TOOL CONDITION MONITORING SYSTEM IN TURNING OPERATION UTILIZING WAVELET SIGNAL PROCESSING AND MULTI-LEARNING ANNS ALGORITHM METHODOLOGY

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Abstract

The present study shows the development of a tool condition monitoring (TCM) system utilizing signal decomposition techniques in an artificial neural networks (ANNs) system. The raw signals obtained from sensors under different machining conditions were examined and reduced to multiple components. The most significant components of each signal were implemented to develop tool-monitoring systems. Over 900 neural-networks structures were tested using a multi-learning algorithm methodology to find an optimized structure for the TCM system. This technique provided systematic test results of the extended number of possible ANN structures with higher accuracy, when compared with the traditional manual trial-and-error methodology. The ANN-TCM system developed in this study showed 97% accuracy from 151 test samples with the reject flank wear size of 0.2 mm or larger. The results demonstrated the successful development of a TCM system, which can be implemented as a practical tool to reduce machine downtime associated with tool changes and to minimize the number of scraps.

Introduction

The metal cutting process, which has played an important role in modern manufacturing history, relied on highly skilled labor until the mid-1950s, when automated machining was introduced to replace traditional labor, decrease production costs, increase productivity, and enhance product quality [1]. Not long afterwards, the industry demanded another task from manufacturers. Products became more individualistic, varied, and complex to manufacture. Manufacturers needed new technologies and methods that would allow small-batch production to gain the economic advantages of mass production [2]. The development of CIM (Computer-Integrated Manufacturing) and FMS (Flexible Manufacturing Systems) seemed to be ideal solutions for increasing machining flexibility in addition to flexibility in routing, process, product, production, and expansion [3].

Although the combination of CIM and FMS technologies showed great promise as a cost-effective solution to meet new demands, CIM-FMS systems could not be implemented until certain prerequisites were met. One major prerequisite was uninterrupted machining to achieve maximum efficiency [4]. Deteriorating process conditions, such as tool condition, often forces manufacturers to interrupt machining processes in order to respond. Thus, developing an effective means of monitoring machine conditions has become one of the most important issues in the automation of the metal-cutting process [5].

Among the many machine conditions requiring monitoring, tool wear is one of the most critical issues for ensuring uninterrupted machining. An effective monitoring system allows for effective tool-change strategies when tools deteriorate, and maintains proper cutting conditions throughout the process [6]. If the monitoring system fails to detect the true cutting-tool conditions, the cutting process could result in poor surface quality, dimensional error, and even machine failure [5]. Furthermore, a reliable tool-wear monitoring system can reduce machine downtime caused by changing the tool, thus leading to fewer process interruptions and higher efficiency. The information obtained from the tool-wear sensors can be used for several purposes, including the establishment of a tool-change policy, economic optimization of the machining operation, on-line process manipulation to compensate for tool wear, and to some extent the avoidance of catastrophic tool failure.

TCM Studies

The traditional process for predicting the life of a machine tool involves Taylor's equation for tool-life expediency: $VT^n = C$, where V is cutting speed, T is tool life based on the amount flank wear, and n and C are coefficients [7]. This equation has played an important role in machine-tool development [8]. Since advanced machining was introduced in the mid-1900s, various methods to monitor tool wear have been proposed, expanding the scope and complexity of Taylor's equation. However, none of these extensions has been applied universally, due to the complex nature of the machining process [9].

Researchers have searched for reliable methods to monitor tool wear. These methods represent an area of active research because tool condition strongly influences the surface finish and dimensional integrity of the work-piece, as well as vibration in the tool. More automated approaches were attempted using computer-numerical-control (CNC) technology. However, the CNC approach also has several obstacles to widespread implementation such as the narrow learning capability of CNC machines, limited flexibility of the CNC controller, relatively large dynamic errors encountered in CNC operations, sensor noises and variability between machines [10]. In spite of the recent introduction of open CNC and STEP-NC for providing improved architectures, where researchers can integrate sensor-signal management systems and customized applications, studies show that it is still a challenge to find proper sensor technologies and signal-process techniques for tool-condition monitoring [11, 12]. Therefore, numerous sensor techniques were introduced and tested in tool-wear-monitoring studies.

