*International Journal of Engineering & Technology*, 7 (4) (2018) 5683-5689

International Journal of Engineering & Technology

*Website: www.sciencepubco.com/index.php/IJET*
*doi: 10.14419/ijet.v7i4.19077*
***Research paper***

# On human to artificial neural network in maintenance applications

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## Abstract

Maintenance is key to meeting sustainability and productivity expectations of repairable industrial systems. The upsurge of growth in complexity of processing equipment has since raised the maintenance function beyond the comprehension of human neural networks, thereby necessitating recourse to artificial intelligence techniques. The nexus between human neural network and artificial neural network was x-rayed in this paper. Attempt was made to present the foundations of artificial neural network modeling techniques and the major contributors to the development of the field. Some of the terminologies associated with human and artificial neural networks were defined and explained with relevant figures. The capability of artificial neural network in predicting the reliability of a case study industrial system, with data taken from a beverage company was illustrated. The two-layer network has one input and output layer apiece, as well as a hidden layer of twenty neurons. The architecture is a feed forward back propagation neural network, while the Levemberg-Marquart training algorithm was employed. It was observed that reliability predictions obtained from ANN model proved very good, considering the very low values of MSE ($1.0256X10^{-3}$) and high value of the regression (0.998742).

***Keywords***: *Artificial Neural Network; Human Neural Network; Maintenance; Reliability Prediction; Repairable System.*

## 1. Introduction

A system consists of a processing unit that operates on some inputs in a describable manner in order to produce intended output. The input can be matter, information or energy while the output may be a product, service or both. The system may be composed of buildings, machines, infrastructure and processing devices. After system design which may involve research, development and translation of novel ideas, techniques and information into a form suitable for production or use, the next stage is installation. From the date of installation onwards, most systems deteriorate with age and usage, unless action is taken to renew or maintain them. The question of when, how and which maintenance should be carried out becomes very important in planning for continued sustenance of optimally designed and proficiently installed systems. The achievement of optimal returns on investment [1] is a major objective of maintenance. Maintenance theorizers and practitioners embrace the techniques of industrial management whose purpose is to ensure the best utilization of human, technical and financial resources. Detailed responsibilities of maintenance executive are discussed elsewhere [2], [3]. The complicating scenarios of many systems have underscored the need for matching techniques to tackle emerging maintenance problems. Enormous scientific know-how is being explored to allow the maintenance manager increase the efficiency of his function.

When systems were less complex than what obtains currently in industries, maintenance tasks remained not only simpler, but straightforward. Approximate optimal solutions resulting from human neuronal activities readily arrested unforeseen stoppages in system processes and industrial systems were returned to operating conditions with little effort. Towards the end of 3rd Industrial revolution and in the existing realities of the 4th Industrial revolution, amplified technological and knowledge growth has brought considerable changes in the pattern and outlook of maintenance. The first implication of this is that effective solution to system maintenance problems became insurmountable with methods easily comprehensible to human neural network (HNN). Thus, realistic and carefully designed maintenance plans that will proficiently match production requirement and schedules had to be implemented in electronic computers in order to ensure maximum system reliability and availability. Researchers have argued that analytical models are efficient means of good maintenance planning and developed such models for various maintenance types [3], [4-6]. As reported in literature [7], such models, as it were, are most often over simplified, old, and infrequently represent the actual system behavior. This assertion qualifies many analytical maintenance models as academic monuments due to difficulty in application to industry, if ever employed in practice. Due to several maintenance function considerations, multi-parametric character, various competing objectives and compound prospective solutions as well as trade-offs [4], migration from HNN to artificial neural network (ANN) could no longer be kept in view. ANN is recommended as an alternative to traditional analytical maintenance planning approaches informed by derivatives of HNN or physical intellectual reasoning. To date, ANN enjoys the advantages of no compulsory knowledge of domestic system parameters, less computational efforts and a condensed solution for multivariable problems. Modeling real world systems with assignable inputs and output, through coding the values and training suitable ANN for

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predicting the output-input behaviour has received commendation [8]. In addition, ANN has the capacity to compute predictable output for a system, from a physical illustration of the system resulting from empirical evidence, instead of a mandatory consideration of the failure history. This paper attempts to elicit the interconnectivity between HNN and ANN, especially as background to those resulting in maintenance planning and control. It is believed that understanding the concept as presented in the paper will spur more interest in assessment and modeling of system failure and repair problems with different ANN approaches that can enhance greater industrial appreciation and application. There is no prior presentation on this wise known to the authors.

