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ORIGINAL ARTICLE

Optimizing process parameters for selective laser sintering based on neural network and genetic algorithm

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Abstract Selective laser sintering (SLS) is an attractive rapid prototyping (RP) technology capable of manufacturing parts from a variety of materials. However, the wider application of SLS has been limited, due to their accuracy. This paper presents an optimal method to determine the best processing parameter for SLS by minimizing the shrinkage. According to the nonlinear and multitudinous processing parameter feature of SLS, the theory and the algorithms of the neural network are applied for studying SLS process parameters. The process is modeled and described by neural network based on experiment. Moreover, the optimum process parameters, such as layer thickness, hatch spacing, laser power, scanning speed, work surroundings temperature, interval time, and scanning mode are obtained by adopting the genetic algorithm based on the neural network model. The optimum process parameters will be benefit for RP users in creating RP parts with a higher level of accuracy.

Keywords Selective laser sintering (SLS) · Process parameter · Neural network model · Genetic algorithm

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1 Introduction

SLS is an attractive process in the new field of rapid prototyping (RP) which is such an advance manufacturing technology that integrates laser technology, precision machinery, computer-aided design (CAD), computer-aided manufacturing, computer numerical control, control technology, and material technology [1]. The main advantages of the RP process are that it does not require any part-specific tooling and it is completely automated. Although this technique was introduced recently, it has been applied in many fields such as automobile manufacturing, architecture, household electric appliance, and medical attendance. Examples of commercial RP systems available on market today are stereo lithography, selective laser sintering (SLS), laminated object modeling, and fused deposition modeling. SLS, originated from the University of Texas at Austin and commercialized by DTM, has attracted the most attention, because the SLS process fabricates without support structure and is capable of a wide range of solid materials such as polycarbonate, nylon, nylon/glass composite, wax, ceramics, and metal–polymer powders [2]. In spite of its potential use in various areas, the use of SLS is limited, since the dimensional accuracy of its products is still inferior to that of conventional machining processes [3]. Therefore, improving the accuracy is a vital means for further generalizing SLS technology. Many researches have tried to improve the accuracy of the SLS product. Li et al. investigated the shrinkage forms and shrinkage rules of the SLS process [4]. John and Carl studied the energy delivery, heat transfer, and sintering process altogether with other pertinent phenomena [5]. Yang et al. studied the shrinkage compensation of SLS by using the Taguchi method [6]. Masood et al. developed the part orientation system using the genetic algorithm (GA) [7]. Bai et al. presented a numerical model of the temperature field during length-alterable line scanning and laser sintering of polymer-coated molybdenum powder, using the finite element method to simulate the temperature field during the laser-sintering process [8]. Arni and Gupta developed a systematic approach to analyze flatness, parallelism, and perpendicularity tolerance of the RP part [9]. Armillotta and Biggioggero analyzed layer thickness and part orientation effect on surface finish through graphical simulation [10]. Shi et al. developed the hybrid of the neural network and expert system. The expert system has been used in the automatic optimization of shrinkage compensation coefficient of SLS and has received satisfying results [11].

Part inaccuracy is mainly result from material shrinkage during the sintering process [12]. The shrinkage causes nonuniform internal stress, which results in deformation of built parts. It is known that both power properties and fabrication parameters have a great influence on the work shrinkage of SLS, with the latter more significant. To minimize shrinkage and to improve the accuracy, the process parameters have to be tuned by an appropriate optimization method. In real workshops, the process parameters are decided by operators, so the accuracy mainly depends on their experience, which is blindfolded and with empirical behavior and lacks necessary theoretical instruction. Thus, this paper attempts to make an effort to understand the relationship between the process parameter and shrinkage and to obtain the optimum SLS process parameters.

