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ORIGINAL ARTICLE

Optimum fixture locating layout for sheet metal part by integrating kriging with cuckoo search algorithm

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Abstract Fixture locating layout has a direct and influential impact on the sheet metal mechanical behavior and dimensional quality during the manufacturing process. The N-2-1 locating principle is adopted to design the fixture locating layout for the sheet metal part to determine the spatial location and restrain the excessive deformation. However, efficient optimal design of fixture layout is not an easy-to-implement and trivial task. The state-of-the-art evolutionary optimization of fixture layout aiming for workpiece deformation control often involves hundreds or even thousands of calls of finite element analysis and therefore is faced with uncomfortable and challenging computation cost and burden. In order to reduce the computational cost and improve the optimization efficiency, a new approach for optimum sheet metal fixture locating layout based on the N-2-1 principle is proposed in this paper. The training and test data sets are generated by running only a few times of finite element analysis on the design sites standing for different fixture locating layouts selected through Latin hypercube sampling. The kriging surrogate model is built based on the training sample set to approximate the implicit function relationship between the fixture locating layout and the concerned sheet metal deformation and meanwhile is compared with back propagation neural network in terms of prediction accuracy by the test sample set. The cuckoo search algorithm is applied to the kriging model to find the optimal fixture locating layout. Flat and curved sheet metal cases based on the "4-2-1" locating scheme are conducted, and the results indicate that the proposed approach is effective and efficient in the design and optimization of the sheet metal fixture locating layout.

Keywords Fixture layout · Sheet metal · Kriging surrogate model · Cuckoo search algorithm · Back propagation neural network

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1 Introduction

Sheet metal is extensively put into use in aerospace, automobile, and shipbuilding industries while it tends to deform out of tolerance throughout the whole manufacturing process [1, 2]. In order to not only determine the spatial location but also constrain the excessive deformation of the sheet metal part, Cai et al. [3] presented the "N-2-1" ($N \geq 3$) locating principle for deformable workpieces by extending the "3-2-1" principle [4] for rigid parts. Hence, one of the key problems as to designing the fixture layout based on either the N-2-1 or the 3-2-1 locating principle is how to find the optimal layout of the fixture locators to minimize the workpiece deformation.

However, it is a non-trivial task to effectively and efficiently obtain the optimum fixture layout to control the general workpiece deformation and ensure its dimensional quality considering that there not always exists the analytical or form-closed expression between the fixture layout and the concerned workpiece deformation subject to manufacturing loading. To that end, a lot of work about fixture layout analysis and modeling for the deformable workpiece has been conducted by many researchers for the past few years. In order to analyze and evaluate the performances of different fixture layouts, finite element analysis (FEA) was introduced and verified to model the workpiece–fixture system and calculate the concerned workpiece deformation to aid the fixture layout design and optimization [5–7] in the beginning. Afterwards, FEA, as a recognized and reliable modeling tool to assess the fixture layout capability in the optimal fixture configuration design, has gained more and more popularity in the research community.

Krishnakumar and Melkote [8] used the genetic algorithm (GA) and FEA to find the optimum fixture layout to minimize the deformation of the machined surface due to clamping and machining forces over the entire tool path. Li and Shiu [9] achieved the optimal fixture configuration design by combining GA and FEA to improve the degree of the metal fit-up for sheet metal assembly with laser welding. By means of FEA, Kulankara et al. [10] applied GA for iterative milling fixture layout and clamping force optimization to minimize the elastic deformation for a compliant workpiece. Liao [11] proposed an optimization method based on GA coupled with FEA to select automatically the optimal numbers and positions of locators and clamps in sheet metal assembly fixture under the gravity effect to improve the dimensional and form accuracy of the workpiece. Kaya [12] carried out fixture locating and clamping position optimization through GA integrated with FEA to reduce the error caused by elastic deformation of the workpiece in machining. Likewise, Padmanaban et al. [13] applied ant colony algorithm (ACA)-based discrete and continuous optimization methods by virtue of FEA to optimize the milling fixture layout so that the workpiece elastic deformation was minimized due to the machining and clamping force. Through FEA calculating the workpiece deformation considering its dynamic response for a given fixture layout, Dou et al. [14] developed both an improved particle swarm optimization (IPSO)-based method and an improved GA (IGA)-based method for the fixture layout optimization to minimize the workpiece elastic deformation during the high-speed slot milling. Li et al. [15] invented a reconfigurable swarm intelligent fixture system for flexible aerospace parts and put forward a GA coupled with an FEA-based optimization procedure to determine the optimal fixture layout for the machining of large deformable sheet metal parts to improve the dimensional quality. Kumar and Paulraj [16] used an integrated optimization tool of GA and an FEA solver to find the optimum fixture layout to minimize the deformation of the workpiece under dynamic machining condition with chip removal effect. Xing et al. [17] proposed a method to bi-objective optimization of fixture layout for auto-body compliant parts satisfying the requirements of assembly tolerance and gravity deformation by a non-domination sorting social radiation algorithm (NSSRA) combined with FEA.

In conclusion, it can be seen that the evolutionary algorithm integrated with FEA has become the accepted and popular approach for optimization of the fixture layout for the deformable workpiece. However, the state-of-the-art evolutionary optimization of the fixture layout often involves lots of time-consuming FEA and therefore is faced with uncomfortable and challenging computation cost and burden. Thus, in order to reduce the computational cost and improve the optimization efficiency, approximation or surrogate models [18], such as response surface methodology (RSM) and back propagation neural network (BPNN), have been introduced and applied to computationally expensive fixture layout optimization for controlling the undesirable deformation of the flexible or deformable workpiece and improving the manufacturing accuracy in recent years.

Li et al. [19] developed a two-stage RSM based on limited use of FEA to obtain a robust fixture configuration to ensure the quality of metal fit-up for sheet metal assembly with laser welding. Hamedi [20] built BPNN with only a few times of FEA to realize the pattern between the clamping forces and state of contact in the workpiece–fixture system and the workpiece maximum elastic deformation and applied GA to determine the optimal clamping forces to reduce the excessive deformation/stress in the machined component. Li et al. [21] presented the three quality design models of a non-linear programming model, a polynomial RSM, and a BPNN-enhanced RSM to achieve the robust fixture planning of a sheet metal assembly with resistance spot weld design. Vasundara et al. [22] constructed BPNN to approximate the function relationship between fixture elements and the maximum elastic deformation of the workpiece determined by FEA and used BPNN and RSM to predict the machining fixture layout to minimize the maximum elastic deformation of the workpiece in the milling. Selvakumar et al. [23] used BPNN to describe the mapping relationship between the fixture layout and the maximum workpiece deformation and combined BPNN and design of experiments (DOEs) to find the optimum machining fixture configuration. Sundararaman et al. [24] developed a sequential optimization approximation method integrated with RSM to design the optimal machining fixture layout to minimize the workpiece deformation during the end-milling operation. Similarly, Lu and Zhao [25] established a BPNN model to predict the sheet metal deformation under different fixture layouts and applied GA to the BPNN model to search the optimal position of the fourth locator based on the “4-2-1” locating scheme. With a BPNN model built to predict the deformation of the workpiece–fixture system, Rex and Ravindran [26] proposed an integrated approach for the optimal fixture layout design to control the maximum elastic deformation of the workpiece during the entire machining process. Qin et al. [27] constructed a BPNN model depicting the function relationship between the fixturing parameters and the workpiece deformation and developed a unified approach by combining BPNN with

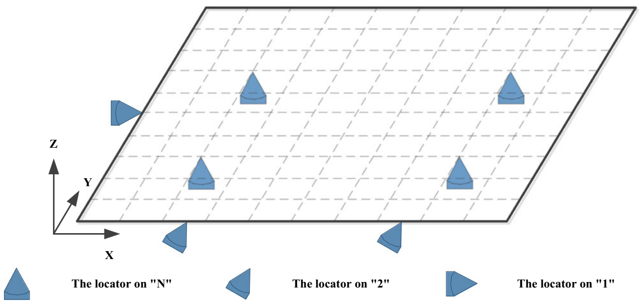


Fig. 1 "N-2-1" locating principle for the sheet metal part

GA to accomplish the machining multifixturing layout planning for the thin-walled workpiece to control the clamping deformation. Sundararaman et al. [28] made use of RSM to model the relationship between position of locators and clamps and maximum deformation of the workpiece during end-milling and optimized the established RSM model by GA and PSO to find the appropriate position of fixture elements to minimize the machining dimensional errors.

