

Comparative Study of ANN and ANFIS Prediction Models For Turning Process in Different Cooling and Lubricating Conditions

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ABSTRACT

The most efficient way to reduce friction and heat generation at the cutting zone is to use advanced cooling and lubricating techniques. In this paper, an experimental study was performed to investigate the capabilities of conventional, minimal quantity lubrication (MQL) and high pressure cooling (HPC) in the turning operations. Process parameters (feed, cutting speed and depth of cut) are used as inputs to the developed artificial neural network (ANN) and the adaptive networks based fuzzy inference systems (ANFIS) model for prediction of cutting forces, tool life and surface roughness. Results obtained by the models have been compared for their prediction capability with the experimentally determined values and very good agreement with experimental results was observed.

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INTRODUCTION

Turning is one of the most important and widely used manufacturing processes in material removal. The simplest way to increase productivity and reduce manufacturing costs in turning is to enhance values of process parameters. However, high productive machining inherently generates high cutting temperature, which reduces cutting process efficiency and output quality characteristics. Conventional cooling is often not effective enough to control high cutting temperature which results in rapid tool wear, reduce tool life, increase in cutting forces and dimensional and form accuracy. Furthermore, friction and heat generation at the cutting zone, if they are high and uncontrolled, involves a greater risk of deterioration in surface quality and impairs the surface integrity. In order to improve the overall performance of the machining process, in terms of temperature control in the cutting zone, various methods of cooling and lubricating have been developed [1, 2, 3, 4, 5, 6, 7, 8]. Among these methods, minimal quantity lubrication (MQL) and high pressure cooling (HPC) represent key technologies with the ability to keep cutting temperature low in order to reduce tool wear.

Nowadays, artificial intelligence techniques are often applied for reliable modeling of machining processes. Modeling and optimization of machining processes with the help of artificial intelligence techniques such as artificial neural networks, genetic algorithms, fuzzy logic, neural-fuzzy systems, etc., can reduce time consuming experiments needed to manufacture good quality products. However, a large number of interrelated parameters (cutting speed, feed, depth of cut, cutting edge angles, etc.), partially understood relations between them, complex, nonlinear and stochastic nature of machining make it extremely difficult to develop a proper model of machining process.

In the past two decades, different modeling methods based on artificial intelligence have been applied by most researchers for prediction of various machining process parameters such as cutting forces, tool wear, tool life, material removal rate and surface roughness of the machined workpiece. A detailed review of papers related to the application of soft computing methods in modeling and optimization of machining processes was presented by Chandrasekaran et al. [9]. The article reviews the application of artificial intelligence methods applied in 142 publications. Luong and Spedding [10] used neural networks for the prediction of machining performance in terms of cutting forces, surface finish and tool life. Al-Ahmari [11] presents a neural networks model for prediction of tool life, surface roughness and cutting force for turning operations. Sharma et al. [12] developed a model for the estimation of cutting forces and surface roughness for hard turning using ANN. Lin et al. [13] predicted cutting force and surface roughness using abductive neural network during turning of high carbon steel. Ozel and Karpat [14] compare regression and neural network models in order to predict surface roughness and tool wear over the machining time in finish hard turning. Quiza et al. [15] carried out an experimental investigation on tool wear prediction with the help of neural network and regression models. Risbood et al. [16] predicted the surface roughness for dry and wet turning using carbide and high-speed steel tools. Ezugwu et al. [17] predicted tool life and failure mode in machining of gray cast iron with ceramic cutting tools.

A number of researchers have used the combination of two or more soft computing tools as an effective strategy for the prediction of various machining process parameters. Balazinski et al. [18] compare the application of the feed forward back propagation neural network, the fuzzy decision support system and artificial neural network based-fuzzy inference system to estimate tool wear in lathe turning.

Sharma et al. [19] present a model for tool wear estimation in turning using an adaptive neuro-fuzzy inference system. Li et al. [20] used neurofuzzy techniques for prediction of feed force by measuring motor current using current sensor in turning center. Chungchoo and Saini [21] proposed an online fuzzy neural network to predict tool wear. Gajate et al. [22] proposed a model for tool wear monitoring on the basis of three neuro-fuzzy approaches (inductive, transductive and evolving neuro-fuzzy systems). Roy [23] proposes ANFIS for predicting surface roughness in the turning operation for set of given cutting parameters (cutting speed, feed and depth of cut).

A literature review indicates that, even though a large number of research papers have been reported in the area of prediction of various cutting process parameters, the performance comparison of artificial intelligence models for modeling these parameters in different cooling and lubricating conditions has not been studied. Keeping this consideration in view, the main objective of this paper is to predict cutting forces, tool wear and surface roughness in the turning process using three methods of cooling and lubricating (conventional, minimal quantity lubrication and high pressure cooling) with two different artificial intelligence methods, namely artificial neural network and adaptive networks based fuzzy inference systems.

