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A hybrid particle swarm optimization and recurrent dynamic neural network for multi-performance optimization of hard turning operation

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Abstract

In the present work, a new hybrid approach combining particle swarm optimization (PSO) algorithm with recurrent dynamic neural network (RDNN), which is described as PSO-RDNN algorithm, is proposed for multi-performance optimization of machining parameters in finish turning of hardened AISI D2. The suggested optimization problem is solved using the weighted sum technique. Process parameters including cutting speed and feed rate are optimized for minimizing operation cost, maximizing tool life, and producing parts with acceptable surface roughness. Based on experimental results, two neural network models were developed for predicting tool flank wear and surface roughness during the machining process. Based on trained neural networks and structured hybrid algorithm, optimum cutting parameters were obtained. The coefficient of determination for trained neural networks was calculated as $R^2 = 0.9893$ and $R^2 = 0.9879$ for predicted flank wear and surface roughness, respectively, which proves the efficiency of trained neural models in real industrial applications. Furthermore, the offered methodology returns a Pareto optimality graph, which represents optimized cutting variables for several various cutting conditions.

Nomenclature

a	Depth of cut
c_1	Cognitive factor of particles in PSO methodology
c_2	Social factor of particles in PSO methodology
C_l	Labor cost
C_0	Overhead cost
C_p	Operation cost
$C_p^{\min}$	Minimum operation cost
$C_p^{\max}$	Maximum operation cost
C_t	Tool cost
F	Function of multi-objective problem
f	Feed rate
$f_{\min}$	Minimum feed rate
$f_{\max}$	Maximum feed rate
$C_p^{\max}$	Best position of other particles in population in PSO methodology
MRR	Material removal rate
R^2	Coefficient of determination
RMSE	Root mean square error
$p_{best\ id}^{(t)}$	Best position of particle in PSO methodology
$rand_i$	Random variable in PSO methodology
Ra	Surface roughness
$Ra_{\max}$	Maximum permissible surface roughness
Ra_{i+1}	Predicted surface roughness after Δt seconds
T	Tool life
$T^{\min}$	Minimum tool life
$T^{\max}$	Maximum tool life

T_c	Tool change time
T_i	Tool idle time
T_p	Production rate
T_s	Tool setup time
V	Volume of the removed material
v	Cutting speed
$v_{\min}$	Minimum cutting speed
$v_{\max}$	Maximum cutting speed
$V_{id}{}^{(t)}$	Velocity of particles in PSO methodology
VB_i	Current tool flank wear
VB_{i+1}	Predicted tool flank wear after Δt seconds
$\mathrm{VB}_{\max}$	Maximum measured tool flank wear
w_1,w_2	Weights of multi-objective problem
$X_{id}^{(t)}$	Current position of particles in PSO methodology
$X_{id}^{(t+1)}$	New position of particles in PSO methodology
Δt	Time of machining

Introduction

Finish turning of hardened materials with hardness greater than 45 Rockwell C (HRC), which is called hard turning, has brought significant profit to manufacturers in various production industries (Namlu *et al.*, 2021). Asan efficient and low-cost alternative to traditional finishing processes such as grinding, hard turning decreases the manufacturing costs and production time and eliminates usage of environmentally harmful coolant (Pourmostaghimi *et al.*, 2020). One of the most important aspects of the hard turning process is the resulted surface roughness. The roughness of the machined surface not only determines the transmission precision but also influences the mechanical performance of components through wear resistance and fatigue strength (Paturi *et al.*, 2018). Because of the high hardness of work pieces, large cutting forces and temperatures at the tool-work piece interface can be encountered in hard turning. This issue can intensify tool wear rate during a turning process that leads to the damage of part surface and results in dimensional or geometrical imperfections (Panday *et al.*, 2018). Therefore, to promote the efficiency of hard turning in terms of tool life, material removal rate (MRR), machining economics, and surface quality, utmost care must be taken in selecting cutting parameters. Conventionally, the cutting parameters are selected conservatively based on the information given in tool manufacturers' manuals or operator's experience. However, these values are starting parameters and cannot offer the optimum cutting condition throughout the machining process (Pourmostaghimi and Zadshakoyan, 2020). Accordingly, optimization of cutting parameters to obtain acceptable surface quality and minimum operation cost is an inevitable choice in today's manufacturing industry. Because of these reasons, many investigations can be found in the literature. The tool steel known as AISI D2 is considered to be a high Carbon high Chromium cold work tool steel classified in the category of difficult to cut materials. This heat-treatable steel which offers hardness in the wide range of applications, is commonly used in different manufacturing industries that is mill rolls, blanking dies, punches, spinning tools, and shear blades (Sharma and Sidhu, 2014). Hard cutting of AISI D2 presents major problems with respect to the current state of machining technology. Therefore, it has been attempted to present an enabling technology for hard turning AISI D2 tool steel (Dumitrescu *et al.*, 2006).

