

Research Article

Multiobjective Optimization of Precision Forging Process Parameters Based on Response Surface Method

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In order to control the precision forging forming quality and improve the service life of die, a multiobjective optimization method for process parameters design was presented by applying Latin hypercube design method and response surface model approach. Meanwhile the deformation homogeneity and material damage of forging parts were proposed for evaluating the forming quality. The forming load of die was proposed for evaluating the service life of die. Then as a case of study, the radial precision forging for a hollow shaft with variable cross section and wall thickness was carried out. The 3D rigid-plastic finite element (FE) model of the hollow shaft radial precision forging was established. The multiobjective optimization forecast model was established by adopting finite element results and response surface methodology. Nondominated sorting genetic algorithm-II (NSGA-II) was adopted to obtain the Pareto-optimal solutions. A compromise solution was selected from the Pareto solutions by using the mapping method. In the finite element study on the forming quality of forging parts and the service life of dies by multiobjective optimization process parameters, the feasibility of the multiobjective optimization method presented by this work was verified.

1. Introduction

Precision forging technology is an advanced technology in recent years; it has important significance for improving mechanics properties of forming and energy saving. However, the forming process is an unsteady large deformation problem, so holes with cracks and other defects often appear; these defects will directly influence the properties and service life of forging parts.

In order to obtain good performance forging parts, recent studies have employed the forging parts optimum by universally adopting two approaches: sensitivity analysis and response surface methodology. In the sensitivity analysis method, Zhao et al. [1, 2] proposed the relationship between preform tool shape and the difference between actual final forging shape and the desired final forging shape objective. And the multiobjective optimum preform tool shape is achieved in the case of axisymmetric disk upsetting problem. Zhao et al. [3] considered the deformation uniformity and deforming force of the final forging, and then the preform die

shape of an H-shaped forging process is designed. Acharjee and Zabaras [4] presented that the continuum sensitivity method is extended to three dimensions to accurately compute sensitivity fields. And the cylindrical billet upsetting preform optimization design was carried out. Guan et al. [5] presented the microstructure optimal design at the aim of obtaining the net-shape parts and the uniformity of the grain distribution in the final parts. Finally, the forming process of a typical H-shaped axisymmetric disk is illustrated as an example and it shows good results. Though the sensitivity analysis optimization theory could solve problems of the forging part quality, but the sensitivity derivation is very difficult for complex metal plastic forming process especially for three-dimensional plastic forming process.

In the response surface optimization method, Yang et al. [6] proposed an approach that combines the finite element method and the response surface method to optimize the preform shapes in order to improve the deformation homogeneity in aerospace forgings. With a typical aero engine disk as an example, the proposed method is verified by

achieving an optimal combination of design variables. Tang et al. [7] employed the neural network approximation model for response surface construction in order to overcome the limitation of quadratic polynomial model in solving nonlinear problems. Optimum was achieved by using pattern search optimization method to search response surface describing relationship between preform shape and die cavity fill ratio. Hu et al. [8] proposed adaptive response surface method with particle swarm optimization intelligent sampling for optimization of initial blank shape and blank hold force in sheet forming process. The results show that developed method is able to produce remarkable metamodel for highly nonlinear problems with multiparameter. Oudjene et al. [9] presented a response surface methodology, based on moving least-square approximation and adaptive moving region of interest for shape optimization problem. The geometries of both the punch and the die are optimized to improve the joints resistance to tensile loading. There are deficiencies about these studies, mainly through optimization of the shape of die to achieve the purpose of optimization forming and less flash. But in fact the quality of forged not only depends on the level of die design but also depends on the forging process parameters.

The present study is aimed at developing an approach to optimizing the process parameters with the combination of RSM and FEM to improve the precision forging parts quality and the service life of die. And the multiobjective optimization of precision forging process parameters is researched. The multiobjective optimization method based on least-square method and Latin hypercube design is proposed. Furthermore, the details of optimizing process parameters are presented with a variable cross section and thickness drive shaft radial precision forging as an example.

