Feed Forward Backpropagation Neural Network Model to Predict Remaining Useful Life Estimation of Ion Implant Tool

Sathyan Munirathinam
Big Data Engineer/PhD Research Scholar
smunirathina@micron.com

Dr.Balakrishnan Ramadoss
Professor & Former Head Department of Computer Applications
National Institute of Technology, India
brama@nitt.edu

***Abstract*-- This paper proposes a feed forward backpropagation neural network (NN) based remaining useful life (RUL) prediction approach. Estimation of remaining useful life (RUL) is an important tool to reduce maintenance cost of equipment. The accurate RUL prediction based on the current and previous health condition of the equipment is essential to make a timely maintenance decision for failure avoidance. In this paper, an artificial neural network (ANN) based method is developed for achieving more accurate remaining useful life prediction of semiconductor manufacturing equipment. The ANN model takes the multiple measurement values at the current and history inspection points as the inputs, and the output is the remaining life hours of the equipment. The ANN RUL prediction uses FeedForward Backpropagation Neural Network (FFBPNN) with Levenberg Marquardt of training algorithm. The effects of changing the number of neurons in the input layer, the number of neurons in the hidden layer, the rate of learning, and the momentum constant are investigated. We employed variable importance analysis in identify critical feature variables to be given as input for an artificial neural network (ANN) to predict the lifetime of tungsten filament. The objective of this research paper is to propose a predictive model to be able to evaluate the health state of tungsten filament and to estimate the RUL of the component.**

***Index Term*-- Degradation Model; Prediction; Remaining Useful Life; Artificial Neural Network**

1. Introduction

Prognostics and health management of semiconductor manufacturing equipments has recently attracted a lot of research interest. Prognostics are the process of predicting the end of (useful) life (EOL) and/or the remaining useful life (RUL) of components, subsystems, or systems. With today's intense marketing competition, it has been an urgent demand in semiconductor manufacturing systems to enhance the production efficiency and lower the manufacturing cost. Many researchers have paid great amount of interest and attention to track the degradation of equipment to plan the maintenance strategies proactively and prevent potential failure. Usually, remaining useful life (RUL) estimation is a widely used form of degradation prediction which can help make maintenance decisions. As such, an appropriate maintenance schedule is essential in manufacturing systems to ensure all operating equipment in healthy condition, reduce failure occurrences, as well as guarantee the production quality. Maintenance actions are optimally scheduled based on the predicted future equipment health condition, so that the equipment replacements can be performed to prevent unexpected failures and minimize total maintenance costs. Accurate health condition prediction is the critical to effective implementation of condition based maintenance. Existing equipment health condition and RUL prediction methods can be roughly classified into model-based methods and data-driven methods. The model-based methods predict the remaining useful life using damage propagation models and data-driven models utilize the manufacturing equipment condition data for RUL prediction. Artificial neural networks (ANNs) have been extensively researched in developing a promising tool for RUL prediction to determine equipment health condition. Neural network methods do not assume the analytical model of the damage propagation, but aim at modeling the damage propagation process, or degradation process, based on the collected condition monitoring data using neural networks and perform health condition prediction. Lee et al. (2006) proposed to extract an overall health indicator based on the collected condition data, and predict future health indicator values using the autoregressive moving average (ARMA) method and Elman neural networks. It is well known fact to achieve a more accurate result, then we should be looking at train the models using more unscheduled breakdown failure histories are used to train the models. Apart from the failure history data, there is suspension data. In order to overcome the problem of a limited amount of historic data, Tian *et al*. [2] proposed a neural network prediction method which can utilize both failure and suspension histories data. Then, for alleviating the fluctuation of degradation indicators, a function generalized from the Weibull failure rate function was used to fit condition indicators [3]. Recently, Lu *et al*. [4] developed an effective RUL prediction method based on a feed-forward neural network. In the paper, only truncated histories were used to train the model. Zhou *et al*. [5] proposed a state space RUL prediction model without linear and Gaussian assumptions. In the model, an efficient Monte Carlo-based algorithm was developed to estimate the parameters. Zhang *et al*. [6] implemented a Bayesian networks-based degradation model. It can achieve accurate RUL values even when the degradation indicator fluctuates over a great range. Besides, maintenance decisions can be made efficiently according to the degradation state identification. Wang *et al*. [14] developed an adaptive RUL prediction method based on a generalized Wiener process. The Wiener process also was used to predict the RUL of 2008 PHM competition data [15]. Lately, an adaptive and nonlinear prognostic model to estimate RUL using a system history of the observed data to date was presented [16]. Ye *et al*. [17] developed a semi-parametric inference method of a simple Gamma-process model and a random-effect variant. This enabled the Gamma process-based degradation model results to be close to the practice. Recently, Ye and Chen [18] systematically investigated the characteristics of an inverse Gaussian process as a degradation model. Then, based on this work, Peng *et al*. [19] studied the inverse Gaussian model from a Bayesian perspective. Recently, Ye and Xie [20] systematically reviewed degradation models, especially for stochastic processes models. However, the efficiency of stochastic processes-based degradation models depends on the proper estimation of some prior distributions and parameters of the model. In addition, a number of failure or suspension histories are needed. To the best of our knowledge, prediction models adaptive to a limited number of conditions monitoring data have not been fully researched yet.