## 2. An overview of ANN: human nervous system in retrospect

The human nervous system (HNS) shown in Fig. 1, is made up of the peripheral nervous system (PNS) as well as central nervous system (CNS). While the brain compartment and spinal cord assembly together constitute the CNS, all other body nerves make up the PNS. In addition, the PNS is subdivided into sensory system which connects receptors to CNS and motor system that house the motor or efferent neurons. The motor system comprises somatic neurons that carry instruction to voluntary muscles and glands and autonomic neurons which carry instructions to involuntary muscles. There are parasympathetic autonomic neurons that operate in relaxed conditions and sympathetic autonomic neurons that take over under emergencies. The interest in nervous system is principally circumstantial to understanding of human neurons, which are the carriers of information signals to and from the human brain. Artificial neural networks derives its principle of operation by mimicking the functionality of this circuit (HNS-CNS).

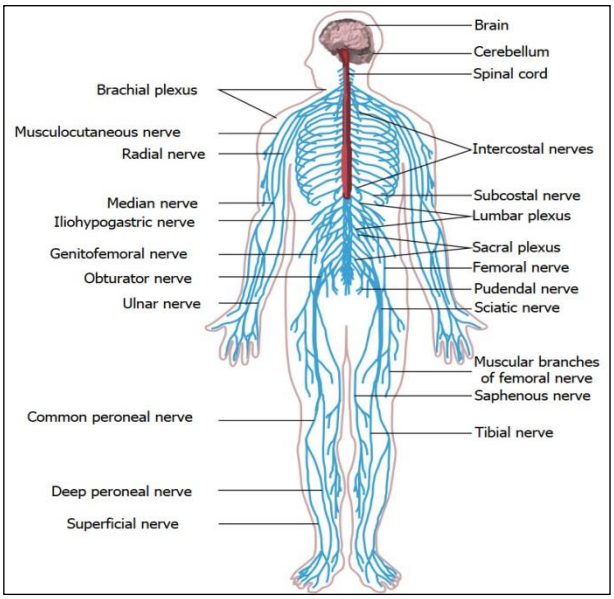



**Fig. 1:** The Human Nervous System [9].

### 2.1. Neural networks

This presentation discuss only the rudimentary ideas underlying neural networks functionality. In particular, the complex mathematical formulations associated with neural networks implementation appear in established literature [10], [11]. A neural network can be idealized as a simple simulation of the biological neuron. Artificial Neural Network algorithms were used as universal function approximates [12].

It is essentially an attempt to implement the functionality of HNS in computerized systems. ANNs are at best analogous to the human brain in function and operation. Heykin [11] presents one of the most concise definitions of a neural network. The author defines neural networks as directed graphs mainly comprising nodes with interrelated activation links and synapses. Some of the outlined characteristics include: 1) possession of an array of synaptic links, one superficially functional bias as well as a probable activation link, 2) the ability of neuron synaptic links to weight varying input signals. While specific local field neurons were defined by the sum of input signals, squashing of the neurons in the field denoted the starting link that sends out a target result.

### 2.2. Background of artificial neural networks

The vast majority of ANN currently used in many fields of study were off-shoots of comprehensive developments and implementations of ideas in HNN. Multidisciplinary collaborations in physical and human sciences peaked towards the end of 19$^{th}$ and early 20$^{th}$ centuries, and were steered by three research colossi- Pavlov, Mah and Helmholtz [13]. Most research output at the time bordered on conventional theories of learning without specific physical models describing neuron behavior. As a result, McCulloch and Pitts [14] remain famous with laying the foundation of the current ANNs applicable in many research areas. The duet researchers first describe how human neural networks simulated in electronic devices can perform arithmetical and logical computations. About six years later, a biological neurons learning mechanism was proposed [15], preparatory to the evolution of the perceptron network that were able to recognize considerable patterns [16]. Widro and Hoff [17] learning rule followed after two years, with provision of a new learning algorithm comparable in structure and competence to the earlier perceptron. The algorithm found application in training adaptive networks. Suffice it to indicate that Neural network learning algorithms developed before and during 1960s were unable to successfully train complex networks, yet significant early success recorded, spurred great interest in neural network modeling. The observed hindrances probably informed the publication of a monograph to comment on weaknesses of the fundamental perceptron network. The said monograph [18] came along with substantial discouragement in working with perceptrons. This limitation coupled with lack of capable experimentation computers suspended ANN research for over a decade. The revolution in neural networks research, in particular; extensive works on self-organizing neural networks [19], followed the discovery of ANNs that could act as memories, independently and concurrently by avid researchers [20-21]. Therefore, research in ANNs which became practically moribund during late 1960s dramatically waxed very strongly in 1980s when both of the experienced hindrances were fully overcome. This period witnessed the description of the deployment of statistical mechanics in understanding some categories of memory capacitated recurrent networks [22]. The step brought succor to ANN modelers and further reinvigorated affiliated research zeal. Accordingly, combined research efforts from independent stakeholders led to the discovery of the back-propagation ANNs, diversely employed in training multifaceted multilayer networks [23]. More recently, different ANN types have applied in many fields of learning and ample research output have constantly evolved in the subject on yearly basis.