2. Theory of Multiobjective Optimization

Multiobjective optimization problem also is called multicriteria optimization problem, which is composed of a set of objective and associated constraint functions. Its mathematical model is shown in the following [10]:

$$\begin{aligned} \min \quad & F(\mathbf{x}) = (F_1(\mathbf{x}), F_2(\mathbf{x}), \dots, F_n(\mathbf{x}))^T \\ \text{s.t.} \quad & g_i(\mathbf{x}) < 0 \quad i = 1, 2, \dots, p \\ & h_j(\mathbf{x}) = 0 \quad j = 1, 2, \dots, q \\ & \mathbf{x}_L \leq \mathbf{x} \leq \mathbf{x}_U \quad \mathbf{x} = (x_1, x_2, \dots, x_m)^T, \end{aligned} \quad (1)$$

where $F(\mathbf{x})$, $g(\mathbf{x})$, and $h(\mathbf{x})$, respectively, are the objective function and inequality and equality constrained function. n , p , and q are number of corresponding functions. \mathbf{x} is the decision vector.

In most cases, each objective function probably conflicts, which does not make the multiobjective optimization problems produce one global optimum solution. However, such solutions exist: one or several objective functions impossible further optimize while the other objective function not deterioration, such a solution called Pareto optimal [11].

Definition 1. If \mathbf{x}^* is non-Pareto optimal which is a point in the search space, there is no x (in the search space feasibility domain) which makes $f_i(x) < f_i(\mathbf{x}^*)$, $i = 1, 2, \dots, N$.

Definition 2. The set which is made up of all non-Pareto-optimal solutions is called Pareto-optimal set of multiobjective optimization problems.

Kalyanmoy Deb's nondominated sorting genetic algorithm-II (NSGA-II) is an improved multiobjective evolutionary algorithm based on NSGA; it can keep the diversity without specifying any additional parameters. It can obtain the true Pareto-optimal solutions by the elite-preserving compared to NSGA. And it is widely used to obtain the set of Pareto-optimal solutions to handle constrained multiobjective optimization problems [12]. So this work adopts the NSGA-II to solve the multiobjective optimization problem.

3. Latin Hypercube Experiment Design

The experimental design is an important link of building response surface model; the sample points selected should be as much as possible to reflect the entire design space. The prediction precision of response surface model depends on the sample point selection, so the sample point selection is very important.

Latin hypercube sampling technique is a kind of constraint random generating uniform sample points experimental design and sampling method, which is a type of design specifically proposed for simulation experiment and a common design method of research on multiple factor experimental design. It has sample memory function and can avoid repeated extraction sample point which has appeared and make distribution at the boundary of sample points involved in sampling [13]. Because each factor can be uniformly applied at each level, therefore, Latin hypercube sampling becomes an effective sample reduction technology. The experimental points produce according to

$$x_j^i = \frac{(\pi_j^i + U_j^i)}{k}, \quad (2)$$

where U is a random number of $[0, 1]$. One has $1 \leq j \leq n$, $1 \leq i \leq k$, where n is number of variables and k is number of experiments. π is independent random arrangement of $(1, 2, \dots, k-1)$.

4. Multiobjective Optimization Function

4.1. Function of Deformation Homogeneity. The forging deformation more homogeneity, local deformation difference smaller, the tissue more homogeneity. Accordingly, internal tissue stress smaller, the crack opportunities caused by the uneven deformation of tissue smaller, the fatigue life of forging parts has increased [14]. When forging parts with uneven deformation, tensile stress in larger areas vulnerable hole or crack, which results in the decrease of forging parts serving time or internal quality of products completely unqualified.

Equivalent strain is an important index to measure the homogeneity of forging deformation. In this work, deformation homogeneity evaluation function of forging parts by variance of all unit equivalent strain of work pieces and whole final forging parts average equivalent strain. Consider

$$F_1 = \sqrt{\frac{\sum_{i=1}^n (\varepsilon_i - \varepsilon_{ave})^2}{n}}, \quad (3)$$

where ε_{ave} is the average equivalent strain of final forging parts $\varepsilon_{ave} = (\sum_{i=1}^n \varepsilon_i)/n$, ε_{max} is the maximum equivalent strain of final forging parts, ε_i is the actual equivalent strain of final forging parts, n is the total element of final forging parts, and F_1 is function of deformation homogeneity.

