


Intelligent and Data-Driven Reliability Evaluation Model for Wind Turbine Blades

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ABSTRACT

Wind energy is generated via the use of wind blades, turbines, and generators that are deployed over a given area. To achieve a higher energy and system reliability, the wind blade and other units of the system must be designed with suitable materials. In this paper, however, a computational intelligent model based on an artificial neural network has been proposed for the evaluation of the reliability of the wind turbine blade designed with the FRP material. The simulation results show that there was a reduction in the training mean square error, testing (re-training) mean square error and validation mean square error, when the number of training epochs is increased by 50% such that the minimum mean square error and maximum mean square error were 0.0011 and 0.0061, respectively. The low validation mean square error in the simulation results implies that the developed artificial neural network has a good accuracy when determining the reliability and the failure probability of the wind turbine blade.

KEYWORDS

Artificial Neural Network, Failure Probability, Fatigue Reliability, FRP Material, Wind Turbine Blade

1. INTRODUCTION

Wind, which is a limitless and a clean energy source (renewable in nature), is one of the oldest alternative source of energy. It has been described by energy researcher as one of the most reliable energy resources ever discovered (Pffaffel et al., 2017), a renewable green energy and harmonious to environment, since it neither consumes fossil fuel nor makes dirty atmosphere (Jiang et al., 2017; Oyedepo, 2012).

This renewable green energy which can be realized via the use of wind blades which can be connected to a turbine and a generator, is deployed over a given area for the purpose of generating electrical energy (Periola & Aikhuele, 2021). In generating the electrical energy, the wind blades of the system are made to turn by the forces of nature (wind), such that it generates a kinetic energy which then fires the turbine to generate the electrical energy output via the generator. The wind blades and the turbine used in the system, are deployed in arrays which usually covers a large geographical area (Aikhuele et al., 2019). This is done with the aim of intercepting the wind at a significant number of points thereby generating a significant electrical energy output. In this manner, wind renewable

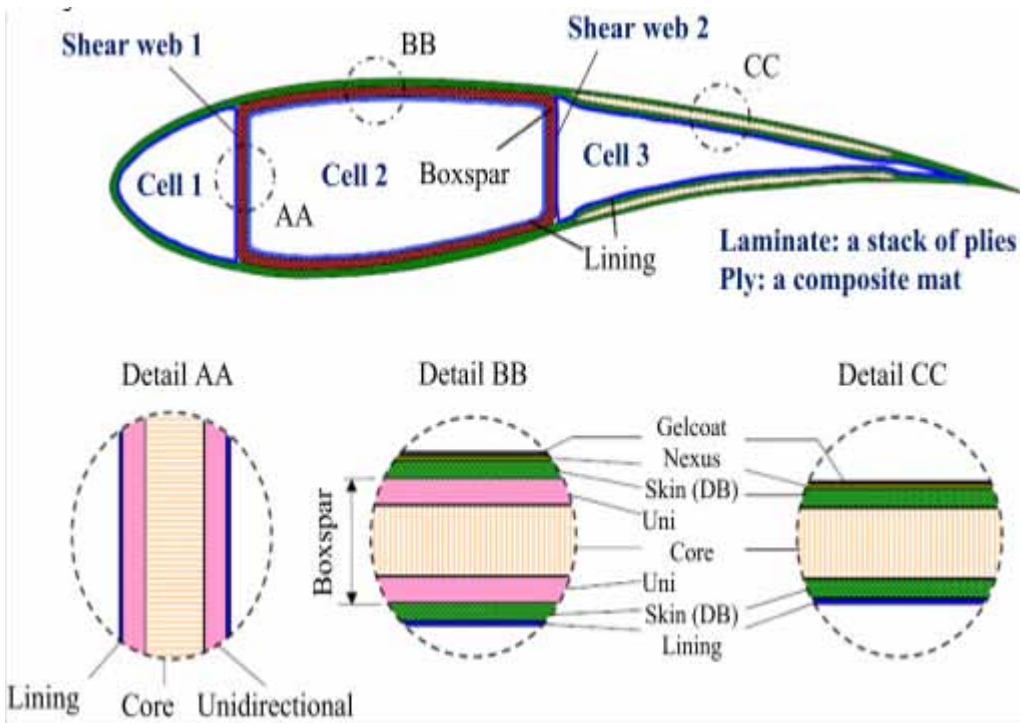
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energy systems are aimed to take advantage of the diversity in wind speeds at different epochs over a given area using the wind blades. To achieve a higher efficiency rate of the wind blade, suitable materials must be chosen for the design and development of each of the units of the system. Figure 1; describe a schematic diagram of a wind blade which consists of layup of a composite material used in various regions of the system.

Figure 1. Schematic diagram of a wind turbine blade (Wang et al., 2016)



Composite materials especially the fibre reinforced plastic (FRP), which have found application recently in the design and development of turbine rotor of the Boeing 787 Dreamliner (Milberg, 2015; Nicolais et al., 2011), is one candidate that can be used in the design of wind turbine blade (Mishnaevsky et al., 2017; Schubel & Crossley, 2012). To fully take advantage and control of the material for the wind turbine blade design and for other engineering purposes, it is important therefore that the reliability of the wind turbine blade designed with this material is adequately studied and investigated. Although, the attractive characteristic of the FRP, particularly its physical and mechanical properties, some of which includes, its high strength and stiffness, low weight characteristic, high durability, damping property, resistance to corrosion, fire and wear, has been studied extensively in literature, and has made it one of the most sorts after material for engineering design (Aikhuele, 2019; Mohammed et al., 2015). The complete benefits of the FRP material for the design of wind turbine blade however, cannot be fully realised in practice, where this is due to the conventional safety factors issues which normally arise as a result of lack of understanding of the uncertainties associated with the material, which research have shown could affect its overall performances.

Uncertainties in FRP components exist at several scales or levels, as such they interact with one another. Some of the scales or levels include; the micro-scale (e.g. bonding of matrix and fibre,

volume ratio, matrix voids, cracks), the ply level (e.g. fibre alignment, thickness) and the component level (e.g. curing, geometry) respectively (Sriramula & Chryssanthopoulos, 2009). Predicting fatigue damage and failure probability due to uncertainties from material properties, operation-ability, manufacturing and external load in wind turbine blade is not an easy task. Although, some authors, have contributed to the uncertainties study of FRP and that of the wind turbine system, however there are some research gaps that still need to be filled in this study area. These gaps, however, have been extensively reviewed in (Hu, 2015; Hurley, 2015).

