Design of an Intelligent Adaptive Control with Optimization System to Produce Parts with Uniform Surface Roughness in Finish Hard Turning

Vahid Pourmostaghimi[1]
Department of Manufacturing and Production Engineering,
University of Tabriz, Iran
E-mail: vahidvpm@tabrizu.ac.ir

Mohammad Zadshakoyan[2, *]
Department of Manufacturing and Production Engineering,
University of Tabriz, Iran
E-mail: zadshakoyan@tabrizu.ac.ir
*Corresponding author

Received: 23 November 2019, Revised: 22 March 2020, Accepted: 19 April 2020

Abstract: In this paper, a real-time intelligent adaptive control with optimization methodology is proposed to produce parts with uniform surface roughness in finish turning of hardened AISI D2. Unlike traditional optimization approaches, the proposed methodology considers cutting tool real condition. Wavelet packet transform of cutting tool vibration signals followed by neural network was used to estimate tool flank wear. Intelligent models (artificial neural networks and genetic programming) were utilized to predict surface roughness and tool wear during machining process. Particle swarm optimization algorithm determined optimum feed rate that resulted in desired surface roughness. Performed confirmatory experiments indicated that the proposed adaptive control method not only resulted in parts with acceptable uniform quality, but also decreased the machining cost up to 8.8% and increased material removal rate up to 20% in comparison with those of traditional CNC turning systems.

Keywords: Adaptive Control, Artificial Neural Networks, Genetic Programming, Hard Turning, Optimization, Particle Swarm Optimization

Reference: Vahid Pourmostaghimi, Mohammad Zadshakoyan, "Designing of an Intelligent Adaptive Control with Optimization System to Produce Parts with Uniform Surface Roughness in Finish Hard Turning", Int J of Advanced Design and Manufacturing Technology, Vol. 13/No. 2, 2020, pp. 1–12.

Biographical notes: Vahid Pourmostaghimi is a PhD student in Mechanical Engineering at the university of Tabriz, Iran. His current research interest includes tool wear monitoring and adaptive control. **Mohammad Zadshakoyan** is an assistant professor in the faculty of Mechanical Engineering at the University of Tabriz, Iran. His main research interests are metal forming and vibrations.

1 INTRODUCTION

Surface roughness of machined parts plays an extremely important role in manufacturing industry and is a crucial factor in the assessment of the machining performance. A reasonably high surface quality is industrially demanded for better fatigue strength, higher corrosion resistant and improved tribological properties. However, excessively high surface quality results more production cost [1]. One of the most applicable finishing processes in industry is hard turning. Hard turning is a cost-effective alternative to conventional finishing processes such as grinding. Reduction of manufacturing costs and time, comparable surface quality and elimination of environmentally harmful coolant are among influential factors that made hard turning an extremely preferred choice over grinding in many industrial applications [2]. One of the most challenging tasks that must be considered in hard turning is high wear rate of cutting tool. The wear of a cutting tool affects the surface quality of the finished product negatively [3].

In traditional CNC machining systems, the cutting parameters are programmed offline and according to handbooks or part programmer's experience. Therefore, in order to prevent any damage to cutting tool or work piece quality, the selected parameters are set extremely conservatively with no provisions for online adjustment. As a result, optimal production condition cannot be achieved. To ensure the effectiveness of machining process and decrease the cost of machining, selection of cutting parameters should be done in real-time and according to real condition of cutting tool. Therefore, an intelligent–based control system, which regulates cutting parameters based on sensory measurement in real-time to achieve optimal machining criteria is inevitably essential [4]. For that matter, adaptive control systems with the ability of online adjustment of cutting parameters in optimal fashion were proposed.

Adaptive control systems are divided into the following groups: Geometric Adaptive Control (GAC), Adaptive Control with Constraints (ACC), and Adaptive Control with Optimization (ACO). GAC systems maintain dimensional accuracy of parts by varying machining parameters. The main purpose of ACC systems is to maximize any given output characteristics, such as cutting force, by adjusting cutting parameters. In ACO systems, the adaptive controller regulates the cutting parameters to optimize a previously defined performance index subjected to specified constraints [5]. A general overview of an ACO system is shown in "Fig. 1". Generally, an ACO system is based on four interrelated sections that are explained as follows:

I. Tool Wear Monitoring (TWM) unit: One of the most important characteristics of ACO systems is to regulate cutting parameters based on real condition of cutting tool. The main function of TWM unit is to provide the ACO system with online information about real state of cutting tool .

II. Estimation unit: This unit defines the process models which are used to predict output characteristics of machining process such as surface roughness and tool wear. In recent years, intelligent techniques such as Artificial Neural Networks (ANN) and Genetic Programming (GP) are widely used in modeling of machining processes. These models are generally developed from offline experiments and their inputs are cutting parameters such as cutting speed, feed rate and depth of cut [6].

III. Optimization unit: The main function of this unit is to find the optimum cutting parameters on the basis of previously defined performance index and specified constraints. Recently, numerous classical and evolutionary optimization algorithms have been studied in machining optimization problems and the successful application of some evolutionary algorithms such as Particle Swarm Optimization (PSO) have been reported. In addition to high accuracy, PSO offers acceptable convergence speed in finding optimum parameters [7].

IV. Interface unit: This unit takes the function of transmission of optimum cutting parameters to numerical control of machine tool. The transmission of selected parameters should be performed in nearly real-time [8].

As shown in "Fig. 1", in each stage of optimization stage, tool wear value is predicted by TWM unit based on signals obtained from sensors. Estimation unit calculates machining output characteristics such as tool wear and surface roughness using intelligent process models and tool wear information. Optimization unit, on the basis of performance index and constraints and using intelligent models, finds optimum cutting parameters. Then, interface unit transmits the optimum cutting parameters to machine tool to be used in next step of machining operation [9].

In the field of using ACO systems in machining operations some research works have been reported. Chang et al. studied an adaptive controller in milling operation. They used two neural networks for modeling the machining process and finding optimal value for feed rate [10]. In a similar research, Ko and Cho adaptively optimized Material Removal Rate (MRR) in milling operation. They also used two networks for modeling of tool wear and finding optimal cutting parameters [11]. Ko and Kim used iteratively learning neural networks and genetic algorithm to simultaneous optimization of removal rate in milling process. Some constraints was imposed on surface integrity of machined parts [12]. Liu and Wang proposed an ACO system in milling process to improve the stability of machine tool and to enhance the effectiveness of machining operation. For this purpose, they considered the cutting force as constraint and used neural network to find optimum cutting parameters. Proposed method increased the efficiency of operation approximately by 15% compared to traditional optimization systems [13]. Ivester and Heigel considered the effect of managerial decisions and measurement uncertainties in adaptive cost optimization of turning operation [14].

