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Process optimization of the serial-parallel hybrid polishing machine tool based on artificial neural network and genetic algorithm

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Abstract A kind of serial-parallel hybrid polishing machine tool based on the elastic polishing theory is developed and applied to finish mould surface with using bound abrasives. It mainly consists of parallel mechanism of three dimensional moving platform, serial rotational mechanism of two degrees of freedom and the elastic polishing tool system. The active compliant control and passive conformity of polishing tool are provided by a pneumatic servo system and a spring, respectively. Considering the contradiction between the machining quality and efficiency, the optimization model of process parameters is found according to different machining requirements, namely single objective optimization and multi-objective optimization, which provide a choice of parameters as a basis for the operators in practice. Many polishing experiments are conducted to collect the data samples. The genetic algorithm integrated with artificial neural network is used for researching for the optimal process parameters in term of the various optimization objectives. This research also lays the foundation for further establishing polishing expert system.

Keywords The serial-parallel hybrid polishing machine tool · Surface roughness · Mould free-form surface · Artificial neural network · Genetic algorithm

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Introduction

Mould polishing with bound abrasives is a kind of finishing process in order to obtain good surface quality and shape accuracy of workpiece. In the machining of mould, it often takes a long time to finish the mould surfaces polishing, which are usually finished by the experienced operators at present. So it is meaningful to develop a kind of special mould polishing equipment. Many automatic finishing equipment used for mould surface polishing have been investigated, which are mostly based on the conventional machine tool structure (Ahn et al. 2002; Wu et al. 2007; Pessoles and Tournier 2009), the industrial robot structure (Furukawa et al. 1996; Tsai and Huang 2006; Fusaomi et al. 2007) and the parallel structure (Li 2002; Brecher et al. 2006; Liao et al. 2008). For the polishing system based on the industrial robot structure, they have many advantages such as greater workspace, good flexibility and so on, and the control of force and position can be finished steadily. However it is relatively difficult for finishing plan and track of free-form surface like computer numerical control (CNC) machine and trajectory error is relatively great. For parallel polishing machine, it is usually faster and stronger than traditional articulated polishing robot. However, their workspaces are usually more limited. In recent years, the hybrid machine tool with serial-parallel conformation has been developed (Huang et al. 2005). This kind of machine structure has the problems of motion inaccuracy due to the low stiffness. The polishing of mould surfaces is often finished by the elastic polishing and polishing force is relatively small, which decrease the requirements for stiffness and accuracy of machine. So this paper presents that the serial-parallel hybrid machine is applied to the finishing process of mould surfaces, which gives full play to the advantage of this machine and provides a kind of finishing equipment for mould manufacture.

It is an important problem for every mould polishing system to deal with the contradiction between quality and efficiency in machining. Among selecting machining parameters in process planning is a very key step, which have effects on the quality and efficiency. The polishing efficiency is relatively low or the better surface roughness can't be obtained if the selected parameters are conservative and far from the optimum values. At present, automation and optimization of manufacturing processes are becoming increasingly important tasks due to the increasing demand for higher precision and productivity in manufacturing processes in modern industry (Lee and Shin 2004). Much work about the polishing process research used for mould polishing with bound abrasives has been done, such as the polishing expert system integrated with sensor information (Ahn et al. 2001), an intelligent polishing system using an acoustic emission-based intelligent monitoring scheme (Ahn et al. 2002), the optimization of process parameters based on the Taguchi method (Tsai and Huang 2006), etc. Levent and Krishnaswamy (1997) presented an overview of robot-assisted die and mould polishing with emphasis on process modeling in the framework of a conceptual automation structure consisting of process, control, surface measurement and planning phases. Above these research results lay a foundation for the establishing of mould polishing expert system and developing of the intelligent polishing machinery like a skilled operator.

In this paper, main structure and work principle of this self-developed serial-parallel hybrid machine tool based on the elastic polishing theory is presented firstly. In order to provide a choice of parameters as a basis for the operators in practice, the optimization model of process parameters is found according to different machining requirements, namely single objective optimization and multi-objective optimization, which enable solve the contradiction between surface quality and machining efficiency. Many polishing experiments were conducted to collect the data samples. The GA integrated with ANN model is used for researching for the optimal process parameters according to the various optimization objectives.

Structure of machine tool and experiment

The serial-parallel hybrid polishing machine tool

Structure diagram of the polishing machine tool is shown in Fig. 1. This machine tool mostly consists of the parallel mechanism, the serial rotational mechanism and the elastic polishing tool system. The parallel mechanism has three degrees of freedom and controls space position of polishing tool. The serial rotational mechanism has two rotational degrees of freedom and controls pose of polishing tool. The