Tool-condition monitoring methods can be classified into direct and indirect methods, depending on the source of signals collected by sensors. Direct methods sense tool conditions by direct measurement of the tool. Direct methods include optical, radioactive, and electrical resistance. Alternatively, indirect methods sense the tool condition by measuring secondary effects of the cutting process, such as acoustic emission (AE), sound vibrations, spindle- and feed-motor current, cutting force, and machining vibration. Direct methods are beneficial because they take close readings directly from the tool itself. By contrast, indirect methods must rely on conditions other than the tool itself to judge the condition of the tool. However, direct methods are limited because the machining process must be interrupted to make the direct measurements [13]. As a result, machine downtime increases, as do costs for tool-condition monitoring.

Since indirect methods do not require access to the tool itself to measure the tool conditions, signals that indicate the tool condition can be gathered in real time, while the machine is running. However, despite the benefits of on-line measurement, indirect methods also have some disadvantages. Since the information (or signals) collected by indirect sensors does not contain direct measurements of the tool conditions, additional systems are required to correlate the indirect measurements with its tool condition. Additionally, indirect measurements are weakened by noise factors associated with the machining process. Noise factors tend to weaken or totally eliminate relationships between the indirect information and actual tool conditions. Many studies have sought to correlate indirect measurements with actual tool conditions using statistical regression techniques [14], fuzzy logic [1], artificial neural networks [15-19] and fuzzy-neural networks [10, 20]. In many of the studies, the relationships between indirect signals and tool condition were weak because unknown factors and noise factors diluted the signals collected by the indirect sensors during machining.

Some studies attempted to eliminate or minimize noise factors from the signals collected by indirect sensors. Wavelet transformation methods were used to remove noise factors from the information collected by the sensors [9], [21]. These studies showed that a wavelet transformation process can increase the correlation between the reduced-noise signals and tool conditions [22]. However, these studies still did not show the relationship between the signal components, which were treated as noise factors, and tool conditions.

A limited number of sensors have been adopted in most studies involving indirect sensing systems. The most widely used indirect sensor is the dynamometer [6], [10], [23], which is not practical because of its high cost and lack of overload protection. The acoustic emission (AE) sensor is another sensing technology that has been used in a number of studies [24], [25], but it is also limited in its application due to its noise integrity. Some studies adopted multi-sensor techniques to improve tool-condition monitoring systems [26-28]. By combining multiple sensing technologies, these studies sought to develop more robust on-line TCM systems.

Experimental Setup

From the review of the past TCM studies, two cost-effective sensor technologies, tri-axial accelerometer and acoustic emission sensor, were employed in this study to detect multiple-direction vibrations and the energy generated from the interaction of tool and work-piece. The accelerometer was mounted under the shank holding the cutting tool with the AE sensor mounted under the work piece. The signals detected by the accelerometer were amplified and transferred to an A/D converter with the signals from the AE sensor, simultaneously. The signals were stored to a computer by a data-acquisition program (DaqView™ by IOtech), which was also utilized to analyze the data. Carbide insert tools (CNMG-432) with variable tool-wear amounts were mounted in a CNC lathe to cut aluminum alloy work pieces (aluminum alloy 6061). Figure 1 shows the illustration of the experimental setup.

Experimental Design

The goal of this study was to develop a tool-condition monitoring system using three machining parameters (spindle speed, feed rate, and depth of cut) and the signals detected by the two sensors. To conduct the experiment, an experimental design was established. A full factorial design was utilized for this experiment in order to examine the full range of independent parameter combinations. A multi-layered perceptron ANN model with a back-propagation learning algorithm was deployed based on the independent s

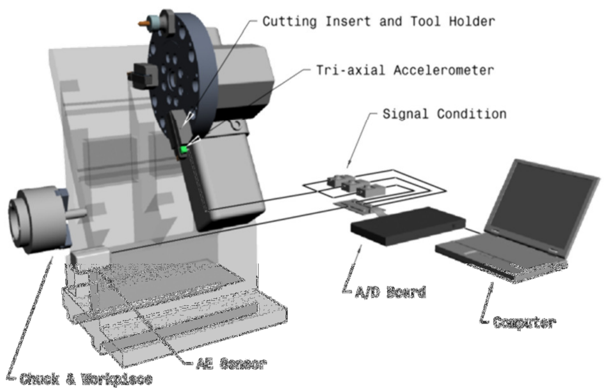

Figure 1. Experimental setup

variables for input neurons. The independent variable utilized in this study were: 3 spindle speeds (SP), 3 feed rates (FR), 3 depths of cut (DC), and signals captured during machining (S_i). Three insert tools with different amounts of flank wear (0.010714 inch, 0.017857 inch, and 0.019643 inch) were measured under a microscope before the machining process began. The measured values were used as the outcome of the developed TCM system.