Dureja *et al.* reported a comprehensive evaluation of various modeling and optimization techniques performed in hard turning processes. They also discussed the integration of various modeling and optimization techniques to achieve desired goals (Dureja *et al.*, 2016). Manivel and Gandhinathan utilized ANOVA technique and signal-to-noise ratio to optimize cutting parameters in the hard turning process. Their research aimed to produce parts with minimum surface quality and maximum tool life (Manivel and Gandhinathan, 2016). Rashid *et al.* (2016) studied the application of signal-to-noise ratio, ANOVA, and multiple regression analysis to minimize surface roughness in the hard turning process. Sharma and Pandey (2016) focused on the selection of optimized cutting parameters and vibration to achieve minimum residual stresses in machined work pieces. Benlahmidi *et al.* considered the effect of cutting parameters and work piece hardness on surface roughness and cutting power in the hard turning process. The results led to an innovative approach based on RSM and ANOVA techniques to obtain optimum cutting parameters (Benlahmidi *et al.*, 2017). Mia and Dhar studied the effect of material hardness and high-pressure coolant jet in hard turning on surface roughness and cutting temperature. Optimization of parameters was performed using the signal-to-noise ratio and Taguchi optimization technique (Mia and Dhar, 2017*a*). Mia and Dhar in another study presented a predictive model for surface roughness using artificial neural networks and support vector regression. The input parameters were cutting speed, feed rate, and material hardness. Using desirability function and GA, the optimum cutting parameters corresponding to minimal surface roughness were calculated (Mia and Dhar, 2017*b*).

Abbas *et al.* minimized machining time considering specified surface roughness in turning of high-strength steel using the Pareto optimization method. In order to predict surface roughness of machined work piece, they used a multilayer perceptron. Then, a Pareto frontier was applied to determine the optimum cutting conditions (Abbas *et al.*, 2017). Mia *et al.* presented a study on the surface roughness, tool wear, and material removal rate in the hard turning process. They obtained optimum cutting parameters to reach optimal values for defined performance indexes (Mia *et al.*, 2018). Narayanan *et al.* (2018) focused on maximizing MRR and minimizing surface roughness by choosing the optimal turning parameters in hard turning processes using carbide insert. Kuntoglu *et al.* conducted a systematic study to determine the optimum cutting conditions, analysis of vibration and surface roughness under different cutting speeds, feed rates, and cutting edge angles using response surface methodology (RSM). They resulted in an acceptable agreement between predicted and measured values with the developed model to predict surface roughness and vibration during turning of AISI 5140 within a 10% error range. The optimum parameters were determined in order to obtain minimum vibration for all components and surface roughness (Kuntoğlu *et al.*, 2020). Kuntoglu *et al.* studied the optimization of different sensorial criteria via the Tool Condition Monitoring System. In their research, an optimization approach was used implementing five different sensors, namely dynamometer, vibration, acoustic emission, temperature and motor current sensors, to a lathe. After that, an response surface methodology-based optimization approach was applied to the measured variables (Kuntoğlu *et al.*, 2020). Although carbon boron nitride (CBN) and ceramic inserts are commonly used in hard turning process, the high cost associated with such tool materials, in comparison with coated carbide inserts, makes them economically unjustifiable (Bouacha *et al.*, 2014). This matter highlighted the economic feature of hard turning more than ever. As a result, some of the researchers made effort to use carbide inserts in the hard turning process (Manivel and Gandhinathan, 2016).

Since hard turning has been considered a cost-effective alternative to other expensive finishing processes; therefore, the cost of operation and final surface roughness of work pieces are of great importance. On the other hand, because of high stresses and temperatures occurred in hard turning, the tool wear rate is intensive. This issue affects resulted surface roughness negatively (Jena *et al.*, 2019). Furthermore, the multi-objective optimization of hard turning process to achieve optimal operation cost and tool life considering resultant surface roughness is extremely vital in hard turning processes. Despite previous investigations in the field of optimization of hard turning processes, no comprehensive research regarding multi-performance optimization of cost and tool life has been reported. The negative effect of tool wear on surface roughness is another important issue that is ignored in the majority of performed researches. Another important problem of previous researches is the shortage of using intelligent techniques in modeling and optimization of the hard turning process, despite proved capabilities of these methods.

Due to the drawbacks of these commonly performed studies, there is still a deep need to perform a thorough research in the field of optimization of the hard turning process considering different machining characteristics such tool life and machined surface and their effect on the production costs. In this regard, the new methodology is presented in this paper to multi-performance optimization of cost and tool life in the hard turning process of AISI D2, which has widely been used in automotive industrial applications, considering the effect of tool wear on resulted surface roughness using intelligent modeling and optimization techniques. Another novel aspect of this work is the application of a new hybrid algorithm which considers the effect of tool life and surface roughness on final manufactured parts and simultaneously presents optimum cutting parameters. The main advantage of the proposed methodology over previous works is that it incorporates a Pareto front optimality graph that facilitate the process of cutting parameters selection according to defined decision-making strategies. For this, a new hybrid algorithm combining the PSO algorithm with RDNN (PSO-RDNN algorithm) along with the weighted sum technique was proposed. Using recurrent dynamic neural network (RDNN) in modeling of flank wear ensures that the real condition of turning process would be reflected. Based on experimental results, two neural networks were trained for predicting tool flank wear and surface roughness during the turning process. Using the offered methodology, the optimum process parameters (cutting speed and feed rate) that resulted in minimum operation cost, maximum tool life, and acceptable surface roughness were calculated and the Pareto optimality graph to represent optimized cutting variables was obtained. The paper is organized as follows: Section "Hybrid PSO-RDNN optimization methodology" describes optimization methodology. Section "Experimentation" is experimentation. In the section "Results and Discussion", the results of the experiments will be represented and discussed. Section "Conclusion" contains conclusion.

