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Prediction of cutting force for self-propelled rotary tool using artificial neural networks

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Abstract

In this paper, a cutting force model for self-propelled rotary tool (SPRT) cutting force prediction using artificial neural networks (ANN) has been introduced. The basis of this approach is to train and test the ANN model with cutting force samples of SPRT, from which their neurons relations are gradually extracted out. Then, ANN cutting force model is achieved by obtaining all weights for each layer. The inputs to the model consist of cutting velocity V, feed rate f, depth of cut a_p and tool inclination angle λ, while the outputs are composed of thrust force F_x, radial force F_y and main cutting force F_z. It significantly reduces the complexity of modeling for SPRT cutting force, and employs non-structure operator parameters more conveniently. Considering the disadvantages of back propagation (BP) such as the convergence to local minima in the error space, developments have been achieved by applying hybrid of genetic algorithm (GA) and BP algorithm hence improve the performance of the ANN model. Validity and efficiency of the model were verified through a variety of SPRT cutting samples from our experiment tested in the cutting force model. The performance of the hybrid of GA–BP cutting force model is fairly satisfactory.

Keywords: Self-propelled rotary tool; Cutting force; Neural network; BP; GA

1. Introduction

Material removal is one of the major and oldest shaping processes for the economic production of machine components. Because of the wide use of engineering materials and alloys steels with high hardness in the aerospace industry, fast and precise machining problems have attracted much attention in manufacturing industries for over the last 30 years. Hence rapid failure of cutting tool leads to deterioration of the work piece surface integrity, loss of geometrical tolerances and increase of machining times. The machining time increase is due to downtime in consequence of the exchanging and resetting of cutting tools furthermore reduction of tool life hence ultimately increases of unit cost. In view of all these above-mentioned machining problems, an attempt has been made to introduce an effective machining method through development of a SPRT system, which can overcome the machining barriers [1].

In 1865, this concept was used in turning operation, then followed the pioneering work in 1960s [2] on metal cutting process using rotary tools from which finally conclusions that *chip length ratio* as high as two [3] could be achieved using rotary tools. Thereafter, Venuvinod and Rubenstein [4] presented a detailed kinematics analysis of chip formation for machining process using the rotary tools. And also Chen [5] studied cutting force in machining of high-performance materials with self-propelled rotary tools. Consequently, many researchers have been attracted by the cutting force parameters because of their importance to the tool structure design and optimization, as well as the real-time control and compensation during the manufacturing processes [6,7].

A large number of parameters influence the cutting forces such as cutting velocity, feed rate, depth of cut, rake angle, nose radius, cutting edge inclination angle, physical and chemical characteristics of the machined part, chip breaker geometry, etc.; therefore, it is a very difficult task to develop a proper cutting force analytic model [8]. Although enormous data related to cutting force is available in machining handbooks, most of such data defines the relationship between a few of the possible cutting parameters whilst keeping the other parameters fixed.

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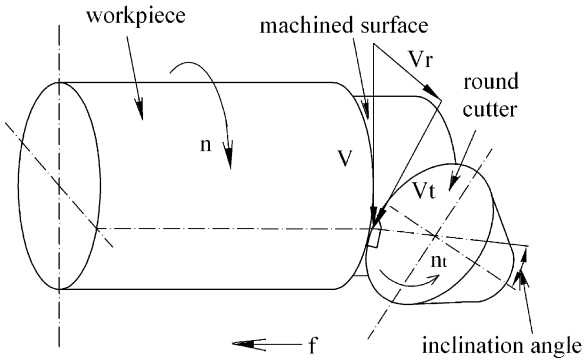


Fig. 1. Mechanism of rotary turning action.

Subsequently this paper aims at developing a model of cutting force with the help of ANN.

2. Analysis of SPRT cutting force

In the pioneering work, Shaw et al. [9] presented a study of a lathe-type of cutting tool in the form of a disk that rotates around its center. The continuous spinning of the tool around its center allows for the use of the entire insert circumference. As a result of tool spinning, a fresh portion of the cutting edge is provided hence a better distribution of tool flank wears over the entire cutting edge. The spinning action of the tool provides a way for carrying the fluid to the tool tip at a high cutting velocity in the case of a journal bearing.

