International Journal of Scientific & Engineering Research, Volume 4, Issue 12, December-2013 7
ISSN 2229-5518

A Hybrid Neural Diagnostics Model for Continuous Estimation of Reliability in Intricate Engineering Systems

Theophilus A. Fashanu and Olumuyiwa S. Asaolu

Abstract — The reliability of some sensitive engineering systems often derives from non-linear interactions at the sub system level. In practice, safety devices are usually implemented in such systems at the microscopic and macroscopic levels. This ensures robust availability and reliability. In addition, real time maintenance schemes are also deployed in high risk systems. Such policies are informed by real time instrumentation. On the whole, systems' configuration and quality of maintenance decision determine reliability and availability. As a rule, such schemes are adaptive in nature. They acquire and process vital in service systems statistics for decision-making. In this regard, non-linear pattern classifiers and discriminant functions are emerging alternatives to conventional tools; especially when ability to acquire and use experience is at an advantage. Thus, using probability safety assessment approach; this work develops a feature extracting artificial neural network processor for continuous statistical monitoring and diagnosis of engineering systems. The aim is to support decision-making associated with system reliability and enhanced availability of high risk systems. In addition to ability to give piece wise description of the health status of the system, our neural diagnostic scheme predicts impending system down time more accurately when compared with the performance of a statistical monitoring tool.

Index Terms— hybrid scheme, neural computing, probability safety assessment, systems availability, systems reliability

1 Introduction

FOR some engineering systems, the criteria for optimum performance, availability and reliability are specified over a very narrow bandwidth of systems parameters and operating conditions. Occasionally, some of these systems fail catastrophically in service at very high financial and human cost. Thus, such systems are classified as intricate or high-risk systems. Structurally, they consist of complex multi-component systems with high level of connectivity. Such networks are often series and parallel coordination of components and subsystems. Thus, the efficiency and reliability of such systems derive from non-linear intra and inter subsystem interactions of components, its architecture, and the prevailing maintainability scheme. Fortunately, for most of these systems, efficiency and state of health can be inferred from some measurable in-service statistics.

Therefore, for this class of engineering systems, automated instrumentation facilitates maintenance decision via online sensors and data processors. To date, many tools are available for this class of decision making. However, in approach; life testing techniques and probability safety assessment are two classical statistical methods for optimizing maintenance strategies. In a comparative analysis, [1] outlined the strengths and drawbacks of the some statistical processors. Though the review seems to have an appeal for probability safety assessment; the approach is still vulnerable to non-optimum inspection frequency along with deficiencies in ability to characterize system non-linearity. In addition, apart from these shortcomings, it is evident that statistical inferencing machines do not incorporate real life experience. To address this problem [2], [3] and [4] proposed some intelligent tools for the assessment of systems reliability. These tools combine statistical information and experience to formulate real time maintenance policies for enhanced systems availability and reliability.

Intelligent tools for fault detection and systems reliability can be grouped as expert systems, qualitative automated reasoning or model based diagnosis. Others are the neural network and evolving distributed intelligence tools such as the web based or multi-agent framework. In contrast to traditional reliability assessment methods that are exclusively based on signal processing and pattern classification techniques. These intelligent tools are able to follow experience, utilize complete domain of developed experts' knowledge in the field and also exhibit ability to learn.

However, as obtained in traditional techniques, systems dynamics and non-linearity pose important challenge to intelligent fault diagnostics tool. Although the neural network has a proven advantage in ability to handle systems non-linearity; it is well-known that systems complexity and large data size elongates its training time to delay fault detection. Specifically, [5] described the limitation of artificial neural network in this regard. Based on this observation, [6] reiterated the needs for further development of the neural network scheme.

Consequently, this work presents the development of a hybrid neural network and probability safety assessment scheme for continuous estimation of reliability in high risk systems. For a numerical example, we consider the energy sector as test case. Thus, our hybrid neural network and probability safety assessment algorithm is herein deployed to estimate system availability and reliability of two power barges belonging to a thermal station located at Egbin in southwest Nigeria.