In this paper, a new approach by integrating kriging with the cuckoo search (CS) algorithm is presented to obtain the optimal fixture locating layout design to minimize the overall deformation for sheet metal part under the gravity effect. With this section included, this paper is made up of eight sections. The remainder of the paper is organized as follows: in Sect. 2, the optimization model of the sheet metal fixture layout is constructed. In Sect. 3, the bases of the prediction models of BPNN and kriging are introduced respectively. In Sect. 4, the fundamentals of the CS algorithm are presented. Section 5 depicts the flowchart of the proposed method. In Sect. 6, two thin sheet metal case studies are presented to verify the effectiveness and efficiency of the method in Sect. 6 and Sect. 7 respectively. The results of the case studies are analyzed and discussed. Finally, this paper is concluded in Sect. 8.

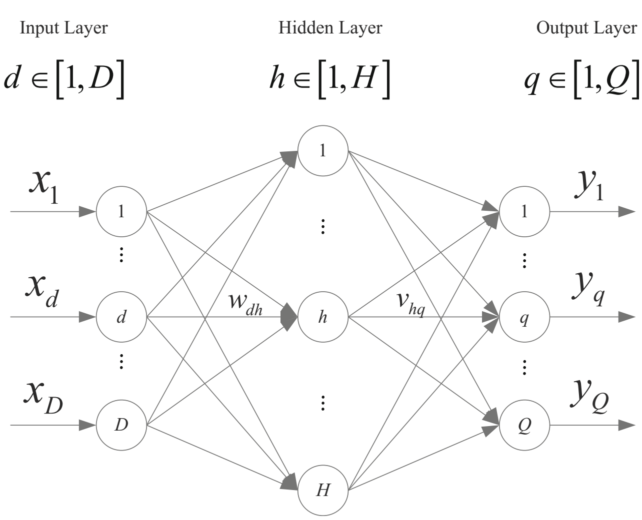


Fig. 2 Network structure of BPNN

2 Problem formulation

2.1 N-2-1 locating principle

Due to the characteristics of the thin wall, large size, and low rigidity, sheet metal always tends to deform which causes dimensional errors and affects manufacturing accuracy. Hence, the sheet metal part is often placed and clamped under an over-constraint condition based on the N-2-1 locating principle during the manufacturing process. As far as this locating principle is concerned, there should be "N" ($N \geq 3$) locators on the primary/first datum plane and "2" and "1" on the second and third datum planes of the sheet metal part, respectively. In other words, the 3-2-1 locating scheme is used to determinately position the part in the spatial location, while (N-3) additional locators are needed to prevent the excessive deformation and supply more supports on the primary datum plane of the sheet metal part. Figure 1 depicts a typical 4-2-1 locating principle, where four locators are required to support sheet metal on the primary datum plane to avoid the excessive deflection of the workpiece. It is obviously concluded that the key activity of the fixture layout design based on the N-2-1 principle is to find the optimum positions of the N locators to minimize the sheet metal part deformation.

2.2 Optimization model

Based on the N-2-1 locating principle, the normal excessive deformation of the sheet metal part under self-weight can be reduced, and then its dimensional quality in turn can be improved. In order to quantify the deformation of the sheet metal part and assess the performances of different fixture locating layouts, the evaluation function is defined as

$$f(\mathbf{X}) = \sqrt{\frac{\sum_{i=1}^{K} \varepsilon_i^2(\mathbf{X})}{K}} \tag{1}$$

where K is the total number of the mesh nodes of the finite element model of the sheet metal part, ε_i is the normal deflection of the i-th mesh node, and $\mathbf{X}$ is called the design variable vector standing for different fixture locating schemes.

In this work, FEA is used to model the fixture–workpiece system and calculate the evaluation function values to form the training data set to construct the BPNN and kriging prediction models. The optimization model for the optimal sheet metal fixture locating layout design can be expressed as

Table 1 Pseudo code of CS

Cuckoo search algorithm
Objective function $f(\mathbf{X})$, $\mathbf{X} = [x_1, x_2, \cdots, x_d]$.
Initialize a population of n host nests $\mathbf{X}_i (i = 1, 2, \cdots, n)$.
while *(t < Maximum number of iterations)*
Get a cuckoo (say i) randomly by Lévy flights.
Evaluate its quality/fitness $f(X_i)$.
Choose a nest among n (say j) randomly.
if $(f(X_i) < f(X_j))$
Replace j by the new solution i.
end if
Abandon a fraction (p_a) *of worse nests.*
Keep the best solutions or nests with quality solutions.
Rank the solutions and find the current best.
end while
Postprocess results and visualization.

$$\begin{cases} \text{Find} : \mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_i, \cdots, \mathbf{x}_j, \cdots, \mathbf{x}_N] \\ \text{Min} : f(\mathbf{X}) = \sqrt{\dfrac{\sum\limits_{i=1}^{K} \varepsilon_i^2(\mathbf{X})}{K}} \\ \text{s.t.} \begin{cases} \mathbf{x}_i, \mathbf{x}_j \in \Omega \\ \mathbf{x}_i \neq \mathbf{x}_j \end{cases} \end{cases} \quad (2)$$

where Ω stands for the set of all the nodes of the finite element mesh model of the sheet metal part and $\mathbf{x}_i$ and $\mathbf{x}_j$ are the position coordinate vectors of the i-th and j-th locators, respectively, where $i, j = 1, \cdots, N$. Besides, the design variable $\mathbf{X}$ must be within the pre-determined set Ω, and in each fixture locating layout scheme, any two locators cannot coincide.

3 Prediction model

3.1 BPNN

BPNN, the most widely used type of artificial neural network (ANN), is a feed-forward neural network with three or more layers, including the input layer, hidden layer, and output layer [29]. It has D input nodes, H hidden nodes, and Q output nodes. It is also proved theoretically that any multivariable function can be approximated to any desired degree of accuracy with a three-layer BPNN. The three-layer BPNN is the most commonly used form of ANN. Figure 2 shows the network structure of a typical three-layer BPNN.

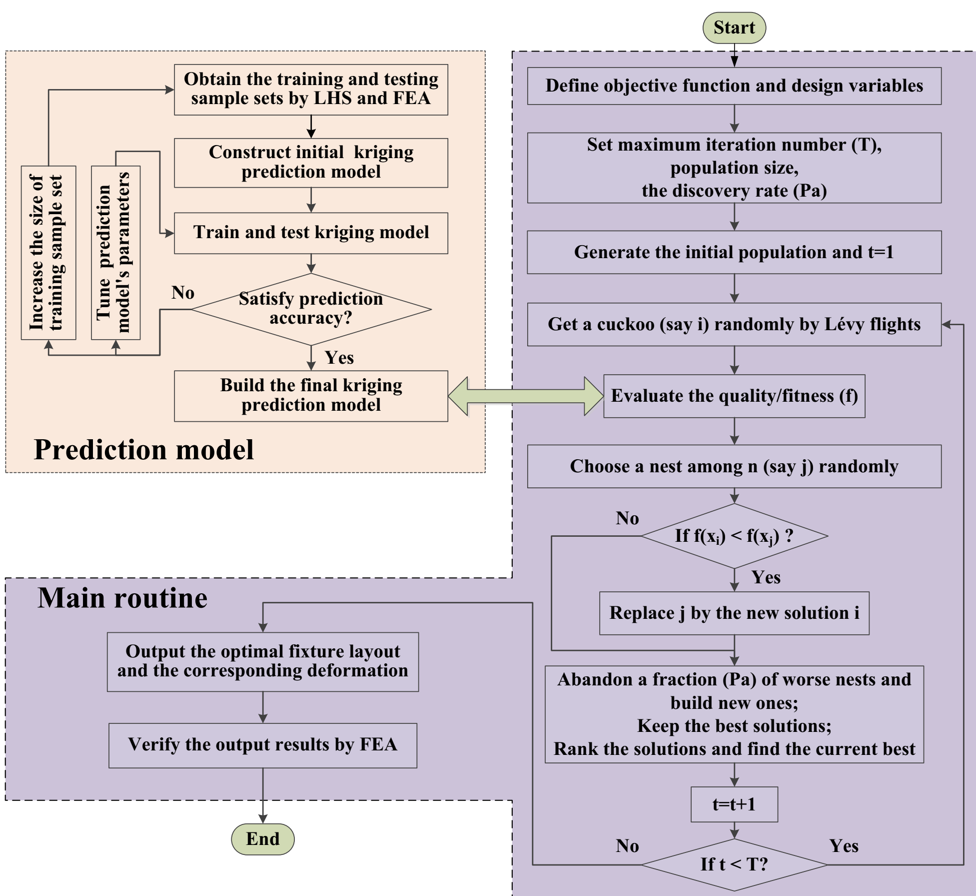


Fig. 3 The flowchart of optimization of the sheet metal fixture locating layout by CS integrated with kriging

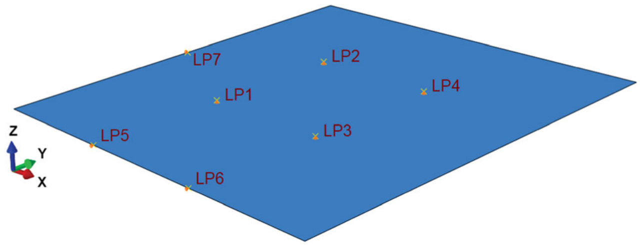


Fig. 4 The initial "4-2-1" fixture locating layout for the sheet metal case

3.2 Kriging

Kriging first appeared in geo-statistics while the use of kriging models for approximating a deterministic computer model was popularized by Sacks et al. [30]. Kriging models the output of a deterministic computer model as a realization of a stochastic process. The basic theory of kriging is described as follows [31].