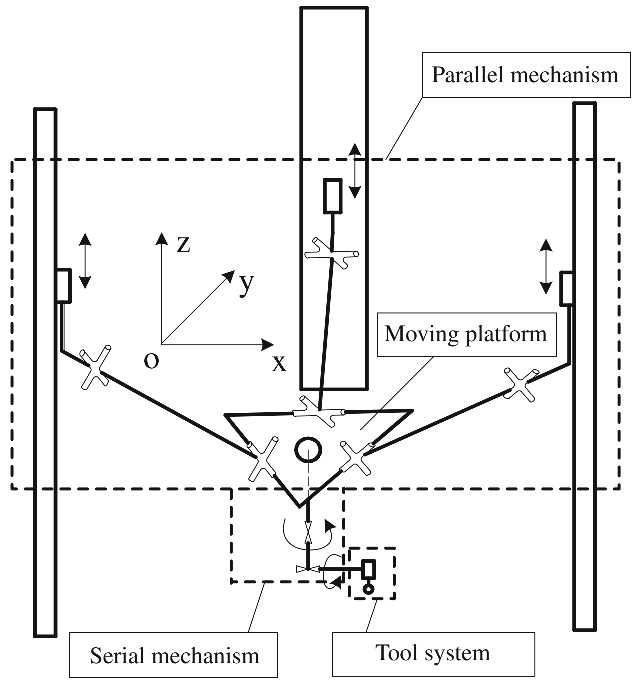


Fig. 1 Structure diagram of the polishing machine tool

end actuator based on the elastic polishing theory is fixed in the serial mechanism. The polishing tool is driven the spindle motor in end actuator and polishing force is controlled by adjusting cylinder pressure of pneumatic servo system. Equal material removal can be obtained by real-timely controlling pressure, velocity and displacement.

Elastic polishing is defined that the tool system using the elastic abrasive tool, such as rubber binder or resin binder, are compliant controlled (i.e. active compliant control and passive compliant control) according to the surface shape of workpiece. The active compliant tool can actively adjust the tool compliance by using actuators. However, the passive compliant tools are made only by employing various passive mechanisms, such as springs, and it relies on compliance in the tool itself to maintain a nominal contact force. The serial-parallel hybrid machine tool is very useful for the polishing of the free-form surface because this machine tool has the advantages of both parallel mechanism and serial mechanism such as the rapid response, the short transmission chain and the high environmental adaptability. Meanwhile, it can compensate the shortcoming of the small workspace of the parallel mechanism. Yu et al. (2004) studied the dynamic characteristics of the hybrid machine tool by means of the theory of dynamics of flexible multi-body systems. The stable status of polishing can be obtained at all periods of the movement of the machine except the beginning of the movement. In addition, CNC system of this machine tool is self-developed parallel double CPU system based on Programmable Multi-Axis Controller (PMAC). Background management and human-machine interface etc. are conducted by industrial Personal

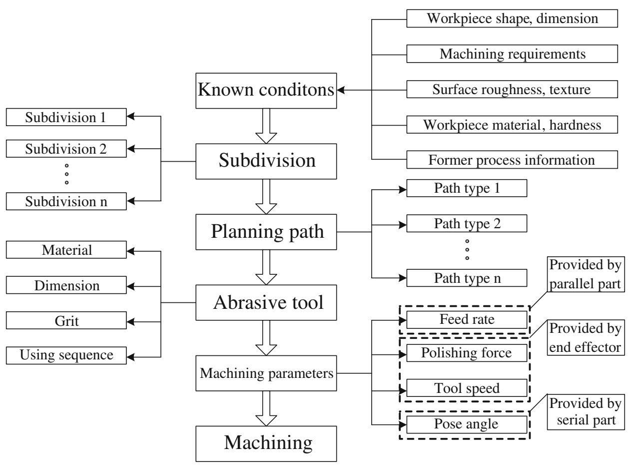


Fig. 2 Process system scheme of the serial-parallel machine tool

Computer (PC). Real-time motion control foreground such as six-axial motion and switch signal control are implemented by PMAC.

The process system scheme of this polishing machine is presented in Fig. 2. A series of steps involves subdividing curved surface, planning path, selecting abrasive tool and machining parameters. Subdivision and path planning for free-from surface have been investigated. These research results play a certain guiding role in practical machining. Selecting machining parameters in process planning is a very key step, which have effects on the quality and efficiency. The following contents is how to selecting machining parameters can meet different requirements considering the contradiction between quality and efficiency.

Polishing experiment

A number of polishing experiments were implemented in the serial-parallel hybrid polishing machine tool. According to the characteristics of machine tool, tool speed n(rotational speed of polishing tool), feed rate Va(movement velocity of moving platform), force F(the axis force acted on the tool pole by pneumatic cylinder) and pose angle $\alpha$are considered process parameters that have great impact on the surface roughness of workpiece in this research. Pose angle is the included angle between the out-normal direction of curved surface and the tool pole axis direction. The about experiment conditions are given in Table 1. By polishing experiments, the training samples and the testing samples are achieved, which are given in Tables 2 and 3, respectively. The parameters in the experiment are determined according to the working range of machine tool and the experience. The average surface roughness before polishing Ra_0 is equal to 3.5 um.