2 Model Development

Considering an n-component system in series or parallel connection with some wearing components at time instant (t). To develop a probability boundary function for a neural network pattern classifier, we define the following probability vector of reliability measures at time t.

$$P^t(t) = (P_1^t(t)P_2^t(t) \dots P_n^t(t)) \qquad (1)$$

$$P_i^t(t) = \begin{cases} m_i^t / m_j^t; & m_i^t \le m_i^{Pl} \\ 1; & {}_i^{Pi} \le m_i^t \le m_i^{Pu} \\ 1 - \left(k_u m_i^{Pu} / m_i^{Pi} m_i^t \right); & m_i^{Pu} \le m_i^t \le k_u m_i^{Pu} \\ 0; \; Otherwise & \end{cases} \qquad (2)$$

Here m_i^t is the observed value of parameter i, m_i^{Pl} is the specified lower limit of the bandwidth of m_i^t if the system is at peak operating condition. m_i^{Pu} is the specified upper limit. k_u is a factor describing the flexibility of the upper limit. Next, we define $r = (r_1\, r_2 \dots r_n)$ as the vector of available maintenance strategies designed to transform measurable parameters of the system to their peak operational values along a path that satisfies the performance index;

$$\sqrt{n \| P_{(t)}^t \|} = \langle r(t), c \rangle \qquad (3)$$

Furthermore given $r(t)$, the transformation of the system's prevailing health status $H(t,r)$ is presumed to proceed via;

$$r(t)\Phi(t)P_t^t(t)^T = H(t,r) \qquad (4)$$

$\Phi(t)$ is the non linear state transition matrix.

We also presume that in real systems, the dynamics of $P^t(t)$ is non-linear and stepwise in nature. Thus;

$$\hat{P}^t(t) = f[P^t(t), \Phi(t), r(t), t] \qquad (5)$$

This implies that the system transition matrix $\Phi(t)$ consists of sequence of transition operations on the conditional state probability vector. Consequently;

$$P_{i(t,\bar{y})}^{t^*} = P\{i|(t,\bar{r}),\bar{r}\} \,.\, P^{t^*}\{i|t^*\} \qquad (6)$$

Here, $P^{t^*}\{i|t^*\}$ is the conditional probability that the next observation of $P_i^t(t)$ will be $P_i^{t^*}(t^*)$ given the instantaneous health status of the system and the prevailing maintenance policy $r(t)$ in the interval $t^* = (t + \Delta t)$.
Given that $\mathbb{g}_i(t)$ is the optimized cost of sustaining measured parameter i at a safe state $m_i^t, \forall t$. Assuming all transitions follow the shortest admissible trajectory. Then according to [7], equations (3), (4) and (6) satisfy the following form of Bellman's equation;

$$\overline{\mathbb{g}}_i(t) = \textstyle\sum_t P\{t|i\} \min_d E_i^*\{e(t,t^*) + \mathbb{g}_i^* | i,t,\bar{r}\} \qquad (7)$$

In this work, $e(t,t^*)$ is a function of defective components in the interval between t and t^*. Clearly, $r(t)$ is optimal if it minimizes equation (7) for all values of i, and t. Thus, this condition facilitates the characterization of the sequence of the transition matrices $\Phi(t)$ for various configurations of $r(t)$ and $P^t(t)$. Therefore, it is possible to approximate hierarchical values of $H(t,r)$ corresponding to various configurations of $r(t)$, $\Phi(t)$ and $P^t(t)$.

2.2 Artificial Neural Network Training Algorithm

Following the primary objective of this work, we propose a health index neural feature extraction scheme of the form;

$$\widetilde{H_\iota}(t,\bar{r}) = W_{io} + \textstyle\sum_{j=1}^m W_{ij} \tilde{\mathbb{g}}_i(t) \qquad i = 1,2,,,n \qquad (8)$$

Equation (8) maps the health index at time t into some state vector

$$\tilde{\mathbb{g}}_i(t) = (\mathbb{g}_1(t), \mathbb{g}_2(t), \dots, \mathbb{g}_n(t)) \qquad (9)$$

The elements of the weight matrix W are computed in the manner of [8] to extract the feature of the one-step health transition function $\Phi(t)$. Applying gradient techniques, and the methods described in [9], it is easy to show that the feed forward ANN process with backward propagation for the extraction w_{ij} at time step k (i.e. $w_{ij}(k)$) using equations (6), (7) and (8) can be written as;

$$E[\Delta w_{i,j}(k)] = \eta E\left[\textstyle\sum_{q=1}^N w_{i,j}(k) \mathbb{g}_q(k) \mathbb{g}_j(k)\right] - \eta E\left[\textstyle\sum_{p=1}^N w_{i,p}(k) \mathbb{g}_p(k) \mathbb{g}_j(k) \sum_{q=1}^i \sum_{l=1}^N w_{q,l}(k) \mathbb{g}_l(k) w_{q,j}(k)\right] \qquad (10)$$

$\eta > 0$, is the learning rate.

