IACSIT International Journal of Engineering and Technology, Vol. 4, No. 4, August 2012

Optimum Design of Combined Cold Extrusion Die for Bevel Gear

Qing-hua Yang, Xin Chen, Bin Meng, and Juan Pan

***Abstract*—A collaborative optimization method for the structure parameters of combined die for bevel gear cold extrusion forming is presented in this paper, combined using finite element analysis, orthogonal experiment, neural network and genetic algorithm. Orthogonal experiment is used to design experimental schemes. Neural network is used to establish mapping relationship between die and process parameters and maximum extrusion force. Genetic algorithm is used to optimize the structure parameters.FEA evaluation validates that the collaborative optimization method presented has the same accuracy as that of conventional FEA based optimization approach, while it overcomes the deficiency of large computational resource consumption since the finite element analysis is relatively independent of optimization process and just provides training samples of neural network and evaluates the optimized results obtained. The collaborative optimization method can provide a fast and effective approach for combined die.**

***Index Terms*—Combined die, optimum design, neural network, genetic algorithm.**

I. Introduction

The pressure on die can be high enough to reduce the strength and life of die in the process of cold extrusion forming, thus correct choice of the materials and heat treatment methods, correct design of structure and optimization parameters for die are important, and the latter is of great significance[1].

Artificial intelligence algorithms such as neural network and genetic algorithm are widely used in the optimization of cold extrusion forming such as the structure parameters of die and the process parameters. The neural network has capabilities of self-learning, self-organization, self-adaptation and non-linear dynamic processing [2~4]. The training samples need to be input and these sample data can be learned and trained by neural network. Then the mapping relationship between input variable and training target can be obtained, which is usually difficult for traditional optimization method, especially dealing with nonlinear problem[5~7]. The genetic algorithm has abilities of global search performance, parallelism and scalability. Its fitness function does not have to be continuously differentiable and the domain can be set arbitrarily, therefore it is not restricted by differentiability of objective function and constraint function, which is also generally required for traditional optimization method[8~10].

This paper describes how to improve the cold forging die of the bevel gear in order to obtain better forming quality, higher die strength and longer life-span using optimization method, which combined using finite element analysis, orthogonal experiment, neural network and genetic algorithm.

Manuscript received May 17, 2012; revised June 17, 2012.

The authors are with the Key Laboratory of E&M, Ministry of Education & Zhejiang Province, Zhejiang University of Technology, 310014, China (e-mail: anjichenxin@126.com).

II. Finite Element Analysis Preparation

The model of combined dies is built by Pro/E. In order to improve the efficiency and decrease computational consumption, only 1/22 model are given, which is shown in Fig. 1. Table I gives the structure parameters of dies.

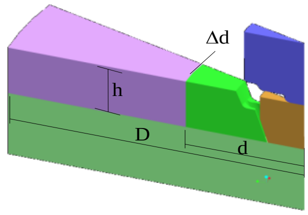


Fig. 1. Model of combined dies of bevel gear.

TABLE I: Structure Parameters of Dies

d (mm)	D (mm)	¢ d (mm)	h (mm)
120	300	0.6	33

Fig. 2 shows simulated stress field obtained by FEA. Maximum stress of inner die appears in the area of tooth root, while the maximum stress of outer die is the area with interference fit.

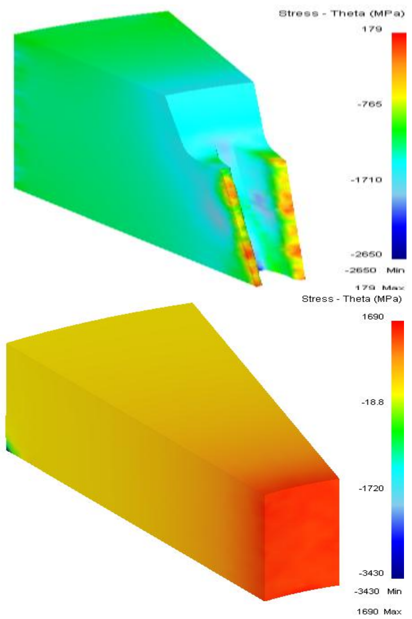


Fig. 2. Circumferential stress field of dies (initial).

The life and strength of combined die depend on to the maximum pulling stress, which is significantly related to the structure parameters of dies. Therefore for the optimization afterwards the cavity dies shape parameters d、D 、h and the magnitude of interference ¢ d are selected as optimization variables and the maximum pulling stress ¾1 、¾2 are set as optimization objective, whose initial value are listed in Table III.

