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Estimation of Boiler's Tubes Life, Artificial Neural Networks Approach

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ABSTRACT

The analysis of creep-damage processes is becoming more and more important in engineering practice due to the fact that the exploitation condition like temperature and pressure are increasing while the weight of the structure should decrease. In the same time the safety standards are increasing too. The accuracy of the mechanical state estimation (stresses, strains and displacements) mainly depends on the introduced constitutive equations and on the chosen structural analysis model.This paper is devoted to the prediction of boiler's tube life using of Artificial Neural Network (ANN) technique. Training data used were obtained from Kapar power station technical reports. Predicted values of the remnant tube life were compared to the experimentally collected data to verify the success of the algorithm; average absolute error obtained was 1.667%. Results obtained show that the designed network is capable of predicting the remnant life of the boiler's tube successfully.Predicting boiler's tube life successfully presented using this method will help maintenance engineers to schedule preventive maintenance procedure in order to minimize maintenance cost and to prevent any consequences of disasters which may happen if the necessary precautions were not taken.

Keywords: *Boiler tube Remnant life estimation; Artificial Neural Network; water-tube boiler.*

Introduction

Modern industrial complexes are equipped with different types of boilers. Boiler tubes are considered as pressure vessels subjected simultaneously to the action of stress and high temperature. The continual increase in the temperatures of

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operation has placed great practical importance on the estimation of boiler's tubes life.

Despite the fact that much effort has been paid to improve the boilers design in order to reduce failure, unfortunately, boiler tubes failure still occurs. Many reasons could cause boiler tubes failure in service condition; corrosion, cracking, Carbide graphitization, Oxidation, Sulfidation, pitting, embrittlement, overheating and manufacturing defects are some of the possible causes. Many reasons are identified as possible causes for boiler tubes failure, however; the creep related causes are found to be the most common failure type for the water tube boiler [1, 2]. Creep is a time-dependent deformation that occurs when a material is stressed at high temperature. Over a period of time with a continued load, the material will eventually rupture. The temperature at which creep becomes important depends on the particular metal [3].

Oxidation and sulfides may form scale on the tubing surface and cause damage, because the scale is easily changed to powder and subject to exfoliation; or the sulfides with their comparatively low melting point may fuse with the tubing surface and cause rapid inter-granular penetration. Sulfide corrosion is a problem often encountered in boilers; it can become a problem when temperatures exceed 260^{o}C [1]. On the other hand, the oxidation process may begin to form a layer of magnetite scale when the tube metal is in contact with the steam over a period of time. This phenomenon will worsen the situation if the exposure is prolonged leading to potential creep rupture [4]. The scale presented after 10,000-hour exposure in steam may be sufficient to cause a temperature increase that will reduce the rupture time for a constant stress as Ennis and Quadakkers [5] was reported.

Fire side wastage is another common cause of creep failure of boiler tubes in addition to the scale formation problem on the inner side of boiler tubes (steam-side).When boiler tubes are experiencing wastage, the hoop stress is going to increase respectively especially when severe oxide cracking and exfoliation occur. On the other hand, the wastage rate of the tube metal could dramatically increase as a result of erosion and/or molten salt corrosion [6].

Many attempts in the literature have been found to correlate creep rate, stress, temperature and time to rupture for boiler tubes design purposes. Each attempt used different approach. While some of the researchers have tried to estimate the remnant tube life by using metallurgy analysis [3,7], other researcher has used chemical analysis, scanning electron microscope and energy dispersive spectroscopy for that purpose [8] and the Larson-Miller parameters (LMP) method have also been used [9]. The LMP is a means of predicting the lifetime of material vs. time and temperature using a correlative approach based on the Arrhenius rate equation.

When the penalty for improper operation is costly (such as the creep rupture failure in boiler tubes) a prototype of the actual design is connected to a real-time simulator of the physical response, giving valuable training experience without fear of a disastrous outcome. Simulation programs are widely used to design equipments so that the final product will be as close as possible to design specs without expenses in process modification.