Some of the research contributions that have been reported include, the probabilistic model developed for the analysis of safety in the wind-turbine rotor blade against fatigue failure by Ronold et al., (1999). The fuzzy inference based model developed for optimizing the performance and for harvesting wind energy by controlling the pitch angle which adjusts the speed of the generator of a wind energy harvesting system by Mitiku & Manshahia, (2018). A multi-scale analysis method developed for addressing and accounting for the effect of the micro-scale, ply and component material configuration in the FRP material by Corradi et al., (2017). The application of a dynamic Kriging (DKG) method (a surrogate uncertainty model) for the reliability design of wind turbine blade made with composite materials by Hu et al., (2016). And the development a fuzzy logic controller which is based on a maximum power point tracking, for the optimization of the wind power by controlling the speed of the generator in a wind energy harvesting system located in remote areas (Mitiku & Manshahia, 2019; Vasant et al., 2019).

Several other methods have also been applied in literature for the uncertainty study of the FRP and that of the wind turbine system, some of which include, models for addressing uncertainties due to material properties in the entire complex system (Ganesan et al., 2020), uncertainties in the wind power penetration and imbalance between generation and consumption (Badmasti et al., 2012), uncertainties due to operation-ability issues of the wind turbine system as reported in (Vasant et al., 2020, 2018), uncertainties in the manufacturing system (Zhang et al., 2019) and in the external load applied to the wind turbine system (Bacharoudis et al., 2015; Odofin et al., 2017).

From the reviewed literatures above, and from the future research work presented by Hu, (2015), it is not hard to see that, much attention have not been given to the wind turbine blade, which is one of the main component that allows for the generation of wind energy (Choubey & Baredar, 2020). Hence, the need to fill these research gaps, some of which include. The development of a turbine control model and an intelligent system for fatigue reliability analysis of the wind turbine blade with special consideration of uncertainties in the material properties, in the operation-ability of the system, manufacturing and external load uncertainties for the wind blade. To the best of my knowledge, no study has reported or has fully addressed or develops an intelligent model for the fatigue reliability analysis of the wind turbine blade. In this paper however, a computational intelligent model based on an artificial neural network have been proposed and presented for the evaluation of the fatigue reliability and failure probability of the wind turbine blade designed with the FRP material.

The study contributes to the fatigue reliability analysis of the wind turbine blade literatures, by presenting a new intelligent predictive model for its evaluation. The model, holistically captures, utilized and investigates the effect of several parameters including wind speed and turbine rotational speed to address a fundamental gap in the fatigue reliability and failure probability literature of the wind turbine blade. It is important to emphasize here also that, the model was able to take advantage of the big reliability data associated with this type wind turbine blade, which is used for the systems modelling.

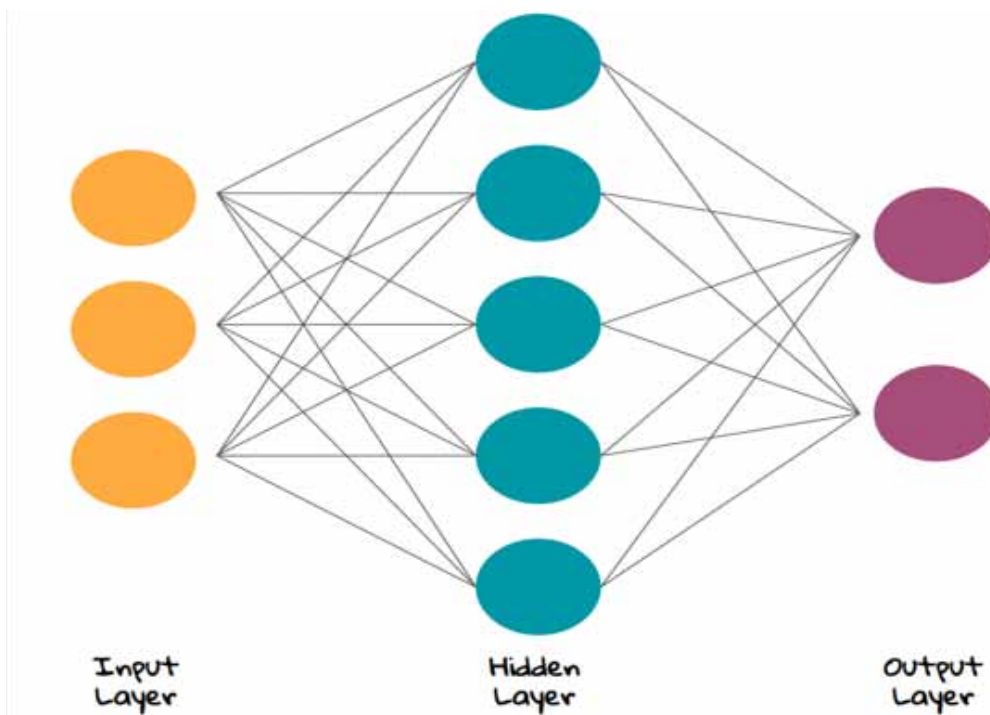
The remaining part of the paper is organized as follows; in section 2, the ANN model is introduced, this is followed by the implementation of the model in section 3, for failure probability and fatigue reliability damage evaluation of an actual Siemens industrial wind turbine of 3.6 MW rated power, which has a wind turbine blade that is designed with a FRP material. In section 4, a detailed managerial implication of the reliability-based model for the wind turbine blade is discussed, finally in section 5, some concluding remarks are presented.

2. ARTIFICIAL NEURAL NETWORK MODEL: AS A RESPONSE METHOD

Artificial Neural Network (ANN) is a computational model that works similar to the biological neurons of the human brain (Bullinaria, 2015). The model which can be trained and tuned such that they are able to make good decisions, allows information to be passed through the architecture of network, where such information are sensed, and then they learn, by adjusting the network to generate a good solution (Sildir et al., 2020).

ANN model are used for modelling non-linear statistical data with complex relationships between their inputs and outputs data (Ouma et al., 2020). Training the neural network is the process used to determine those complex relationships and patterns in the data set (Işığışık et al., 2020). A typical ANN model architecture (see Figure 2) can exist in, either of the following forms; as a feed-forward neural network, recurrent neural network, regulatory feedback neural network or radial basis neural network etc. (Abbas et al., 2015; Boutaba et al., 2018).

