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Optimization of milling parameters using artificial neural network and artificial immune system†

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Abstract

The present paper is an attempt to predict the effective milling parameters on the final surface roughness of the work-piece made of Ti-6Al-4V using a multi-perceptron artificial neural network. The required data were collected during the experiments conducted on the mentioned material. These parameters include cutting speed, feed per tooth and depth of cut. A relatively newly discovered optimization algorithm entitled, artificial immune system is used to find the best cutting conditions resulting in minimum surface roughness. Finally, the process of validation of the optimum condition is presented.

Keywords: Milling; Ti-6Al-4V; Artificial neural network; Artificial immune system

1. Introduction

Although in contemporary times modern machining technology has expanded significantly, milling remains a crucial part of machining processes. Milled surface roughness has a great impact on the functional properties of a product. It is widely accepted that high quality milled surfaces improve fatigue strength and corrosion resistance [1, 2]. Surface roughness helps determine and evaluate surface quality of a product. Due to its effect on the functional characteristics of a product such as friction, wearing, light reflection, heat transmission and lubrication, surface roughness gives the product an acceptable quality. With a decrease in surface roughness, the product quality will increase. Machining parameters such as feed, spindle speed and depth of cut and non-controlled parameters, such as work-piece non-homogeneity, tool wear, machine motion errors, chip formation and other random disturbances all have effects on surface roughness. It has been shown that both controlled and non-controlled parameters cause relative vibrations in the cutting tool and work-piece [3].

Titanium alloys play a crucial role in aerospace industry for their role in minimizing aircraft weight and consequently, for reducing the costs incurred upon. They have superior properties like corrosion and erosion resistance, high temperature applicability, and superior strength-to-weight ratio to ensure efficient fuel consumption for economic operation of flights as well as longer operational life. Machining of these materials has been found to be difficult [4, 5], needing high investment, and requiring specialized cutting tools. Many researchers all over the world attempted to optimize the cutting conditions to achieve the desired surface roughness of the work-pieces.

Kadirgama et al. presented a statistical model to determine surface roughness when milling hastelloy C-22HS by PVD and CVD coated carbide cutting tools under various cutting conditions [6]. In their paper, the results obtained from the mathematical models were in good agreement with those obtained from the machining experiments. An another research, Ji et al. conducted an experimental research on machining characteristics of SiC ceramic with end electric discharge milling [7]. Their proposed technique was able to effectively machine a large surface area on SiC ceramic at low cost without any environmental pollution.

Lee et al. [8] offered a novel technique for mass production of a high quality worm which could be substituted instead of the common milling process. In this paper, the cutting characteristics of worm machining on an automatic lathe were investigated for two types of milling processes and those processes were compared with each other. The simulation results were confirmed through numerous experiments. The experimental results revealed the cutting characteristics of each milling process and the efficiency for mass production of a high quality worm.

Brezak et al. investigated the flank wear regulation using artificial neural networks [9]. Their paper primarily deled with determination of a tool wear regulation model that could ensure the maximum allowed amount of tool wear rate within a

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predefined machining time, while simultaneously maintaining a high level of process productivity. The proposed model was structured using two well-know neural network schemes.

Yildiz et al. [10] developed a new hybrid optimization approach by hybridizing the immune algorithm with hill climbing local search algorithm to maximize the total profit rate in milling operations. Zarei et al. [11] presented a harmony search (HS) algorithm to determine the optimum cutting parameters for multi-pass face milling.

Lo [12] used adaptive neuro-fuzzy inference system (ANFIS) to predict the surface roughness in end milling process. Input parameters included spindle speed, feed rate, and depth of cut. The ANFIS was modeled using triangular and trapezoidal membership functions. The average error of prediction of surface roughness for triangular membership function was found less than or around 4%. Chen and Savage [13] used fuzzy net-based model to predict surface roughness under different tool and work piece combination for end milling process. Speed, feed and depth of cut, vibration, tool diameter, tool material, and work piece material are used as input variables for fuzzy system. The authors found that the predicted surface roughness is within an error of 10%.

In another study, Ho et al. [14] applied an adaptive neural fuzzy inference system (ANFIS) with the hybrid Taguchi-genetic learning algorithm to predict the surface roughness of the work-piece in the end milling process. This algorithm was used to determine the most appropriate membership functions as well as the optimal premise and consequent parameters by minimizing the root-mean-squared-error criterion. Experimental results proposed that the algorithm applied in conjunction with ANFIS method outperforms the ANFIS approaches given in the MATLAB package.