Another RUL prediction technique proposed by Wu et al. (2007) based on ANN, where the ANN output is predicted as the remaining life percentage of the equipment. This method lacks accuracy in prediction and also robustness of this predictive model. In this research paper, we propose a new modified version of ANN based method for achieving more accurate prediction of RUL prediction and also to increase the performance of the computation of the model. . The remainder of this paper is organized as follows. The proposed ANN method is presented in section “The proposed ANN remaining useful life prediction method”. Section 5 “Experiments and Results” demonstrates the case study, in which the proposed ANN method is validated using the data collected from the ION implant. The last section concludes with the research.

2. MOTIVATION

Existing data-driven and model-based RUL prediction approaches perform well for different problems, but often it is not clear how to retrieve the model, the needed health feature or complete run-to-failure data is needed for training. Furthermore, the computational cost of many algorithmic approaches is too high with limited infrastructure resources. To overcome these drawbacks, a RUL framework is proposed in this paper that requires acceptable and unacceptable performance data for training. It consists of health feature extraction and RUL prediction. The main advantages of the framework are its simplicity, a small online computational cost and an integrated health feature creation. Like other data-driven approaches this framework requires certain amount of historical data for its training. It is usable for different operating modes with information about the operating mode as part of the input vector. Due to the permanently collected measurements in semiconductor process control systems, this data often already exists. The performance degradation is assumed to be Weibull distributed, which is very common and true in many applications. RUL is usually selected as the degradation indexes for remaining life prediction and it is used for proactively schedule the maintenance actions. In this paper, degradation indicators extracted from Tungsten Filament in Ion Implant tool.

3. BACKGROUND

3.1 ION IMPLANT

Ion Implantation is a material engineering process and one of the most significant processes in Semiconductor Manufacturing. This process is carried out by Implanter Tool by which ions of material from material substrate are accelerated in an electric field. The major maintenance issue of such Ion Implant tool concerns the breaking of the tungsten filament contained within the ion source of the tool. This kind of unscheduled breakdown can happen on a monthly basis, and the associated maintenance operations can last up to 4 to 5 hours. The tungsten filament is changed every time when the Implant tool reaches a predefined amount of working hours. This is a typical Run-to-failure (R2F) maintenance approach, which can suffer from three main drawbacks: (i) filament ‘life’ exploitation, where filament is usually changed when it would still be usable; (ii) filament faults can still take place and (iii) Man hours to fix the filament breakage. This research is proposed to estimate the lifetime of the filament through statistical estimate by relying on the historical data and current values of the equipment feature variables acting on the process (such as filament currents, voltages, pressures and so on).

(a) New Filament (b) Broken Filament

Ion implantation is a single process step which occurs several times during wafer fabrication and is typically one of the most complex ones. The ion implantation tool (implanter) is used to impinge charged atoms upon the wafer to systematically change electrical characteristics of the wafer surface (see Wolf, 2003). Therefore, the ions are generated in an ion source and extracted in form of an ion beam. One part of the ion source of an implanter is the filament. It is stressed during the implanter operation and breaks on a highly irregular basis every few days. Figure 1 show the new filament and broken filament conditions. The breakdown and the resulting tool downtime leads to a highly undesired loss in productivity. Thus, a well-defined point of time for changing the filament can increase the throughput and reduce downtime and maintenance costs.

For example, knowledge of the remaining lifetime of the filament right before a weekend could prevent expensive weekend assignment of engineers and reduce manpower costs. Therefore we try to find a statistical model using Artificial Neural Network for predicting the filament break.

