An approach to the optimal design of technological parameters in the profile extrusion process

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Abstract

An approach for the optimal design of technological variables in the profile extrusion process was proposed, which integrates a finite element simulation technique, an artificial neural network and a genetic algorithm and configures a reasonable die-hole layout for a non-symmetric profile extrusion process. The comparisons between computed and experimental results indicated that the optimal design model is effective and feasible. The numerical simulation for an angle aluminum extrusion process was conducted using the optimal results of the die-hole layout. The mesh distortions at different stages of the extrusion process were described in detail. The distribution of the velocity at the die opening was also obtained. This is helpful for the proper determination of the profile extrusion technology and optimization of the die design.

Keywords: Profile extrusion; Parameters optimization; Numerical simulation; Artificial neural network; Genetic algorithm

1. Introduction

The computational modeling of extrusion is now well established. Within the last 20 years, the finite element method (FEM) has become a powerful technique to simulate metal-forming processes. Nowadays, the finite element numerical simulation not only can describe precisely the metal flow process, but also can give the fixed values of various physical fields, which is a powerful tool to carry out the optimal design of technological parameters and to predict defects in the deformation process [1]. However, a lot of trial-and-error computer tests are required in order to study the influence of the various technological parameters on the forming process. If the optimal design of the technological parameters is conducted using the finite element method, many calculations are required, which results in the waste of resource. The orthogonal test method is a scientific experimental approach based on the development of probability and mathematics statistics, including the equalization disperse and regularity comparison [2]. This method can reflect relatively all-around situation with few experiments, which can consider many factors and targets. The artificial neural network (ANN) is an artificial intelligent approach simulating the manner of the brain neural delivering information, which can provide a new approach to solve the simulation of non-linear system and to make the prediction for unknown models [3,4]. ANN possesses the characteristics of auto-organize, auto-learn, auto-adapt and non-linear dynamic manage, etc. which can considerably reduce the numerical simulation time. The genetic algorithm (GA) is a scientific optimal approach simulating the creature evolutionary mechanism on computer with the natural choice and genetic mechanism [5,6]. GA is a huge parallel, stochastic and auto-adapting search algorithm that borrows the operations and themes from natural evolution, which can solve the optimal problems of both the continuous derivative function and the discrete derivative function. In this paper, ANN was adopted to set up the system model and GA was used to figure out the optimal problem of assembled parameters such as the selection of technological parameters in the design of a profile extrusion die.

2. An approach to the optimal design of the technological parameters

Because the extrusion section is complex in the profile extrusion process, the metal flow from the extrusion die is not uniform, which causes the crosscracking, bending, distorting and twisting on the extruded product. To improve the quality of
the piecework, the die-hole layout must be taken into account in the design of the profile extrusion die, which is the optimal problem of assembled parameters. In this paper, an approach to the optimal design of technological parameters is presented based on our previous work [7], integrating FEM, ANN and GA, shown in Fig. 1. The functions of various model blocks are presented as follows:

1. **Optimal prepared model block.** The optimal objective function and main technological parameters are determined with this model block. The restrain scopes of the technological parameters are determined on the basis of the practical experience.

2. **Orthogonal test model block.** Based on the orthogonal principle, a standard pattern—orthogonal table is specified, which arranges the test scheme. A few tests are used to gain the interaction of the design parameters, which can reduce numerical simulation time.

3. **Numerical simulation model block.** Based on the plastic finite-element method, the numerical simulations of the profile extrusion-forming process are conducted with the scheme supplied by an orthogonal test to acquire the objective functional values and to prepare the learning samples for the artificial neural network. The numerical simulation based on the optimal results is carried out to provide the helpful information for the die design.

4. **Artificial neural network model block.** The network model is trained by the learning samples of the numerical simulation results, which is served as the knowledge source after trained and tested. The objective parameter function values required by GA are gained by the spread application ability of multiplayer ANN.

5. **Genetic algorithm and optimal model block.** GA having global convergence is used as the optimal algorithm. The main technological parameters in the profile extrusion process are optimized with the objective functional values obtained by the ANN model.

6. **Result output.** The main optimal technological parameters are exported with this model block, the results such as the stress and strain are also exported by the numerical simulation model block.

### 3. Optimization of the technological parameters for a non-symmetric angle aluminum profile extrusion process

#### 3.1. Selection of the objective function

The selection of the objective function is associated with the specific research object. It is important to balance the metal flow velocity in the profile extrusion process. For this purpose, the standard deviation of the velocity field (SDV) is chosen as the objective function. SDV is defined as

\[
SDV = \sqrt{\frac{\sum_{i=1}^{N} \left(V_i - V_{ave}^Z\right)^2}{N}}
\]

where \( N \) is the nodal point number in an interested region, \( V_i \) is the axial nodal velocity in a given plane, and \( V_{ave}^Z \) is the average axial velocity in a given plane. The optimal goal is to make it the minimum for SDV of the extruded product.