## 3. Materials and methods

The work employed both quantitative and qualitative research design approaches. The data used were mainly of secondary type which involves but not limited to literature and online sources. It was necessary to illustrate the theoretical depictions on a real world system to enhance understanding. Accordingly, the maintenance and repair data of a real World Industrial system was obtained. Although, maintenance data collection normally occurs outside the framework of ANN applications, interested readers can refer to existing literature [24]. The data set used was the failure data for a compressor system [25]. The fundamental assumption that the data as abstracted from the case study system ($CO_2$ compressor at the Utilities Department of a beverage plant) were completely and accurately correct has to be made, because there was

no better means of authenticating the data. The methods elaborating normalization and conversion of data into the form amenable to ANN modelling procedures was used, so that computerized system based calculations can be made and reasonable conclusions drawn. The qualitative aspect of the research tends to x-ray various ANN model categories which give researchers and practitioners some degree of freedom and allow spontaneity instead of enforcing a set of pre-determined architectures which might not describe the researchers' thoughts, specific system concerns and interests appropriately or accurately. The authors believe that this approach creates the clement atmosphere for practitioners to explore many ANN paradigms. The remainder of the presentation presents an overview of the human nervous system as background to invention of ANN. The developmental and progressive implementation growth of ANN is recapped. The scheme of neuron as it relates to the biological cell is illustrated to properly link the process to ANN computing procedure. The various types of ANN that can be explored in modeling system maintenance is discussed. The paper presents concise diagrams describing the information flow through artificial neurons, with the learning and training pedagogies. An application to the reliability prediction of an example maintainable system is demonstrated using ANN techniques already presented in the paper.

### 3.1. Artificial neuron system

A compact scheme of conventional artificial neuron shown in Fig. 2, can be likened to the biological cell, which is made up of unbounded capacity for accepting input variables. This qualifies a perfectly trained ANN to be able to accept several inputs. Accordingly, ANNs have been applied in tackling unprecedented and hitherto costly multi-combinatorial problems in industries and other spheres. Fig. 5 shows some input signals which are acted upon by the appropriate weights before being summed and transferred to an output element. The result of the exercise is normally recomputed by an activation function.

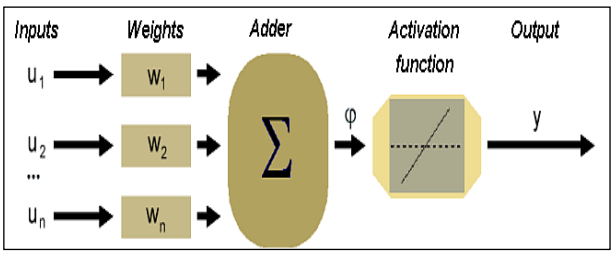



**Fig. 2:** Fundamental Artificial Neuron Model.

The activation potential of equation (1), φ, can be developed or processed with the aid of several activation functions in ANN field. Equation (2) presents a mathematical description of output signal for linear activation function. If ANNs are trained with the aid of equation (2), a linear neural networks results. Artificial neurons can equally be trained with threshold activation functions according to the dependence of equation (3). Both the sigmoid and hyperbolic functions presented in equation (4) and equation (5) respectively are usually employed during ANN training to take care of some non-linearity effect of bio-inspired neurons. Fig. 3 presents graphs of particular activation functions.

$$\varphi = \sum_{i=1}^{P} u_i w_i \quad (1)$$

$$y = K\varphi \quad (2)$$

$$y = \begin{cases} 1 \; for \; \varphi > \varphi_h \\ 0 \; for \; others \end{cases} \quad (3)$$

$$y = \frac{1}{1+\exp(-\beta\varphi)} \quad (4)$$

$$y = tgh\left(\frac{\alpha\varphi}{2}\right) = \frac{1-exp(-\alpha\varphi)}{1+exp(-\alpha\varphi)} \quad (5)$$

While $\varphi_h$ represents a given constant threshold value, α and $\beta$ are parameters.