To test the flexibility of the newly developed TCM system, additional sets of machining parameters and conditions were employed. These sets includes additional values for spindle speed, feed rate, depth of cut, and tool conditions (0.007143 inch and 0.014285 inch), which are not used in the analysis and system development. After the experimental design, each cutting condition—including cutting conditions from the flexible data set—were randomly reorganized before the machining was performed in order to eliminate any systemic integration from the cutting conditions. Table 1a shows the training data set employed in this study and Table 1b shows the flexible data set employed in this study.

TCM System Development

Signal Decomposition Process

A total of 270 data sets containing raw signals were obtained from the experiment. Since the traditional time-domain analysis does not provide a clear method for analyzing raw signal data due to the randomness of each of the data points, numerous sets of conditions were tested. Among the many characteristics, the adjusted mean values of each membrane were employed to represent responses of sensors to each of the machining conditions, including machining parameters and tool conditions. However, the raw signal data restrain other machining effects including the effects of machining parameters and machining environments. Therefore, it is necessary to reduce the raw signals into multiple

Table 1. Experimental Design

	SP	500			1,000			1,500		
FR	**DC**	**.01**	**.02**	**.03**	**.01**	**.02**	**.03**	**.01**	**.02**	**.03**
.01		S_{01}	S_{02}	S_{03}	S_{10}	S_{11}	S_{12}	S_{19}	S_{20}	S_{21}
.02		S_{04}	S_{05}	S_{06}	S_{13}	S_{14}	S_{15}	S_{22}	S_{23}	S_{24}
.03		S_{07}	S_{08}	S_{09}	S_{16}	S_{17}	S_{18}	S_{25}	S_{26}	S_{27}

	SP	625		825	
FR	**DC**	**.015**	**.025**	**.015**	**.025**
.015		S_{28}	S_{29}	S_{32}	S_{33}
.025		S_{30}	S_{31}	S_{34}	S_{35}

components and adopt only the significant components for development of the TCM system.

Among a number of signal-processing techniques, Daubechies wavelet was employed for its fairly quick calculation results and simple programming structure under Matlab and its Wavelet Toolbox environment. In this study, a D4 wavelet program was developed. In the past, wavelet transformation methodology has been used to eliminate the noise factors. In this study, however, components of noise factors and significant responses to tool condition are indistinguishable. In order to find the most significant component of tool condition, a series of statistical data analyses were performed. Figure 2 shows an example of the reduction process. Table 2 shows the statistical analysis results of the components of each signal. The analysis results show that component 6 (C6) of the x, y, and z direction vibrations and the original raw signal of the AE sensor show stronger relationships to tool condition than the others. This indicates that by utilizing the 6^{th} component of the vibration signal—obtained by wavelet reduction of the raw vibration signal and the raw signal of the AE sensor—a more accurate TCM system can be produced.

ANNs Structural Developments

Artificial neural networks provide an artificial means of making some of the same kinds of decisions that a highly skilled machine operator would make before, during, or after the machining process [17]. Human operators learn to make accurate judgments of tool conditions based on relationships observed during the machining process. As human operators gain experience, their sensitivity to these relationships increases. More recent experience reinforces or adjusts the patterns developed from prior experience. ANNs work in a similar fashion, continually training themselves to accurately judge tool conditions. By adjusting the weights among neural-network nodes until the number of test errors falls to an acceptable level, the nonlinear relationships among the factors and tool condition are updated and tested.

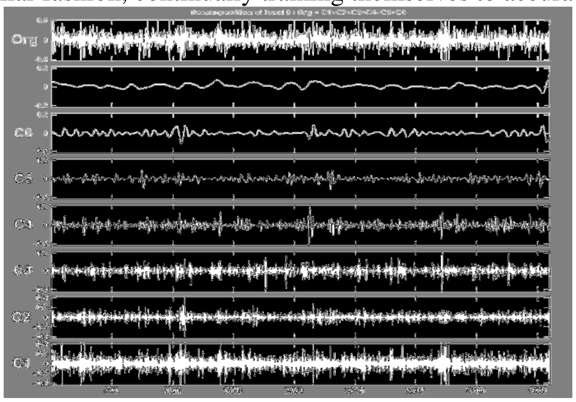

Figure 2. Example of signal reduction by wavelet transformation

Table 2. Correlation factors of tool wear and signal

Signal	Org	Cmp1	Cmp2	Cmp3	Cmp4	Cmp5	Cmp6
X	.0415	.0007	.0368	.0793	.2660	.2413	.5369
Y	.0958	.0136	.0266	.0288	.0727	.0753	.3618
Z	.0030	.0199	.0431	.0577	.1929	.2002	.5134
W	.1214	.0874	.0864	.0595	.0792	.0306	.0427

