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ORIGINAL ARTICLE

Selection of optimum cutting condition of cobalt-based superalloy with GONNS

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Abstract Machining of new superalloys is challenging. Automated software environments for determining the optimal cutting conditions after reviewing a set of experimental results are very beneficial to obtain the desired surface quality and to use the machine tools effectively. The genetically optimized neural network system (GONNS) is proposed for the selection of optimal cutting conditions from the experimental data with minimal operator involvement. Genetic algorithm (GA) obtains the optimal operational condition by using the neural networks. A feed-forward backpropagation-type neural network was trained to represent the relationship between surface roughness, cutting force, and machining parameters of face-milling operation. Training data were collected at the symmetric and asymmetric milling operations by using different cutting speeds (V_c), feed rates (f), and depth of cuts (a_p) without using coolant. The surface roughness (Ra_{asymt}, Ra_{symt}) and cutting force (Fx_{asymt}, Fy_{asymt}, Fz_{asymt}, Fx_{symt}, Fy_{symt}, Fz_{symt}) were measured for each cutting condition. The surface roughness estimation accuracy of the neural network was better for the asymmetric milling operation with 0.4% and 5% for training and testing data, respectively. For the symmetric milling operations, slightly higher estimation errors were observed around 0.5% and 7% for the training and testing. One parameter was optimized by using the GONNS while all the other parameters, including the cutting forces and the surface roughness, were kept in the desired range.

Keywords Surface roughness · Cutting forces · Surface milling · Stellite 6 · CNC milling · Artificial neural networks · GONN · Genetic algorithm

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1 Introduction

Stellite 6 is a cobalt-based superalloy. It is widely used by the nuclear, aerospace, biomedical, and gas turbine industries for its high heat, corrosion, and wear resistance [1–4]. Machining of Stellite 6 will be more important with increasing use of the alloy for wires, plates, and welding electrodes [5, 6]. Machining of hard superalloys is difficult. Minimization of tool-chip contact area, use of sharp cutting edges, and selection of small cutting depths make the machining possible. Slow cutting speeds and feed rates ease the machining of superalloys by reducing heat generation [4]. To obtain the desired surface quality, extensive experimentation and experience is necessary. In this study, the use of genetically optimized neural network system (GONNS) is proposed to determine the optimal machining parameters with minimal human involvement from a set of experimental data. Almost, all computational methods have limitations. If there is no consistent trend or the relationship between the inputs and outputs drastically change within the modeling space, GONNS could not model the relationship with neural networks. The paper will investigate the feasibility of the GONNS for modeling and optimization of

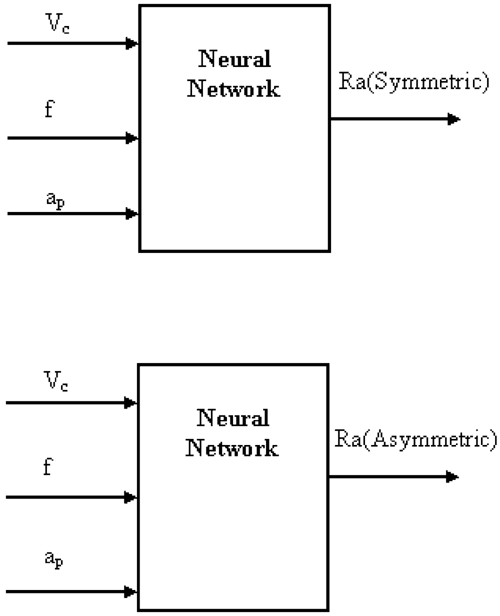

Fig. 1 Neural network structure

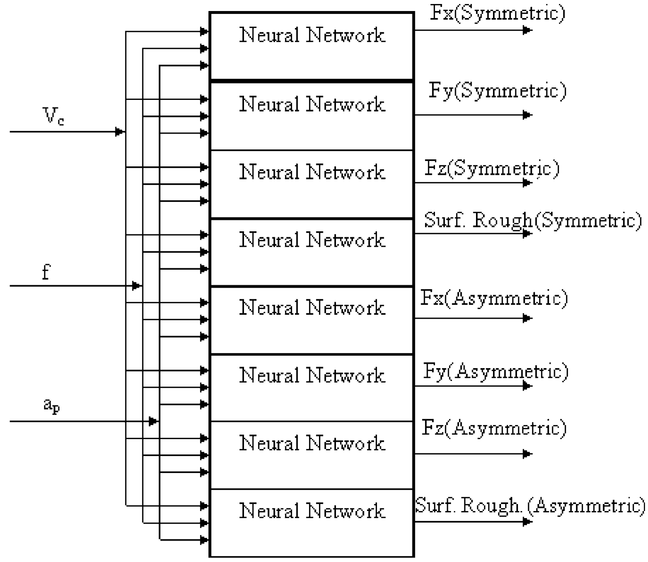

Fig. 2 Neural network structure

the surface roughness of very hard and difficult to cut materials such as Stellite 6.

