An assembly process parameters optimization method for precision assembly performance

Chao Shao, Xin Ye¹, Lei Wang, Zhijing Zhang, Dongsheng Zhu and Jiahui Qian
Department of Mechanical Engineering, Beijing Institute of Technology, 5 South Zhongguancun Street, Haidian District, Beijing 100081, China;
¹E-mail: yexin@bit.edu.cn

Abstract. There are only few works in literature that suggest an assembly process optimization method based on manufacturing errors in the precision manufacturing area. A multi-objective assembly process parameters evaluation and optimization method for precision assembly performance of microstructures with manufacturing errors has been proposed in this paper. Based on the model with manufacturing errors, the ABAQUUS software is used for simulation and calculation, and the assembly performance evaluation indexes of the microstructures under different assembly process parameters, such as stress value, stress distribution value and pose offset, are obtained. The mapping model of the key assembly process parameters and assembly performance is established based on BP neural network. Finally, the best assembly process parameters for the optimal assembly performance are solved based on the genetic algorithm, and the method has been verified by the optimization results of preload forces of the 3D mechanism, which can be used to guide and monitor the assembly process quantitatively in the precision manufacturing area.

1. Introduction
At present, most of precision microstructures are still in the manual assembly stage [1]. In the assembly process, problems such as low accuracy and inefficiency, poor consistency and reliability are common, and the assembly process parameters should be evaluated and optimized [2].

Many researchers have studied the evaluation and optimization method of assembly process parameters. In order to adapt to variations and satisfy the performance requirements, the relationship model between the process parameters and system performance based on Gaussian Process Regression has been built, and experiments were performed using a peg-in-hole process [3, 4]. And then the improved genetic algorithm based on neural network had been proposed, which could effectively improve the search efficiency [5, 6]. The learning-based evolutionary algorithm to optimize the dual peg-in-hole assembly process has been proposed, which only required little prior knowledge instead of modeling for the complex contact states [7, 8]. An online parameter optimization method by combining GPR with Bayesian Optimization Algorithm has been developed to optimize the assembly process parameters [9]. To increase the efficiency of the GA based methods, Artificial Neural Network (ANN) is utilized to model whether the parameters are “good” or “bad” to filter the candidate parameters first without performing any experiment [10]. A multi-objective genetic algorithm for flow shop scheduling has been proposed. Based on the weighted values of multi-objective functions with variable weights, individuals were selected for cross-operation. The optimization problem of bi-objective functions with concave Pareto array was solved by operation selection strategy [11].
However, the evaluation indicator of assembly performance is relatively single and one-sided. The existing optimization method of assembly process parameter is oriented to low assembling accuracy. It does not pay attention to the influence of the manufacturing errors of the parts on the assembly performance index. These methods are not suitable for the optimization of precision assembly parameters of the microstructures with manufacturing errors. This paper proposed the multi-objective assembly process parameters evaluation and optimization method for assembly performance of microstructures with manufacturing errors.

2. Multi-objective Evaluation Method of Assembly Performance

In order to ensure the assembly performance of the assembled parts, including the assembly precision, precision stability and consistency of the product, the key assembly performance indexes or optimization objectives need to be evaluated are shown in Table 1.

| Assembly force/(moment) | Symbol | Implication | Acquisition mode |
|-------------------------|--------|-------------|-----------------|
| Force/(moment)          | $F/T$  | Tightening torque | Torque wrench   |
| Maximum stress value of key position | $\sigma_{\text{max}}$ | The maximum stress value of the value | FEM calculation |
| Stress uniformity       | $H_{\text{cr}}$ | $H_{\text{cr}} = -\sum_{i=1}^{m} p_i \ln(p_i)$ | FEM calculation |
| Datum variation of mating surface | $(\Delta x, \Delta y, \Delta z, \Delta \alpha, \Delta \beta, \Delta \gamma)$ | Between the actual the ideal coordinate system | Numerical calculation |