Iqbal et al. [15] applied a fuzzy inference system to enhance the tool life and improve the work-piece surface quality by optimizing the effective parameters. Their research examined application of an expert system to use the experimental data in optimizing the hard-milling parameters. It was an attempt to study the effects of work-piece material hardness, cutter's helix angle, milling orientation and coolant upon tool life, work-piece surface roughness, and cutting forces.

Comparison of Bayesian networks and artificial neural networks to determine the quality of machining process was conducted by Correa et al. [16]. The aim of their research was to supervise the machining processes to detect the interferences with negative effect on the production time and product caliber. The case in that paper was to compare the two different machine learning classification approaches to predict the surface roughness in high-speed machining. The prediction of surface roughness was one of the most pivotal factors to achieve the mentioned objective.

In another research, Zain et al. [17] applied the artificial neural network and simulated annealing techniques to determine the optimal process parameters in abrasive water jet machining operation. The parameters were traverse speed, water jet pressure, standoff distance, abrasive grit size and abrasive flow rate. They investigated the quality of the cutting of machined work-piece by looking to the average roughness value (Ra). The optimal values were calculated to obtain the minimum value of Ra.

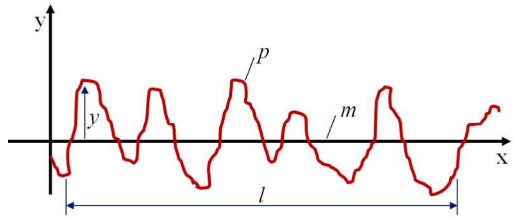

Fig. 1. Illustration of surface roughness.

In another work, Minimizing surface roughness via determining the optimal cutting conditions by genetic algorithm was accomplished by Zain et al. [18]. In their research, the effect of the radial rake angle of the tool as well as speed and feed rate cutting conditions on the surface roughness was investigated. In machining, cutting conditions were optimized in order to minimize the surface roughness value. Furthermore, by considering the real machining case study, a regression model was developed to determine the fitness function of genetic algorithm.

This paper presents the optimization of milling effective parameters including cutting speed, feed per tooth and depth of cut to obtain the optimal surface roughness of the work-piece. First, the experimental data are fed into a multi-perceptron neural network in order to predict the inexperienced cases. Then, a newly applied optimization algorithm entitled artificial immune system is used to anticipate the optimal values of the parameters. The values achieved are verified experimentally. The comparison of the results shows an acceptable agreement.

The paper is divided into the following sections: (1) the surface roughness is described; (2) the experimental data are presented and discussed in detail; (3) the concepts of multi-perceptron neural network are explained and a specific version of the expert system is applied to predict the surface roughness of the work-piece; and (4) finally, the basics of artificial immune systems are elaborated and this optimization algorithm is used to find the optimal conditions of the milling process.

2. Surface roughness description

Surface roughness is defined as irregular deviations on a scale smaller than the scale of waviness. In other words, surface roughness is described as irregularities wrought by different machining processes.

In Fig. 1 standard terminology and symbols for describing surface roughness are given. The profile p is the contour of any specific section through a machined surface on a plane perpendicular to the surface. In measuring the average roughness height, sampling length l is taken into consideration. The mean line m of the profile p is located in such a way that the

Table 1. Chemical and mechanical properties of Ti-6Al-4V.

Chemical compositions		Mechanical properties	
Al	6.75	Tensile strength (MPa)	960-1270
V	4.02		
Cr	< 0.01	Modulus of elasticity tension (GPa)	100-120
Cu	< 0.02		
Fe	0.16	Yield strength (MPa)	830
Mn	0.03		
Mo	< 0.03	Density (kg/m^3)	4430
Nb	0.03		
Sn	0.06	Hardness (Hv)	320–370
Zr	< 0.01		
SI	0.03	Thermal conductivity (W/mK)	7
Ti	Balance		

sum of areas above the mean line (within the sampling length l) is equal to the sum of areas below it. Surface roughness can be described in different manners. One of the most useful international parameters of surface roughness is average roughness, often denoted as Ra. Ra is defined as the arithmetic value of the movement of the profile from centerline along the sampling length:

$$R_a = \frac{1}{l}\int_0^l \left| y(x) \right| dx \tag{1}$$

where y is the ordinate and l is the sampling length of the profile curve [19].