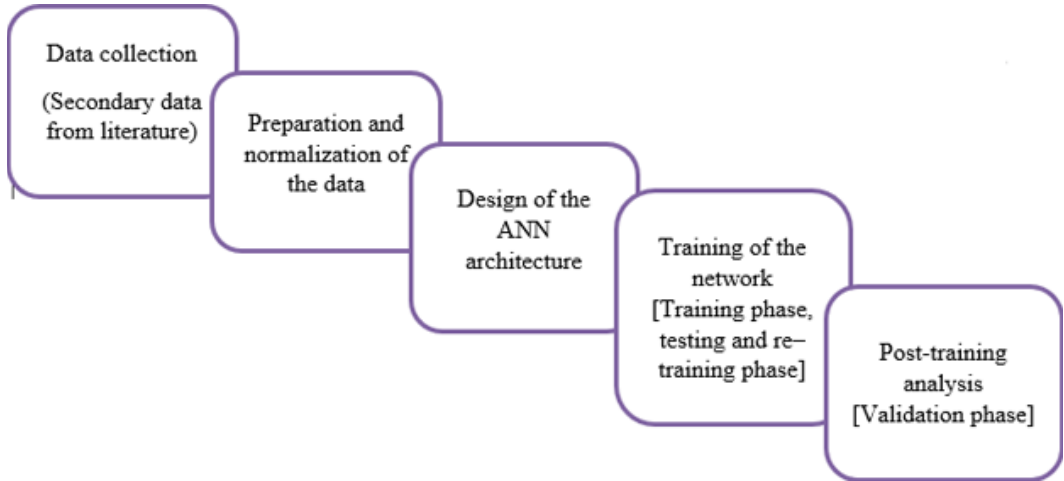
Figure 2. A typical ANN model architecture



When information are passed through the architecture of ANN model, they starts from the input layer and end at the output layer (Anand & Suganthi, 2017). It is important to note here that, the information (statistical data) can take various ways going from the input layer to the output layer in the network. Each of the network routes has different points, such that when they get to their destination (output layer), the scores are summed up to determine the best network route for information presented as statistical data (Tambouratzis et al., 2019). To achieve the objective of study, a flowchart in Figure 3, which show the procedure for the evaluation of the fatigue reliability and failure probability of the wind turbine blade designed with the FRP material have been presented. The flowchart shows the key stages that have been adopted in the realization of the study objective. These stages includes;

(1) the collection the necessary reliability and failure data; (2) the preparation and normalization of the data; (3) the design of the ANN architecture; (4) training of the network; and finally (5) the post-training analysis and implementation of the network.

Figure 3. Flowchart showing the key stages in the methodology.



3. NUMERICAL IMPLEMENTATION OF THE ANN MODEL

In the implementation of the ANN model for failure probability and fatigue reliability damage evaluation, the study has adopted the parameters of an actual Siemens industrial wind turbine of 3.6 MW rated power (with a wind turbine blade, designed with FRP), at the Walney 1 wind farm site originally presented by Arany et al., (2015). The information and parameters of the Siemens industrial wind turbine are shown in Table 1.

3.1. Assumption for ANN Model Implementation

To make the ANN model simpler and easy to implement, the following assumptions for the flow of information from one layer of the system to another can be summarized as follows.

- (a) The artificial neurons (Input Layer, Hidden Layer and output Layer) are arranged in sequentially as shown in Figure 2,
- (b) The artificial neurons within the same layer don't interact nor communicate with each other.
- (c) All the inputs parameters enters the ANN model through the input layer and passes through the output layer,
- (d) At the same level, all the hidden layers has the same activation function,
- (e) At consecutive layers, the artificial neurons are densely connected and finally,
- (f) All the inter-connected network has their own weight and biased associated with them.

Table 1. Information and parameters of the Siemens industrial wind turbine

Turbine data	Parameters
Turbine type	Siemens SWT-3.6-107
Turbine power	3.6MW
Turbine rotational speed	5–13 rpm
Operational wind speed range	4–25 ms ⁻¹
Number of blades	3
Tower and support structure data	
Hub height from mean sea level	$H = 83.5$ m
Tower top diameter	$D_t = 3$ m
Tower bottom diameter	$D_b = 5$ m
Monopile/substructure diameter	$D_p = 6$ m
Rotor and blade data	
FRP material	
Turbine rotor diameter	$D = 107$ m
Rotor overhang	$b = 4$ m
Blade root diameter	$B_{root} = 4$ m
Blade tip chord length	$B_{tip} = 1$ m
Blade length	$L = 52$ m
Site data	
Mean sea depth	21.5 m
Average distance from closest shore	19 km
Yearly mean wind speed	9 ms ⁻¹
Dominant wind direction	West/south-west
Estimated fetch	60 km

3.2. Simulation and Analysis of Results

The performance of the trained artificial neural network is done considering three phases. These are the training phase (training), testing and re-training phase (second training) and validation phase. In the training phase, the weights of the artificial neural network (ANN) are adapted by considering the training data and training objective. The testing and re-training phase is also deemed as the training phase, however, in this case, the ANN's weights are also re-adapted to reduce the prediction mean square error. The validation process is one in which new data is used as an input to the ANN and a re-computation of the ANN mean square error is executed. The ANN performance is to determine if the well trained artificial neural network is suitable for predicting the fatigue reliability and failure probability of the wind turbine. To achieve this, different ANN configurations were analysed, starting with Tables 2, were the configuration parameters for the first set of 5 ANNs were analysed.

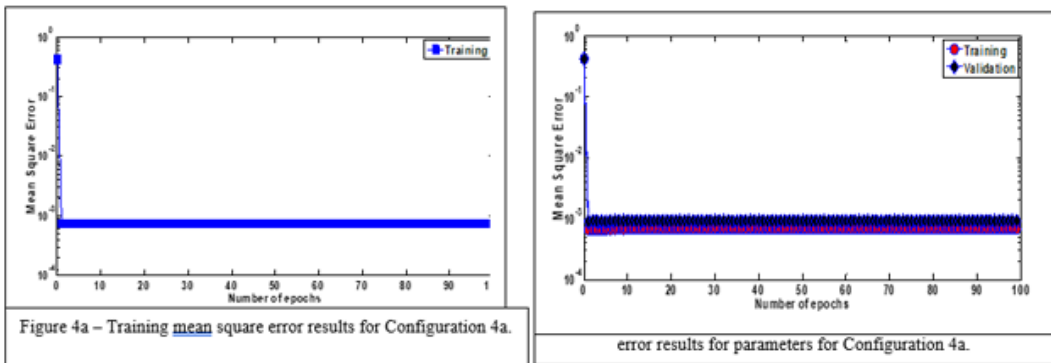
Table 2. Shows the configuration parameters for the first set of 5 ANNs