#### 3.2. Selection of the design variable and its restrain scope

Calculation of the die land length in the profile extrusion process is conducted under the certain layout of the die hole. First, the proper die-hole layout is found with the well-balanced metal flow velocity in the front of ensuring the die strength. Second, the fluctuation of the metal flow velocity is

Fig. 1. Optimal design model of technological parameters.

Fig. 2. Design figure of die-hole layout for a non-symmetric angle aluminum profile extrusion process.
the least with design of the non-equal die land length. An aluminum angle has a common profile, that is, its two-side length is not equality in general. The die-hole layout is determined generally by experience and trial-and-error testing. Fig. 2 shows the design figure of the die-hole layout for a non-symmetric angle aluminum profile extrusion process.

3.3. Steps and result discussions

(1) The dimensions A and B in the die-hole layout are chosen as the design variables. SDV is chosen as the target function. The assembled scheme between the parameters A and B is constructed using the orthogonal test method. The constructed levels and factors are presented in Table 1.

(2) SDV is acquired with the plastic finite element method for each assembled parameter. Then a couple of the study samples are composed with it. The table constructed by the orthogonal test method is shown in Table 2.

(3) Building up a neural network (NN) model. A three-layer error back propagation NN is applied as the network structure of the system model under the trial and error test. Each node represents an artificial neuron and neurons in the same layer are affected only by neurons in the previous layer. The nodes in the input layer and the output layer, equal the eigenvalue of the input and output patterns, respectively, while the nodes in the hidden layer are determined by numerical trials. The knowledge contained in the example data is acquired via the improved back propagation (BP) learning algorithm. The parameters of the BP network are chosen as follows: the nodes in the input layer are two, the nodes in the hidden layer are five and the node in the output layer is one. Following samples in Table 2, the trained neural network is served as a knowledge source to obtain the target functional values, which are used by GA. The comparisons between the predicted network values and the calculated ones in the finite element simulation are shown in Table 3. From Table 3, it is seen that errors between in the SDV predicted values and in the FEM calculated ones are within 5%, which indicates that the trained network has a good expansion nature. Thus, it can be served as a knowledge source for the backward optimal model.

(4) GA emulates some of the processes of natural genetic systems, namely, natural populations evolve according to the principles of genetic reproduction, mutation and ‘survival of the fittest’ to fit the nature during the course of evolution. GA maps, the search domain into a natural

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**Table 1**
Levels and factors of orthogonal test

| Levels | Factors | A (mm) | B (mm) |
|--------|---------|--------|--------|
| 1      | 9       | 19     |
| 2      | 12      | 22     |
| 3      | 15      | 25     |
| 4      | 18      | 28     |
| 5      | 21      | 31     |
| 6      | 24      | 34     |

**Table 2**
Orthogonal table

| No. | Factors | SDV |
|-----|---------|-----|
|     | A       | B   |
| 1   | 1       | 1   | 0.293 |
| 2   | 1       | 3   | 0.289 |
| 3   | 1       | 5   | 0.296 |
| 4   | 1       | 2   | 0.291 |
| 5   | 1       | 4   | 0.293 |
| 6   | 1       | 6   | 0.301 |
| 7   | 2       | 1   | 0.289 |
| 8   | 2       | 3   | 0.289 |
| 9   | 2       | 5   | 0.289 |
| 10  | 2       | 2   | 0.291 |
| 11  | 2       | 4   | 0.285 |
| 12  | 2       | 6   | 0.294 |
| 13  | 3       | 1   | 0.286 |
| 14  | 3       | 3   | 0.283 |
| 15  | 3       | 5   | 0.284 |
| 16  | 3       | 2   | 0.284 |
| 17  | 3       | 4   | 0.283 |
| 18  | 3       | 6   | 0.285 |
| 19  | 4       | 1   | 0.289 |
| 20  | 4       | 3   | 0.283 |
| 21  | 4       | 5   | 0.283 |
| 22  | 4       | 2   | 0.284 |
| 23  | 4       | 4   | 0.281 |
| 24  | 4       | 6   | 0.284 |
| 25  | 5       | 1   | 0.284 |
| 26  | 5       | 3   | 0.281 |
| 27  | 5       | 5   | 0.261 |
| 28  | 5       | 2   | 0.283 |
| 29  | 5       | 4   | 0.279 |
| 30  | 5       | 6   | 0.280 |
| 31  | 6       | 1   | 0.288 |
| 32  | 6       | 3   | 0.283 |
| 33  | 6       | 5   | 0.279 |
| 34  | 6       | 2   | 0.285 |
| 35  | 6       | 4   | 0.281 |
| 36  | 6       | 6   | 0.279 |

