A neuro-fuzzy approach for estimating mean residual life in condition-based maintenance systems

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Abstract: This paper presents a framework for online reliability estimation of physical systems utilising degradation signals. Most prognostics methods promoted in the literature for estimation of mean-residual-life of individual components utilise trending or forecasting models in combination with mechanistic or empirical failure definition models. In the absence of sound knowledge for the mechanics of degradation and/or adequate failure data, it is not possible to establish practical failure definition models. However, if there exist domain experts with strong experiential knowledge, one can establish fuzzy inference models for failure definition. This paper presents a neuro-fuzzy approach for performing prognostics under such circumstances. The proposed approach is evaluated on a cutting tool monitoring problem. In particular, the method is used to monitor high-speed-steel drill-bits used for drilling holes in stainless steel metal plates.

Keywords: mean residual life; degradation signal; prognostics; reliability estimation; neural networks; fuzzy logic.


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Research interests include application of statistical and computational intelligence techniques for engineering problem solving with particular interest in Condition-Based Maintenance systems.

1 Introduction

With very few exceptions, most contemporary reliability engineering methods are geared toward estimating a ‘population’ characteristic(s) of a system, subsystem or component [1]. The information so extracted is extremely valuable for manufacturers and others that deal with product in relatively large volumes. On the contrary, end users are typically most interested in the behaviour of a ‘particular’ component used in their system to arrive at optimal component replacement and/or maintenance strategies leading to improved system utilisation, while reducing risk and maintenance costs. The traditional approach in addressing this need is to resort to condition-based-maintenance (CBM) practices. CBM typically involves mounting non-intrusive sensors on the component to capture degradation signals (such as temperature, force, vibration, acoustic emission, voltage, noise, etc.) and subsequent interpretation of these signals for the purpose of developing a customised maintenance policy. Given recent advances in the areas of non-intrusive sensors, data acquisition hardware and signal processing algorithms, combined with drastic reductions in computing and networking costs and proliferation of information technology products that integrate factory information systems and industrial networks with web-based visual plant front-ends, it is now possible to realise systems that can deliver cost effective diagnostics, prognostics and CBM for a variety of industrial systems. The basic elements necessary for successful diagnostics, prognostics and CBM are illustrated in Figure 1.

Figure 1  Basic elements of diagnostics and prognostics for CBM
Most CBM methods are primarily limited in performing diagnostics rather than estimating the mean-residual-life (MRL) of the component (i.e., prognostics). In the event, one can develop effective degradation signal forecasting models and precisely define component failure in the degradation signal space, then, one can move beyond the state classification approach or diagnostics to a more vigorous online reliability estimation scheme for the individual unit (see for example: [1,3,4]) [5]. However, in practice, without extensive knowledge for the mechanics of degradation and/or adequate failure data, it is nearly impossible to develop a practical failure definition model that precisely defines failure in the degradation signal space (or a transformation thereof).

In this paper, we suggest the incorporation of fuzzy inference models to introduce the definition of failure in the degradation signal space using expert opinion and/or empirical data. With regard to forecasting the degradation signals into the immediate future for the purpose of prognostics, we propose the use of focused time-lagged feed-forward networks (focused-TLFNs). While classical methods of time-series forecasting (such as ARIMA modelling and state-space modelling) are equally appropriate, we employ focused-TLFNs for their universal approximation nature, non-parametric behaviour and tremendous success in the industry [6]. The paper is organised as follows: Section 2 briefly outlines the performance reliability theory that relates the degradation signal space to the health or well-being of the component. Section 3 presents an approach for developing failure definition models using fuzzy inference systems. Section 4 presents results from a drilling process case study. Finally, Section 5 offers some concluding remarks and identifies future research issues.

## 2 Performance reliability theory

The discussion that follows is borrowed heavily from [1] and is included here to enhance the readability of this paper. The theory, by itself, is not the focus of this paper.