3. Material and methods

In this section, we are going to describe the methods necessary to conduct our research. This section consists of three separate sub-sections. A concise description of experimental approach, a brief introduction to artificial neural network and eventually an explanation of artificial immune system are the consecutive methods which are clarified here.

3.1 Experimental approach

In the present study, the results of milling experiments carried out using a FB4MB milling machine are reported. The cutter was 40 mm in diameter and with six inserts, designated as type R390-1806 12M-PM manufactured by SANDVIK.

The work-piece material was Ti-6Al-4V Titanium alloy. Its mechanical and chemical properties are shown in Table 1.

A block with dimensions of 300 mm (length) × 80 mm (width) × 120 mm (height) provided work-piece for carrying out the cutting experiment, a schematic view of which is given in Fig. 2.

The effects of cutting speed, feed per tooth and depth of cut on surface roughness were examined via a three -factor/five-level full factorial design. Using Taylor Hobson Surftronic + 3 which is shown in Fig. 3, the surface roughness value of the machined work piece was measured.

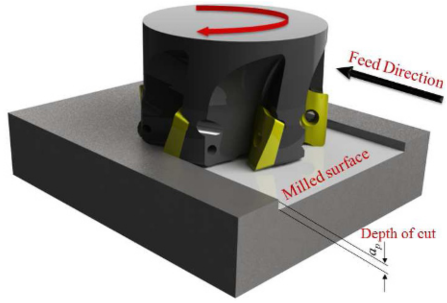

Fig. 2. Schematic view of the face milling.

Fig. 3. Taylor Hobson Surftronic +3.

The ranges of cutting parameters are selected based on recommendation of SANDVIK Tools Catalog [20]. The factors and levels included cutting speed 60, 75, 90, 115 and 120 m/min, feed 0.05, 0.1, 0.15, 0.2 and 0.25 mm/tooth, depth of cut 0.3, 0.6, 0.9, 1.2 and 1.5 mm, respectively. Table 2 presents the result of experiment. Values indicate the surface roughness obtained from the experiments. In this table, Vc represents the cutting speed in (m/min), F_z is the feed rate in (mm/tooth) and ultimately, a_p represents the depth of cut in (mm). The remaining numbers are the surface roughness values in μm in different cutting conditions. Moreover, the data which are not highlighted are applied in the training process of the neural network, whereas the highlighted cells are used in the testing process, as discussed in the following sections.

3.2 Application of artificial neural network to predict the milling parameters

Artificial neural network is a powerful tool to model the problems especially those with no authentic governing equation for their behaviors. The model obtained using artificial neural network can learn and mimic the human thinking process. The structure of a feed-forward artificial neural network shown in Fig. 4 consisted of one input layer, one or some hidden layers and finally one output layer. In all layers, there are some nodes called neurons. Although many researchers worked on presenting some rules to make a perfect structure, until now, there is not any definite rule to specify a perfect structure. The only way for producing an appropriate structure is trial and error. This process is conducted to find the apt

Table 2. Experimental data of milling process.

	$F_z = 0.05$	$F_z = 0.1$	$F_z = 0.15$	$F_z = 0.2$	$F_z = 0.25$
$a_p = 0.3$					
$V_c = 60$	1.96	2.03	2.4	2.15	2.46
$V_c = 75$	1.82	2.02	2.52	2.19	2.71
$V_c = 90$	1.39	1.46	1.71	1.78	1.85
$V_c = 105$	1.04	1.09	1.12	1.17	1.24
$V_c = 120$	0.93	0.99	1.14	1.43	1.53
$a_p = 0.6$					
$V_c = 60$	1.86	1.95	2.3	2.05	2.4
$V_c = 75$	1.72	1.92	2.36	2.12	2.61
$V_c = 90$	1.24	1.36	1.61	1.68	1.75
$V_c = 105$	0.94	0.93	1.02	1.07	1.11
$V_c = 120$	0.89	0.94	1.04	1.33	1.36
$a_p = 0.9$					
$V_c = 60$	1.78	1.89	2.23	1.96	2.31
$V_c = 75$	1.63	1.83	2.27	2	2.52
$V_c = 90$	1.11	1.27	1.52	1.59	1.68
$V_c = 105$	0.85	0.9	0.93	0.98	1.02
$V_c = 120$	0.86	0.91	0.93	1.22	1.27
$a_p = 1.2$					
$V_c = 60$	1.72	1.83	2.17	1.91	2.27
$V_c = 75$	1.58	1.77	2.22	1.94	2.46
$V_c = 90$	1.05	1.19	1.46	1.51	1.62
$V_c = 105$	0.73	0.85	0.87	0.92	0.94
$V_c = 120$	0.75	0.87	0.9	1.16	1.24
$a_p = 1.5$					
$V_c = 60$	1.76	1.86	2.22	1.95	2.3
$V_c = 75$	1.63	1.8	2.25	1.98	2.5
$V_c = 90$	1.12	1.24	1.5	1.53	1.65
$V_c = 105$	0.81	0.87	0.91	0.95	0.98
$V_c = 120$	0.81	0.88	0.95	1.2	1.29