3.2 Artificial Neural Networks (ANN)

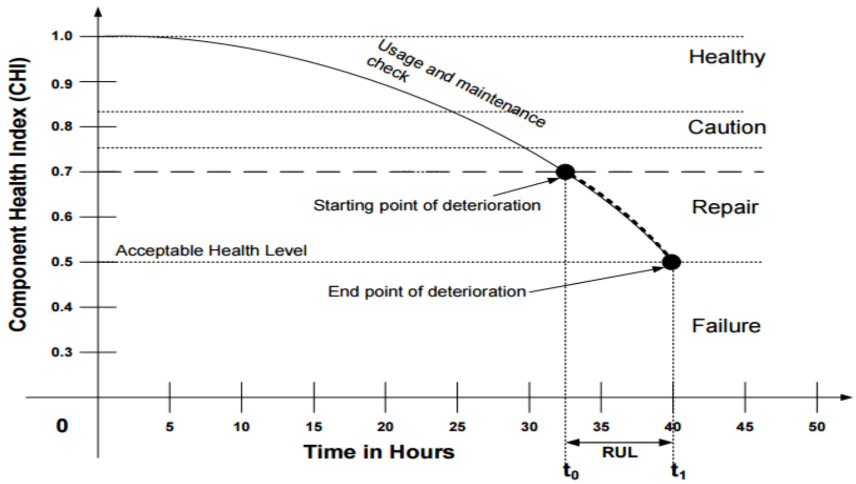
Artificial Neural Network (ANN) based methods have been extensively investigated for equipment health condition prediction and the methods have shown great promise in achieving more accurate equipment remaining useful life prediction. ANNs are computational models for information processing inspired by the neural structure of the brain. ANNs consist of a number of interconnected processing nodes called neurons. The neurons are usually organized in a sequence of layers, including an input layer, a single or a set of intermediate layers, and an output layer. The input layer receives input data to the network but does not perform any computations. The output layer gives the network’s response to the specified input. The intermediate layers, which are also called the hidden layers, are typically connected to the input and output layers. Each neuron in the hidden and output layers receives the signals from all the neurons in a layer above it and then performs a weighted summation and transfer function of the inputs. ANN is a data-driven model. ANN-based models can be created directly from the operational data from the “original equipment manufacturers” performance. Though neural networks have many advantages like good fitting of time series data, their extrapolability is poor, especially for long term prediction utilizing ANN for prediction is currently not available due to two key challenges:

(1) An ANN prediction model typically doesn’t provide a single remaining life prediction value.
(2) ANN prediction models are not more accurate and efficient numerical methods.

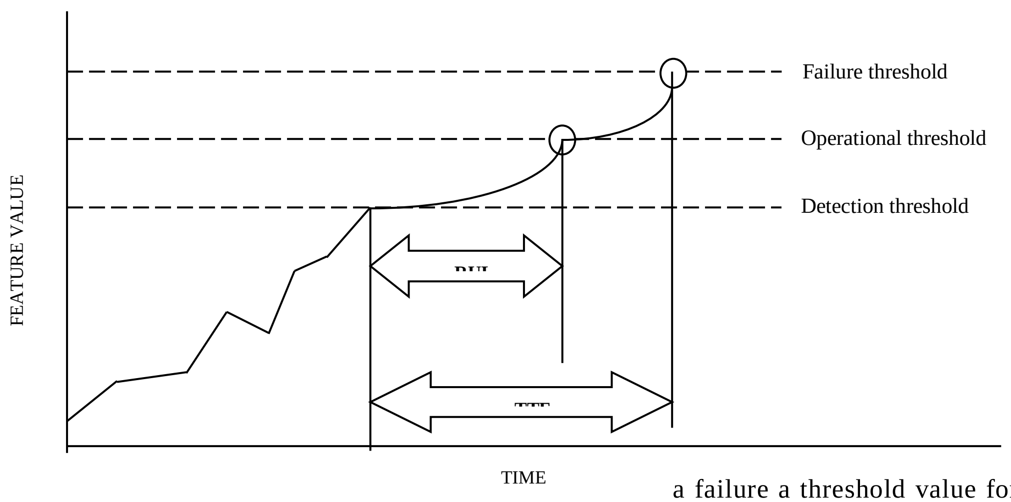
ANNs have been applied in a number of different ways for prognostics. The most common use of ANNs is in time series prediction, where the current degradation state is predicted into the future until it exceeds a threshold value. Typically, in a feed-forward ANN, previous values of the degradation index are used as the inputs to generate a one-step a-head prediction. The generated output is then fed back as an input to the next iteration, to generate long-term predictions. ANNs can also employ to estimate the current degradation index, using system features as inputs. The degradation index can then be prediction into

3.3 Remaining Useful Life (RUL)

Remaining useful life (RUL) is the useful left on equipment before equipment fails to operate within acceptable limits. RUL is calculated very similar to TTF, except that instead of a failure threshold, there is an upper operating limit threshold. As shown in Figure 5, the operating threshold for RUL is lower than the failure threshold, which results in a lower value for RUL than TTF. This is reasonable since it is desirable to repair the system before failure, while still utilizing any useful life before maintenance. However RUL is very application dependent as the specified tolerances must be defined for a given system. Because of this, the results are given for TTF instead of RUL.



Time to failure (TTF) is the amount of time left before a system reaches a failure. In this model, failure is a theoretical event that occurs when a feature value crosses some predetermined failure threshold. The TTF is calculated anytime the feature value crosses a particular value of interest called the detection threshold. The TTF estimate is set to zero before the feature value crossed the detection threshold. After the detection threshold is crossed, the TTF is calculated by propagating the current feature track forward n time steps based on the methodology further discussed. The TTF estimate is the difference between the current time step and the time of the predicted threshold crossing.