Let \( \{y(s)\} \) represent a scalar time-series generated by sampling the performance degradation signal (or a transformation thereof). Suppose that \( \{y(s)\} \) can be described by a non-linear regressive model of order \( p \) as follows:

\[
y(s) = f(y(s-1), y(s-2), \ldots, y(s-p)) + \epsilon(s)
\]

where \( f \) is a non-linear function and \( \epsilon(s) \) is a residual drawn from a white Gaussian noise process. In general, the non-linear function \( f \) is unknown and the only information we have available to us is a set of observables: \( y(1), y(2), \ldots, y(S) \), where \( S \) is the total length of the time-series. Given the data set, the requirement is to construct a physical model of the time-series. One could use any number of parametric methods (such as Box and Jenkin’s ARIMA models) and non-parametric methods (such as multi-layer perceptron neural networks and temporal processing neural networks) for building such time-series models. Given the universal approximation properties of feed-forward networks (see [6–7]) and their success with forecasting problems [8], we recommend the use of focused-TLFNs for developing degradation signal forecasting models. Specifically, the network is designed to make a prediction of the sample \( y(s) \), given the immediate past \( p \) samples \( y(s-1), y(s-2), \ldots, y(s-p) \), as shown by

\[
\hat{y}(s) = \hat{f}(y(s-1), y(s-2), \ldots, y(s-p)) + \epsilon(s).
\]
The non-linear function \( \hat{f} \) is the approximation of the unknown function, \( f \) which is computed by the neural network. The network is trained in general to minimise some cost function (\( J \)) of the prediction error

\[
e(s) = y(s) - \hat{y}(s), \quad p + 1 \leq s \leq S
\]

using any of the first- or second-order gradient search algorithms, while maintaining generalisation. See [6] for a detailed discussion of focused-TLFNs, their training methods and training issues. Note that a single network can be trained to simultaneously work with many degradation signals and also allow different prediction orders for different signals. Of course, the number of input nodes and output nodes in the network will increase (as well as network complexity) with an increase in the number of degradation signals modelled by the network.

Now, let \( F(t) \) denote the probability that failure of a component takes place at a time or usage less than or equal to \( t \) (i.e., \( F(t) = P(T \leq t) \)), where the random variable \( T \) denotes the time to failure. From the definition of conditional probability, the conditional reliability that the component will fail at some time or usage \( T > t + \Delta t \), given that it has not yet failed at time \( T = t \) will be:

\[
R\left( (t + \Delta t) | t \right) = \frac{1 - P(T \leq t + \Delta t)}{P(T > t)}.
\]

Let \( y = [y_1, y_2, \ldots, y_m] \) denote the vector of \( m \) degradation signals (or a transformation thereof) being monitored from the system under evaluation. Let \( y^{\text{PCL}} = [y_1^{\text{PCL}}, y_2^{\text{PCL}}, \ldots, y_m^{\text{PCL}}] \) denote the vector of deterministic performance critical limits (PCLs), which represent an appropriate definition of failure in terms of the amplitude of the \( m \) degradation signals. For any given operating/environmental conditions, performance reliability can be defined as “the conditional probability that \( y \) does not exceed \( y^{\text{PCL}} \) for a specified period of time or usage.” Obviously, the above definition directly applies to the case where the amplitudes of the degradation signals are preferred to be low (lower-the-better signals with higher critical limits), and can be easily extended to deal with higher-the-better signals (with lower critical limits) and nominal-value-is-best signals (with two-sided critical limits) and any combinations in between. Without the loss of generality, for illustrative purposes, let us make the assumption here that all the \( m \) degradation signals are of lower-is-better type signals.