In face-milling operations, cutting conditions, tool geometry, tool condition, use of coolant, stability of the machine, cutting method, tool, and work piece materials determine the surface roughness [7–17]. The cutting conditions include the feed rate, depth of cut, number of inserts, and cutting speed. The nose radius and flank width are the influential tool geometry parameters. The tool condition is mainly represented by the progressive tool wear and edge fracture. To estimate the surface roughness, statistical [7] and numeric [12] methods have been proposed. Influence of vibration [11], coolant [13], and tool geometry [16] on the surface quality has been carefully studied, and the most influential parameters have been identified [15]. Artificial neural networks (ANNs) [18–21] and analytical models [22, 23] have been used to correlate the machining conditions with the surface roughness for various materials.

The genetic algorithm (GA) [24] may estimate a large number of parameters of an objective function by using a search method which emulates the natural selection process. Compared to other optimization methods, GA is more robust avoiding converging to local minima. It works effectively, with linear, non-linear, even rule-based systems. Some of the previous GA applications include health monitoring [25], diagnostic of machining operations [26], selection of optimal parameters for cutting processes [27–29], prediction of surface roughness [30], and prediction of tool wear [31].

GONNS is an automated software environment with its own modeling and search tools. GONNS [32–35] uses multiple backpropagation (BP)-type neural networks to represent the relationship(s) between the inputs and outputs of the considered system. GA searches for the optimal solution by minimizing or maximizing one of the outputs and all the other outputs are kept at the desired range. GONNS have two important advantages over the conventional optimization techniques. First, the conventional optimization methods require an analytic expression to represent the relationship between the inputs and the outputs. GONNS learns the relationship from the training data. The user only needs to estimate the number of the hidden neurons of the neural network by considering the complexity of the relationship. It is necessary to estimate either an analytical or an empirical model for the system when the conventional methods are used. Later, the parameters of this model should be estimated with a curve-fitting process. GONNS simplifies

Table 1 Properties of the developed backpropagation-type ANN

NN properties	
Iteration number	1,000,000
Momentum constant	0.5
Learning rate	0.5
Algorithm	Backpropagation
NN structure	3–10–1
Goal	1e–4
Error algorithm	Root mean square error

Table 2 Properties of developed genetic algorithm

Generation step	10,000
Population size	6
Child number	1
Crossover probability	0.01
Creep mutation coefficient	0.01

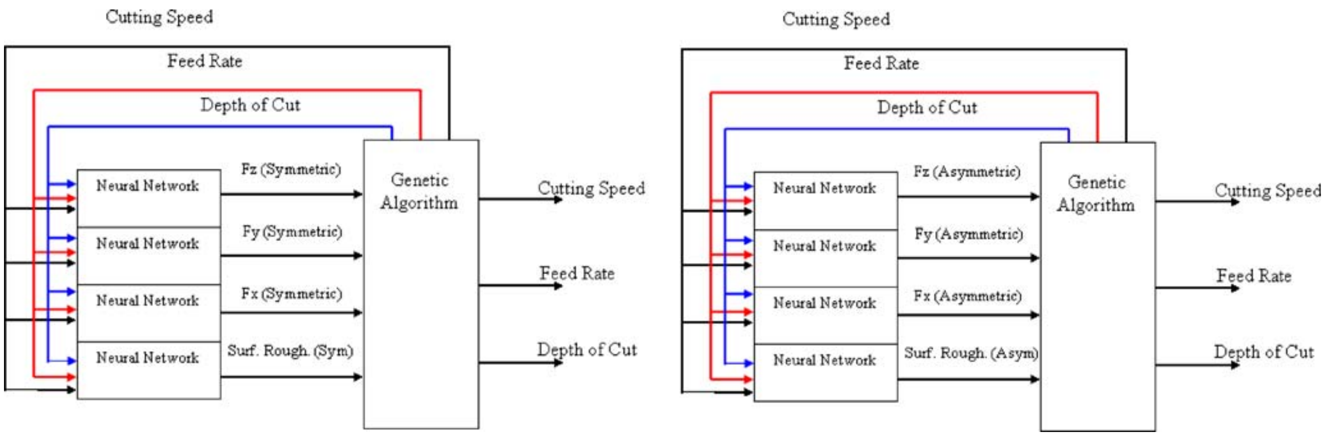

Fig. 3 The architecture of the proposed GONNS for the symmetrical (*left*) and asymmetrical (*right*) machining operation

modeling. Second, almost all the other optimization programs minimize or maximize an objective function provided by the user. We believe it is difficult and time-consuming writing this expression. GONNS creates the objective and/or penalty functions automatically to let the user to reach to his goals conveniently.

In this paper, the surface roughness and cutting force estimation performance of the ANNs were evaluated for the Stellite 6 alloy to determine if a consistent relationship could be established between the machining conditions of this very hard material and surface quality. GONNS was used to determine the optimal operating conditions. Since many papers have described the theory of the ANN, GA, and GONNS, we will discuss them in the other sections very briefly.

2 Proposed procedure

2.1 Neural network design

In this study, the performance of the backpropagation-type ANN was first evaluated by preparing a three input–one output–two ANN. The structure of feed-forward BP network is presented in Fig. 1. The inputs of the network were cutting speed (V_c), feed rate (f), and depth of cut (a_p). The outputs of the neural network were symmetrical and asymmetrical surface roughness (Ra_{sym} and Ra_{asym}).

The selected iteration number, momentum constant, learning rate, learning algorithm, number of the hidden layers and nodes, targeted error to stop the iterations, and procedure for calculation of the error are presented in Table 1.