Hybrid PSO-RDNN optimization methodology

Recurrent dynamic neural network

Recently, intelligent modeling and control techniques such as genetic programming (GP) (Zadshakoyan and Pourmostaghimi, 2015, 2018), support vector machine (Hu *et al.*, 2019), fuzzy logic (Mars *et al.*, 2020), regression trees (Juez-Gil *et al.*, 2019), k-nearest neighbors algorithm (k-NN) (Grzenda and Bustillo, 2019), artificial neural networks (Bustillo *et al.*, 2021), and ANFIS models (Qazani *et al.*, 2022) have found popularity in various engineering areas. Among these methods, ANN has attracted the special attention of researchers. Because of its parallel structure, ANN is faster than other algorithms. Furthermore, since ANN is independent from parameters, the parameter variations cannot influence the results of modeling. In comparison with traditional methods such as regression, ANNs are more global and more flexible. Moreover, ANNs have good learning and adaptation capability, which makes them widely applicable in system modeling, image processing, decision making, and function optimization (Nametala *et al.*, 2020). Recurrent dynamic neural network (RDNN) is a type of ANN, which has more complexity in structure compared with static neural networks. Because of special interconnections between network elements, RDNNs can analyze time-dependent data (Wu *et al.*, 2018).

RDNNs are suitable for modeling and prediction of time series. In other words, when any input data is transferred to a certain network element, it can be memorized and recalled with subsequent inputs. Therefore, past information can be employed to predict both current and future system states (Amozegar and Khorasani, 2016). This unique ability of RDNN can be effectively utilized in modeling of flank wear. A simple RDNN is shown in Figure 1.

In the present study, two neural networks were trained as follows:

1. A three-layer RDNN with 10 neurons in each hidden layer was trained to predict tool flank wear (VB_{i+1}) during the turning process. Inputs of this network were current tool flank wear (VB_i), cutting speed (v), feed rate (f), and time of machining (Δt) in which flank wear grows from VB_i to VB_{i+1}.
2. A three-layer feed forward neural network with 10 neurons in each hidden layer was trained to predict surface roughness (Ra_i) during the process. Inputs of this network were tool flank wear (VB_i), cutting speed (v), and feed rate (f).

Particle swarm optimization

In recent years, nature inspired metaheuristic algorithms have been widely used in the optimization of engineering and

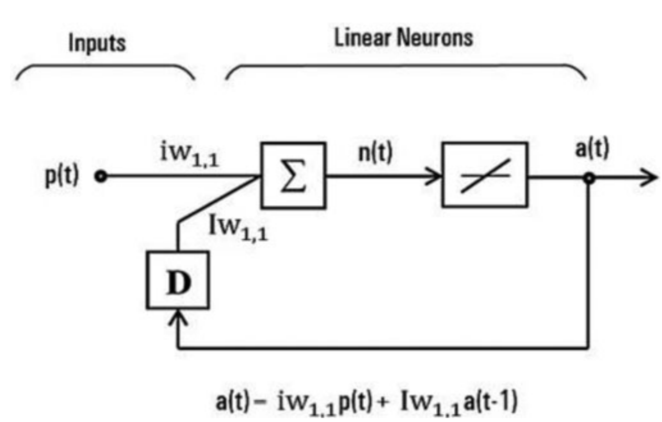

Fig. 1. Schematic view of RDNN (Amozegar and Khorasani, 2016).

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manufacturing issues. In this regard, successful applications of some algorithms such as SA (Khanghah *et al.*, 2015), GA (Rahman *et al.*, 2017), PSO (Pourmostaghimi and Zadshakoyan, 2019), and artificial bee colony (ABC) (Prasanth and Raj, 2017) in the optimization of hard turning has been reported. Among them, PSO has found special popularity because of easy programming and implementation routine, handling complex objective functions, ability in finding global minima, and flexibility in integrating with other modeling and optimization algorithms to form a hybrid optimization algorithm (Weiss-Cohen *et al.*, 2017). PSO is a population-based search algorithm and is composed of particles. Each particle represents a solution to the problem, which is assumed to be solved. These particles try to find the answer in search space by changing their positions. Each particle has two factors: fitness and velocity. The fitness of each particle is determined by the objective function to be optimized. The velocity of particle shows its movement direction and is defined as follows (Wang *et al.*, 2018):

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

In which $X_{id}^{(t)}$ and $V_{id}^{(t)}$ represent respectively the position and velocity of particle i in d dimensional space. $p_{best\ id}^{(t)}$ and $g_{best\ id}^{(t)}$ stand for the best position of particle i and the best position of other particles in population until generation t, respectively. Inertia weight factor w regulates the dynamic of movement of each particle. In Eq. (1), $rand_1$ and $rand_2$ are random variables selected from the range [0 1], c_1 is a cognitive factor, and c_2 is a social factor of particles. The particles update their positions using the calculated velocity as follows (Wang *et al.*, 2018):

$$X_{id}^{(t+1)} = X_{id}^{(t)} + V_{id}^{(t-1)}, \quad (2)$$

where $X_{id}^{(t+1)}$and $X_{id}^{(t)}$ are the new position and previous position of particle i. The optimization process continues until the best solution is obtained or desired iteration is reached (Wang *et al.*, 2018). The parameters configuration used in the PSO implementation stage in this research is given in Table 1.

Process model

To optimize tool life and operation cost in the hard turning process, a new hybrid algorithm combining the PSO algorithm with RDNN (PSO-RDNN algorithm) is proposed. The core part of the proposed structure is an artificial modeling unit in which two previously trained neural networks are employed respectively to predict tool flank wear and surface roughness during the turning process. A schematic view of neural networks is illustrated in Figure 2. The first neural network is an RDNN for predicting tool flank wear during machining. For a certain v and f, and for known VB_i, VB_{i+1} in next Δt seconds of machining can be predicted. Since the gradually increasing tool flank wear has a manner similar to time series (Yao and Fang, 1992), by using RDNN in the modeling of flank wear, the real condition of the turning process is reflected. The second neural network is applied to predict surface roughness during the machining process. The output of the first neural network, VB_{i+1}, along with the same v and f are inputs of the second neural network. This network determines the roughness values in Δt intervals.