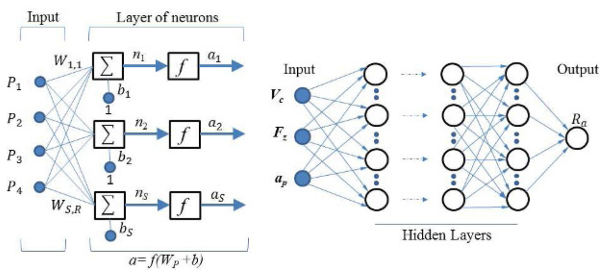

Fig. 4. Structure of the artificila neural network.

number of hidden layers and the number of the neurons at each layer for a specific problem.

As shown in Fig. 4, the input parameters enter the input layer. Therefore, the number of neurons in the input layer equals the number of input parameters. There are some hidden layers to connect the input layer to output layer by multiplying them to some weight factors and adding some biases.

The output value from the last neuron in the left part of Fig. 4 may be computed by the following relation:

$$a_s = f(n_s) = f\left(\sum_{s=1}^{R} W_{S,R} P_R + b_s\right) \tag{2}$$

where a_s, f, $W_{S,R}$, P_R and b_s are output value, firing function, weight factors, input values for each layer and biases, respectively.

There are some factors which affect the capability of artificial neural network in modeling problems such as network structure, number of training and testing data, network algorithm and eventually, transfer, training, learning, and performance functions. In this study, we used MATLAB toolbox to create a model which predicts the surface roughness of under milling work-piece vs. different cutting parameters. Feed-forward back propagation (BP), Bayesian regularization (trainbr), hyperbolic tangent sigmoid function (tansig), Hebb weight learning rule (learnh) and mean squared error (MSE) are selected for the network algorithm, training function, transfer function, learning function and performance function, respectively. To diminish the error between the real target value and the output value, the BP algorithm is usually applied in the feed-forward artificial neural network.

This algorithm reduces the error by updating weights and biases in the network. The general description of this network algorithm can be summarized as below:

1. The input data are fed into the network and the errors between real target values and the proposed target values by the network are computed.

2. The sensitivities start to propagate from the output layer toward the input layer and based on this phenomenon, the weights and biases are updated.

The complete descriptions of various functions applicable to the production of artificial neural network and the mathematical relations of different network algorithms can be found in Refs. [21, 22].

3.3 Artificial immune system

The artificial immune system models the ability of natural immune system to detect the foreign cells in the body [23, 24].

It is inspired by natural immune system working against the foreign cells. When foreign cells enter the body, they are recognized by lymphocytes. Lymphocytes are produced in bone and then maturate. There are three types of mature lymphocytes: immature cells which do not encounter antigens; active cells which are activated in conflict with antigens and begin reproduction, and memory cells responsible for saving the specifications of the foreign cells. Due to the memory cells, the next conflict with the same or similar antigens is accomplished sooner than before.

The lymphocytes may identify familiar cells as foreign cells. Therefore, they are tested before encountering with antigens.

Lymphocytes which recognize familiar cells as foreign cells are killed. This stage is called negative selection.

Having identified the foreign cells, lymphocytes connect to antigens and begin to reproduce. In this stage, the other familiar cells with stimulant are stimulated. Lymphocytes with high affinities are reproduced too. Some of the reproduced cells convert to plasma and secrete antibody to kill foreign cells. Others convert to memory cell to save foreign cells specifications. We use some of the mentioned concepts to describe the algorithm applied to optimization.

