Optimization Design of Parameters with Hybrid Particle Swarm Optimization Algorithm in Multi-hole Extrusion Process

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Abstract. In this paper, we present a Hybrid Particle Swarm Optimization (HPSO) algorithm that combines the Particle Swarm Optimization (PSO) algorithm with the Genetic Algorithm (GA) method. The algorithm is used for investigating the plastic deformation behavior of titanium alloy (Ti-6Al-4V) in a multi-hole extrusion process. The simulation used rigid-plastic finite element (FE) DEFORMTM-3D software to obtain the minimum mandrel bias angle and exit tube bending angle. Results of the simulation indicate that these two angles were significantly less than 0.3 degrees, suggesting that metaheuristic algorithms based on HPSO and FE analysis could be used for general multi-hole extrusion processes.

Keywords: Multi-hole extrusion, Particle Swarm Optimization, Finite element, Genetic Algorithm.

1 Introduction

In recent years, extruded titanium has been widely used in various engineering fields. While the titanium alloy (Ti-6Al-4V) is a typical type of two-phase titanium alloy, it does possess characteristics of high economic value, such as its light weight, high strength, corrosion resistance, and high-temperature oxidation resistance [1]. As market demand and quality requirements increased, most of the industry began to favor the economically efficient multi-hole mold that can help improve production efficiency in the extrusion process. However, in the multi-hole extrusion molding process, billet plastic deformation in complex multi-hole molding processes can lead to excessive extrusion pressure on high-strength alloys, which can generate non-symmetrical material flow in the mandrel. The most important of these factors are hole location, billet temperature, extrusion speed, and friction. The objective of this study is to use the extrusion process to seek out the optimal parameter combination that could generate minimum bias in the molding process.

Numerous past studies have discussed extrusion generated bias in molding. For example: Peng and Sheppard [2] used finite element analysis in their research on multi-hole extrusion process on the mold. They analyzed the amount and distribution

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of holes on the mold and their impact on extrusion load and material flow. Chen et al. [3] used DEFORMTM-3D software to analyze the impact of process parameters, such as billet temperature, extrusion speed, billet size, and hole location on the extrusion process in a single, porous, aluminum alloy. Their results indicated that hole location makes a significant impact on the exit tube bending angle generated by the extrusion process. Most previous research findings were based on traditional methods of analyzing multi-hole extrusion process; only a few were based on evolutionary algorithms designed to analyze parameters from the extrusion process. Among evolutionary algorithms, PSO is a technique commonly used to solve optimization problems [4-5]. Relative to GA, PSO does not use operators such as GA selection, crossover, and mutation. Thus, PSO takes less computing time [6] and widely used in many different fields [7]. Though the advantage of PSO is in its fast convergence, it is rather easy to fall into the trap of local optimal solution at later stages of calculation [8]. To overcome problems with local optimal solution and early convergence, other evolutionary algorithms were adopted in PSO calculation in order to move away from the local optimal solution trap [9-11]. In this paper, HPSO was design to investigate mandrel eccentric angle and the exit tube bending angle in multi-hole seamless tube extrusion under various extrusion parameter conditions.

