A REVIEW ON ARTIFICIAL NEURAL NETWORK MODELS FOR SHORT TERM WIND POWER PREDICTION

Joseph N. Mathenge [1], D.K Murage [2], J.N Nderu [3] and C.M Muriithi [4]

***Abstract* —** There has been a growing global need to develop tools or models that are able to perform accurate wind power prediction in a power system. This arises from the fact that modern day power systems have inclined towards using renewable sources of energy; key among them being solar and wind. On one hand, solar power is relatively predictable and easily dispatchable while on the other hand, wind power is highly variable and intermittent hence making it have limited dispatchability. Current research is geared towards developing tools that can easily and accurately predict the short term wind power expected and hence make it a dispatchable resource. There have been many algorithms developed by researchers across the world to do short term prediction of wind power. However, one tool still remains supreme among all and that is the artificial neural network. This is due to its learning ability. This paper reviews the use of artificial neural networks in short term wind power prediction. The aim is to achieve accuracy that shall make wind power a fully dispatchable resource to ensure power systems gain from this free resource.

***Keywords*—** Artificial Intelligence, Artificial Neural Networks, Short Term Wind Power Prediction.

I. INTRODUCTION

THE adoption of the Kyoto Protocol in 1997 ignited a shift in the focus of countries from fossil fuels to renewable energy sources thus opening up one of the biggest research areas in science. The technology around renewables has and is still growing at a very high rate, something that has seen the developed as well as the developing nations embrace renewables more and more [1]. Wind has been the most widely accepted renewable energy source to be adopted by many power systems around the world [2]. Currently, the bulk of energy requirements in the world comes from fossil fuels and these are getting depleted at a very fast rate. On top of that they also have a huge negative impact on the environment in terms of their carbon footprint. These are among the reasons why the world is inclining towards investing in renewable sources of energy.

Wind energy is considered to be among the most economical sources of energy considering the fact that no fuel cost is incurred since wind occurs freely in nature. Due to its intermittent nature however, integrating it into the grid poses great challenges. This brings about the need for the development of highly accurate prediction methods to ensure reliability of the power system [3]. The prediction problem can either be a short term problem, medium term or a long term problem. The solution selected to solve this problem is also dependent on the time frame in question.

The most important among these for power system operators is the short term analysis since this allows power system operators make critical decisions about the running of the grid. The predicted output is compared with the actual output from a wind turbine or a wind farm and if the results are agreeable within a given margin of error then the method is considered accurate. In mature grids, power marketers are surcharged in the event that they underrate or overrate the quantity of wind power that shall be injected to the grid at any one time [1].

In this paper, the use of neural networks in short term wind prediction is critically analyzed to determine its effectiveness and how previous researchers have been able to enhance the tool.

II. REVIEW

A. Forecasting Time Horizons

There are four forecasting time scales according to S.M Lawan et.al, 2014 [4] as presented in Table I below:

Time Horizon	Range
Very short-term	Few seconds to 30 mins ahead
Short-term	30 mins to 6 hours ahead
Medium-term	6 hours to 1 day ahead
Long-term	1 day to 1 week or more ahead

Table I: Wind Prediction Time Scales

The most popular time horizon with researchers and power system operators is the very short term and the short term horizons. Both of these time horizons of interest are greatly involved in electricity market clearing as well as dispatch of wind power. Time is of the essence when it comes to working with short horizons and the method chosen to solve this problem should provide optimal solutions with minimal computation times. For the results to be acceptable, the predicted values of wind power need to be really close to the actual values to ensure efficient running of a power system with significant wind power penetration.

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B. Forecasting Methods

There are four categories of wind speed/wind power forecasting:

- Persistence model – This was the pioneer model to be used in the wind speed/wind power prediction problem. It has been used as a benchmark from which all other developed models have to be compared to in order to establish their effectiveness. The persistence model assumes that the wind speed at time t = t+x is the same as wind at time = t. This argument only holds for very short term predictions. As the time frame of interest increases the accuracy of the persistence model reduces [4].
- Numerical Weather Prediction (NWP) model – This is mainly dependent on meteorological data for its accuracy. It is also referred to as the physical model of wind speed/power predictions. Its inputs are normally weather parameters that affect the wind speed at a given area. It involves complex mathematical models and hence have high computational times.
- Statistical model and ANNs – Are mainly used for short term prediction problems. They are easy to understand since they use the black box approach unlike the difficult mathematical models in NWP model. Mostly, historical wind power data alone is sufficient for use in this model. The more variables the data has, the better the relationship drawn between the inputs and predicted output and hence better performance of the model.
- Hybrid models – These involve the use of two or more models with the aim of solving a prediction problem. A statistical model can be used in conjunction with a physical model, combination of one model that solves the short term problem and another solving the medium term problem, combination of statistical models among many other hybridization forms that can exist. The level of hybridization is only limited by the creativity of the researcher.