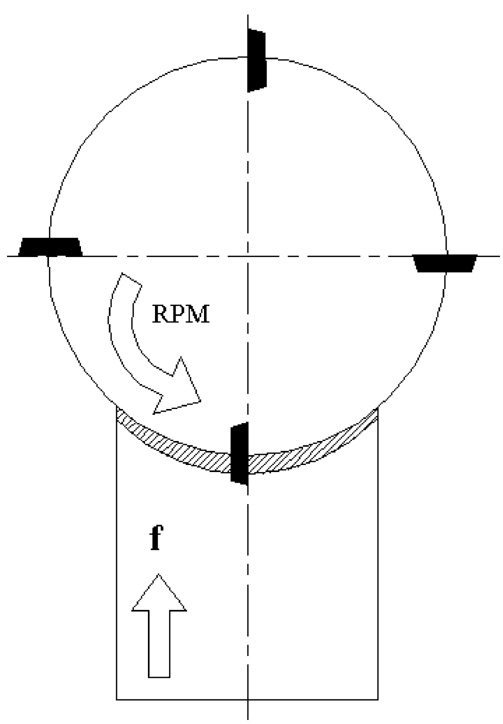

Fig. 4 Symmetric face milling

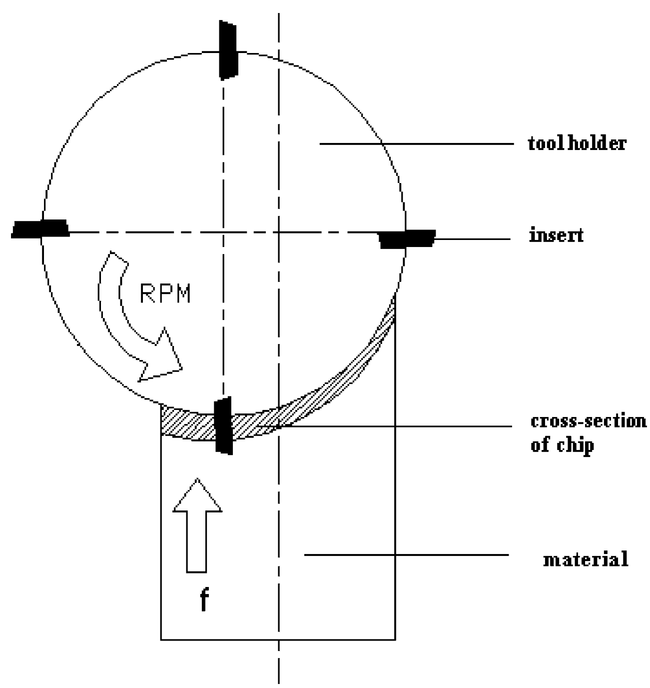

Fig. 5 Asymmetric face milling

Table 3 Cutting parameters for face milling

Cutting speeds	(m/min)	30, 35, and 40
Feed rate	(mm/min)	60, 70, 80, 90, and 100
Depth of cut	(mm)	0.25, 0.50, and 0.75
Width of cut	(mm)	50
Feed rates per tooth	(mm/tooth)	0.10
Coolant	–	Dry

Two separate GONNS were prepared to model and optimize the symmetrical and asymmetrical cutting separately. Each GONNS represented the relationship between three inputs and each one of the four considered outputs. The inputs were the cutting speed (V_c), feed rate (f), and depth of cut (a_p). The outputs of eight neural networks were two surface roughness values (Ra_{sym} and Ra_{asym}) and cutting forces (Fx_{symt}, Fy_{symt}, Fz_{symt}, Fx_{asymt}, Fy_{asymt}, Fz_{asymt}). The diagram of the neural networks of the GONNS is presented in Fig. 2. The selected iteration number, momentum constant, learning rate, learning algorithm, number of the hidden layers and nodes, type of the transfer function, targeted error to stop the iterations, and procedure for calculation of the error are presented in Table 1.

2.2 Genetic algorithm

The inputs of the genetic algorithm were surface roughness and three force components. There were two separate GONNS. One of them was for the symmetrical, and the other one was for asymmetrical cutting. The inputs of the GA for the symmetrical cutting were Ra_{sym}, Fx_{symt}, Fy_{symt}, and Fz_{symt}. The inputs of the GA for the asymmetrical cutting GONNS were Ra_{asym}, Fz_{asymt}, Fx_{asymt}, Fy_{asymt}, and Fz_{asymt}. The outputs of the genetic algorithm were cutting speed (V_c), feed rate (f), and depth of cut (a_p). The selected generation step, population size, child number, crossover probability, and creep mutation coefficient are presented in Table 2.

2.3 GONNS design

ANNs may model any linear, non-linear, or even logical system without any analytical or empirical model. The user only selects the number of the nodes at the single hidden layer of our GONNS program. GA is selected for its flexibility and robustness against local minimas. GONNS use the ANN–GA combination to model the system and optimize one of the outputs while the others are kept within the selected range by the operator. The proposed GONNS for the current problem is presented in Fig. 3. Four BP-type ANNs and one genetic algorithm was used for each optimization system. The program searched the optimal depth of cut, feed rate, and cutting speed to minimize or maximize one of the four parameters while the other parameters were kept at the desired range. This approach has two advantages over the conventional objective functions which use a weight coefficient for each parameter:

1. In many applications there are critical values for parameters. When the values of those parameters are not within these boundaries, optimization results are not acceptable. In our approach, these boundaries are directly given. In the conventional approach, the weights have to be adjusted, and optimization has to be repeated until the values of these parameters are found within the boundaries.
2. Most of the conventional optimization programs require the user to write the objective function and to determine the weight factors for the parameters. In our program, the user does not need to write any code although we allow him to give the objective function if he wants to.