X: x-direction vibration, Y: y-direction vibration, Z: z-direction vibration, W: AE signal, Org: original signal, Com1 – 6: signal components

Determining the network's structure (the number of hidden layers and nodes of each layer) that performs best is one of the biggest challenges in the process of developing ANNs. Many machining-tool studies tested only a limited number of cases by trial-and-error in order to determine the appropriate structure [15], [26]. Investigating a limited number of cases of the ANN structure often leads to a low probability of obtaining the best-performing system with the available data. In addition, in a trial-and-error methodology, the researcher has to spend a great amount of time modifying the ANNs structure, including the numbers of hidden layers and nodes; and, each structure must be trained until the test results are valid. As a result, this method requires a great deal of time in order to optimize the network training time and output results [29].

A novel method for finding the optimized ANN structure for tool-condition monitoring is proposed in this study. In order to avoid the problems of the traditional manual method (inefficient, time consuming, and potential inaccuracy) to build the ANN structure, a computer-assisted ANN-structure search methodology was employed. The proposed methodology tests all possible structures with a simplified learning process (quick-propagation) and short-training iteration, providing fitness scores for each structure to allow focus on a limited number of structures with higher scores and higher possibilities of accurate explanation of the outcome. The following is a discussion of the process of ANN-structure construction and selection.

For the input layer of an ANN-based TCM system, three machining parameters (spindle speed, feed rate, and depth of cut), three accelerometer signals (three direction vibrations), and acoustic emission (AE) sensor signals were employed. The output layer has one node (the amount of flank wear of the tool used in each cutting condition). For the accelerometer and AE signals, the best signal components of each signal were utilized since they exhibited a closer relationship with tool conditions than raw signals. In order to utilize the data in ANNs training, a preprocessing of the data is required to give equal initial weights for the input layer. All input layer node data (machining conditions and sensor signals) were transformed into the range between -1 and 1, and the output node (the amount of flank wear) was transformed into the range between 0 and 1 (normalization).

After the preprocessing, the best-performing ANN structure was determined using a computer-assisted neural-networks-structure search method. This methodology verifies the performance of all possible structures systematically, based on the criteria of interest. In this study, the number of hidden layers was limited to one and two (both cases were tested), and the number of nodes per hidden layer was limited to thirty, due to the limitations in available computing power. Therefore, the number of possible structures for the ANN system is 930. Each of these possible structures was tested and scored based on its fitness to the tool conditions. During the test, a simplified learning algorithm (quick-propagation) was utilized to shorten the learning time with a limited number of iterations. Table 3 shows the top 25 ANN structures selected by the process, based on the fitness scores of each. The results show that the structure with two hidden layers had a better performance fitness compared with the single hidden-layer structure. An irregular relationship between the degree of fitness and the structure of ANN systems (the number of nodes in each hidden layer) was also observed. From the test results, the top 22 structures (all with a fitness score of 400 or more) were studied further to determine the best fit for the TCM system.

A new series of neural-networks training was performed with the top 22 ANN structures. A total of 405 data sets were used as training data, including three spindle speeds, feed rates, and depths of cut, with five tool conditions. A back-propagation learning algorithm was utilized as the network learning algorithm for an in-depth learning process.