SLS process parameter of effecting shrinkage is a nonlinear and multitudinous input system. It is difficult to relate the process parameter to part shrinkage by using the conventional mathematical method. With the advantage and developing of the neural network, widespread usage has been found in function approximation [13]. Neural network has been successfully applied in various areas of research [14–16]. It has shown that theoretically, a three-layer neural network can closely approximate nonlinear function, provided the function is continuous and nonsingular [17]. In this paper, neural network based on the process-modeling technique is proposed, which can relate the process parameters to part shrinkage ratio (shrinkage ratio is defined as the ratio of the difference between the desired value and the actual value and the desired value). The process model obtained by the network can predict how much shrinkage was achieved for a given setting of the process parameters, thus providing prior knowledge of the dimensional accuracy before actually making the prototype part. Based on the neural network model, the GA possesses ability to search the optimum process parameters of SLS.

2 Mathematic model

Accuracy modeling of the SLS process is important because it provides information necessary for process parameters optimization. The SLS manufacturing procedure is a nonlinear complex multivariable system. So, it is difficult to model the contribution of process parameters to the shrinkage ratio by using the convention mathematical method. Neural network is superior to other methods in modeling and analyzing nonlinear complex systems. It is particularly suitable for process problems with inexactitude and fuzzy information. It is appropriate to apply neural network for the simulation of the SLS manufacturing procedure. After training, neural network can reflect the relation of SLS process parameters to processing shrinkage ratio and the relational expression implied in the neural network.

In this section, the SLS process is modeled by neural network. SLS is a complex technology involving many different process parameters. The shrinkage ratio is a function of a number of factors. The important parameters are layer thickness (l_t), layer power (w), hatch spacing (d_h), scanning speed (v), interval time (T_s), surroundings temperature of working (T_e), and scanning mode (F). The process parameters can be expressed as the following.

$$x = [x_1\, x_2\, x_3\, x_4\, x_5\, x_6\, x_7]' = [l_t\, d_h\, w v T_e\, T_s\, F]' \tag{1}$$

The shrinkage ratio can be expressed as functions of x:

$$y = f(x) \tag{2}$$

The mathematical expressions given in Eq. 2 show how the process parameters affect the shrinkage ration, where NN represents the neural network function that yields y.

$$y = NN(x) \tag{3}$$

The network is able to show the dependence of the shrinkage ratio on process parameters, which is very useful information for machine designers as well as machine users.

Table 1 The ranges of process parameters

l_t (mm)	d_h (mm)	w (W)	v (mm/s)	T_e (°C)	T_s (s)
0.1–0.24	0.08–0.15	8–20	1,300–3,000	78–95	0–4

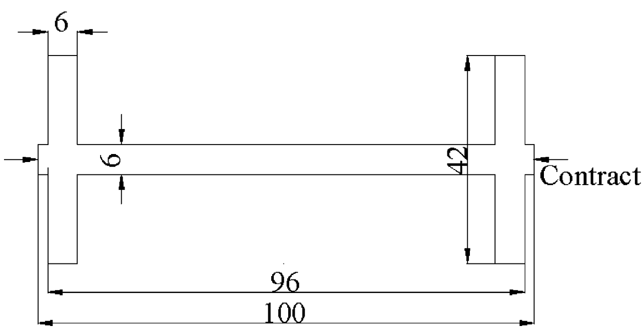

Fig. 1 The shrinkage test model

The network adopted here is back propagation (BP) model. In general, the neural network is composed of network, weighting coefficients, input variables, output variables, and training data.

The training data are very important for the accuracy of network results. In order to obtain the correct sets of training and test data needed for the neural network, it is necessary to carry out a series of experiments. Specimens used in this study were prepared using HBI, which is a composite of polystyrene developed by the Centre of Rapid Manufacturing of Huazhong University of science and Technology in China. The ranges of process parameters are shown in Table 1. There are two styles of canning mode: One is direction change canning and the other is subarea and direction change canning. Specimens with the simple shape and size shown in Fig. 1 have been made in an high-resistivity polycrystalline silicon machine SLS sintering system developed at the Centre of Rapid Manufacturing of Huazhong University of Science and Technology in China. The characteristic dimension of "contract" is used to define the shrinkage of SLS products in this paper. Measurements were conducted by using a Vernier micrometer with an accuracy of ±0.01 mm, based on the average value over the same specimen several times. The shrinkage ratio was calculated according to the following equation:

$$Y(\%) = \left(\frac{C_{\mathrm{CAD}} - C_{\mathrm{mea}}}{C_{\mathrm{CAD}}}\right) \times 100\% \tag{4}$$

where C_{CAD} is the CAD model value of contract, and C_{mea} is the measured value of contract. From the experimental data, six data sets were randomly selected as testing sets as shown in Table 2. The other 27 data sets were used for training the neural network shown in Table 3.

The fundamental idea of BP algorithms is to minimize the error between the desired and actual outputs through adjusting the weights by back-propagating the error from output layer to hidden layer. The details of implementing the proposed algorithm are as follows.

1. Initialize weights. Set all weights to small random numbers.
2. Calculate network output.
3. Calculate network error. The error function E_{AV} is defined as the integral of total squared error of $e_j(n)$ between an output $y_j(n)$ and the experimental result $Y_j(n)$ of the output layer as follows:

$$e_j(n) = Y_j(n) - y_j(n) \tag{5}$$

and

$$E_{\mathrm{AV}} = \frac{1}{2N}\sum_{n=1}^{N} e_j^2(n) \tag{6}$$

where the N is the total number of training sets. E_{AV} evaluates the learning status. If $E_{\mathrm{AV}} \leq \varepsilon$ (ε is preliminary definition, and $\varepsilon \geq 0$; in this paper, ε=0.00001), stop; otherwise, proceed to step 4.

4. Adjust weights according to the gradient methods. And, apply Levenberg–Marquardt optimality theory [18] to adjusting weights.

In order to simplify the architecture of the BP neural network model, only one layer will be used. The prediction accuracy and generalization of the network can be improved by choosing the proper number of hidden neurons.

When the sigmoid function is selected as the activation function of the hidden layer, the BP neural network will have an improved prediction performance.

Table 2 Test sets for the neural network

Part number	l_t (mm)	w (W)	v (mm/s)	d_h (mm)	T_s (s)	T_e (°C)	F
2	0.16	8	1,300	0.14	0	93	2
6	0.16	11	1,800	0.14	0	80	1
15	0.24	9	1,300	0.14	1	80	2
24	0.16	18	2,400	0.15	3	84	1
31	0.2	15	2,000	0.15	3	84	1
33	0.2	12.5	2,000	0.1	0	95	1

Table 3 Training sets for neural network

Part number	l_t (mm)	w (W)	v (mm/s)	d_h (mm)	T_s (s)	T_e (°C)	F
1	0.1	8	1,300	0.08	1	78	1
3	0.1	12	3,000	0.08	0	80	2
4	0.16	12	3,000	0.14	1	93	1
5	0.12	11.5	1,800	0.1	2	93	2
7	0.12	20	3,000	0.1	0	93	1
8	0.16	20	3,000	0.14	2	78	2
9	0.24	20	3,000	0.14	0	93	2
10	0.24	20	3,000	0.1	2	80	1
11	0.24	10.5	1,800	0.14	2	93	1
12	0.24	10	1,800	0.1	0	78	2
13	0.24	14.5	3,000	0.14	0	78	1
14	0.24	15	3,000	0.08	1	93	2
16	0.24	8.5	1,300	0.08	0	93	1
17	0.16	15	2,000	0.12	3	84	2
18	0.16	15	2,000	0.15	4	87	1
19	0.16	15	2,400	0.12	4	84	1
20	0.16	15	2,400	0.15	3	87	2
21	0.16	18	2,000	0.12	3	87	1
22	0.16	18	2000	0.15	4	84	2
23	0.16	18	2,400	0.12	4	87	2
25	0.2	18	2,400	0.15	4	87	1
26	0.2	18	2,400	0.12	3	84	2
27	0.2	18	2,000	0.15	3	87	2
28	0.2	18	2,000	0.12	4	84	1
29	0.2	15	2,400	0.15	4	84	2
30	0.2	15	2,400	0.12	3	87	1
32	0.2	15	2,000	0.12	4	87	2