Table 1 Parameters of polishing experiment

Item	Condition
Tool diameter	ϕ15 mm
Tool shape	Sphere
Bond type	Resin
Abrasive grit	$240^{\#}$
Abrasive material	White aluminium oxide (WA)
Workpiece shape	Plane
Workpiece material	45 Steel

Table 2 Training samples for ANN model

No.	Tool speed n(rpm)	Feed rate Va(m/min)	Force $F(N)$	Pose angle α(°)	Ra(um)
1	600	0.2	40	30	1.014
2	600	0.4	10	40	1.542
3	600	0.6	20	50	1.521
4	600	0.8	30	60	1.813
5	800	0.2	10	50	1.495
6	800	0.4	20	60	1.518
7	800	0.6	30	30	0.997
8	800	0.8	40	40	1.449
9	1,000	0.2	20	60	1.176
10	1,000	0.4	30	50	0.745
11	1,000	0.6	40	40	0.893
12	1,000	0.8	10	30	1.538
13	1,200	0.2	30	40	0.415
14	1,200	0.4	40	30	0.551
15	1,200	0.6	10	60	1.543
16	1,200	0.8	20	50	1.272

Table 3 Testing samples for ANN model and prediction results

No.	Tool speed n(rpm)	Feed rate Va(m/min)	Force $F(N)$	Pose angle $\alpha(°)$	Ra (um)	
					Experiment	Prediction
1	800	0.2	10	30	1.319	1.201
2	800	0.6	10	50	1.706	1.658
3	800	0.2	30	30	0.785	0.638
4	800	0.6	30	50	1.171	1.212
5	1,200	0.2	30	30	0.365	0.332
6	1,200	0.6	30	50	0.752	0.814
7	1,200	0.2	10	30	0.898	0.957
8	1,200	0.6	10	50	1.286	1.476

Polishing force was measured with force sensor (NS-TH1 type). The average surface roughness of workpiece after polishing was measured with a geometric profile tester (SRM-1D type). Average surface roughness Ra is calculated by taking the average of 10 different positions.

Surface roughness and polishing efficiency

Prediction model of surface roughness

Polishing is a kind of complex material removal operation involving rubbing, ploughing and cutting. The surface roughness of workpiece is related to the polishing pressure, feed rate, tool speed, the abrasive grain size etc. There are many about the prediction models of surface roughness at present. Benardos and Vosniakos (2003) presented the various methodologies and practices that are being employed for the prediction of surface roughness. The approaches are classified into those based on machining theory, experimental investigation, designed experiments and artificial intelligence. Many researches are carried out to achieve the surface roughness model of polishing, which involve machining theory (Xi and Zhou 2005; Savio et al. 2009), experimental investigation (Ahn et al. 2001; Márquez et al. 2005), designed experiments (Tsai and Huang 2006) and artificial intelligence.

Computing intelligence techniques, such as artificial neural network (ANN), genetic algorithms (GA) and so on, have been widely applied in many engineering optimization problems (Brinksmeier et al. 1998; Westkämper and Schmidt 1998; Zhang et al. 2009). Among artificial neural networks (ANNs) are widely accepted as a technology offering an alternative way to simulate complex and ill-defined problems. They have been used in diverse applications in control, robotics, pattern recognition, forecasting, power systems, manufacturing, optimization (Malakooti and Raman 2000), signal processing, etc., and they are particularly useful in system modeling (Shen et al. 2007). ANNs has been widely applied in prediction of surface roughness of part at present, such as milling machining (Benardos and Vosniakos 2002; Oktem et al. 2006) and the electrical discharge machining (Markopoulos et al. 2008). ANN theory, the nonlinearity tool is good at solving nonlinearity problem with characters of nonlinearity map, self-organizing configuration and high-parallel process. Network framework based on back-propagation (BP) is applied most broadly as a kind of ANN model, because it solves the problem that multilayer network with hidden layer studies difficultly. A feed forward BP neural network is used for modeling surface roughness in this paper.

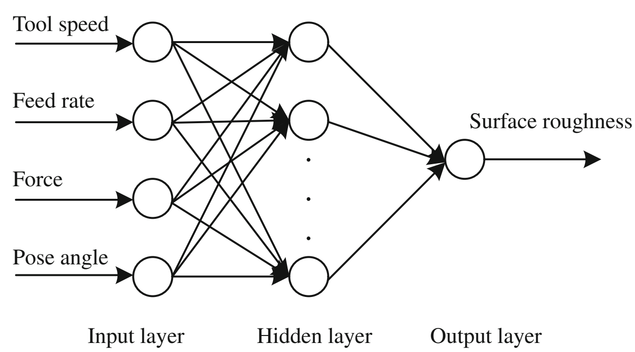


Fig. 3 The structure of BP neural network

A neural network is composed of a set of neurons grouped in layers. Usually three types of layers are used: input layer, hidden layer and output layer. The neural network architecture used in this study is shown in Fig. 3 in terms of above experiments. It is seen from this figure that the network consists of one input layer (four neurons), one hidden layer and one output layer (one neuron). Neurons in input layers are tool speed, feed rate, force and pose angle, respectively. Neuron of output layer is average surface roughness of workpiece. The node number of the hidden layer determined by train trials is equal to 6. In this study, the sample data is divided into two groups, namely the training samples and the