S/N		4a	4c	4c	4d	4d
1	Size of Input Layer	2	2	2	2	2
2	Size of Hidden Layer	45	45	45	45	45
3	Size of Output Layer	1	1	1	1	1
4	Number of Hidden Layers	1	1	1	1	1
5	Input Layer Transfer Function	tansig	tansig	tansig	tansig	tansig
6	1 ST Hidden Layer Transfer Function	Tansig	tansig	tansig	tansig	tansig
7	2 ND Hidden Layer Transfer Function	N/A	N/A	N/A	N/A	N/A
8	Output Layer Transfer Function	purelin	purelin	purelin	purelin	purelin
9	Input Layer Bias	Yes	Yes	Yes	Yes	Yes
10	First Hidden Layer Bias	Yes	Yes	Yes	Yes	Yes
11	Second Hidden Layer Bias	N/A	N/A	N/A	N/A	N/A
12	Output Layer Bias	No	No	No	No	No
13	Number of Training Samples	2212	2212	2212	2212	2212
13	Pre – processing function	logsig	logsig	logsig	logsig	logsig
14	Proportion of training samples	90%	80%	70%	70%	70%
15	Proportion of validating samples	5%	10%	15%	20%	10%
16	Proportion of testing samples	5%	10%	15%	10%	20%
17	Training Mean Square Error	0.0011	0.011	0.0011	0.0011	0.0011
18	Testing Mean Square Error	0.0013	0.0025	0.0013	0.0014	0.0058
19	Validation Mean Square Error	0.0011	0.0013	0.0012	0.0015	0.0067
20	Corresponding Figure	Figure 1	Figure 2	Figure 3	Figure 4	Figure 5
21	Number of Iterations	1000	1000	1000	1000	1000
22	Training Algorithm	Levenberg Marquadt	Levenberg Marquadt	Levenberg Marquadt	Levenberg Marquadt	Levenberg Marquadt
23	MSE Target	0.00001	0.00001	0.00001	0.00001	0.00001
24	Number of Actual Iterations	1000	1000	1000	1000	1000
25	Training Duration	0:02:35		0:02:10	0:01:51	0:01:32
26	Number of Validation Checks	999		999	997	874
27	Gradient	0.0000201		0.000106	0.0000376	0.00158
28	Mu	0.0000001		0.0000001	0.0000001	0.0000001

From the above Table, it is not hard to see that the proportion of samples used for training, testing and validation are different for each of the ANN configuration. Here, five (5) ANN configurations were considered, and these configurations include configuration 4a, 4b, 4c, 4d and configuration 4e respectively. The proportions of the samples were given as , where and are the proportion of data samples used in the training, testing and validation respectively.

The concerned proportions are;,, , and respectively for the configuration 4a, 4b, 4c, 4d and 4e. The results for the artificial neural network mean square error for the training process in the case of configuration 4a is shown in the Figure 4a. While, the testing mean square error, the re-training mean square error and validation mean square error are shown in Figure 4b.

Figure 4. Results for configuration 4a



In Figure 5a, the result of the ANN training mean square error for configuration 4b is presented, while the results in Figure 5b shows the testing and re-training of the network, alongside the validation mean square error for the configuration 4b. The result in Figure 6a describes the mean square error for the initial ANN training process in the case of configuration 4c. Figure 6b shows the mean square error for the training (re-training) and validation error for ANN with configuration 4c. A similar set of results are presented for configuration 4d and 4e, and the results are shown in Figure 7 and 8 respectively for the mean square error of the initial training of configuration 4d and 4e respectively. As well as the testing and re-training of the network, alongside the validation mean square error for the configuration 4d and 4e. The results presented in Figures 4, 5, 6, 7 and 8, were conducted for a training epoch having 1000 iterations. On the overall, the validation mean square error has minimum and maximum values of 0.0011 and 0.0067, respectively. In this case, there are 45 neurons in the hidden layer.

Figure 5. Results for configuration 4b

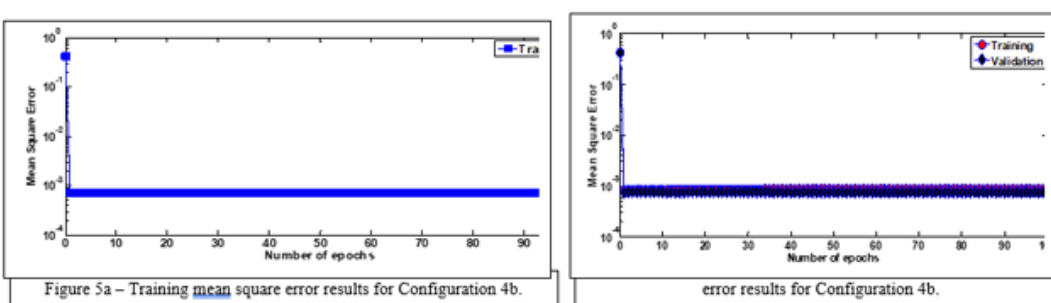


Figure 6. Results for configuration 4c

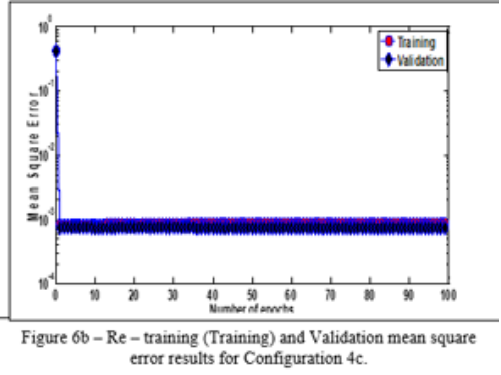
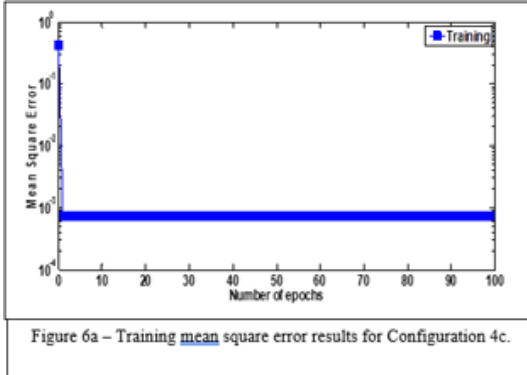


Figure 7. Results for configuration 4d

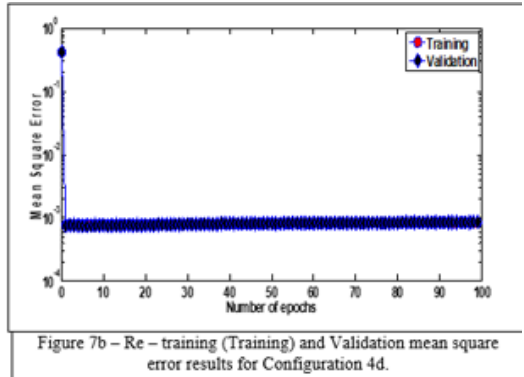
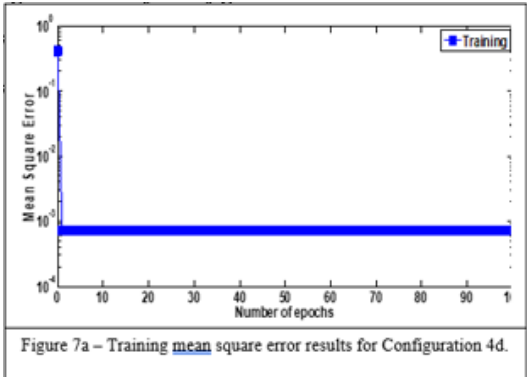


