

Research Article

Application of ANOVA and Taguchi-based Mutation Particle Swarm Algorithm for Parameters Design of Multi-hole Extrusion Process

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Abstract: This study presents the Taguchi method and the Particle Swarm Optimization (PSO) technique which uses mutation (MPSO) and dynamic inertia weight to determine the best ranges of process parameters (extrusion velocity, eccentricity ratio, billet temperature and friction coefficient at the die interface) for a multi-hole extrusion process. A $L_{18}(2^1 \times 3^7)$ array, signal-to-noise (S/N) ratios and analysis of variance (ANOVA) at 99% confidence level were used to indicate the optimum levels and the effect of the process parameters with consideration of mandrel eccentricity angle and exit tube bending angle. As per the Taguchi-based MPSO algorithm using DEFORMTM 3D Finite Element Analysis (FEA) software, the minimum mandrel eccentricity and exit tube bending angles were respectively calculated to be 0.03° , which are significantly less than those based on Genetic Algorithm (GA) and the Taguchi method, respectively. This indicates that the Taguchi-based MPSO algorithm can effectively and remarkably reduce the warp angles of Ti-6Al-4V extruded products and the billet temperature is the most influencing parameter. The results of this study can be extended to multi-hole extrusion beyond four holes and employed as a predictive tool to forecast the optimal parameters of the multi-hole extrusion process.

Keywords: F-value, multi-hole extrusion, signal-to-noise, Taguchi-based MPSO

INTRODUCTION

Because of increasing quality requirements and productivity, many manufacturers are adopting multi-hole extrusion to avoid a high extrusion ratio, to decrease the die deformation and to reduce costs (Guan *et al.*, 2012). In multi-hole extrusion process, the billet is pushed through a shaped die with more than one hole. The mandrel in complex multi-hole die processes produces asymmetric friction in a squeezed billet, causing an asymmetric out-flow velocity difference inducing mandrel bending (Müller, 2006). This can cause the mandrel eccentricity and exit tube bending angles of the overall extrusion process. Thus, several parameter conditions in the extrusion process must be chosen and controlled properly. Numerous research studies were done to analyze the deformation behavior and design parameters of a single-hole or multi-hole extrusion process. Ulysse and Johnson (1998) used analytical and semi-analytical upper-bound solutions to obtain the extrusion pressure, exit angles and velocities of the emerging products in a single extrusion die and multi-hole extrusion die. They calculated the angles of dead zone to determine the hole position. Peng and Sheppard (2004) used Finite Element Analysis (FEA) to create an analytical model for multi-hole extrusion process. They studied the amount and distribution of

holes on the die and their effects on material flow extrusion load and eccentric angle of the mandrel. Lee *et al.* (2005) developed the models of mandrel deflection during the extrusion process. They investigated the mandrel deformation and fracture behavior in condenser tube extrusion by using FEA. Chen *et al.* (2008) analyzed the effects of various parameters on a two-hole extrusion process. They analyzed the bending angle of extruded tubes at the exit of the extrusion dies with various extrusion velocities and various initial extrusion temperatures using FEA.

Hsiang and Lin (2007) analyzed the influence of various process parameters on the hot extrusion of magnesium alloy tubes using the Taguchi method and analysis of variance (ANOVA) to obtain the excellent quality characteristic of extruded parts. They concluded that the billet heating temperature, initial extrusion velocity and container temperature affect the mechanical properties of extruded products. The Taguchi method can reduce or avoid expensive trial-and-error experiments and obtain the main effects of design parameters to ensure optimal quality (Movahedi *et al.*, 2011). It is a fractional factorial design and has the good reappearance of experiment evaluating the effects of various process parameters and their interactions on the required characteristics (Ko *et al.*, 1998) ANOVA was performed to determine the

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significant process parameters and estimate their contributions. This study uses the Taguchi method and ANOVA to obtain the degree of significance for each process parameter and a design with preferable quality within the preset range of parameters. Signal-to-noise (S/N) ratio was utilized to determine the optimal set of process parameters.

A canonical PSO algorithm with mutation mechanism (MPSO) was adopted to find the best combination of process parameter values. Each particle in PSO is assigned with a randomized velocity according to its own and the search-optimization process of its companions. During the past several years, PSO has been used for parameter design of the several manufacturing processes (Abeykoon *et al.*, 2011; Rao *et al.*, 2008; Zain *et al.*, 2010; Malviya and Pratihari, 2011); however, its application to extrusion process design was not common. In this study, we investigate the minimal mandrel eccentricity and exit tube bending angles of a Ti-6Al-4V billet in the multi-hole extrusion process optimization. The proposed approach generates the global optimal solutions for the important process parameter values based on the searching experiences of the solutions during the evolutionary process to further improve the solution qualities.