2.1. Evaluation of pose deviation method after assembly

There are some manufacturing errors on the part surface, so we established the part model with manufacturing errors, which is the key step of optimization calculation. In the assembly process of the part with manufacturing errors on the mating surface and the base part, there are at least three points of contact on the contact surface. Then, the mating surface with manufacturing errors on the assembled parts is set as A and B respectively. It is assumed that the plane equations $P_A$ and $P_B$ of the three points on plane A and the three points on plane B are expressed as:

$$
\begin{align*}
P_A : a_1 x + b_1 y + z + c_1 &= 0 \\
P_B : a_2 x + b_2 y + z + c_2 &= 0
\end{align*}
$$

The corresponding normal vectors are respectively: $n_1 = [a_1, b_1, 1], n_2 = [a_2, b_2, 1]$. In the actual assembly process, when the parts are assembled, the surface A of target part will contact the face B of base part by translation and rotation under the assembly force. Under the influence of the manufacturing errors, the assembling parts can not be aligned without any assembly errors, and the assembly error of two parts after assembly can be represented as $(\Delta x, \Delta y, \Delta z, \Delta \alpha, \Delta \beta, \Delta \gamma)$. Therefore, the assembly error after assembly can be used to evaluate the assembly process parameters.

2.2. The method of stress uniformity evaluation

This paper uses information entropy to evaluate the probability of stress occurrence, and to evaluate the uniformity of stress distribution. The more uniformly the stress is distributed, the greater the information entropy value is. Based on the finite element calculation, we can get the stress value of each unit and normalize it according to the Equation (2).

$$
\sigma_{\text{cr}} = \frac{\sigma_{\text{cr}}}{\sum_{i=1}^{n} \sigma_i}
$$

2
Where, $\sigma_i$ represents the stress value of the $i$th unit; $\sigma'_i$ represents the stress value of the normalized $i$th unit; the number of model units is $m$.

Therefore, the entropy of strain uniformity distribution is defined as follows:

$$H_s = \sum_{i=1}^{m} \sigma_i \ln(\sigma'_i)$$

(3)

The formula of stress entropy after normalization is:

$$H_{s'} = \frac{H_s}{H_{\text{max}}} = \frac{H_s}{\ln(m)}$$

(4)

2.3. Maximum stress value of key parts

In order to achieve precision assembly, the greater the assembly stress, the worse the stability of assembly accuracy. As time goes on, the accuracy consistency of the product is poor. Therefore, the stress value of key parts can be used to evaluate the product performance. The smaller the maximum value, the better the assembly performance is.

3. Multi-objective Optimization Method of Assembly Performance

In this paper, the shape features of the mating surface of the assembled part are extracted based on measured data on CMM firstly, and the 3D model of the assembled part with manufacturing errors is established. The boundary conditions such as constraints and external forces were imposed successively. By adjusting the process parameters, the stress value, stress distribution value and pose deviation value can be obtained by simulation calculation. According to the multi-objective optimization algorithm, different target weights are applied to establish the nonlinear mapping rule of key assembly process parameters and assembly performance, and then solve the optimal solution to obtain the optimized assembly process parameters. The optimized assembly process parameters can quantitatively guide the assembly process to achieve the best assembly performance. The specific optimization technical route of assembly process parameters is shown in Figure 1.

Figure 1. Assembly process parameter optimization method based on assembly performance.

The parameters of assembly process were studied quantitatively, and the function of assembly optimization were established. Finally, the established mathematical model used to optimize the assembly process was as follows:

$$\text{Optimize assembly process parameters: } X = [x_1, x_2, \ldots, x_n]^T$$

(5)
The optimization goal

\[
\begin{align*}
\text{Key parts} & \quad \sigma_{\text{min}} \to \min \\
\text{Stress uniformity} & \quad H_{\text{max}} \to \max \\
\text{Deviation of pose after assembly} & \quad (\Delta x, \Delta y, \Delta z, \Delta \alpha, \Delta \beta, \Delta \gamma) \to \min
\end{align*}
\]