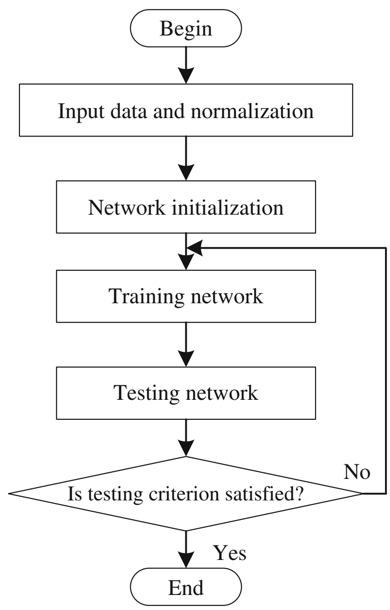


Fig. 4 Flowchart of ANN model

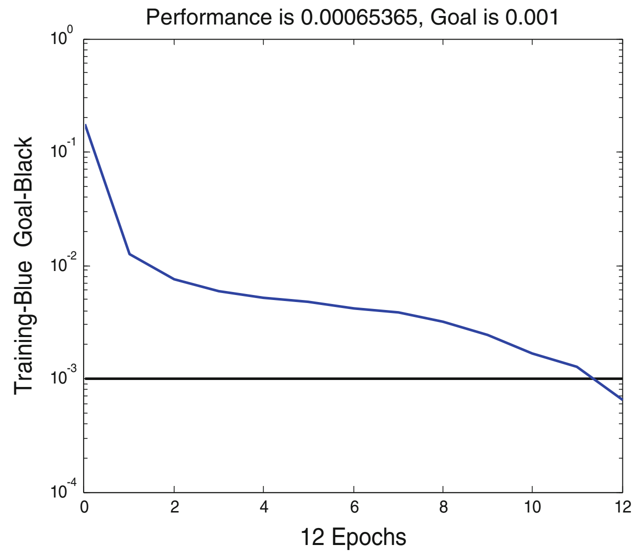


Fig. 5 The training epoch versus MSE

testing samples. It has to be stressed that the testing samples do not participate in the training process. The testing samples are only used to test the trained ANN. Training program of neural network is shown in Fig. 4. The basic steps of ANN model can be summarized as follows:

Step 1: Input data and normalization
For stability reasons it is necessary to normalize the values of input and output to a specific range, which is commonly between −1 and +1. To decrease calculation error, sample data is normalized the range [0.1, 0.9]. Normalization equation is given as follows:

$$x_{\text{in}} = 0.1 + 0.8 \times (x - x_{\min})/(x_{\max} - x_{\min}) \quad (1)$$

where x is the sample value before normalization, x_{in} is the sample value after normalization, $x_{\min}$ and $x_{\max}$ are the minimum and maximum value of sample data, respectively. Denormalization equation is expressed as

$$y_{\text{out}} = y_{\min} + (y - 0.1) \times (y_{\max} - y_{\min})/0.8 \quad (2)$$

where y is the output value, y_{out} is the output value after denormalization, $y_{\min}$ and $y_{\max}$ are the minimum and maximum value of output data, respectively.

Step 2: Network initialization
The powerful Levenberg-Marquardt (LM) algorithm, which dramatically improves the ability to generalize and the required training time, is selected for training the ANN. The activation function of the hidden layers is the Tan-sigmoid transfer function. Linear transfer function was used for the output layer.

Step 3: Training network
During the training, input data is presented to the network and the output data of the network is compared with a desired output. The training stops when mean square error (MSE) is less than the goal value (0.001) during training. Figure 5 shows the training epoch versus MSE.

Step 4: Testing network
The trained neural network is tested using testing samples in Table 3. The ANN model is saved when sum square error (SSE) of prediction results is less than the goal value (0.03). The results predicted from the ANN model are compared with experimental results shown in Table 3. Average relative error is equal to 0.0906. It can be seen from this table that prediction results of ANN model presents a good agreement with experimental results. It can basically map the relationship between input parameters and output parameter.

Polishing efficiency

The polishing efficiency is defined as follows: for a specified area, the amount of surface roughness reduced by a polishing task with a certain time span (Tsai and Huang 2006):

$$E_f = \frac{\Delta Ra A}{T} = \frac{(Ra_0 - Ra)A}{T} \quad (3)$$

where E_f is the polishing efficiency, Ra_0 is average surface roughness before polishing, Ra is average surface roughness after polishing, A is the area polished and T is the total polishing time. According to the elastic mechanics, it is assumed that the pressure distribution is Hertzian at the contact between the tool and the workpiece surface. The contact region between the tool and the workpiece is different at various forces. The width and depth of the material removal profile increase with increasing polishing force (Zhang et al. 2002), namely the contact area and removal depth also increase when polishing force increases in certain conditions. However, polishing area per unit time is mainly related to feed rate in this research. The effect of force on the polishing efficiency is mainly the material removal depth, namely related to Ra. So E_f is calculated as follows:

$$E_f = (Ra_0 - Ra)VaL \tag{4}$$

where L is contacting width orthogonal to feed rate direction in contact region between tool and workpiece.