2 Research Method

2.1 Application of FE Modeling

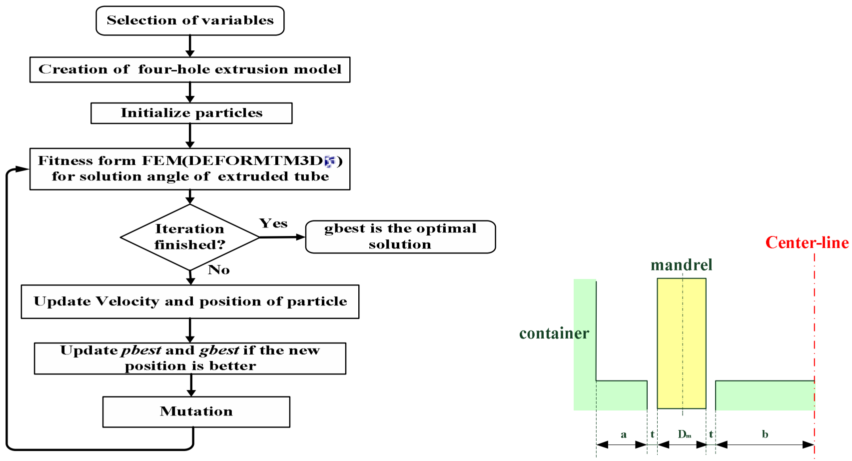
This study used rigid-plastic FE simulations with DEFORMTM-3D software for its research into the multi-hole tube extrusion molding process. DEFORMTM-3D is designed to simulate the distribution of metallic materials in the mold, such as ductile failure value, post deformation temperature, plastic flow speed, and stress and strain. The software is composed of a combination of multiple modules. Its main structure is divided into the pre-processing, post-processing, and multi-function modules, and the simulation engine.

2.2 Optimize Parameter for Multi-hole Extrusion Processes

This study used the HPSO algorithm with FE modeling technique to analyze the effect of various process characteristics on mandrel bias angle and exit tube bending angle in the extrusion molding process. These characteristics include hole position, billet temperature, extrusion speed, and friction coefficient. The process simulation and characteristics are shown in Fig. 1(a) and (b)

2.3 HPSO Algorithm

The search space in PSO is multi-dimensional. As such, the particle group can refer to the optimum experience of an individual or a group in selecting its corrective approach. It can select an objective optimization approach to calculate the fitness of



(a) (b)

Fig. 1. (a) The process simulation. (b) Process characteristics.

each particle value. During the iteration process, the speed of each particle is calculated as shown in Eq. 1:

$$v_i(t+1) = \omega v_i + c_1 r_1 (p_{id} - x_i(t)) + c_2 r_2 (p_{gd} - x_i(t)) \quad (1)$$

Where, t is the current iteration number, ω is inertia weight, and c_1 and c_2 are learning factors. In this study, ω was set to 0.9, C_1 was set to 2, and C_2 was set to 1.5, while r_1 and r_2 were random values in the range of [0,1]. x_i is the current position of the particle, p_{id} is the optimal solution for each individual particle, and p_{gd} is the optimal solution for all particle groups. The position of each particle is calculated using Eq. 2.

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2)$$

The main objective of mutation operator in GA is to prevent particles from falling into the trap of local optimal solution. Since excessive mutations can destroy the original particle position, the rate of mutation occurrence in GA is therefore set rather low. In this study, the mutation ratio was set to 10%. L is the lower limit of the parameter, U is the upper limit of the process parameter, and r_3 is a random value in the range of [0, 1]. The HPSO algorithm is designed to always update the variables specified in these equations until termination conditions are reached.

$$x_i = L + r_3(U - L) \quad (3)$$

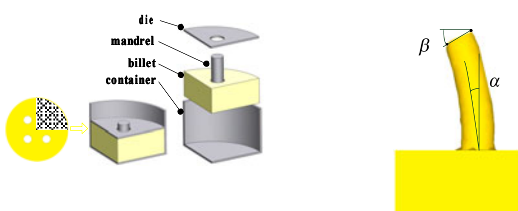
2.4 Extrusion Parameter Setting

The plastic deformation behavior in the multi-hole extrusion molding process and exit tube bending angle is critically important. These factors include hole location, billet temperature, extrusion speed, and friction. In this study, the billet diameter was set to 100 mm, mandrel length was set to 50 mm, billet thickness was set to 50 mm, and the billet temperature range was set to 150 to 900 °C. The grid was divided into 40,000 elements. The mold was assumed to be rigid. The range of the extrusion molding speed was set to 0.3 mm/s to 1.2 mm/s, and the friction coefficient range of the billet and mold interface was set to between 0.1 and 0.5. Among these, hole position had a huge impact on the multi-hole extrusion process, with its range set to 0.35 to 0.65. As indicated in Fig. 1(b), a is the minimum distance between hole and container, b is the minimum distance between the hole and the center of mold, Dm is the mandrel diameter, and t is tube thickness. Hole position *e* is defined as in Eq. 1 (a) and Fig. 1 (b).