The experiment set-up of typical machining process using the rotary tool and its main motions are shown in Fig. 1. In SPRT cutting process, the spinning action is achieved by the interaction between the tool and the chip, which requires the cutting edge to be oblique with the cutting velocity (V). The tool rotational velocity (V_t) is a function of the cutting velocity and the inclination angle (λ) between the axis of the work piece and axis of tool inserts. Obviously, the inclination angle λ is very important since it determines the SPRT cutting performance.

The resolving of the three components for total cutting force F_c and their momentum analysis is shown in Fig. 2. To keep the force equilibrium, F_c should intersect its rotating axis, which is the key characteristic of rotary tool cutting force.

Whatever analytical model is used, it can hardly cope with the complexity of the cutting process. Also, for developing an analytical model, proper methods for extracting general relationships from existing machining data are required. Instead of attempting to find analytical relationships between machining parameters by the use of statistical approaches, this paper aims at developing SPRT cutting force model with ANN trained by non-structured manufacturing data.

3. Description of neural networks

ANN offers an alternative way to simulate complex and ill-defined problem [10]. In this paper, the force model involves four operating parameters of SPRT, namely cutting velocity V, feed rate f, depth of cut a_p and tool inclination angle λ; and also the three components of the cutting forces F_x, F_y and F_z, which are selected to train the ANN. A highly simplified model of a three-layer ANN includes an input layer, a hidden layer and an output layer (as shown in Fig. 3).

3.1. Back propagation algorithm

One of extensively used ANN models for system modeling application is the multilayer perceptron model based on the BP [11]. In the BP algorithm learning based, the initial weights of connections are randomly chosen. Suppose we have N learning examples with each example having n inputs and l outputs, the input vector can be described as $X_j = (X_{1j}, \ldots, X_{nj})$ and the output vector as $A_j = (A_{1j}, \ldots, A_{lj})$, $1 \le j \le N$. The learning process takes place using the following two steps:

1. *Forward propagation*: The input vector X_j is fed into the input layer and an output vector $O_j = (O_{1j}, \ldots, O_{lj})$ is generated on the basis of the current weights $W = (W_{1l}, \ldots, W_{nl})$. The

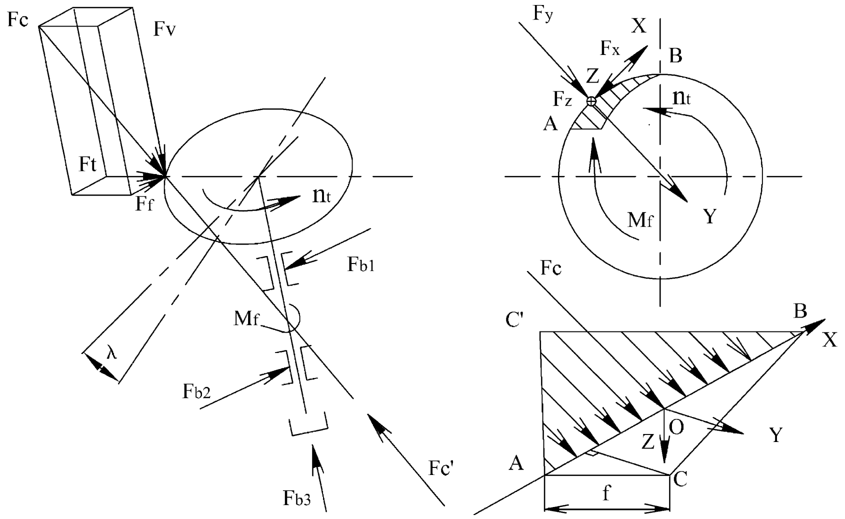


Fig. 2. Analysis of self-propelled rotary tool cutting force.