ANNs have been widely used in prediction models for power systems and in other fields due to their learning ability – something that makes neural networks stand out when compared to any other tool. This paper focuses on reviewing the performance of ANNs in wind speed/wind power predictions in grids globally.

C. Artificial Neural Network (ANN):

ANNs are a non-linear mapping architecture that borrow from the neurons structure and operation of the human brain. The ANN is a robust tool of prediction, more so, for situations where data relationships are unknown and are seeking to be established. The forecasting of wind speed is such a problem. The relationship between one wind speed and the next is a non-linear function that cannot be accurately predicted. ANNs learn from any correlated patterns that are observed in the input data sets and set target values. As a result of this pattern, it is able to forecast the next expected outcome based on the input data sets and target values.

Training an ANN allows it to be used to predict the outcome of new independent input data. ANNs mostly deal with data that is considered vague and noisy which at times changes erratically. Hence, they are ideally suited for modeling of a wind power data prediction tool since such data is complex and often non-linear [5]. Neural networks perform pattern matching tasks that have a large number of highly interconnected nodes. This interconnection of neurons, just like in the human brain, gives ANNs the ability to learn and generalize training patterns from the training data. This strong learning capability of ANNs is the main advantage that makes it the best tool for use in wind speed prediction in a power system.

The structure of a neural network consists of three layers:

i. Input layer
ii. Hidden layer
iii. Output layer

The input layer accepts the input data to the ANN. This data is referred to as training data, or the simulation data. The hidden layer (or layers) is where modification and manipulation of the inputs takes place. It gives the neural network the ability to generalize the training data that is fed into it. Also, the interconnection of the neurons is defined in this stage. It is the hidden layer that determines the quality of the solution provided by the neural network. The final layer is the output layer and this gives a single output from the ANN.

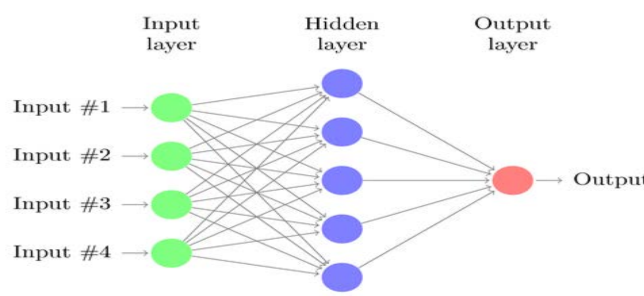

Fig. 1. Architecture of an ANN [5].

D. Previous Research

The history of ANNs dates back to 1959 when Rosenblatt introduced the single layer perceptron network. This would later be improved in 1962 by Minsky and Papert who introduced the multilayer perceptron network after proving the inadequacies of the single layer perceptron network. To date, the multilayer perceptron (MLP) network is the most common [6]. In 1968, Rumelhart et al introduced the back propagation network (BPN) for use in training of the MLP model. BPN provides a very efficient method of updating the weights of the neural network and this is key to ensure the accuracy of the ANN. A schematic of the BPN is as shown in Fig. 2 below:

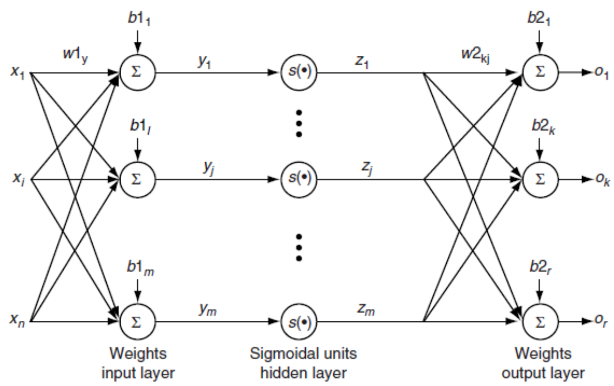

Fig. 2. Schematic of a BPN [6].