4.2. Function of Material Damage. Material damage value at a point is the integral quantity about strain, which reflects the material fracture tendency. When material damage reaches the critical damage value, the material will break. And less than the critical damage value, reflecting the material fracture trend [15]. The smaller the forging internal damage value, the smaller the chance of cracking in use of process. Thus forging products serving relatively prolonged, the fatigue life is relatively increased.

According to different fracture criterion, there are various definitions of forming damage. This work adopts Cockcroft & Latham model to describe the damage characteristics, the mathematical model as shown in (4). Considering minimum internal damage after forging deformation, adopts maximum damage C_{max} of forging all unit for measuring forging deformation damage index. So the function of forming damage is shown in (5). One has

$$C_i = \int_0^{\varepsilon_f} \frac{\sigma^*}{\bar{\sigma}} d\varepsilon, \quad (4)$$

$$F_2 = C_{max}, \quad (5)$$

where $\bar{\sigma}$ is the equivalent stress, σ^* is the maximum stress, when $\sigma_1 \geq 0$, $\sigma^* = \sigma_1$, when $\sigma_1 < 0$, $\sigma^* = 0$, ε_f is equivalent strain material fracture, ε is equivalent strain, C_i is value of forming damage, C_{max} is maximum damage of forging parts, and F_2 is function of material damage.

4.3. Function of Forming Load. The forming load directly determines the equipment tonnage. If the forming loads are lower, smaller tonnage equipment can complete the product manufacturing. In addition, smaller forming load can also reduce equipment wear and impact fatigue [16] and so can prolong the service life of the equipment and die, thus a corresponding reduction the production cost. The bigger forming load will increase wear between the forged parts and hammer. For a long time, it will cause the cavity size of hammer inconsistent the forged parts accuracy and size requirement, that the forged parts substandard quality.

The practice found that the real influence of die life is the peak load stroke curve of process of precision forging. Therefore this work adopts peak of load stroke curve as the forming load objective function:

$$F_3 = F_{max}, \quad (6)$$

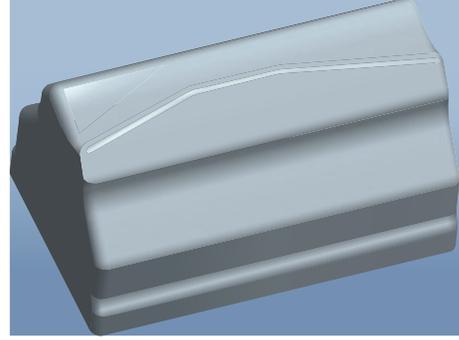


FIGURE 1: Geometric model of hammer.

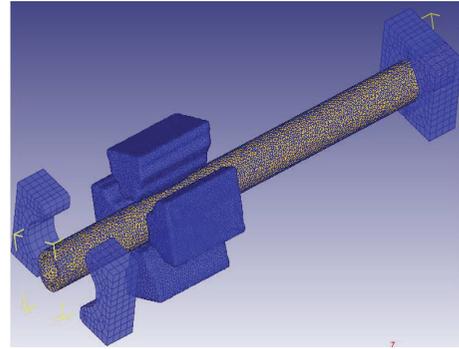


FIGURE 2: Finite element model.

where F_{max} is the maximum load of forging processes and F_3 is the forming load objective function.

5. Case Study

5.1. Establishment of Finite Element Model. Numerical simulation of radial forging billet dimensions is $\phi 41 \text{ mm} \times 5 \text{ mm} \times 580 \text{ mm}$, its material is alloy steel 34MnB5, the hammer and collet materials are Cr12MoVA, and the geometric model of hammer is shown in Figure 1. Figure 2 describes the FE model of billet forming by radial forging, the hammer and billet use four-node tetrahedron element, and collet uses eight-node hexahedron element. Coulomb friction model adopts hammer and billet, and the friction force $F = \mu \sigma_y / \sqrt{3}$, where μ is the friction coefficient and σ_y is yield stress of billet material.