4. PROPOSED FEED FORWARD BACKPROPAGATION ANN MODEL

We present a Feed Forward Backpropagation ANN method based on the modified version of the ANN prediction method developed by Wu et al. (2007), and refer to it as the “Modified Wu’s method”. In the original version of Wu’s method, they considered only one condition monitoring measurement, and developed a feed-forward ANN model with three inputs and one output, with current time t, the current measurement and the measurement at (t−1) as the inputs and the life percentage as the output. The life percentage is the ratio between the current age of the unit and its failure time. There is not always a single indicator/variable that represents the health condition of a piece of equipment. Moreover, if we can find a single indicator, it is very difficult to establish a failure a threshold value for the indicator. It is true that health condition of a piece of equipment deteriorates with time and we can assume that the true inherent health condition decreases monotonically with time.

However, this model cannot handle many practical situations in which monitoring data is collected at discrete inspection time points that are not equally spaced. Moreover, typically there is more than one indicator that is correlated with the degradation of the equipment, and they should be incorporated into the ANN model to produce more accurate RUL prediction results. Bearing these in mind, we propose a modified version of Wu’s model. The structure of the modified model is shown in Fig. 1. The ANN model has an input layer, an output layer and two hidden layers. The reason we use an ANN with two hidden layers instead of one is that we find it is able to produce more reliable results according to our experiments. The inputs to the ANN include the age values and the condition monitoring measurements at the current inspection point and those at the previous inspection point. We only consider two measurements in Fig. 1, but more measurements can be handled by adding more input nodes to the ANN model. Specifically, t_i is the age of the equipment at the current inspection point *t*, and t_{i-1} is the age at the previous inspection point i – 1;

Input Layer – Feeds past and present data values into the next (hidden) layer. The black circles represent nodes.

Hidden Layer – Encapsulates several complex functions that create predictors and often these functions are hidden from the user. Black circles in the hidden layer represent the mathematical functions that modify the input data; these functions are called neurons.

Output Layer – Collects the predictions made in the hidden layer and produces the final result: the model's prediction.

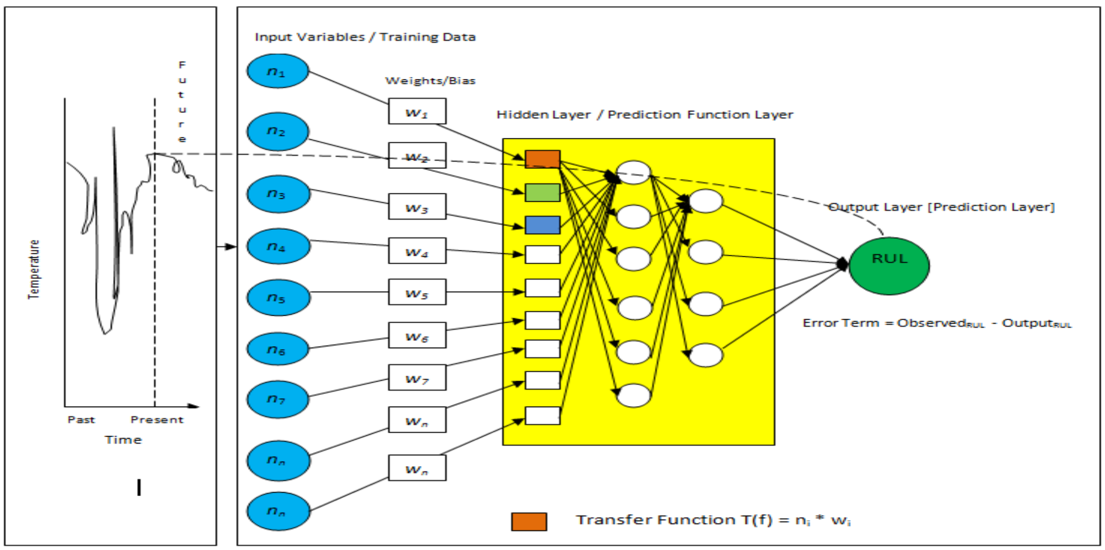


Fig. 2 ANN Model: 14-H-1

We have adopted FFBPNN (Feed Forward Back propagation Neural Network) for our prediction model. FFBPNN is an iterative process operation. In the feed forward process, the input patterns fed into the input layer of the system. Each hidden layer does the computation and forwards the activation values to the next layer in the chain of the network and eventually the results reach the output layer. The output layer computes the errors based on the observed output and desired output. These errors will then back propagated by using the Backpropagation formula, from the output layer through the hidden layers and finally reach the input layer. The modification of weights done during the every iteration of feeding all patterns. The learning process will be terminated when the total error is within an acceptable level or when the limit of the number of iterations has been reached. The output of the proposed ANN model is the reasonable life time of the equipment (RUL) in hours. This neural network model consists of an input layer that comprises all the variables of interest. Each of these feature variables labeled as a neuron (n_i), is multiplied by a random number known as weight (w_i) initialized between -1 and +1. The product (n_i * w_i) is then passed to a Transfer Function so that it activates the neurons in the Hidden Layer/Function Layer.

