TOOL CONDITION MONITORING OF FRICTION DRILLING PROCESS USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

By

MOHD ZURRAYEN BIN ABDUL MUTALIB

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June 2021

Chair : Mohd Idris Shah Ismail, PhD
Faculty : Engineering

Friction drilling is a new progressive hole-making method. The interaction of the rotating conical tool and the thin workpiece produces heat allowing penetration of the tool and soften the work-piece forming a hole and bush in one process. The process is environmentally friendly since bush formation creates no material wastage and requires no coolant fluid during the machining process. However, performing the machining process with a worn tool can increase the friction between the tool-workpiece and the late replacement of the worn tool may cause an unpredictable machine breakdown. The focus of the present study is to develop an AI-based expert system for tool condition monitoring (TCM) in the friction drilling process. Thus, the TCM was developed by detecting the machining signals through signal processing and pattern recognition. Subsequently, the tool condition was predicted by the artificial intelligence (AI) approach. A tungsten carbide tool was used in this experiment of friction drilling on medium carbon steel AISI 1045. As preliminary experiments, to determine optimal processing parameters in the friction drilling process by considering multi-performance characteristics (i.e., bush length and roundness error), an effective grey relational analysis (GRA) approach has been used. Tool wear characteristics were quantified of friction drilling by analyzing the changes in tool shape and weight reduction. TCM in the friction drilling process was developed based on the vibration signal collected through accelerometer sensors of the machining signals through a low-pass filter. Three approaches AI-model such as Artificial Neural Network (ANN), Fuzzy Logic (FL), and Adaptive Neuro-Fuzzy Inference System (ANFIS) used to boost the efficiency of the prediction system to anticipate the state of the tool in terms of the tool length and angle. The outcomes of the established models were compared in terms of prediction accuracy to find the best performing model. Therefore, real-time condition monitoring took part to verify the TCM system for the friction drilling process. The GRA obtained 3000 rpm of spindle speed and 50 mm/min of feed rate the best combination of processing to achieve a greater bush length and lower roundness error. The tool wear characteristic can be

confirmed that the abrasive wear revealed in the conical region with circular grooves. The adhesive wear was observed at the tool centre and conical regions, and oxidation wear was identified with a dark burned appearance at the tool surface. The development of the AI-model model shows excellent performance, which the R-squared correlation shows the ANFIS model was 97.2% and 97.1% for tool length, and the angle at the training phase seen an increase to 98.4% and 98.2% in the testing phase. It was verified in the real-time TCM experiments that the ANFIS-based expert system was successfully developed and utilized in monitoring the tool condition by categorizing the level of condition into three distinct categories, i.e., good, half-life, and worn-out conditions.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PEMANTAUAN KEADAAN ALAT PROSES PENGGERUDIAN GESERAN MENGGUNAKAN SISTEM INFERENSI NEURO-FUZZY ADAPTIF