5.2. Establishment of Approximation Model. In this work, the DEFORM-3D command flow mode called by using a special program, realize the numerical simulation in the process of radial precision forging process parameters are modified and generation of the database file. The Latin hypercube experiment design is shown in Table 1. Since the variation range of process parameters is extremely different, data are encoded. The midpoint of the design parameter is 0, transformed into $[-1, 1]$ interval. The scope of process parameters distribution is as follows. Collet axial speed v is $[420, 900] \text{ mm/min}$. Billet rotating speed n is $[48, 120] \text{ r/min}$. Hammer radial feed rate δ is $[1.4, 2.2] \text{ mm}$. Friction coefficient μ between hammer and

TABLE I: Latin hypercube experiment design.

Number	Process parameters				Response parameters		
	v	n	δ	μ	Deformation homogeneity	Forming damage	Forming load
1	-1	-1	-0.5	1	-0.807974899	-0.349462366	-8.15E - 01
2	-1	-0.5	0.5	0.5	-0.198448732	-0.553763441	-4.07E - 01
3	0	0.5	-0.5	0	-0.710235424	-0.672043011	-6.91E - 01
4	1	1	0.5	0	-0.11542186	-0.612903226	-1.85E - 01
5	-1	0.5	1	-1	0.413360945	0.596774194	-1.23E - 01
6	-0.5	0	-1	1	-0.733967691	-0.317204301	5.06E - 01
7	0	-0.5	-1	-1	-0.900535044	-1	-8.52E - 01
8	-0.5	0.5	0	-0.5	-0.376545319	-0.198924731	-6.54E - 01
9	1	-0.5	0	1	-0.283542069	-0.47311828	-1.11E - 01
10	-0.5	1	-0.5	0.5	-0.578156956	-0.295698925	-7.65E - 01
11	1	-1	1	-0.5	0.277190734	-0.112903226	9.38E - 01
12	-0.5	-0.5	1	0	0.161482936	-0.387096774	1.23E - 02
13	-1	0	0	0	-0.116539325	1	2.96E - 01
14	1	0	-0.5	-1	-0.262092083	-0.47311828	6.42E - 01
15	0.5	0	1	0.5	1	0.26344086	1.00E + 00
16	-0.5	-1	0.5	-1	0.215016087	-0.064516129	2.47E - 02
17	0.5	-1	-1	0	-0.921354846	-0.505376344	-4.94E - 01
18	-1	1	-1	-0.5	-1	-0.166666667	-1.00E + 00
19	0	1	1	1	-0.019837283	0.370967742	-2.10E - 01
20	0.5	-0.5	-0.5	-0.5	-0.503113372	-0.731182796	-5.43E - 01
21	0.5	1	0	-1	0.603947195	0.446236559	5.06E - 01
22	1	0.5	-1	0.5	-0.948096355	-0.76344086	-6.30E - 01
23	0	0	0.5	-0.5	0.327992928	-0.11827957	6.30E - 01
24	0.5	0.5	0.5	1	0.212566918	-0.150537634	7.28E - 01
25	0	-1	0	0.5	-0.602382212	-0.467741935	-6.42E - 01

billet is [0.1, 0.5]. Deformation homogeneity function F_1 is [0.192, 0.563]. Material damage function F_2 is [0.207, 0.579]. Forming load function F_3 is [2.18E + 05, 3.80E + 05]N.

Response surface methodology (RSM) can be used to build the approximation model and multiobjective optimization. The second-order response surface model, which has a good balance between accuracy and cost, is applied in this work. The final quadratic models of response equations are presented in the following:

$$\begin{aligned}
F_1 &= -0.11840 + 0.13378v + 0.078733n + 0.65796\delta \\
&\quad - 0.15456\mu + 0.056288vn + 0.11192v\delta \\
&\quad - 0.034017v\mu - 0.060703n\delta - 0.14624n\mu \\
&\quad - 0.080621\delta\mu - 0.17849v^2 - 0.23454n^2 \\
&\quad - 0.00160802\delta^2 + 0.18211\mu^2, \\
F_2 &= -0.27431 - 0.20124v + 0.19554n + 0.34261\delta \\
&\quad - 0.056612\mu - 0.24011vn + 0.089466v\delta \\
&\quad - 0.039315v\mu + 0.20128n\delta - 0.026057n\mu \\
&\quad - 0.14810\delta\mu + 0.10899v^2 - 0.039490n^2 \\
&\quad - 0.10976\delta^2 + 0.12995\mu^2,
\end{aligned}$$

$$F_3 = 0.056413 + 0.33893v + 0.026853n + 0.48907\delta$$

$$- 0.075685\mu - 0.063155vn + 0.35008v\delta$$

$$- 0.31407v\mu - 0.041490n\delta + 0.034315n\mu$$

$$- 0.29989\delta\mu - 0.068393v^2 - 0.65978n^2$$

$$+ 0.069412\delta^2 + 0.31878\mu^2.$$

(7)

The analysis of variance (ANOVA) statistical analysis techniques are used to check the fitness of response surface approximation model. The major statistical parameters used for evaluating model fitness are R^2 and adjusting R^2 (R^2_{adj}). Generally speaking, the larger the values of R^2 and R^2_{adj} , the better the fitness. The accuracy evaluation indexes of response surface model are shown in Table 2. The data shows that the complex correlation coefficient R^2 and the adjusting complex correlation coefficient R^2_{adj} are close to 1.

The experiment was carried out by comparing forging loads between the actual and response surface model results. The experiment was conducted at GFM SKK-10 cold forging machine, and the forging loads were measured in the radial

TABLE 2: The ANOVA table of mean for the approximation model.

Parameters	Response index		
	F_1	F_2	F_3
R^2	0.9698	0.9559	0.9464
R^2_{adj}	0.9275	0.9159	0.8913

forging processing. Table 3 lists the forging load from the response surface model results comparison with the experimental results. It can be found that the results of response surface model are in agreement with the experimental results. That means the response surface prediction model has high precision and can accurately reflect the mathematical relation between objective function and design parameter and can replace the actual physical model for multiobjective optimization calculation.

5.3. Multiobjective Optimization and Analysis. In this study, the NSGA-II was adopted in the optimization process and the optimization parameters are set as follows. The population size is 200, the maximum number of generations is 200, the mutation probability is 0.3, and crossover probability is 0.7.

Figure 3 shows all Pareto-optimal solutions obtained by NSGA-II in the multiobjective optimization. It can be

concluded that NSGA-II could provide a variety of alternative design solutions. Among the Pareto-optimal solutions, it is clearly found that none of the solutions is absolutely better than any other: any one of them is an acceptable solution. Figures 4–6 show the Pareto-optimal solutions vary with deformation homogeneity, material damage, and forming load. The results show that there are collisions between objective F_1 and F_2 , F_2 and F_3 . Reducing F_1 will usually increase F_2 and vice versa. Reducing F_2 will increase F_3 and vice versa. There are no collisions between objective F_1 and F_3 . Reducing F_1 will usually decrease F_3 and vice versa.

In the current work, after the Pareto-optimal solution sets are obtained in the multiobjective optimization, the satisfaction function f is defined as (8) by the mapping method to find the compromise solution. The smaller f is, the better the solution will be. The option 91 in Figure 3 is selected as satisfactory solution based on the satisfaction function defined in (8), shown in Table 4. It shows the initial and optimal value of each design parameter, the deformation homogeneity function increases by 26.92% to 0.297, and the forming load function increases by 3.83% to $2.71E+5N$, while the material damage function decreases by 12.76% to 0.294 compared with the original design parameters:

$$f = \sqrt{\left(\frac{F_1 - F_{1\min}}{F_{1\max} - F_{1\min}}\right)^2 + \left(\frac{F_2 - F_{2\min}}{F_{2\max} - F_{2\min}}\right)^2 + \left(\frac{F_3 - F_{3\min}}{F_{3\max} - F_{3\min}}\right)^2}, \quad (8)$$

where $F_{1\max}$ $F_{1\min}$ are the maximum and minimum values of F_1 among the Pareto-optimal sets, $F_{2\max}$ $F_{2\min}$ are the maximum and minimum values of F_2 among the Pareto-optimal sets, and $F_{3\max}$ $F_{3\min}$ are the maximum and minimum values of F_3 among the Pareto-optimal sets.