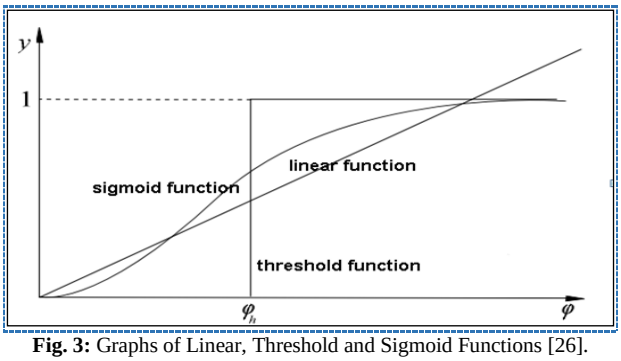



**Fig. 3:** Graphs of Linear, Threshold and Sigmoid Functions [26].

### 3.2. Types of neural networks (architecture)

Three categories of neural networks distinguishable structure-wise and the direction of flow of input signals can be identified. Feed-forward neural networks (FFNN) are made up of linear directional one-layer and multi-layer networks, while the other category; recurrent networks and cellular networks possess signal return and reprocess ability, as well as lattice-like structure respectively. Particular training techniques are usually adopted for different neural network. In FFNN, the signal flow has only one direction. Neurons from preceding layers connect only with the neurons of succeeding layers as displayed in Fig. 4. Fig. 5 present the structure of the multi-layer counterpart, usually made up of input layer, one or more hidden layers, and output layers. The multilayer ANN learning algorithm essentially determines some set of weights that minimize or maximize the performance indices as the case may be. Some authors (Pang-Ning et al., 2005) prefer minimization of total sum of squared errors of equation (6), as the stopping criteria.

$$E = \sum_i [Y_i - f(W_i - X_i)]^2 \quad (6)$$

The term $f(W_i - X_i)$ designates the predicted sample that can be function of the weights in the vicinity of the hidden and output nodes respectively.

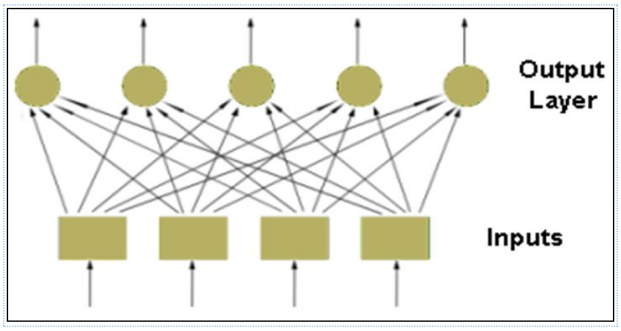



**Fig. 4:** Single Layer ANN [13], [27].

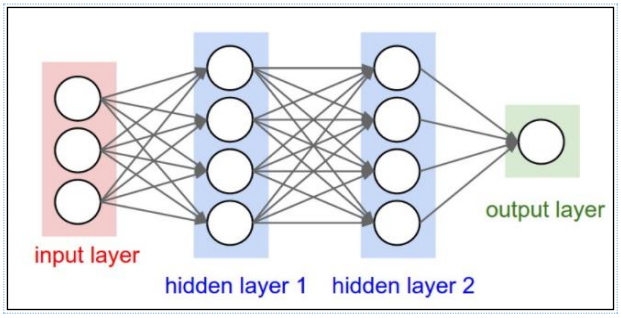



**Fig. 5:** Multiple Layer ANN [27].

The most distinguishing characteristic of the recurrent artificial neural networks (RANN) is the feedback loops. In the design,

output information from one layer is re-connected to its inputs. This makes dynamic effects in network operation possible. In particular, input information of a succeeding layer comprises both output and input results of the preceding layer. The information network is demonstrated in Fig. 6 through Fig. 7.

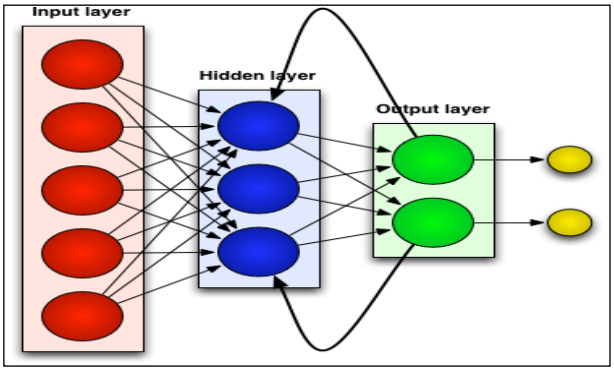



**Fig. 6:** Output driven Operation in RANN [28].

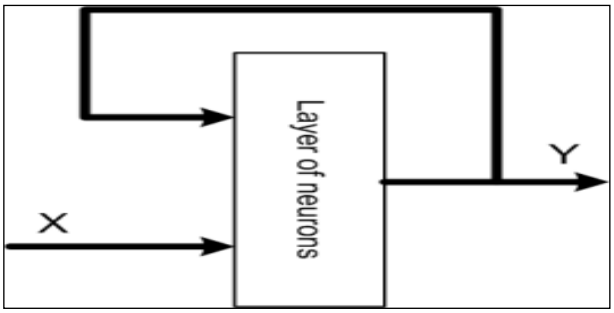



**Fig. 7:** Schematic Representation of RANN [11].

Cellular neural networks possess a lattice structure arrangement in its neurons. Most of the connections are usually non-linear. A typical example of such networks is Kohonen Self-Organizing-Map shown in Fig. 8.