Oleh

MOHD ZURRAYEN BIN ABDUL MUTALIB

Jun 2021

Pengerusi : Mohd Idris Shah Ismail, PhD
Fakulti : Kejuruteraan

Penggerudian geseran adalah kaedah pembuatan lubang progresif baru. Interaksi alat kerucut berputar dan bahan kerja nipis menghasilkan haba yang memungkinkan penembusan alat dan melembutkan bahan kerja membentuk lubang dan sendal dalam satu proses. Prosesnya mesra alam kerana pembentukan sendal tidak menghasilkan pembaziran bahan dan tidak memerlukan cecair penyejuk semasa proses pemesinan. Walau bagaimanapun, melakukan proses pemesinan dengan alat yang sudah usang dapat meningkatkan geseran antara benda kerja alat dan penggantian alat yang haus lambat boleh menyebabkan kerosakan mesin yang tidak dapat diramalkan. Fokus kajian ini adalah untuk mengembangkan sistem pakar berasaskan AI untuk pemantauan keadaan alat (TCM) dalam proses penggerudian geseran. Oleh itu, TCM dikembangkan dengan mengesan isyarat pemesinan melalui pemprosesan isyarat dan pengecaman corak. Selepas itu, keadaan alat diramalkan oleh pendekatan kecerdasan buatan (AI). Alat karbida tungsten digunakan dalam eksperimen penggerudian geseran pada keluli karbon sederhana AISI 1045. Sebagai eksperimen awal, untuk menentukan parameter pemprosesan yang optimum dalam proses penggerudian geseran dengan mempertimbangkan ciri-ciri pelbagai prestasi (panjang sendal dan ralat kebulatan), pendekatan analisis relasi kelabu (GRA) yang berkesan telah digunakan. Ciri kehausan alat dihitung dari penggerudian geseran dengan menganalisis perubahan bentuk alat dan penurunan berat badan. TCM dalam proses penggerudian geseran dikembangkan berdasarkan isyarat getaran yang dikumpulkan melalui sensor getaran yang mengumpulkan isyarat pemesinan melalui saringan lulus rendah. Tiga pendekatan model AI seperti Rangkaian Neural Buatan (ANN), Logik Fuzzy (FL), dan Sistem Inferensi Neuro-Fuzzy Adaptif (ANFIS) yang digunakan untuk meningkatkan kecekapan sistem ramalan untuk menjangkakan keadaan alat dari segi panjang dan sudut alatan. Hasil dari model yang ditetapkan dibandingkan dengan ketepatan ramalan untuk mencari model yang berprestasi terbaik. Oleh itu, pemantauan keadaan masa nyata mengambil bahagian untuk

mengesahkan sistem TCM untuk proses penggerudian geseran. GRA memperoleh kelajuan gelendong 3000 rpm dan kadar suapan 50 mm/min gabungan pemprosesan terbaik untuk mencapai panjang sendal yang lebih besar dan ralat kebulatan yang lebih rendah. Pada kehausan alat, ciri dapat disahkan bahawa haus kasar muncul di kawasan kerucut dengan alur bulat. Haus pelekat diperhatikan di pusat alat dan kawasan kerucut, dan keausan pengoksidaan dikenal pasti dengan penampilan yang terbakar gelap di permukaan alat. Perkembangan model AI menunjukkan prestasi yang sangat baik, dimana korelasi R-kuadrat menunjukkan model ANFIS adalah 97.2% dan 97.1% untuk panjang alat, dan sudut pada fasa latihan menyaksikan peningkatan menjadi 98.4% dan 98.2% pada fasa ujian. Hal ini disahkan dalam eksperimen TCM masa nyata bahawa sistem pakar yang berbasis ANFIS berjaya dikembangkan dan digunakan dalam memantau keadaan alat dengan mengkategorikan tahap kondisi menjadi tiga kategori yang berbeza, yaitu keadaan baik, separuh baik, dan usang.

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I certify that a Thesis Examination Committee has met on 29 June 2021 to conduct the final examination of Mohd Zurrayen Bin Abdul Mutalib on his thesis entitled "Tool Condition Monitoring of Friction Drilling Process Using Adaptive Neuro-Fuzzy Inference System" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U. (A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

Members of the Thesis Examination Committee were as follows:

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Faculty of Engineering
Universiti Putra Malaysia
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Facultyof Engineering
Universiti Putra Malaysia
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Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Internal Examiner)

Akira OKADA, PhD
Professor
Faculty of Engineering
Okayama University
Japan
(External Examiner)

____
Zuriati Binti Ahmad Zukarnain
PhD
Professor and Deputy Dean
School of Graduate Studies
Universiti Putra Malaysia

Date:

This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

Mohd Idris Shah Bin Ismail, PhD
Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Nawal Aswan Bin Abdul Jalil, PhD
Associate Professor, Ir.
Faculty of Engineering
Universiti Putra Malaysia
(Member)