Figure 7 is the equivalent strain contours of forging parts (forging by optimal process parameters). It shows that the deformation homogeneity function increases by 23.93% to 0.290, and the error of approximation model and finite element model is 2.41%. Figure 8 is the material damage contours of forging parts (forging by optimal process parameters). It shows that the maximum damage of forging parts decreases by 15.43% to 0.285, and the error of approximation model and finite element model is 3.16%. Figure 9 is the forming load of die (forging by optimal process parameters). It shows that the maximum damage of forging parts increases by 0.77% to $2.63E+5N$, and the error of approximation model and finite element model is 3.04%. That means the response surface approximation model has high prediction precision.

6. Conclusions

In order to obtain good performance precision forging parts, a multiobjective optimization method for precision forging

process parameters is proposed based on the combination of numerical optimization techniques and finite element simulation technology.

- (1) Based on numerical simulation, a method of character precision forging forming parts quality and improving the service life of die is proposed. The proposed method can cut down the number of experiments by using the Latin hypercube experimental method to build response surface approximation model.
- (2) Mathematical model of the multiobjective optimization was established based on the second-order response surface method, and NSGA-II was used to obtain the Pareto-optimal solutions. It is clearly found that there are collisions between deformation homogeneity, material damage, and forming load. The satisfaction function is defined by the mapping method, which is used to obtain the optimal solution.
- (3) A variable wall thickness shaft radial precision forging was conducted as case study. In order to solve the conflict between the evaluation function of forming quality and the service life of die, the multiobjective

TABLE 3: Comparison of the forming load in the radial forging process.

Sample number	Collet axial speed	Billet rotating speed	Hammer radial feed rate	Friction factor	Load by exp.	Load by RSM model
1	660 mm/min	84 r/min	2.0 mm	0.2	317 KN	326 KN
2	780 mm/min	102 r/min	2.0 mm	0.5	322 KN	334 KN

TABLE 4: Multiobjective optimization results.

Design parameters	v /mm/min	n /r/min	δ /mm	μ	F_1	F_2	F_3
Initial	500	70	1.5	0.4	0.234	0.337	$2.61E + 5$
Optimal	580	66	1.7	0.31	0.297	0.294	$2.71E + 5$

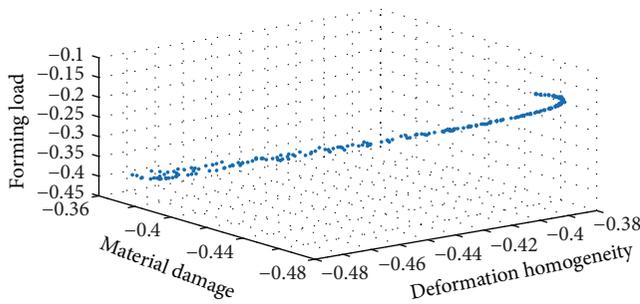


FIGURE 3: Pareto-optimal front sets.

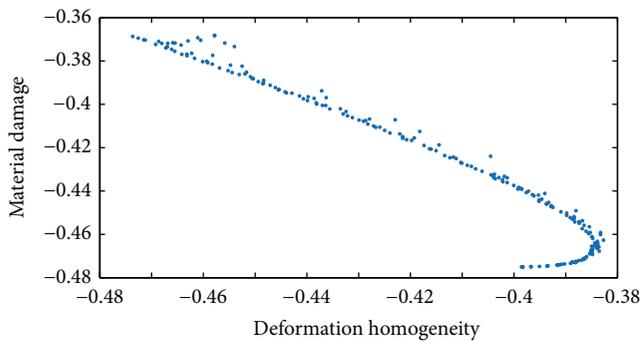


FIGURE 4: Deformation homogeneity and material damage.