Erosion or corrosion causes the tube to become progressively thinner and as a result of which the primary stress in the tube increases with time. Extensive elastic-plastic finite element analysis needs to be performed to obtain the primary stresses in the localized thinned section of a tube.

One of the powerful methods that are currently available for the design and life assessment of the components that operate within the creep range is the reference stress (RS) method. An efficient and effective method for computing an approximate value for RS is described that combines a lower-bound theorem and finite element decartelization by Zarrabi and Motalagh [10]. The resulting quadratic programming is solved by an active set of finite element formulation algorithm. The verification and application of the proposed method are also described. Purbolaksono et al. [11] used a finite element modeling to investigate reheater tube failure. Data obtained from visual inspection, i.e. oxide scale thickness and tube geometry, were used to generate a finite element model. They have found that the failed tube had experienced higher temperature exposure and had operational stress exceeding the allowable stress values for quite prolonged period.

Based on the review of the literature done, most of the boiler tubes failure cases were investigated by experimental or visual inspection, hardness test, microstructure examination, and ultrasonic or physical scale thickness measurement or material identification and finite element simulation and imperial formulas. For the author's knowledge, very few studies investigating the failure prediction using Artificial Intelligence were reported in the literature yet. In this paper, boiler tubes life assessment is proposed utilizing Artificial Neural Networks.

There have been an increasing research interest of Artificial Neural Networks (ANNs) in recent years, and many efforts have been made on applications of Neural Networks to various problems [12, 13]. ANNs are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems. They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with non-linear problems and, once trained, can perform prediction and generalization at high speed, They are particularly useful in system modelling such as implementing complex mappings.the solution proposed in this paper involves the determination of the boiler's tube life according to the ANN prediction based on the training of the network with real data were obtained from dimensional measurements for the scale thickness of the reheater tube samples taken from Kapar Power Station Malaysia [14,15]. To validate the efficiency of the proposed method, predicted values using the proposed approach will be compared to the actual data of the available reports.

Fundamentals of Artificial Neural Networks

The fundamental idea underlying the design of the network is that the information entering the input-layer is mapped as an internal representation in the units of the hidden-layer and the outputs are generated by this internal representation rather than by the input vector. Given that there are enough hidden neurons, input vectors can always be encoded in a form so that the appropriate output vector can be generated from any input vector.

Figure 1 shows the developed ANN model. The outputs of the units in input-layer are multiplied by appropriate weights W_{ij} and these are fed as inputs to the hidden layer. Hence if O_i are the output of units in input layer, then the total input to the hidden-layer is:

$$Sum_B = \sum_i O_i W_{ij} \tag{1}$$

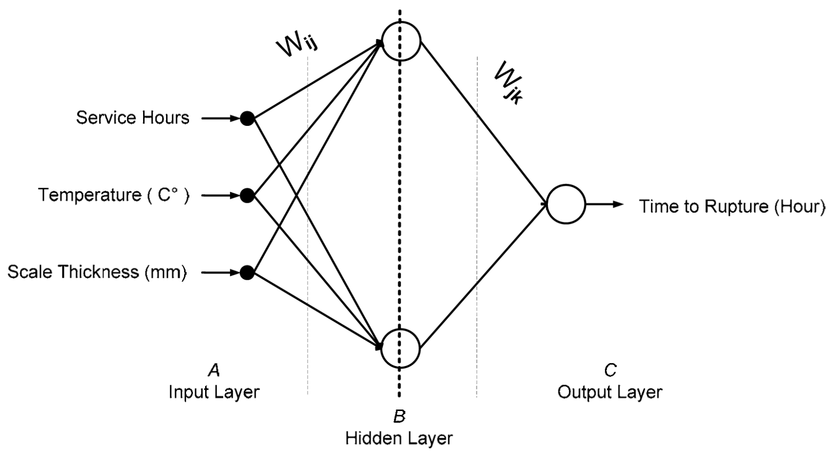

Figure 1: The Topology of the Designed Network.

And the output O_j of a unit in hidden-layer is:

$$O_j = f(sum_B) \tag{2}$$

Where f is a non-linear activation function, it is a common practice to choose the sigmoid function given by:

$$f(O_j) = \frac{1}{1 + e^{-Oj}} \tag{3}$$

as a nonlinear activation function.