TAGUCHI METHOD

The Taguchi method provides a comprehensive understanding of the individual and combined effects of various design parameters based on a minimum number of experimental trials (Al-Arifi *et al.*, 2011; Wang *et al.*, 2011). The design parameters used in Taguchi's approach are divided into different levels according to the response of each parameter to the quality characteristics. The responses of the process parameters are further transformed into a signal-to-noise (S/N) ratio. The standard S/N ratios generally used are as follows: the Smaller-The Better (STB), the Nominal-The Better (NTB), or the Higher-The Better (HTB). This study employs the S/N ratio of the STB quality characteristic to minimize the mandrel eccentricity angle and exit tube bending angle of Ti-6Al-4V titanium alloy billet in the multi-hole extrusion process. The S/N ratio describing the STB characteristics is as follows (Lin and Chou, 2010):

$$S / N = -10 \log \left(\frac{1}{n} \sum_{i=1}^n y_i^2 \right) \quad (1)$$

where, n is the number of iterations under the same design parameters, y_i indicates the measured results and

i indicates the number of design parameters in the Taguchi OA. The S/N ratio response diagram of various parameter levels shows a design with preferable quality within the preset range of parameters. In addition to the S/N ratio, ANOVA is employed to obtain the effect of the process parameters. The ANOVA method used in the Taguchi method is a statistical technique primarily adopted to evaluate the significance levels of control process parameters and the response of each parameter.

OPTIMIZATION FORMULATION

This study formulates the process parameter design problem as a constrained optimization problem. The design parameters represent the design variables of the objective functions in this optimization problem. In this section, we consider two objective functions based on the mandrel eccentricity angle α and exit tube bending angle β , as illustrated in Fig. 1.

$$\min (|\alpha(X)|, |\beta(X)|) \quad (2)$$

Note that the angles α and β have an absolute value which is strictly greater than or equal to 0° . In Eq. (2), X is a vector of n design variables: $X = (x_1, x_2, \dots, x_n)^T$. We used the weighting method to simplify the objective functions. The fitness function $F(X)$ formed by summing the weighted normalized objectives with a weight vector $(\omega_1, \omega_2)^T$ is as follows:

$$\begin{aligned} \text{Min } F(X) &= \omega_1 \times |\alpha(X)| + \omega_2 \times |\beta(X)| \\ \text{subject to } X^L &\leq X \leq X^U \end{aligned} \quad (3)$$

The constraint condition restricts each design variable to take a value within a lower X^L and an upper X^U bound. ω_1 and ω_2 ($\in [0, 1]$) are the weighting values of $\alpha(X)$ and $\beta(X)$, respectively. Since Eq. (3), also called fitness function, does not change if all weights are multiplied by a constant, it is the usual practice to choose weights such that their sum is one, that is, $\omega_1 + \omega_2 = 1$. $\alpha(X)$ and $\beta(X)$ are affected mutually and equally crucial on deformation behavior of forming materials in the extrusion process. Therefore, ω_1 and ω_2 were set to 0.5 in Eq. (3):

$$e = b/(a+b); 0 \leq e < 1 \quad (4)$$

Equation (4) is defined as eccentricity ratio e , which represents the hole position; a is the distance between the hole and container, b is the distance

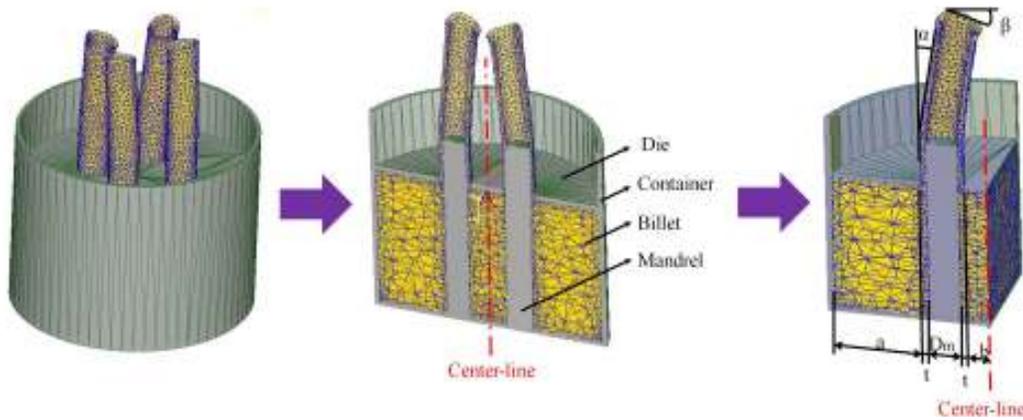


Fig. 1: FE modeling in multi-hole extrusion model. (mandrel eccentric angle α and exit tube bending angle β)

between the hole and the center-line of billet and D_m is the mandrel diameter.