By changing the number of the hidden neurons while training the model, the proper number of the hidden neurons can be selected by observing the training results of the model. The trained results are given in Table 4, while the predicted results ones can be seen in Table 5. Table 4 shows that it fits well under the conditions of the sample data when the hidden neurons vary from five to ten. Table 5 shows the predicted results of the test sets by varying the hidden neurons from five to ten. As can seen from Table 5, the prediction accuracy of the neural network rapidly increases when the hidden neurons vary from five to eight. When the neurons increase continuously, the prediction accuracy is poor.

So, in this paper, the neural network structure is fully connected and consists of one hidden layer. The neural network has seven inputs, one output, and one hidden layer with eight nodes and is trained by the experimental data. After training, the neural network can reflect the relationship between the process parameters and the manufacturing shrinkage ratio. The simulation and the experiment results for training, and test sets are shown in Figs. 2 and 3, respectively. Figure 3 shows that the maximal simulation error of the test sets is 0.2761, the minimum error is 0.0435, and the average error of the simulation is 0.126. Thus, it is easy to see that the prediction performance accuracy of the neural network is reasonably which indicates the reliability of neural network. After we have obtained the neural network model describing the SLS process, the effects of the process parameters on shrinkage ratio can be predicted.

Table 4 Trained results of the training sets using different numbers of hidden neurons

	The number of the hidden neurons					
	5	6	7	8	9	10
The average relative error (%)	0.0580	0.0571	0.0647	0.01847	0.0142	0.0069

Table 5 Predicted results of the testing sets using different numbers of hidden neurons

	The number of the hidden neurons					
	5	6	7	8	9	10
The average relative error (%)	0.4638	0.2026	0.1433	0.066	0.3665	0.2288

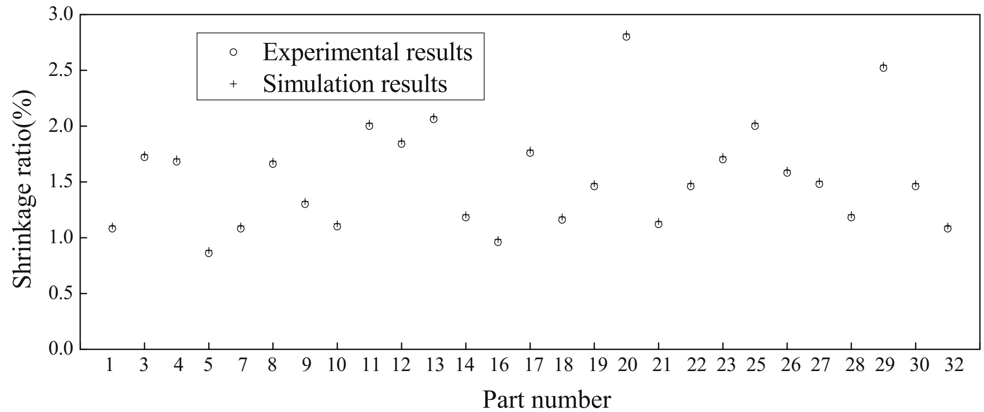

Fig. 2 Experimental results and simulation results of training sets

3 Process parameters optimization

In Section 2, the relation between process parameters and the shrinkage ratio has been obtained. But, the model based on the neural network cannot give the explicit function of the input and output. To find the SLS optimum process parameters, the global minimum of an objective function has to be searched. A gradient-based optimization method cannot find the global optimum [19]. It is difficult to search the global optimum through the traditional search method. Therefore, the GA is preferred. A GA is a stochastic optimization method, based on the principle of natural selection: the survival of the fittest individuals in a population [20]. GA implements methods of nature. Natural systems show a high level of robustness. This is the result of their adaptation to many different environments and operation to locate the global optimum without being attracted to the local optima [21].

