracy, which may be as a result of complications arising from feedback systems. Finally, the RBF network that for its nature is more capable of dealing with non-linear data type performs the worst thus making the entire experiment suggest that the RBF may not be ideal for this particular data set or experiment.

The following table comparing the performance of different neural network models based on Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics:

Table 1: RMSE and MAE values of models.

Model	RMSE	MAE
Feedforward Neural Network (FNN)	92.27	45.10

Nonlinear Autoregressive with Exogenous Inputs (NARX)	117.08	66.10
Back-Propagation Neural Network (BPNN)	94.12	49.35
Radial Basis Function (RBF) Network	115.74	71.85

The Table 1 highlights that the Feedforward Neural Network (FNN) performs the best with the lowest RMSE and MAE values, indicating its higher accuracy in predicting wind power output compared to the other models.

Conclusion

In conclusion, a realization of this paper points to the fact that machine learning algorithms have a substantial prop as far as increasing the predictability and hence the addressability of wind power is concerned, a key element in the global transition to sustainable power. Based on the active experimentation of different kinds of neural network models and through the examination of the discovered results, this paper has shown that machine learning is not only a feasible method in solving the highly-volatile nature of wind energy but also significantly contributes to the incorporation of this type of renewable energy into power systems. Feedforward Neural Networks (FNNs), Nonlinear Autoregressive Networks with Exogenous Inputs (NARX), Back-Propagation Neural Networks, and Radial Basis Function (RBF) Networks which were adopted yielded deep understanding into the behavior as well as reliability in the forecast of wind power.

Based on the results of the tested models, the Feedforward Neural Network (FNN) performed superb, it provided the least error rate compared to the other models hence provided accurate wind power. This shows that the FNN is indeed capable to address the challenges relating to the wind power data and provides an efficient and practical tool for the energy sector stakeholders to predict and plan the wind generated power supply. On the contrary, both the NARX and Back-Propagation models were slightly less accurate but they also predict the values with reasonable accuracy expected from simpler models such as FNN and it can also be seen that simpler models can be more accurate most of the time depending on the data characteristics and the requirements of the forecasts.

Moreover, mixed results were gotten from the last type of Neural Network known as the Radial Basis Function (RBF) Network, despite its capability of dealing with their non- linear data. This result indicates that the kind of architecture and cost optimization in the network might representations, and probably, this model needs to be fine- tuned in order to meet up with the challenging nature of wind energy data. This paper not only brings the knowledge addition to the existing knowledge repository of the academics and researchers but also offers solution-oriented findings, which can be used, specifically for improving the operations of wind farms. Even a small enhancement in wind power prediction will help utilities balance the supply and demand aptly to reduce cost and thereby limit the usage of other energy types that pollute the environment. Further research could analyze how such hybrid models that include the benefits of various neural networks could be utilized in the future as well as analyzing the effectiveness of more complex machine learning algorithms with a possibility to enhance the precision of estimations of wind power.

References

[1] M. A. Hanif, F. Nadeem, R. Tariq and U. R "Renewable and Alternative Energy Resources," Aca Press, 2021. Information Engineering: Springer Berlin Heidelberg 2, pp. 553-558, 2012.

[2] S. R. Sinsel, R. L. Riemke and V. H. Hoffmann, "Chall and solution technologies for the integration of va renewable energy sources—a review," renewable e vol. 145, pp. 2271-2285, 2020.

[3] A. Razmjoo, L. G. Kaigutha, M. V. Rad, M. Marzban Marzband, A. Davarpanah and M. J. R. E. Denai, Technical analysis investigating energy sustaina utilizing reliable renewable energy sources to reduce emissions in a high potential area," Renewable Energ 164, pp. 46-57, 2021.

[4] A. Qazi, F. Hussain, N. A. Rahim, G. Hardaker Alghazzawi, K. Shaban and K. Haruna, "To sustainable energy: a systematic

review of renewable e sources, technologies, and public opinions," IEEE app. 63837-63851, 2019.

[5] M. o. E. a. M. Resources, "wind map of jordan," 1 9 online https://www.memr.gov.jo/ebv4.0/root_storage/en/eb_l age/wind_map_of_jordan.pdf.

[6] K. T. Ateş, "Estimation of short-term power of wind tu using artificial neural network (ANN) and s intelligence," Sustainability, vol. 15, no. 18, p. 13572.

[7] W. H. Lin, H. W, P. Wang, K. M. Chao, H. C. Lin, Yang and Y. H. Lai, "Wind power forecasting with learning networks: Time-series forecasting," A Sciences, vol. 11, no. 21, p. 10335, 2021.

[8] F. Ekinci, T. Demirdelen and M. Bilgili, "Modelling of turbine power output by using ANNs and A techniques," In 2017 Seventh International Conferen Innovative Computing Technology (INTECH), pp. 126 2017.

[9] T. N. E. R. C. (NERC), "Wind Projects," 8 2024. [Online Available: http://www.nerc.gov.jo/EN/List/Wind_Proj

[10] V. K. Ojha, A. Abraham and V. Snášel, "Metahe design of feedforward neural networks: A review o decades of research," Engineering Applications of Art Intelligence, vol. 60, pp. 97-116, 2017.

[11] P. Senthil Kumar, " Improved prediction of wind speed machine learning," EAI Endorsed Transactions o Energy Web, vol. 6, no. 23, 2019.

[12] J. Li, J. H. Cheng, J. Y. Shi and F. Huang, "Brief introd of back propagation (BP) neural network algorithm a improvement," In Advances in Computer Science.

[13] J. Ghosh and A. Nag, "An overview of radial basis fu networks," Radial basis function networks 2: new adv in design, pp. 1-36, 2001.

[14] G. A. Montazer, D. Giveki, M. Karami and H. Ras "Radial basis function neural networks: A review," Co Rev, vol. 1, no. 1, pp. 52-74, 2018.

[15] T. Chai and R. R. Draxler, "Root mean square error (R or mean absolute error (MAE)," Geoscientific development discussions, vol. 7, no. 1, pp. 1525-1534,