Optimization of process parameters

In this research, two kinds of optimization cases are presented in detail, namely single objective optimization (surface roughness) and multi-objective optimization (surface roughness and polishing efficiency). Single objective optimization should be selected if minimum surface roughness is only required. To ensure better surface roughness and high polishing efficiency at the same time, multi-objective optimization should be selected.

Optimization model

(1) Single-objective optimization
Decision variables
Tool speed n(rpm), feed rate V_a(m/ min), force $F(N)$, pose angle $\alpha(°)$.
Objective function
Minimum surface roughness $Ra : f_1(X) = f_1[n, Va, F, \alpha]$, namely the prediction model of surface roughness based on the ANN.
Variable bounds

$$600 \le n \le 1{,}200(\text{rpm}),\ 0.2 \le V_a \le 0.8(\text{m/ min}),$$
$$10 \le F \le 40(N),\ 30 \le \alpha \le 60(°)$$

Fitness function
Fitness function $F_1(X)$ is defined by

$$F_1(X) = 1/f_1(X) \tag{5}$$

(2) Multi-objective optimization
Decision variables
Tool speed n(rpm), feed rate V_a(m/ min), force $F(N)$, pose angle $\alpha(°)$.
Objective function
Minimum surface roughness $Ra : f_1(X) = f_1[n, Va, F, \alpha]$, namely the prediction model of surface roughness based on the ANN.
Maximum polishing efficiency $E_f : f_2(X) = f_2[n, Va, F, \alpha] = (Ra_0 - Ra)VaL$
Variable bounds

$$600 \le n \le 1{,}200(\text{rpm}),\ 0.2 \le V_a \le 0.8(\text{m/ min}),$$
$$10 \le F \le 40(N),\ 30 \le \alpha \le 60(°)$$

Fitness function
In order to solve many goals conflicts mutually in multi-objective optimization, the weight coefficient method is used for transforming the multi-objectives to the simple target. Fitness function $F_2(X)$ is defined by

$$F_2(X) = 1/(M + w_1 f_1(X) - w_2 f_2(X)) \tag{6}$$

where M is a predefined constant to ensure a positive fitness function, w_1 and w_2 are weight coefficients for $f_1(X)$ and $f_2(X)$, respectively.

GA optimization based on ANN model

GA is one of the most powerful and broadly applicable optimization techniques in engineering design problems, especially approaches of GA integrated with other techniques have been applied in production planning (Morad and Zalzala 1999; Moon et al. 2006) and process optimization (Sedighi and Afshari 2009). Shen et al. (2007) proposed a combining artificial neural network and genetic algorithm method to optimize the injection molding process. Hou et al. (2007) applied the parameter design of the Taguchi method, response surface method and genetic algorithm to set the optimal parameters for a nano-particle milling process. The GA is a stochastic search technique based on the mechanism of natural selection and natural genetics to imitate living beings for solving difficult optimization problems with high complexity and an undesirable structure. In GA, a highly effective search of the solution space is performed, using a population of strings representing possible solutions to evolve through the basic random operators of selection, crossover and mutation. In this study, the detailed procedures of GA/ANN optimization are shown in Fig. 6. The basic steps are summarized as follows:

Step 1: Initialization
Represent the problem variables as a chromosome of a fixed length, and choose the size of a

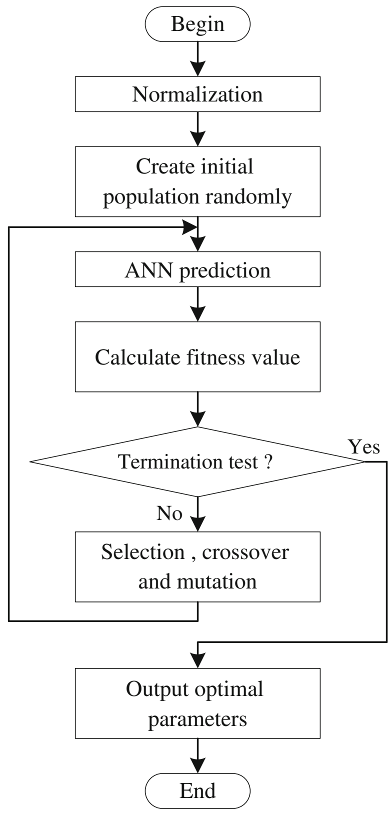


Fig. 6 Flowchart of GA integrated with ANN model optimization

chromosome population, the crossover probability and the mutation probability.

Step 2: Randomly generate an initial population of chromosomes

A binary string representation for coding chromosome is adopted and each process parameter that is normalized in the interval of 0.1 ∼ 0.9 is encoded into 20 binary digits.

Step 3: ANN prediction

Objective function values are calculated by ANN simulation using current population.

Step 4: Calculate fitness value

In this step, the fitness function based on ANN model is used to calculate the fitness value of each chromosome. Higher fitness value indicates goodness of the solution, so the chromosomes that have the best fitness value are preserved.

Step 5: Termination test

A pre-set generation number is used as the stopping criteria in this research. If a pre-set stopping condition is not satisfied, go to Step 6. Otherwise, the algorithm stops and the optimized parameters are output.