EXPERIMENTAL DESIGN AND SET-UP

The schematic layout of the experimental setup for the current study is shown in Figure 1. The turning operations were carried out on the universal lathe VDF Boehringer. This machine tool is equipped with a standard system dosing of cooling and lubrication fluid in the cutting zone, while facilities for MQL and HPC techniques are separately added on the lathe. All experiments were carried out using coolant with a 3% vegetable oil-based emulsion. In conventional flooding, a free fall from above is used with pressure of $p_{CON} = 0.3$ MPa and flow rate of $Q_{CON} = 2$ l/min. In MQL machining mixing method outside nozzle was used. Pressure of $p_{MQL} = 0.3$ MPa and a flow rate of $Q_{MQL} = 0.0005$ l/min was set. For the effective application of oil mist it is important to adjust proper setting location of the nozzle. In this experiment, mixed jet was directed at the cutting zone with its nozzle located $H_n = 30$ mm away from the tool tip, at an angle of $\nu_{MQL} = 90^\circ$ of the cutting edge and at an angle of $\psi_{MQL} = 30^\circ$ from clearance face. In HPC machining the pressure was set at $p_{HPC} = 50$ MPa and the flow rate at $Q_{HPC} = 2$ l/min. A standard sapphire orifice with a diameter of $d_{HPC} = 0.4$ mm, commonly used in water jet cutting applications, was mounted and installed at a distance of $H_n = 30$ mm from the tool cutting edge in order to assure its use in the core zone of the jet and to avoid variations in the diameter of the jet and the radial distribution of the pressure. The coolant jet was directed at the cutting edge ($\nu_{HPC} = 90^\circ$), and $\psi_{HPC} = 30^\circ$ from clearance face at a low angle (about 5°) with the tool rake face. As can be noted from the experimental set-up, flow pressures and flow rates are selected in such a way that the flows at conventional and HPC methods are equal, while pressures are equal at conventional and MQL methods. This allows to study the effects of these cooling techniques on machining performance in detail and to define issues for further optimization of the turning process.

The cutting tool inserts used in the experiments were SNMG 1204 08 NMX with 0.8 mm nose radius. In order to provide a constant and laminar jet during high pressure jet assisted machining, an insert does not have chip breaking geometry on the rake face. All machining experiments were carried out on a 150×250 mm workpiece which is made from steel Ck45.

In order to measure the cutting forces, the cutting tool was mounted on the static dynamometer (Kistler 9259A). The measurement chain further includes a charge amplifier (Kistler 5001), a spectrum analyzer (HP3567A), and a PC for data acquisition and analysis. Tool wear measurements were acquired with a CCD camera mounted on a Mitutoyo TM510 microscope aided with imaging software. Surface roughness was measured with a stylus type instrument Mitutoyo - Surftest SJ-301.

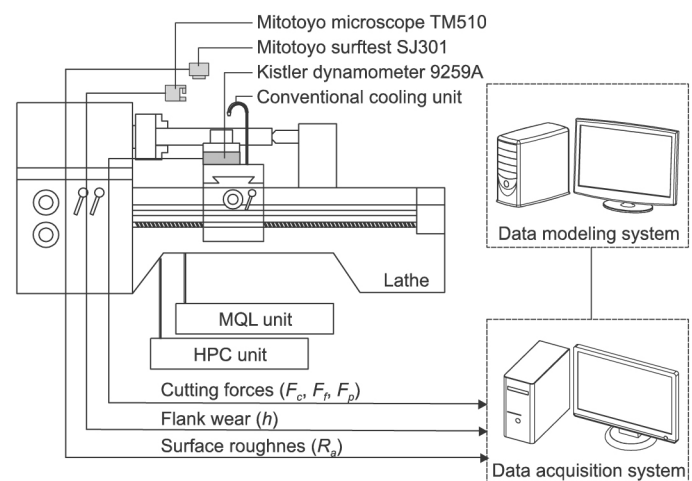


Figure 1. Schematic layout of experimental setup

In this research, for all three different cooling and lubricating conditions, three levels of depth of cut, four levels of feed rate, and three levels of cutting speeds were used (Table 1) as variables for modeling cutting forces, tool wear and surface roughness. With the cutting parameters defined and according to their levels, 108 experiments in total were realized. The cutting process was interrupted at different time intervals in order to measure progressive flank wear and surface roughness. The maximum flank wear criteria for each insert were assigned to be approximately 0.25 mm or if an interval of time of cutting reaches value of 20 min.

Table 1. Design factors and their levels

Turning factor	Levels			
	1	2	3	4
Method of cooling/lubricating	Conv.	MQL	HPC	-
Depth of cut [mm]	1.5	2.0	2.5	-
Feed [mm/rev]	0.224	0.280	0.355	0.400
Cutting speed [m/min]	210	320	400	-