However, any input-output function that possesses a bounded derivative can be used in place of the sigmoid function. If there is a fixed, finite set of input-output pairs, the total error in the performance of the network with a particular set of weights can be computed by comparing the actual and the desired output vectors for each presentation of an input vector. The error at any output unit e_K in the output-layer can be calculated by:

$$e_K = d_K - O_K \tag{4}$$

Where d_K is the desired output for that unit in output-layer and O_K is the actual output produced by the network. The total error (E) at the output can be calculated by:

$$E = \frac{1}{2} \sum_k (d_K - O_K)^2 \tag{5}$$

Learning comprises changing weights so as to minimize the error function (E) by the gradient descent method. It is necessary to compute the partial derivative of (E) with respect to each weight in the network. Equations (1) and (2) describe the forward pass through the network where units in each layer have their states determined by the inputs they received from units of lower layer.

The backward pass through the network that involves "back propagation"of weight error derivatives from the output-layer back to the input-layer is more complicated. For the sigmoid activation function given in equation (3), the so-called delta-rule for iterative convergence towards a solution which stated in general as:

$$\Delta W_{JK} = \eta \delta_K O_J \tag{6}$$

Where η is the learning rate parameter, and the error δ_K at an output-layer unit K is given by:

$$\delta_K = O_K (1 - O_K)(d_K - O_K) \tag{7}$$

And the error δ_J at a hidden-layer unit is given by:

$$\delta_J = O_J (1 - O_J) \sum_k \delta_K W_{JK} \tag{8}$$

Using the generalize delta rule to adjust weights leading to the hidden units is back propagating the error-adjustment, which allows for adjustment of weights leading to the hidden-layer neurons in addition to the usual adjustments to the weights leading to the output-layer neurons.

A back propagation network trains with two step procedure, the activity from the input pattern flows forward through the network and the error signal flows backwards to adjust the weights using the following equations:

$$W_{IJ} = W_{IJ} + \eta \delta_J O_I \tag{9}$$

$$W_{JK} = W_{JK} + \eta \delta_K O_J \tag{10}$$

Until for each input vector the output vector produced by the network is the same as (or sufficiently close to) the desired output vector. Number of hidden neurons and the learning factor are determined by trial and error [12, 16].

ANN Implementation

A supervised feed forward ANN was designed using C programming language to learn the system's input / output relationship. The network consists of input, output and one hidden layer; the input vector for the network consists of tube service hours, temperature and the scale thickness, while the output vector was the time to rupture due to creep. As can be seen in Figure 1, every neuron in the network is fully connected with each other, sigmoid transfer function was used as an activation function, and Generalized backpropagation Delta learning Rule (GDR) algorithm was used in the training process. All control datasets values had been scaled individually so that the overall difference in the dataset was maximized.

The ANN was trained using actual data taken from technical reports from the Kapar Power Station Malaysia [14, 15, 17] shown in Table 1. Training data used were for a reheater tube located at the first raw facing the burner. The average operating steam pressure was 46 Bar while the flue gas temperature was reported at around 800°C.

Table 1: Reheater Tube's Remnant Life Data [17]

Service Hours	Temperature °C	Scale Thickness (mm)	Time to Rupture (Hour)
0	592.86	0.000	336441
250	595.47	0.0565	281888
500	596.31	0.0748	266465
1000	597.37	0.0983	248134
2500	599.2	0.1396	219495
5000	601.03	0.1816	194261
10000	603.34	0.2359	166629
20000	606.26	0.3066	137411
40000	609.74	0.3993	109349
60000	612.55	0.4672	91103
80000	614.64	0.5233	79551
92525	615.54	0.5547	75065

Data from the above table can be drawn to show the relationship among all the effecting parameters on the remnant life in graphic form. Figure 2 shows the relationship between tube's metal temperature and the service hours.