optimization was carried out. After the optimization, the deformation homogeneity and forming load were increased, while the material damage was reduced compared to original process parameters. The feasibility of the proposed multiobjective optimization method was verified by numerical simulation.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

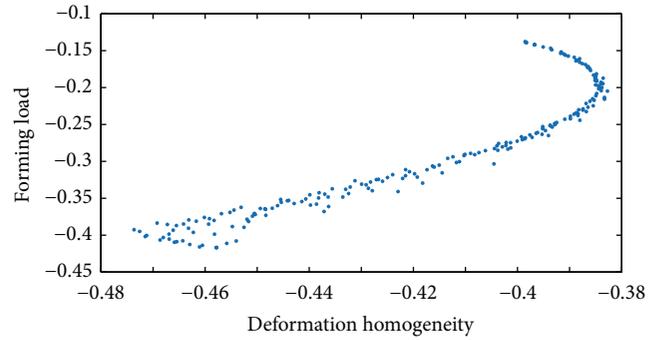


FIGURE 5: Deformation homogeneity and forming load.

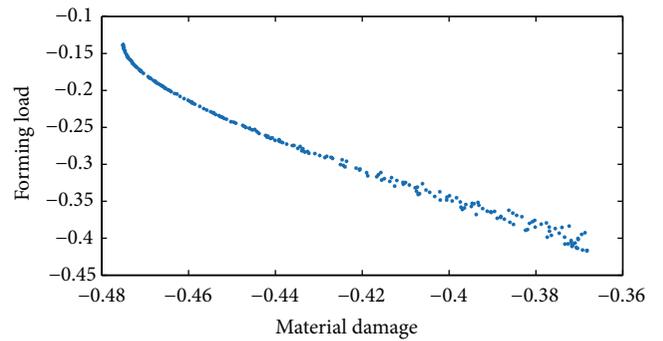


FIGURE 6: Material damage and forming load.

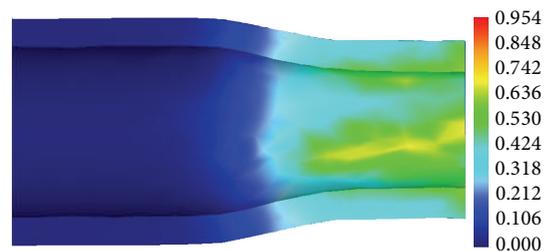


FIGURE 7: Contours of equivalent strain.

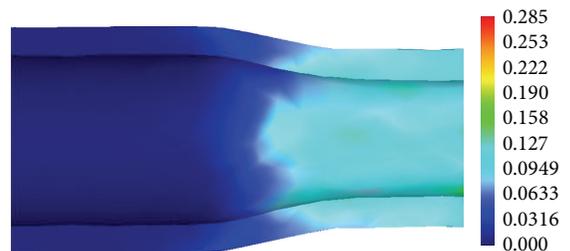


FIGURE 8: Contours of damage.

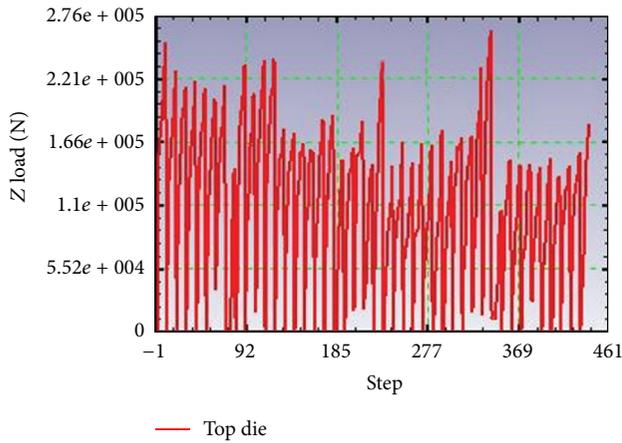


FIGURE 9: Forming loads of die.