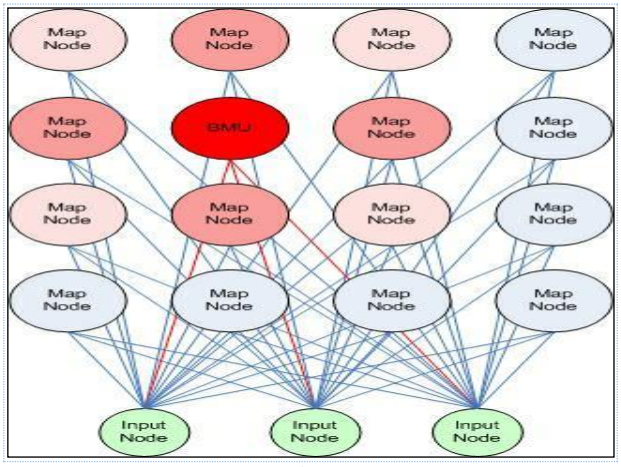



**Fig. 8:** Kohonen Self-Organizing Map [29].

## 3.3. Artificial neural network training algorithm

Training in neural networks can occur in two basic methods [30]. It is termed incremental, if the weights and biases get updated whenever there is new input information fed into the network. On the other hand the neural network weights and biases can wait for all of the input information to be presented to it before updating. In the event of this, it is called batch training. Particular algorithms have been developed, which can be employed in training neural networks. Table 1 present some of the tested algorithms. When the network training is completed, the nodes need not be presented with the same kind of input or input in the neighbourhood in future, as it has been trained to recognize diverse features inside the input perspective. At present, no particular training algorithm has obtained professional approval for any neural network architecture. The common approach remains experimenting with different algorithms and locating the one with fastest convergence for the considered application.

**Table 1:** Selected Neural Network Training Algorithms [31]

| Function | Algorithm |
|---|---|
| Trainlm | Levenberg-Marquardt |
| Trainbr | Bayesian Regularization |
| Trainbfg | BFGS Quasi-Newton |
| Trainrp | Resilient Backpropagation |
| Trainscg | Scaled Conjugate Gradient |
| Traincgb | Conjugate Gradient with Powell/Beale Restarts |
| Traincgf | Fletcher-Powell Conjugate Gradient |
| Traincgp | Polak-Ribiére Conjugate Gradient |
| Trainoss | One Step Secant |
| Traingdx | Variable Learning Rate Gradient Descent |
| Traingdm | Gradient Descent with Momentum |
| Traingd | Gradient Descent |

### 3.3.1. Stopping criteria and network validation

As suggested in literature [32], training can be deemed to have completed in the event of the following possibilities: 1) The Euclidean norm in the determinant performance vector accomplish a significantly small slope threshold, 2) The total gradient of the average squared error in emerging iterations or epochs becomes insignificant (very small), 3. The performance of the generalization has either peaked or become adequate. Mathematically speaking, models (7) through (11) summarize most of the frequently applied performance and stopping criteria frequently encountered in practice [7], [12].

$$TSSE = \sum_{j=1}^{n}\left(d_j - p_j\right)^2 \tag{7}$$

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n}\sum_{i=1}^{m}\left(d_{ji}-p_{ji}\right)^2}{nm}} \tag{8}$$

$$MAPE = \frac{1}{nm}\sum_{j=1}^{n}\sum_{i=1}^{m}\left|\frac{d_{ji}-p_{ji}}{d_{ji}}\right| \times 100 \tag{9}$$

$$R^2 = \frac{\left(\sum_{j=1}^{n}(d_j-\bar{d})(p_j-\bar{p})\right)^2}{\sum_{j=1}^{n}(d_j-\bar{d})^2 \cdot \sum_{j=1}^{n}(p_j-p)^2} \tag{10}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - s_i)^2 \tag{11}$$