Step 6: Selection, crossover and mutation

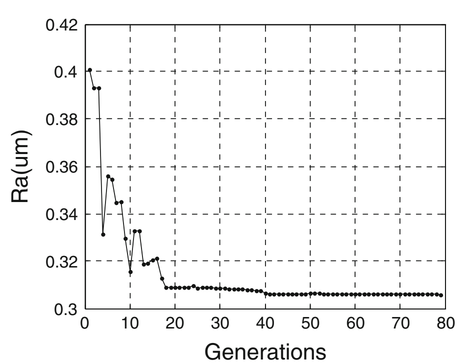
The selection, crossover and mutation are used to reproduce the new population to replace the current population in next generation. Selection is an operation to select two parent chromosomes from the current population for mating (crossover or mutation). In this research, a pair of chromosome is selected from the entire population according to their fitness values. The crossover operation is used to create a pair of offspring chromosomes. The mutation operation is applied to generate the new chromosome by a pre-set mutation probability. When a number of offspring chromosomes are created, then go to step 3.

One important step for the evolutionary search is to define the fitness function, which is related to the objective function and the constraints of the problem, because the genetic algorithm will seek to increase the fitness as it operates.

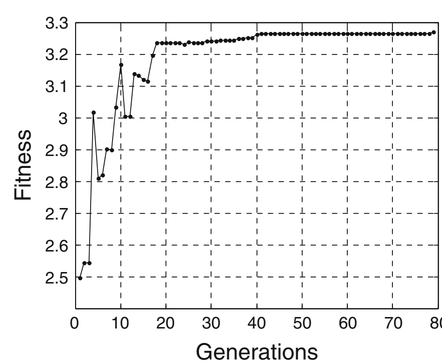
Optimization results

For a single objective optimization, after several test runs, initialization parameters that are found to give better solution are as follows: number of iterations: 100, population size: 80, crosser over probability: 0.9, mutation probability: 0.03, total string length: 80, bits per variable: 20. Figure 7a shows the variation of surface roughness with generations, and Fig. 7b shows the variation of fitness of the best solution with generations. With an increase of generation, surface roughness

Fig. 7 GA optimization for single objective



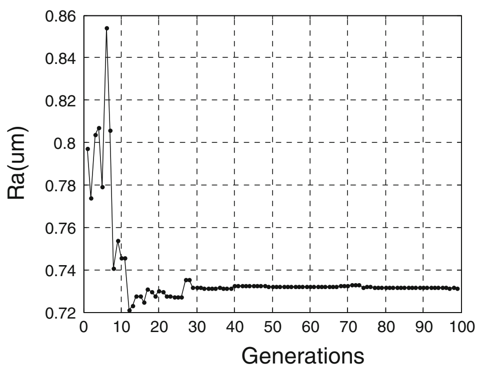
(a) Variation of surface roughness with generations



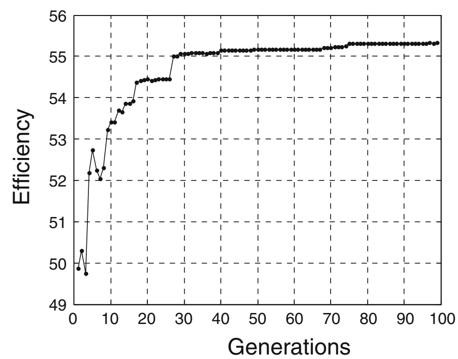
(b) Variation of fitness with generations

Table 4 Experiment results of the optimized and unoptimized process parameters

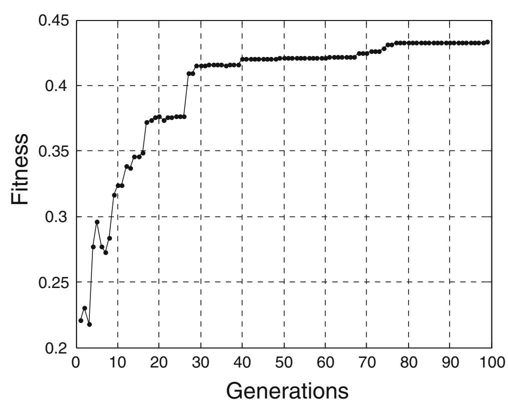
No.	Tool speed n(rpm)	Feed rate Va(m/min)	Force $F(N)$	Pose angle $\alpha(°)$	Surface roughness (um)		Polishing efficiency (um cm^2/min)	
					Experiment	Prediction	Experiment	Prediction
1. Single objective	1,195	0.2106	31.1	30.6	0.362	0.306	16.47	16.82
2. Multi-objective	1198.1	0.7993	32.3	30.3	0.814	0.731	53.72	55.33
3. Unoptimized (1)	800	0.6	30	50	1.171	1.212	34.94	34.32
4. Unoptimized (2)	1,200	0.6	30	50	0.752	0.814	41.22	40.29



(a) Variation of surface roughness with generations



(b) Variation of polishing efficiency with generations



(c) Variation of fitness with generations

Fig. 8 GA optimization for multi-objective

decreases and fitness value increases gradually. Fitness value is basically unchangeable and equal to 3.2680 when generation is greater than 40. The optimized process parameters are given in Table 4.