Figure 8. Results for parameters for configuration 4e

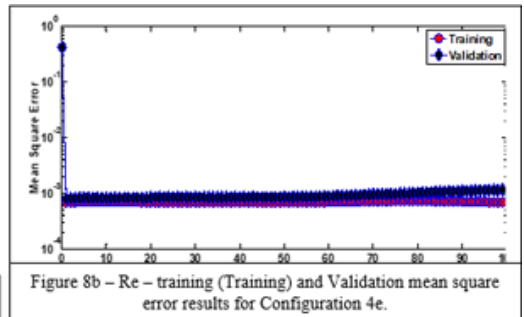
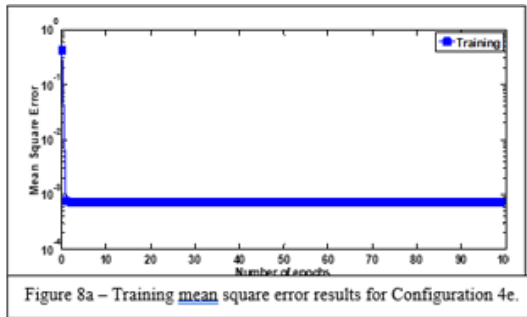


Table 3. Increase in hidden layer size from 45 to 50

S/N		5a	5b	5c	5d	5e
1	Size of Input Layer	2	2	2	2	2
2	Size of Hidden Layer	50	50	50	50	50
3	Size of Output Layer	1	1	1	1	1
4	Number of Hidden Layers	1	1	1	1	1
5	Input Layer Transfer Function	tansig	tansig	tansig	tansig	tansig
6	1 ST Hidden Layer Transfer Function	Tansig	tansig	tansig	tansig	tansig
7	2 ND Hidden Layer Transfer Function	N/A	N/A	N/A	N/A	N/A
8	Output Layer Transfer Function	purelin	purelin	purelin	purelin	purelin
9	Input Layer Bias	Yes	Yes	Yes	Yes	Yes
10	First Hidden Layer Bias	Yes	Yes	Yes	Yes	Yes
11	Second Hidden Layer Bias	N/A	N/A	N/A	N/A	N/A
12	Output Layer Bias	No	No	No	No	No
13	Number of Training Samples	2212	2212	2212	2212	2212
13	Pre – processing function	Logsig	logsig	Logsig	logsig	Logsig
14	Proportion of training samples	90%	80%	70%	70%	70%
15	Proportion of validating samples	5%	10%	15%	20%	10%
16	Proportion of testing samples	5%	10%	15%	10%	20%
17	Training Mean Square Error	0.0011	0.011	0.0011	0.0011	0.0012
18	Testing Mean Square Error	0.0014	0.0058	0.0012	0.0020	0.0020
19	Validation Mean Square Error	0.0012	0.0011	0.0013	0.0015	0.0511
20	Corresponding Figure	Figure 6	Figure 7	Figure 8	Figure 9	Figure 10
21	Number of Iterations	1000	1000	1000	1000	1000
22	Training Algorithm	Levenberg Marquadt	Levenberg Marquadt	Levenberg Marquadt	Levenberg Marquadt	Levenberg Marquadt
23	MSE Target	0.00001	0.00001	0.00001	0.00001	0.00001
24	Number of Actual Iterations	1000	1000	1000	1000	1000
25	Training Duration	0:02:04	0:02:20	0:01:57	0:01:39	0:01:58
26	Number of Validation Checks	991	997	999	999	999
27	Gradient	0.0000306	0.000471	0.0000968	0.000556	0.00330
28	Mu	0.0000001	0.000001	0.0000001	0.0000001	0.0000001

Figure 9. Results for parameters for configuration 5a

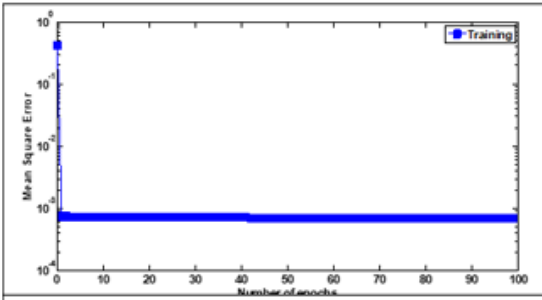


Figure 9a – Training mean square error results for Configuration 5a.

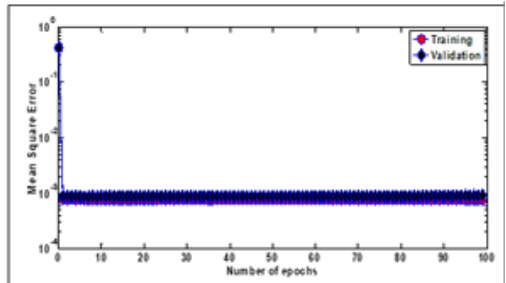


Figure 9b – Re-training (Training) and Validation mean square error results for Configuration 5a.

Figure 10. Results for parameters for configuration 5b

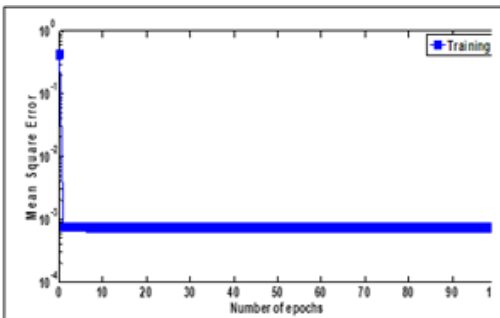


Figure 10a – Training mean square error results for Configuration 5b.

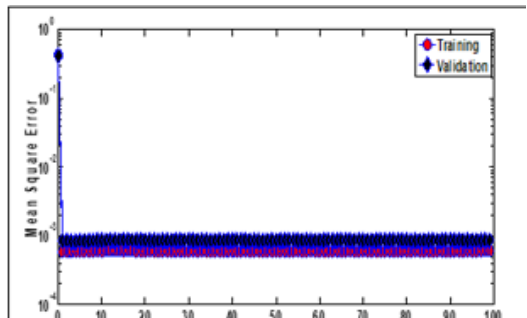


Figure 10b – Re-training (Training) and Validation mean square error results for Configuration 5b.