In compact matrix form, equation (10) can be written as

$$\frac{E[\Delta w_{i,j}(k)]}{\eta} = W_{i_*}(k)C(k) - \textstyle\sum_{q=1}^{N-1} \left(W_{i_*}(k)C(k)W_q^T(k) \right) - W_{i_*}(k)\, C(k) W_i^T(k) W_{i_*}(k) \qquad (11)$$

where $\quad C(k) = (\mathbb{g}_1(k), \mathbb{g}_2(k) \dots \mathbb{g}_{N-1}(k))$

The neurons in Equations (10) and (11) are activated by the non linear strategic function

$$\mathbb{g}_m(k) = \frac{1}{1 + \exp(-\sum_{m=0}^k W_m(k))} \qquad (12)$$

To investigate the consistence and accuracy of the developed feature extraction scheme, we follow the stability criterion derived in [10] from a Lyapunov stability analysis. With respect to equations (11) and (12) the condition for global asymptotic stability of the feature extraction process is given as

$$(\|W(k)^T\|_2 + \|W(k)^{-T}\|_2)^2 \le \frac{2\eta - \|C(k)\|_2}{\|C(k)^{-1}\|_2} \qquad (13)$$

ISSN 2229-5518

Considering uniformly sampled data space, so that the data acquisition interval Δt *is* constant. Also, given the symmetry of the hidden layers of our neural network architecture, it can be easily verified that the choice of a symmetric positive definite matrix $C(k)$ with $Max|C(i,j)| < 2\eta$ and the normalisation $w_{i,j}(k) = \frac{w_{i,j}(k)}{Max|w_{i,j}(k)|}$ in equation (11) guarantees stability in the sense of equation (13).

3 Power Barge Instrumentation Procedure

To test our algorithm, we consider the problem of monitoring the health of two power barge systems belonging to an independent thermal plant operator in Nigeria. For this purpose, instrumentation parameters are sampled at a frequency of 0.01Hz on the test barges. On each of them, processing is decentralized to the subsystems level. That is the subsystem with poorest condition determines systems' overall health status. Some sensitive barge subsystems that are considered in this study include Turbine Support Legs TSLs, Main Transformer (MT), Lubrication System (LS), Water Cooling System (WCS), and Exhaust Gas System (EGS). At the time of this work, maintenance decisions on the facility are based on the Computerized Maintenance Management Software (CMMS), this is assisted by the specification of the safe bandwidths of the corresponding acquired data. Specifically, these include temperature, air filter pressure, frequency and amplitude of vibration e.t.c.

3.1 Model Application

We adapt the neural computing network to extract the elements $w_{i,j}$ of the transition matrix at discrete time state (k). Using Equation (2), the measured EGTs are transformed into probability measures at the input nodes. To train the network, corresponding availability measure at the output node is obtained from the normalized CMMS assessment. Learning is initiated with an order of magnitude analysis. On these test barges, the analysis converged on the EGTs as the instrumentation data of interest.

Probability measures corresponding to TTXD1, through TTXD4 were admitted as inputs into each of the input nodes. For all layers, learning starts with $w_{i,j} = w_{j,i} = 0.025$. These values are updated using equation (9) until $\left|w_{i,j}(n+1) - w_{i,j}(n)\right| < tol = 0.001$ is satisfied. At the end of a training cycle, the EGT measurement on any of the input nodes with

$$Min^{\left(\sum_{k=1}^{4}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\sqrt{w_{i,j}^2+w_{j,i}^2}\right)_k\right)} \qquad (10)$$

is replaced with the next available measurement. Here m and n are the numbers of perceptrons in the $kth\ and\ (k+1)th$ layers respectively. This dimension reduction cycle is repeated until all the EGTs and TSs have been considered in the forward and backward directions. Conversely, to deduce the health status of the Barges from the EGT measurements; the corresponding probabilistic measures as expressed in equation (2) are used as inputs to the neural feature extraction algorithm, and the normalised weights $w_{i,j}/w_{j,1}$ are subsequently applied to compute $H(t,r)$.