Given a set of m design sites $S=[s_1, \cdots, s_m]^T$ with $s_i \in R^d$ $(i=1 \cdots m)$ and responses $Y=[y_1, \cdots, y_m]^T$ with $y_i \in R^q$ $(i=1 \cdots m)$, a model y that expresses the deterministic response $y(\mathbf{X}) \in R^q$ is adopted, for a d-dimensional input $\mathbf{X} \in R^d$, as a realization of a regression model F and a random function Z. As shown in Equation (3), $F(\beta, \mathbf{X})$ is a simple linear regression of β, which models the drift of the process mean over the domain. $z(\mathbf{X})$ models the systematic lack of fit or deviations from the linear model, which "pulls" the response surface through the data by weighting the correlation of nearby points.

$$y(\mathbf{X}) = F(\beta, \mathbf{X}) + z(\mathbf{X}) \tag{3}$$

Table 2 The physical properties of material

Material properties	Value
Mass density	2.8×10^3 kg/m^3
Young's modulus	7.12×10^{10} Pa
Poisson ratio	0.33

Table 3 Experimental results of Kriging

Size of training sample set	RRMSE	θ	β	σ^2
20	12.53%	(0.3536 1.1892)	0.0733	0.3429
25	16.94%	(2.0000 1.6818)	0.0162	0.4181
30	13.72%	(1.6818 2.1810)	0.1386	0.3087
35	4.10%	(2.4395 0.5128)	0.1534	0.3325

Table 4 Experimental results of BPNN

The node number of hidden layer	RRMSE	The node number of hidden layer	RRMSE
1	28.07%	6	19.94%
2	11.61%	7	16.39%
3	12.39%	8	12.97%
4	17.36%	9	16.35%
5	9.34%	10	15.42%

Table 5 Training parameters in BPNN

Control parameters of artificial neural network	
The number of neurons in the input layer	2
The number of neurons in the output layer	1
The number of hidden layers	1
The number of neurons in each hidden layer	5
Learning rate	0.001
Learning goal	0.00001
Maximum no. of epochs	5000
Activation functions for hidden layers	Tansig
Activation functions for output layers	Purelin
Training algorithm	Levenberg–Marquardt

Table 6 Training data set

Number	Coordinate	$F(\mathbf{X})$ (mm)
1	(161.9772, 81.1932)	1.0158
2	(145.0505, 223.0571)	0.8351
3	(395.4016, 29.2258)	0.9437
4	(309.8945, 362.1514)	0.0759
5	(174.8505, 170.7964)	0.8490
6	(65.8072, 231.3852)	0.9252
7	(322.7448, 249.9206)	0.1294
8	(293.8180, 293.0752)	0.0725
9	(53.9721, 144.0472)	0.9994
10	(79.9302, 35.5940)	1.0217
11	(384.2890, 205.4715)	0.3541
12	(235.0065, 13.2105)	0.8609
13	(7.9509, 316.7078)	0.7693
14	(30.9616, 8.5675)	1.0268
15	(88.6570, 382.9899)	1.0175
16	(343.5808, 323.0967)	0.0539
17	(195.8835, 374.8272)	0.3662
18	(246.8888, 214.6711)	0.3550
19	(223.0924, 91.6990)	1.0134
20	(39.2572, 107.5059)	1.0129
21	(360.1186, 350.8068)	0.0651
22	(134.0593, 388.9405)	0.7684
23	(102.9744, 126.9032)	1.0212
24	(260.7580, 340.6854)	0.1194
25	(207.2954, 68.5509)	0.9700
26	(159.6271, 254.7227)	0.5953
27	(304.7776, 150.0831)	0.4439
28	(368.5857, 307.2193)	0.0868
29	(278.3501, 125.2683)	0.7388
30	(123.7801, 50.3063)	1.0074
31	(91.9748, 175.9507)	1.0230
32	(188.0769, 268.3836)	0.3900
33	(19.9838, 79.9142)	1.0217
34	(336.2449, 186.4122)	0.3213
35	(263.8231, 274.9026)	0.1336

Table 7 Testing data set

Number	Coordinate	$F(\mathbf{X})$ (mm)
1	(188.7118, 66.7153)	0.9837
2	(200.9617, 164.1008)	0.7972
3	(358.543, 20.0141)	0.8463
4	(386.9502, 295.3885)	0.1283
5	(281.0795, 256.6747)	0.1384
6	(145.3987, 372.0698)	0.6392
7	(267.6340, 118.8267)	0.8901
8	(75.1635, 218.8847)	0.9707
9	(3.3694, 358.7171)	0.8311
10	(114.5809, 126.9143)	1.0101

The regression model $F(\beta, \mathbf{X})$ is a linear combination of p chosen functions:

$$F(\beta, \mathbf{X}) = \beta_1 \cdot f_1(\mathbf{X}) + \cdots + \beta_p \cdot f_p(\mathbf{X}) = \sum_i^p \beta_i \cdot f_i(\mathbf{X}),$$

where the coefficients $\{\beta\}$ are regression parameters. The random process $z(\mathbf{X})$ is assumed to be a Gaussian stationary process with mean zero and covariance:

$$E\left[z\left(\mathbf{X}^i\right), z\left(\mathbf{X}^j\right)\right] = \sigma^2 R\left(\theta, \mathbf{X}^i, \mathbf{X}^j\right) \quad (4)$$

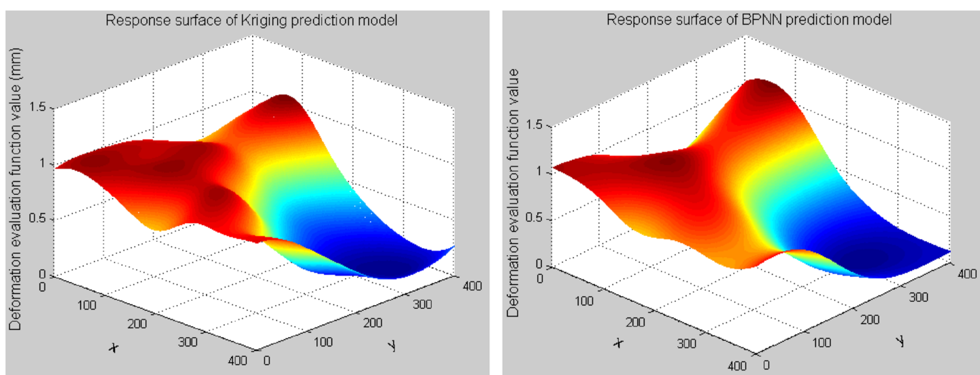
between $\mathbf{X}^i$ and $\mathbf{X}^j$, where σ^2 is the process variance and $R(\theta, \mathbf{X}^i, \mathbf{X}^j)$ is the correlation model with parameters θ. The correlation function is defined as

$$R\left(\theta, \mathbf{X}^i, \mathbf{X}^j\right) = \exp\left[-\sum_{k=1}^{d} \theta_k \left|\mathbf{X}_k^i - \mathbf{X}_k^j\right|^2\right], (i, j = 1, \cdots, m) \quad (5)$$

where d is the dimension number of the design variable and θ_k is the k-th parameter corresponding to k-th design variable. Ordinary kriging, whose regression part equals a constant β, is the most commonly used form of kriging employed to approximate expensive computer models.