In the process of multi-objective optimization calculation, there are often contradictions in the optimization of multiple optimization objectives. Therefore, when the multi-objective minimum value is calculated, each component value of the optimization objective can be expressed as

\[ f_k(X) \in \mathbb{R}^+, \quad (k = 1, 2, K) \]

that is, there is an optimal target component value. Then the expression of the optimization target can be written as

\[ f(X) = (f_1(X), f_2(X), \ldots, f_K(X)), \quad \text{here } X \in \mathbb{E}^n \]

This paper adopts the linear weighting method to solve the multi-objective optimization problem, which can transform multiple optimization objectives into a single objective for solving. Therefore, multi-objective optimization can be equivalent to Equation (8), \( \omega_k \) is the variable weight coefficient.

\[ F(X) = \omega_1 f_1(X) + \omega_2 f_2(X) + \ldots + \omega_k f_k(X) \]  

(7)

4. Assembly parameters optimization case validation

This paper takes a 3D mechanism as an example to verify the assembly process optimization method of microstructures with manufacturing errors based on multiple objectives. As shown in Figure 2, target part with face A is assembled to the base part with face B, and they are fixed by three locking screws. Due to the manufacturing errors of the part itself, the assembly stress caused by different preload forces of the three screws is different. Therefore, this paper takes the preload forces of the three screws as the optimized assembly process parameters, and takes the maximum stress, stress uniformity and pose deviation after assembly as the optimization objective to improve the assembly performance.

![Figure 2. Assembly of key parts of the 3D mechanism.](image)

Firstly, a 3D part model with manufacturing errors is established, and the error surface fitting point cloud is shown in Figure 3(a). It can be seen that the fitting point surface is not an ideal plane due to manufacturing errors. The part model with manufacturing errors is meshed, and the coordinate values of all the nodes of the part A are obtained. The part B is imposed by full constraint, and different preload forces are applied to the three screws.

According to the knowledge gained from the experience of workers, the preload force value of the three screws is between 300~400N, different preload forces ranged from [300, 400] are applied to the three screws. Due to the manufacturing errors of the mating surfaces of the parts, the different preloads of the three screws have different effects on the assembly performance parameters. Different values of three preload forces corresponding to the orthogonal experiment are designed as shown in Table 2.

Through the simulation calculation, the stress values of all the nodes of the part A under the three assembly forces, the coordinate values of all the nodes after assembly, and the displacement values of all the nodes are obtained. After fitting the mating surface under preload forces, the geometric centre coordinate value and angle between the normal vectors of the loaded surface and no loading surface before final assembly were calculated. Therefore, the offset and rotation offset of the mating surface
after applying the preload force can be obtained and written into Table 2. Here, when the preload is (325,325,325), the coordinate fitting point cloud of the mating surface of part A after simulation calculation is shown in Figure 3(b). The stress and strain nephograms extracted by simulation calculation under this working condition are shown in Figure 4.

Table 2. Assembly performance parameters under different assembly process parameters.