$$e = \frac{b}{a+b} \;;\; 0 \le e \le 1 \tag{4}$$

2.5 Constructing a Multi-hole Extrusion Model

This study used Solid Work 2010 for component modeling of multi-hole extrusion. The multi-hole seamless tube extrusion process was set with the hole number as 4, the container diameter as 100 mm, the hole diameter as 13 mm, and billet length as 50 mm. The choices for tube selection (mandrel diameter of 9 mm and tube thickness of 2 mm) and hole position in the multi-hole extrusion process was complied based on the center of symmetry principle, with a quarter of the model intercepts entered into the FE software for modeling analysis, which is shown in Fig. 2 (a).



(a) (b)

Fig. 2. (a)Three-dimensional FE modeling of multi-hole extrusion model (b) Exit tube bending angles α and β

2.5 Initialization and Fitness Assessment of PSO

In this algorithm, 20 particles were randomly selected at the start, with each particle consisting of a combination of four parameters. Then FE software DEFORMTM-3D was employed to assess the modeling of the multi-hole seamless tube extrusion model by looking at the fitness of its eccentric angle α and exit tube bending angle β (Fig.2(b)). Smaller α and β angles indicate a better fit.

3 Simulation Results

This study used HPSO algorithm in combination with FE modeling techniques to analyze the impact of various process parameters on the mandrel and exit tube bending angles during the extrusion molding process. The results are shown in Fig. 3(a), 3 (b) and Fig.4.

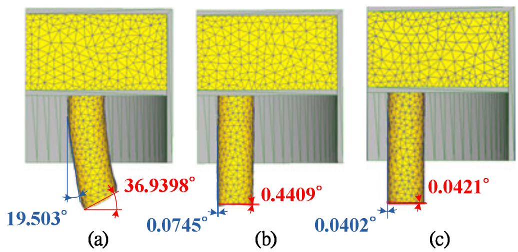


Fig. 3. (a) Results from parameter modeling in parent generation (b) Results of modeling using GA (c) Results of modeling using HPSO

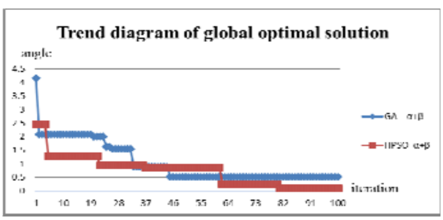


Fig. 4. Convergence comparison of average value in each generation (α + β) using GA and HPSO

As can be seen in Fig. 3 (a), 3(b) and 3(c), the mandrel bending angle was reduced from 19.5030 ° to 0.0402 °, while the exit tube bending angle was reduced from 36.9398 ° (initial generation) to 0.0421 ° (after 100 iterations). The resulting optimal solutions were quite good in that they are better than those generated from GA. It is revealed from Fig. 4 that 100 iterations of optimization calculation using HPSO were able to generate a solution with the minimum parameter combination, based on mandrel eccentric angle (*α*) and exit tube bending value (*β*) for the multi-hole seamless tube extrusion molding process. As can be seen in Table 2, the hole location (*e*) was 0.4, billet temperature (*T*) was 658 °C, extrusion speed (*V*) was 0.57, the friction coefficient (*F*) was 0.16, the minimum angle (α) was equal to 0.0421°, and the minimum angle (*β*) equaled 0.0402°.

4 Discussions

The results from the modeling demonstrate that during the extrusion process, the ability of HPSO to find an optimal solution for the extrusion parameter is better than that of GA, especially in terms of accuracy. HPSO is indeed fit to use as a solution generator algorithm for addressing problems arising from the extrusion process. HPSO can be effectively utilized to improve the exit tube bending and mandrel eccentric angles during the extrusion molding process.

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