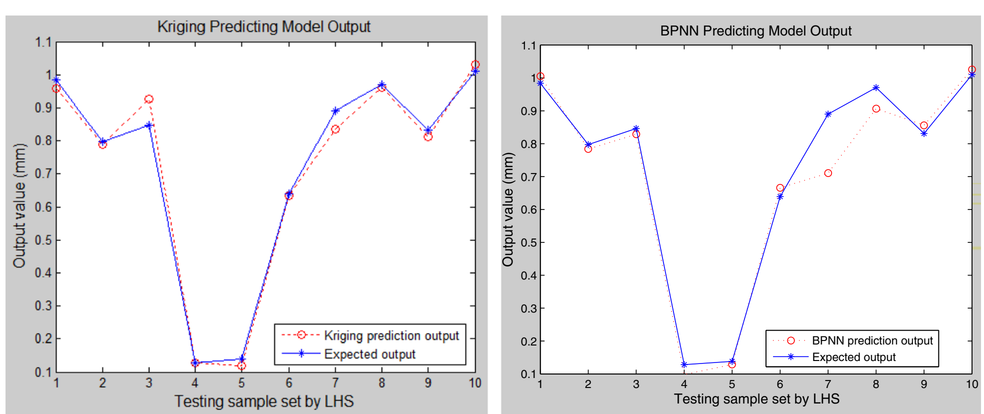
4 Cuckoo search algorithm

The CS algorithm, developed by Yang and Deb, is a new meta-heuristic algorithm based on the obligate breeding parasitic behavior of some cuckoo species combined with the Lévy flight behavior of some birds and fruit flies [32, 33]. For the past few years, the CS algorithm has been applied to many areas of optimization with promising



(1) (2)

Fig. 5 The response surfaces of kriging and BPNN prediction models



(1) (2)

Fig. 6 The output curves of kriging and BPNN prediction models

Table 8 The relative errors of the prediction models

Prediction model	Relative error
BPNN	9.34 %
Kriging	4.10 %

efficiency [34], such as engineering design [35], manufacturing [36], etc. For simplicity, the breeding behavior of cuckoos can be idealized as the following three simple rules:

1. Each cuckoo lays one egg each time in a randomly chosen nest.
2. The best nests with high quality of eggs (solutions) will carry over to the next generations.
3. The number of the available host nests is fixed, and a host can discover an alien egg with a probability $p_a \in [0, 1]$.

On the basis of these three rules above, the basic steps of the CS can be summarized as the pseudo code described in Table 1.

For a cuckoo i, the new positions $x_i^{(t+1)}$ can be calculated by

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus Lévy(\lambda) \tag{6}$$

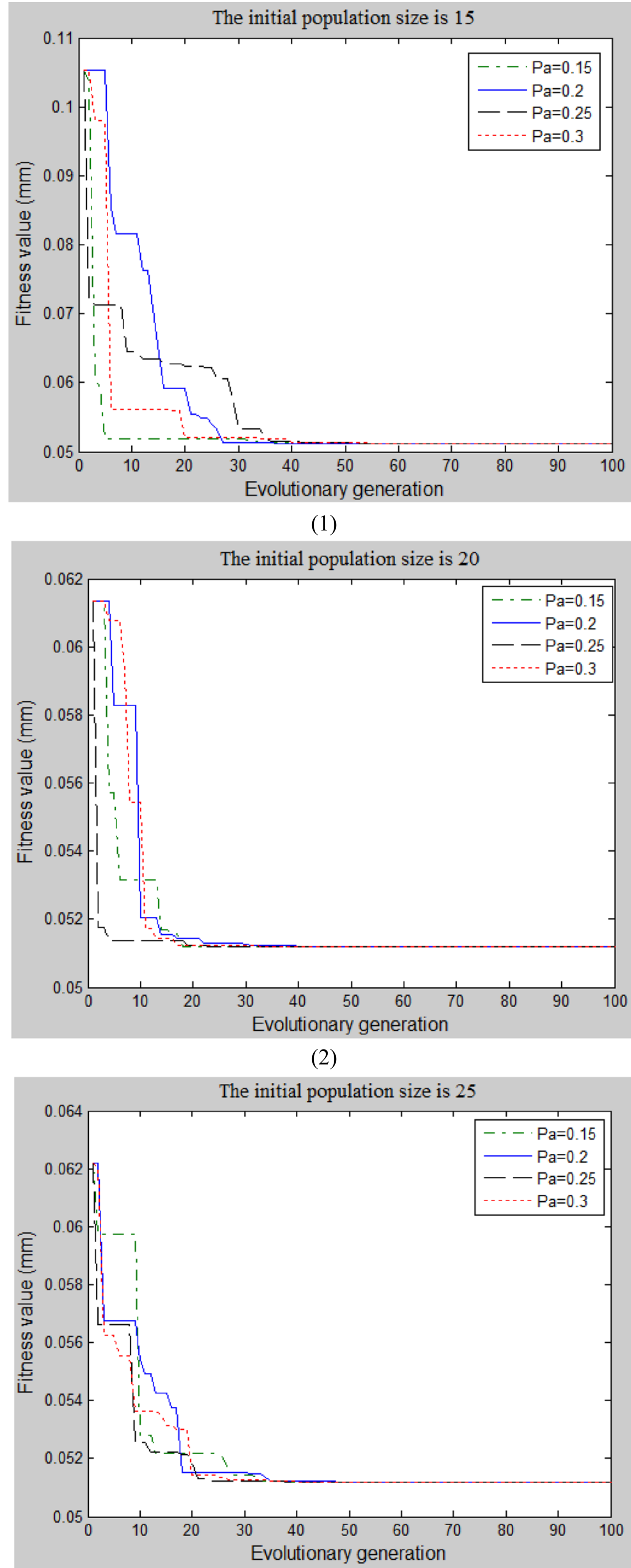
where $\alpha > 0$ is the step size which should be related to the scale of the problem of interest, and $\alpha = 1$ is used in most cases. It is found that $n = 15$ to 25 and $p_a = 0.15$ to 0.30 are sufficient for most optimization problems. The symbol $\oplus$ means entry-wise multiplications. Lévy flights essentially provide a random walk while their random steps are drawn from a Lévy distribution for large steps:

$$Lévy \sim u = t^{-\lambda}, \quad (1 < \lambda \leq 3) \tag{7}$$

which has an infinite variance with an infinite mean.

5 Proposed approach

In this paper, a new approach to optimizing the sheet metal fixture locating layout based on the N-2-1 locating principle by integrating kriging with the CS algorithm is proposed. The presented method consists of two main stages. At the first stage, the kriging prediction model is built based on the training data set and then compared to BPNN in terms of prediction accuracy based on the testing dataset. The training and testing data sets are obtained by Latin hypercube sampling (LHS) [37] and limited times of FEA. At the second stage, CS is directly applied to the established kriging model to search the optimal



(3)

Fig. 7 The convergence of CS for the case study

fixture locating layout to minimize the overall deformation of the sheet metal part under the gravity effect.

Table 9 Optimization results and comparison

The population size	Pa	The optimal layout of L4	The minimum deformation by CS	The corresponding deformation by FEA	Relative error
15	0.15	(342.8856, 335.0987)	0.0512 mm	0.0521 mm	1.73 %
	0.2	(342.8641, 335.1053)	0.0512 mm	0.0521 mm	1.73 %
	0.25	(342.8959, 335.0626)	0.0512 mm	0.0521 mm	1.73 %
	0.3	(342.7994, 335.0963)	0.0512 mm	0.0521 mm	1.73 %
20	0.15	(342.8729, 335.0947)	0.0512 mm	0.0521 mm	1.73 %
	0.2	(342.866, 335.0991)	0.0512 mm	0.0521 mm	1.73 %
	0.25	(342.8845, 335.0807)	0.0512 mm	0.0521 mm	1.73 %
	0.3	(342.8978, 335.1042)	0.0512 mm	0.0521 mm	1.73 %
25	0.15	(342.8686, 335.0868)	0.0512 mm	0.0521 mm	1.73 %
	0.2	(342.8764, 335.0839)	0.0512 mm	0.0521 mm	1.73 %
	0.25	(342.8694, 335.1002)	0.0512 mm	0.0521 mm	1.73 %
	0.3	(342.8504, 335.1029)	0.0512 mm	0.0521 mm	1.73 %

During the iterative optimization process, the fitness values are obtained by calling the kriging surrogate model instead of FEA to save the computation cost and increase the optimization efficiency. The flowchart of the optimum fixture locating layout design for the sheet metal part by integrating kriging with the CS algorithm is depicted in Fig. 3.