Azizan Bin As'ary, PhD
Senior Lecturer
Faculty of Engineering
Universiti Putra Malaysia
(Member)

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LIST OF ABBREVIATIONS

ACO	Ant Colony Optimization
AI	Artificial Intelligent
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
CNC	Computer Numerical Control
DFT	Discrete Fourier Transform
DOE	Design of Experiment
EDX	Energy Dispersive X-ray Spectroscopy
FCAR	Friction Contact Area Ratio
FFT	Fast Fourier Transform
FIS	Fuzzy Inference System
FL	Fuzzy Logic
GA	Genetic Algorithm
GRA	Grey Relational Analysis
GRG	Grey Relational Grade
HSS	High Speed Steel
MSE	Mean Square Error
MF	Membership Function
MISO	Multiple Input Single Output
MIMO	Multiple Input Multiple Output
MOO	Multi-Objective Optimization
PSD	Power Spectral Density
PSO	Particle Swarm Optimization
PO	Pareto Optimization

RMS	Root Mean Square
SEM	Scanning Electron Microscopy
SA	Simulated Annealing
TCM	Tool Condition Monitoring
WC	Tungsten Carbide

CHAPTER 1

INTRODUCTION

1.1 Background and motivation

The hole-making process is one of the most important operations in the manufacturing industry. It is a class of machining operations that specifically used to removes material and creates a hole. Drilling is a major hole-making process and takes up a large part of the manufacturing process. Also, it is stated that all the existing mechanical parts contain holes, and it represents approximately 40% of all cutting operations performed in the industry (Guiotoko et al., 2017). Drilling requires a rotating cylindrical tool bit that has two cutting edges at the working end and feeds into the solid materials or enlarges existing holes using multi-tooth cutting, metal is extruded by the edge of the chisel, and shear cutting is carried out by the lips of the tool (Sun et al., 2018; Tolouei and Shah, 2012). The various types of cutting tools are available for drilling, but the most common tool is the twist drill. The drilling process needs to consider the machine, tool, work material, and cutting conditions such as feed force and velocity (Kudla, 2001). Therefore, a machined hole can be characterized by several different parameters or features that determine the hole-making operation and tool required, such as diameter, tolerance, thread, and depth.

The low durability of conventional drilling tools and required a coolant to prolong the service life of the drilling tool (Guiotoko et al., 2017). However, cutting fluids cause serious health troubles as well as cost in the field of maintenance (Faverjon et al., 2015). Recent technological development over conventional drilling is friction drilling. Friction drilling is a new trend of hole-making without chips, with a maximum thin-walled structure of 12 mm thickness of the material (Alphonse et al., 2017). Moreover, the durability of the tool is not required any cutting fluid in the friction drilling process. Therefore, this technique is the most recent trend in hole making which is currently applied in all major mechanical industries. Thus the durability of a friction drilling tool for non-conventional drilling has been used for this research.

The thin-walled structure has a specific function in lightweight construction. Using detachable joints in a thin-walled structure can be noticed as a unique advantage for lightweight construction (Biermann and Liu, 2014). Friction drilling is a new alternative process that mainly used to create a hole, and also possible for joining thin-walled structures by making a screw thread (Milan et al., 2014) compared to the conventional drilling methods that required additional nut or stud welding to join thin-walled structures together as shown in Figure 1.1. As a new progressive of the non-conventional hole-making method, the friction drilling process utilizes the heat generated from the drilling tool's rotational friction to soften the thin-walled workpieces. Subsequently, simultaneous, it forms the bush and boss on the bottom and top sides of the workpiece, respectively, after the process completed, as shown in Figure 1.2 (Miller et al., 2005; Miller et al., 2006b; Boopathi et al., 2006). The thickness of the bush observed two times the workpiece thickness (Krishna et al., 2010). The bushing aims to increase thickness for threading and available clamp load (Miller et al. 2006a). Unlike traditional chip removal processes, the main mechanism is that no cutting fluid was required, and no chip was produced (Chow et al., 2008). Therefore, friction drilling can develop high efficiency, better surface quality, and a green machining process without environmental impact (Miller et al., 2006a).