The flowchart of the used algorithm is shown in Fig. 4. The details of implementing the proposed algorithm are as follows:

Step 1. Generate the initial population. The initial population is randomly created within the domain of the search space. The members of the population are finite-length string structures called chromosomes. In this paper, the SLS process parameter is coded by a method of binary representation, and each chromosome is coded to represent a set of the process parameter including layer thickness, hatch spacing, laser power, scanning speed, work surroundings temperature, interval time, and scanning mode and is coded into a 27-bit string segments as shown in Fig. 5.

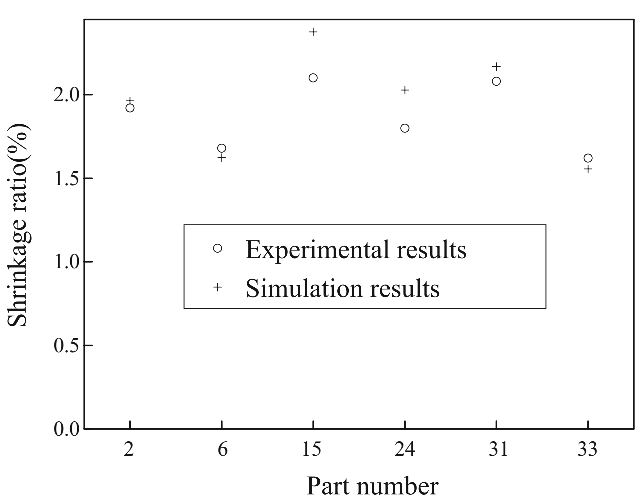

Fig. 3 Experimental results and simulation results of testing sets

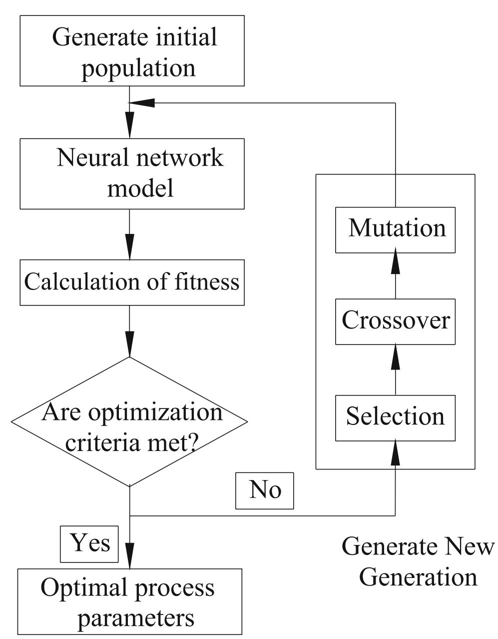

Fig. 4 Optimization of process parameters using genetic algorithm

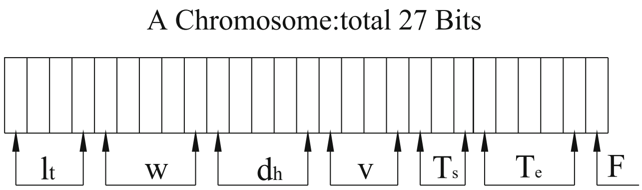

Fig. 5 Binary representation for optimization of a chromosome

Table 7 Experimental results of optimum process parameters

Part number	Shrinkage ratio (%)
1	0.128
2	0.130
3	0.129
4	0.128
5	0.128
6	0.129

Step 2. Utilize the neural network to calculate the fitness of chromosome. Each chromosome is assigned a fitness. The fitness of a chromosome defines the survival or the ability to create offspring to the next generation. In this problem, the process parameters of a small shrinkage are regarded as the one having a higher fitness. Therefore, the fitness function can be defined as reciprocal of the shrinkage ratio which obtains from the neural network simulation.

Step 3. The GA terminates if the maximum number of generation is reached. Otherwise, proceed to step 4.

Step 4. Generate new populations. There are three fundamental operations involved in generating new populations.