6 Flat sheet metal

6.1 Modeling

In this section, the presented method by CS integrated with kriging for sheet metal fixture locating layout optimization under the gravity effect is demonstrated and verified by an aluminum alloy sheet metal case based on the 4-2-1 locating scheme. As shown in Fig. 4, the dimension of the sheet metal is 400 × 400 × 1 mm^3 and the physical material properties are all listed in Table 2. The "4" locating points (LP) on the primary datum plane are LP1, LP2, LP3, and LP4, and the "2" locating points on the second datum plane are LP5 and LP6 while the "1" locating point on the third datum plane is LP7. Set the coordinates of the fixed locating points LP1, LP2, LP3, LP5, LP6, and LP7 as (100, 100), (100, 300), (300, 100), (133,

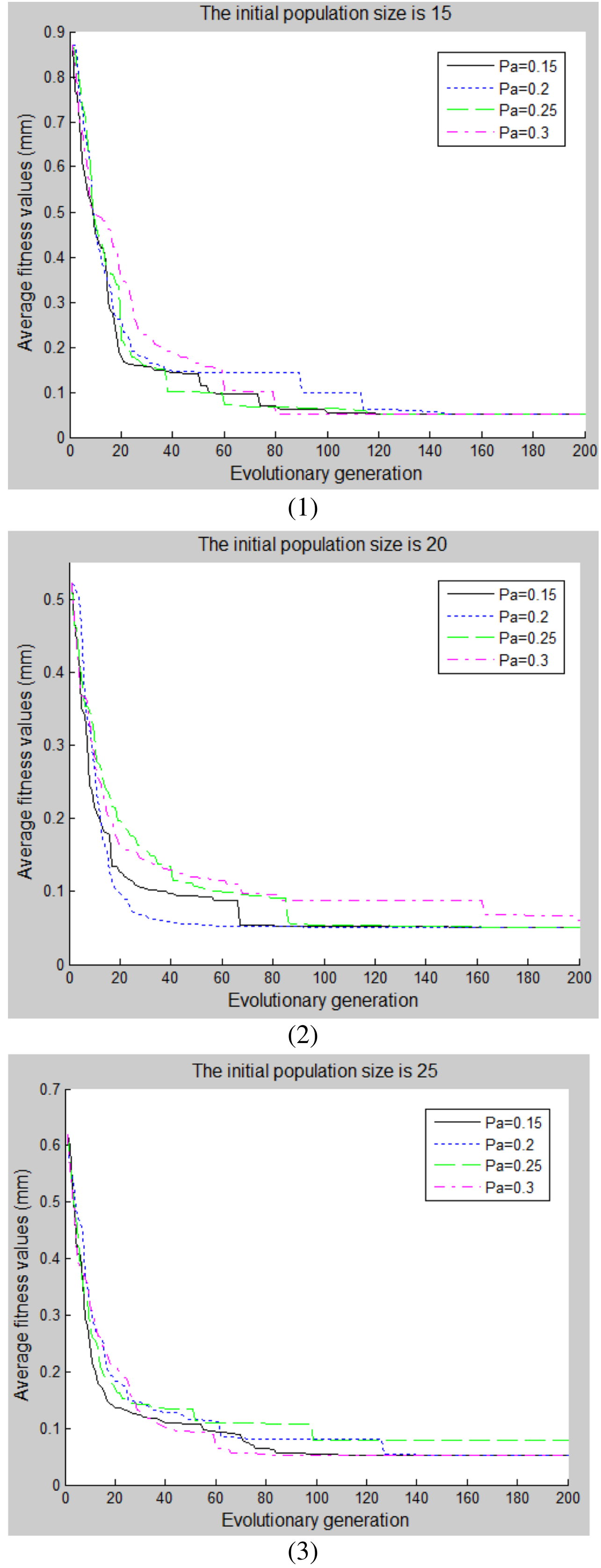


Fig. 8 The average fitness values by CS

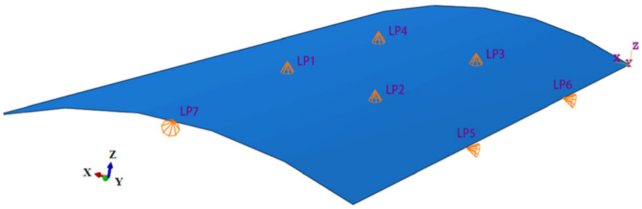


Fig. 9 The initial "4-2-1" fixture locating layout for the sheet metal case

0), (267, 0), and (0, 200), respectively. The locating point to be optimized is LP4, and its coordinate is denoted as (x, y).

The training and testing data sets are generated by LHS and FEA. In order to calculate the evaluation function values of the training and testing data sets, the commercial finite element software ABAQUS™ [38] is employed to compute the overall deformation of the sheet metal part under its deadweight. The element type of the FEA model of the sheet metal part is S4R while the size of the element is 1 mm × 1 mm. In our implementation, after several trials as listed in Tables 3 and 4, the kriging and BPNN surrogate models are built by learning the same training data set of the size of 35, tested, and compared by calculating the relative root mean squared error (RRMSE) on the same testing data set of the size of 10.

In this case, the kriging model is built via a MATLAB™ kriging toolbox, Design and Analysis of Computer Experiments (DACE) [31], while the BPNN model is built via a MATLAB™ neural network toolbox [39]. In kriging, the correlation parameter is initially set as [1, 1]; in BPNN, the input layer has two neurons ($D = 2$), which respectively represent the x and y entries of the coordinate of LP4. The output layer has one neuron ($Q = 1$), that is, the evaluation function value $F(\mathbf{X})$ for

Table 10 Experimental results of Kriging

Size of training sample set	RRMSE	θ	β	σ^2
20	28.98%	(1.4142, 1.2968)	-0.1250	0.4578
25	17.37%	(0.7071, 1.8340)	0.0180	0.4841
30	16.75%	(1.0000, 4.0000)	0.0730	0.4085
35	11.60%	(4.0000, 2.8284)	0.1046	0.3537
40	4.5%	(3.0550, 2.5689)	8.4463e-04	0.5047

Table 11 Experimental results of BPNN

The node number of hidden layer	RRMSE	The node number of hidden layer	RRMSE
1	38.47%	6	22.1%
2	31.42%	7	18.08%
3	34.53%	8	36.74%
4	22.71%	9	21.23%
5	25.82%	10	32.91%

Table 12 Training parameters in BPNN

Control parameters of artificial neural network	
The number of neurons in the input layer	2
The number of neurons in the output layer	1
The number of hidden layers	1
The number of neurons in each hidden layer	7
Learning rate	0.001
Learning goal	0.00001
Maximum no. of epochs	5000
Activation functions for hidden layers	Tansig
Activation functions for output layers	Purelin
Training algorithm	Levenberg–Marquardt

Table 13 Training data set

Number	Coordinate	$F(\mathbf{X})$ (mm)
1	(72.2600, 249.3793)	0.1691
2	(47.1657, 218.4460)	0.1215
3	(176.5980, 595.4355)	0.1111
4	(163.1431, 475.6371)	0.1304
5	(89.6089, 266.3623)	0.0867
6	(17.7182, 90.9497)	0.1040
7	(114.7608, 482.0971)	0.0874
8	(31.3087, 444.0416)	0.1964
9	(109.8100, 82.8087)	0.0201
10	(60.2288, 111.5251)	0.1958
11	(51.2881, 577.6557)	0.1966
12	(140.3128, 355.9528)	0.0600
13	(97.4332, 0.1539)	0.0395
14	(153.7955, 57.2449)	0.0168
15	(38.7002, 122.0751)	0.1161
16	(126.2051, 539.5105)	0.0685
17	(0.0333, 310.0206)	0.1699
18	(158.2165, 378.7688)	0.1321
19	(131.2357, 335.3345)	0.0488
20	(189.4498, 72.4614)	0.0169
21	(22.0148, 540.7169)	0.1840
22	(182.8470, 201.8509)	0.0131
23	(91.3464, 176.2288)	0.0455
24	(118.6941, 396.3214)	0.1962
25	(59.5260, 316.2679)	0.1926
26	(12.7452, 226.5661)	0.1286
27	(171.7996, 457.7624)	0.1626
28	(29.3398, 563.3589)	0.1866
29	(67.7359, 430.3237)	0.1934
30	(121.7390, 194.1703)	0.0187
31	(195.8650, 153.6931)	0.0147
32	(103.4596, 283.0208)	0.0650
33	(192.9882, 24.6612)	0.0213
34	(40.5788, 519.0619)	0.1929
35	(76.4971, 406.7172)	0.1960
36	(138.7906, 149.6814)	0.0149
37	(6.2008, 362.3388)	0.1892
38	(148.5454, 40.6789)	0.0172
39	(83.6128, 506.2449)	0.1394
40	(169.9695, 292.6743)	0.0263