TABLE III: INITIAL VALUE OF OPTIMIZATION VARIABLES AND OPTIMIZATION OBJECTIVE

d(mm)	D(mm)	¢ d(mm)	h (mm)	¾1(M Pa)	¾2(M Pa)
120	300	0.6	33	179	1690

III. OPTIMIZATION PROCESS

A. Establishment of Neural Network

The input and objective parameters are the basic of establishment of neural network, according to the above analysis, d、D 、¢ d、h are selected as input parameters, and ¾1 、¾2 are selected as objective parameters. Orthogonal experiment can obtain relatively high quality parameters with less numbers of experiments. Thus it is introduced to design experimental scheme and obtain training samples for neural network prediction. Table IV shows the L9 (3^4) orthogonal experiment table and result of finite analysis.

TABLE IV: ORTHOGONAL EXPERIMENT TABLE

No.	Input parameters				Finite analysis results	
	d (mm)	D (mm)	¢ d (mm)	h (mm)	¾1 (M P a)	¾2 (M P a)
1	120	300	0.4	33	6.09	974.628
2	120	330	0.6	36	-1537.2	1392.803
3	120	360	0.8	39	-3395.72	1764.982
4	150	300	0.6	39	-630.188	1140.236
5	150	330	0.8	33	-994.203	1612.659
6	150	360	0.4	36	635.845	806.709
7	180	300	0.8	36	-655.68	1316.745
8	180	330	0.4	39	827.458	734.177
9	180	360	0.6	33	108.145	1054.094

Considering the large difference of magnitude among the sample data, it is necessary to normalize the sample data before establishing network. Using the Function 1 to normalize the date in interval [0, 1].

$$\overline{x_i} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

x_i is input data, $x_{\min}$ is the minimum input data, $x_{\max}$ is the maximum input data.

In order to perform the linear regression analysis, enough test data needs to be obtained. 20 groups of data are generated randomly in the MATLAB with the predefined intervals of input parameters（d ∈ [120,180]; ∈ [300, 360]; ¢ d ∈ [0.4,0.8];h ∈[33,39]），then the trained neural network is used to obtain predicted maximum pulling stress, which is listed in Table V.

TABLE V: 20 GROUPS INPUT DATA AND PREDICTED RESULTS

No.	Input parameters				Predicted results	
	d (mm)	D (mm)	¢ d (mm)	h (mm)	¾1 (M P a)	¾2 (M P a)
1	144.62	312.16	0.74146	37.167	-1572.2	1319.4
2	173.62	340.33	0.63743	36.728	574.25	823.21
3	123.47	350.29	0.59862	37.769	-1641.9	1333.9
4	141.17	301.18	0.75991	38.741	-1626.2	1330.7
5	168.79	340.88	0.72865	36.136	624.73	808.21
6	120.59	322.77	0.65796	38.281	-1641.8	1333.9
7	128.33	349.91	0.72719	34.038	-1626.2	1334.4
8	132.17	330.17	0.66409	38.878	-1641.3	1333.8
9	131.92	342.57	0.53679	34.629	-1633.1	1331.7
10	156.23	325.73	0.51589	34.514	-639.49	1119.3
11	136.33	318.28	0.53648	38.254	-1640.1	1333
12	131.93	311.38	0.61363	37.424	-1638.7	1332.8
13	120.92	311.61	0.69085	33.819	-1627	1331.2
14	164.81	340.93	0.52372	33.071	817.98	739.48
15	146.71	318.17	0.7354	38.363	-1612.8	1328
16	175.91	332.5	0.62723	34.195	827.45	734.18
17	147.96	309.05	0.54817	34.792	-1245.9	1249.5
18	145.12	341.87	0.6811	36.969	-1616.4	1328.9
19	170.77	322.7	0.61863	34.706	827.08	734.5
20	151.51	351.6	0.57795	35.815	-1551.1	1314.4

Then linear regression analysis function is established where ¾1 、¾2 are set as independent variables f_1 、f_2 and d、D 、¢ d、h are set as independent variables x_1 、x_2 、 x_3 、x_4 , finally we can obtain:

$$f_1(x) = -494.3 - 46.687x_1 + 2.9517x_2 + 147.84x_3 - 107.24x_4 \tag{2}$$

$$f_2(x) = 2092.7 - 11.704x_1 - 0.676x_2 - 40.148x_3 + 26.029x_4 \tag{3}$$

$(120 < x_1 < 180, 300 < x_2 < 360, 0.4 < x_3 < 0.8, 33 < x_4 < 39)$.