For multi-objective optimization, after several test runs, initialization parameters that are found to give better solution are as follows: number of iterations: 100, population size: 100, crosser over probability: 0.9, mutation probability: 0.03, total string length: 80, bits per variable: 20, $Ra_0 = 3.5$, $M = 50$, $w_1 = 0.6$, $w_2 = 0.4$. Figure 8a and b show the variation of surface roughness and polishing efficiency with generations, respectively. Figure 8c shows the variation of fitness of the best solution with generations. With an increase of generations, surface roughness decreases and polishing efficiency and fitness value increase gradually. Fitness value is basically unchangeable and equal to 0.4335 when generation is greater than 80. The optimized process parameters are given in Table 4.

Experimental verification

Experiments were conducted in the serial-parallel hybrid polishing machine tool using the optimized process parameters. Experiment results are given in Table 4. In addition, Experiment result of using unoptimized process parameters is also given in Table 4 for comparative analysis. It can be seen from Table 4 that the predicted results are consistent with the experimental results. For single objective optimization, the prediction value of surface roughness is basically the same as no. 5 of the testing sample, and this result is smaller than other all training samples and testing samples. For multi-objective optimization, although surface roughness is lager than that of single objective, this result is satisfactory and the polishing efficiency relatively increases.

The increase of tool speed raises the number of the abrasive grains participating in the cutting on workpiece surface, as a result surface roughness can be decrease rapidly and polishing efficiency also increase, so all the optimized results of tool speed in above two cases are high and close to 1,200 rpm. The decrease of feed rate increases the number of the abrasive grains participating in the cutting on workpiece surface, so optimized result of feed rate for minimum surface roughness is low. But polishing efficiency is low at this condition, so feed rate for multi-objective optimization is close to 0.8 m/ min. The material removal rate increases with the increase of pressure in certain range, and the material removal rate ceases to increase with any further increase in the pressure. The optimal polishing force in above two cases is about 30 N because in certain conditions too great pressure can not obtain high removal rate and may decrease surface quality. Change of pose angle results in the change of pressure and polishing velocity at the same time. So when choosing pose angle, it is important to consider synthetically the change of pressure and velocity in polishing region in order to obtain smaller surface roughness and high polishing efficiency.

Conclusions

The serial-parallel hybrid polishing machine tool based on the elastic polishing is investigated and applied to the mould surface polishing with bound abrasives, which can give full play to the advantage of this machine and provide a kind of finishing equipment for mould manufacture. This polishing machine consists of parallel mechanism of three dimensional moving platform, serial rotational mechanism of two degrees of freedom and elastic polishing tool system. The parallel mechanism controls the spatial position of the polishing tool and serial mechanism controls the pose of the polishing tool. The elastic polishing tool system enable realize active control provided by the pneumatic servo system and passive conformity provided by a spring.

The process system scheme of this polishing machine is analyzed. The optimization model of process parameters is found according to the different machining requirements in this paper, namely single objective optimization model and multi-objective optimization model, which solves the contradiction between quality and efficiency in machining from the practical application and provides a choice of parameters as a basis for the operators in practice. The optimization method of GA based on ANN is used for finding the optimal parameters for mould polishing. Comparison between optimization results and experimental results provide reasonable quantitative agreement. By comparative analysis, it is concluded that minimum surface roughness can be obtained for a single objective optimization, and better surface roughness and high polishing efficiency can be obtained for multi-objective optimization.

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References

Ahn, J. H., Lee, M. C., Jeong, H. D., Kim, S. R., & Cho, K. K. (2002). Intelligently automated polishing for high quality surface formation of sculptured die. *Journal of Materials Processing Technology, 130–131*, 339–344.

Ahn, J. H., Shen, Y. F., Kim, H. Y., Jeong, H. D., & Cho, K. K. (2001). Development of a sensor information integrated expert system for optimizing die polishing. *Robotics and Computer Integrated Manufacturing, 17*, 269–276.

Benardos, P. G., & Vosniakos, G. C. (2002). Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments. *Robotics and Computer Integrated Manufacturing, 18*, 343–354.

Benardos, P. G., & Vosniakos, G. C. (2003). Predicting surface roughness in machining: a review. *International Journal of Machine Tools & Manufacture, 43*, 833–844.

Brecher, C., Lange, S., Merz, M., Niehaus, F., Wenzel, C., & Winterschladen, M. (2006). NURBS based ultra-precision free-form machining. *Annals of the CIRP, 55*(1), 547–550.

Brinksmeier, E., Tönshoff, H. K., Czenkusch, C., & Heinzel, C. (1998). Modelling and optimization of grinding processes. *Journal of Intelligent Manufacturing, 9*, 303–314.

Furukawa, T., Rye, D. C., Dissanayake, M. W. M. G., & Barratt, A. J. (1996). Automated polishing of an unknown three-dimensional surface. *Robotics & Computer-Integrated Manufacturing, 12*(3), 261–270.