Other neural network models that have been developed are the radial basis function network by Powell in 1985 and the recurrent neural network by Elman in 1990. They have both been proved to have excellent performance in dealing with non-linear approximation problems [6].

The output of a wind turbine is given as [7]:

$$P_{wind} = \frac{1}{2}\sigma A v^3$$

Where:
σ – Air density in kg/m^3
A –Swept area of the wind turbine/Cross section area of the turbine
v – Upstream wind speed

Variables that fall under inputs to wind prediction tools fall within the range of parameters that affect generation from wind plants. They include: air density, wind speed, humidity, amongst other variables. Accuracy is analyzed based on the ME, MSE, MAE, RMSE, comparison with the persistence model etc. to establish how the proposed system performs based on the actual values of wind power and comparatively with other prediction tools. ANNs can either be used alone, in a hybrid state or in conjunction with other algorithms.

In 2006, C. Potter and M. Negnevitsky implemented an ANFIS model for use in wind power forecast in Tasmania with wind speed and wind direction as the inputs [8]. The results obtained gave an error of 4% and were limited to accuracy within a 2.5 min ahead forecast only. When the same data was analyzed using persistence, a 30% error was observed hence showing the robustness of a hybrid form of neural networks (ANFIS).

In 2007, a recurrent fuzzy neural network was developed by Barbounis and Theocharis [9] to perform multistep forecasts from 15mins to 3 hours ahead. The combination of fuzzy and neural networks was observed to improve the results obtained. ANFIS combines the advantages of fuzzy and neural networks hence giving more accurate results with reduced computation times. Palomares *et al* in [10] compares the performance of the ARIMA and neural network models. The back propagation model with Levenberg Marquardt training comes out as more powerful compared to the ARIMA model. It, however, consumes more computation capacity in form of memory.

The neural network was coupled with the Markov chain model in [11], by Pourmousavi in 2011, for very short term wind prediction achieving a MAPE of 3.1439. The persistence model posted a MAPE of 3.6821 for the same data set. Again, it is observed that modifying neural networks with the Markov chain further improves its performance in short term wind power prediction.

In 2016, Vijendra Singh [7] used a feed forward neural network with supervised learning using back propagation is used. The ANN structure used is shown in Fig. 3 below:

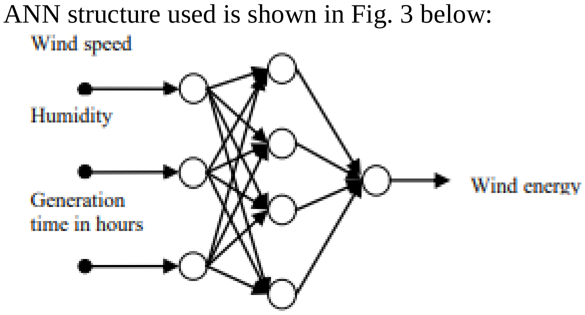

Fig. 3. Feed Forward Neural Network Proposed by [7]

Training of the network was done in batch mode in ranges from 10 mins to 60 mins. The MSE was set at 0.0001. After 300 iterations, the MSE stabilized at 0.0070 hence proving that the ANN used alone is a powerful prediction tool. It was observed that as the forecast period increases from 10 mins to 60 mins, the error grew hence confirming that ANNs are better suited for short term predictions.

In 2016, Hasan Masrur in [12] used hourly wind mean data for prediction. Using the nntool in MATLAB with the Levenberg-Marquardt feed forward back propagation. Various scenarios were tested and gave a MAPE of between 1.1 and 13.7. According to the MAPE criterion of determining precision, a MAPE value of less than 10% indicates high prediction, 10%-20% good prediction and over 50% inaccurate prediction. From the MAPE values obtained by [12], the neural network can again be confirmed to be a good tool for short term prediction.

ANFIS in wind power forecast was compared with Genetic Algorithm Back Propagation Neural Network and ANNs in [13] and results in Table II were noted:

Criterion	ANN	GA_BPNN	ANFIS
MAE	31.87	29.14	28.39
MAPE	5.86	4.59	4.45
RMSE (kW)	48.45	46.83	46.06
MSE (kW)	2346.87	2192.35	2121.5

Table II: Results of a comparative analysis of ANFIS, ANNs and GA-BPNN in short term wind power prediction.