Operation cost can be expressed as follows (Zuperl and Cus, 2003):

$$C_p = T_p\left(\frac{C_t}{T} + C_1 + C_0\right) \quad (3)$$

In which T is tool life. The parameters C_t, C_1, and C_0 stand for tool cost, labor cost, and overhead cost, respectively. Their values are given in Table 2. T_p is the production rate and can be formulated as (Zuperl and Cus, 2003):

$$T_p = T_s + V\left(\frac{1 + T_c/T}{\text{MRR}}\right) + T_i, \quad (4)$$

where V is the volume of the removed material. T_s, T_c, and T_i parameters are the tool setup time, tool change time, and tool idle time, respectively. The value for T_s, T_c, and T_i parameters are shown in Table 2.

MRR is obtained as follows:

$$\text{MRR} = 1000 \times v \times f \times a. \quad (5)$$

Multi-objective optimization

Several methods and techniques have been proposed to multi-objective optimization of machining operations with conflicting objectives. For instance, teaching–learning-based optimization algorithm (Lin *et al.*, 2015), gray relational analysis (Mia *et al.*, 2017), response surface methodology (Bagaber and Yusoff, 2017), and nondominated sorting methods (Wang *et al.*, 2014). Each method has its characteristics and uses the special procedure to solve problems. In this research, two conflicting objectives, operation cost, C_p, and tool life, T, were optimized using the weighted sum approach. Any increase in cutting parameters leads to a decrease in operation cost and tool life. On the contrary, decreased cutting parameters would increase both operation cost and tool life. It is aimed at machining processes to decrease operational cost and increase tool life simultaneously. Accordingly, multi-objective problem is defined and different weights for objective functions are applied to obtain different Pareto optimal solutions. Since the objective functions usually are different in dimension, it is also necessary to normalize objective functions. Therefore, the defined multi-objective problem in the weighted sum method in this research can be explained as follows:

$$F(C_p, \text{MRR}) = w_1 * \frac{T - T^{\min}}{T^{\max} - T^{\min}} - w_2 * \frac{C_p - C_p^{\min}}{C_p^{\max} - C_p^{\min}}, \quad (6)$$

where

$$w_1 + w_2 = 1 \quad (7)$$

Table 1. PSO parameters configuration

Population size	20
Range of inertia weight	0.6–0.8
Cognitive factor	2
Social factor	2
Stopping criteria	Maximum generation of 100

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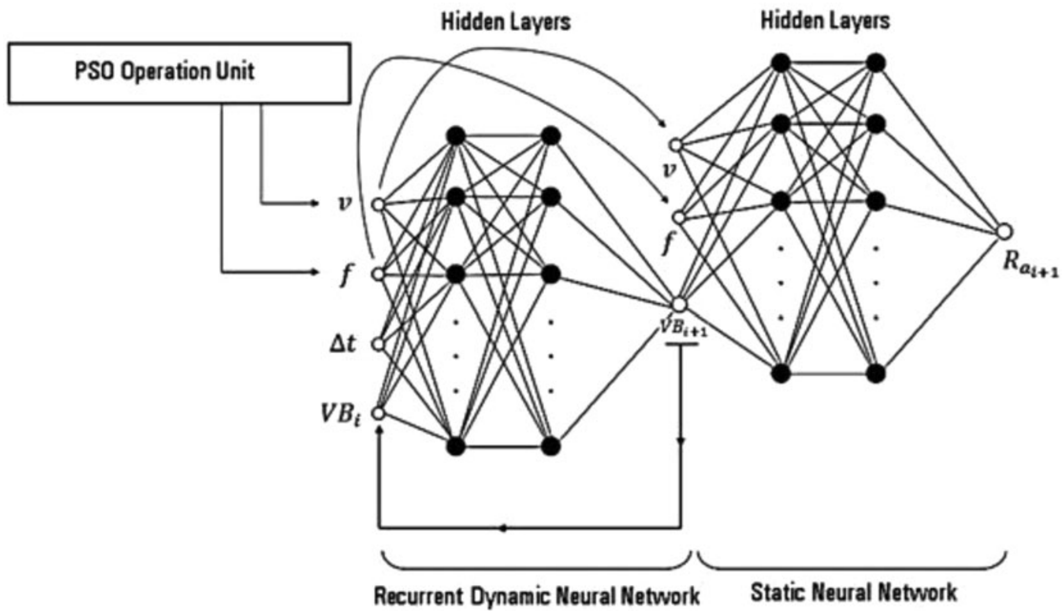

Fig. 2. View of artificial modeling unit applied in modeling of machining characteristics VB_{i+1} and Ra_{i+1}.

Table 2. The value of cutting coefficients (Zuperl and Cus, 2003)

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

C_p^{max}, C_p^{max}, T^{max}, T^{min} are maximum and minimum operation cost and maximum and minimum tool life obtained in experiments, respectively, w_1 and w_2 are weights. Some constraints on process parameters are taken into account as follows:

$$v_{\min} \leq v \leq v_{\max}, \tag{8}$$

$$f_{\min} \leq f \leq f_{\max}. \tag{9}$$

Surface roughness has to be smaller than the permissible value ($Ra_{\max}$):

$$Ra \leq Ra_{max} \tag{10}$$

The flowchart of the suggested PSO-RDNN optimization methodology is shown in Figure 3. The optimization process starts with the generation of the first random population in the PSO operation unit, considering the constraints given by Eqs (8)–(10).