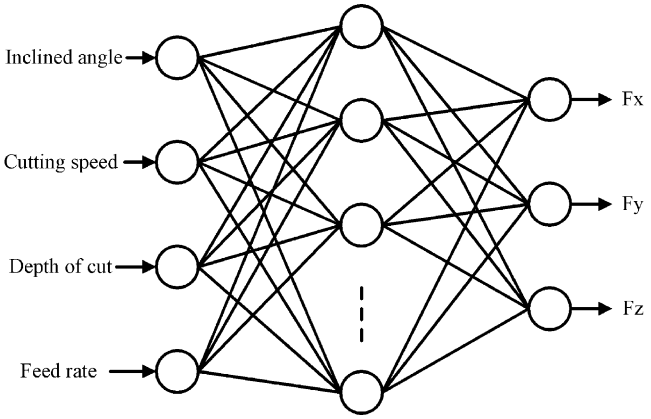


Fig. 3. The neural network model for prediction of the SPRT cutting forces.

value of O_j is compared with the actual output A_j and the output differences are summed to generate an error function E defined as

$$E = \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{N}(A_{ij} - O_{ij})^2 \tag{1}$$

2. *Error back propagation*: In this step, the error from Eq. (1) is back propagated by performing weights update using gradient descent as follows:

$$\Delta W_{nl} = -\frac{\partial E}{\partial W_{nl}}\eta \tag{2}$$

where $0 < \eta < 1$ is a parameter controlling the convergence rate of the algorithm. The process of forward propagation and error back propagation continues until E converges to a predefined small value. ΔW_{nl} is accumulated and updated after a complete run of all the N examples for our research.

However, the basic BP algorithm described above is often very slow to converge in real practice. Just as Hopfield nets can sometimes get stuck in undesired spurious attractor states, multilayer perceptions can also get trapped in some undesired local minimum status. This is an unfortunate artifact that plagues all energy minimization schemes. In order to overcome the obstacles of these problems, BP algorithm has adopted many improvement techniques. Initializing the BP weights with GA contains many merits hence attracts the scholars and researchers interesting [12].

3.2. Hybrid of GA–BP neural networks

GA is probabilistic heuristic search processes based on natural selection. And its modern form is derived mainly from Holland's work in the 1960s [13] and the second edition of Holland's classic 1975 book Adaptation in Natural and Artificial Systems [14]. GA is capable of solving wide range of complex optimization problems only using three simple genetic operations (selection, crossover and mutation) on coded solutions (strings, chromosomes) for the parameter set, not the parameters themselves in an iterative fashion. GA considers several points in the search space simultaneously, which reduces the chance of convergence to a local optimum [15,16]. Adopting the GA to select the initialize BP weights containing the information of SPRT cutting force in a large scope, the hybrid of GA–BP ANN model improves the cutting force mapping precision.

The hybrid network learning process consists of two stages: firstly employing GA to search for optimal or approximate-optimal connection weights and thresholds for the BP network, then using the BP to adjust the final weights, in which the sigmoid function is used as the activation function. The steps of learning optimal value for network weights are achieved using the hybrid of GA–BP algorithm as shown in Fig. 4. At first, the populations initialization is done; then performance of tournament selection; followed by crossover with probability P_c and mutation with probability P_m. Inverse value of the learning error is taken as the fitness function that is calculated to find the best fitness population member. If the GA terminating condition is false, the program returns for tournament selection; otherwise, it continues to select potential candidates and compute holdout sample weights. In this way, the ANN weights and thresholds are initialized as genes of best fitness pop member followed by propagation of the inputs forward and then back propagate the errors. If the BP stopping condition is false, the weights and