|   | $F_1/N$ | $F_2/N$ | $F_3/N$ | $H_{as}$  | $\sigma_{max}/MPa$ | $d/\mu m$ | $\theta/°$ |
|---|---------|---------|---------|-----------|---------------------|-----------|-----------|
| 1 | 300     | 300     | 300     | 0.96624   | 228.06              | 3.1618    | 0.0076    |
| 2 | 400     | 300     | 300     | 0.96498   | 284.68              | 3.1034    | 0.0084    |
| 3 | 300     | 400     | 300     | 0.96525   | 234.39              | 3.1317    | 0.0074    |
| 4 | 300     | 300     | 400     | 0.96542   | 267.05              | 3.1288    | 0.007    |
| 5 | 300     | 400     | 400     | 0.96503   | 267.23              | 3.0949    | 0.0068    |
| 6 | 400     | 300     | 400     | 0.96497   | 284.51              | 3.0676    | 0.0078    |
| 7 | 400     | 400     | 300     | 0.96495   | 284.62              | 3.0727    | 0.0082    |
| 8 | 400     | 400     | 400     | 0.96496   | 284.5               | 3.034     | 0.0076    |
| 9 | 325     | 300     | 300     | 0.96606   | 242.35              | 3.1466    | 0.0078    |
| 10| 350     | 300     | 300     | 0.96578   | 256.51              | 3.1318    | 0.0080    |
| 11| 375     | 300     | 300     | 0.96541   | 270.6               | 3.1174    | 0.0082    |
| 12| 300     | 325     | 300     | 0.96609   | 231.57              | 3.1553    | 0.0076    |
| 13| 300     | 350     | 300     | 0.96587   | 231.56              | 3.1468    | 0.00753   |
| 14| 300     | 375     | 300     | 0.96557   | 231.55              | 3.1387    | 0.0075    |
| 15| 300     | 300     | 325     | 0.96613   | 231.52              | 3.1554    | 0.0074    |
| 16| 300     | 300     | 350     | 0.96595   | 240.39              | 3.1461    | 0.0073    |
| 17| 300     | 300     | 375     | 0.96568   | 253.73              | 3.1369    | 0.0071    |
| 18| 325     | 325     | 325     | 0.96591   | 244.7               | 3.1315    | 0.0076    |
| 19| 350     | 350     | 350     | 0.96556   | 257.67              | 3.0977    | 0.0076    |
| 20| 375     | 375     | 375     | 0.96524   | 270.45              | 3.0647    | 0.00762   |

Figure 4. Stress and strain nephograms extracted when preload is (325,325,325).
When different preload forces were applied, the assembly performance indexes that stress values, the evaluation entropy of stress uniformity, the component pose translation and the component pose rotation can be obtained. To establish the mapping model between assembly process parameters and assembly performance indexes, there are three inputs and four outputs, and the four outputs are correlated with each other, so the type of nonlinear mapping function is not clear. Neural network is the best way to solve the problem when the model type is not clear. BP neural network is used to establish a nonlinear mapping model between three preloads and four assembly performance indexes. The BP neural network is used to train the data calculated by ABAQUS simulation as shown in Table 2.

The first 18 sets of data calculated by simulation was used to training nonlinear mapping model in MATLAB, and the remaining 2 sets of data are used as test data. Considering that the BP neural network based on the gradient descent method is easy to fall into the local optimum situation, this paper uses the Levenberg-Marquardt search algorithm to solve the problem. The training weights and offsets as shown in Equation (8) are obtained, which is the transfer matrix model between output layer and input layer of each layer. The following genetic optimization calculation is based on the weight matrix and bias vector of the neural network. The optimal iteration number and gradient value obtained by the training result are shown in Figure 5. The minimum mean square error (Mean Squared Error) of the test data is 0.017, which satisfies the mapping requirements. According to the established neural network model, we can solve the optimal assembly process parameters.

\[
W = \begin{bmatrix}
-0.7432 & -2.103 & -0.6896 \\
0.8091 & -2.144 & 1.9143 \\
-0.824 & 0.8668 & 1.6526 \\
0.1816 & -1.429 & 2.4979 \\
-1.719 & -1.429 & 2.4979 \\
0.1816 & 0.8668 & 1.6526 \\
-1.719 & -1.429 & 2.4979 \\
0.1816 & 0.8668 & 1.6526 \\
-1.719 & -1.429 & 2.4979 \\
0.1816 & 0.8668 & 1.6526 \\
-1.719 & -1.429 & 2.4979 \\
0.1816 & 0.8668 & 1.6526 \\
-1.719 & -1.429 & 2.4979 \\
0.1816 & 0.8668 & 1.6526 \\
-1.719 & -1.429 & 2.4979 \\
0.1816 & 0.8668 & 1.6526 \\
-1.719 & -1.429 & 2.4979 \\
\end{bmatrix}
\]

\[
b = \begin{bmatrix}
-3.0519 \\
-1.8568 \\
0.9622 \\
-0.2473 \\
-0.2416 \\
1.0962 \\
-1.7879 \\
3.5059 \\
\end{bmatrix}
\]

Based on the nonlinear mapping model of the assembly process parameters between the assembly performance indexes established by the neural network, the optimization target is established according to the Equation (8). The fuzzy entropy of the stress uniformity evaluation index is reciprocated, so that the multiple optimization targets take the minimum value. Therefore, this paper uses genetic algorithm to obtain the three assembly process parameters that minimize the objective function.