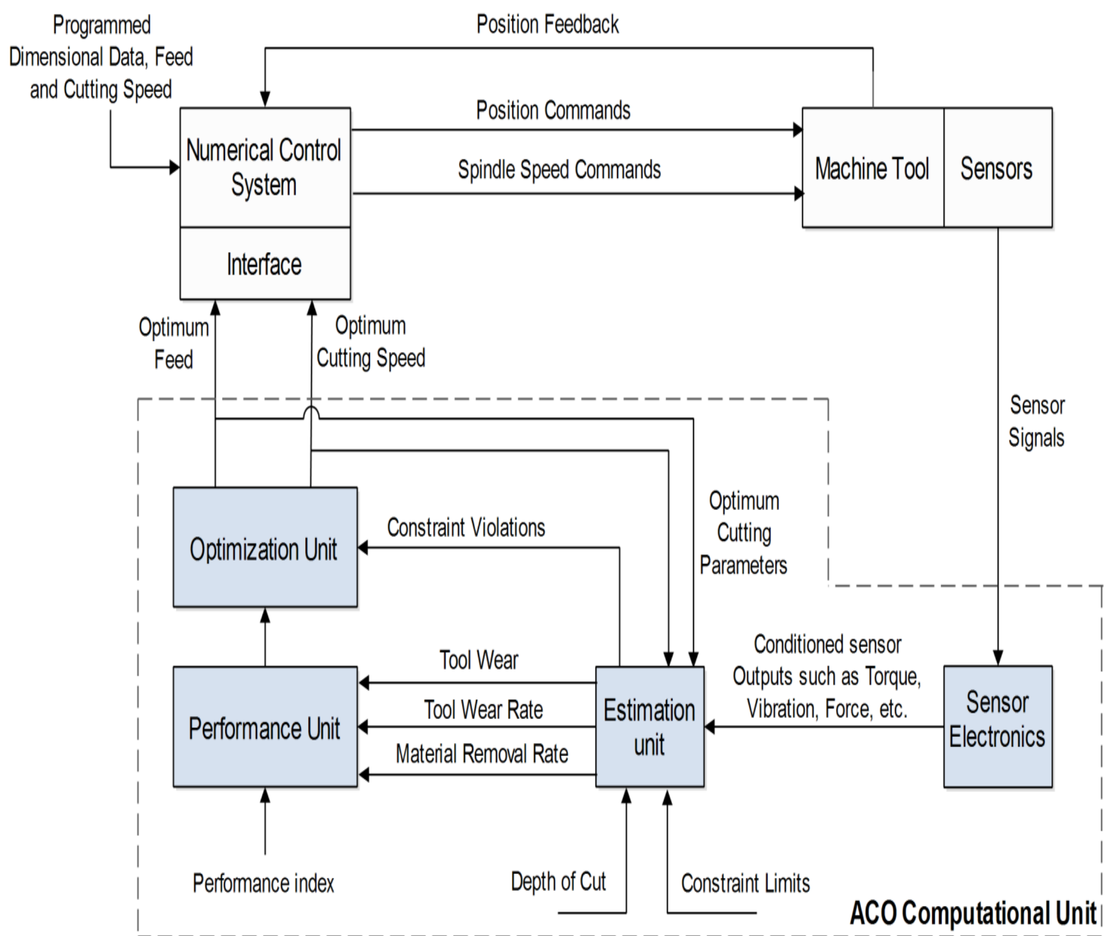

Fig. 1 Adaptive control with optimization scheme [4].

Abellan et al. studied an ACO methodology in optimization of face milling operation. They defined a desirability function based on tool life, surface roughness and MRR. They used three intelligent models to predict tool wear, surface quality and tool life. The proposed technique improved the desirability function 10% compared to traditional optimization techniques [15]. Silva et al. investigated an ACO technique to adaptive optimization of production cost in hard milling operation. They utilized a dynamometer for online TWM during milling process. The results showed that not only the production cost reduced about 13% compared to traditional optimization method, but also parts with acceptable surface quality was produced [4]. Chandrasekaran et al. studied fuzzy set-based strategy to real-time optimization in turning process. In proposed method, flank wear was measured off-line in each machining pass. Based on measured wear values and defined production cost, new cutting parameters were calculated [16]. Coppel et al. proposed an ACO system for optimization of micro milling operation subjected to permissible surface quality. They used dynamometer for online wear monitoring of cutting tool. They also investigated the efficiency of various evolutionary optimization algorithms in their research and proposed PSO algorithm for its accuracy and convergence speed [8]. Despite previously performed wide research in the field of application of ACO systems in machining operations, no comprehensive work has been reported about the industrial application of ACO techniques in turning operations investigating the impact of tool wear on surface roughness. This shortage is more sensible in hard turning operations that are being used widely in manufacturing industry. On the other hand, referring to the discussed literature, the majority of them used production cost or MRR as performance index, while the uniformity of surface roughness is another important index of machining, which must be considered thoroughly. Another dominant issue of these commonly performed researches, which makes them economically unjustifiable, is the use of expensive sensory system in TWM unit. Due to the drawbacks of performed investigations, there is a great need to devise a low-cost and efficient ACO strategy in hard turning considering the uniformity of machined surface roughness. The present research proposed an online ACO method for production of parts with uniform surface roughness in hard turning of AISI D2 based on real condition of cutting tool. The constraints of optimization were limitations on surface quality and cutting parameters. Tool flank wear is predicted using wavelet packet transform of tool vibration signals and neural network. The proposed method regulates feed rate during turning process to produce parts with uniform surface roughness.

The paper is organized as follows: Section 2 explains the proposed ACO procedure. Experimental setup is presented in section 3. In section 4, results of experiments are described and discussed, and section 5 presents conclusions of the research.

2 PROPOSED METHODOLOGY

2.1. Modeling and Optimization Techniques

In order to predict surface roughness and tool flank wear, predictive models should be used in estimation unit. For this purpose, two intelligent techniques were selected included GP for predicting tool flank wear and ANN for estimating surface roughness. Moreover, the optimization of process to achieve uniform surface roughness was performed using PSO algorithm.

