METHODS TO ESTIMATE MACHINE REMAINING USEFUL LIFE USING ARTIFICIAL NEURAL NETWORKS

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Abstract: In this paper, a general methodology for remaining useful life estimation based an indirect methodology is presented. Gearbox failure data, recorded using a mechanical test bed at the Applied Research Laboratory, Penn State University, is used. The machine remaining useful life estimation method used in this paper is indirect method, in the sense that it predicts first the behavior of some system parameters known to be sensitive to the machine operating status, use those predicted values in order to find the predicted machine status through the fuzzy system definitions, and then estimate the remaining useful life by measuring the time from the present time to the time where the death status was detected. Some machine parameters such as temperature, vibration spectrum and level, and acoustic emission, are used in such analysis. Machine operating regions are divided into normal operation, abnormal operation, and no operation or death. Every parameter limits is defined in each region. Prediction models are used to predict the time trajectory of the machine parameters starting from some history measurements. Those predicted trajectories could be used to determine the machine death status point in time. The remaining time to death can be estimated form such models within some appropriate certainty and error tolerance. Neural networks and fuzzy logic system modeling techniques are used for machine parameter prediction due to their known ability for non-linear system modeling, robustness, generalization, and modeling decision uncertainty.

Key Words: Decision making; diagnosis; fuzzy logic; maintenance; neural networks; prediction; prognosis; remaining useful life; vibration analysis.

Introduction: Machine remaining useful life of running machinery is very important information if known within a certain confidence level and tolerance. If machine remaining useful life is known with some certainty and within some acceptable tolerance they can be used in potential system planning [1,2]. That type of planning will lead to more efficient production, less down times, less inventory size, cost saving, and smooth system upgrade. If a machine death time is known within a certain acceptable error limits, an early planning can be made to have a replacement in time, which might lead to a big saving in cost, an appropriate selection for installation time, and avoidance to sudden machine breakdown.

However, prediction is one of the hardest problems to solve especially for non-linear and chaotic systems [3,4]. Most of the real life systems belong to non-linear and chaotic systems. Even though prediction cannot be achieved with high accuracy for such systems, but for very short time in the future, knowing something about the future is important even if not very accurate. For example, weather forecasting can be achieved with reasonable accuracy only for the coming few days. However, it is also important to predict weather for the next weeks, months and years even with very low certainty and very high prediction error.

Literature has focused some attention in the past few years for finding techniques for estimating machine remaining useful life (RUL) [1,5]. This problem is still in need for some extra efforts in the coming years, to come up with improved models and methods. Most of the RUL estimation methods are based on direct methods that use some history of machine measurements in order to directly estimate the machine remaining useful life or time to death [5]. In this paper, machine RUL will be assumed to be the remaining time to death. And death will be defined as the time when the machine will be no longer useful, which can be due to a major defect in the machine, very low efficiency operation, the machine becoming out-dated, or machine becoming impossible to operate. The machine RUL method presented in this paper is an indirect method that is based on prediction of the future time trajectory of some machine parameters. Those parameters are correlated to the machine different operating status regions. Knowing the correlation of the deviation of some parameters from some nominal value to the machine status, and the parameter predicted deviation in a specific time would lead to good knowledge of the remaining time to reach such operating status. Neural network prediction models in conjunction with some fuzzy logic based decision-making algorithms are use to implement this indirect methodology.

Neural network parameter prediction-models are used due to their ability for non-linear system modeling, and generalization [6,7]. Fuzzy logic operating region-locators are used due to their ability to model uncertainty and continuous logic variables in real world problems [8-10].

Machine Failure Data [11]**:** The gearbox failure data used in this paper are obtained through the Applied Research Laboratory (ARL), at Penn State University. The data was recorded at the ARL using a MDTB (Mechanical Diagnostic Test Bed) that is functionally a motor-driven-train-generator test stand. The gearbox is driven at a set input speed using a 30 Hp, 1750-rpm AC (drive) motor, and the torque is applied by a 75 Hp, 1750 rpm AC (absorption) motor. The maximum speed and torque are 3500 rpm and 225 ft-lbs, respectively. The speed variation is accomplished by varying the frequency to the motor with a digital vector drive unit. A similar vector unit capable of controlling the current output of the absorption motor accomplishes the variation of the torque. The MDTB has the capability of testing single and double reduction industrial gearboxes with ratios from about 1.2:1 to 6:1. The gearboxes are nominally in the 5-20 Hp range. The system is sized to provide the maximum versatility to speed and torque settings. The motors provide about 2 to 5 times the rated torque of the selected gearboxes, and thus the system can provide good overload capability.