The optimization algorithm works as described in the following steps. First, N number of antibody population are generated randomly in [0 1] domain.

$$MP = \{x_1, x_2, x_3, ..., x_N\} \tag{3}$$

where

$$\begin{aligned} x_1 &= \{x_{11}, x_{12}, x_{13}, \ldots, x_{1d}\} \\ x_2 &= \{x_{21}, x_{22}, x_{23}, \ldots, x_{2d}\} \\ &\vdots \\ x_N &= \{x_{N1}, x_{N2}, x_{N3}, \ldots, x_{Nd}\} \end{aligned}$$

in which d is the number of function variables. The randomly created populations are evaluated and the fittest ones are selected based on their higher affinities. The unselected populations are deleted from the rest of the process. Then, we extend the main population as follows:

$$EP = \begin{Bmatrix} c_1 \\ c_2 \\ c_3 \\ \vdots \\ c_n \end{Bmatrix} \tag{4}$$

where

$$\begin{aligned} c_1 &= \{x_1, x_1, ..., x_1\} = \{q_1, q_2, ..., q_{nc}\} \\ c_2 &= \{x_2, x_2, ..., x_2\} = \{q_{nc+1}, q_{nc+2}, ..., q_{2nc}\} \\ &\vdots \\ c_n &= \{x_n, x_n, ..., x_n\} \end{aligned} \tag{5}$$

where q_i is the ith antibody of the extended population, ci is the clone of xi antibody and EP is the extended population. The number of copies from each antibody is $n_c = \beta \times n$ and the total number of the extended population is $N_c = n \times n_c$. The extended population should be mutated as follows:

$$\begin{aligned} c_i^* &= q_i + \alpha \times rand \qquad i = 2, 3, \ldots, nc+2, \ldots, 2nc, 2nc+2, \ldots \\ c_i^* &= q_i \qquad\qquad\qquad i = 1,\ nc+1,\ 2nc+1 \end{aligned} \tag{6}$$

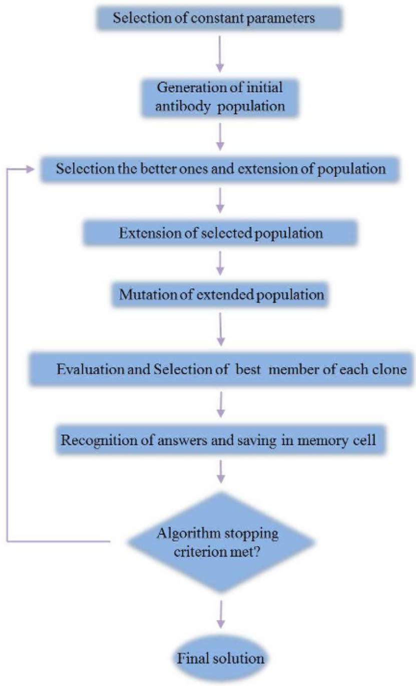

Fig. 5. Flowchart of artificial immune system algorithm.

where α is the mutation rate and rand is a matrix With a dimension similar to that of extended population. Each of its members is generated randomly in [-1, 1] domain and c_i^* is the mutated antibody of qi. Mutated populations are evaluated by the cost function and the best member of each clone is replaced instead of the deleted antibodies in the main population. Second, the answers are recognized and saved in memory cell. Then, the affinity between memory cell antibody and main population antibody is calculated. Antibodies with high affinities are detected within the main population and replaced by new antibodies. The instruction above is repeated until the algorithm stopping condition was met [25]. Fig. 5 shows the algorithm solution method graphically. This algorithm has the ability to find global extremum in addition to finding any number of local extremums.

4. Results and discussion

This section presents the results of the applied neural network and optimization algoritm in predicting the behavior of the surface roughness in various experimental conditions as well as finding the optimal values of the effective milling parameters to achieve the minimum value of the surface roughness. These parameters were introduced earlier in this section. First, the results of application of a multi-perceptron neural network are presented and the optimization process is consecutively studied.

