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Model development based on evolutionary framework for condition monitoring of a lathe machine

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ABSTRACT

The present work deals with the vibro-acoustic condition monitoring of the metal lathe machine by the development of predictive models for the detection of probable faults. Firstly, the experiments were conducted to obtain vibration and acoustic signatures for the three operations (idle running, turning and facing) used for three experimental studies (overall acoustic, overall vibration and headstock vibration). In the perspective of formulating the predictive models, multi-gene genetic programming (MGGP) approach can be applied. However, it is effective functioning exhibit high dependence on the complexity term incorporated in its fitness function. Therefore, an evolutionary framework of MGGP based on its new complexity measure is proposed in formulation of the predictive models. In this proposed framework, polynomials known for their fixed complexity (order of polynomial) are used for defining the complexity of the generated models during the evolutionary stages of MGGP. The new complexity term is then incorporated in fitness function of MGGP to penalize the fitness of models. The results reveal that the proposed models outperformed the standardized MGGP models. Further, the parametric and sensitivity analysis is conducted to study the relationships between the key process parameters and to reveal dominant input process parameters.

1. Introduction

Maintenance is considered to attribute almost half of the operating costs of any manufacturing operations carried out in the industry. Consequently, this has motivated researchers for building the condition monitoring systems for the complex machines, since they allow for a significant reduction in the machinery maintenance costs, and most importantly, the early detection of potentially disastrous faults. Besides the detection of the early occurrence and seriousness of a fault, it drives identification of components that are deteriorating without even opening the machine for inspection. Machine condition monitoring can be defined as a field of technical activity in which the selected physical parameters associated with a machinery operation are observed for the purpose of determining the integrity of machine (system) integrity [1,3]. Once this has been estimated, maintenance activities can be scheduled only when needed, which results in optimum use of resources. The reason behind employing the machine condition monitoring is to generate accurate and quantitative information on the present condition of a machine (for example, lathe) in order to optimally schedule maintenance, achieve maximum productivity, and still avoid unexpected catastrophic failures. It also results in improved risk maintenance and increased machine reliability [2,4–6].

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Vibration monitoring and acoustic emissions are the two most effective and commonly used methods for condition monitoring of machines [6–8]. Vibration condition monitoring has been a trusted method for the past thirty years. However, the time and effort required to obtain machine signatures is much more as compared to acoustic condition monitoring. The acoustic method has significant advantages in terms of lower costs of experimental setup and the ease of application. The issue of placement of accelerometers and connections to amplifiers is completely eliminated and is instead replaced by a single hassle free acoustic noise level meter. Alternatively, the computational intelligence (CI) methods such as genetic programming (GP), support vector regression and artificial neural network (artificial neural network) can also be applied on the collected vibration and acoustic data to build the models that can be used to monitor the mechanical condition and derive the approximate time of a functional failure of different parts, resulting in scheduled maintenance [9–16].

Among the CI methods, GP evolves the model structure and its coefficients automatically [17–22]. Set of variants of GP has been developed. Among them, multi-gene genetic programming (MGGP) is widely used, since it evolves a model formed by combination of a set of genes. Despite of having a good number of applications in engineering fields, MGGP tends to generate the models that may not give a satisfactory performance on the test data. Based on the previous applications of MGGP conducted by authors [16–18], the two main reasons that may be attributed to such poor performance are as follows:

(1) *Defining the complexity of the MGGP model:* Complexity of the evolved models during evolutionary stages of MGGP is defined by number of nodes of the tree. This implies that Sin (x) and $-x$ will have same complexity, but it is not at all true. Complexity term is a component of the fitness function which monitors the evolutionary search and the convergence rate towards achieving the optimum solution. Therefore, determining its correct value is essentially important for the effective functioning of the algorithm by driving the convergence towards an optimum solution.

(2) *Difficulty in selection of the best model:* In the context of selection of the best model, generally, it is selected based on the minimum training error. However, it is observed that this best model may not perform best on the testing data. It was found that there are other models in the population that perform better than the best model with a little compromise on training error.

These two issues requires a thorough investigation and therefore forms a motivation part for authors in developing a framework that can tackle such issues resulting in evolution of generalized models for effective condition monitoring of the lathe machine.

1.1. Present work and objective

An evolutionary framework of MGGP based on its new complexity measure is proposed in the condition monitoring of the lathe system. Three experiments (overall acoustic, overall vibration and headstock vibration bearing) on lathe are conducted in the three operating conditions: Idle run, turning and facing. For each of the operating condition, the peak noise level in decibels (dB) is measured as an indicator for the scheduled maintenance. In the context of development of evolutionary framework, polynomials known for their fixed complexity (order of polynomial) are proposed for defining the complexity of the models evolved during evolutionary stages of MGGP. Minimum order of the polynomial which best fits the model is considered as the complexity of that model. The order term is then incorporated in its fitness function to evaluate the performance of models. Classification methods (k-nearest neighbour and SVM) are further incorporated to improve the selection of the best model. The proposed method is applied on the data obtained from the experiments and its performance is compared to that of the standardized MGGP approach based on the five statistical metrics.

2. Experimental study on lathe system

2.1. Experimental set-up

Data acquisition is the initial and one of the most important phases of condition monitoring which involves recording the vibration and acoustic signals of the metal lathe. Signal processing techniques such as Fast Fourier Transform (FFT) are then applied to analyze the data. Initial set of experiments were carried out on six different metal lathes for three days. In order to obtain vibration signatures, a piezoelectric accelerometer having a sensitivity of 101.3 mV/g is used. After cleaning the surface, it is mounted on the bearing housing, perpendicular to the shaft center-line, using adhesives. Alignment of lathe is done prior to mounting. As the output of the accelerometer is of low level and contains some unwanted frequencies, some form of pre-processing is required before analyzing the data. A 4-input, 1-output vibration collector system [23] (Spider-81 Vibration Controller System) amplifies the output data of the accelerometer and converts the data into frequency domain using Electronic Data Management (EDM) software. The entire process cycle for vibration data acquisition is shown in Fig. 1.

The acoustic signatures are obtained using a noise level meter [24]. Fourteen equidistant grid points are selected around the lathe machine as shown in Fig. 2 and the sound level is measured at each point for every lathe machine. The noise level meter is kept at a distance of 0.2 m from the base of lathe machine and the readings are taken in the absence of any external noise field. The Noise level meter consists of a transducer, preamplifier, amplifier and an analysis module. A condenser microphone is used as a transducer for measuring the sound pressure level which is directly obtained on a readout screen. An FFT module converts the time domain data into frequency domain. The entire process flow is shown in Fig. 3.

2.2. Specifications of lathe system

The six lathe machines (Figs. 4 and 5) were analyzed for vibration specific acceleration values (g-peak) and peak