3 Experimental procedure

The experiments were performed by using 9 kW JohnFord WMC-850 CNC milling machine. Symmetrical (Fig. 4) and asymmetric (Fig. 5) face-milling operations were performed [4]. The cutting parameters were selected by considering the ISO 8688-1 tool life test guidelines [24] and presented in Table 3. Uncoated inserts which are the most suitable for the rough milling at slow feed rate and cutting speed were used in the tests. The inserts with 0.18 mm chamfer were installed to the face-milling cutter. Their hardness was 78 Rockwell C and had 2° angle with the contact surface during the machining operation.

The workpiece material was Stellite 6 with 44 Rockwell C hardness. Chemical composition of the workpiece is presented in Table 4. At the beginning of the tests, the dimensions of the workpiece were 50 mm×70 mm×120 mm. Cobalt is a soft and easy to machine material. The carbon, chrome, and tungsten content of Stellite 6 give it the ductility, resistance to corrosion, and strength which makes it a superalloy.

4 Surface roughness and cutting force measurements

The diagram of the experimental setup is presented in Fig. 6. Three-component three-axis Kistler 9265B dyna-

Table 4 Chemical composition of Stellite 6

Element	C	Si	Mn	Cr	Ni	Mo	W	Ti	Fe	Ta	Co
Weight (%)	1.09	1.07	0.49	28.17	1.92	0.96	5.17	0.01	2.88	0.04	Balanced

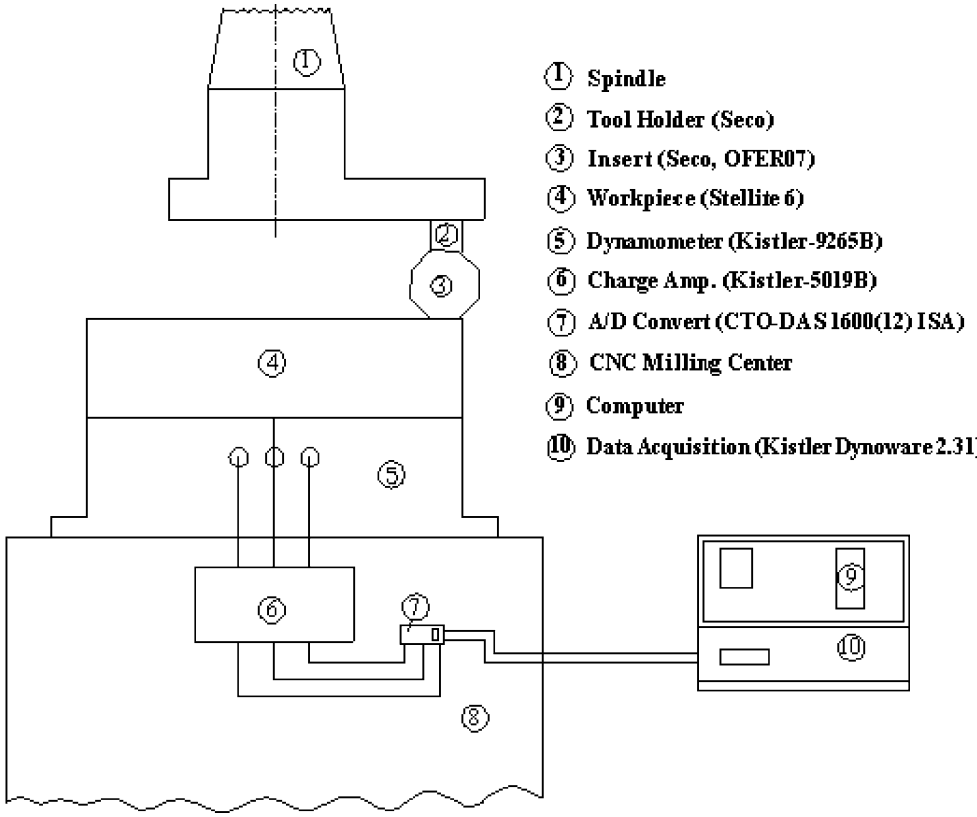

Fig. 6 Experimental setup [4]

mometer was used to measure the cutting forces. The signals of the dynamometer were connected to Kistler 5019B charge amplifier which outputs analog voltage according to the selected gains with a microprocessor-based circuit. The signals were digitized by using CTO-DAS 600 812 ISA A/D converter. Data were displayed with a Kistler DynoWare 2.31 software and transferred to Excel spreadsheet for analysis.

The cobalt-based superalloy was cut by using uncoated hard metal inserts. The averages of the cutting force components (F_x, F_y, and F_z) were calculated and presented in Appendix.