Since a neural network, trained over past degradation signals collected from other similar components, keeps providing us with an estimate of \( y \) into the future, denoted by \( \hat{y}(t_f) \), under the assumption that the change in \( y \) from the current time point \( (t_c) \) to the predicted time point \( (t_f) \) is either monotonically decreasing or increasing, the reliability that the component will operate without failure until \( t_f \) is given by:

\[
R\left( (T \geq t_f) | t_c \right) = \int_{y_1=\infty}^{y_1^{\text{PCL}}} \cdots \int_{y_m=\infty}^{y_m^{\text{PCL}}} \frac{g(\hat{y}(t_f))}{\hat{y}_i(t_f)^{y_i^{\text{PCL}}}} dy_1 dy_2 \cdots dy_m
\]

where \( g(\hat{y}(t_f)) \) denotes the probability density function of \( \hat{y}(t_f) \). The assumption here is that \( y_i^{\text{PCL}} \) is a constant for any given \( i \) and is independent of \( y_i(t_c) \). Under these conditions, the failure space is bounded by orthogonal hyperplanes. If the independence
assumption is not justified, one could use a hyper-surface to define the failure boundary [4]. If need be, one could even relax the assumption of a deterministic boundary and replace it with a stochastic boundary model. However, such an extension is non-trivial.

For the special case where there exists just one lower-the-better degradation signal, this process is illustrated in Figure 2. The shaded area of $g\left(\hat{Y}(t_i)\right)$ at any $t_i$ denotes the conditional-unreliability of the unit. That is, given that the unit has survived until $t_c$, the shaded area denotes the probability that the unit will fail by $t_f$. Given $r_{\text{MRL}}$, the least acceptable reliability, one can estimate $t_{\text{MRL}}$, the time instant/usage at which the reliability of the unit reaches $r_{\text{MRL}}$. Thus, one can calculate the MRL to be the time difference between $t_c$ and $t_{\text{MRL}}$.

**Figure 2** Degradation signal forecasting model coupled with a failure definition PCL to estimate MRL

3 Fuzzy inference models for failure definition

Most prognostics methods in the literature for online estimation of MRL utilise trending or forecasting models in combination with mechanistic or empirical failure definition models. However, in spite of significant advances made throughout the last century, our understanding of the physics of failure is not quite complete for many electro-mechanical systems. In the absence of sound knowledge for the mechanics of degradation and/or adequate failure data, it is not possible to establish practical failure definition models in
the degradation signal space. Under these circumstances, the sort of procedures illustrated in Section 2 are not feasible. However, if there exist domain experts with strong experiential knowledge, one can potentially establish fuzzy inference models for failure definition. In this section, we suggest the incorporation of fuzzy inference models to introduce the definition of failure in the degradation signal space using domain experts with strong experiential knowledge. While the trending or forecasting subcomponent will predict the future states of the system in the degradation signal space, it is now the task of the fuzzy inference model to estimate the reliability associated with that forecast state. If one were to compare this procedure with that discussed in Section 2, it is equivalent to replacing the right hand side of equation (5) with a fuzzy inference model.

One might argue that probabilistic models could be potentially used for modelling experiential knowledge of domain experts. However, it is widely accepted that classical probability theory has some fundamental shortcomings when it comes to modelling the nature of human concepts and thoughts, which tend to be abstract and imprecise. While probability theory is developed to model and explain randomness, fuzzy arithmetic and logic is developed to model and explain the uncertain and imprecise nature of abstract thoughts and concepts. Over the last three decades, since Lofti Zadeh authored his seminal paper in 1965 on fuzzy set theory [9], the scientific community had made major strides in extending the set theory to address applications in areas such as automatic control, data classification, decision analysis and time series prediction [10].