Table 14 Testing data set

Number	Coordinate	$F(\mathbf{X})$ (mm)
1	(44.9747, 189.5570)	0.1132
2	(34.8981, 524.7431)	0.1898
3	(169.8809, 431.1429)	0.1914
4	(186.0185, 105.3885)	0.0151
5	(2.1819, 4.2442)	0.1232
6	(80.8142, 339.0010)	0.1740
7	(69.0557, 588.2043)	0.1822
8	(117.2275, 284.9350)	0.0412
9	(137.0141, 383.0373)	0.1192
10	(154.8498, 151.6027)	0.0142

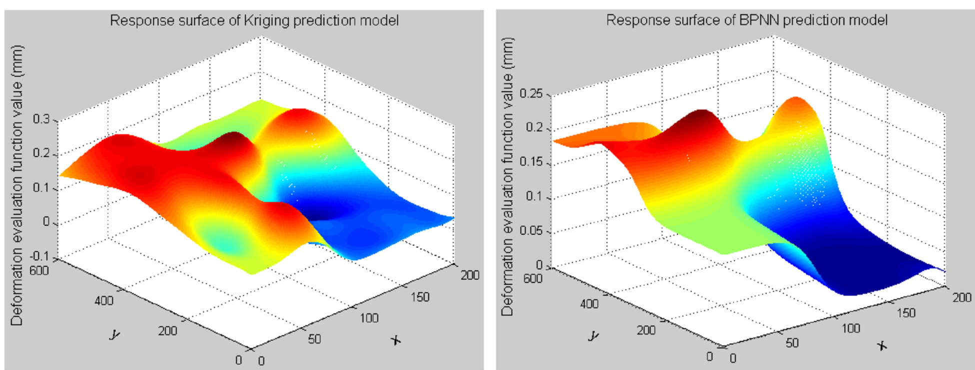
sheet metal deformation. The hidden layer has five neurons ($H = 5$). Specific training parameters in BPNN and the training and testing data sets for BPNN and kriging are shown in Tables 5, 6, and 7).

6.2 Results and discussion

In this section, the response surface models of kriging and BPNN approximating the implicit function relationship between the fixture locating layout and the overall sheet metal deformation are established as shown in Fig. 5. Besides, the output curves are depicted in Fig. 6 and the corresponding relative errors are listed in Table 8.

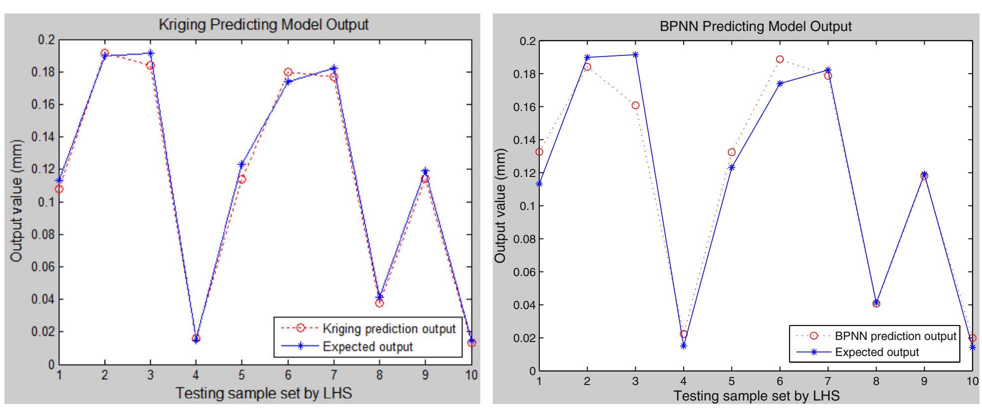
Compared with the BPNN model trained and tested with the same sample sets, the kriging-based prediction model is of higher precision and is more stable. Hence, the kriging model describing the mapping relationship between the fixture locating layout scheme and the corresponding sheet metal deformation is used for the subsequent sheet metal fixture locating layout optimization in this paper. Then, CS is applied on the established kriging prediction model to search the optimal design variable $\mathbf{X}$ for the minimum $f(\mathbf{X})$ on the platform of MATLAB™. And the fitness values of each generation during the iterative optimization procedure are calculated through the kriging model instead of FEA. Figure 7 shows the convergence of CS.

The optimal layout and the corresponding minimum deformation after 100 iterations by CS are shown in Table 9. For further comparative analysis, the deformation of the sheet metal part with the optimal layout of LP4 is also calculated by FEA. The results are also listed in Table 9. It can be seen from the table that the result obtained by the proposed approach shows fine agreements with that by FEA and that the



(1) (2)

Fig. 10 The response surfaces of kriging and BPNN prediction models



(1) (2)

Fig. 11 The output curves of kriging and BPNN prediction models

Table 15 The relative errors of the prediction models

Prediction model	Relative error
BPNN	18.08 %
Kriging	4.50 %

final relative error (1.73 %) is within the general engineering precision requirement (5 %).

The optimization procedure of the average fitness by CS for the fixture locating layout design is shown in Fig. 8. It can be seen that the convergence curve is smooth during the whole search process and the final average fitness value (0.0518 mm) is very close to the final minimum fitness value (0.0512 mm). Therefore, the CS algorithm is robust and stable in sheet metal fixture locating layout optimization.

7 Curved sheet metal

7.1 Modeling

As shown in Fig. 9, the dimension of the sheet metal is 200 × 600 × 1 mm^3 and the physical material properties are all listed in Table 2. The 4 locating points (LP) on the primary datum plane are LP1, LP2, LP3, and LP4, and the 2 locating points on the second datum plane are LP5 and LP6 while the 1 locating point on the third datum plane is LP7. Set the coordinates of the fixed locating points LP1, LP2, LP3, LP5, LP6, and LP7 as (134, 400), (66, 400), (66, 200), (0, 400), (0, 200), and (100, 600) respectively. The locating point to be optimized is LP4, and its coordinate is denoted as (x, y).

The training and testing data sets are generated by LHS and FEA. The element type of the FEA model of the sheet metal part is S4R while the size of the element is 1 mm × 1 mm. After several trials as listed in Tables 10 and 11, the kriging and BPNN surrogate models are built by learning the same training data set of the size of 40, tested, and compared by calculating the relative root mean squared error (RRMSE) on the same testing data set of the size of 10.

In kriging, the correlation parameter is initially set as [1, 1]; in BPNN, the input layer has two neurons (D = 2), which respectively represent the x and y entries of the coordinate of LP4. The output layer has one neuron (Q = 1), that is, the evaluation function value $F(\mathbf{X})$ for sheet metal deformation. The hidden layer has five neurons (H = 7). Specific training parameters in BPNN and the training and testing data sets for BPNN and kriging are shown in Tables 12, 13 and 14.

7.2 Results and discussion

In this section, the response surface models of kriging and BPNN approximating the implicit function relationship between the fixture locating layout and the overall sheet metal deformation are established as shown in Fig. 10. Besides, the output curves are depicted in Fig. 11 and the corresponding relative errors are listed in Table 15.