The number of neurons in the hidden layer determines how well a problem can be learned. A default number of hidden neurons were chosen according to the following formula:

Number of hidden neurons = ½ (inputs + outputs) + sqrt (Number of patterns in the training set)

A neural network with K inputs, p hidden neurons and 1 output has p(k+2)+1 weights to be estimated.

To train the ANN training samples are repeatedly presented as inputs to the neural network and output is computed in a feed-forward process. For each input set, the net produces a value that describes its current classification of the training sample. The output value is then compared with the production data. If the outputs are different, an error term is computed from the difference between the observed data and the network output.

Error Value = Observed Value – Network Output Value

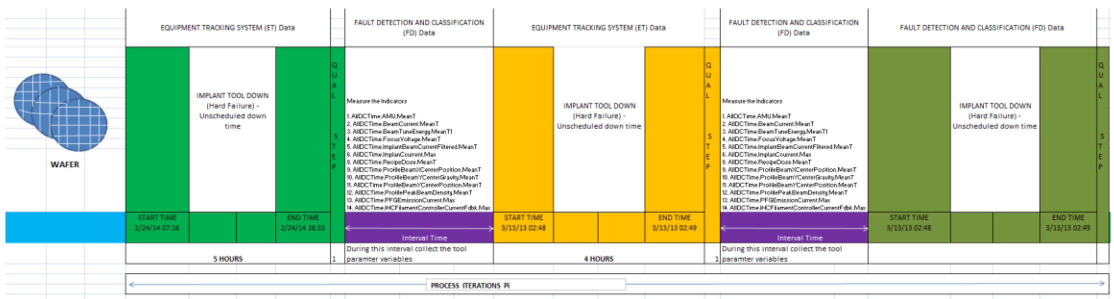
The error value that is computed is subsequently propagated backward to the model so that the connection weights are either increased or decreased depending on how much each weight contributed to the overall error. The process of measuring network error on training samples is repeated until the network error in classifying training samples becomes negligibly small. The important element in ANN model is to find the best transfer function for each of the nodes. We have applied sigmoid function (called as logistic function) and its formula looks like this:

$$f(\text{input}) = \frac{1}{1 + e^{-\text{input}}}$$

Here f is the activation function that activates the neuron, and e is widely used mathematical constant that has the approximate value of 2.718. Sigmoid functions have derivatives that are positive and easy to calculate. They are continuous, can serve as types of smoothing functions, and are also bounded functions. This combination of characteristics, unique to sigmoid functions, is vital to the workings of a neural network algorithm – especially when a derivative

The procedure of the proposed method is given as follows:

Step 1: First step is to colWe start from the available failure history data, which includes the age values and actual condition monitoring measurement values at inspection points for each failure history.

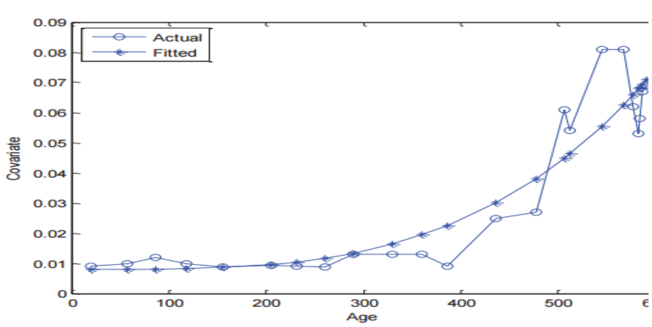


Step 2: Each measurement series for a failure history is fitted using the Generalized Weibull-FR function. The age values and the fitted measurement values at inspection points for all failure histories are used to construct the ANN training set.

Generalized Weibull FR Function as follows:

$$\hat{Z}\,(t) = Y + k\,\frac{\beta}{\alpha^{\beta}}\,t^{\beta-1}$$

Y is the covariate value, k is a parameter introduced to scale the fitted measurement values to any ranges. $(\frac{\beta}{\alpha^{\beta}}\,t^{\beta-1})$ is the failure rate function for the 2-parameter Weibull distribution.



Step 3: The ANN validation set is constructed using the age values and the actual measurement values at inspection points for all failure histories.