**Figure 3** Sugeno FIM with two inputs \((X, Y)\) and one output \((F)\)

In the context of prognostics and failure definition, Sugeno fuzzy inference model (FIM), illustrated in Figure 3(a), is particularly attractive for failure definition for three reasons: 1) It makes a provision for incorporating subjective knowledge of domain experts and experienced operators, 2) model can be viewed as a feed-forward neural network
(labelled adaptive-network based fuzzy inference systems or ANFIS), and hence, can be adapted using empirical/historical data coupled with gradient search methods [11], and 3) computationally efficient for the absence of a de-fuzzification operator prevalent in other fuzzy inference models. The illustrated two-input ($X$ and $Y$) one-output ($F$) Sugeno FIM carries two membership functions for each of the two input variables, namely, $A_1, A_2$ and $B_1, B_2$. The model is made of two rules. For example, Rule-1 states that if $X$ is $A_1$ and $Y$ is $B_1$, then the output is given by $f_1 = p_1x + q_1y + r_1$. Here, $A_1$ and $B_1$ denote linguistic variables (such as ‘thrust is low’ or ‘vibration is high’). Even though the consequent of each rule constitutes a first-order model, the overall relationship is often highly non-linear. The equivalent ANFIS model is shown in the illustration as well.

For the application considered here, typically, the number of input variables for the Sugeno FIM will be equal to the number of degradation signals under investigation and there is one output variable predicting the reliability of the unit (i.e., $r(t)$). The number of membership functions and the number of rules needed to fully describe the failure definition will be dictated by the specific application and input from domain experts. In the absence of first-principles models, rules can be initially formulated with the help of domain experts and experienced operators. All the parameters of the Sugeno FIM can be adapted to best describe any historical dataset using the ANFIS framework. For more details regarding Sugeno fuzzy inference models or their ANFIS equivalents, see [10].

4 Drilling process case study

4.1 Experimental setup

In this research, a drilling operation was chosen as the physical test-bed for the reason that it is a commonly used machining process and a dynamometer was available in-house for measuring online the thrust-force and torque acting on the drill-bit. Machining literature has shown that there is a strong correlation between thrust-force (and torque) acting on a drill-bit and the bit’s future life expectancy [12]. Hence, these signals are appropriate degradation signals for estimating, online, the drill-bit reliability.

The experimental setup consists of a HAAS VF-1 CNC milling machine, a workstation with LabVIEW software for signal processing, a Kistler 9257B piezo-dynamometer for measuring thrust-force and torque, and a National Instruments PCI-MIO-16XE-10 card for data acquisition. The experimental setup is depicted in Figure 4.

4.2 Actual experimentation

A series of drilling tests were conducted using quarter-inch drill-bits on a HAAS VF-1 Machining Center. Stainless steel bars with quarter-inch thickness are used as specimens for the tests. The drill-bits were high-speed twist drill-bits with two flutes, and were operated under the following conditions without any coolant: feed-rate of 4.5 inches-per-minute (ipm) and spindle-speed of 800 revolutions-per-minute (rpm).

Twelve drill-bits were used in the experiment. Each drill-bit was used until it reached a state of physical failure, either due to macro chipping or gross plastic deformation of the tool tip due to excessive temperature. Collectively, the drill-bits demonstrated significant variation in life (varying between eight and twenty five successfully drilled holes) even though they came from the same manufacturer in the same box. This further
validates the need to develop good online reliability estimation methods to help end users arrive at optimal tool or component replacement strategies.

The thrust-force and torque data were collected for each hole from the time instant the drill penetrated the work piece through the time instant the drill tip protruded out from the other side of the work piece. The data was initially collected at 250 Hz and later condensed using RMS techniques to 24 data points per hole, considered normally adequate for the task at hand. Throughout the rest of this paper, in all illustrations, one time unit is equivalent to the time it takes to drill 1/24th of a hole. For illustrative purposes, data collected from drill-bit #8 is depicted in Figure 5.