Where $MSE$ and $TSSE$ are the mean square error and total sum of squared error respectively,
RMSE and MAPE are the root mean square error and mean absolute percentage error respectively,
$d_{ji}$ is the $ith$ component of the output for the $jth$ pattern;
$p_{ji}$ represents the $ith$ component of the fitted output from the network for the $jth$ pattern;
$\bar{d}$ and $\bar{p}$ are the average of the desired output and predicted output respectively
$n$ and $m$ stands for the number of patterns and the number of variable outputs respectively,
$s_i$ and $t_i$ represent network output values and the target outputs respectively
N refers to the number of samples presented to the network for the training exercise
$R^2$ represent the coefficient of determination, which equals 1 for a faultlessly simulated data or very close relationship.
The value is zero for a random relationship.
The smaller the values of $TSSE$, $RMSE, MAPE, MSE$ and the larger the value of $R^2$, the better the model performance and more close the network is to the real situation. Finally, the network performance has to be examined for possible changes in the training process; training algorithm, network architecture or the underlying data sets. The training record is first observed closely and regres-

sion plots created, upon satisfaction with the training result. The essence of the regression plot is to study the relationship between the outputs-target nexus in the network. The network outputs and targets are exactly equal for perfectly trained networks, otherwise; some differences will be observed irrespective of magnitude.

### 3.4. Data handling

The data as obtained from case studies or experimentation cannot be applied to the neural network. It has to be prepared to conform to the language registry of the network. This exercise is a very important consideration in developing a neural network and upon it lays the success of any neural network model. Pre-processing steps are useful it provides the basis of analyzing the response of the trained ANN. It should therefore be done prior to presenting the network with the input data. First line practice is usually dividing the collected data into subsets, so that different sets of sample data are used for training, validation and testing [33], [34]. The basic thing is to exercise care in ensuring that the considered training set covers all spectrum of data available. The partition adopted can be subjected to modification if it is discovered that the model performance falls short of expectations. Post-processing step might be required to achieve meaningful interpretation of results. This warrants reconverting the output of the trained ANN into its original format. Several preprocessing routines have been suggested in the past [10], [32], [1]. The min-max [35] approach has received wild application. As presented in equation (12), the procedure entails normalizing the original data, $P$, say, with minimum value (p min) in an array of rank-ordered data set, such that; the maximum value in the data ($p\ max$) can be changed into a normalized value ($pn$). When this approach is the choice, the normalized data set is tested for correctness by ensuring that all values lie between -1 and +1 [35].

$$pn = \frac{2(p-p_{min})}{p_{max}-p_{min}} - 1 \tag{12}$$

Some common normalization processes are inbuilt in majority of ANN software, which enable the software to create the selected procedure. The selected normalization procedure remains part of the network object during and after training. The advantage is that new data sets coming into the network get automatically preprocessed after the initial creation of the network.

## 4. Application to reliability prediction of a particular system

It has been stated that most systems begin to deteriorate after installation and commissioning due to age and usage. Though in some cases, systems can fail due to causes that are not known (chance failure). The general performance of most systems before eventual unwanted and unplanned stoppage can be represented by Fig. 12. Maintenance actions are recommended between the point of failure initiation event and acceptable loss of performance in order to avert catastrophic failure. Neural network is used in this example to retain the system in its acceptable reliability level. Maintenance data collection (MDC) is usually outside the purview of Neural Network applications. Readers can refer to existing literature [24] for necessary acquaintance with MDC. The data set used for illustrating neural network modeling in this presentation comprises times-to-failure (TTF) data for a compressor system. The basic assumption that the data as collected from the case study system ($CO_2$ compressor at the Utilities Department of a beverage plant) were completely and accurately correct has to be made. It consists of 52 TTF data points and corresponding reliability values deduced empirically using the non-parametric equation [23]. The data was based on every report of malfunctioning of the system from the failure initiation event to the catastrophic failure point. That is; the system was deemed to have failed once it is outside the stable zone. Fig. 9 shows possible failure degrees and reliable performance degrees of typical repairable systems while model (13) is an empirical solution for reliability evaluation.