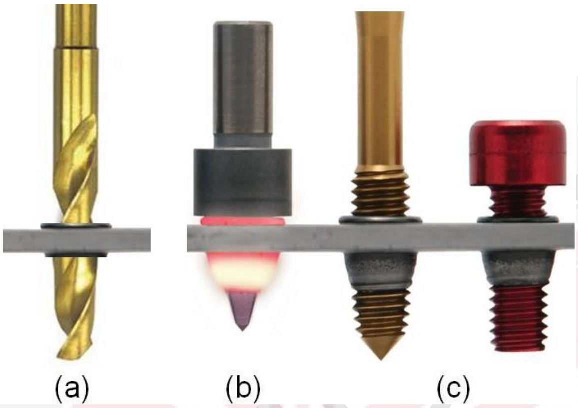

Figure 1.1: Comparison between (a) conventional drilling, (b) friction drilling and (c) screw threading on thin-walled structure after friction drilling

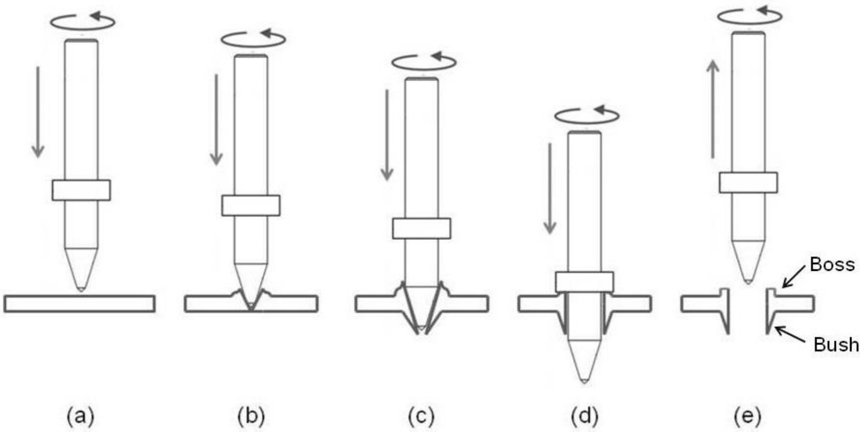

Figure 1.2: Stages of friction drilling process

Nowadays, most process parameters are done by trial-and-error. This is time-consuming, costly, highly subjective, and machine- and material-specific, and subsequently affected the product quality. Due to unknown cause-and-effect relationships between the manufacturing process parameter settings, including tool wear and process characteristics, the resulting quality is highly variable and creates significant limitations. In manufacturing industries, the tool life features can be determined by how well the tool's condition is maintained. To maintain a reasonable production rate, usually cutting speed and feed rate are increased. However, the increase in these cutting conditions may lead to increased tool wear and a rougher surface finish. The tool wears a time-dependent process, deteriorates the surface finish and induces burr formation (Matsumura et al., 2010; Katz and Li, 2004). The tool wear depends on the cutting force, cutting temperature, and velocity (Ariffin et al., 2014). Tool life and wear addressed to summarize the wear mechanisms and types in different tools and workpiece materials and tool geometry, aiming to improve tool life (Pereira et al., 2017). Tolouei and Shah (2012) mentioned that the choice of tooling and cutting conditions depends upon many factors that include workpiece and cutting tool materials, workpiece, and cutting tool geometry.

The machining vibration is a crucial factor in the investigation of tool wear according to the relative motion between tool and workpiece. The amount of pressure with the type of material being drilling, especially spindle speed and feed rate, which had the most influence on the vibration, so an adaptive system to monitor this vibration and at the same time lead to a better product. Many researchers investigate the tool wear based on vibration signal analysis for other conventional machining processes that include drilling (Hassan et al., 2018), milling (D' Addona et al., 2016), turning (Zhang and Chen, 2008) and grinding (Chen and Li, 2007) processes. Therefore, the tool condition monitoring (TCM) framework needs to be developed and implemented to ensure that it is carried out with the desired condition. In a real-time method, this device was ideally able to calculate the condition of the instrument. These should give immediate feedback on the tool condition to be used to maintain the desired results.