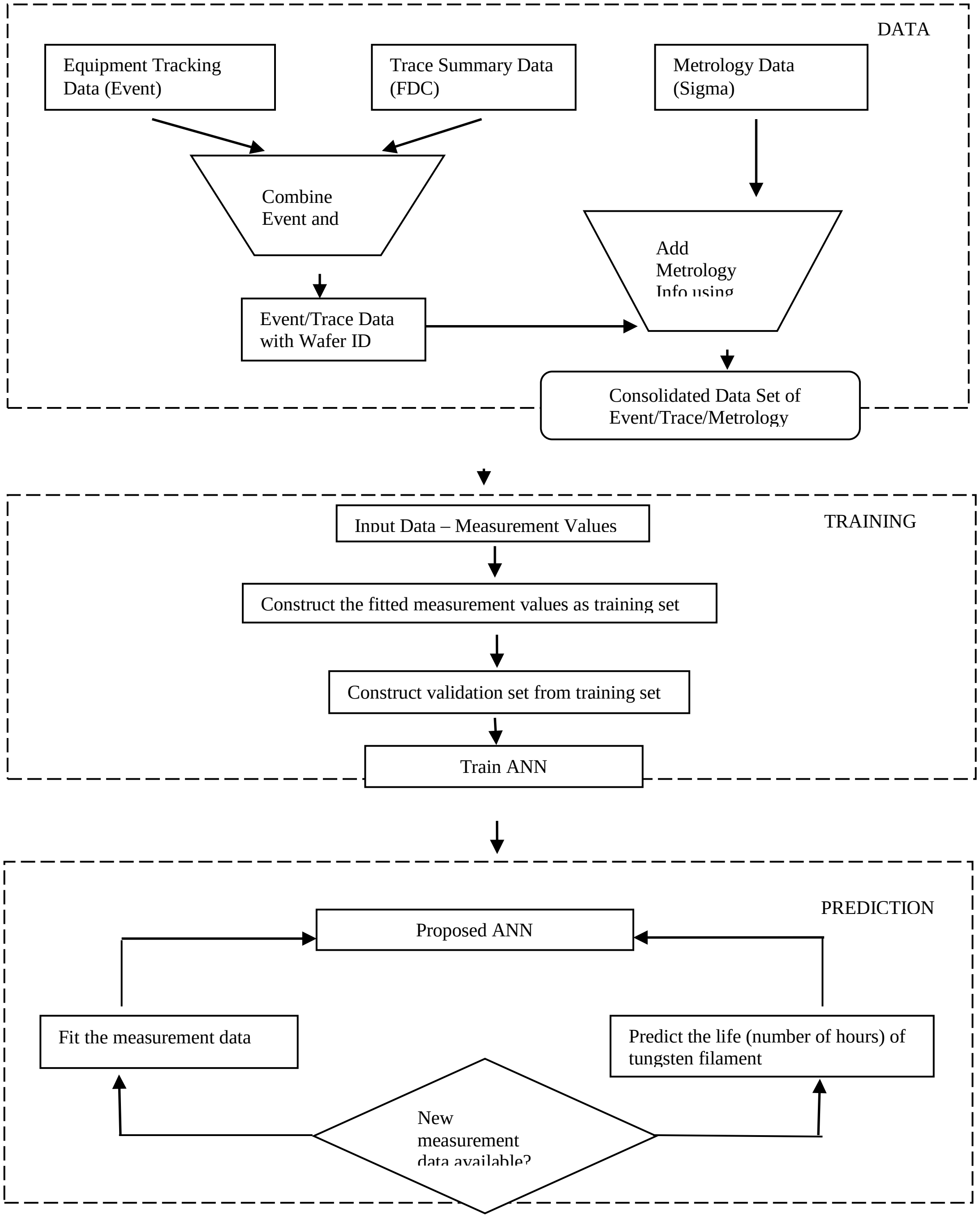
Step 4: Train the ANN model based on the training set and the validation set using the LM algorithm. After Step 3, the ANN training process is completed, and the trained ANN model is obtained for RUL prediction. For a piece of equipment which is currently being monitored, the following steps are for the RUL prediction for the equipment.

Step 5: At a given inspection point, we first fit each measurement series based on the measurement values up to the current time. The fitted measurement values at the current and previous inspection points, as well as the age values at these two inspection points, are used as the inputs to the trained ANN model.

Step 6: The predicted life percentage value at the current point is calculated using the trained ANN model.