Surface roughness strongly influences the coefficient of friction, wear characteristics, light reflection, heat transmission, lubricant holding capability, coating, and fatigue resistance of materials [37]. In this study, the average surface roughness which is often quoted with Ra was measured by using Mahr M1 perthometer [4, 39]. Ra is calculated by averaging the departure of the profile from the centerline as presented in Fig. 7. The following equation was used for calculation of the Ra [38].

$$\mathrm{Ra} = \frac{1}{L}\int_0^L |Y(x)|\mathrm{d}x$$

Ra The arithmetic average deviation from the mean line
Y The ordinate of the profile curve

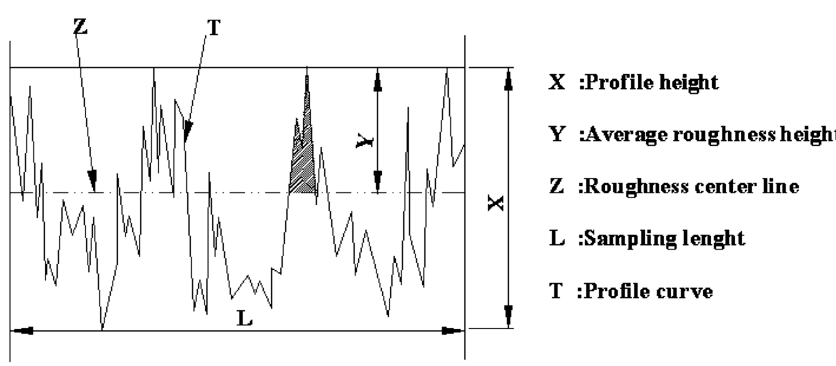

Fig. 7 Surface roughness profile

The same signals were captured at the each experiment. They were the averages of the F_x, F_y, and F_z components and the average surface roughness (Ra). For calculation of the average force components, about 1,000 values collected in a 3-s time interval.

5 Results and discussion

The objective of this study is to propose a convenient method for estimation of the surface roughness after a series of data is collected at different feed rates, depth of cuts, and spindle speeds. All the other conditions including the use of coolant, machine tool, fixture, CNC program, and the characteristics of the inserts were fixed in out of the experiments. If the user wants to consider the influence of these conditions, the data should be collected for possible cases. For example, data could be collected for the different values of coolant flow rates. The neural networks have the flexibility to accommodate these changes. However, the number of the necessary experiments will drastically increase with the considered conditions. That is why we fixed the listed conditions in our experiments.

In this study, two 3 input−1 output and eight 3 input–1 output ANNs were used. The accuracy of the ANN was

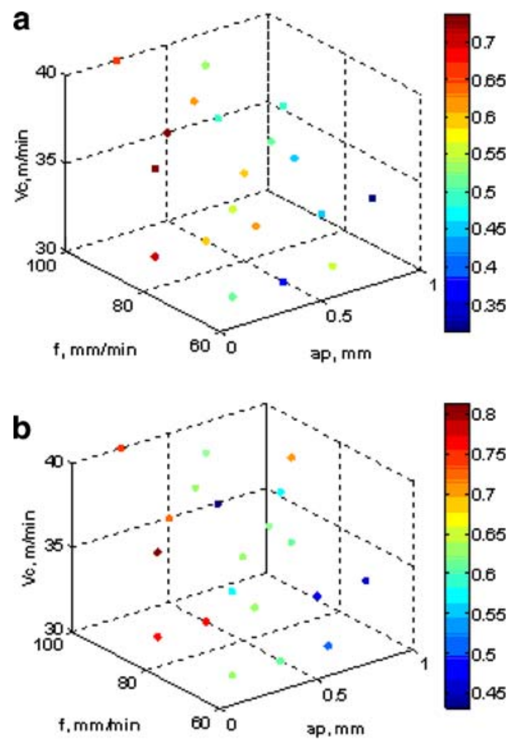

Fig. 9 Surface roughness estimation performance of the three input–one output ANN for symmetric face-milling operations, testing cases. **a** Measured surface roughness. **b** ANN estimation

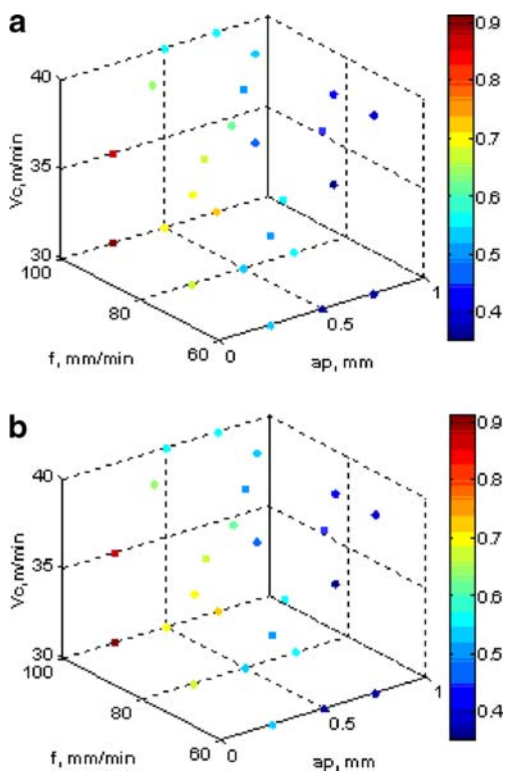

Fig. 8 Surface roughness estimation performance of the three input–one output ANN for symmetric face-milling operation, training cases. **a** Measured surface roughness. **b** ANN estimation