**Figure 4** Experimental setup for capturing thrust-force and torque degradation signals from a ¼” HSS drill-bit

**Figure 5** Plots of thrust-force and torque signals collected from drill-bit #8
4.3 Focused-TLFN for forecasting degradation signals

A focused-TLFN was designed for time-series forecasting of the thrust-force and torque signals. The data collected from the twelve drill-bits were clustered into three sets. Data from drill-bits #1 to #8 were set aside for network training, drill-bits #9 to #10 for network validation and the last two drill-bits for network testing. Various network configurations were tested using a formal experimental design. The variables considered include: prediction order $p$, number of hidden layers, number of nodes per hidden layer and learning rate. Extensive analysis revealed that the network with the best generalisation has the architecture reported in Table 1. Note here that a single network is used for simultaneously forecasting both the thrust-force and torque degradation signals. Besides, it was noticed that the generalisation capability of the network improves if the network was tasked to make simultaneous one-step-ahead predictions as well as six-step-ahead predictions for each of the degradation signals (resulting in four network output nodes). Page constraints prevent us from reporting in detail the network training issues. For illustration purposes, we present predicted as well as desired thrust-force signal values for drill-bit #12 in Figure 6.

<table>
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<th>Training scheme</th>
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<td>Learning adaptation rate: 0.1</td>
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<td>Minimum learning rate: 0.00000001</td>
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<td>Training parameters adaptation frequency: 50 epochs</td>
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<td>Maximum training epochs: 1000</td>
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<td>Acceptable training error per node: 0.000001</td>
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<tr>
<td>Acceptable percentage change of error over slope Segment: 1.0</td>
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<td>Slope segment: 200 epochs</td>
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4.4 Sugeno FIS for failure definition

Experimental data has revealed a lot of variation between drill-bits, in the amplitudes of thrust-force and torque observed during the final hole. This invalidates the concept of a deterministic critical limit for establishing failure definition in the thrust-force and torque signal space. While one could potentially introduce a probabilistic critical plane, here, we utilise fuzzy logic to introduce an FIS failure definition model in the degradation signal space. The thrust-force and torque predictions from the focused-TLFN model will be the two-dimensional input space of the FIS model. The FIS model in return is expected to estimate the conditional reliability of the drill-bit.
It was decided initially to use two membership functions for representing the ‘low’ and ‘high’ linguistic levels for each of the degradation signals. Sigmoid membership functions were considered appropriate for three reasons: 1) They are open-ended on one side, 2) they are monotonous functions (always increase or decrease but not both), and 3) they are compatible with most ANFIS training algorithms. Past experience suggested that thrust-force typically varies between 0 to 3000 N for the drilling operation at hand. Similarly, it was common to see torque vary between 0 to 6 N.m. Initially, the membership functions were set up to equally divide the ranges of the variables, as illustrated in Figure 7((a) and (c)) for thrust-force and torque, respectively. It was expected that ANFIS training would address any misrepresentations in these membership functions.

Two rules were initially formulated with the understanding that more rules can be added to address any serious violations by the FIS model. The rules are as follows:

a) IF thrust-force is low AND torque is low, THEN, drill-bit reliability = 1.0.

b) IF thrust-force is high AND torque is high, THEN, drill-bit reliability = 0.0.

Thus, the consequent of each rule constitutes a zero-order model. The resulting FIS model relationship is illustrated in Figure 8(a). It is clear that the overall relationship is highly non-linear and certainly seems plausible. At this stage, it was decided to extract training data to further refine the FIS model using the ANFIS framework. The training, validation and testing datasets used for developing the focused-TLFN forecasting model were once again exploited to refine the FIS model. The reasoning behind the generation of training data is as follows. Given any drill-bit and the provided operating conditions, it
is totally reasonable to assume that the drill-bit will survive the very first hole. This implies that the FIS model should estimate the drill-bit reliability to be 1.0 when exposed to the sort of thrust-force and torque conditions witnessed during the machining of the first hole for all the eight training set drill-bits. Similarly, it is only reasonable to expect the FIS model to estimate the drill-bit reliability to be 0.0 when exposed to the sort of thrust-force and torque conditions witnessed during the machining of the last hole for all the eight training set drill-bits. Thus, in total, 16 data points were developed from the eight training set drill-bits. Validation and testing datasets were also developed similarly using the corresponding drill-bit data. Note that while labelled data could be generated for representing extreme states of the drill-bits, it is not easily possible to develop any such data for intermediate states (i.e., states other than those representing either an extremely sharp/good or extremely dull/bad drill-bits). Training the ANFIS formulation of our FIS model using these datasets resulted in the final relationship illustrated in Figure 8(b). The corresponding changes to the membership functions by the ANFIS training algorithms are also illustrated in Figure 7. Close observation of Figures 7 and 8 reveals that the FIS model is predominantly utilising the torque degradation signal in comparison with the thrust-force signal for estimating the online reliability of the drill-bit. This is partially attributed to the fact that torque exerted on a drill-bit is more sensitive to most of the failure modes that dominate drilling operations (i.e., it offers better signal-to-noise ratio in comparison with the thrust-force signal).