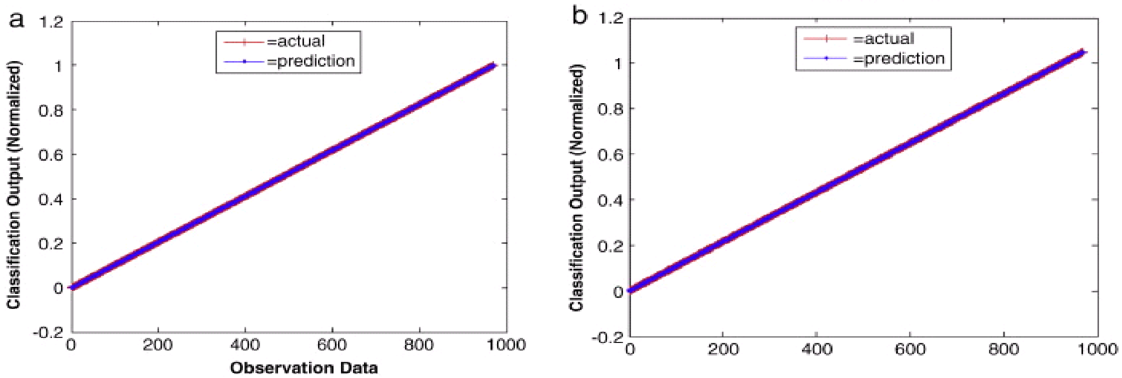
Step 7: The RUL is calculated based on the current age of the equipment and the predicted life percentage. For example, if the current age is 400 days and the predicted life percentage is 80%, the predicted failure time would be 400/80% = 500 (days), and the RUL would be 500 − 400 = 100 (days).

Step 8: When new inspection data is available, repeat Step 4 to Step 6 based on the available data, and updates the RUL prediction.



5. Experiments and Results

The proposed ANN predictive model generates more accurate equipment RUL prediction. The three important aspects of this model are: (1) Proposed FFBPANN model predicts the remaining life of the equipment in number of hours, compared to the life percentage of the unit. Thus, we do not have to define the failure threshold, which is hard to clearly define in many practical applications. The unit is failed when the life hours reaches to 0. (2) The proposed ANN method does not require the identification of the time when the incipient fault occurs. In practical applications, it is usually hard to identify the incipient fault time for an available failure history based on the collected condition monitoring measurements. However, if the incipient fault time can be properly identified in some applications, the incipient fault times can be considered to be age 0 for the histories. The proposed ANN method can still be used, and its prediction accuracy is expected to be improved comparing to directly using the available failure histories. In these experiments, data is collected from the equipment (Tungsten Filament) to validate the model.



In the proposed ANN method for RUL prediction, we use the failure history data to train the ANN and then use the trained ANN model to predict the RUL of a new unit, which has not yet failed. In this case study, we have 8 unscheduled downtime filaments break failures. Thus, we can use just 1 filament failure histories to construct the ANN test to test the prediction and use the remaining 10 failure histories to construct the ANN training set and the validation set to train the ANN model. After that, we can use a different failure history to construct the ANN test set to test the prediction performance and use the remaining 10 failure histories to train the ANN. We can repeat this process until we go through all the failure histories. Using the approach described above, the test failure history is not involved in the ANN training process, and we can make full use of the data available to test the prediction performance of the ANN method at as many inspection points as possible to achieve accurate prediction performance evaluation. The Generalized Weibull-FR function is used to fit each of two measurements for the 11 failure histories. Results show that the function can fit each of the measurement series very well, although different measurement series have different length, different values ranges, and times that the measurement values start to show obvious increase. Figure 4 shows the actual measurement series and the corresponding fitted measurement series for Measurement 1 for one of the failure histories. For the 10 failure histories used for ANN training, the fitted measurement values at the inspection time points and the corresponding age values are used to construct the ANN training set, and the actual measurement values are used to construct the validation set. The ANN model we use has two hidden layers with three hidden neurons in the first hidden layer and two hidden neurons in the second hidden layer. From our experiments, such ANN configuration is found to be able to produce better prediction results compared to other ANN configurations with different number of hidden neurons. The LM algorithm for the ANN training is run five times, and the trained ANN corresponding to the lowest training MSE is selected for the prediction performance testing.

10. Conclusion

Accurate equipment remaining useful life prediction is very significant for effective maintenance to improve reliability and also to reduce overall maintenance cost of the equipment. Artificial neural network models have shown great promise in achieving more accurate equipment remaining useful life prediction. This paper develops an ANN method for achieving more accurate remaining useful life prediction of equipment. The ANN model takes the age and multiple measurement values at the present and previous inspection points as the inputs, and the life percentage as the output. The generalized Weibull-FR function is used to fit each condition monitoring measurement series for a failure history, and the fitted measurement values are used to form the ANN training set to reduce the effects of the noise factors that are irrelevant to the equipment degradation. When the trained ANN is used for RUL prediction, the inputs to the trained ANN are generated by fitting the available measurement values for the current unit using the generalized Weibull-FR function. The validation mechanism is introduced in the ANN training process to improve the prediction performance of the ANN model. In addition, the proposed ANN method does not require the definition of a failure threshold, which is hard to clearly define in many practical applications. The proposed ANN method is validated using the data collected from the ION implant tool. Experiment results show that the proposed ANN method can produce satisfactory RUL prediction results, which will assist the maintenance optimization. A comparative study is performed between the proposed ANN method and the Modified Wu's method, and the results demonstrate the clear advantage of the proposed approach in achieving more accurate predictions. The key contribution of this paper is showing on the process of developing a Feed Forward Artificial Neural Network model to predict time to failure (RUL – remaining useful life) for the tungsten filament in ION Implant Tool.