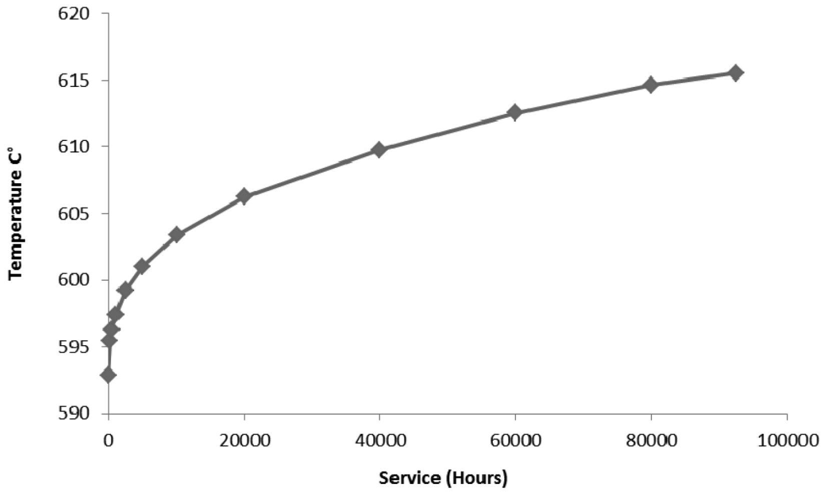

Figure 2: Relationship between Service Hours and Tube's Metal Temperature

As can be seen from Figure 2, tube's metal temperature is increasing when the service hours of the boiler increasing. The same can be seen for the scale thickness shown graphically in Figure 3 below, the formation of the scale is increasing with the boilers service hours increasing.

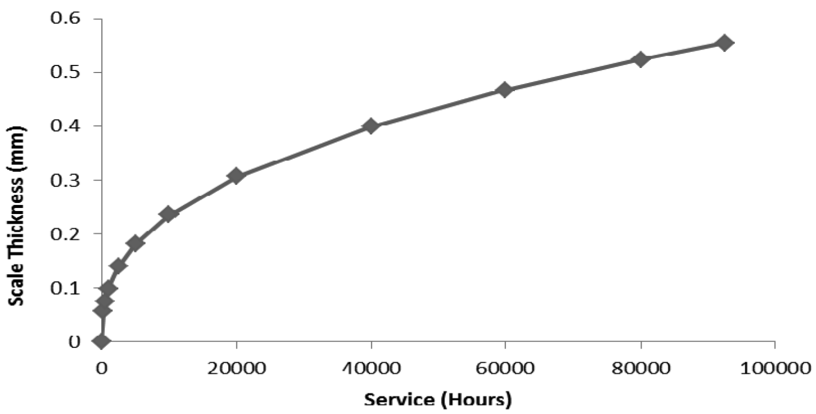

Figure 3: Relationship between Service Hours and Scale Thickness

Figure 4 shows the relationship between the time to rupture and the service hours, as this graph show the time to rupture decrease as the service hours increase.

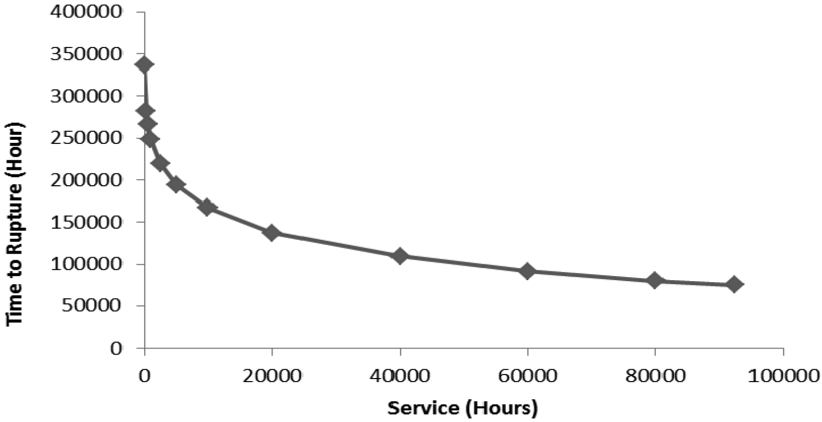

Figure 4: Relationship between Time to Rupture and Service Hours

To learn the target parameter (Time to rupture), a training process was carried out using the obtained data from the technical reports. The designed network shown in Figure 1 was trained by presenting several target points that the network had to learn, number of neurons in the hidden-layer was set to 6 with a constant learning factor of 0.4 by trial and error. Figure 5 shows the building knowledge process for the system.