For each member composed of v and f, and considering Δt = 5 s and $VB_0 = 0$, flank wear VB_1 is calculated using RDNN. If the obtained flank wear, VB_1, was less than defined maximum flank wear, $VB_{\max}$, the value for surface roughness, Ra_1, would be calculated. For members with acceptable roughness ($Ra_1 < Ra_{\max}$), the process of optimization will continue. For the next Δt = 5 s, the same operations would be performed. Since the limitations of the process is values defined for tool life (T) or surface roughness ($Ra_{\max}$), if in any stage of the process the flank wear or surface roughness values violated from defined limitations, the optimization will be terminated and for corresponding cutting parameters the tool life and operation cost will be calculated. If the optimum condition or a specific number of generations is reached, the optimum cutting parameters will be reported. Otherwise, applying PSO operators, the new population will be created. The same process will be repeated for new population until obtaining optimum cutting speed and feed rate that result in the optimal tool life and operation cost. This process is performed for different set of weights (w_1 and w_2). Then, a Pareto optimal set of solutions is extended to evaluate both objectives simultaneously with the optimal decision variables and regarding defined constraints.

Experimentation

An EMCOTURN CNC lathe was employed to perform hard turning experiments in dry cutting condition. An AISI D2 alloy steel round bar (diameter of 60 mm and length of 250 mm) with the following chemical composition were machined: 1.53% C; 0.367% Si; 0.344% Mn; 11.537% Cr; 0.94% Mo; 1.02% V. After heat treatment and tempering (quenching in a vacuum atmosphere at 1000–1030°C and two-stage tempering at 600°C), an average hardness of 46 ± 1 HRC for parts was achieved. The selected insert was a TiN-coated tungsten carbide tool type TNMG220408 with grade NC3030. The geometry of insert include: −6° rake angle, 6° clearance angle, 60° major cutting edge angle, −6° cutting edge inclination angle, and 0.8 mm nose radius. Utilized insert along with relevant tool holder are shown in Figure 4.

Since the research was designed for finish hard turning, the depth of cut was selected to be 1 mm. To train neural networks, experimental tests were performed in various cutting conditions.

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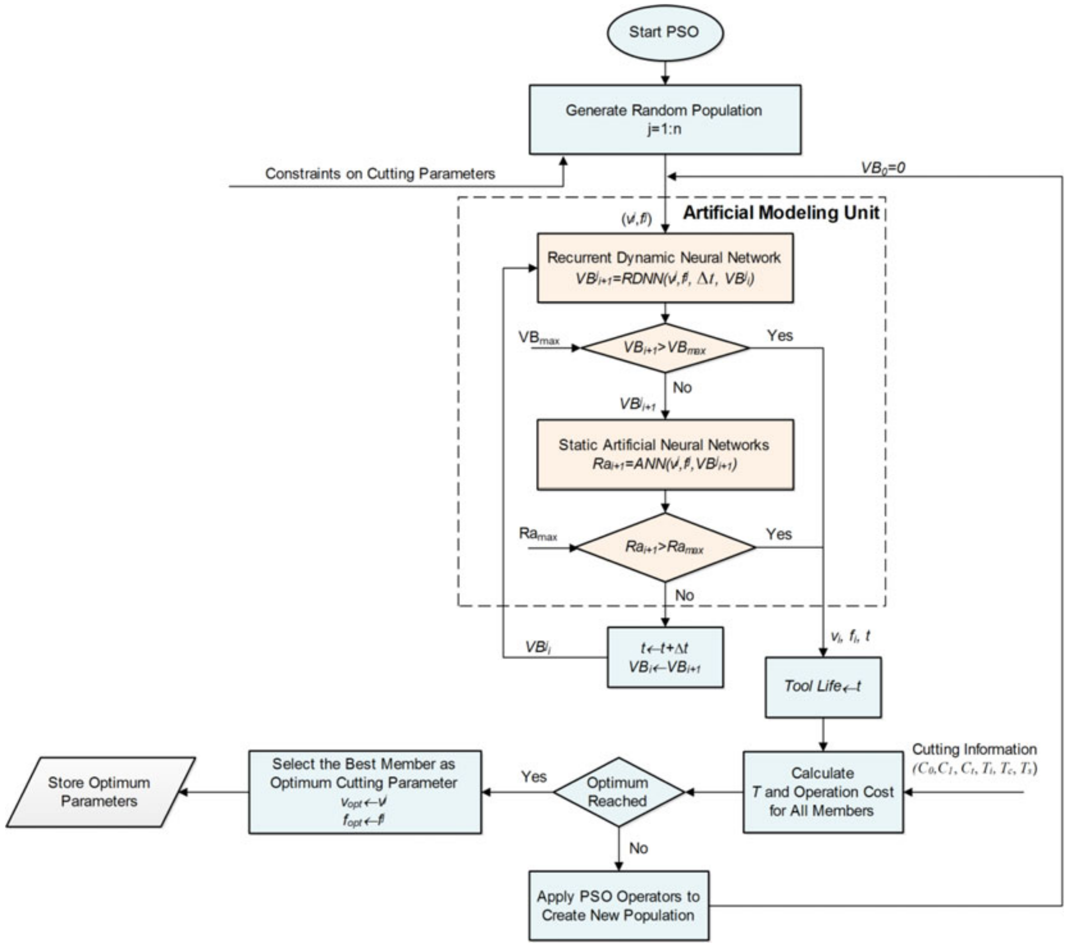

Fig. 3. Flowchart of proposed hybrid optimization methodology.