Figure 11. Results for parameters for configuration 5c

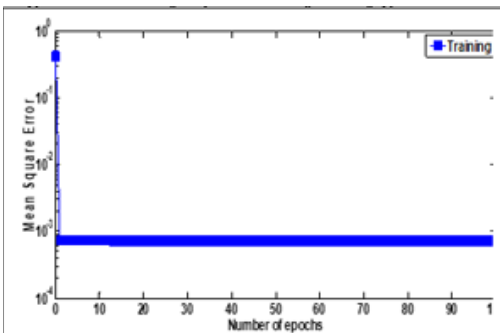


Figure 11a – Training mean square error results for Configuration 5c.

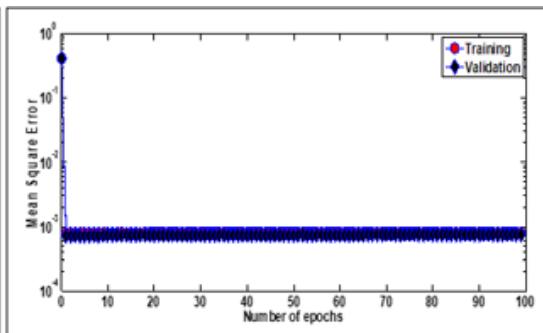


Figure 11b – Re-training (Training) and Validation mean square error results for Configuration 5c.

Figure 12. Results for parameters for configuration 5d

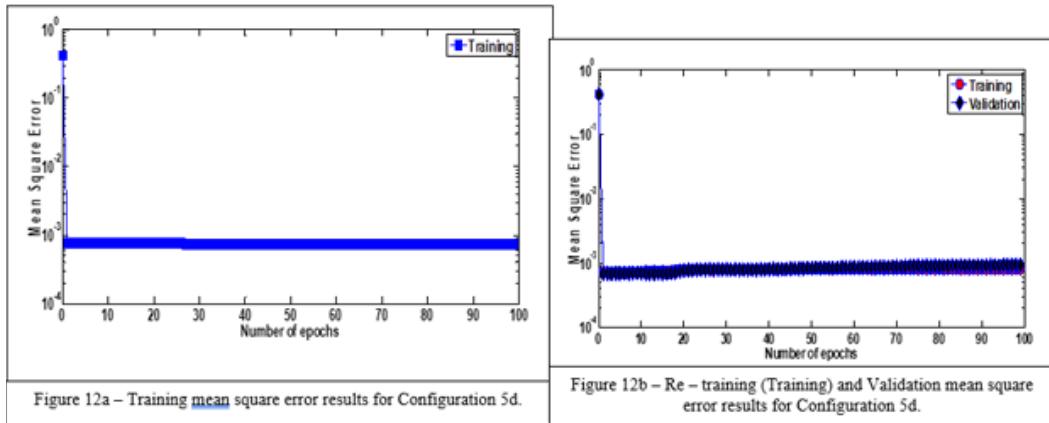
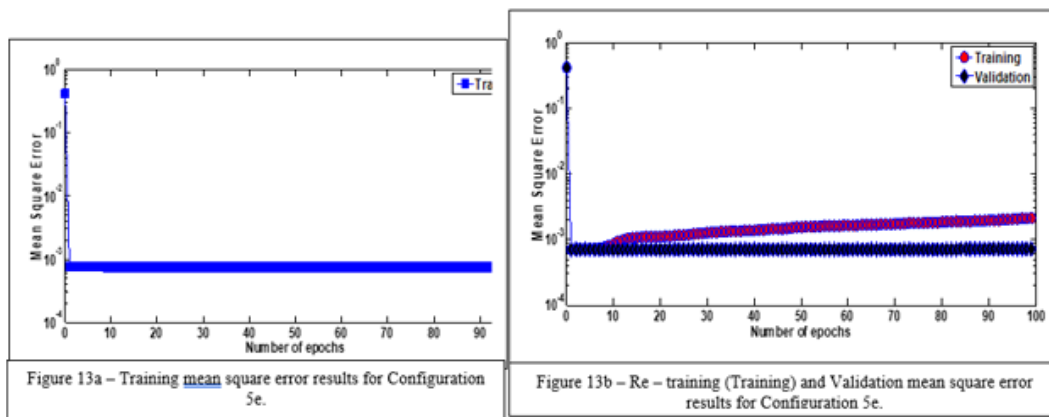


Figure 13. Results for parameters in configuration 5e



In order to reduce the validation error in the network, the size and number of neurons in the hidden layer is increased. The hidden layer size was increased from 45 to 50 as show in Table 3. In this case the results are presented in Figures 9, 10, 11, 12 and 13 respectively, such that Figure 9a, 10a, 11a, 12a and 13a shows the initial training mean square error for configuration 5a, 5b, 5c, 5d and 5e respectively. While the testing, re–training and validation mean square error for the configuration 5a, 5b, 5c, 5d and 5e respectively are shown in the Figure 9b, 10b, 11b, 12b and 13b. In this case, it is observed that the maximum validation mean square error increased to 0.0511. This is an increase from 0.0067 (when size of the hidden layer is 45) to 0.0511 (when size of the hidden layer is 50).

In the attempt to obtain a more reduced validation mean square error, the number of training epochs is increased from 1,000 to 2,000 while the size of the hidden layer is changed back to 45 as shown in Table 4. The results of the ANN performance is shown in Figure 14, 15, 16, 17 and 18, such that Figure 14a, 15a, 16a, 17a and 18a shows the initial training mean square error for configuration 6a, 6b, 6c, 6d and 6e respectively. While the testing, re–training and validation mean square error for the configuration 6a, 6b, 6c, 6d and 6e respectively are shown in the Figure 14b, 15b, 16b, 17b and 18b. From the Figures, it is not hard to see that there are reduction in the training mean square error,

testing (re-training) mean square error and validation mean square error. This shows that increasing the number of training epochs by 50% from 1000 to 2000 reduces the validation mean square error. In this case, the minimum mean square error and maximum mean square error are 0.0011 and 0.0061, respectively.

Table 4. Increase in number of training epochs from 1000 to 2000.