REFERENCES

[1] B. Bergman. On the estimation of the wei bull modulus. Journal of Materials Science Letters, 3(8):689-692, 1984.

[2] B. E. Boser, 1. M. Guyon, and Y. N. Vapnik. A training algorithm for optimal margin classifiers. In Proceedings of the fifth annual workshop on Computational learning theory, CO LT '92, pages 144-152, New York, NY, USA, 1992. ACM.

[3] C. Cortes and Y. Vapnik. Support-vector networks. Machine Learning, 20(3):273-297, 1995.

[4] N. Cristianini and 1. Shawe-Taylor. An Introduction to Support Vector Machines: And Other Kernel-Based Learning Methods. Cambridge University Press, 2000.

[5] R. de Padua Moreira and C. Nascimento. Prognostics of aircraft bleed valves using a svm classification algorithm. In Aerospace Conference, 2012 IEEE, pages 1-8,2012.

[6] D. Galar, U. Kumar, and Y. Fuqing. Rul prediction using moving trajectories between svm hyper planes. In Reliability and Maintainability Symposium (RAMS), 2012 Proceedings - Annual, pages I -6, jan. 2012.

[7] A. K. Jardine, D. Lin, and D. Banjevic. A review on machinery diagnostics and prognostics implementing condition-based maintenance.Mechanical Systems and Signal Processing, 20(7):1483 - 1510, 2006.

[8] S. Jianzhong, Z. Hongfu, Y. Haibin, and M. Pecht. Study of ensemble learning-based fusion prognostics. In Prognostics and Health Management Conference, 2010. PHM '10., pages 1-7,2010.

[9] H.-E. Kim, A. C. Tan, J. Mathew, and B.-K. Choi. Bearing fault prognosis based on health state probability estimation. Expert Systems with Applications, 39(5):5200 - 5213, 2012.

[10] H.-E. Kim, A. C. C. Tan, J. Mathew, E. Y. H. Kim, and B.-K. Choi. Machine prognostics based on health state estimation using svm. In 1. Gao, J. Lee, L. Ma, and 1. Mathew, editors, Third World Congress on Engineering Asset Management and Intelligent Maintenance Systems Conference, pages 834-845, Beijing China, 2008. Springer.

[11] Y. Peng, M. Dong, and M. Zuo. Current status of machine prognostics in condition-based maintenance: a review. The International Journal of Advanced Manufacturing Technology, 50:297-313, 2010.

[12] Y. Peng, H. Wang, J. Wang, D. Liu, and X. Pengo A modified echo state network based remaining useful life estimation approach. In Prognostics and Health Management (PHM), 2012 IEEE Conference on, pages I -7, june 2012.

[13] 1. C. Platt. Fast training of support vector machine using sequential minimal optimization. In Advances in Kernel Methods - Support Vector Learning, pages 41-65. Microsoft Research Redmond, MIT Press, 1998.

[14] A. Saxena and K. Goebel. C-mapss data set. NASA Ames Prognostics Data Repository, 2008.

[15] X.-S. Si, W. Wang, C.-H. Hu, and D.-H. Zhou. Remaining useful life estimation a review on the statistical data driven approaches. European Journal of Operational Research, 213(1): I - 14, 20 II.

[16] 1. Sun, H. Zuo, W. Wang, and M. G. Pecht. Application of a state space modeling technique to system prognostics based on a health index for condition-based maintenance. Mechanical Systems and Signal Processing, 28(0):585 - 596, 2012.

[17] D. Tax and R. Duin. Support vector data description. Machine Learning, 54:45-66, 2004.

[18] F. Vieira, C. de O liveira Bizarria, C. Nascimento, and K. Fitzgibbon. Health monitoring using support vector classification on an auxiliary power unit. In Aerospace conference, 2009 IEEE, pages 1 -7, march 2009.

[19] W. Weibull. A statistical distribution function of wide applicability. Journal of Applied Mechanics, 18:293-297, 1951.

[20] A. Wi dodo and B.-S. Yang. Support vector machine in machine condition monitoring and fault diagnosis. Mechanical Systems and Signal Processing, 21(6):2560 - 2574, 2007.

[21] E. Zio and F. D. Maio. Fatigue crack growth estimation by relevance vector machine. Expert Systems with Applications, 39(12): 10681 - 10692, 2012.