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Product quality management based on CNC machine fault prognostics and diagnosis

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Abstract. This paper presents a new fault classification model and an integrated approach to fault diagnosis which involves the combination of ideas of Neuro-fuzzy Networks (NF), Dynamic Bayesian Networks (DBN) and Particle Filtering (PF) algorithm on a single platform. In the new model, faults are categorized in two aspects, namely first and second degree faults. First degree faults are instantaneous in nature, and second degree faults are evolutional and appear as a developing phenomenon which starts from the initial stage, goes through the development stage and finally ends at the mature stage. These categories of faults have a lifetime which is inversely proportional to a machine tool’s life according to the modified version of Taylor’s equation. For fault diagnosis, this framework consists of two phases: the first one is focusing on fault prognosis, which is done online, and the second one is concerned with fault diagnosis which depends on both off-line and on-line modules. In the first phase, a neuro-fuzzy predictor is used to take a decision on whether to embark Conditional Based Maintenance (CBM) or fault diagnosis based on the severity of a fault. The second phase only comes into action when an evolving fault goes beyond a critical threshold limit called a CBM limit for a command to be issued for fault diagnosis. During this phase, DBN and PF techniques are used as an intelligent fault diagnosis system to determine the severity, time and location of the fault. The feasibility of this approach was tested in a simulation environment using the CNC machine as a case study and the results were studied and analyzed.

1. Introduction

The failure of CNC refers to the numerical control machine losing functionality wholly or partially. Once the machine is broken, it is difficult for a professional to find the reason for the breakdown in a short time or even repair it fast, which hinders productivity.

Condition Based Maintenance (CBM) is a philosophy of using sensors in equipment for the purposes of monitoring, diagnosis, and prognostics to facilitate optimal maintenance. CBM has the potential to significantly reduce costs in order to avoid catastrophic failures and to determine more efficiently the intervals required for maintenance schedules [1]. The economic ramifications of CBM are manyfold since they affect labor requirements, replacement part costs, routine maintenance scheduling, increased capacity, enhanced logistics, and supply chain performance [1, 2].

The point of CNC machine fault diagnosis is about identifying, localizing, determining, and classifying the severity of equipment failure, whereas prognostics is the process of predicting the remaining-useful-life (RUL) [3]. The primary challenge is usually to overcome uncertainties and achieve a high degree of accuracy in reasoning out the health state of equipment with sensory signals. The major technical challenges with effective diagnostics are as follows [4]: 1) sensory signal statistics
tends to be quasi-stationary and varies as a function of operating conditions and ambient conditions, 2) machine character can be quite variable due to differences in machining, part-size variations, fastener tightness, wear variations, replacement-part variations, and aging, and 3) features indicative of machine health can be obscured by signals from other sources, number of transmission paths, and by noise. An adequate automated decision support system is required to deal with the challenges in the fault diagnosis task. This system makes it possible to diagnose faults in an uncertain environment. Extensive research has been done to develop fault diagnosis methods based on analytical methods [5, 6], or artificial intelligence techniques [7, 8]. A new recent noticeable trend is the combination of different techniques.

This paper is mainly focused on designing CNC fault prognostics and diagnosis systems framework by combining NF, DBNs and PF ideas to tackle the problem of fault diagnosis. A CNC diagnosis expert system is an intelligent computer’s application program based on expert knowledge and common Expert System’s construction mechanisms. It is composed of a knowledge base, an inference machine, a dynamic fact library, an explanation facility, a knowledge acquisition mechanism, a user interface, etc.

The feasibility of this approach was tested in a simulation environment using a CNC machine as a case study with the results further studied and analyzed. The rest of the paper is organized as follows: Section 2 presents a new fault classification model. Section 3 contains a proposed system framework. Section 4 describes the experiment and results while the conclusion and future prospects are given in Section 5.

2. Fault Classification Model
In this paper, the fault is considered to be any abnormality that impedes the proper functioning of a machine or part of a machine occurring as a result of interactions and reactions of certain factors called symptoms affecting output. Before classifying faults, it is important to mention that the kinds of faults under consideration in this paper are hardware related. In the new model, machine faults are categorized in two degrees based on fault development time. The first category is instantaneous faults which are also referred to as degree-1 faults symbolized by \( f^1 \). These faults need less than 1 second to mature, so they are noticed suddenly after they have occurred, but for the sake of simplicity this category has been extended to cover all faults that occur within less than 60 seconds. A good could be the breakage time of machine hardware components. Predicting these kinds of faults is more complicated. The second category of faults is evolutionary faults also referred to as degree-2 faults symbolized by \( f^2 \). Degree-2 faults are evolutional and their development process can be represented chronologically. Ideally, the development process of these faults can be divided into three stages viz. initial, growth and mature stages. They often start as tiny units of faults and develop with time until the machine comes to a halt. These faults are relatively less complex to predict using past and current statistics.