Fig. 4. Tool holder, tool insert type TNMG220408, and measured tool flank wear.

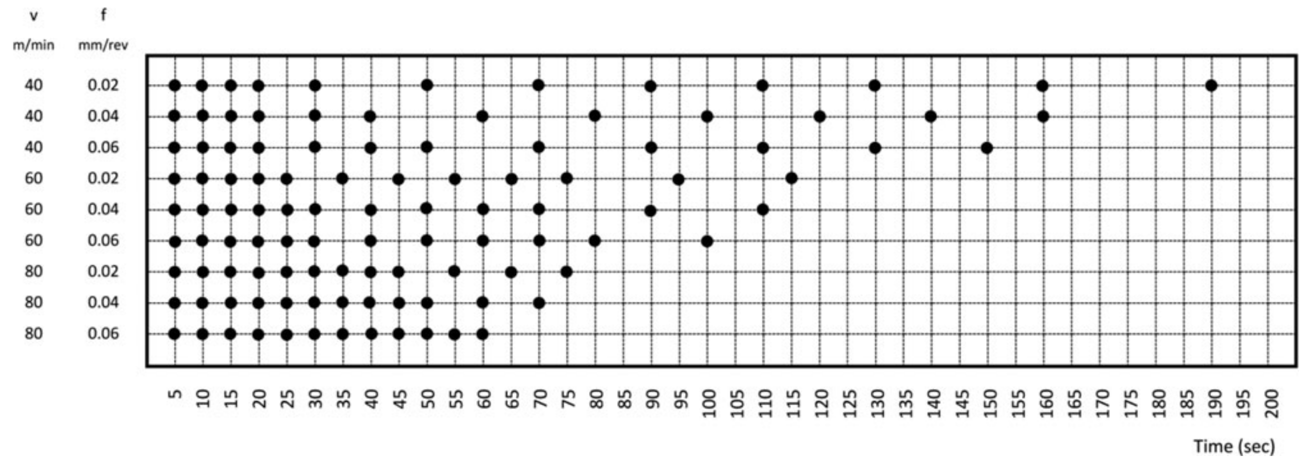

Fig. 5. Cutting parameters and corresponding sampling times.

Cutting speeds (v) were 40, 60, and 80 m/min and selected values for feed rate (f) were 0.02, 0.04, and 0.06 mm/rev. For each cutting couple, 12 tests were performed until the end of tool life ($VB_{max} = 0.3$ mm). The sampling times for selected cutting parameters are shown in Figure 5. Permissible maximum surface roughness (Ra_{max}) was considered 0.4 µm. Some extra tests also were carried on to validate the accuracy of trained neural networks. Because of the high wear rate in initial moments of the turning process, more data were collected in this period to enhance the precision of trained neural networks. Two statistical measures including coefficient of determination, R^2, and root mean square error, *RMSE*, were employed to fitness evaluation of trained neural networks.

To measure tool flank wear, a light source microscope with a magnification of 36× equipped with an imaging processing software was utilized. An illustration of tool insert and measured tool flank wear is shown in Figure 4. A Taylor Hobson S100 surface profilometer was employed to assess the roughness of machined parts. The selected value for cut-off length for assessing surface roughness was 0.5 mm. The final obtained value for both tool flank wear and surface roughness is the mean of three regarding measured values which is performed according to the given sampling times in Figure 4. The experimental setup is demonstrated in Figure 6.

Results and discussion

Neural networks

In this research, two neural networks were trained to predict output characteristics of the turning process. The first was a recurrent dynamic neural network to predict tool flank wear in the next Δt seconds (VB_{i+1}). The second network was a three-layer feed-forward network trained to predict the value of surface roughness during the turning process (Ra_{i+1}). This network was used to avoid the process of selecting cutting parameters that could result in unacceptable surface roughness. According to specified cutting parameters, 100 tests were designated to train neural networks. Also, 12 validation tests were performed to assess the correctness of the proposed intelligent models.

In Table 3, the results of measurements for flank wear and surface roughness for validation tests were compared with regarding values obtained from neural models. The accuracy of neural models in terms of R^2, coefficient of determination, and *RMSE*, root mean square error, for both the training and validation tests is shown in Table 4. The given results show that trained neural networks have acceptable accuracy to be used in real industrial applications with confidence.

(a) (b)

Fig. 6. Experimental setup: (a) CNC machine tool and (b) surface profilometer.

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Table 3. Measured and predicted values using neural networks

Test No.	Cutting speed (m/min)	Feed (mm/rev)	Time (s)	VB_i (mm)	Flank wear, VB_{i+1} (mm)		Surface roughness, Ra_{i+1} (µm)	
					Measured	RDNN predicted	Measured	ANN predicted
1	40	0.04	20	0.269	0.288	0.281	0.51	0.5359
2	60	0.02	20	0.245	0.314	0.292	0.45	0.467
3	60	0.04	5	0.108	0.137	0.144	0.27	0.281
4	80	0.02	5	0.206	0.221	0.2296	0.28	0.288
5	40	0.035	15	0.232	0.271	0.2491	0.4	0.413
6	50	0.05	10	0.091	0.132	0.1248	0.38	0.3877
7	70	0.03	15	0.149	0.19	0.1798	0.23	0.215
8	85	0.06	5	0.092	0.126	0.1142	0.42	0.4411
9	40	0.04	10	0.126	0.143	0.1295	0.32	0.3341
10	60	0.02	5	0.08	0.099	0.1102	0.18	0.1622
11	60	0.06	20	0.209	0.25	0.2342	0.46	0.497
12	80	0.04	10	0.081	0.131	0.149	0.31	0.342