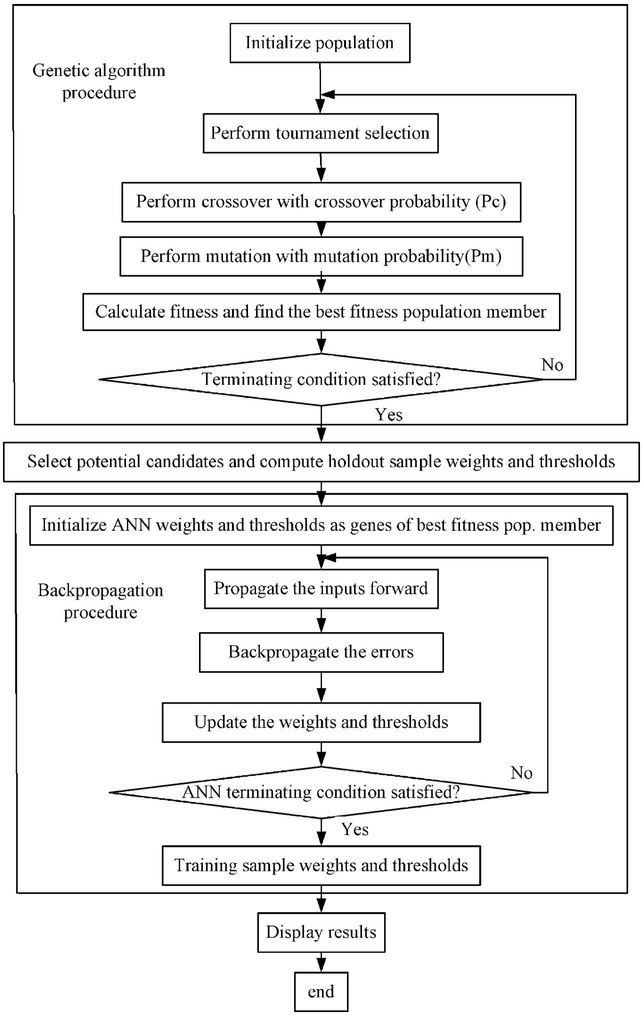


Fig. 4. The flowchart of a three-layer GA–BP neural network model.

thresholds are updated; otherwise, they are saved and provided for future prediction of the SPRT cutting forces.

4. Modeling and predicting method

The developed model for cutting force can be used for simulation purposes and for defining threshold force values in monitoring systems for cutting tool condition by specifying the cutting conditions.

4.1. Description of the experimental set-up

To develop the model of SPRT cutting force, a comprehensive experimental procedure is carried out during the turning. Dry turning experiments are performed using a C620 lathe. Low carbon steel (30C%) bar of 41 mm diameter is used. The experimental were conducted using carbide tool insert with a diameter of 38 mm. The tool holder is installed in the square turret of the lathe. The cutting force components are registered by SDC-CJ4 high precession dynamometer that was made in BeiHang University (Fig. 5). The signals are collected by personal computer with aid of a data acquisition card of 12-bit multiplexed analog inputs.

4.2. Description of the neural networks modeling

The objectives of the model in this study are to approximate the connection weights and the thresholds prediction for the correct solutions. They can be represented by the average prediction accuracy of the training data, which is applied to the fitness function. The parameters to be searched only utilize the training data information.

Table 1
GA parameters and their values

GA parameters	Value
Population (P)	100
Cross-over probability (P_c)	0.1
Mutation probability (P_m)	0.05
Maximum iterations (termgen)	1000

Table 2
BP parameters and their values

BP networks parameters	Value
Networks topology structure	4-21-3
Initial weights	Random of (0,1)
Learning rate (l_r)	0.025
Momentum rate (m)	0.9
Learning adjusting coefficient (l_a)	0.8
Force adjustment coefficient (u)	0.2

A three-layer feed-forward ANN performed with the BP algorithm and the hybrid of GA and BP algorithm, respectively are developed to model the SPRT cutting force (as shown in Fig. 3). During preliminary experiments, it was proved to be sufficiently capable of extracting the force model from unstructured machining data. There are four neurons in the input layer representing cutting velocity V, depth of cut a_p, feed rate f and tool inclination angle λ and three neurons in the output layer representing component force F_x, F_y and F_z.

The selected parameters and their corresponding values are listed in Tables 1 and 2. In this study, GA operates the process of crossover and mutation on initial chromosomes and iterates until the *stopping condition* is satisfied. As shown in Table 1, for controlling parameters of the GA search, the population size P is set to 100 organisms.

Based on the experience of BP, 21 neurons are employed in the hidden layer, so that the networks topology structure is set as 4-21-3 as shown in Table 2. The strings used in the hybrid algorithm for this study have the following encoding. The first 147 bits represent the connection weights between the input layer and the hidden layer, as well as the hidden layer and the output layer. The following 28 bits are the threshold for force predic-

Fig. 5. The experimental set-up.