2.1.1. Genetic programming

Genetic Programming (GP) is an evolutionary computational method that operates on a set of numbers and functions to optimize complicated problems using computer programs consisting of various functions and terminals [17]. The process of genetic programming starts with creation of initial population or members. Then, by means of genetic operators such as crossover and mutation, new population is generated and takes the place of current population. The fitness value of created population is assessed to find the probable results that solve the problem with minimum error [18]. In this research, to predict the value of flank wear in various times of machining, a genetic equation was developed according to “Eq. 1”.

$$VB_{i+1} = F(v, f, \Delta t, VB_i) \tag{1}$$

In this equation, v is cutting speed and f is feed rate. VB_i and VB_{i+1} are current tool flank wear and tool flank wear after Δt seconds of machining respectively. The parameters used to perform genetic programming are given in “Table 1”.

Table 1 GP parameters

Population size	30
Max. number of nods	250
Crossover rate	0.1
Mutation rate	0.044
Selection method	Tournament
Stopping criteria	Maximum generation of 2000
Function set	$+, -, \times, 1/x, x^2, x^3, exp$

2.1.2. Artificial neural networks

Biologically inspired from human neural system, ANNs can learn from experimentally obtained data and then extract a reliable relationship between inputs and outputs [19]. ANNs accurately model the behavior of the system. As powerful universal approximating technique, they have the ability of learning from given patterns and adaptation with existing condition of any system. ANN is composed of large number of simple elements (neurons) that have compact interrelations. The functionality of these relations is determined during learning process [20].

Two neural networks were trained in this research. The first one was trained to predict surface roughness of produced parts. This network was a 3-layer feed-forward network with 10 neurons in hidden layers that was trained by Levenberg-Marquardt algorithm. Its inputs were flank wear (VB_i), cutting speed (v), and feed rate (f). The second network was implemented in online tool wear monitoring. Structurally similar to the first one, it has 3 layers with 10 neurons in hidden layers and was trained by Levenberg-Marquardt algorithm. Its inputs were cutting speed (v), feed rate (f) and the *RMS*s of wavelet coefficient of the appropriate signals extracted from tool vibrations.

2.1.3. Particle swarm optimization

Particle Swarm Optimization (PSO) is an optimization algorithm imitating the social behavior of fishes and birds in seeking for food. This algorithm has become one of the most widely used optimization algorithms because of flexibility in integrating with other algorithms to form a hybrid method, handling complex objective functions, easy implementation and programming routine, having few adjustable parameters and not being stuck in local minima. Similar to other evolutionary optimization techniques, PSO is a population-based search algorithm in which each particle stands for population and represents a probable solution [21]. Particles by changing their positions in search space try to find the optimum solution. Each particle has two factors: fitness and velocity. The fitness value of each particle can be calculated by an objective function, which assumed to be optimized. Velocity of each particle determines the direction of its movement. Each particle stores its best value achieved so far called p_{best}. Moreover, the best value, which is achieved by any other individual particle in the group, named g_{best}, is shared among all particles. Velocity is defined for any particle based on these two values according to “Eq. 2”.

$$V_{id}^{(t+1)} = wV_{id}^{(t)} + c_1 rand_1\left(p_{best\ id}^{(t)} - X_{id}^{(t)}\right) + c_2 rand_2\left(g_{best\ id}^{(t)} - X_{id}^{(t)}\right) \quad (2)$$

Where, $X_{id}^{(t)}$ and $V_{id}^{(t)}$ are the position and velocity of particle i respectively in d dimensional space. $p_{best\ id}^{(t)}$ and $g_{best\ id}^{(t)}$ are best position of particle and best position of a member in population until generation t respectively. w is the inertia weight factor that controls the dynamic of movement of particles. $rand_1$ and $rand_2$ are random variables changing in the range [0 1]. c_1 and c_2 are cognitive factor and social factor respectively. After calculating the velocity, the particles update their positions using the obtained velocity according to “Eq. 3”.

$$X_{id}^{(t+1)} = X_{id}^{(t)} + V_{id}^{(t-1)} \quad (3)$$

This process continues until the best solution or desired iteration is reached [22]. The parameters used for PSO implementation is given in “Table 2”.

Table 2 PSO parameters configuration

Population size	15
Range of inertia weight	0.45-0.85
Cognitive factor	2
Social factor	2
Stopping criteria	Maximum generation of 100

2.2. Tool Wear Measurement Strategy

Because of gradually increasing tool wear, the machining process has extremely changing nature. This leads to remarkable changes in cutting temperature, forces and other disturbances. These factors extremely influence the optimal cutting conditions. On the other hand, tool wear negatively affects the surface quality of machined parts. This issue is more critical in hard turning, which is assumed an economic and reliable alternative to other finishing processes. To predict the surface roughness of parts during machining process, having information about the condition of cutting tool is inevitable. Therefore, to optimize the performance of machining process, real state of cutting tool must be considered. For online assessment of tool wear value, wide varieties of techniques have been proposed. These techniques can be classified in two groups: direct and indirect methods. Flank wear in direct methods is measured directly by any loss in tool or change in tool geometry using radioactivity, optical sensors, electrical methods and other similar methods. These methods have high accuracy, but due to complex machining conditions and interruption of chips, coolants and other disturbances, using them in real industrial conditions is impossible to a certain extent. Indirect wear measurement techniques are based on calibration procedures. In other words, by using some sensory systems, correlated machining parameters such as vibration, cutting force, temperature, and acoustic emission with flank wear are measured. This method practically is more easier to perform though the accuracy is relatively low and amount of calculations is high compared to direct methods [23]. Among mentioned indirect methods, the use of vibration signals has received special popularity because of its accurate interpretation ability and fast data collection [24]. The main source of vibration in turning is the rubbing between chip and part against cutting tool. Pattern of resulted vibrations changes with tool wear increasing. Therefore, the value of tool wear can be measured by using vibrations. To record these vibration signals, an accelerometer as the sensing device is used [25].