Since friction drilling is not a material removal process and all drilled-hole materials transformed to form bush and boss, it considered a physically complex, non-linear, and dynamic process. Moreover, the heat generation between tool and workpiece changes the material properties and microstructural characteristics (Chow et al., 2008), not only to the workpiece but also to the drilling tool. Therefore, the tool wear has significant effects on the quality and quantity of the process (Somasundaram et al., 2012). These motivate the development of the TCM system to sustain the friction drilling process's performance without interruption of the drilling operation, under minimum human supervision. TCM capability of identifying and locating machining system defects is essential for machining without an operator.

A significant factor affecting the machined surface features is tool wear. In any metal cutting process, tool wear means the gradual failure of cutting tools due to regular operation. Over the years, many techniques used to monitor and detect tool wear in metal cutting in general. As cutting proceeds, the tool wear increases, directly affecting the tool life (Ambhore et al., 2015). Tool wear processes generally occur depending upon the cutting conditions, workpiece and tooling material, and the tool inserted geometry. Cutting processes can naturally generate vibration due to the fluctuation of cutting forces. Moreover, the tool's wear brings additional components to the vibrations (Kilundu et al., 2011).

In developing a TCM system, the optimum parameter is important to develop for improving performance and reduce tool wear. Hence, prolong the life of the drilling tool needs to be considering in this TCM. The tool life is important to improve the cutting performance (Matsumura and Shirakashi, 2010) and to achieve this, the subdivision of the drilling cycle is divided into sections and only monitoring those sections in which the most significant change occurs over the tool life (Heinemann and Hinduja 2012). It is possible to identify the final tool life stage and replace the worn-out tool shortly before a fracture occurs, thus improving the overall tool utilization. Therefore, the TCM system was able to utilize the prolonged tool life.

An artificial intelligence (AI) technique is a part of TCM that can predict the tool condition during the machining process, with minimum changes to the tool, significantly reducing the machining time and cost (Tolouei and Shah, 2012). The prediction model plays a vital role in TCM systems. It provides a decision-making system that uses all sensor signal data features to predict the tool wear states (Siddhpura and Paurobally, 2013). Conventional models and AI-based models have been widely applied to tool wear prediction over the past decades (Adnan et al., 2015). An effective prediction of the tool condition depends on the different models developed and evaluated for tool wear analysis. AI-based model is an effective and efficient strategy to developed and determine tool wear condition monitoring (Kaya et al., 2011). It is an attractive and powerful soft computing approach that establishes a machine learning technique (Kumar and Hynes, 2020). Compared to the conventional model for achieving better prediction accuracy in the conventional model, many researchers made efforts to improve the models' structure or combine them with other advanced methods (Wei et al., 2019). Accordingly, to predict tool wear accurately and reliably under different cutting conditions, many improved conventional models and conventional hybrid models are generated (Peng et al., 2019).

Some previous research in monitoring various machining processes using AI-based models has been done. Li et al. (1996) proposed an AI-based algorithm in the drilling process. The system has excellent performance with the tests is a fast, effective, and simple method for dealing with multi-sensor, multi-class, and overlapped classification problems. The monitoring system of tool wear in the turning process based on the methodology proved reliable and practical through the AI-based model (Gao and Xu, 2005). Furthermore, an expert system model has been applied to predict surface roughness in thermal friction drilling (Kumar and Hynes, 2020). A high degree of closeness with 99.23% is observed between the experimental and predicted results. The AI-based model can be utilized as an appropriate method for the smart classification of various milling tool wear states and offers a good performance of the designed tool wear monitoring system (Khajavi et al., 2016). Therefore, the expert system has proven as a promising approach for monitoring the tool condition and machining process.