Fusaomi, N., Tetsuo, H., Zenku, H., Masaaki, O., & Keigo, W. (2007). CAD/CAM-based position/force controller for a mould polishing robot. *Mechatronics, 17*, 207–216.

Hou, T. H., Su, C. H., & Liu, W. L. (2007). Parameters optimization of a nano-particle wet milling process using the Taguchi method, response surface method and genetic algorithm. *Powder Technology, 173*, 153–162.

Huang, T., Li, M., Zhao, X. M., Mei, J. P., Chetwynd, D. G., & Hu, S. J. (2005). Conceptual design and dimensional synthesis for a 3-DOF module of the trivariant—a novel 5-DOF reconfigurable hybrid Robot. *IEEE Transactions on Robotics, 21*(3), 449–456.

Lee, C. W., & Shin, Y. C. (2004). Modeling of complex manufacturing processes by hierarchical fuzzy basis function networks with application to grinding processes. *Journal of Dynamic Systems, Measurement, and Control, Transactions of the ASME, 126*, 880–890.

Levent, G., & Krishnaswamy, S. (1997). An overview of Robot-assisted die and mould polishing with emphasis on process modeling. *Journal of Manufacturing System, 16*(1), 48–58.

Li, Y. P. (2002). Theoretical study on a non-transmission high efficient parallel camber grinding machine. *Journal of Materials Processing Technology, 129*, 551–554.

Liao, L., Xi, F. F., & Liu, K. F. (2008). Modeling and control of automated polishing/deburring process using a dual-purpose compliant toolhead. *International Journal of Machine Tools & Manufacture, 48*(12–13), 1454–1463.

Márquez, J. J., Pérez, J. M., Ríos, J., & Vizán, A (2005). Process modeling for robotic polishing. *Journal of Materials Processing Technology, 159*, 69–82.

Malakooti, B., & Raman, V. (2000). An interactive multi-objective artificial neural network approach for machine setup optimization. *Journal of Intelligent Manufacturing, 11*, 41–50.

Markopoulos, A. P., Manolakos, D. E., & Vaxevanidis, N. M. (2008). Artificial neural network models for the prediction of surface roughness in electrical discharge machining. *Journal of Intelligent Manufacturing, 19*, 283–292.

Moon, C., Seo, Y., Yun, Y., & Gen, M. (2006). Adaptive genetic algorithm for advanced planning in manufacturing supply chain. *Journal of Intelligent Manufacturing, 17*, 509–522.

Morad, N., & Zalzala, A. (1999). Genetic algorithms in integrated process planning and scheduling. *Journal of Intelligent Manufacturing, 10*, 169–179.

Oktem, H., Erzurumlu, T., & Erzincanli, F. (2006). Prediction of minimum surface roughness in end milling mold parts using neural network and genetic algorithm. *Materials and Design, 27*, 735–744.

Pessoles, X., & Tournier, C. (2009). Automatic polishing process of plastic injection molds on a 5-axis milling center. *Journal of Materials Processing Technology, 209*, 3665–3673.

Savio, G., Meneghello, R., & Concheri, G. (2009). A surface roughness predictive model in deterministic polishing of ground glass moulds. *International Journal of Machine Tools & Manufacture, 49*, 1–7.

Sedighi, M., & Afshari, D. (2009). Creep feed grinding optimization by an integrated GA-NN system. Journal of Intelligent manufacturing, doi:10.1007/s10845-009-0243-4.

Shen, C. Y., Wang, L. X., & Li, Q. (2007). Optimization of injection molding process parameters using combination of artificial neural network and genetic algorithm method. *Journal of Materials Processing Technology, 183*, 412–418.

Tsai, M. J., & Huang, J. F. (2006). Efficient automatic polishing process with a new compliant abrasive tool. *International Journal of Advanced Manufacturing Technology, 30*, 817–827.

Westkämper, E., & Schmidt, T. (1998). Computer-assisted manufacturing process optimization with neural networks. *Journal of Intelligent Manufacturing, 9*, 289–294.

Wu, X. J., Kita, Y., & Ikoku, K. (2007). New polishing technology of free form surface by GC. *Journal of Materials Processing Technology, 187–188*, 81–84.

Xi, F. F., & Zhou, D. (2005). Modeling surface roughness in the stone polishing process. *International Journal of Machine Tools & Manufacture, 45*, 365–372.

Yu, M., Zhao, J., Zhang, L., & Wang, Y. Q. (2004). Study on the dynamic characteristics of a virtual-axis hybrid polishing machine tool by flexible multi-body dynamics. *Proceedings of the Institution of Mechanical Engineers, Part B Journal of Engineering Manufacture, 218*(9), 1067–1076.

Zhang, L., Tam, H. Y., Yuan, C. M., Chen, Y. P., & Zhou, Z. D (2002). An investigation of material removal in polishing with fixed abrasives. *Proceedings of the Institution of Mechanical Engineers, Part B, Journal of Engineering Manufacture, 216*, 103–112.

Zhang, Y. F., Huang, G. Q., Ngai, B. K. K., & Chen, X. (2009). Case-based polishing process planning with fuzzy set theory. Journal of Intelligent manufacturing, doi:10.1007/s10845-009-0259-9.