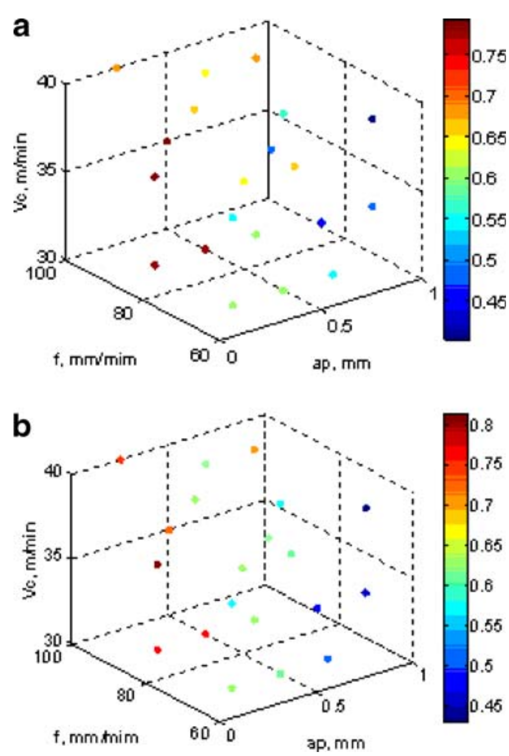

Fig. 10 Surface roughness estimation performance of the three input–one output ANN for asymmetric face-milling operations, training cases. **a** Measured surface roughness. **b** ANN estimation

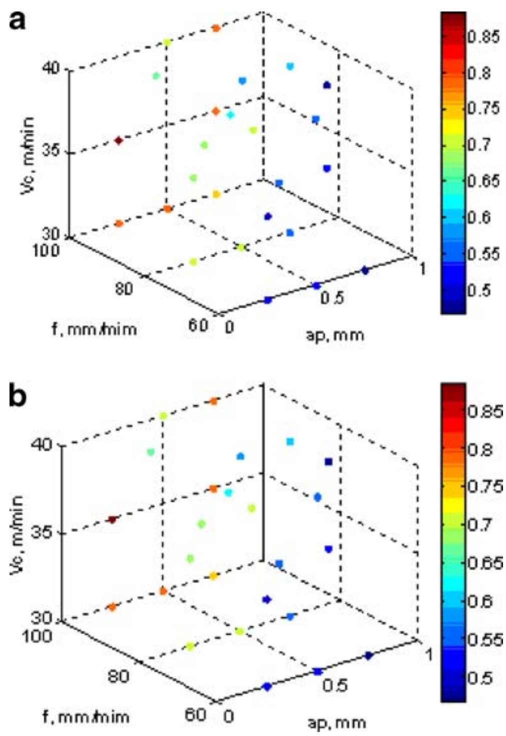

Fig. 11 Surface roughness estimation performance of the three input–one output ANN for asymmetric face-milling operations, testing cases. **a** Measured surface roughness. **b** ANN estimation

evaluated by comparing the two 3 input–1 output ANN's estimations with actual values after the training process. The eight 3 input–1 output ANNs were used by the GONNS.

Performance of the GONNS depends on the characteristic of the data. Less than 1% estimation error has been observed when the optimal point is estimated at the surfaces of the following equations [33]:

$$f_1 = \sin(\times) + \sin(y) \quad (1)$$

$$f_2 = 0.4(\times - 1.8)^2 + 0.4\sin(y-2)^2 - 1 \quad (2)$$

GONNS is expected to perform well as long as the boundaries are covered with smooth surfaces. GONNS is an effective optimization algorithm for the selection of the optimal cutting conditions since experimental results indicate a constant trend and smooth change at the outputs for different values of the inputs.

The two 3 input–1 output ANN predicted the symmetric and asymmetric surface roughness by using backpropagation-type neural network. The training and testing data were collected at the feed rates of 60, 70, 80, 90, and 100 m/s; cut depths of 0.25, 0.50, and 0.75 mm; and cutting speeds of 30, 35, and 40 m/s. Seventy-five cases were used for training, and 60 cases were used for testing. The ANN program made 1,000,000 iterations. The training of the neural network took about 3 h with a microcomputer which uses Intel® Core 2 CPU 6400 microprocessor operating at 2.13 GHz.

The operational parameters of the ANN are presented in Table 1. The training was repeated with five to 45 nodes located at the single hidden layer. The minimum estimation errors were observed when ten nodes were used. The average estimation errors for the Ra_{asmt} were 0.4% and 5% for the training and test cases, respectively. Estimation errors for the Ra_{smt} were slightly higher with 0.5% for training and 7% for testing.

Cutting speed (V_c, meter per minute), feed rate (f, millimeter per minute), depth of cut (a_p, millimeter), and surface roughness (Ra_{symt} and Ra_{asmt}, micrometer) relations are presented in Figs. 8, 9, 10, and 11. The x axis is the depth of cut, y axis the feed rate, and z axis the cutting speed. The color indicates the surface roughness. Experiment results are presented in Figs. 8a, 9a, 10a, and 11a ANN presentations.