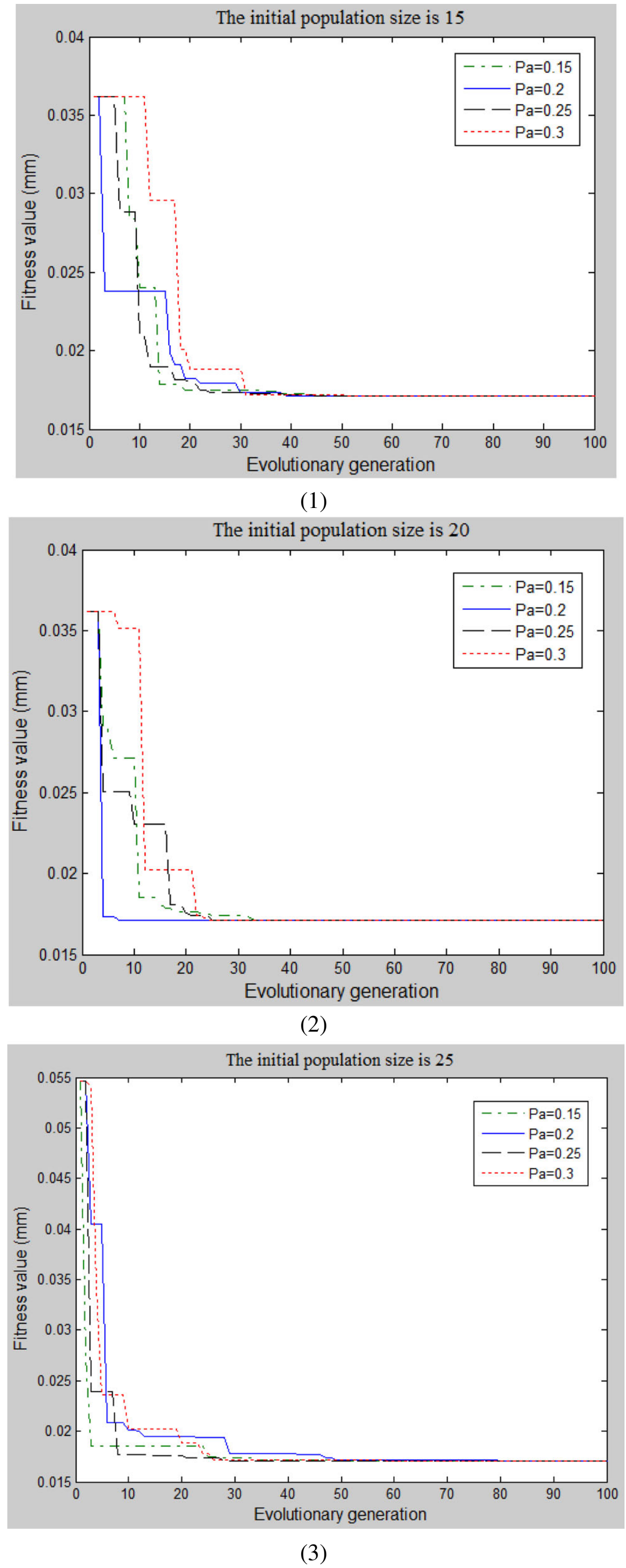


Fig. 12 The convergence of CS for case study

Table 16 Optimization results and comparison

The population size	Pa	The optimal layout of L4	The minimum deformation by CS	The corresponding deformation by FEA	Relative error
15	0.15	(145.6605, 280.6541)	0.017102 mm	0.01684 mm	1.56 %
	0.2	(145.6771, 280.6489)	0.017102 mm	0.01684 mm	1.56 %
	0.25	(145.6789, 280.5691)	0.017102 mm	0.01684 mm	1.56 %
	0.3	(145.713, 280.6364)	0.017102 mm	0.01684 mm	1.56 %
20	0.15	(145.6698, 280.6427)	0.017102 mm	0.01684 mm	1.56 %
	0.2	(145.66, 280.6498)	0.017102 mm	0.01684 mm	1.56 %
	0.25	(145.6803, 280.5097)	0.017102 mm	0.01684 mm	1.56 %
	0.3	(145.6569, 280.5393)	0.017102 mm	0.01684 mm	1.56 %
25	0.15	(145.6719, 280.7397)	0.017102 mm	0.01684 mm	1.56 %
	0.2	(145.5721, 280.8061)	0.017102 mm	0.01684 mm	1.56 %
	0.25	(145.6665, 280.6348)	0.017102 mm	0.01684 mm	1.56 %
	0.3	(145.6582, 280.8737)	0.017102 mm	0.01684 mm	1.56 %

Compared with the BPNN model trained and tested with the same sample sets, the kriging-based prediction model is of higher precision and is more stable. Hence, the kriging model describing the mapping relationship between the fixture locating layout scheme and the corresponding sheet metal deformation is used for the subsequent sheet metal fixture locating layout optimization in this paper. Then, CS is applied on the established kriging prediction model to search the optimal design variable **X** for the minimum $f(\mathbf{X})$ on the platform of MATLAB™. And the fitness values of each generation during the iterative optimization procedure are calculated through the kriging model instead of FEA. Figure 12 shows the convergence of CS.

The optimal layout and the corresponding minimum deformation after 100 iterations by CS are shown in Table 16. For further comparative analysis, the deformation of the sheet metal part with the optimal layout of LP4 is also calculated by FEA. The results are also listed in Table 14. It can be seen from the table that the result obtained by the proposed approach shows fine agreements with that by FEA and that the final relative error (1.56 %) is within the general engineering precision requirement (5 %) (Table 16).

The optimization procedure of the average fitness by CS for the fixture locating layout design is shown in Fig. 13. It can be seen that the convergence curve is smooth during the whole search process and the final average fitness value (0.0171 mm) is very close to the final minimum fitness value (0.017102 mm). Therefore, the CS algorithm is robust and stable in sheet metal fixture locating layout optimization.

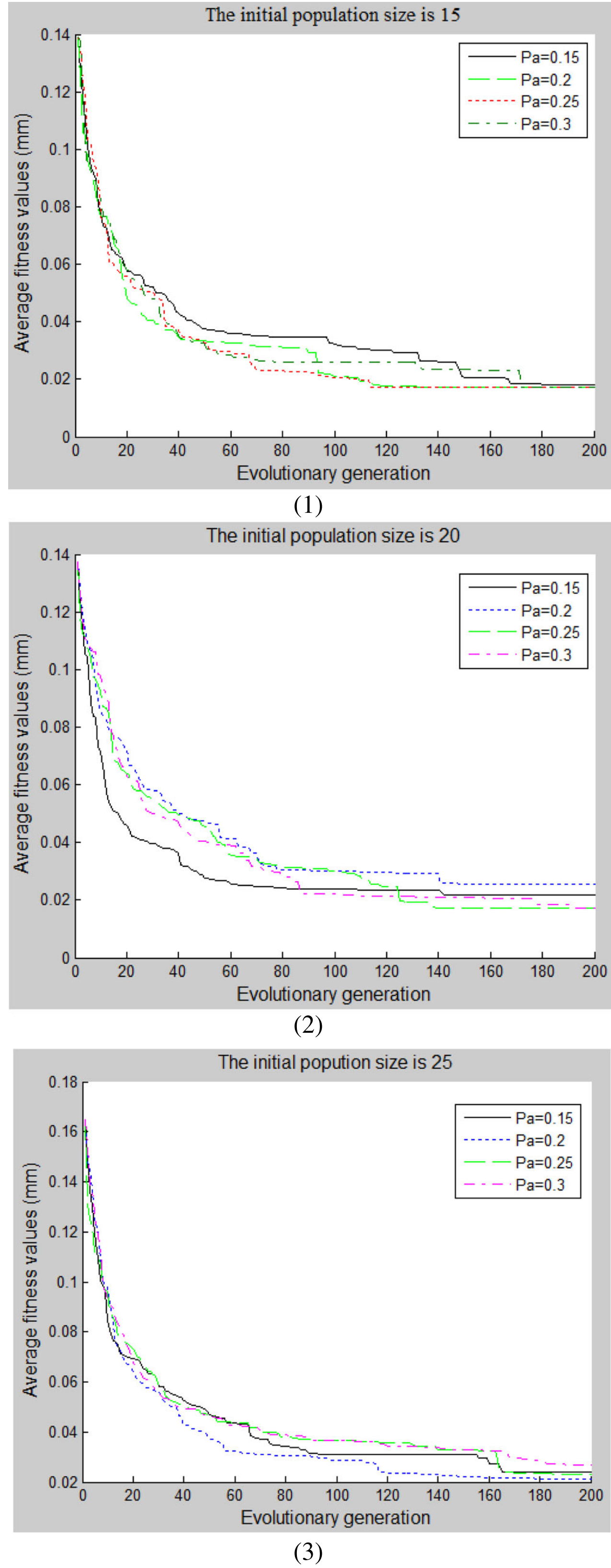


Fig. 13 The average fitness values by CS

8 Conclusions

In this paper, the prediction models based on kriging and BPNN are established and compared in terms of prediction accuracy based on the same training and testing data sets. The optimization method by integrating CS with kriging for the design and optimization of the sheet metal fixture locating layout is developed and verified via two sheet metal cases based on the 4-2-1 locating scheme. The main conclusions are drawn as follows:

1. The kriging- and BPNN-based prediction models are built respectively to approximate the implicit function relationship between the fixture locating layout and the overall sheet metal deformation under its self-weight, and the comparison results show that the kriging model is of higher precision and is more stable based on the same training data set.
2. The approach by combining kriging with CS is proposed and validated through the aluminum alloy sheet metal case. The results of the case study indicate that the presented method is more efficient than those by evolutionary algorithm directly coupled with FEA and can save the computation cost and improve the efficiency in sheet metal fixture locating layout optimization under the condition of ensuring the engineering precision requirements.
3. By virtue of the high precision and robustness of the kriging surrogate model, and the stability and few parameters to be fine-tuned of CS, the proposed method has huge potential and can be further extended and applied to deformation control-oriented fixture layout design and optimization subject to complex conditions at machining, assembly, and measuring stages during the whole manufacturing process at the industrial level due to its generality.