**Figure 7** Plots of membership functions before and after ANFIS training. (a) Thrust-force MFs – before training. (b) Thrust-force MFs – after training. (c) Torque MFs – before training. (d) Torque MFs – after training.
4.5 Online reliability estimation

For illustrative purposes, the overall reliability degradation plots developed using the focused-TLFN forecasting model and the trained Sugeno FIS failure definition model are shown in Figure 9 for drill-bits #1 and #9. Here, conditional reliability is equivalent to the definition offered in equation (4). That is, the probability that the drill-bit will survive one more time unit (under the same operating conditions) given that it has survived thus far. The unconditional reliability or simply reliability is the product of all the conditional reliabilities from the time the drill-bit is put into service to the current time unit. One can make the following two observations from Figure 9: 1) Degradation in the health of the drill-bit can be determined well before the bit reaches its final hole allowing ample time for an operator to make timely bit replacement to avoid any failure and 2) identical units operated under identical operating conditions can exhibit significant dissimilarities in overall behaviour (drill-bit #9 failed in hole #16 whereas drill-bit #1 goes on to complete at least 20 holes). Collectively, these two points represent the most important reason why CBM is gaining ground in industry.

All the FIS calculations reported here are performed using the fuzzy logic tool box available from MathWorks, Inc. along with the basic MatLab computing environment. The focused-TLFNs are implemented using in-house software developed using C programming language.
5 Conclusion and suggestions for future research

The primary objective of this work was to demonstrate that fuzzy inference models could be used to introduce failure definition in the degradation signal space using expert opinion and/or empirical data. This is particularly valuable for carrying out prognostics activities in the absence of sound knowledge for the mechanics of degradation and/or lack of adequate failure data. The drilling process case study has demonstrated the feasibility of online reliability estimation for individual components using the proposed neuro-fuzzy approach. However, there are still several unanswered questions. For example, there is no evidence that all types of failure modes prevalent in critical equipment could be adequately captured by the proposed Sugeno FIS model. Secondly, the inability to easily generate labelled training data for the ANFIS model from intermediate states (i.e., when the unit is neither brand new nor completely worn out) might jeopardise the interpolation capability of the FIS model. This issue, however, may not be significant from a practical perspective, for in general, there is not a lot of interest in the intermediate states, at least from the standpoint of CBM. Typically, there is no provision to estimate MRL using the proposed method for the suggested neural network forecasting models are not capable of making long-term forecasts. This is beginning to change with the introduction of the so called structural learning neural networks [13]. Means to develop confidence intervals is of paramount importance as well, without which, there is no provision to gauge the accuracy of the overall prognostics procedure.

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References

2 Diagnostics has traditionally been defined as the ability to detect and sometimes isolate a faulted component and/or failure condition. Prognostics builds upon the diagnostic assessment and is defined here as the capability to predict the progression of this fault condition to component failure and estimate the mean-residual-life.
5 The use of degradation signals for estimating a ‘population’ characteristic is not new either. See for example [15–19].
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