Selection The selection is that which is going to survive from a set of candidate chromosomes. In this paper, the fitness value is calculated for each chromosome by using the fitness function, which is defined in the previous section. The individuals obtain a fitness that represents their reproduction probability. The best individual in every subpopulation is selected. The selection method is universal stochastic sampling [22].

Crossover The crossover process is a reform operation for the survival candidates. In natural system, a set of creatures creates a new set of the next generation by crossing among the creatures. In the same way, the crossover process is performed by changing pieces of chromosomes using information of old chromosomes. The pieces are crossed in couples of chromosomes selected at random [23].

Mutation The mutation process is held to escape the local minima in the search space in the artificial genetic approach. All variables in an individual obtained after crossover have a small chance on mutation [24].

Step 5. Return to step 2.

The main controlling parameters of GA include crossover probability, mutation probability, and maximum number of generation. The values are 0.82, 0.05, and 150, respectively [25]. In this paper, the final optimization result is studied by changing the population size effects. When the size of the population is too small, the search band of GA is limited, which results in a premature convergence phenomenon. While a rather large population size can reduce the possibility of trapping in local optimization, the calculation time increases and rends slower convergence. The fitness value and shrinkage ratio are shown in Table 6, when the population size is 15, 20, 22, 25, 28, 30, 35, and 40. The result shows that as the population size increases, the fitness tends to rather rapidly increase but to nearly flatten off for beyond a population size of 30. So, the size of the population is selected as 30.

The optimum SLS process parameters are given by the following:

Layer thickness=0.2 mm, hatch spacing=0.12 mm, laser power=18 W, scanning speed=1,800 mm/s, surrounding temperature of working=93°C, interval time=1 s, and scanning mode is subarea and direction change scanning.

Table 6 Fitness values and shrinkage ratio value vs. population size

	Population size							
	15	20	22	25	28	30	35	40
Fitness average value	1.3115	2.1988	2.8893	3.12305	6.3331	7.7580	7.8431	7.9051
Fitness maximum value	1.3858	2.3866	3.11526	3.2733	7.5700	7.9051	7.9051	7.9051
Shrinkage ratio average value (%)	0.7625	0.4548	0.3461	0.3202	0.1579	0.1289	0.1275	0.1265
Shrinkage ratio minimum value (%)	0.7216	0.419	0.321	0.3055	0.1321	0.1265	0.1265	0.1265

4 Experimental verification

To verify the optimization result, experiments were performed using the optimum process parameter. The shrinkage ratio was measured five times under the same condition layer thickness=0.2 mm, hatch spacing=0.12 mm, laser power=18 W, scanning speed=1,800 mm/s, surrounding temperature of working=93°C, interval time=1 s, and scanning mode is subarea and direction change scanning. The repeatability of the shrinkage ratio was found to be good. Table 7 shows the measured results. For practicality, the optimization result has been applied to manufacture some perfect goods.

5 Conclusion

In this paper, GA has been applied to determine the optimal SLS process parameter based on minimum shrinkage ratio. The relation between process parameters and shrinkage ratio is modeled and described by neural networks, since the SLS process parameter is a nonlinear and multitudinous system. The neural network has been verified experimentally. Based on the neural network, the GA searches the optimal process parameter, so that the part manufacture under the optimal process parameter yields minimum shrinkage. In practice, the optimal process parameter can instruct the manufacturing. So, the following can be reported:

1. In the optimization, when the size of population is 30, the GAs search the global optimum with reasonable convergence speed.
2. The optimal process parameters are layer thickness (l_t)=0.2 mm, hatch spacing (d_h)=0.12 mm, layer power=18 W, scanning speed (V)=1,800 mm/s, surrounding temperature of working (T_e)=93°C, interval time (T_s)=1 s, and scanning mode (F) is subarea and direction change canning.
3. The optimization method combines the neural network with GA, which can apply to nonlinear and multitudinous systems.
4. The shrinkage ratio obtained by the neural network can provide information for shrinkage compensation of SLS.

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