Ten accelerometers and an acoustic microphone are placed on the test bed. The microphone, placed in proximity to the test bed, provides a frequency range up to 22 kHz, which is almost twice the bandwidth of human audible range. A total of 32 thermocouples are available for temperature readings on the MDTB. The highest sampling speed required was 20 kilo Samples (kS)/s for the accelerometers and 44.1 kS/s for the microphone. The thermocouples are sampled at 1 S/s.

Methodology: The machine remaining useful life (RUL) estimation methodology developed in this paper is based on a machine parameter prediction technique along with knowledge about the different operating regions of the machine. In this method, it is assumed that the operating status of a specific machine is reflected into clear changes in a set of its parameters, such as vibration, temperature, current, voltage, power, speed, etc. These define the machine state trajectory in a multidimensional space. Those parameters that are most sensitive to the machine operating status should be selected for the analysis. Mapping of the machine state trajectory to individual two-dimensional subspaces is used in order to simplify the analysis. Certainly, a prior analysis to the machine and its parameters, and their correlation to the change of operating status are needed.

Three operating status regions are assumed Normal Operation (Health), Abnormal Operation (Sickness), and Death (no operation, or non-useful operation), as shown in Figure 1. In reality there is no sharp changes between those regions and the borderlines plotted on the graph are artificial borderlines to approximate the different operating regions. A more realistic representation was developed using fuzzy logic description methods. This representation is illustrated in Figure 2. This fuzzy membership function representation allows easier handling of the terminology, continuous representation of logical functions, smooth transition of status, and easier decision-making process. This fuzzy representation for machine status is an integral part of the machine RUL estimation process developed in this paper. However, the actual measurements are used to tune those fuzzy membership functions to each type of machine separately.

When a machine is in a normal operating status, it is guaranteed that all of its parameters will be bounded in a specific region. This region will be very narrow in the first operating period, and will be in a close proximity with the rated values of the machine parameters. However, it will become wider as the machine becomes older. This transition will happen gradually. Some parameters will increase while others will decrease due to the machine degradation process. Examples for the accelerated degradation trajectories reflected into vibration information measured by accelerometers mounted on the MDTB, or what can be called a machine state transition on two-dimensional maps are shown in Figures 3 and 4. Figure 3 shows the root mean square (rms) value of the machine vibration versus time in seconds, measured during run #10 using accelerometer # 2. And Figure 4 shows the rms value of the machine vibration versus time in seconds, measured during run #10 using accelerometer # 5. These transitions are driven by the actual internal physical changes in the machine, which can take place in any similar active system, such as any rotating machinery. For the same type of machine, some units may experience an increasing trend of some of their parameters while others experience a decreasing trend, due to their unique manufacturing and operating conditions. However, this increase or decrease in itself may not correlate to the machine operating status as long as it is bounded within certain limits. In other words the relative change in a specific parameter is more indicative of the machine operating status than its absolute value. This is why those operating regions were generated based on the deviation from the baseline value that indicates the machine condition at its birth (when it first came online). Some machine maintenance may also create a sudden shift of the machine parameter trajectory from one operating region to another, such as from the abnormal to the normal region, and needs to be taken into account during the analysis.

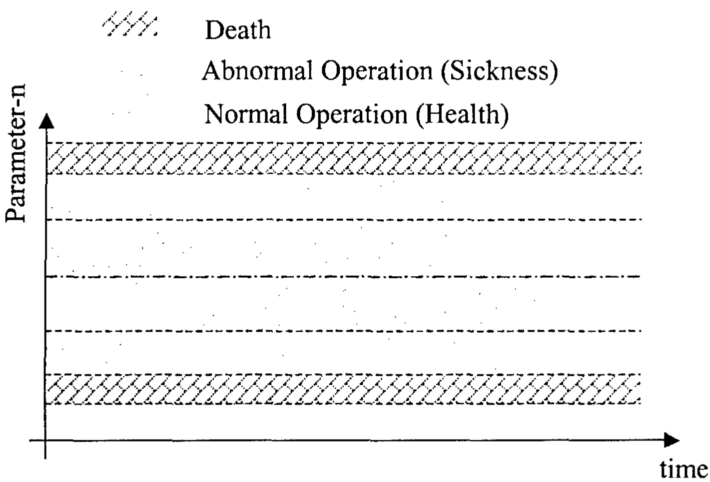

Figure 1. Graphical representation of the definitions for machine operating status regions.

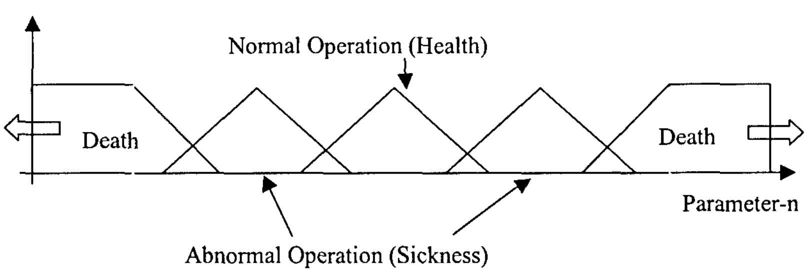

Figure 2. Fuzzy membership function definitions for machine operating status regions.