In the present research, an online tool wear measuring system was developed using neural networks and wavelet packet transform of extracted vibration signals from cutting tool. Since the machining direction has more dominant signals than other two directions, the vibration signals was collected in this direction by using an accelerometer fitted in tool holder [26]. Among the obtained features, the most correlated ones with flank wear were selected. Then, a neural network was trained to predict tool flank wear. Inputs of this network were cutting speed (v), feed rate (f), and RMSs of selected features. A schematic illustration of devised strategy for online tool wear measurement is demonstrated in “Fig. 2”.

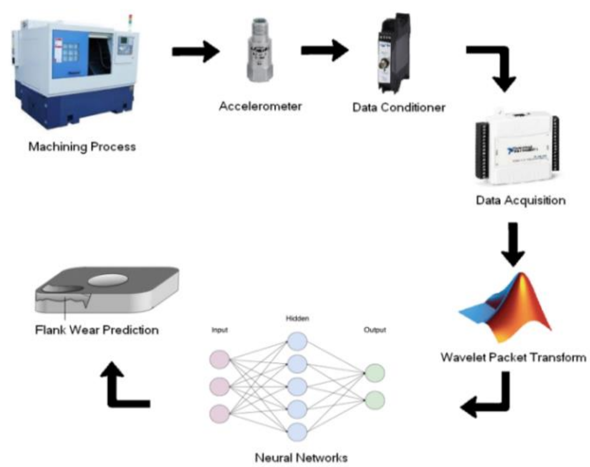

Fig. 2 Schematic diagram of tool wear measurement strategy.

2.3. Optimization Procedure Description

To achieve uniform surface roughness in hard turning, cutting parameters should be regulated online and based on real condition of cutting tool. The aim of proposed ACO is to keep the surface roughness as near as possible to maximum permissible surface roughness. Following constraints are placed on the cutting parameters and surface roughness:

$$\begin{aligned} &\text{Performance index:} && Ra \leq Ra_{max} \\ &\text{Constraints:} && v_{min} \leq v \leq v_{max} \\ & && f_{min} \leq f \leq f_{max} \end{aligned} \tag{4}$$

In which parameters are as defined and given in “Table 3”.

Table 3 Constraints information

Parameter	Description	Value
v_{min}	Minimum cutting speed	40 m/min
v_{max}	Maximum cutting speed	80 m/min
f_{min}	Minimum feed rate	0.02 mm/rev
f_{max}	Maximum feed rate	0.06 mm/rev
Ra_{max}	permissible surface	0.2 , 0.4 µm

The limitations on cutting parameters are mainly due to economic and organizational issues. Lower feed rates will improve the surface quality though negatively influence MRR. On the contrary, higher feed rates improve the MRR, but at the same time worsen surface quality of produced parts. Similar problems can be encountered when selecting cutting speed. The value of cutting speed has direct relationship with removal rate. Nevertheless, higher values for cutting speed remarkably intensify tool wear rate, which is not desirable. Therefore, the values for cutting speed and feed rate are limited to the specific range. The flow chart of proposed ACO strategy is demonstrated in “Fig. 3”.

The proposed system starts with wear measuring unit. In this unit, vibration signals are conditioned and decomposed via wavelet packet transform. Among decomposed features, the features that have the most correlation with tool flank wear are detected and their *RMS*s are calculated. These values along with corresponding cutting parameters are fed to neural network, which has been learnt to estimate the value of flank wear.

Based on calculated flank wear, optimization unit tries to find the optimum feed rate that results roughness as near as possible to specified surface roughness. A population composed of specified cutting speed and random feed rates are created as initial population in the optimization unit. Created population along with calculated tool flank wear is sent to estimation unit. In this unit, the value for tool flank wear and surface roughness for next Δt seconds for each member of population is predicted using GP and ANN respectively. The predicted values in estimation unit, returned to optimization unit. To assure the quality of produced parts, the ACO system has to ensure that the work pieces with surface roughness higher than permissible value will not be produced. So, the members that result unacceptable surface roughness will be deleted from population. A member of population with maximum surface roughness is selected as the best member with optimum feed rate. Interface unit transmits the optimum cutting parameters to numerical control of machine tool to be used in next Δt seconds of machining. This process continues until the maximum value of 0.3 mm be reached for tool flank wear.

In order to demonstrate the efficiency of proposed methodology, a comparison should be made between the proposed method with traditional optimization method. For this purpose, operation cost and MRR of both methods would be compared. In order to have a more comprehensive investigation on performance of ACO in hard turning, two values for maximum permissible surface roughness were targeted: 0.2 µm and 0.4 µm. For traditional method, the same PSO algorithm and intelligent models would be applied to find optimum constant cutting speed and feed rate that result in the minimum cost along with maximum targeted surface roughness. The optimum constant cutting speed would be used as specified cutting speed in ACO system. Operation cost can be expressed as equation 5 [27]:

$$C_p = T_p\left(\frac{C_t}{T} + C_1 + C_0\right) \tag{5}$$

In which T is tool life, and C_t, C_1 and C_0 are tool cost, labour cost and overhead cost respectively. T_p is production rate, and can be defined as equation 6 [27]:

$$T_p = T_s + V\left(\frac{1+T_c/T}{MRR}\right) + T_i \tag{6}$$

V is volume of the removed material and T_s, T_c and T_i are tool set-up time, tool change time and tool idle time respectively. The value for C_t, C_1, C_0, T_s, T_c and T_i are given in “Table 4” [27].

Table 4 Value of cutting coefficients

Parameter	Value
C_t	13.55 $
C_1	0.31 $/min
C_0	0.31 $/min
T_s	0.12 min
T_c	0.26 min
T_i	0.04 min