The performances of the eight 3 input–1 output neural networks were evaluated on the training data. Their performance is outlined by listing the average estimation errors in Table 5 for the training cases. The inputs were cutting speed (V_c), feed rate (f), and depth of cut (a_p). The eight outputs of eight neural networks were surface roughness (Ra_{sym} and Ra_{asym}) and cutting force (Fx_{asymt}, Fy_{asymt}, Fz_{asymt}, Fx_{symt}, Fy_{symt}, and Fz_{symt}).

Optimization was performed many times and reasonable estimations were obtained. The display of the GONNS is presented for three cases. The minimization of the z direction force was requested for asymmetrical face-milling operation in Fig. 12 and acceptable surface roughness, and x and z direction average forces were inputted. The GONNS made reasonable suggestions for the cutting speed, feed rate, and depth of cut. In Fig. 13, symmetrical face milling was considered. Minimization of the surface roughness was requested and the ranges of the acceptable forces were presented.

The optimal values (maximum and minimum) of each output and the corresponding operational parameters including depth of cut, feed rate, and cutting speed were calculated by using the GONNS and listed in Table 6. The boundaries of the outputs other than the optimized one and

Table 5 Total absolute percentage error

	F_z (%)	F_y (%)	F_x (%)	Surface roughness (%)
Symmetric	0.5167	0.3658	0.6428	0.9792
Asymmetric	0.1605	0.3744	0.04769	0.3643

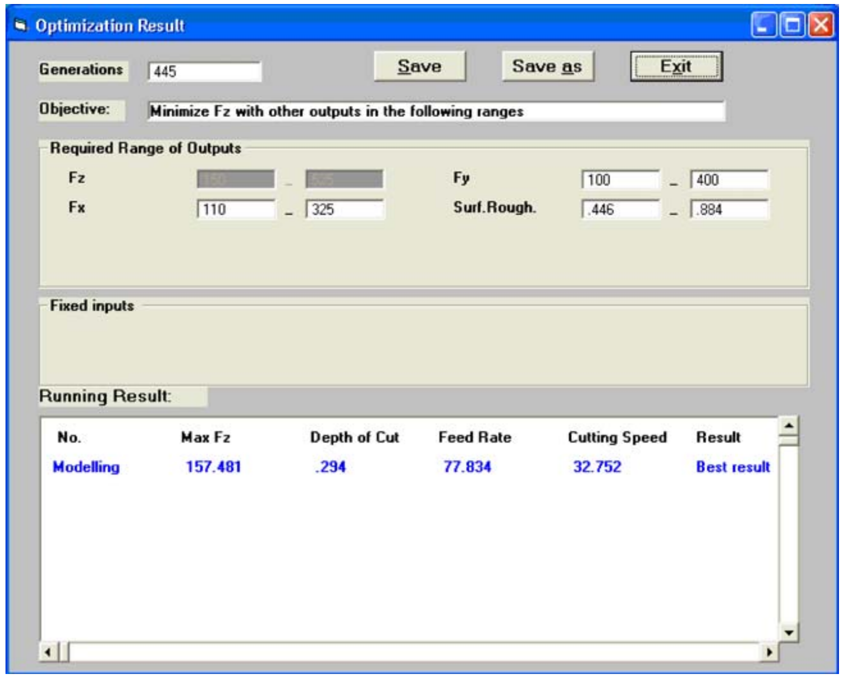

Fig. 12 The recommended operating conditions by the GONNS to minimize the z direction cutting force in the asymmetrical face-milling operation

the operational parameters were the full range either used or observed in the experiments.

If the user wants to see how the optimum cutting conditions change at different wear levels, the experimental data may be collected with the worn tools. GONNS may have one more input or one of the current input parameters may be removed by fixing that parameters. As we mentioned earlier, GONNS may deal with more than three input parameters; however, the number of the needed experiments will drastically increase and estimation accuracy may suffer.

6 Conclusions

In this study, extensive data were collected during the face milling of Stellite 6 superalloy. The data were mainly used to evaluate the feasibility of the GONNS for selection of the