S/N		6a	6b	6c	6d	6e
1	Size of Input Layer	2	2	2	2	2
2	Size of Hidden Layer	45	45	45	45	45
3	Size of Output Layer	1	1	1	1	1
4	Number of Hidden Layers	1	1	1	1	1
5	Input Layer Transfer Function	tansig	tansig	Tansig	tansig	tansig
6	1 ST Hidden Layer Transfer Function	Tansig	tansig	Tansig	tansig	tansig
7	2 ND Hidden Layer Transfer Function	N/A	N/A	N/A	N/A	N/A
8	Output Layer Transfer Function	purelin	purelin	purelin	purelin	purelin
9	Input Layer Bias	Yes	Yes	Yes	Yes	Yes
10	First Hidden Layer Bias	Yes	Yes	Yes	Yes	Yes
11	Second Hidden Layer Bias	N/A	N/A	N/A	N/A	N/A
12	Output Layer Bias	No	No	No	No	No
13	Number of Training Samples	2212	2212	2212	2212	2212
13	Pre – processing function	logsig	logsig	Logsig	logsig	logsig

Table 4 continued on next page

Table 4 continued

S/N		6a	6b	6c	6d	6e
14	Proportion of training samples	90%	80%	70%	70%	70%
15	Proportion of validating samples	5%	10%	15%	20%	10%
16	Proportion of testing samples	5%	10%	15%	10%	20%
17	Training Mean Square Error	9.29×10^{-4}	9.13×10^{-4}	9.49×10^{-4}	8.67×10^{-4}	9.19×10^{-4}
18	Testing Mean Square Error	9.29×10^{-4}	0.0011	0.0053	0.0011	0.0029
19	Validation Mean Square Error	0.0061	0.0011	0.0054	0.0012	0.0013
20	Corresponding Figure	Figure 11	Figure 12	Figure 13	Figure 14	Figure 15
21	Number of Iterations	2,000	2,000	2,000	2,000	2,000
22	Training Algorithm	Levenberg Marquadt	Levenberg Marquadt	Levenberg Marquadt	Levenberg Marquadt	Levenberg Marquadt
23	MSE Target	0.00001	0.00001	0.00001	0.00001	0.00001
24	Actual Iterations	2,000	2,000	2,000	2,000	2,000
25	Training Duration	0:08:04	0:05:16	0:06:13	0:04:49	0:05:43
26	Validation Checks	1983	1957	1994	1996	1980
27	Gradient	0.0000877	2.08×10^{-6}	6.56×10^{-5}	0.000412	0.000673
28	Mu	1.00×10^{-7}	1.00×10^{-7}	1.00×10^{-7}	1.00×10^{-8}	1.00×10^{-7}

Figure 14. Results for parameters of configuration 6a

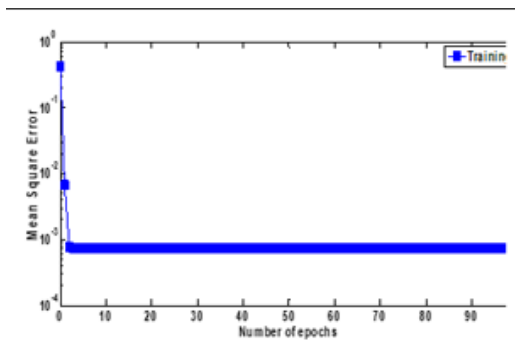


Figure 14a – Training mean square error results for Configuration 6a.

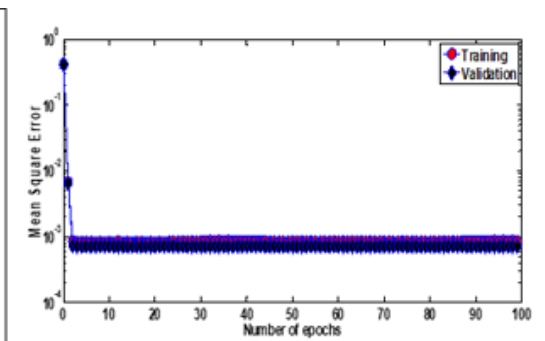


Figure 14b – Re-training (Training) and Validation mean square error results for Configuration 6a.

3.3. Discussion of the Results

From the results above, it can be concluded that a low validation mean square error implies that the developed artificial neural network has a good accuracy when determining the fatigue reliability and failure probability using the given input big data of the wind speed, turbine rotational speed and the other parameters. This occurrence of a low validation mean square error implies that the given parameters in the ANN model, is able to predict the wind turbine blade fatigue reliability and failure probability accurately and this meets, the goal of the proposed research and intelligent solution.

Furthermore, it can be deduced from the above results also, that the evaluation of the fatigue reliability and failure probability of the wind turbine blade using the intelligent model (ANN), has less errors, has the ability to learn, robust, easier to obtain, safer and has less mathematical complexity as compare to the analytical fatigue reliability and failure probability of the wind turbine blade presented in (Arany et al., 2015). It can also be established that, the fatigue reliability and failure probability of the wind turbine blade can be obtained using even fewer or hyper-parameter and with insufficient knowledge or data as compared to traditional algorithms. The intelligent model (ANN) however, is computationally expensive which is one of it weakness.

Figure 15. Results for parameters of configuration 6b

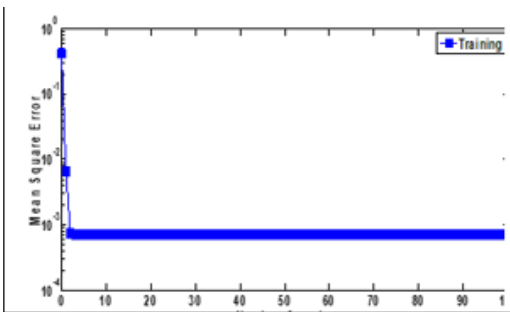


Figure 15a – Training mean square error results for Configuration 6b.

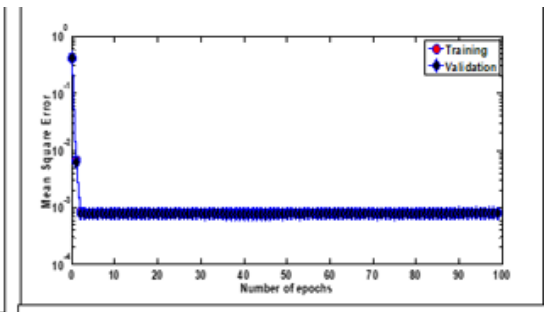


Figure 15b – Re – training (Training) and Validation mean square error results for Configuration 6b.

Figure 16. Results for parameters of configuration 6c

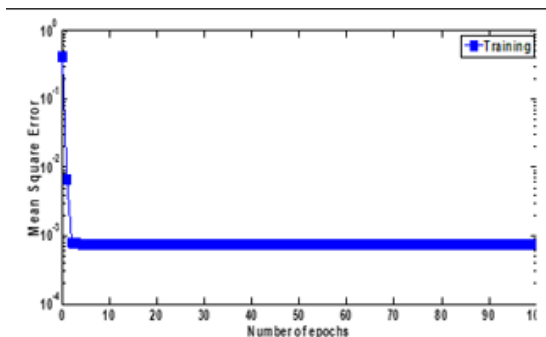


Figure 16a – Training mean square error results for Configuration 6c.