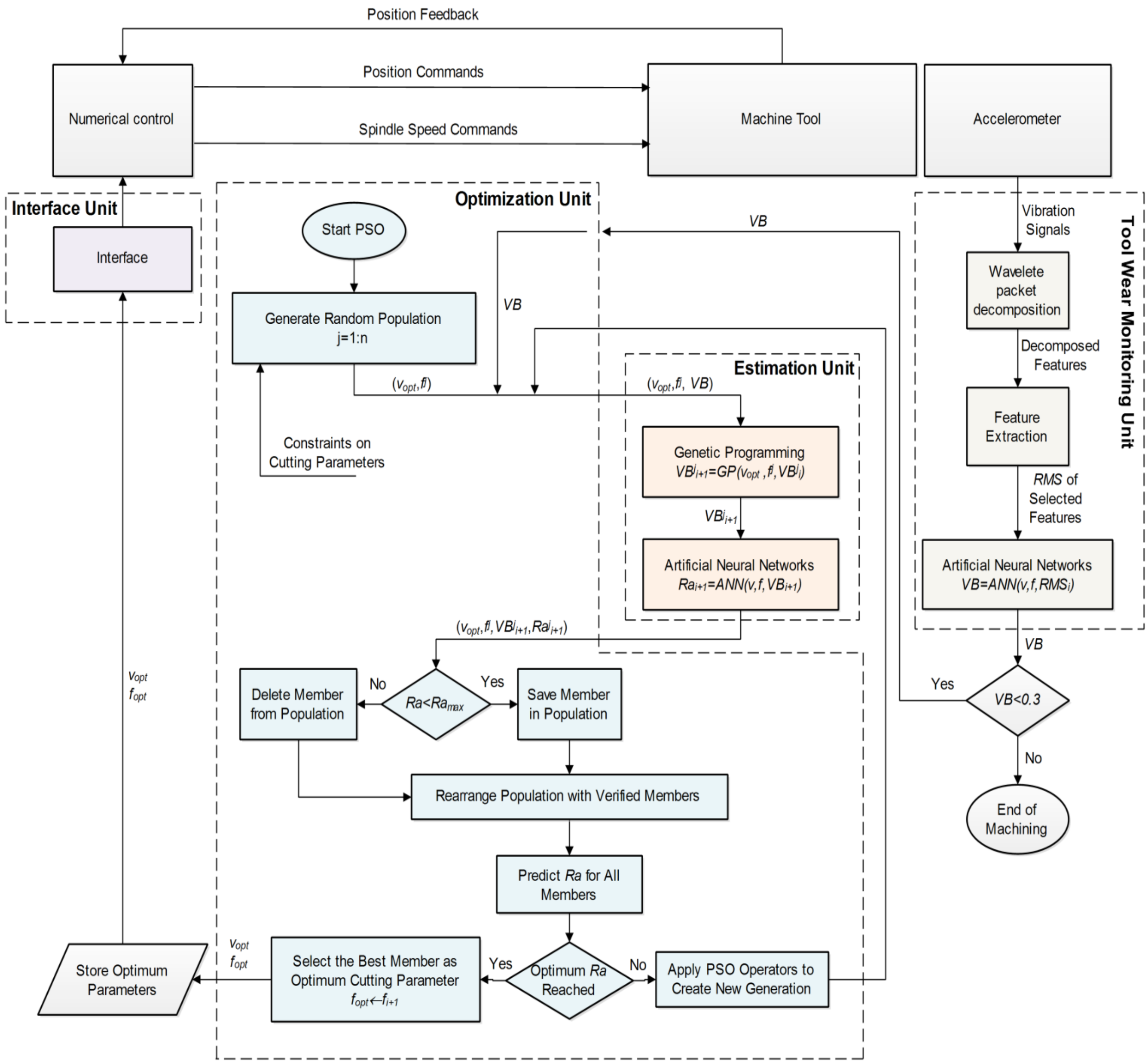

Fig. 3 The flow chart of proposed ACO system.

3 EXPERIMENTAL SETUP

The instrumentation setup for proposed ACO methodology is shown in “Fig. 4”. The setup consisted of lathe and tool, material, tool wear measuring apparatus and interface device. The machining condition along with selected material and machine tool specifications are listed in “Table 5”. For each cutting condition, consisted of a cutting speed and feed rate, 12 tests in various times were performed to study the effect of tool wear and cutting parameters on extracted vibration signals. Therefore, totally 108 tests were carried on until end of tool life. Furthermore, some extra machining tests in various cutting conditions were tested to validate the accuracy and reliability of trained intelligent models.

Table 5 Experimental condition and instrumentation

Work material	AISI D2 with hardness 46 HRC
Machine tool	EMCOTURN CNC lathe machine
Tool insert	TNMG 220408 (grade NC3020, TiN coated)
Lubrication	Dry
Cutting speed	40, 60 and 80 m/min
Feed rate	0.02, 0.04 and 0.06 mm/rev
Depth of cut	1 mm

Two statistical measures were used to fitness evaluation of intelligent models: coefficient of determination, R^2, and root mean square error, *RMSE*. A light source microscope with magnification of 36x and image processing software were utilized to measure the value of tool flank wear. To measure the surface roughness of machined parts, a Taylor Hobson S100 surface profilometer was employed.
A CTC AC102 accelerometer with sensitivity of 100±5% mV/g was mounted on holder as near as possible to insert to capture vibration signals. The measuring frequency range of accelerometer was 1 Hz to 5 kHz. A signal conditioner, which was powered by a 10 V supplier, was used to amplify signals. To transmit the vibration signals from conditioner to MATLAB software, a NI USB DAQ 6008 data acquisition card with sampling rate 10 kHz was utilized.

Fig. 4 Experimental set-up used in the present study.

Tool wear measuring and optimization process was performed in Δt=10 seconds intervals. After finishing optimization process in each step, optimum cutting parameters were transmitted to numerical control of CNC machine tool via the NI USB DAQ 6008.

4 RESULTS AND DISCUSSION

4.1. Intelligent Modeling

Using primary “Eq. 1”, a genetic equation was developed to predict tool flank wear in next Δt seconds of machining process based on performed experiments. The equation is as follows:

$$VB_{i+1} = VB_i + e^{(v^2+v+(f-7.004)\times 7.004\times f)} + \left[\frac{(e^v-\Delta t)}{6.558} \times (2\times v-6.9)\right] + (v\times\Delta t)^4 \times (f+5.3753) \quad (7)$$

In which, VB_i is current tool flank wear and VB_{i+1} is predicted tool flank wear after Δt seconds of machining with corresponding cutting parameters *v* and *f*. Having the value of predicted flank wear (VB_{i+1}), the value for surface roughness in next Δt seconds (Ra_{i+1}) can be predicted using previously trained neural network. The results of validation tests for both GP and ANN models are given in “Table 6”.
The fitness values of GP and ANN models for both the training and validation tests are given in “Table 7”. The results indicate that the trained intelligent models have sufficiently high accuracy to be used in estimation unit of an ACO system reliably.