B. Genetic Algorithm Optimization

In the genetic algorithm the fitness function is the indicator of survival chance of population individuals, which shall be established firstly.

The optimization objective is absolute value of the maximum stress of inner die and absolute value of the difference between peek stress and the admissible stress(1100MPa) of outer die, which are respectively 827.458MPa and 664,982MPa,we can obtain the fitness functions:

$$g_1(x) = |f_1(x)| = |\text{-}4944.3\text{-}46.687x_1 + 2.9517x_2 + 147.84x_3 \text{-}107.24x_4| \tag{4}$$

$$g_2(x) = |f_2(x) - 1100| = |992.7\text{-}11.074x_1 - 0.676x_2 - 40.148x_3 + 26.029x_4| \tag{5}$$

Then convert the Multi-objective optimization to single-objective optimization, and we obtain the final fitness function.

$$\begin{aligned} Fit(g(x)) &= 0.5Fit(g(x_1)) + 0.5Fit(g(x_2)) = \\ & 0.5(327.458 - |4944.3 + 46.687x_1 - 2.9517x_2 - 147.34x_3 + 107.24x_4|) \\ & + 0.5(664.932 - |992.7 - 11.074x_1 - 0.676x_2 - 40.143x_3 + 26.029x_4|) \end{aligned} \quad (6)$$

The genetic algorithm toolbox embedded in MATLAB is called, and Fig. 3 shows the variation trend of the fitness value with the generation. We obtain the steadily maximum fitness value when it goes to the 25th generation, and the value is presented in Table VI.

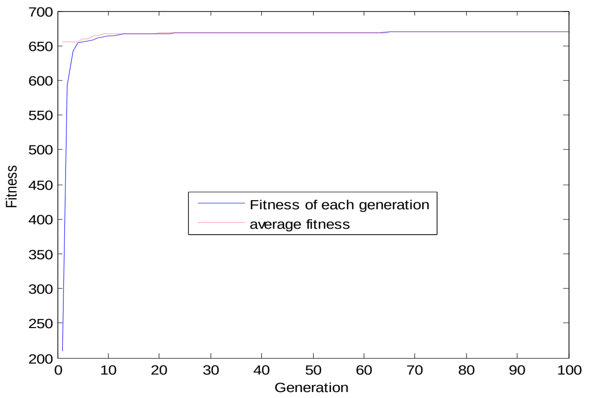


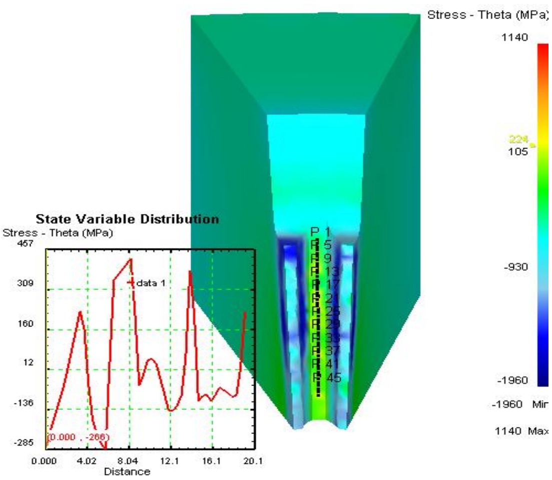
Fig. 3. Variation trend of the fitness value with generation.

TABLE VI: OPTIMIZED RESULTS OBTAINED BY GENETIC ALGORITHM.

x_1 (mm)	x_2 (mm)	x_3 (mm)	x_4 (mm)	$Fit(g(x))$ ((MPa)
165.322	324.1004	0.4997	35.4776	669.342

IV. OPTIMIZATION EVALUATIONS

Rebuild the model according to the optimized results in Table VII, and finite analysis is again performed. Fig. 4 shows the circumferential pulling stress of die by Deform, and the value is given in Table VII. The peak stress of inner die is 290.64MPa, which is relatively small to the admissible stress of YG15(1800MPa). And the peak stress of outer die is 1079.143MPa, is very closed to the admissible stress of 30CrMnSiNi2A(1100MPa).Thus the optimization method is suitable to the model and the result also achieve the purpose expected.