4.1 Results of application of artificial neural network

To predict the surface roughness of the work-piece in vari-

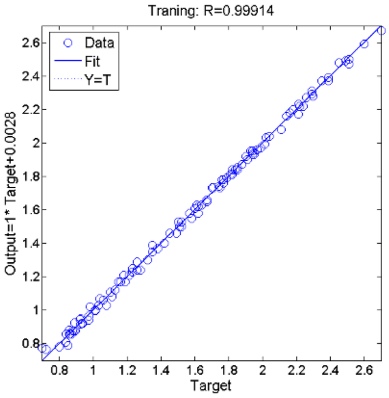

Fig. 6. Graphical representation of the proposed network.

ous experimental conditions, we investigated the different structures of the neural networks including different numbers of hidden layers and the numbers of the neurons at each layer. It is clear that the number of neurons in the input and output layers are determined by the numbers of input and output parameters respectively which are 3 and 1. The former denotes the input parameters including cutting speed, feed per tooth and depth of cut and the latter denotes the final layer, which is surface roughness. The experimental data presented in Table 2, excluding the colored ones, are fed into the network to train it. The excluded data are retained to investigate the performance of the network.

The performance of the applied artificial neural network is investigated by comparing the experimental data and the output values from the network. Fig. 6 shows the graphical form of this comparison. It is worth noting that in order to have a good prediction, the line in the figure should approximately have the slope of around 1 and the distribution of the data should be in the vicinity of this line. It is obviously seen that both of the mentioned criteria are satisfied in our study.

The investigation process of the neural network performance regarding the milling problem is presented in Table 3. The data in this table are those excluded from training process of the network. This table shows the comparison of the experimental data and the corresponding predicted values from the neural network. As shown in the last column of this table, all of the error values are less than 5 percent and even the majority is less than or about 2 percent which offers a conspicuous agreement and consequently, a striking performance potency of the neural network with the proposed structure.

It can be concluded that the neural network, with the optimum structure, is a lucrative approach to predict a target specially the surface roughness of the work-piece for different cutting conditions.

4.2 Results of the application of artificial immune system

This section presented the results of application of artificial immune system in finding the optimal cutting conditions. The optimization function was the surface roughness of the work-

Table 3. Comparison of neural network predictions with experimental measurement for test set.

Cutting condition			Surface roughness		
V_c (m/min)	F_z (mm/tooth)	a_p (mm)	Experiment	Neural network	Error (%)
0.3	120	0.05	0.93	0.963	3.548
0.3	105	0.1	1.09	1.0409	4.504
0.3	60	0.15	2.4	2.4027	0.112
0.3	75	0.2	2.19	2.2092	0.876
0.3	90	0.25	1.85	1.8512	0.064
0.6	105	0.05	0.94	0.9315	0.904
0.6	75	0.1	1.92	1.9114	0.447
0.6	60	0.15	2.3	2.3182	0.791
0.6	120	0.2	1.33	1.3124	1.323
0.6	90	0.25	1.75	1.7552	0.297
0.9	60	0.05	1.78	1.7765	0.196
0.9	120	0.1	0.91	0.8899	2.208
0.9	90	0.15	1.52	1.5106	0.618
0.9	105	0.2	0.98	0.974	0.612
0.9	75	0.25	2.52	2.5168	0.126
1.2	90	0.05	1.05	1.0769	2.561
1.2	60	0.1	1.83	1.8521	1.207
1.2	105	0.15	0.87	0.8949	2.862
1.2	120	0.2	1.16	1.1802	1.741
1.2	75	0.25	2.46	2.495	1.422
1.5	75	0.05	1.63	1.5955	2.116
1.5	90	0.1	1.24	1.2391	0.072
1.5	120	0.15	0.95	0.9365	1.421
1.5	60	0.2	1.95	1.9391	0.558
1.5	105	0.25	0.98	0.9548	2.571

piece and the effective parameters are those described before which their upper and lower bounds as well as the mentioned function are considered as follows:

Minimize $Ra(a_p, F_z, V_c)$, Subject to:
$0.3\ mm < a_p < 1.5\ mm$
$0.05\ mm/tooth < F_z < 0.25\ mm/tooth$
$60\ m/min < V_c < 120\ m/min.$

It is worth noting that the optimal values of the effective parameters depend on some criteria such as number of clones per antibody, mutation probability, number of antibodies and the stopping criteria. Hence, in this section, we are going to elaborate the optimization procedure step by step for the current subject.