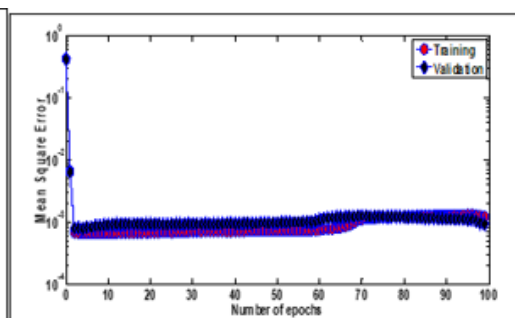


Figure 16b – Re – training (Training) and Validation mean square error results for Configuration 6c.

Figure 17. Results for parameters of configuration 6d

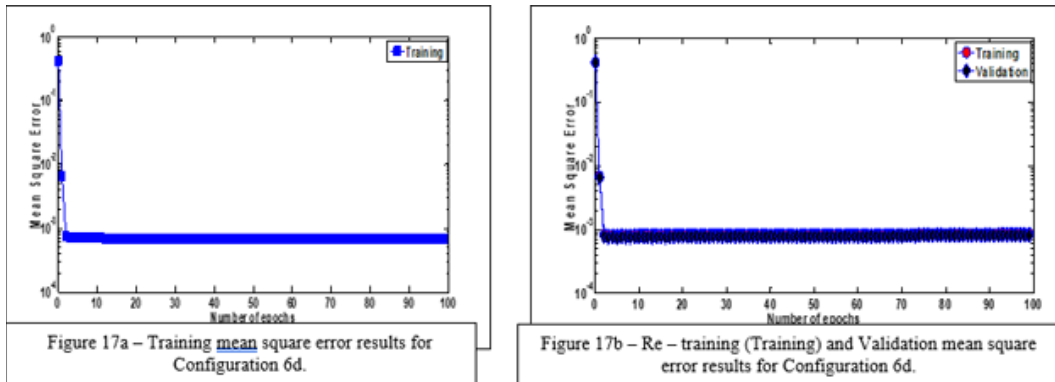
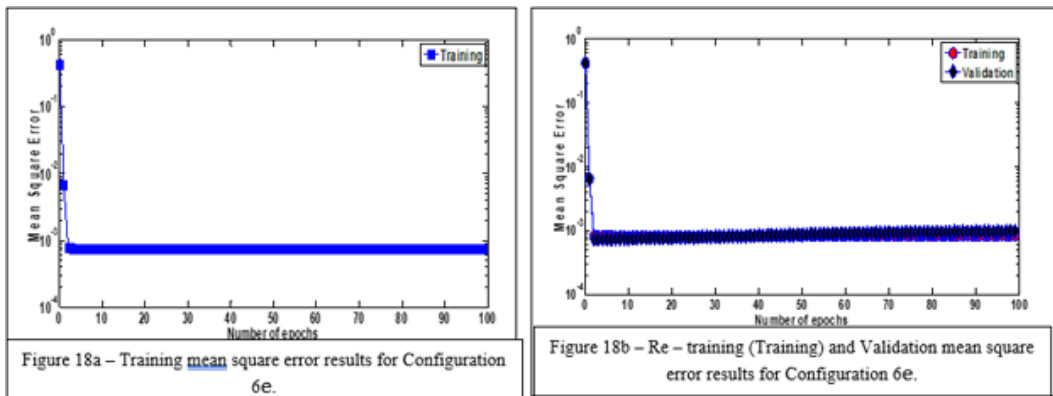


Figure 18. Results for parameters of configuration 6e



4. MANAGERIAL IMPLICATION OF THE RELIABILITY-BASED MODEL FOR THE WIND TURBINE BLADE

The developed reliability-based model has several managerial implications for the wind turbine blade, first the simulation result show how the parameters most especially the turbine rotational and operational wind speed affects the fatigue reliability of the wind turbine blade and the overall wind turbine system. The result provides reliability experts with the opportunity to understand the behaviour of the wind turbine blade and when the wind turbine blade parameters and data are varied.

Secondly, the simulation results demonstrate the capability of the ANN-based model to accurately predict the fatigue reliability of the wind turbine blade, which depends on the input parameters and data used by smoothing the fatigue response and reducing the convergence problems. Thirdly, the results provide an improved insight in understanding the dynamic performance of the ANN algorithm as a fatigue reliability simulation model. The model resulted in a significant computational cost reduction in the prediction of probabilities of failure in the wind turbine blade. Fourthly, the implementation of ANN model is a unified framework and it can be applied to evaluate the reliability of other kind of structural safeties in industrial systems and. Finally, the ANN-based model used for the fatigue reliability evaluation of the wind turbine blade, is considered a robust and an efficient alternatives to traditional reliability methodologies.

5. CONCLUSIONS

In this paper, a computational intelligent model based on an artificial neural network has been implemented for the evaluation of the fatigue reliability and failure probability of the wind turbine blade designed with the FRP material. The simulation results shows that, there was a reduction in the training mean square error, testing (re-training) mean square error and validation mean square error. When the number of training epochs is increased by 50% that is from 1000 to 2000, also the result shows a reduction in the validation mean square error. Such that, the minimum mean square error and maximum mean square error reduces to 0.0011 and 0.0061 respectively. The low validation mean square error in the simulation results implies that the developed artificial neural network has a good accuracy when determining the fatigue reliability and the failure probability of the wind turbine blade.

Furthermore, it can be deduced from the results that the evaluation of the fatigue reliability and failure probability of the wind turbine blade using the intelligent model (ANN), has less errors, robust, has the ability to learn, easier to obtain, safer and less complicated than the traditional analytical fatigue reliability and failure probability of the wind turbine blade presented in literature. It can also be established that, the fatigue reliability and failure probability of the wind turbine blade can be obtained using even a fewer or hyper-parameter, and with an insufficient knowledge or data as compared to traditional algorithms.

6. LIMITATION AND FUTURE RESEARCH DIRECTION

Although the study have been able to achieve its set objective, however, it is limited with the expensive computational simulation of the ANN model and it's heavily reliance on big data which has made it unattractive to researchers and organization with no access to big data. Also, the study have been limited with the lack of performance comparison with other intelligent models like support vector machine, learning vector quantization and the Naïve Bayes model.

In the future however, the study will be focus on the comparison of several intelligent models for the evaluation of the fatigue reliability and failure probability of the wind turbine blade. The development of a state-of-the-art framework for predicting the long-term process performance of the wind turbine blade and the and finally, the optimization of future operating conditions for the turbine blade.

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