![Neural network configuration diagram](a) The neural network configuration diagram

![Best Validation Performance is 0.616642 at epoch 4](b) The mean square error of training results

**Figure 5.** Neural network training results.
According to the definition of each initial parameter of the genetic algorithm and the preliminary tentative calculation, the values of each parameter are shown in Table 3.

| Population size | Evolutionary algebra | Crossover probability | Mutation probability | Generation gap |
|-----------------|----------------------|-----------------------|----------------------|----------------|
| 50              | 100                  | 0.8                   | 0.3                  | 0.8            |

The change of the average fitness value and the maximum fitness value of the population in the process of genetic optimization based on MATLAB is shown in Figure 6. It can be seen from the Figure 6 that the average fitness value of the population tends to be stable when it reaches about 10 generations, and the optimum value of the three assembly parameters is (332.3 370.3 373.5). Through multi-objective optimization of assembly process for assembly performance, the optimum assembly process parameters are obtained, which can guide the quantitative implementation of assembly process, ensuring the optimum assembly performance index.

![Figure 6](image)

**Figure 6.** The production process with Genetic Algorithm.

### 5. Conclusions

The multi-objective assembly process parameters evaluation and optimization methods for assembly performance of precision microstructures with manufacturing errors have been proposed in this paper. The mapping model of the key assembly process parameters and assembly performance was established based on BP neural network. The best assembly process parameters for the optimal assembly performance were solved based on the genetic algorithm. For three screw pre-tightening forces, the optimization method of assembly process parameters was verified, which could be used to guide and monitor the assembly process quantitatively. Future work should focus on the experimental verification of optimized assembly process parameters, and computing and comparing the optimized assembly process parameters based on other optimum algorithms.

**Acknowledgements**

This work was financially supported by the NSFC (51575052)&(U1537215).

**Reference**

[1] Sun Y and Liang Y 2004 Micro-scale and meso-scale mechanical manufacturing *CHIN J Mech Eng* 40 1-6
[2] Zhang Z, Jin X and Zhou M 2007 Precise and microminiature manufacturing theory, technology and its appliance CHIN J Mech Eng 43 49-61
[3] Cheng H and Chen H 2014 Online parameter optimization in robotic force controlled assembly processes IEEE Int Conf Robot Autom 3465-3470
[4] Zhang B Gravel D and Zhang G 2011 Robotic force control assembly parameter optimization for adaptive production IEEE Int Conf Robot Autom 464-469.
[5] Aryanezhad M and Hemati M 2008 A new genetic algorithm for solving nonconvex nonlinear programming problems Applied Mathematics Computation 199 186-194
[6] Mahfoud S and Goldberg D 1995 Parallel recombinative simulated annealing: a genetic algorithm Parallel Comput 21 1-28
[7] Hou Z Philipp M Zhang K Guan Y Chen K and Xu J 2018 The learning-based optimization algorithm for robotic dual peg-in-hole assembly Assem Autom 38 369-375
[8] Daoud S Chehade H Yalaoui F and Amodeo L 2014 Efficient metaheuristics for pick and place robotic systems optimization J Intell Manuf 25 27-41
[9] Cheng H and Chen H 2014 Online parameter optimization in robotic force controlled assembly processes IEEE Int Conf Robot Autom 3465-3470
[10] Marvel J and Newman W 2011 Model-assisted stochastic learning for robotic applications IEEE Trans Autom Sci Eng 8 835-845
[11] Murata T and Ishibuchi H 1996 Multi-objective genetic algorithm and its applications to flow shop scheduling Computers & Industrial Engineering 30 957-968