Create an initial random population of the antibodies. In this step, 52 antibody population are created randomly in the range [0 1]. Because the problem has three input parameters (cutting speed, feed rate per tooth and depth of cut), then d in Eq. (3) equals 3. Ten created antibody population are presented in

Table 4. Initial population of the AIS optimization technique in [0 1].

Antibody	Depth of cut	Feed rate per tooth	Cutting speed
X_1	0.81	0.16	0.66
X_2	0.91	0.97	0.04
X_3	0.13	0.96	0.85
X_4	0.91	0.49	0.93
X_5	0.63	0.80	0.68
X_6	0.10	0.14	0.76
X_7	0.28	0.42	0.74
X_8	0.55	0.92	0.39
X_9	0.96	0.79	0.66
X_{10}	0.96	0.96	0.17

Table 5. The parameters of artificial immune system.

AIS parameter	Numerical value
Number of initial population	N = 52
Number of clones per antibody	n = 26
Mutation rate	$\alpha = 0.05$
Extension coefficient	$\beta = 0.05$
Maximum number of iterations	max_it = 500 it
End condition (number of iterations without update in the best values)	300 iterations

Table 4.

Evaluate the created population and select half of them based on the cost function values. In this stage the initial randomly created population are fed into the ANN and the corresponding results are sorted. Half of them are remained and the rest are deleted form the rest of the process.

Create a set of clones and expand the selected population. In this stage, the selected population are expanded according to Eq. (5). It should be noted that n_c which is the number of copies from each antibody is $n_c = \beta \times n = 0.5 \times 26 = 13$ and the total number of extended population is $N_c = n \times n_c = 26 \times 13 = 338$ Mutate each clone based on Eq. (6) and add them to the previous clones instead of the deleted antibodies. The mutation rate is selected $\alpha = 0.05$. This step can help the algorithm from avoiding trapping in the local extremums.

Evaluate and select the best answers.

Stop, if the stopping criteria are met or return to the second step if they are not met. The stopping criteria and other parameters of the AIS optimization algorithm used for the current case are presented in Table 5. These parameters presented in this table are obtained using trial and error to achieve the best solutions.

The proposed cutting parameters were verified by the optimization algorithm experimentally and the experimental datum presented in Table 5 shows a good agreement with the proposed surface roughness.

The optimization process is conducted 50 times and the best value is represented here. Fig. 7. shows the history of the optimization process. Vertical axis presents the values of the surface roughness during this process and the horizontal axis shows the tenfold generations.

Table 6. The results of the optimization process and their experimental validation.

Optimum cutting condition				Surface roughness		
Algorithm	V_c (m/min)	F_z (mm/tooth)	a_p (mm)	Experiment	Neural network	Error (%)
AIS	112	0.05	1.27	0.7	0.68	2.85

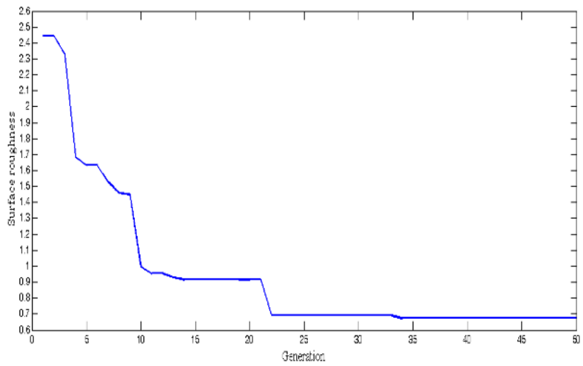

Fig. 7. The history of optimization process.

The applied optimization algorithm found the optimum cutting parameters and their corresponding optimal surface roughness according to Table 6.

It can be concluded from the optimum results that less feed rates lead to the best surface roughness and the other two remaining parameters may vary in the search space according to milling conditions. Although, in this study, these values tend to upper bounds rather than to the lower ones.

5. Conclusions

The prediction of different cutting conditions including various depth of cuts, feed rates per tooth and cutting speeds on the surface roughness of the work-pieces made of Ti-6Al-4V is conducted using artificial neural networks. There were good agreements between the experimental values and the predicted results. Furthermore, artificial immune system, which is an optimization algorithm was applied to find the best cutting conditions leading to minimum surface roughness. The results indicate that in order to have an extra finished surface in face milling process, the feed rate should be the possible lowest value with different values for other two variables, according to problem condition. It was also observed that the cutting speeds and depths of cut tended to approach their upper bounds.

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