1.2 Problem statement

The process of a hole forming in friction drilling is thermal softening, and the penetration into the workpiece by the drilling tool is followed. The tool is spin at high speed to establish an adequate temperature, and thrust is applied to form a hole. It generates high temperatures, and during the drilling process, it affects the characteristics and tolerances that are achievable (Miller et al., 2006b). Therefore, the drilling tool becomes dull and leads to a shortened service life (Kaya et al., 2014). Tool wear in friction drilling is a crucial factor that may affect the desired hole diameter's characteristics and tolerances. It has been generated by the high temperature and forces generated where the tool nearly penetrates the workpiece. The stress is high inside the hole, causes material compression, and requires the highest thrust to penetrate the workpiece process (Dehghan et al., 2017). The increasing cutting force is caused by tool wear; the increased cutting force may intensify the tool's wear. (Wang et al., 2016).In the meantime, the excessive heat produced in the cutting zone results in high energy concentrations on the workpiece's surface. (Sharma and Sidhu, 2014). The machining parameters' effect on machined parts is not always precisely known and plays a very important role in the efficient use of machine tools and directly affects the quality of the product. (Wong and Hamouda, 2002). Thus, it becomes difficult to recommend the machining process's optimum machinability data, and the selection of these parameters needs to be monitoring.

Method parameters such as feed rate, spindle speed, the drilling tool's geometry, workpiece and drilling tool material properties, and workpiece thickness affect the friction drilling tool's performance characteristics. (Ku et al., 2011). The most important and critical parameters in the friction drilling method are feed rate and spindle speed. Both parameters are very important to provide the highest yields of friction to be generated, which can largely affect the value of axial thrust force and torque during the friction drilling process (Ku et al., 2011), and tool wear (Dehghan et al., 2018). The drilled hole quality and bush length can indicate the friction drilling process's efficiency (Miller et al., 2006b). The bushes and holes generated by this process could be applied to increase the workpiece's thickness for threading. Therefore, since many process parameters are required for fabricating the high quality of the drilled hole, it is crucial to improve the process performance by determining the friction drilling process's optimum process parameters.

The ability to monitor the machining process's behaviour is important from a research perspective and in industrial applications such as condition monitoring, process optimization, and adaptive control. The main reasons for such applications are to reduce production losses due to machining running failure and reduce maintenance hence decreasing production costs in an automated manufacturing environment. Performing the machining process with a worn tool can increase the friction between the tool-workpiece and degrade product quality (Ambhore et al., 2015). Moreover, the worn tool may increase power consumption, and late replacement of worn tools may cause unpredictable machine breakdown at any time (Yumak et al., 2006). In order to accomplish these objectives, it is very important to measure the condition of the tool in the process so that when the tool profile is lost or does not comply with the specified form, the tool can be replaced, resulting in an increase in the total cost of production due to an increase in product scrap or rejection.

Tool condition monitoring and life prediction play an important role in improving machine productivity, maintaining the machined part's quality and integrity, minimizing material waste, and reducing cost for sustainable manufacturing (Wang et al., 2013). Over the years, several approaches have been used in metal cutting to track and diagnose tool wear. For the intelligent prediction of tool wear, the ANN method was often used. It is necessary to improve an ANN's performance since the precision of the multi-sensor integration method depends on the precision of pattern recognition (Kuo et al., 1999). The backpropagation neural network is typically the most widely used neural network in manufacturing-related research (BPNN). BPNN needs to practice for a long period of time, however, so its application is constrained. Besides, ANNs do not seem to be more sensitive. In some cases, they may be less sensitive than the other sensor integration schemes considered to deterministic sensor-based information errors (Kuo et al., 1999).