Degree-2 Fault Evolution Analysis
Degree-2 degradations are a subsection of degree-2 faults dealing mainly with cutting tools and wear off of cutting edges. This branch of faults evolves in three distinct stages viz. initial, growth and mature stages. It can be represented graphically as follows.

Degree-2 degradation is a loss of tool material in volume or weight during an operation. And the amount of degradation is equal to the volume of tool size lost or worn out. Such tool degradation is the difference between the original size of the cutting edge before operation and the final size after operation. Hence this can be expressed mathematically as:

\[
\Delta S = S_i - S_f, \quad i = 1, 2, 3, \ldots n
\]

where \( S \) is the size of the cutting edge and \( i \) is the number of operation. Total degradation is given in the summation of the difference per operation, expressed as:

\[
Tf_d^2 = \sum_{i=1}^{n} S_i
\]  

(1)
Machine tools, however, have diverse shapes, so depending on the dimensions of the contact area of a tool, the amount of degradation per operation or per unit time can be calculated.

Theorem 1: In the first stage of the classification model, degree-2 degradation occurs slowly and as such assumes a gentle curve.

Proof: In machine operation it is normal for cutting tools to start operation with a slow cutting speed and increase in speed as the operation progresses. Hence during the initial stage, the factors that promote tool degradation such as temperature and cutting speed are minimal and thus their effects are mild or dormant.

Theorem 2: In the second stage of the model, degree-2 degradation rises sharply.

Proof: The sharp rise in the degradation in the second stage is usually due to higher temperature levels generated by high cutting speed. Higher temperatures weaken the cutting edge and make it more susceptible to degradation.

Theorem 3: In the third stage of the classification model, degree-2 degradation begins to retard and therefore assumes a gently increasing slope until tool failure.

Proof: In machine operation it is recommended that the cutting operation finishes with a lowering speed to enable a smooth finish and also avoid accidents. This is accompanied by a reduction in speed, loss of temperature through worn off particles and, more importantly, the degradation reaches its carrying capacity.

Theorem 4: Degree-2 faults which are a bigger set that includes degree-2 degradations, evolve exponentially with time and can be modelled with the Gompertz growth function. The intensity of degradation is inversely proportional to the tool life determined by Taylor’s equation and it can be express mathematically as follows:

\[ V T^n = C \]  

(2)

where V is the cutting speed, m/min; T is tool life, min; and n and C are parameters that depend on feed, depth of cut, work material, and tooling material, but mostly on material (work and tool). But from Theorem 4 the intensity of degree-2 can be expressed symbolized by \( f_{m}^{2} \):

\[ f_{m}^{2} \alpha \frac{1}{T^n} \]  

which implies

\[ f_{m}^{2} = \frac{K}{T^n} \]  

(3)

where K is a constant of proportionality. Besides Taylor’s tool life equation, only the effect of cutting velocity variation on tool life has been considered. But practically, the variation in feed (S₀) and depth of cut (i) also affect tool life to some extent [1]. Taking into account the effects of all those parameters, Taylor’s tool life equation has been modified as:

\[ TL = \frac{C^T}{V_c S_0 i} \]  

(4)
The equation (3) will take the form:

$$f_m^2 = \frac{\kappa V_x^2 S_y^2 c^2}{c_T}$$

(5)

Proof: Degree-2 faults are tiny units of faults which may be referred to as strains that arise with time due to the aging of machine parts, overloading and unprofessional practices causing strain. Given initial fault or set of faults, the magnitude or severity of the fault will intensify due to aging, overloading, temperature effects and other factors. And if the machine continues to be used without resolving the initial faults, it will result in more faults. And the emergence of more faults means more interactions and reactions among faults which will accelerate sharply the development of the existing faults until the point of saturation where no further interactions or reaction can impact the fault development. At this moment, the machine or part of the machine will come to a halt. Thus the fault lifetime development curve is one that rises gently initially and then sharply for a period of time and finally ends gently at the saturation stage. This best fits the Gompertz growth function, hence proved.