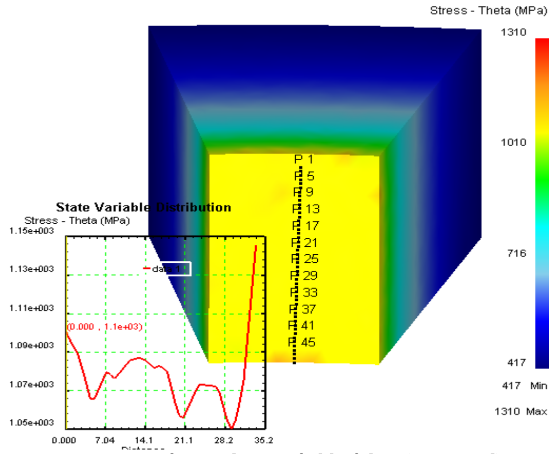


Fig. 4. Circumferential stress field of dies (optimized).

TABLE VII: OPTIMIZED VALUE OF OPTIMIZATION VARIABLES AND OPTIMIZATION OBJECTIVE

d(mm)	D (mm)	¢ d(mm)	h(mm)	¾1(M Pa)	¾2(M Pa)
165.322	324.1004	0.4997	35.4776	290.64	1079.143

Finally, in consideration to the restriction of experiment conditions, a 1/3 model of the combined die with the optimal solution was manufactured, which shows in Fig. 5, and was used for cold forging testing. An experiment for test strain was designed to analyze influence of the interference fit within the combined die to stress distribution. Results show that die strength can be improved significantly with the optimized combined die design.

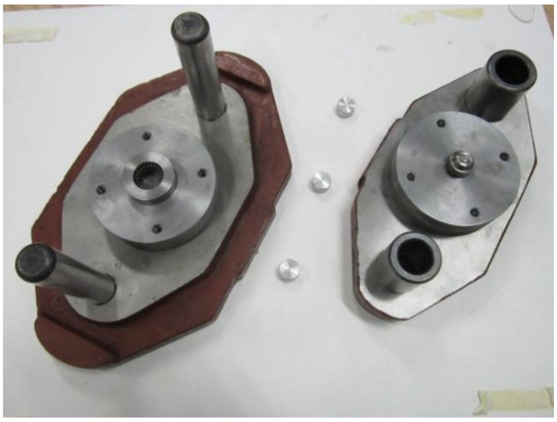


Fig. 5. Die and formed bevel gear

V. CONCLUSIONS

A collaborative optimization method for the combined die of bevel gear is presented in this paper, combined using finite element analysis, orthogonal experiment, neural network and genetic algorithm. Adopted orthogonal method to figure out test groups that contain structural characteristics of the die, obtained training data for neural networks via FEA, established neural networks, obtained the interpolated function by using linear regression analysis on neural networks, adopted genetic algorithm to optimize the global optimal solution of the mathematical function. The optimal solution was used for FEA, and then the feasibility of collaborative optimization of the combined die could be verified.

REFERENCES

[1] S. Z. Hong, "Practical cold extrusion technology," "Mechanical industry press," P. R. China, 2004.
[2] G. Y. Lin, X. k. Chen, and J. Jiang, et al, Natural Science Journal of Xiangtan University. vol. 28, pp. 89-94, 2006.
[3] M. Noorani-Azad, M. Bakhshi-Jooybari, and S. J. Hosseinipour, et al, *Journal of Materials Processing Technology*, vol. 164–165, pp. 1572–1577, 2005.
[4] D. F. Zhang, "Application and design of neural network in MATLAB(Mechanical Industry Press," P. R. China 2009.
[5] J. H. Huang, S. G. Li, and J. J. Rao, et al, *China Mechanical Engineering*, vol. 15, pp. 648-654, 2004.
[6] L. Zou, J. C. Xia, and X. Y. Wang, et al, *Journal of Materials Processing Technology*. vol. 142, pp. 659–664, 2003.
[7] S. K. Lee, D. C. Ko, and B. M. Kim, *International Journal of Machine Tools & Manufacture*. vol. 40, pp. 1457–1478, 2000.
[8] Y. J. Lei, S. W. Zhang, and X. W. Li, et al, "Application of genetic algorithm toolbox in MATLAB Xi Dian University Press," P. R. China 2009.
[9] Z. G. Luo, X. Wang, and J. Li, et al, *China Mechanical Engineering*. vol. 20, pp. 1704-1707, 2009.
[10] H. Ou, C. G. Armstrong, and M. A. Price, *Journal of Materials Processing Technology*. vol. 132, pp. 21–27, 2003.