O’Donnell et al. (2001) underline the high noise level in vibration and acoustic signals as an additional difficulty for TCM. The sensor fusion method for TCM; its effect is limited at present (Zhang et al., 2015). Baruah and Chinnam (2007) study the drilling process's prognostic problem and applied the Hidden Markov model (HMM) to build the prognostic system. However, this model is difficult to generalize cutting conditions, which is not present in the training set. Lin and Makis (2003) predict the probability of failure by using recursive filters. However, the calculation time is long and might not apply to TCM applications. They noticed that a reliable tool wear evaluation could be obtained based on one signal feature using conventional statistical methods. However, its measured feature depends not only on tool wear but also on various other process parameters and random disturbances.

Tooling is a high cost, ideally, cutting tools should be maximally utilized to reduce manufacturing costs; in practice, cutting tools usually are replaced and discarded after a certain period of usage to avoid defects caused by tool failure, even though the cutters may still be functional. Frequent tool replacement is not only adding machining costs but also impairs productivity. As such, the importance of tool condition monitoring has been recognized for manufacturing industries to operate at productivity achievement. However, most TCM is developed for conventional machining such as drilling, turning, grinding, etc. But for the friction drilling process, the TCM system has not yet been developed, due to a lack of research on non-conventional machining.

According to the issues mentioned above, the fundamental study on friction drilling, parametric optimization and artificial intelligence approach to monitoring tool wear is needed to be carried out. In sequence, the issue needs to be given high considerations in this research are listed below:

1. Prolong the life of the drilling tool needs to be considered in the machining process, hence the optimum parameter is important to develop for improving performance and reduce tool wear.

2. The nature of the frictional between drilling tool and workpiece generates heat and leads to the wear on drilling tool. A study on characterizations of tool wear in friction drilling is important to be investigated.

3. Since the high thrust force and high speed rotational generate heat, machining with worn tools also produced a high vibration that affects the workpiece's quality. Thus, the study on the vibration analysis is conducted with the statistical data.

4. The AI-based algorithm can anticipate an output parameter with high accuracy. Therefore, the AI-based algorithm effectively develops an offline and online predictive model for monitoring tool wear and a tool condition classification.

1.3 Research objectives

The main objective of this research work is to develop an AI-based expert system for TCM in the friction drilling process. To achieve this aim, the present research objectives can be listed as follows:

1. To determine the optimize process parameters in friction drilling by evaluating the bush length and roundness error.

2. To characterize the tool wear in the friction drilling process and its effects to drilled hole diameter.

3. To develop the AI-based expert system by processing the vibration signals for TCM in friction drilling process.

4. To verify the developed AI-based expert system of in-process vibration sensing in real-time TCM for friction drilling process.

1.4 Significance of the study

In metal cutting operations, one of the significant obstacles to realizing full automation is cutting tool-state prediction, where tool-wear is an important factor in productivity and manufacturing efficiency. From a process automation viewpoint, a sensing system must be devised to detect the progress of tool condition during cutting operation so that tool failures can be identified and replaced at that time (Xiaoli et al., 1997). Tool wear monitoring is one of the most crucial and inevitable processes in present-day manufacturing systems. In the manufacturing industry, 20% of downtime attributed to tool failures (Kurada and Bradley, 1997). The tool condition could be monitored through process monitoring. Therefore, the combined decision is better than using only one kind of signal for both classifications of tool wear condition and prediction of tool wear quantity (Zhang et al., 2015). A worn tool is directly affected by the quality of the product. Thus the tool condition monitoring is strongly required (Ertunc et al., 2001).

Tool life prediction is an integral part of achieving sustainable production by improving a computer system's overall efficiency, so a thorough and systematic study is required. Several attempts have been made over the past two decades to improve instrument state tracking and life prediction techniques (Rehorn et al., 2005; Teti et al., 2010). The tool wear or life prediction model is one common approach for evaluating machining efficiency. Tool wear condition prediction is important to ensure the required surface finish of the component and replace cutting tools at the right time (Krishnakumar et al., 2015). Tolouei and Shah (2012) reported that properly defined operation sequences and an effective algorithm could minimize the time needed for machining, setting-up, and tool changing. Hence, to avoid tool failure, there is a real need to monitor the cutting tool wear progression from the beginning of the cutting process. With an effective monitoring system, the worn tool can be changed in time to avoid unexpected downtime (Dimla and Lister, 2000).