Table 6 Experimental validation tests

					GP Flank wear VB_{i+1} (mm)		ANN Surface roughness (μm)	
Test No.	Cutting speed (m/min)	Feed rate (mm/rev)	Time (sec)	VB_i (mm)	Measured	Predicted	Measured	Predicted
1	40	0.04	20	0.269	0.288	0.2958	0.51	0.5359
2	60	0.02	20	0.245	0.314	0.2841	0.45	0.467
3	60	0.04	5	0.108	0.137	0.1513	0.27	0.281
4	80	0.02	5	0.206	0.221	0.2476	0.28	0.288
5	40	0.035	15	0.232	0.271	0.2581	0.4	0.413
6	50	0.05	10	0.091	0.132	0.1158	0.38	0.3877
7	70	0.03	15	0.149	0.19	0.1879	0.23	0.215
8	85	0.06	5	0.092	0.126	0.1132	0.42	0.4411
9	40	0.04	10	0.126	0.143	0.1365	0.32	0.3341
10	60	0.02	5	0.08	0.099	0.1033	0.18	0.1622
11	60	0.06	20	0.209	0.25	0.2435	0.46	0.497
12	80	0.04	10	0.081	0.131	0.156	0.31	0.342

Table 7 The accuracy of intelligent models for training and validation data sets

	Training data set		Validation data set	
	R^2	*RMSE*	R^2	*RMSE*
Genetic Programming	0.9902	0.0102	0.9473	0.0163
Neural Network	0.9879	0.0154	0.9553	0.0203

4.2. Tool Wear Monitoring

Tool wear measuring is an essential task in ACO systems employed for machining operations. In the proposed ACO system, an efficient tool wear measuring strategy was proposed using the wavelet packet transform of tool vibration signals. During cutting experiments, vibration signals were gathered by accelerometer and relevant tool flank wear was measured carefully. Then, using wavelet packet transform, vibration signals were decomposed into 4 levels consisting of 16 sub-band features.

Each feature belongs to a specific frequency band ranging from [0-312.5] Hz to [4687.5-5000] Hz. Precise consideration of the *RMS* values of features revealed that the effect of tool wear could be only traced in 4 decomposed features, which included 2nd, 6th, 11th and 14th sub-band features. These features are corresponded to [312.5-625] Hz, [1562.5-1875] Hz, [3125-3437.5] Hz and [4062.5-4375] Hz frequency ranges respectively. Similar correlation between decomposed features of vibration signals and gradually developing tool wear was reported in previous researches [28]. The *RMS* values of extracted features along with cutting parameters were fed to the neural network that was trained to estimate tool flank wear. The accuracy of trained network for both train and validation tests were obtained as given in “Table 8”.

Table 8 Fitness values of trained neural network for online tool wear measuring system

	R^2	*RMSE*
Training	0.9934	0.0104
Validation	0.9511	0.0261

The results show that the wavelet coefficients from the machining vibration signals are sensitive to the variation of tool flank wear and cutting parameters. It also can be concluded that there is relatively good agreement between results of measurements and predicted values obtained by neural networks. More information about the results can be found in [23].

4.3. Traditional Optimization Results

To prove the effectiveness of suggested ACO strategy, a comparison was made between the resulted production cost and MRR of this method and that of traditional optimization method with constant cutting parameters. Two sets of experiments were performed with different values for maximum surface roughness, 0.2 and 0.4 μm. For maximum surface roughness of 0.4 μm, constant cutting parameters were calculated as v=62.5 m/min and f=0.0375 mm/rev to reach minimum operation cost. With these cutting parameters, operation cost of 15.92 $ was resulted and MRR was 2.39 cm^3/min.

Constant cutting parameters for getting maximum surface roughness of 0.2 μm with the minimum cost were calculated as v=65 m/min and f=0.02 mm/rev. Using these cutting parameters, operation cost was calculated 17.11$ and MRR was obtained as 1.27 cm^3/sec.

4.4. ACO Results

ACO system starts adaptive process with fresh tool (*VB*=0). The main purpose of the proposed ACO system is to find the next feed rate that produces surface roughness as near as possible to Ra_{max}. All cutting parameters during ACO process were selected according to defined performance index and specified constraints. For precise investigation of proposed methodology, two sets of experiments were arranged with Ra_{max}= 0.2 and 0.4 μm. The ACO process lasted until flank wear of 0.3 mm was reached.

The value of cutting speed was sat to 62.5 /min. The variation of feed rate along with produced surface roughness for Ra_{max}= 0.4 μm is shown in “Fig. 5”.

As it can be seen from “Fig. 5”, by passing time and gradually increasing tool wear, ACO system adjusted feed rate to compensate the negative effect of tool wear on surface quality. The effect of feed rate on surface roughness is remarkable. In initial seconds of machining, tool flank wear is trivial and therefore, relatively high values for feed rate was selected. In the times to come, with increasing tool flank wear, the selected feed rates were decreased step by step to its minimum value of 0.025 mm/rev. By doing this, ACO tried to compensate the negative effect of tool wear on produced surface roughness. As it can be realized from “Fig. 5 (b)”, the roughness produced during process is in permissible range (Ra<0.4 μm) until the end of process. At the end of operation, overall cost of operation was calculated as 14.51 $ that is 8.8% lower compared to traditional optimization method. On the other hand, overall MRR was obtained as 2.66 cm^3/sec, which shows 11.3% grows.

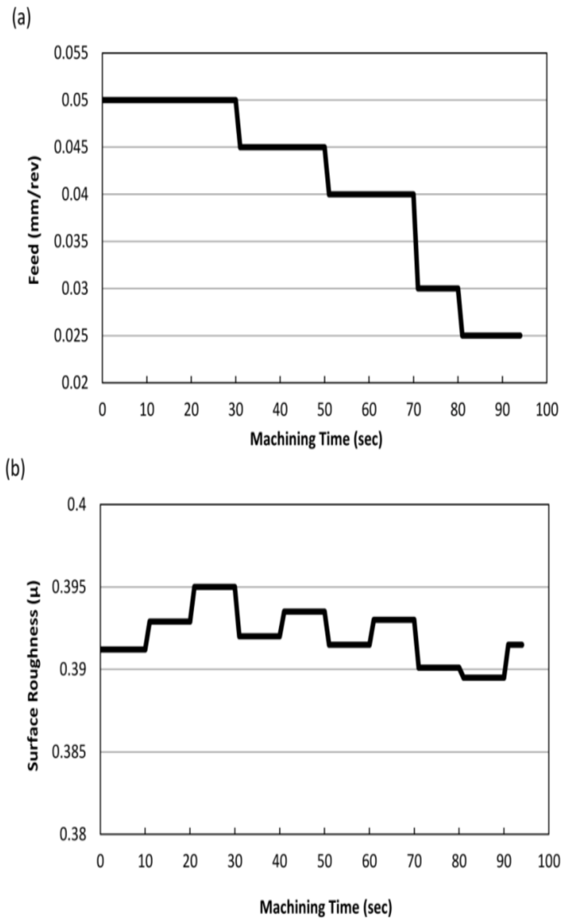

Fig. 5 Variation of feed rate and surface roughness during ACO process for obtaining Ra_{max}=0.4 µm.