Table 4. The accuracy of intelligent models for training and validation data sets

	Training data set		Validation data set	
	R^2	RMSE	R^2	RMSE
RDNN model for flank wear (VB_{i+1})	0.9893	0.0114	0.9321	0.0244
ANN model for surface roughness	0.9879	0.0154	0.9553	0.0203

In Figure 7, experimentally obtained values for tool life regarding various cutting speeds and feed rates are shown. As can be seen, any increase in cutting speed decreases tool life notably. The effect of feed rate on tool wear is less than the effect of cutting speed. According to the illustration, the maximum tool life corresponds with minimum cutting speed and feed rate. Another important point that can be concluded from Figure 7 is the effect of feed rate in various cutting speeds. In lower cutting speeds, increasing the feed rate results more rapid tool flank wear compared with that of higher speeds.

The same results have been reported by Özel *et al.* (2007) and Gaitonde *et al.* (2009).

Optimization results

Considering different values for w_1 and w_2, defined multi-objective problem according to Eq. (6) was solved using the weighted sum method. To find optimum cutting parameters, the suggested hybrid PSO-RDNN algorithm was employed and various optimal solutions corresponding to selected w_1 and w_2 varying from 1 to 10, were obtained as summarized in Table 5. Tool life and surface roughness values for corresponding cutting speeds and feed rates were measured after finishing the process. As can be seen, all resulted values for roughness are in a permissible range (Ra <0.4 µm).

The results given in Table 5 reveal the effect of weights on the optimization process. According to the defined multi-objective problem, for $w_1 = 1$ and $w_2 = 0$, the cost function is equal to tool life. In this condition, operation cost has no importance and the optimization process searched for cutting speeds and feed rates that resulted in higher tool life. Therefore, low values for cutting speed and feed rate were selected. This matter decreased MRR and increased operation cost notably. On the contrary, when $w_1 = 0$ and $w_2 = 1$, Eq. (6) gives operation cost. Selected cutting parameters resulted in lower operation costs, and therefore, tool life decreased drastically. Based on the information given for operation cost and tool life in Table 5, the Pareto front of solution space is illustrated in Figure 8. Between the two mentioned optimum conditions, various values were defined for w_1 and w_2. By increasing the value of w_1 and consequently decreasing of w_2, various ranges of optimum condition could be obtained. It can be induced that an increasing value of w_1 corresponds with relative increasing the cutting speed and feed rate and decreasing the resulted tool life.

Point 1 corresponds to the minimum cutting speed and feed rate. As it can be seen, any increase in cutting parameters decreases tool life and operation costs simultaneously. At point 11, which corresponds to maximum cutting speed and feed rate, the minimum tool life and operation cost would be achieved. Considering the obtained Pareto front specifies two different zones. From points 1 to 3 (zone 1), the steep gradient in the Pareto front can be seen. In this zone, a significant decrease in tool life and a moderate decrease in operation cost can be detected. From points 4 to 11 (zone 2), operation cost decreased more severely and the tool life has a small decrease. Given Pareto front and corresponding cutting information makes the analysis of selected parameters and decision making regarding with hard turning process easier. First, in the cases that the tool life is more important, cutting parameters associated with zone 1 should be selected. However, this important point needs to be considered that lower values of cutting speed and feed rate lead to low MRR and high operation costs. Secondly, in conditions in which high production volume and lower operation cost are of great importance and tool life can be neglected, cutting parameters corresponding to zone 2 should be chosen in machining operation. In this case, because of the higher values of selected cutting speeds and feed rates, high MRR could be achieved.

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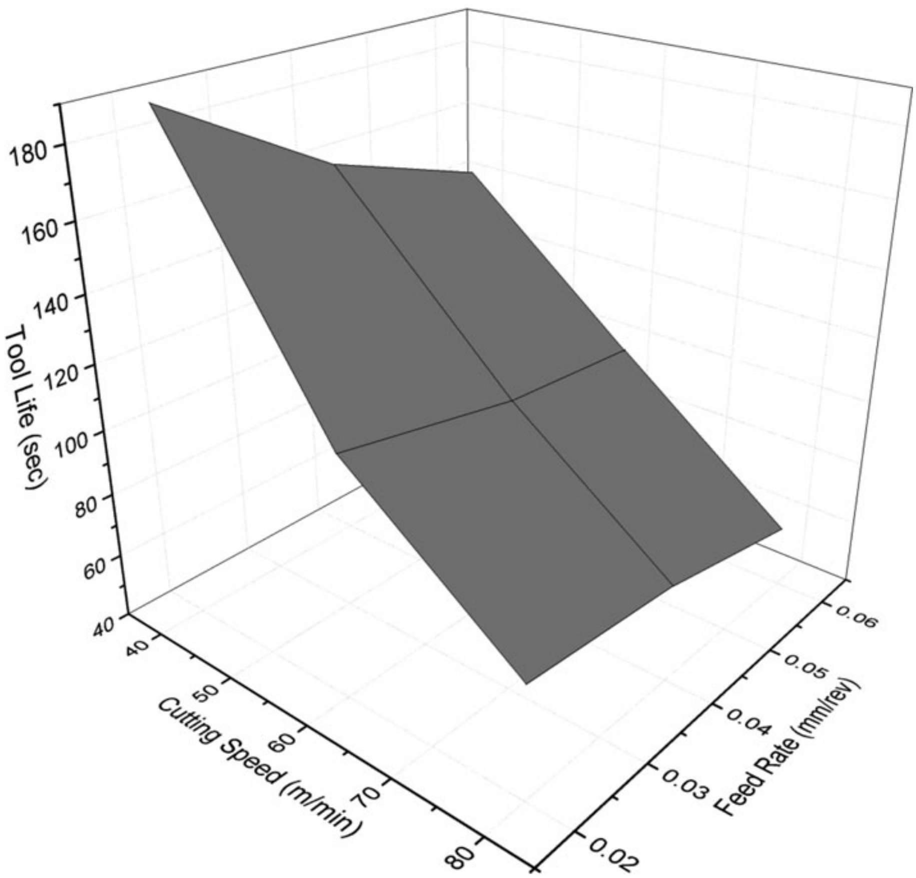