4 Summary of Results

The parameters short listed for analysis on Power Barge A by the dimension reduction process include; TTXD3, TTXD5, TTXD17 and TTXSPL. Correspondingly, on Power Barge B, we have TTXD2, TTXD8, TTXD14 and TTXD17. For each of the Barges, 2300 recorded data points were used for network training. The convergence condition is satisfied after an average of 5863 epochs. Training and validation were performed in Matlab R2008a environment on a 1.83GHz Intel iCore 3 processor. The maximum duration for training and validation recorded is 117seconds. Tables 1a and 1b show the extracted weight vectors for connections linking the first/second $(k = 2)$ and the second/third second $(k = 3)$ layers.

Table 1a: Weights Vectors between First and Second Hidden Layers on Power Barges A and B

Barge A($w_{i,j}$)	Barge B($w_{i,j}$)
$0.479_{1,1}$	$0.782_{1,1}$
$2.316_{1,2}$	$-1.017_{1,2}$
$-1.509_{1,3}$	$-1.219_{1,3}$
$0.825_{1,4}$	$2.007_{1,4}$
$1.713_{2,1}$	$0.722_{2,1}$
$-0.913_{2,2}$	$3.117_{2,2}$
1 $.230_{2,3}$	$0.416_{2,3}$
$0.081_{2,4}$	$-1.212_{2,4}$

Table 1b: Weights Vectors between Second and Third Hidden Layers on Power Barges A and B

Barge A($w_{i,j}$)	Barge B($w_{i,j}$)
$1.715_{1,1}$	$0.643_{1,1}$
$1.839_{1,2}$	$2.016_{1,2}$
$0.939_{2,1}$	$-1.119_{2,1}$
$1.331_{2,2}$	$1.108_{2,2}$
$-0.063_{3,1}$	$1.713_{3,1}$
$1.027_{3,2}$	$1.301_{3,2}$
$0.933_{4,1}$	$1.230_{4,1}$
$1.087_{4,2}$	$-1.471_{4,2}$

Individually, Tables 1a and 1b show the dependence of the $w_{i,j}$'s on the current and past records of instrumentation parameters. Along with equation (10), these tables and their complements for $(k = 1)$ and $(k = 4)$ facilitate a categorization of the effectiveness of the instrumentation process, their reach-ability on the state of the subsystem(s) and effect on the overall performance of the EGS.

Figures 1 and 2 validate the performance of our hybrid neural computing scheme using the outcome of the CMMS as benchmark. This comparative analysis was carried out for eighteen hours of a day that Barge B was shut down for corrective maintenance.

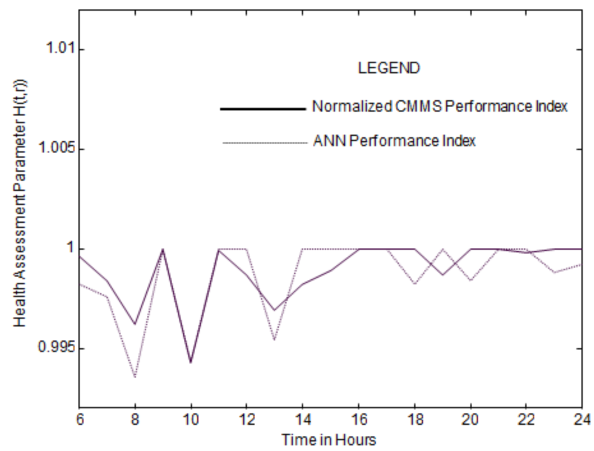

Fig.1. Comparative Analysis of Hybrid Neural Computing Scheme and CMMS Assessment on Barge A

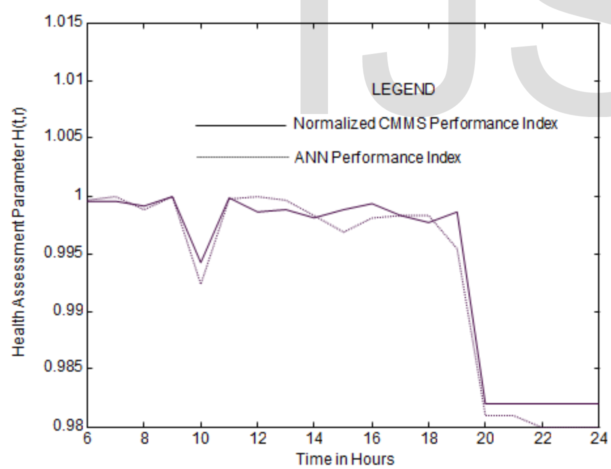

Fig.2. Comparative Analysis of Hybrid Neural Computing Scheme and CMMS Assessment on Barge B

Summarily, three hierarchical levels of performance are specified for the outcomes of H (t, r) as classified in Table 2.