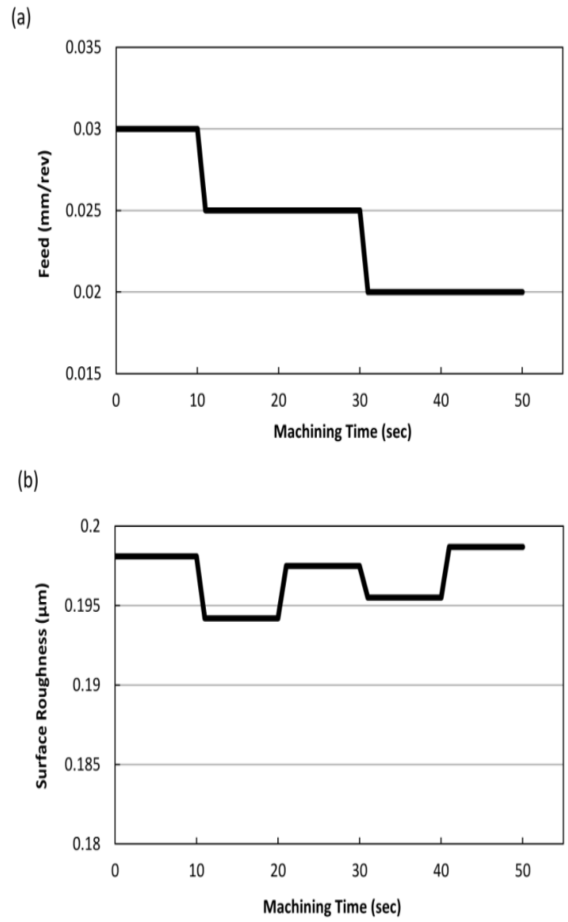

Fig. 6 Variation of feed rate and surface roughness during ACO process for obtaining Ra_{max}=0.2 µm.

Adjusted feed rate and obtained surface roughness for Ra_{max}= 0.2 µm is shown in "Fig. 6". The cutting speed was considered 65 m/min, which is equal to corresponding constant optimum cutting speed. Similar manner for selected feed rates was reported as in Ra_{max}= 0.4 µm. It can be seen that the adaptively selected feed rate values became lower to obtain desired surface roughness. The surface roughness over the entire machined surface was in permissible limit ("Fig. 6 (b)"). In this case, operation cost and MRR was obtained as 1.53 cm^3/sec and 16.17 $ respectively. Results show 5.5% reduction in costs and 20% growth in MRR in comparison with traditional optimization method.

5 CONCLUSION

The rate of tool wear is extremely high in hard turning processes. Since part surface quality is influenced drastically by tool wear, traditional optimization approaches, because of their inability in considering the effect of tool wear, cannot offer optimal cutting condition. Therefore, cutting parameters should be adjusted in real time and according to current tool state. In this work, an intelligent adaptive control with optimization system to produce work pieces with uniform surface roughness in finish hard turning of AISI D2 was presented. Considering the real condition of cutting tool, the proposed system was able to adjust feed rate to achieve relatively uniform and acceptable surface quality. For this purpose, an online tool wear measuring strategy was developed using neural networks and wavelet packet transform of extracted vibration signals from cutting tool. Intelligent models, included artificial neural network and genetic programming, were employed to predict surface roughness and tool flank wear during machining process. Then, using particle swarm optimization algorithm, optimum cutting parameters were calculated. For fresh cutting tool, the strategy of ACO system was to choose higher feed rate values to reach to specified surface roughness. As tool wear increased, the selected feed rates were decreased to compensate the negative effect of tool wear on surface roughness. Finally, the proposed ACO system resulted in work pieces with acceptable and relatively uniform surface roughness, which led to remarkable reduction in machining costs and increase in MRR. In order to prove the effectiveness of the proposed ACO technique, two different values for Ra_{max} were considered as desired surface roughness of machined parts. The results obtained from experiments showed that the proposed ACO system decreased the cost of machining 8.8% and increased MRR 11.3% when Ra_{max}=0.4 μm compared to traditional optimization technique with constant cutting parameters. For Ra_{max}=0.2 μm, cost decreased about 5.5% and MRR increased by 20%.

To outline a direction for future work in the relevant field, authors suggest to assess the ability of various sensory systems designed for tool wear monitoring, designing adaptive optimization systems with different performance indexes and constraints such as temperature, vibration and other machining characteristics.

REFERENCES

[1] Gaitonde, V., Karnik, S., Figueira, L., and Davim, J. P., Machinability Investigations in Hard Turning of AISI D2 Cold Work Tool Steel with Conventional and Wiper Ceramic Inserts, International Journal of Refractory Metals and Hard Materials, Vol. 27, No. 4, 2009, pp. 754-63.

[2] Pereira, R. B. D., Da Silva, L. A., Lauro, C. H., Brandão, L. C., Ferreira, J. R., and Davim, J. P., Multi-Objective Robust Design of Helical Milling Hole Quality on AISI H13 Hardened Steel by Normalized Normal Constraint Coupled with Robust Parameter Design, Applied Soft Computing, Vol. 75, 2019, pp. 652-85.

[3] Pourmostaghimi, V., Zadshakoyan, M., and Badamchizadeh, M. A., Intelligent Model-Based Optimization of Cutting Parameters for High Quality Turning of Hardened AISI D2, AI EDAM, Vol. 26, No. 7, 2020, pp. 1725-30.

[4] Silva, J. A., Abellán-Nebot, J. V., Siller, H. R., and Guedea-Elizalde, F., Adaptive Control Optimisation System for Minimising Production Cost in Hard Milling Operations, International Journal of Computer Integrated Manufacturing, Vol. 27, No. 4, 2014, pp. 348-60.