3. Proposed System Framework

The system framework in this paper is a hybrid one that mainly integrates a Neuro-fuzzy system with the Dynamic Bayesian Networks and Particle Filtering algorithm on a single platform. The method relies on the utilization of the monitoring data provided by the sensors installed on a CNC machine to track its tool’s fault evolution. The proposed system may be used to assess the degradation state of any physical component such as drill bits, milling cutters, tool bits, rolling elements and many others.

In the online module the extracted features are stored in intelligent databases and are continually fed into a Neuro-fuzzy predictor leading to the stage of fault prognosis which will be explained in detail later. But more importantly, the main activity of this stage is to decide whether to proceed on CBM or Fault diagnosis. In a situation where the degradation threshold is below a certain limit called a CBM limit, which according to the proposed classification model comprises the initial and growth stages of the fault evolution curve, a decision is taken for a CBM action to terminate the development of the fault. On the other hand, if the threshold is beyond the CBM limit, then it is regarded as a critical condition and a command is given for the commencement fault diagnosis. And this leads to the final phase where the full system is modeled in probabilistic terms by a Dynamic Bayesian Network. The probabilistic model parameters are studied offline and the structure of the model is found by studying the structure of a discrete Bayesian network. The failure probabilities of each machine tool based on evidences are updated periodically and the Bayesian network is used to select the machine tools with a high probability of failure.

Below is a diagrammatic representation of the framework:

![Diagram](image_url)
Fault Prognosis
Several definitions exist for industrial prognostics [9, 10, 11], and the main highlighted points include: the system’s actual state, the projection (or extrapolation) of the latter, and the estimation of the remaining time before failure. These definitions have been normalized by the ISO 13381-1 standard [12] in which prognostics is defined as the estimation of the operating time before failure and the risk of future existence or appearance of one or several failure modes. This standard defines the outlines of prognostics, identifies the data needed to perform prognostics and sets the alarm thresholds and the limits of the system’s reset (total shut-down). The main steps to perform prognostics, as defined in the standard, are summarized in Fig. 3:

**Figure 3.** Prognostics steps according to ISO 13381-1 [13]

Neuro-Fuzzy Predictor
The NF predictor is a neural network-based fuzzy system. The NF predictor used in the paper is similar to that of Wilson Q. Wang, M. Farid Golnaraghib and Fathy Ismail [14] except for the membership function where the Gompertz growth function and the defuzzification rule are used instead of the first of maximum (FOM). The prediction reasoning is conducted by fuzzy logic. The fuzzy inference structure is determined by expertise, whereas its membership functions (MFs) are trained by using NNs. Four input parameters are used for one-step-ahead prediction. If two membership functions are assigned to each input variable: SMALL (S) and LARGE (L), then 16 rules are formulated for this forecasting operation [14]. For notational simplicity, these rules are represented in a general form:

\[ R_j: IF \left( x_{t-3T} \text{ is } A'_1 \right) \ AND \ \left( x_{t-2T} \text{ is } A'_2 \right) \ AND \ \left( x_{t-T} \text{ is } A'_3 \right) \ AND \ \left( x_t \text{ is } A'_4 \right) \]

\[ \text{then } x_{t+r} = c_j x_t \]

where

\[ c_j x_t = c_1 x_{t-3T} + c_2 x_{t-2T} + c_3 x_{t-T} + c_4 x_t + c_5 \]

\[ j = 1, 2, \ldots, 16 \]

The network architecture of this NF system is shown in Fig. 4. It is a six-layer feedforward network in which each node performs a particular function on the incoming signals. The links represent the flow direction of signals between nodes, but all of them have unity weights. The nodes in Layer 1 only transmit input signals to the next layer. In Layer 2, each node acts as an MF, SMALL or LARGE. Through comparison, Gompertz functions are chosen as MFs in this case, which are expressed as:

\[ \mu_{A'_j}(x) = \exp(m'_j - b'_j c^T) \]

If the max-product operator is applied here, the rule firing strength is:

\[ \mu_j = \mu_{A'_1}^{(x_{t-3T})} \mu_{A'_2}^{(x_{t-2T})} \mu_{A'_3}^{(x_{t-T})} \mu_{A'_4}^{(x_t)} \]

\[ j = 1, 2, \ldots, 16 \]