Fig. 7. Tool life in various cutting speeds and feed rates.

Table 5. Pareto optimal solutions for tool life and operation cost as outcomes of the optimization process

No.	w_1	w_2	Cutting speed (m/min)	Feed rate (mm/rev)	Operation cost $	Tool life (s)	Surface roughness (μm)
1	1	0	40	0.02	1.9	190	0.381
2	0.9	0.1	43.2	0.023	1.87	182	0.379
3	0.8	0.2	48.6	0.026	1.77	162	0.393
4	0.7	0.3	51.7	0.031	1.49	128	0.386
5	0.6	0.4	56.2	0.036	1.32	112	0.391
6	0.5	0.5	61.6	0.041	1.2	99	0.395
7	0.4	0.6	63.1	0.043	1.09	88	0.378
8	0.3	0.7	67.9	0.048	1	80	0.382
9	0.2	0.8	72	0.053	0.92	72	0.392
10	0.1	0.9	77.9	0.057	0.81	68	0.388
11	0	1	80	0.06	0.71	63	0.392

Conclusion

In this work, a new hybrid algorithm referred to as the PSO-RDNN algorithm combined with the weighted sum technique was applied for multi-objective optimization of machining parameters in finish turning of hardened AISI D2. Cutting speed and feed rate were optimized for maximizing tool life and minimizing operation cost with operation constraints on cutting parameters and surface roughness. Experimental-based neural network models were developed for predicting tool flank wear and surface roughness during the process. The following conclusions can be made:

1. The coefficient of determination for trained neural networks was calculated as $R^2 = 0.9893$ and $R^2 = 0.9879$ for predicted flank wear and surface roughness, respectively, which showed the efficiency of trained neural models in real industrial applications.
2. Based on trained neural networks and structured hybrid algorithm, optimum cutting parameters were obtained. The

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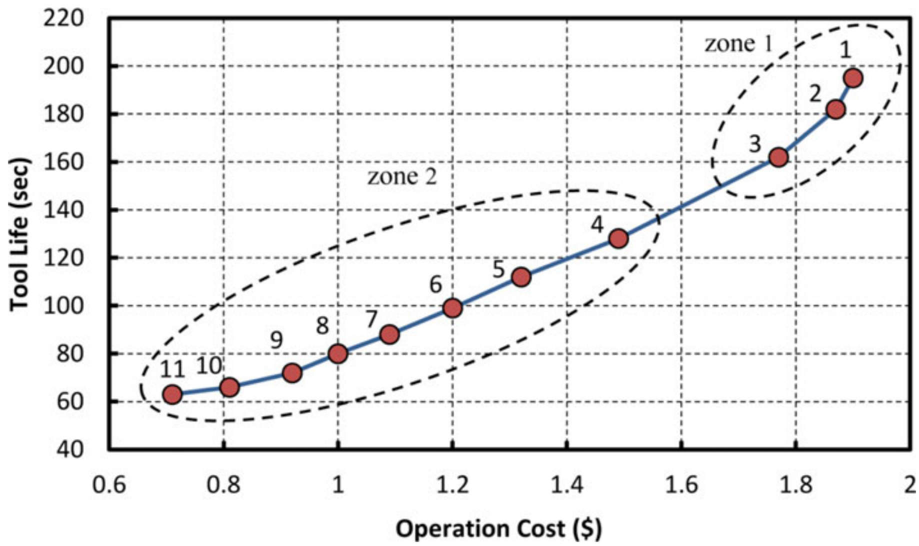

Fig. 8. Pareto front.

suggested optimizing methodology also returns a Pareto optimality graph, which represents optimized cutting variables. The Pareto front line offers a notable amount of decisive information to handle cutting parameters in a logical manner. Confirmation experiments also showed the reliability of the proposed methodology in optimization of the hard finish turning process.

It was found that increasing cutting speed and feed rate accompany with increasing with MRR, but it also decrease tool life severely. On the other hand, by decreasing these parameters, tool life could be increased, although MRR decreased drastically. Therefore, using obtained Pareto front graph could help researchers to select cutting conditions according to their financial and technical strategies.

Since the machining of hardened material is commonly performed with CBN and ceramic inserts, it is advisable that the presented optimization methodology to be executed by mentioned tools to evaluate the effectiveness of the proposed technique. Also as future work, the proposed methodology should be expanded to include more comprehensive performance indexes such as MRR, production rate, and machining time. More realistic constraints also need to be considered such as cutting force and cutting power in hard turning processes.

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