Table 3
The cutting force in the x-, y- and z-direction collected through the experimental runs

Inclined angle λ (°)	Cutting velocity (m/min)	Depth of cut (mm)	Feed rate (mm/rev)	Cutting force (N)		
				F_x	F_y	F_z
30	59.2	0.3	0.08	10.7	264.2	684.3
			0.12	12.5	248	703.1
			0.16	12.6	293.3	700.8
			0.20	16.2	366.6	702
40	78.5	0.2	0.08	5.5	97.4	631.4
			0.12	8.4	102.6	639.6
			0.16	9.3	137.9	664.2
			0.20	9.8	186.8	686
40	98.5	0.4	0.08	33.6	184.2	653.5
			0.12	34.8	230.25	705.2
			0.16	59.7	399.1	698.4
			0.20	56.1	602.8	713.7
50	47.6	0.6	0.08	12.0	302.7	734.1
			0.12	29.6	343.5	743.3
			0.16	65.3	327.3	758.1
			0.20	48.3	369.8	739.7

tion. The effect of the following two main training parameters on the training error convergence is also investigated. This includes the learning rate l_r that controls the speed of the adaptation of the connection weights between the neurons, and the momentum rate m that takes into account the rate of the last change of the connection weights. The training process is supervised by the desired outputs (the three cutting force components) of the network. All of the training samples values are scaled to fit into the normalized range of 0–1.

The experimental design for collecting data was set as the following combination of machining cuts: feed rate at 0.08, 0.12, 0.16, 0.20 mm/rev; depth of cut at 0.2, 0.3, 0.4, 0.6 mm; cutting velocity at 47.6, 59.2, 78.5, 98.5 m/min; inclined angle at 30°, 40° and 50°.

After the neural network set-up is completed, 192 experimental runs are conducted and the part results are shown in Table 3. The samples were divided into two sets. The first set is the learning set for the ANN training, while the other set represents the holdout set for cutting force prediction to verify the efficiency and correctness of the cutting force model. With these collected data, the ANN system is ready to launch its training scheme.