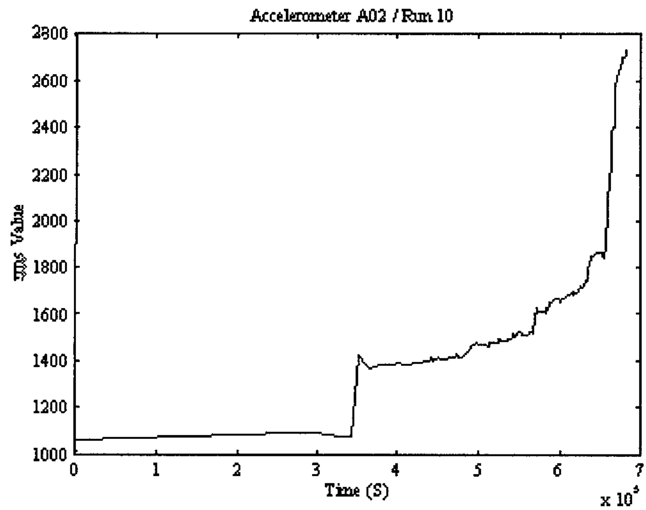

Figure 3. The rms value of the machine vibration versus time in seconds, measured during run #10 using accelerometer # 2.

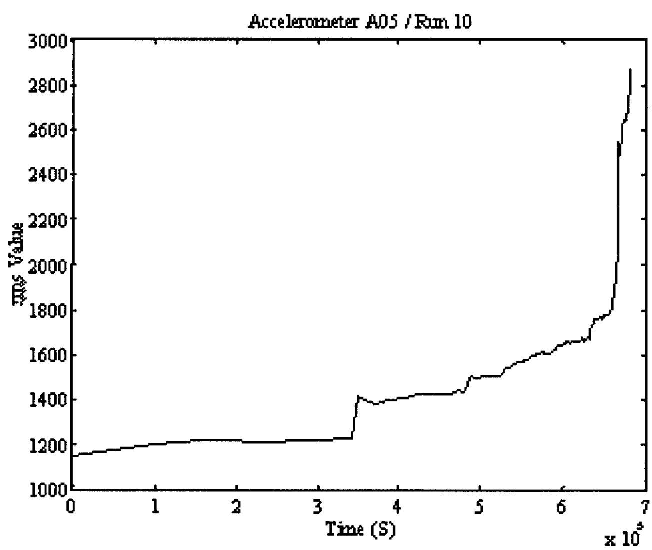

Figure 4. The rms value of the machine vibration versus time in seconds, measured during run #10 using accelerometer # 5.

When a machine parameter transition is recorded in that manner, machine monitoring and diagnosis can be performed using those actual online measurements. Machine monitoring is very useful for many operation and maintenance applications. The remaining useful life estimation is crucial to many other planning and maintenance considerations. The machine remaining useful life estimation will be based not on the measured parameter value but on the predicted parameter value from some measured history data. The state trajectory of the predicted parameter transition will indicate when the machine move from one operating region to another. Now the problem has been simplified to a straightforward prediction problem. Even though prediction of non-linear systems is very hard to achieve, it is hoped that some appropriate prediction models will be built and improved with time. Those models will use some history values in order to predict future values. Linear systems are the easiest to predict, where few history points are enough to predict long time in the future. Unfortunately, linear systems almost do not exist in practice, and prediction problem becomes one of the most challenging problems to solve. Some non-linear systems though are predictable within limits and with variable prediction errors. Chaotic systems, which are a category of nonlinear systems, are not predictable due to their sensitive dependence on initial conditions [3,4,12]. Meaning that a minute change in the initial operating point might lead to a completely different time trajectory, which makes the prediction problem for such systems almost impossible to solve, at least in the time domain.