GOOD PERFORMANCE	$0.995 \leq H(t, r) \leq 1.0$
TOLERABLE PERFORMANCE	$0.995 \leq H(t, r) \leq 0.990$
EMERGENCY CONDITION	$H(t, r) < 0.990$

Table 2: Hierarchical Classification of the EGS Performance Levels

According to the classification on Table 2, subsystems with good performance conditions are continuously monitored. The CMMS recommends sequence of adaptive maintenance policies for subsystems with tolerable performance index, whereas Barge with emergency state in any of its subsystems is shut down for corrective maintenance.

Compared with the CMMS output, the computational accuracy of the hybrid neural computing scheme is evaluated as 99.72%. To obtain this efficiency, we have used the normalized CMMS performance index as training and validation data. Also, by using a neural network architecture that simulate system's configuration at the component level, our hybrid neural diagnostics scheme has the advantage of enhanced trouble shooting when compared with the CMMS. To be precise, the break down in Barge B as shown in Figure 2 was traced to a worn outlet valve relating to TTXD14. This is as indexed in the $H(t,r)$ obtained by our hybrid neural computing scheme.

4.1 Conclusion

This work developed a hybrid neural computing scheme to demonstrate that a combination of the traditional probability safety assessment technique with an intelligent tool (precisely the artificial neural network) can significantly improve on the precision and diagnostic ability of devices that are deployed for continuous monitoring of intricate engineering systems. The hybrid scheme has inherent abilities to characterize the interplay between subsystems and components, reduce instrumentation sample space and accelerate trouble shooting to enhance systems availability. This hybrid form has the advantage of improved convergence rate of the neural computing algorithm. However, for real time health monitoring of high risk engineering systems, the scheme should be developed further to minimize the lag time between data acquisition and health inference.

Acknowledgments

The authors are grateful to Mr. J. Adeyemo and the Management of AES Nigerian Barge Operation for supporting this work.

References

[1] Yang Y., and Klukte G., (2000) Lifetime Characteristics and Inspection Schemes for Levy Degradation Process. IEEE Transactions on Reliability. 49, 377-382.

[2] Hole K. and Netland L. H. (2010). Toward Risk Assessment of Large-Impact and Rare Events. IEEE Security and Privacy Vol. 8, pp. 21-27.

[3] Nokata M. and Tejima N.(2004). "A Safety Strategy for Rehabilitation Robots". Advances in Rehabilitation Robotics Springer-Verlag Berlin Heidelberg pp. 177 – 185.

[4] Wang L. and Singh C. (2008). Population –based Reliability Evaluation of generation Systems with Wind Power Generation. IEEE transaction on Power Systems, 23(3) 1336 - 1345
[5] Hermann N.(1995). On the Probabilistic Interpretation of Neural Network Classifiers and Discriminative Training Criteria. IEEE Transactions on Pattern Analysis and Machine Intelligence., 7(2), 107-119.
[6] Kobbacy K. A.H. (2004). On the Evolution of an Intelligent Maintenance Optimization System. Journal of Operations Research Society., 55(2), 139-146.
[7] Bertsekas, D.P., Homer, M. L. Logan, D. A. Patek, S. D. and Sandell, N. R. (2000). Missile Defense Interceptor Allocation by Neuro-Dynamic Programming. IEEE Transactions on Systems, Man, and Cybernetics., A30(1), 42-51.
[8] Kolmogorov A. N. K. (1957). On the Representation of Continuous Functions of many Variables by Superposition of Continuous Functions of One Variable and Addition. Dokl. Akad. Nauk SSSR..,114, 953-956.
[9] Kil R. M.(1993).Parameter Estimation of a Network with Kernel Functions of Bounds and Locality. In Science of Artificial Neural Networks II, Proc. SPIE., 1966, 284-295.
[10] Yucel E. and Arik, S. (2012). New Sufficient Criteria for Global Robust Stability of Neural Networks with Multiple Time Delay. TWMS J. App. Eng. Math. Vol. 2, No. 1, pp. 1-18.