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References

- [1] G. Q. Zhao, E. Wright, and R. V. Grandhi, "Preform die shape design in metal forming using an optimization method," *International Journal for Numerical Methods in Engineering*, vol. 40, no. 7, pp. 1213–1230, 1997.
- [2] G. Q. Zhao, X. W. Ma, X. H. Zhao, and R. V. Grandhi, "Studies on optimization of metal forming processes using sensitivity analysis methods," *Journal of Materials Processing Technology*, vol. 147, no. 2, pp. 217–228, 2004.
- [3] X. H. Zhao, J. F. Li, X. H. Huang, G. Q. Zhao, and G. C. Wang, "Optimal preform die shape design through controlling deformation uniformity and deforming force in metal forging," *Journal of Mechanical Engineering*, vol. 45, no. 5, pp. 193–197, 2009.
- [4] S. Acharjee and N. Zabarar, "The continuum sensitivity method for the computational design of three-dimensional deformation processes," *Computer Methods in Applied Mechanics and Engineering*, vol. 195, no. 48–49, pp. 6822–6842, 2006.
- [5] J. Guan, G.-C. Wang, and G.-Q. Zhao, "The microstructure optimal design using sensitivity analysis methods in forging process," *Journal of Plasticity Engineering*, vol. 14, no. 6, pp. 6–10, 2007.
- [6] Y. H. Yang, D. Liu, Z. Y. He, and Z. J. Luo, "Optimization of preform shapes by RSM and FEM to improve deformation homogeneity in aerospace forgings," *Chinese Journal of Aeronautics*, vol. 23, no. 2, pp. 260–267, 2010.
- [7] Y.-C. Tang, X.-H. Zhou, and J. Chen, "Preform tool shape optimization and redesign based on neural network response surface methodology," *Finite Elements in Analysis and Design*, vol. 44, no. 8, pp. 462–471, 2008.
- [8] W. Hu, L. G. Yao, and Z. Z. Hua, "Optimization of sheet metal forming processes by adaptive response surface based on intelligent sampling method," *Journal of Materials Processing Technology*, vol. 197, no. 1–3, pp. 77–88, 2008.
- [9] M. Oudjene, L. Ben-Ayed, A. Delamézière, and J.-L. Batoz, "Shape optimization of clinching tools using the response surface methodology with Moving Least-Square approximation," *Journal of Materials Processing Technology*, vol. 209, no. 1, pp. 289–296, 2009.
- [10] A. Sadollah, H. Eskandar, and J. H. Kim, "Water cycle algorithm for solving constrained multi-objective optimization problems," *Applied Soft Computing*, vol. 27, pp. 279–298, 2015.
- [11] C. Bazgan, F. Jamain, and D. Vanderpooten, "Approximate Pareto sets of minimal size for multi-objective optimization problems," *Operations Research Letters*, vol. 43, no. 1, pp. 1–6, 2015.
- [12] S. Chatterjee, K. Abhishek, S. S. Mahapatra, S. Datta, and R. K. Yadav, "NSGA-II approach of optimization to study the effects of drilling parameters in AISI-304 stainless steel," *Procedia Engineering*, vol. 97, pp. 78–84, 2014.
- [13] M. Ai, K. Li, S. Liu, and D. K. J. Lin, "Balanced incomplete Latin square designs," *Journal of Statistical Planning and Inference*, vol. 143, no. 9, pp. 1575–1582, 2013.
- [14] X. H. Zhao, G. Q. Zhao, G. C. Wang, and T. H. Wang, "Preform die shape design for uniformity of deformation in forging based on preform sensitivity analysis," *Journal of Materials Processing Technology*, vol. 128, no. 1–3, pp. 25–32, 2002.
- [15] X.-W. Chen, J. Wang, J. Chen, and Y. Xue, "Technological parameter optimization of gear billet hot forging process with damage minimization," *Journal of Shanghai Jiaotong University*, vol. 39, no. 7, pp. 1070–1072, 2005.
- [16] T. Kroiß, U. Engel, and M. Merklein, "Comprehensive approach for process modeling and optimization in cold forging considering interactions between process, tool and press," *Journal of Materials Processing Technology*, vol. 213, no. 7, pp. 1118–1127, 2013.



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