The robustness of ANNs both in its original state and in hybrid form is noted. The values of errors obtained in the three methods being compared are in the same neighborhood of each other. However, it is noted that hybrid forms of ANNs perform comparatively better.

In [14], research is done on the accuracy of neural networks in wind power prediction by testing three different scenarios as shown in Fig.4 below:

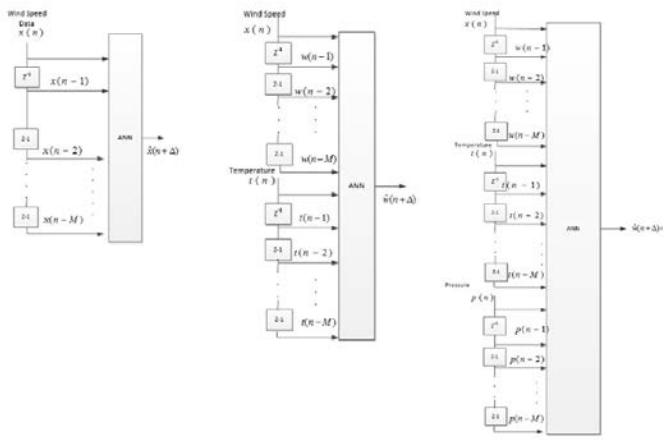

Fig. 4: Scenario 1 – Wind speed data only, Scenario 2 – Wind speed and temperature data, Scenario 3 – Wind speed, temperature and pressure data [14].

For each scenario, the RMSE and MAE values were computed for forecast lead time, Δ of 30 and 90. The results obtained are as tabulated below:

Forecast lead time, Δ = 30		
Scenario	RMSE	MAE
1	0.6508	0.5046
2	0.6502	0.5040
3	0.6494	0.5032

Table III – RMSE and MAE performance for three scenarios in [14] with forecast lead time Δ = 30.

Forecast lead time, Δ = 90		
Scenario	RMSE	MAE
1	0.6940	0.5537
2	0.6903	0.5470
3	0.6759	0.5360

Table IV – RMSE and MAE performance for three scenarios in [14] with forecast lead time Δ = 90.

It can be noted in Tables III and IV that the performance of scenarios 2 and 3 outperform the results obtained for scenario 1. This serves to prove that in as much as the neural network is a powerful tool, there is also the need process the data being fed into the network more. The more shallow or limited the data fed into the neural network is, the less accurate the solution obtained as is observed in scenario 1. When more variables that affect wind speed are introduced, the solution becomes more optimal since the neural network is able to draw more relationships from the more information fed into it.

The results reviewed above are just but samples in a huge matrix of research that has been done to determine the robustness of neural networks in wind speed and wind power predictions across the globe. In a review by [6], neural networks are seen to have been used for the last two decades in solving the wind forecast problem with great success. ANNs post more accurate results, competitive computation times, and minimal errors compared to non – ANN models. When hybridized or used in combination with other superior models, the results are improved with better accuracy and reduced computation times [6].

III. DISCUSSION ON PERFORMANCE OF ANN MODELS

Neural network models have proved to be very robust tools in handling non-linear problems. Wind forecasting is a non-linear problem and neural networks have posted very significant success in solving it. Optimal solutions have been obtained using ANNs alone and even better solutions obtained when the ANN is hybridized or used in conjunction with other superior algorithms. Neural network models are seen to have very competitive computation times, accurate results with minimal margins of error and proves that wind speed and wind power can be predicted in advance for use in optimizing power system operation and planning.

The approach that the neural network is employed in to solve the wind forecast problem is only limited to the imagination of the researcher. A lot of work can still be done using this robust tool by improving its performance through hybridization or combination with other tools to improve the results further. In addition to this, pre-processing of data before feeding it into the neural network model is a great determinant of the performance of the model. As is the case with any computer system, the garbage in-garbage out principle still applies here. If the input to the model is flawed, the neural network shall draw wrong connections in the data leading to an output that is not optimal.

IV. CONCLUSION

Bulk wind power injection into the grid has brought to the spotlight the importance of prediction tools in power systems. No other source of energy has ever given power system operators a more difficult time to integrate into the grid than renewables with stochastic nature. The wind harnessing technology has matured since its inception and prediction tools are becoming better by the day with minimal computation times and accurate results with smaller margins of error. Wind is bound to be converted from a non-dispatchable resource to a dispatchable resource with precise forecasts and planning making grids across the word benefit from this free resource.

V. REFERENCES

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