$$R(t) = 1 - \frac{i-0.3}{n+0.4} \tag{13}$$

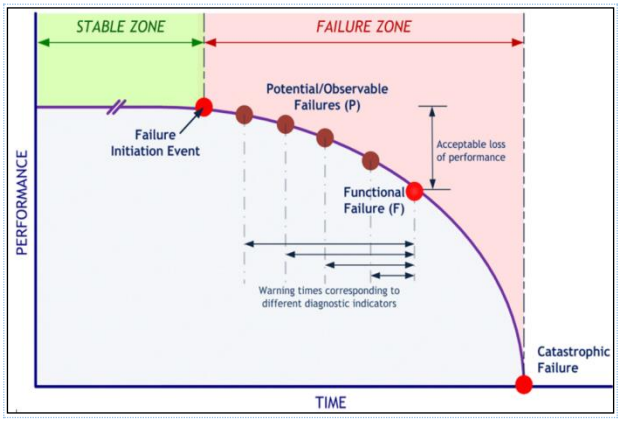



**Fig. 9:** System Performance Curve [36].

### 4.1. Training the ANN with illustrative example of compressor reliability prediction

Artificial neural network implementation tools appear in many developed soft computing devices. MATLAB Software is a very good example of such package, where there is a compact neural network tool. It was employed in carrying out NN training and validation exercise in this presentation. The collected data was normalized and partitioned. It is normal to divide the entire data spectrum into three parts. Considering the nature of the problem, a feed forward architecture was hypothesized for the data. The authors were lucky to achieve the error goal within few trials. This is not always the case as some neural networks can run into weeks before training is completed. The chosen architecture, nature of data and training algorithm can all affect training speed. Training was accomplished with seventy percent of the total data while the remaining thirty percent were used for validation and testing (that is; 15% for each). More than two thirds of the data was used in this research to ensure a very good training. The quantity can be reduced for significantly large data where so many examples will be presented to the network. Training always stops when there exist no further sign of improvement in generalization irrespective of partitioning ratio, training algorithm or architecture, as indicated by chosen performance criteria. As displayed in Fig. 10, very good result was recorded with the chosen architecture, called multilayer feed-forward Back Propagation network. That is; when the network had one input layer, twenty hidden layers as well as one output layer. At the point, the performance criteria, that is; mean square error during training, validation and testing were respectively $1.02564 \times 10^{-3}$, $3.85361 \times 10^{-3}$ and $1.7329 \times 10^{-3}$. The R values at these points were 0.998742, 0.994995 and 0.996133 for training, validation and testing respectively. Other configurations were tried but did not give any better result. The training algorithm, namely, Levenberg-Marquardt optimization (TrainLM in MATLAB jagon) can be said to be sufficient for the work. Hyperbolic transfer function designated by Tansig, used for neurons in the input and hidden layers equally contributed to the quick convergence of the network during training and validation. To present a visual appreciation of the result, plots of the training, validation and testing are displayed in Fig. 11 while Fig. 12 present respective regression plots for the different exercises.