To verify the success of the algorithm, the predicted values of the remnant life were compared to the experimentally collected data. The average absolute error was 1.667% after 10,000 Iterations. Figure 6 graphically shows the deviation of the predicted values of the remnant life from the actual values. Results obtained show that the designed network is capable of learning and predicting the remnant life of the boiler's reheater tube life successfully.

Conclusions

An Artificial Neural Network approach was proposed in this paper in order to give an advanced warning of failure in water tube type boilers. Predicted boiler's tube life using the proposed method was verified with actual data and the results were in good agreement.

The effectiveness of this method which was graphically shown, will give a clear indication to the maintenance engineers to schedule regular maintenance in

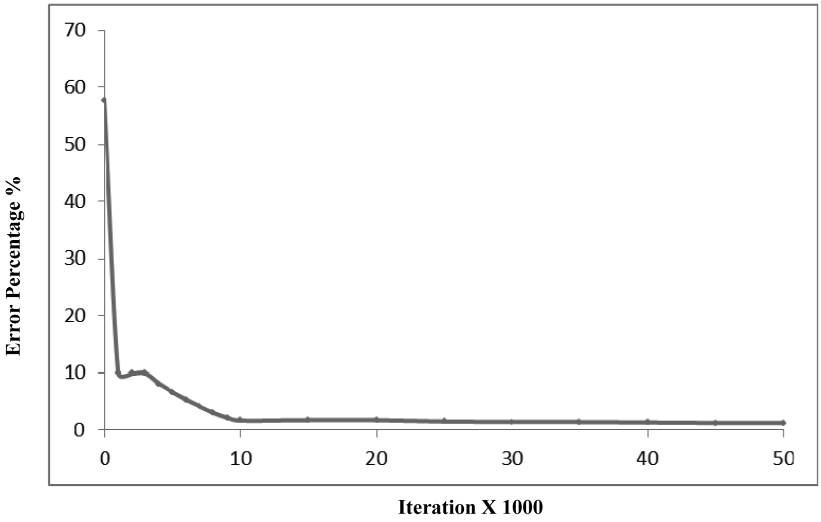

Figure 5: Building Knowledge Curve for the System

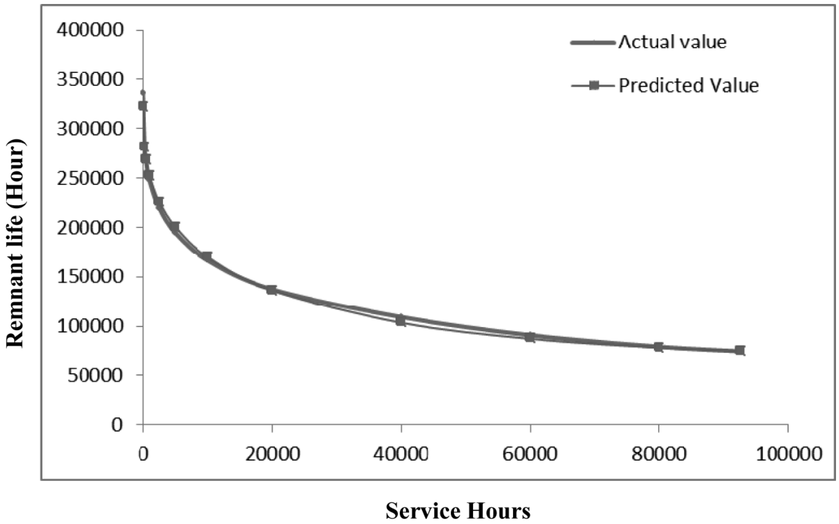

Figure 6: The Deviation of the Predicted Values of the Remnant Life from the Actual Values

order to anticipate tube's failure. Predicting tube's life will prevent catastrophic disasters and minimize maintenance costs.

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