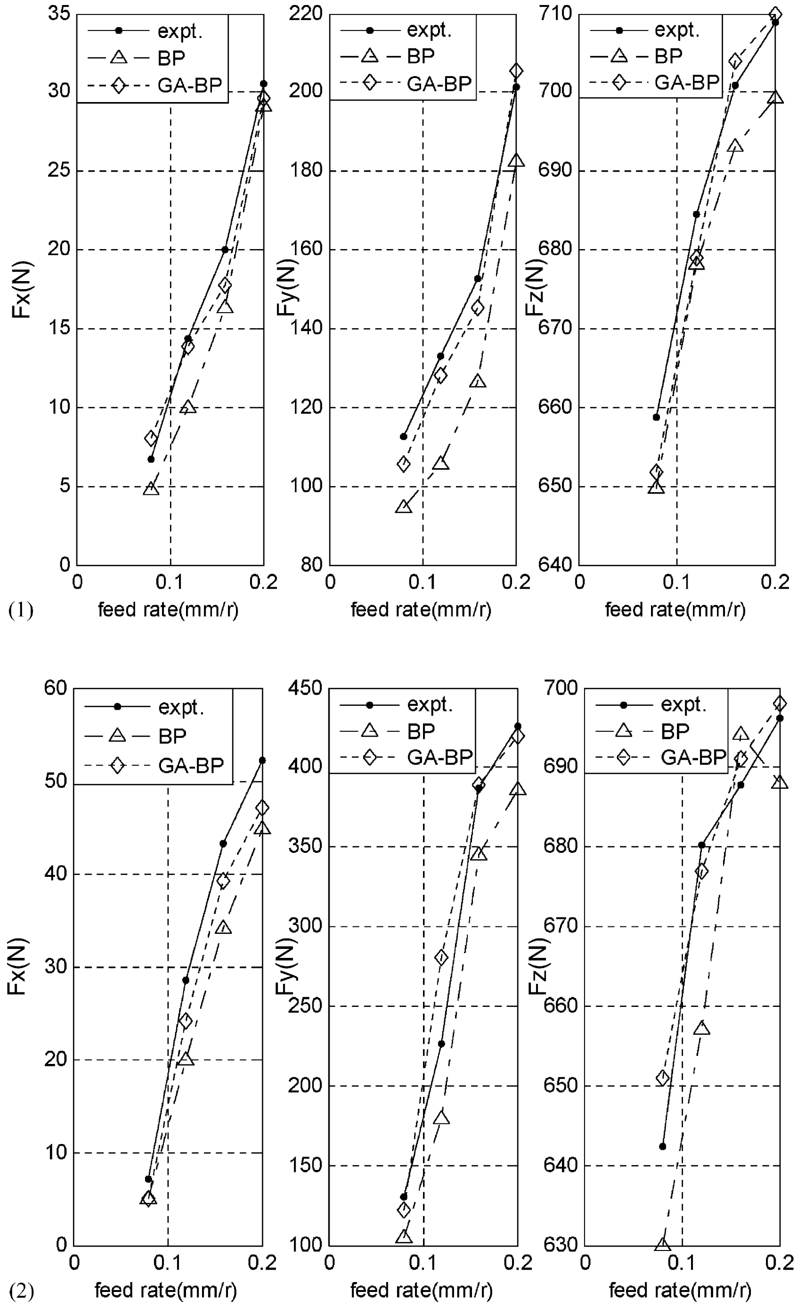
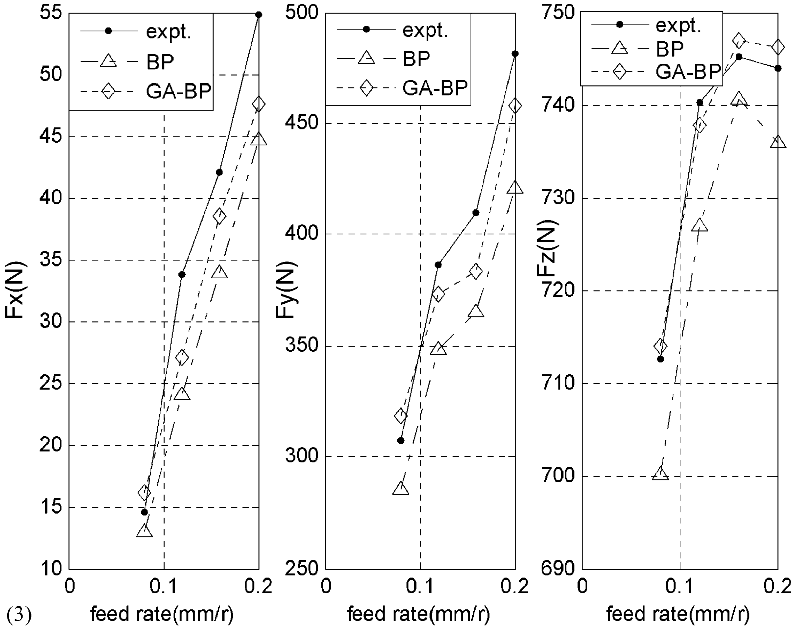


Fig. 6. The experimental curve and predicted curve of cutting force in different cutting condition: (1) $\lambda = 30°$, $V = 78.5$ m/min, $a_p = 0.2$ mm; (2) $\lambda = 40°$, $V = 98.5$ m/min, $a_p = 0.3$ mm; (3) $\lambda = 50°$, $V = 59.2$ m/min, $a_p = 0.4$ mm.



(3)

Fig. 6. (*Continued*).

5. Results and discussion

Two models in accordance with the methods of determining the connection weights of BP and hybrid of GA–BP are compared with the real experimental results in Fig. 6. The increasing of cutting operating parameters value leads to the increasing of corresponding cutting component forces. But when the operating parameters get up to a certain degree, the forces increase slowly. This phenomenon is perhaps a result of a lot of cutting heat generated by friction and deform of larger volume removal material. It is worth paying attention to the fact that there is a shade of difference for prediction accuracy between the training data and the holdout data for hybrid of GA–BP. There is, however, a wide difference between the training data and the holdout data for the BP model, especially when the cutting parameters are bigger. This result may be caused by the fact that the globally searched discretization process simplifies the learning process and eliminates the irrelevant patterns. This prevents the network from falling into the problem of over-fitting and may enhance the generalizability.