It is assumed that the systems under discussion in this paper are non-linear and are not chaotic. This means that such systems are predictable within limits and with some prediction error, based on the nature of the system and the prediction method used. The prediction time step is also a factor in the prediction error. Prediction time step is decided based on the nature of the system and the solution method used. Generally, one time step can be predicted with very high accuracy. One time step prediction may give a prediction trajectory that is very comparable to the actual trajectory. However, the prediction extent in that case is very limited, only one time step in the future which might not be very useful in case of prediction of machine remaining useful life. In case of prediction of machine RUL iterative prediction can be used. In the iterative prediction scheme, every predicted point is added to the previous history points as if it was an actual point and used to predict the next future point. If one-step prediction is used, a very small prediction error is expected, but when iterative prediction is used the error is multiplied every time prediction is repeated, which will create a big deviation of the predicted trajectory from the actual trajectory. This deviation is expected to grow more with larger prediction time. Certain confidence level or certainty in the prediction and consequently in the RUL prediction needs to be established. For example, if this model predicts the machine RUL is time (t) then a certainty (C) for that decision needs to be provided to the user, in order for that information to be useful for practical applications. This certainty will be formulated as a function of the accurate prediction probability and the degree of fuzzy membership of the operating status on which the decision was made. The accurate prediction probability will be computed using two methods. The first method assumes a uniform probability distribution, meaning that the one step prediction is achieved with the same probability anywhere in the operating spectrum. In this case the total iterative prediction probability of accurate prediction can be computed as:

$$P^t = (P^1)^n \tag{1}$$

Where P^t is the total accurate prediction probability and P^1 is the one step accurate prediction probability.

The second method assumes that the distribution of the prediction probability is changing over time, and the total iterative prediction probability can be computed as:

$$P^t = P^1 P^2 \Lambda\ P^n \tag{2}$$

Where $P^1, P^2, \Lambda\ P^n$ are the accurate prediction probabilities at time steps 1, 2, ... n.

The degree of fuzzy membership of any system parameter is estimated using the fuzzy membership function definitions similar to those shown in Figure 1. A simple rule base will be used to decide the operating status of the machine at any point. After plugging the different parameter values into that fuzzy system, a decision will be made about the status of the system. This decision is a fuzzy set, which results from the fuzzy system inferencing process that involves both implication of individual rules and aggregation of the collective rules. Defuzzifying this output, a crisp number reflecting its degree of membership to a specific operating region will be given. That number (Z^{death}), estimated using the fuzzy output membership functions, along with the accurate prediction probability (P^t) defined above will be used to generate a total certainty level in the decision as follows:

$$C = Z^{death} P^t \tag{3}$$

And the machine estimated RUL would be computed as:

$$RUL = n\Delta t \tag{4}$$

Where n is the number of points predicted until a death region was located, and Δt is the prediction time-step.

In addition to the certainty in that decision, an estimated error margin, or tolerance, needs to be provided, and that will be computed as an error bar around the estimated RUL as:

$$RUL = n\Delta t \pm n\Delta t \sigma_c \tag{5}$$

Where σ_c is the estimated standard deviation of the iterative prediction at the current estimation point.

A more conservative estimate can be computed as:

$$RUL = n\Delta t \pm n\Delta t(1 - C) \tag{6}$$

And a less conservative or more optimistic estimate can be computed as:

$$RUL = n\Delta t \pm n\Delta t(1 - C)\sigma_c \tag{7}$$

Prediction Models: There are several methods in the literature for non-linear system prediction [3,6,8,10,12]. Some of those are based on time series prediction [13]; others are based on multiple input single/multiple output non-linear system modeling [6,8]. Neural network models are the easiest and fastest to build in addition to many other advantages such as robustness, generalization, learning, and model free estimation [6,8,10]. Neural networks are capable of modeling non-linear systems [7,13]. Neural networks were adopted before for time series prediction and multiple input single/multiple-output system modeling [6,7,13]. The neural networks multiple-input single-output models will best suit the problem in hand. Since the RUL estimation deals, most of the time, with dynamic systems and components, dynamic neural network are preferred over static neural networks, for such applications, due to their ability for modeling of system time behavior. Therefore recurrent neural networks are used to predict the machine state trajectory for the problem in hand, especially that this type of neural networks is known to be capable of modeling system time behavior.

Conclusion: A general methodology was developed for estimation of machine remaining useful life using history data. This method is indirect method that starts with defining parameters sensitive to the machine operating regions and transitions, defining some fuzzy operating regions, and then building prediction models for those parameters. If machine parameters time trajectory can then be predicted with some known accuracy, and a fuzzy logic decision making system can detect the machine operating status with some certainty, then an estimate for the machine remaining useful life can be computed with a known certainty and a known tolerance. In this method, neural network models are used to predict the future trajectory of the machine parameters from some measured history data with some estimated probability of success. Neural network models are adopted due to their known ability for modeling non-linear system behavior. However the dynamic neural network models are expected to outperform the static neural models for such applications due to their ability for modeling of system time behavior. The output of those prediction models is plugged into a fuzzy logic decision-making system in order to locate the machine operating regions at any time with some certainty. These methods are tested using practical failure data for gearboxes from machine diagnostic test-bed at the Applied Research Laboratory. Some of those actual failure data have been analyzed, but the prediction models have not been yet fully developed for this type of data and methodology.

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