All the rule firing strengths are normalized in Layer 4. After the linear combination of the input variables in Layer 5, predicted output \( x_{t+r} \) is obtained in Layer 6 using the FOM (first of maximum) defuzzification,

\[ x_{t+r} = \frac{\sum_{j=1}^{16} \mu_j (c'_1 x_{t-3T} + c'_2 x_{t-2T} + c'_3 x_{t-T} + c'_4 x_t + c'_5)}{\sum_{j=1}^{16} \mu_j} \]
is the normalized rule firing strength. Next is the training process. The above stated NF system has 96 parameters to be optimized in training (16 premise MF parameters and 80 consequent parameters). In order to improve the training efficiency and eliminate the possible trapping due to local minima, a hybrid learning algorithm [15, 16] is employed in this case. It is a combination of the gradient descent approach and least-squares estimate, which is briefly described next. For \( p \)th training data pair \((x^{(p)}_{t-3r}, x^{(p)}_{t-2r}, x^{(p)}_{t}, x^{(p)}_{t-r})\), \( d^{(p)} \) \( p = 1, 2, \ldots, P \); \( P \) is the total number of the training data pairs. \( d^{(p)} \) is the desired future value. The error function can be defined as:

\[
E_p = \frac{1}{2} (x^{(p)}_{t-r} - d^{(p)})^2
\]  

(11)

The objective function for all the data sets is:

\[
E = \sum_{p=1}^{P} E_p = \frac{1}{2} \sum_{p=1}^{P} (x^{(p)}_{t-r} - d^{(p)})^2
\]  

(12)

The premise parameters in Eq. (4) are updated using the gradient descent approach and the resulting parameters are optimized using least-squares estimate as being briefly described. Given that there are the MF parameters and \( P \) training pairs, \( P \) linear equations in terms of the consequent parameters can be formed as follows:

\[
A_y = d
\]  

(13)

Fault Diagnosis

Fault diagnosis consists of the determination of the type, size, and location of a fault, together with the time of detection. Fault diagnosis methods mainly use classification techniques or reasoning methods [6]. Classification techniques include statistical methods, neural networks and fuzzy clustering. Reasoning methods mainly include first order logic, fuzzy logic and Bayesian networks. In this paper, a dynamic Bayesian Network is employed.

Bayesian Networks

Bayesian networks are a helpful tool to model multi-fault, multi-symptom dependency relations: every fault and every symptom is modelled by a random variable with a finite range of possible values. A graph is constructed with a node for each variable. The graph constructed has an edge from one node to another, whenever the first node models a fault directly exhibiting the symptom modelled by the second.

In general, Bayesian networks are a representation of probability distributions over complex domains. Formally, probability spaces, defined as the set of possible assignments to some set of
random variables $X_1, \ldots, X_n$, each of which has domain $\text{Dom}[X_i]$ of possible values, are considered. Formally, a Bayesian network is defined by a directed acyclic graph together with a local probabilistic model for each node. There is a node in the graph for each random variable $X_i, \ldots, X_n$. The edges in the graph denote direct dependency of variable $X_i$ on its parents $\text{parents}(X_i)$. The graphical structure encodes a set of conditional independence assumptions (each node $X_i$ is conditionally independent of its non-descendants given there are its parents). The qualitative independence assumptions, implied by the network structure, combined with the conditional probability distributions associated with the nodes, are enough to specify a full joint distribution through the following equation (4), known as the chain rule for Bayesian networks [17]:

$$p(X_1, \ldots, X_n) = p(X_i \perp \text{parents}(X_i)) \quad (14)$$

In discrete networks, an explicit description of the joint distribution requires a number of parameters that are exponential in $n$ (the number of variables). Bayesian networks derive their power from the ability to represent conditional independencies among variables, which allows them to take advantage of the “locality” of causal influences. A variable is independent of its indirect causal influences given that there are its direct causal influences. The proposed diagnosis system consists of two phases:

Phase I

The implementation of the first phase consists of the following steps:

1) Facts, assumptions, knowledge base. In this block, a table describes the behaviour of all the machine tools which constitute the CNC machine, as well as the behaviour of their respective fault symptoms. This is illustrated by a table with all possible combinations of fault symptoms, as a result the data are generated for the Bayesian network of the full system.

2) Discretization. The continuous variable is discretized.