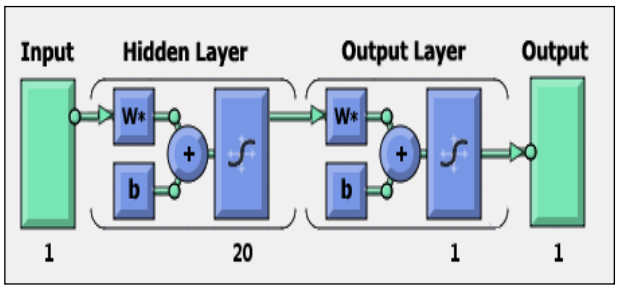



**Fig. 10:** ANN Model for Compressor Reliability Prediction.

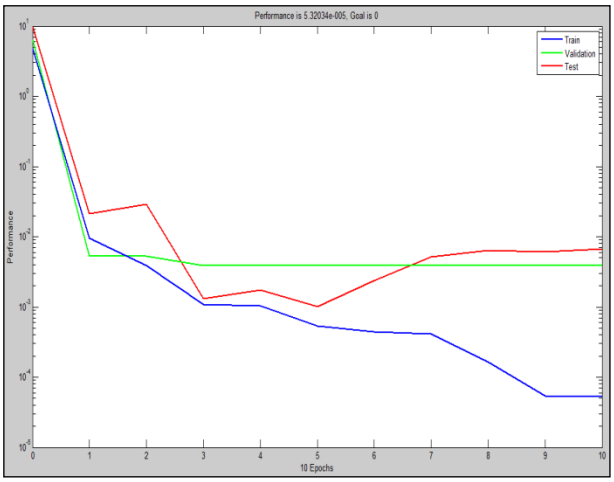



**Fig. 11:** Plots of the Training, Validation and Testing.

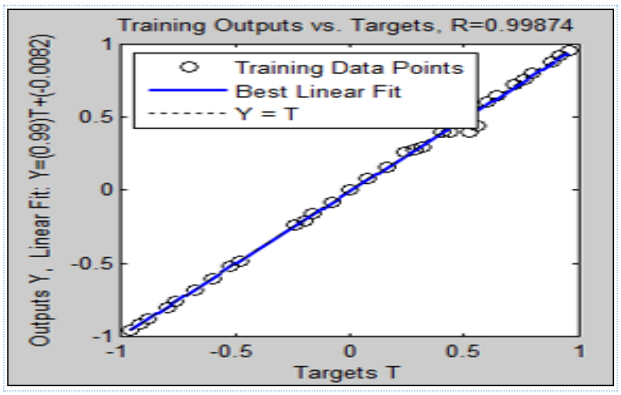



**Fig. 12:** Regression Plot for Training.

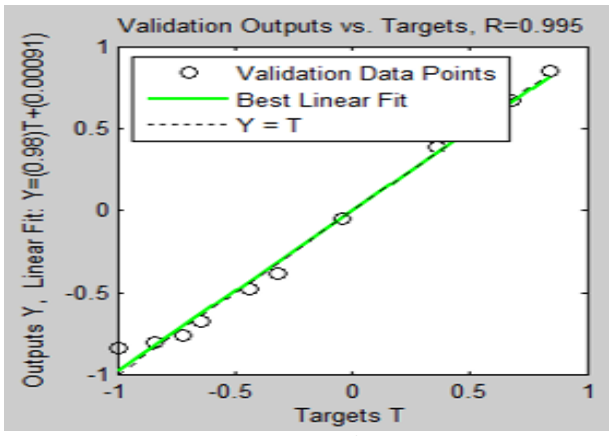



**Fig. 13:** Regression Plot for Validation.

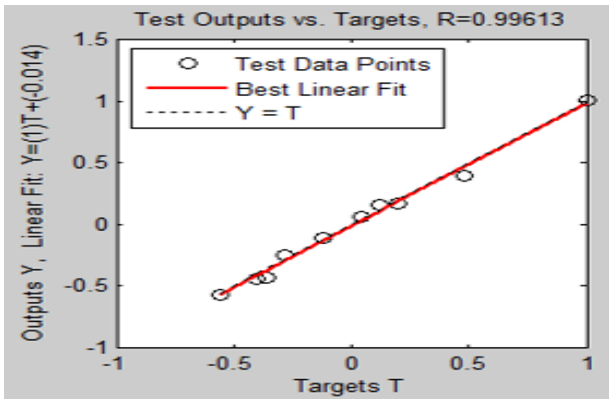



**Fig. 14:** Regression Plot for Testing.

## 5. Discussion

The interconnectivity between human neural network and artificial neural network has been x-rayed. The similarities has aided in the development of powerful computing tools that are assisting in solving and optimizing problems from several engineering and allied disciplines. While complete learning in human neural networks involves complicated processes that are not clearly understood yet, it has provided sufficient insight to the design and implementation of ANNs that can handle multiple variable (input) problems for optimal administration of science, Engineering, innovation and Mathematics. The result obtained with the illustrative trained neural network model in this paper predicts the reliability of the compressor very well, given the very low values of MSE ( $1.02564 \times 10^{-3}$ ) and high value of the regression (0.998742). Analytical procedures can provide close means of modeling simple to moderate multi-parametric scenarios. This closeness is in no way a statement of close competition between conventional Mathematical procedures and ANN in tackling real World complex industrial problems. Neural Network models are designed to handle stochastic and complex data analysis problems. When the problem involves few data sets, statistical and Mathematical analysis tools are normally recommended. However, the ANN approach presented here is only as background to the procedure of its application when multivariate and complex analytic problems are involved.

## 6. Conclusion

The major cleavage of this paper is to provide an assessment of the nexus between HNN and ANN which ushered-in the use of Neural Network-based methodologies in system maintenance. The work is aimed at deepening understanding of the descent of ANNs from human neural network activities. Artificial neural network was x-rayed and its relationship and derivatives from human neural networks delineated. Attempt was made to present the foundations of neural network modeling techniques and the major contributors to the development of the field. Some of the terminologies associated with both biological (human) and artificial neural networks were defined and explained with relevant Fig.s. Overall, use of ANN technique in predicting the reliability of a case study industrial system was illustrated. The two-layer (1, 20, 1) feed forward back propagation neural network was trained to predict the reliability of a $CO_2$ compressor unit. That means an architecture comprising one input layer, twenty hidden layers and one output layer. It was observed that reliability predictions obtained from ANN model proved very good, considering the very low values of MSE ($1.02564 \times 10^{-3}$) and high value of the regression (0.998742). The result shows that ANNs are good means of system maintenance planning. The major essence of the presentation is to clear the ambiguity that has characterized the field of neural network understanding and application. Specific data size for different algorithms was not studied. Future research efforts can be

constituted to address the trial and error approach used in selecting suitable architecture in order to save some training time.

## Acknowledgement

The material and financial assistance of the NRF-TWAS fellowship: award number PD-TWAS160531166951; UID: 105554, towards this paper are hereby acknowledged. The support of University of Nigeria Nsukka (UNN) towards the completion of the research cannot be overstressed. However, opinions expressed and conclusions arrived at, are those of the authors and are not necessarily to be attributed to either NRF-TWAS or UNN.

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