It is confirmed that the hybrid of GA–BP network predicts the SPRT cutting force more accurately than the BP network during the training period, which is very important to real-time control. From above analyses it can be seen that the SPRT cutting force model with hybrid of GA–BP network can be used to determine the optimum operating parameters for provision of recommendations to engineers and operators or directly control system to keep the SPRT work more efficiently.

6. Conclusions

Neural network as performed in this study provides a new approach to model cutting force of SPRT. This approach significantly reduces the complexity of modeling, and considers non-structure operator parameters more conveniently. Apparently, it is very useful for defining threshold forces in monitoring systems of cutting tool condition from the cutting force model in real commercial production. Considering the disadvantages of BP such as convergence to local minima in the error space, a hybrid of GA–BP algorithm has been developed to improve the performance of the ANN cutting force model, which gives more precise prediction than the standard BP algorithm does. Although the performance of the hybrid of GA–BP cutting force model shows fairly satisfactory, there remains much to be done before a really practical SPRT cutting force predicting model can be built, for instance, more parameters related to SPRT cutting force like material property should be considered.

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References

[1] C. Wuyi, C. Xing, Z. Guojin, G. Zuduan, High speed machining of hardened steel using CBN tipped rotary cutting tools, transformation of science and technology into productive power, in: Proceedings of the 11th International Conference on Production Research (ICPR), 1991, pp. 23–27.

[2] N. Ramaswamy, F. Koenigsberger, Experiments with self-propelled rotary cutting tools, in: Proceedings of the Ninth IMTDR Conference, Part 2, 1968, pp. 945–959.

[3] P.K. Venuvinod, G. Barrow, Recent progress in machining with rotary tools, in: Proceedings of the Fifth AIMTDR Conference, University of Roorkee, April 10–12, 1972, pp. 173–181.

[4] P.K. Venuvinod, C. Rubenstein, The principle of equivalent obliquity and its application to rotary cutting, Ann. CIRP (1983), pp. 53–58.

[5] P. Chen, Cutting temperature and force in machining of high-performance materials with self-propelled rotary tools, JSME Int. J. Ser. III 35 (1) (1992) 180–185.

[6] H.A. Kishawy, C.E. Becze, D.G. McIntosh, Tool performance and attainable surface quality during the machining of aerospace alloys using self-propelled rotary tools, J. Mater. Process. Technol. 152 (3) (2004) 266–271.

[7] K.M. Patel, S.S. Joshi, D.V. Bhoir, Cutting forces in machining using self-propelled round inserts face-milling cutter, in: Proceedings of the International Conference on CAD, CAM, Robotics and Autonomous Factories, 2003.

[8] S. Tamas, Cutting force modeling using artificial neural networks, J. Mater. Process. Technol. 92–93 (1999) 344–349.

[9] M.C. Shaw, P.A. Smith, N.H. Cook, The rotary cutting tool, Trans. ASME 74 (1952) 1065–1076.

[10] Q. Zhu, J.M. Jones, A. Williams, K.M. Thomas, The predictions of coal/char combustion rate using an artificial neural network approach, Fuel 78 (14) (1999) 1755–1762.

[11] R.J. Erb, Introduction to back propagation neural network computation, Pharm. Res. (1993) 165–170.

[12] R.S. Sexton, B. Alidaee, R.E. Dorsey, J.D. Johnson, Global optimization for artificial neural networks: a tabu search application, Eur. J. Operat. Res. 106 (2/3) (1998) 570–584.

[13] J.H. Holland, Universal Spaces: A Basis for Studies in Adaptation, Automata Theory, Academic Press, New York, 1966, pp. 218–230.

[14] J.H. Holland, Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology Control and Artificial Intelligence, 2nd ed., MIT Press, 1992.

[15] F.Y. Partovi, M. Anandarajan, Classifying inventory using an artificial neural network approach, Comput. Ind. Eng. 41 (4) (2002) 389–404.

[16] N. Jiang, Z. Zhao, L. Ren, Design of structural modular neural networks with genetic algorithm, Adv. Eng. Software 34 (1) (2003) 17–24.