**Table 3**
Comparison between the predicted values of network and the calculated ones of finite element method

| No. | A (mm) | B (mm) | Predicted SDV | Calculated SDV | Errors (%) |
|-----|--------|--------|---------------|----------------|------------|
| 1   | 10.1   | 32.3   | 0.302         | 0.315          | 4.2        |
| 2   | 13.4   | 20.8   | 0.277         | 0.282          | 1.6        |
| 3   | 16.5   | 23.7   | 0.288         | 0.294          | 2.0        |
| 4   | 19.3   | 21.1   | 0.284         | 0.281          | -1.2       |
| 5   | 20.8   | 30.5   | 0.272         | 0.260          | -4.5       |
| 6   | 22.6   | 31.2   | 0.279         | 0.283          | 1.6        |
population’ genetic space, and variables into chromosomes (namely individuals) that are composed of genes. All chromosomes form a population and each individual is evaluated according to the given fitness function. In such a mechanism, the main characters of each individual in the current generation are able to pass down to the next generation and chromosomes will be reproduced and hybridized, and mutated by a certain probability. Generally, the elitists trend to achieve the operation of the crossover, by which the excellence trains are created, thereby leading to the preferable solutions. Clearly, GA is eligible for finding the global optimum solution proceeds not by incremental changes to a single structure but by maintaining a population of solutions from which the new structures results via genetic operators. The die structural parameters $A$ and $B$ are optimized with GA. The population size is chosen as 100, the chromosome length as 16, the crossover probability as 0.3, the mutation probability as 0.001 and the genetic maximum number of generation as 8–10. The results acquired with GA are shown in Table 4. Original SDV in the center of mass (10.1, 5.1) is 0.331. Final optimized minimum SDV is 0.259, which represents a 21.6% reduction. It is indicated that the optimal result is remarkable. The last optimal die-hole layout is $A = 20.6$ mm and $B = 29.8$ mm.

### 4. Numerical simulation for a non-symmetric angle aluminum profile extrusion process

#### 4.1. Simulation result analysis

The material of workpiece is aluminum 6062, its relationship between the flow stress and strain is given by [8]:

$$\bar{\sigma} = 209(e)^{0.122} \text{N/mm}^2$$  \hspace{1cm} (2)

The calculational parameters are as follows: initial billet height, 40 mm; diameter of the extrusion container, 100 mm; die bearing length, 4 mm; extrusion ratio, 55.7; friction coefficient between the die and billet, 0.25; initial billet temperature, 480 °C; die temperature, 450 °C; the heat transfer coefficient, 40 W/(m² K); and press-ram speed, 2 mm/s.

Based on the optimized die-hole layout, the numerical simulation for a non-symmetric angle aluminum profile extrusion process is conducted using the finite-element technique. The initial billet is discretized with a non-homogeneous mesh in order to reduce the computational time (shown in Fig. 3(a)). The model is used by an eight-node hexahedron element with 5696 nodes and 4724 elements.

The initial mesh and deformed mesh in the extrusion process are shown in Fig. 3. It is clear that the mesh distortion of the deformed zone increases as the deformation increases. But the heights of the extruded metal on various

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**Table 4**

| Iterative times | Design variables | SDV |
|-----------------|------------------|-----|
|                 | $A$ (mm) | $B$ (mm) |     |
| 1               | 5.1     | 10.1     | 0.331 |
| 2–3             | 15.2    | 19.3     | 0.289 |
| 4–6             | 18.4    | 27.6     | 0.279 |
| 8–10            | 20.6    | 29.8     | 0.259 |

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Fig. 3. Grid distortions of billet in different stage. (a) 0th incremental step (b) 78th incremental step. (c) 104th incremental step (d) 170th incremental step.
sides are uniform. The velocity distribution at the die opening is shown in Fig. 4 where a uniform metal flow is obtained, which indicates that the optimized die-hole layout is reasonable.

4.2. Experimental verification

In order to verify the correctness of the proposed optimal design model, which integrates a numerical simulation, ANN and GA, an angle aluminum profile extrusion die was designed using the optimal die-hole layout acquired in the above section (shown in Fig. 5). The extruded product is accorded entirely with the requirement of drawing in the first trial time. The product of the angle aluminum profile extrusion is shown in Fig. 6, which indicates that the construction of the optimal design model for technological parameters is effective and feasible.

5. Conclusions

The technological parameters for a non-symmetric angle aluminum profile extrusion process were optimized based on the optimal design model proposed in this paper. Through the example analysis, it was indicated that the optimal design model is effective and feasible, in which an intelligent way for the extrusion technological and the die design is found. It is widely applied to study the problem of the engineering design for the metal plastic forming process with expert system, artificial neural network, FEM and optimal method.

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