This research could answer the questions about the effective parameters, tool life, and precise dimension that effectiveness of in-process monitoring for tool condition in the friction drilling process. This research's findings are expected to contribute a practical technique to analyze the vibration signal with effective pattern recognition for development on prediction modelling of tool wear in friction drilling. They are also providing a significant approach in the tool condition monitoring system to minimize downtime related to tool damaged and affected the drilled hole quality.

1.5 Scope and limitation of research

The vibration is a very important factor to evaluate the tool wear in a real-time process (Wang et al. 2013). This study used an indirect sensing method via a vibration signal during the friction drilling process for a tool condition monitoring

(TCM) system. This research's scope is not limited to develop AI-based models for tool wear prediction, which has not yet been fully studied in previous research works. It also covers the optimization of process parameters and characterization of tool wear, which are important before the TCM study.

1. The process parameters used are spindle speed and feed rate only, which both are the most significantly influence in producing larger bush length and roundness hole drilled in the friction drilling process (El-Bahloul et al., 2015; Özek and Demir, 2013).

2. Multi-objective optimization of process parameters is conducted by evaluating the bush length and roundness error as multi-output responses using grey relational analysis (GRA). It provides an efficient solution to uncertainty, multi-inputs and discrete data problem. Subsequently, it can develop the relation between machining parameters and performance (Shah et al., 2014; Durairaj et al., 2013).

3. An indirect sensing method via a vibration signal is collected using an accelerometer-piezoelectric sensor mounted on the spindle head of the CNC milling machine to correlate the signal patterns with tool wear. Tool wear was evaluated with the dimension change of vibration signals. The vibration signatures have significant variations with the tool state (Shankar et al., 2019). It was confirmed that utilization of vibration signals was consistent with tool wear and is sufficient to develop the correlation (Chuangwen and Hualing, 2009).

4. The predictive models are developed using an AI-based expert system of artificial neural networks (ANN), fuzzy logic (FL), and adaptive neuro-fuzzy inference system (ANFIS) to predict the TCM in terms of reduction of tool length and changes of tool angle. It is compatible and used in modelling the machining process to solve machining problems and can be used successfully to establish various tool wear monitoring systems (Salimiasl and Özdemir, 2016; Roshan et al., 2013; Zain et al. 2010).

1.6 Thesis organization

The thesis presents the research work on TCM of friction drilling process using an expert system, and it consists of five chapters are briefly described as follows:

Chapter 1 introduces the background and motivation of this research. Problems statement, research objectives, significance, and scope of this study are also mentioned in this chapter.

Chapter 2 reviews the previous works that related to the friction drilling process. It includes an overview of the friction drilling process, multi-objective optimization, characterization of tool wear, and monitoring and signal acquisition. It comprehensively reviews the signal processing and the development of AI-based expert system in TCM.

Chapter 3 explain the methodology implemented in this research. It includes the materials used and the design of experiments. The main equipment employed for experimental work is explained, including the measuring devices and engineering software to design and generate the prediction model of tool wear. The vibration analysis and feature extraction for signal processing and development of AI-based models are also presented.

Chapter 4 discusses the results of experimental, modeling, and verification of real-time TCM. Experimental results cover the parametric optimization, characterization of tool wear, and signal collection and processing. The development of AI-based models is analyzed and compared to define the best model for TCM. Then, the TCM model in real-time is verified and discussed.

Chapter 5 presents the overall conclusions of this research work. The main contribution of this thesis on the development of the AI-based expert system on TCM in friction drilling and some recommendations for future work are stated in this chapter.

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