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References

1. Saadat M, Cretin C (2002) Dimensional variations during Airbus wing assembly. Assem Autom 22(3):270–276. doi:10.1108/01445150210436482
2. Hu SJ, Camelio J (2006) Modeling and control of compliant assembly systems. Cirp Annals-Manuf Technol 55(1):19–22. doi:10.1016/s0007-8506(07)60357-6
3. Cai W, Hu SJ, Yuan JX (1996) Deformable sheet metal fixturing: principles, algorithms, and simulations. J Manuf Sci Eng-Trans Asme 118(3):318–324. doi:10.1115/1.2831031
4. Asada H, Andre B (1985) Kinematic analysis of workpart fixturing for flexible assembly with automatically reconfigurable fixtures. Robot Autom, IEEE J 1(2):86–94
5. Amaral N, Rencis JJ, Rong YM (2005) Development of a finite element analysis tool for fixture design integrity verification and optimisation. Int J Adv Manuf Technol 25(5–6):409–419. doi:10.1007/s00170-003-1796-6
6. Siebenaler SP, Melkote SN (2006) Prediction of workpiece deformation in a fixture system using the finite element method. Int J Mach Tools Manuf 46(1):51–58. doi:10.1016/j.ijmachtools.2005.04.007
7. Ratchev S, Phuah K, Liu S (2007) FEA-based methodology for the prediction of part-fixture behaviour and its applications. J Mater Process Technol 191(1–3):260–264. doi:10.1016/j.jmatprotec.2007.03.020
8. Krishnakumar K, Melkote SN (2000) Machining fixture layout optimization using the genetic algorithm. Int J Mach Tools Manuf 40(4):579–598. doi:10.1016/s0890-6955(99)00072-3
9. Li B, Shiu BW (2001) Principle and simulation of fixture configuration design for sheet metal assembly with laser welding. Part 2: optimal configuration design with the genetic algorithm. Int J Adv Manuf Technol 18(4):276–284. doi:10.1007/s001700170068
10. Kulankara K, Satyanarayana S, Melkote SN (2002) Iterative fixture layout and clamping force optimization using the genetic algorithm. J Manuf Sci Eng-Trans Asme 124(1):119–125. doi:10.1115/1.1414127
11. Liao YG (2003) A genetic algorithm-based fixture locating positions and clamping schemes optimization. Proc IME Part B-J Eng Manuf 217(8):1075–1083
12. Kaya N (2006) Machining fixture locating and clamping position optimization using genetic algorithms. Comput Ind 57(2):112–120. doi:10.1016/j.compind.2005.05.001
13. Padmanaban KP, Arulshri KP, Prabhakaran G (2009) Machining fixture layout design using ant colony algorithm based continuous optimization method. Int J Adv Manuf Technol 45(9–10):922–934. doi:10.1007/s00170-009-2035-6
14. Dou JP, Wang XS, Wang L (2012) Machining fixture layout optimisation under dynamic conditions based on evolutionary techniques. Int J Prod Res 50(15):4294–4315. doi:10.1080/00207543.2011.618470
15. Xiong L, Molfino R, Zoppi M (2013) Fixture layout optimization for flexible aerospace parts based on self-reconfigurable swarm intelligent fixture system. Int J Adv Manuf Technol 66(9–12):1305–1313. doi:10.1007/s00170-012-4408-5
16. Kumar KS, Paulraj G (2014) Analysis and optimization of fixture under dynamic machining condition with chip removal effect. J Intell Manuf 25(1):85–98. doi:10.1007/s10845-012-0677-y
17. Xing YF, Hu M, Zeng H, Wang YS (2015) Fixture layout optimisation based on a non-domination sorting social radiation algorithm for auto-body parts. Int J Prod Res 53(11):3475–3490. doi:10.1080/00207543.2014.1003662
18. Simpson TW, Booker AJ, Ghosh D, Giunta AA, Koch PN, Yang RJ (2004) Approximation methods in multidisciplinary analysis and optimization: a panel discussion. Struct Multidiscip Optim 27(5):302–313. doi:10.1007/s00158-004-0389-9
19. Li B, Shiu BW, Lau KJ (2003) Robust fixture configuration design for sheet metal assembly with laser welding. J Manuf Sci Eng-Trans Asme 125(1):120–127. doi:10.1115/1.1536172
20. Hamedi M (2005) Intelligent fixture design through a hybrid system of artificial neural network and genetic algorithm. Artif Intell Rev 23(3):295–311. doi:10.1007/s10462-004-7187-z
21. Li B, Hu Y, Tang H, Yu HJ, Hu H (2008) A comparative study on quality design of fixture planning for sheet metal assembly. J Eng Des 19(1):1–13. doi:10.1080/09544820601058634
22. Vasundara M, Padmanaban KP, Sabareeswaran M, RajGanesh M (2012) Machining fixture layout design for milling operation using FEA, ANN and RSM. In: Rajesh R, Ganesh K, Koh SCL (eds) International conference on modelling optimization and computing, vol 38. Procedia engineering. Elsevier Science Bv, Amsterdam, pp. 1693–1703. doi:10.1016/j.proeng.2012.06.206
23. Selvakumar S, Arulshri KP, Padmanaban KP, Sasikumar KSK (2013) Design and optimization of machining fixture layout using

ANN and DOE. Int J Adv Manuf Technol 65(9–12):1573–1586. doi:10.1007/s00170-012-4281-2

24. Sundararaman KA, Guharaja S, Padmanaban KP, Sabareeswaran M (2014) Design and optimization of machining fixture layout for end-milling operation. Int J Adv Manuf Technol 73(5–8):669–679. doi:10.1007/s00170-014-5848-x
25. Lu C, Zhao HW (2015) Fixture layout optimization for deformable sheet metal workpiece. Int J Adv Manuf Technol 78(1–4):85–98. doi:10.1007/s00170-014-6647-0
26. Rex FMT, Ravindran D (2015) An integrated approach for optimal fixture layout design. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture: 0954405415590991
27. Qin G, Wang Z, Rong Y, Li Q (2015) A unified approach to multi-fixturing layout planning for thin-walled workpiece. Procthe IME Part B: J Eng Manuf: 0954405415585240
28. Sundararaman K, Padmanaban K, Sabareeswaran M (2015) Optimization of machining fixture layout using integrated response surface methodology and evolutionary techniques. Proc IME Part C: J Mech Eng Sci: 0954406215592920
29. Haykin SS, Haykin SS, Haykin SS, Haykin SS (2009) Neural networks and learning machines, vol 3. Pearson Education Upper Saddle River
30. Sacks J, Welch WJ, Mitchell TJ, Wynn HP (1989) Design and analysis of computer experiments. Stat Sci: 409–423
31. Nielsen HB, Lophaven SN, Sondergaard J (2002) DACE, a MATLAB kriging toolbox. Informatics and mathematical modelling Lyngby–Denmark: Technical University of Denmark, DTU
32. Yang XS, Deb S (2009) Cuckoo search via Lévy flights. In: Abraham A, Herrera F, Carvalho A, Pai V (eds) 2009 World Congress on nature & biologically inspired computing. World Congress on Nature and Biologically Inspired Computing. Ieee, New York, pp. 210–214. doi:10.1109/nabic.2009.5393690
33. Yang X-S, Deb S (2010) Engineering optimisation by cuckoo search. Int J Math Model Numer Optimisation 1(4):330–343
34. Yang XS, Deb S (2014) Cuckoo search: recent advances and applications. Neural Comput Appl 24(1):169–174. doi:10.1007/s00521-013-1367-1
35. Durgun I, Yildiz AR (2012) Structural design optimization of vehicle components using cuckoo search algorithm. Mater Test 54(3): 185–188
36. Yildiz AR (2013) Cuckoo search algorithm for the selection of optimal machining parameters in milling operations. Int J Adv Manuf Technol 64(1–4):55–61. doi:10.1007/s00170-012-4013-7
37. McKay MD, Beckman RJ, Conover WJ (2000) A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. Technometrics 42(1):55–61. doi:10.2307/1271432
38. Simulia DS (2012) Abaqus 6.12 documentation. Providence, Rhode Island, US
39. Hudson B, Hagan M, Demuth H (2012) Neural network toolbox for use with MATLAB. User's Guide, the Math works