3) Bayesian network. The specialized software Power Constructor1 developed to learn a Bayesian network from data is included here. It uses databases in the form of discrete variables. A Bayesian network uses evidence from a set of variables and looks at the rest of variables to predict the possible faults that could be presented. The Hugin 2 software was used to make inferences and analysis.

Phase II

Fault diagnosis in this context is to determine the degradation state of CNC machine tools over time given that there is a stream of observations. Complex nature of the CNC machine and noisy environment makes it difficult to determine the true state at any point in time with certainty. Uncertainty at every point should be considered explicitly. To represent uncertainty about the degradation state of a machine tool, the Particle Filtering (PF) implemented algorithm is employed. The main purpose of Particle Filters in this work is to update the Bayesian belief [18]. The basic idea is to simulate the behavior of machine tools degradation. Each particle predicts future behavior of the system in a Monte Carlo approach. The particles that match the monitored tool behavior are kept and the others are thrown away. [19] describes a number of PF-based algorithms for state estimation which have demonstrated good results on diagnosis problems.

More specifically, the implementation of the second phase consists of the following steps:

1) Subset of explanations. Once data have been analyzed, a subset of explanations is given where a possible fault is located in the system. This is just a subset of the results taking into account only those with major values in probability, as indicated.

2) Discretization JMLG. Combining Hidden Markov Models and State Space Models, a hybrid model can be generated, which provides a rich representation for processes [17]. This model is called the Jump Markov Linear Gaussian (JMLG) model, as depicted in Figure 5.
In the model, $z_t$ is the discrete mode switch variable, $x_t$ is the real-valued state variable, $u_c$ and $y_t$ are the observable variables. (See [20] for detailed definitions and the learning procedure.)

3) Particle Filtering. This final block of the diagnosis system will make different decisions depending on the results in Phase I according to the following statements. (a) If the probability of failure of the machines does not change, then Particle Filters will continue monitoring the same machines to find damaged components. (b) If the probability of failure in a non-monitored machine increases to a warning level, then a Particle Filter must be started to monitor this machine. (c) If the probability of failure in a monitored machine increases, then the Particle Filter must increase its reliability taking a greater number of particles. If the probability of failure in a monitored machine decreases, then the Particle Filter must reduce the number of particles in the first stage. If the tendency remains, the Particle Filter must stop in that machine.

4. Experimentation And Results

Phase I

The wear diagnostic and prognostic method presented in this paper was tested on the “prognostic data challenge 2010” database [21] which contains several histories of a high-speed CNC milling machine. The cutting parameters were: the spindle speed of the cutter was 10400 rpm, the feed rate was 1555 mm/min, the $Y$ depth of cut (radial) was 0.125 mm and the $Z$ depth of cut (axial) was 0.2 mm. Once the database has been created, this file is opened with Power Constructor to create the preliminary Bayesian network and then this information is exported to Hugin. Figure 6 shows the Bayesian network for the CNC machine where tools are discrete variables and faults are discretized continuous variables.

Using Hugin code, inferences were made on certain variables which predict the behaviour of the system as shown in Figure 9. The figure shows the tool status which consists of two variables namely degradation. Below is the analysis report.
From the analysis report it can be seen that 480 cases were simulated and tool 1 was predicted as the degrade tool with an error rate of 0.42, which indicates that the level of accuracy was high. Below is the fault evolution curve for tool 1 after prediction.

In figure 8, there are three distinct stages of the tool fault evolution, which confirms the statement that the tool fault evolution or degradation assumes a Gompertz curve.

In Figure 9 class F, a degradation cut-off point of 81.31% is given with the remaining useful tool life of 18.60%. After 480 cases of simulations, tool 1 was predicted as the most damaged tool with a degradation level of 77.56%. But since the percentage of degradation is less than 81.31%, it means that tool 1 is not in a critical condition and the recommended action will be to proceed on conditional based maintenance. Below is a snapshot of the analysis report.
5. Conclusions And Future Work
The paper describes a new approach to fault prognostics and diagnosis in a universal CNC machine by combining the ideas of Neuro-Fuzzy networks with dynamic Bayesian learning inference and particle filtering on a single platform. The main contribution is the newly proposed fault classification model.

An integrated CNC expert system was able to predict the tool with a higher level of degradation before critical damage could occur and a recommendation was made for CBM action to rectify the fault.

The authors wish to integrate Kalman filter with neural networks in a similar fashion and so that to compare the accuracy of both approaches.

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