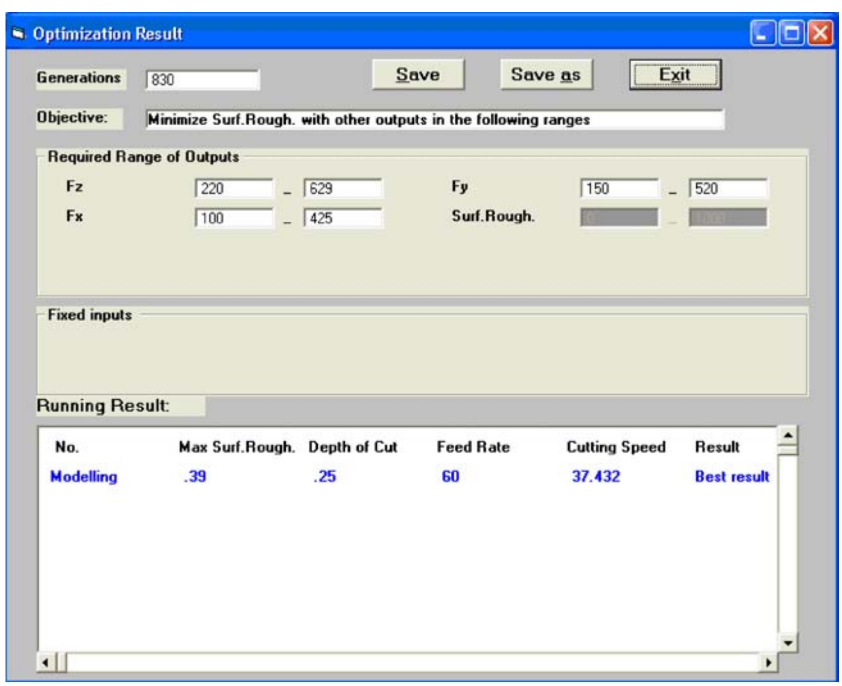

Fig. 13 The recommended operating conditions by the GONNS to minimize the surface roughness in the symmetrical face-milling operation

Table 6 Optimization results for single output of the ANNs (max and min) and the operating values including depth of cut, feed rate and cutting speed. The other outputs were allowed to take any value observed in the experiments

Optimize to minimize 1 parameter while keeping the other in the desired range		Optimized output values		Estimated input values to work at the optimal conditions					
				Depth of cut (mm)		Feed rate (mm/min)		Cutting speed (m/min)	
		Maximum	Minimum	Maximum	Minimum	Maximum	Minimum	Maximum	Minimum
Symmetric	F_z (N)	667.396	205.453	0.484	0.369	100	61.56	38.902	30
	F_y (N)	473.965	150.83	0.635	0.25	94.921	60	33.73	30.001
	F_x (N)	511.03	86.579	0.43	0.255	98.407	60	35.918	31.97
	Surface roughness (μm)	0.914	0.39	0.25	0.25	99.999	60	33.124	37.432
Asymmetric	F_z (N)	553.072	157.48	0.541	0.294	96.087	77.834	36.838	32.752
	F_y (N)	399.281	81.722	0.75	0.25	99.909	67.338	39.999	32.966
	F_x (N)	337.215	94.194	0.567	0.282	96.57	62.372	32.712	32.612
	Surface roughness (μm)	0.913	0.365	0.25	0.75	100	60	33.36	38.132

optimal machining parameters. In addition, accuracy of the ANN estimations was tested when they represented the machining operations.

Inspection of the experimental data indicated that the surface roughness improves with increasing cutting speed and decreasing feed rate as expected. Symmetrical cutting generally had better surface roughness values. A consistent relationship was observed between the operational parameters and the outputs of the machining operation: surface roughness and cutting forces. This relationship was represented by the ANNs. When the ANN estimated the surface roughness from the operational parameters, the accuracy was better for the asymmetric milling operation with 0.4% and 5% for training and testing cases, respectively. For the symmetric milling operations, slightly higher estimation errors, around 0.5% and 7% for the training and testing, were observed.

The ANNs of the GONNS learned the characteristics of the forces and surface roughness with less than 1% error during their training. The estimations of the GA were very similar to a human operator, who would carefully evaluate the trends and select the operating conditions. GONNS was found to be an effective multipurpose optimization tool in the study. Elimination of the need for either development of an analytical model or estimation of an empirical expression was the most important advantage of the method.

Appendix

Table 7 Asymmetric experiment cutting force results

Trail no.	a_p, mm	f, mm/min	V_c, m/min	F_z, N	F_y, N	F_x, N
1	0.25	60	30	150	110	120
2	0.25	70	30	200	100	120
3	0.25	80	30	200	100	110
4	0.25	90	30	260	120	120
5	0.25	100	30	270	140	150
6	0.25	60	35	250	100	130
7	0.25	70	35	255	90	140
8	0.25	80	35	250	120	130
9	0.25	90	35	270	130	160
10	0.25	100	35	320	150	180
11	0.25	60	40	225	175	140
12	0.25	70	40	260	150	165
13	0.25	80	40	300	210	180
14	0.25	90	40	330	240	200
15	0.25	100	40	355	260	225
16	0.5	60	30	250	255	200
17	0.5	70	30	275	260	225

Trail no.	a_p, mm	f, mm/min	V_c, m/min	F_z, N	F_y, N	F_x, N
18	0.5	80	30	350	300	230
19	0.5	90	30	350	325	245
20	0.5	100	30	375	330	250
21	0.5	60	35	375	250	300
22	0.5	70	35	450	275	250
23	0.5	80	35	475	300	310
24	0.5	90	35	525	325	320
25	0.5	100	35	530	350	325
26	0.5	60	40	325	225	170
27	0.5	70	40	350	250	185
28	0.5	80	40	375	270	210
29	0.5	90	40	480	300	225
30	0.5	100	40	490	310	250
31	0.75	60	30	250	200	250
32	0.75	70	30	325	200	260
33	0.75	80	30	400	210	275
34	0.75	90	30	400	225	280
35	0.75	100	30	415	250	310
36	0.75	60	35	375	250	175
37	0.75	70	35	400	270	150
38	0.75	80	35	425	300	150
39	0.75	90	35	450	310	200
40	0.75	100	35	500	330	220
41	0.75	60	40	320	300	200
42	0.75	70	40	450	320	220
43	0.75	80	40	475	345	225
44	0.75	90	40	500	375	250
45	0.75	100	40	525	400	275

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