Table 3. Summary of the top 25 ANN structures

ID	Architecture*	Number of weight	Fitness score	Train error
236	7-14-8-1	409	448.703	0.00332
195	7-29-6-1	767	431.531	0.00298
101	7-19-3-1	444	427.816	0.00312
738	7-12-26-1	605	425.111	0.00344
598	7-12-21-1	535	425.080	0.00328
852	7-14-30-1	761	423.547	0.00323
242	7-20-8-1	577	422.291	0.00336
327	7-21-11-1	674	421.018	0.00325
851	7-13-30-1	711	418.271	0.00338
351	7-17-12-1	569	411.719	0.00342
138	7-28-4-1	681	411.177	0.00300
272	7-22-9-1	657	410.725	0.00348
739	7-13-26-1	651	405.973	0.00359
239	7-17-8-1	493	404.659	0.00318
111	7-29-3-1	674	404.409	0.00345
189	7-23-6-1	611	402.797	0.00368
269	7-19-9-1	570	401.746	0.00376
150	7-12-5-1	311	401.460	0.00347
271	7-21-9-1	628	401.443	0.00326
245	**7-23-8-1**	**661**	**401.366**	**0.00318**
580	7-22-20-1	921	401.267	0.00345
267	7-17-9-1	512	401.249	0.00341
737	7-11-26-1	559	399.767	0.00366
222	7-28-7-1	771	396.488	0.00340
214	7-20-7-1	555	394.358	0.00324

* Input Layer – Hidden Layer 1 – Hidden Layer 2 – Output Layer

Learning rates and momentum values for each neural network were arranged by the negotiation of the speed of convergence and the prevention of divergence during the training. The number of iterations for training was set at 50,000 and each structure was run four times. This setup routine helped to ensure that the learning results avoid a local solution, which is a false response of neural networks during the process of node-weight adjustment during training.

During the training iterations, the convergence of the system was checked by monitoring the system training error, error improvement, and error distribution. Figure 3 shows an example of training and its monitoring process. The test results show the successful convergence of all 22 network systems with high R-squared scores, which indicates fitting level between the neural-networks outcomes and the expected outcomes. The score range was between 0.831101 (networks ID: 150) and 0.996173 (networks ID: 245), which indicated that the tool conditions used in the training procedures can be explained by the input variables up to 99.61%. However, the results could be from the learning characteristic of neural networks and does not always indicate the prediction capability of the network structures. Therefore, the prediction capability of the networks' structures was tested with the test data set, which was not used in the process of training. The 22 network systems were able to explain the test data set with an accuracy range between 73.65% (network 150) and 87.78% (network 245). From its higher accuracy, network 245 (7-23-8-1) was nominated as the best structure for the ANN-based TCM system in this study.

Results and Conclusion

With the selected ANN structure, a test was performed based on the criterion of detecting the rejecting tool condition (0.00787 inch [0.2 mm] or bigger), which could practically be adopted as a "STOP-GO" tool in the real manufac

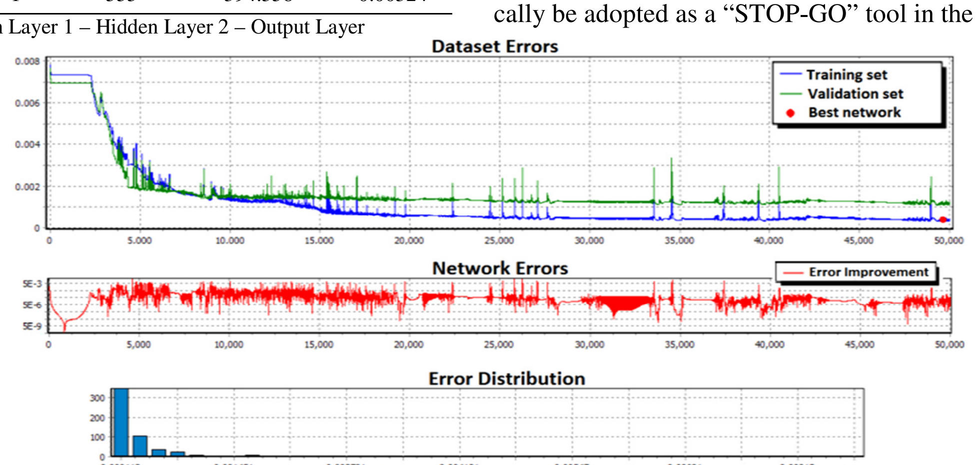

Figure 3. Summary of the training results of network 245 (Correlation: 0.99813, Training time: 0:50:50)

turing environment. The developed ANN-based TCM system successfully predicted 146 tests out of a total of 151. From the 62 "sharp tool" tests, five samples were predicted as a "worn tool" (Type II error). Within the 89 "worn tool" tests, zero samples were predicted as a "sharp tool" (Type I error). Overall, the developed ANN-based prediction model can identify the tool condition with 97% accuracy.

In subsequent studies, enlarging the number of machining parameters, tool conditions, types of insert tool, and different work-piece materials is recommended for more variable machining conditions. Increased numbers of hidden layers and nodes of ANN systems is also recommended with higher computational power.

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