[5] Wang, G., Feng, X., Tool Wear State Recognition Based On Linear Chain Conditional Random Field Model, Engineering Applications of Artificial Intelligence, Vol. 26, No. 4, 2013, pp. 1421-7.

[6] Zadshakoyan, M., Pourmostaghimi, V., Cutting Tool Crater Wear Measurement in Turning Using Chip Geometry and Genetic Programming, International Journal of Applied Metaheuristic Computing (IJAMC), Vol. 6, No. 1, 2015, pp. 47-60.

[7] Shukla, R., Singh, D., Experimentation Investigation of Abrasive Water Jet Machining Parameters Using Taguchi and Evolutionary Optimization Techniques, Swarm and Evolutionary Computation, Vol. 32, 2017, pp. 167-83.

[8] Coppel, R., Abellan-Nebot, J. V., Siller, H. R., Rodriguez, C. A., and Guedea, F., Adaptive Control Optimization in Micro-Milling of Hardened Steels—Evaluation of Optimization Approaches, The International Journal of Advanced Manufacturing Technology, Vol. 84, No. 9-12, 2016, pp. 2219-38.

[9] Koren, Y., Editor Adaptive Control Systems for Machining, American Control Conference, 1988; 1988, IEEE, pp. 1161-7.

[10] Chiang, S. T., Liu, D. I., Lee, A. C., and Chieng, W. H., Adaptive-Control Optimization in End Milling Using Neural Networks, International Journal of Machine Tools & Manufacture, Vol. 35, No. 4, 1995, pp. 637-60.

[11] Ko, T. J., Cho, D. W., Adaptive Optimization of Face Milling Operations Using Neural Networks, Journal of Manufacturing Science and Engineering, Vol. 120, No. 2, 1998, pp. 443-51.

[12] Ko, T. J., Kim, H. S., Autonomous Cutting Parameter Regulation Using Adaptive Modeling and Genetic Algorithms, Precision Engineering, Vol. 22, No. 4, 1998, pp. 243-51.

[13] Liu, Y., Wang, C., Neural Network Based Adaptive Control and Optimisation in the Milling Process, The International Journal of Advanced Manufacturing Technology, Vol. 15, No. 11, 1999, pp. 791-5.

[14] Ivester, R. W., Heigel, J. C., Smart Machining Systems: Robust Optimization and Adaptive Control Optimization for Turning Operations: Society of Manufacturing Engineers; 2000.

[15] Abellan, J., Romero, F., Siller, H., Estruch, A., and Vila, C., Book Title: Advances in Robotics, Automation and Control, CHAPTER 1: Adaptive Control Optimization of Cutting Parameters for High Quality Machining Operations Based On Neural Networks and Search Algorithms, 1 st Edition, InTech, Vienna, Austria, 2008, pp. 472-81.

[16] Chandrasekaran, M., Muralidhar, and M., Dixit, U., Online Optimization of a Finish Turning Process: Strategy and Experimental Validation, The International Journal of Advanced Manufacturing Technology, Vol. 75, No. 5-8,

[17] Zakeri Mehrabad, V., Pourmostaghimi, V., Tool Wear Modeling in Drilling Process of AISI1020 and AISI8620 Using Genetic Programming, ADMT Journal, Vol. 10, No. 1, 2017, pp. 93-100.

[18] Zadshakoyan, M., Pourmostaghimi, V., Genetic Equation for The Prediction of Tool–Chip Contact Length in Orthogonal Cutting, Engineering Applications of Artificial Intelligence, Vol. 26, No. 7, 2013, pp. 1725-30.

[19] Cakar, T., Cil, I., Artificial Neural Networks for Design of Manufacturing Systems and Selection of Priority Rules, International Journal of Computer Integrated Manufacturing, Vol. 17, No. 3, 2004, pp. 195-211.

[20] Kumru, M., Kumru, P. Y., Using Artificial Neural Networks to Forecast Operation Times in Metal Industry,

International Journal of Computer Integrated Manufacturing, Vol. 27, No. 1, 2014, pp. 48-59.

[21] Zadshakoyan, M., Pourmostaghimi, V., Book Title: Advancements in Applied Metaheuristic Computing, CHAPTER 5: Metaheuristics in Manufacturing: Predictive Modeling of Tool Wear in Machining Using Genetic Programming, 1 st edition, IGI Global, USA, 2018, pp. 118-42.

[22] Pourmostaghimi, V., Zadshakoyan, M., Book Title: Optimization for Engineering Problems, CHAPTER 4: Optimization of Cutting Parameters during Hard Turning using Evolutionary Algorithms, 1 st edition, Wiley Online Library, USA, 2019, pp. 77-99.

[23] Pourmostaghimi, V., Zadshakoyan, M., and Sadeghi, M. H., Vibration Based Assessment of Tool Wear in Hard Turning using Wavelet Packet Transform and Neural Networks, International Journal of Advanced Design & Manufacturing Technology, Vol. 12, No. 2, 2019, pp. 17-26.

[24] Bhuiyan, M. S. H., Choudhury, I. A., Investigation of Tool Wear and Surface Finish by Analyzing Vibration Signals in Turning Assab-705 Steel, Machining Science and Technology, Vol. 19, No. 2, 2015, pp. 236-61.

[25] Siddhpura, M. A., Siddhpura, A. M., and Bhave, S., Editors. Vibration as a Parameter for Monitoring the Health of Precision Machine Tools, International Conference on Frontiers in Design and Manufacturing Engineering (ICDM), Coimbatore, India; 2008

[26] Fang, N., Pai, P. S., and Mosquea, S., Effect of Tool Edge Wear On the Cutting Forces and Vibrations in High-Speed Finish Machining of Inconel 718: an Experimental Study and Wavelet Transform Analysis, The International Journal of Advanced Manufacturing Technology, Vol. 52, No. 1-4, 2011, pp. 65-77.

[27] Zuperl, U., Cus, F., Optimization of Cutting Conditions During Cutting by Using Neural Networks, Robotics and Computer-Integrated Manufacturing, Vol. 19, No. 1-2, 2003, pp. 189-99.

[28] Xiaoli, L., Zhejun, Y., Tool Wear Monitoring with Wavelet Packet Transform—Fuzzy Clustering Method, Wear, Vol. 219, No. 2, 1998, pp. 145-54.