PARTICLE SWARM OPTIMIZATION WITH MUTATION (MPSO)

PSO algorithm: Kennedy and Eberhart (1995) proposed the Particle Swarm Optimization (PSO) method in 1995. The concept of PSO was inspired by the social behavior of fish schooling or bird flocking (Qasem and Shamsuddin, 2010). Each particle in the PSO search space represents a potential solution to the optimization problem and is defined as a group of variables. It is associated with two vectors, which are the position and velocity vectors. In n -dimensional search space, the two vectors associated with each particle i are $X_i = (x_{i,1}, x_{i,2}, \dots, x_{i,n})$ and $V_i = (v_{i,1}, v_{i,2}, \dots, v_{i,n})$, respectively. Each particle updates its solution based on its own best exploration and the best swarm overall experience to find its fitness value using iterative updating. During this iteration process, the updated position and velocity of each particle are calculated as shown in Eq. (5-7). The global best position and velocity term are updated after each iteration.

$$V_i(k+1) = \psi(k) \times V_i(k) + c_1 \times r_1 \times (pbest_i(k) - X_i(k)) + c_2 \times r_2 \times (gbest(k) - X_i(k)) \quad (5)$$

$$X_i(k+1) = X_i(k) + V_i(k+1) \quad (6)$$

$$\psi(k+1) = \psi(k) \times 0.99 \quad (7)$$

where, k is the current iteration number, $0 \leq \psi < 1$ is a dynamic inertia weight which determines how much the previous velocity is preserved, 0.99 is a decay factor in the inertia weight per iteration, r_1 and r_2 are uniformly distributed random values in $[0, 1]$ and the learning factors c_1 and c_2 represent the weights of the stochastic

acceleration terms that lead each particle toward the local best and global best solutions. $X_i(k)$ and $V_i(k)$ are the position and the velocity of particle i at the k th iteration, respectively. The position of each particle is updated by using the velocity $V_i(k+1)$. $pbest_i(k)$ is the best position encountered by particle i during its research; $gbest(k)$ is the best particle position based on the swarm group.

Description of MPSO algorithm: As mentioned above, the searching process and area of the canonical PSO algorithm greatly depend on $pbest$ and $gbest$. The effect of $pbest$ and $gbest$ in PSO gradually decreases as the number of iterations increases. Therefore, we combine the canonical PSO method with the GA mutation called "MPSO" to obtain a broader searching area for improving the global search capability of solutions. The MPSO algorithm uses a real-coded mutation operator to increase the diversity of solutions. The mutation operation only occurs if a randomly generated number within $[0, 1]$ is less than or equal to the given mutation probability. When a mutation is operated, the number of design variables is multiplied by a random value within $[0, 1]$ to determine which variable in each particle should be mutated in the variable space. The real-parameter mutation operators used in MPSO are as follows:

$$X_{i,t}(k+1) = X_{i,t}^L(k+1) + r_4 \times [X_{i,t}^U(k+1) - X_{i,t}^L(k+1)] \quad (8)$$

where, $t = \text{ceil}(r_3 \times n)$, $n \in \mathbb{Z}$.

In Eq. (8), r_3 and r_4 are random numbers in $[0, 1]$. The ceiling function $\text{ceil}(r_3 \times n)$ is defined as the function that outputs the smallest integer greater than or equal to $(r_3 \times n)$. t is the variable sequence position of getting mutation in variable space X . If some particle of each iteration mutated, it would be randomly selected one of the design variables as mutation between its upper and low limits. Equation (8) shows the updated

design variables after mutation of each updated particle from Eq. (7). The MPSO algorithm was designed to repeatedly update the variables specified in Eq. (5)-(8) until reaching termination conditions.

IMPLEMENTATION PROCEDURES

This study uses the Taguchi-based MPSO algorithm with FEA to analyze the various parameter conditions on the mandrel eccentricity angle and exit tube bending angle in the multi-hole extrusion process. The iterative computation of the MPSO algorithm was first computed using MATLAB and subsequently implement the FEA modeling for each iteration. Figure 2 presents the architecture of the Taguchi-based MPSO algorithm to optimize the process parameters during the extrusion process. The steps are described as follows:

- Step 1:** Select the quality characteristic. This study implements a smaller-the-better quality characteristic.
- Step 2:** Select the effect factors on the mandrel eccentricity angle and exit tube bending angle, such as billet thickness, extrusion velocity, four-hole eccentricity ratio, billet temperature, friction coefficient, hole diameter, tube thickness and the hole's draft angle. These factors can potentially affect the warping angles of the extruded parts in multi-hole extrusion.
- Step 3:** Select an orthogonal array $L_{18} (2^1 \times 3^7)$. The layout of $L_{18} (2^1 \times 3^7)$ was randomly determined by the DEFORMTM finite element software.
- Step 4:** Calculate the S/N ratio of each experimental run based on the results of the mandrel

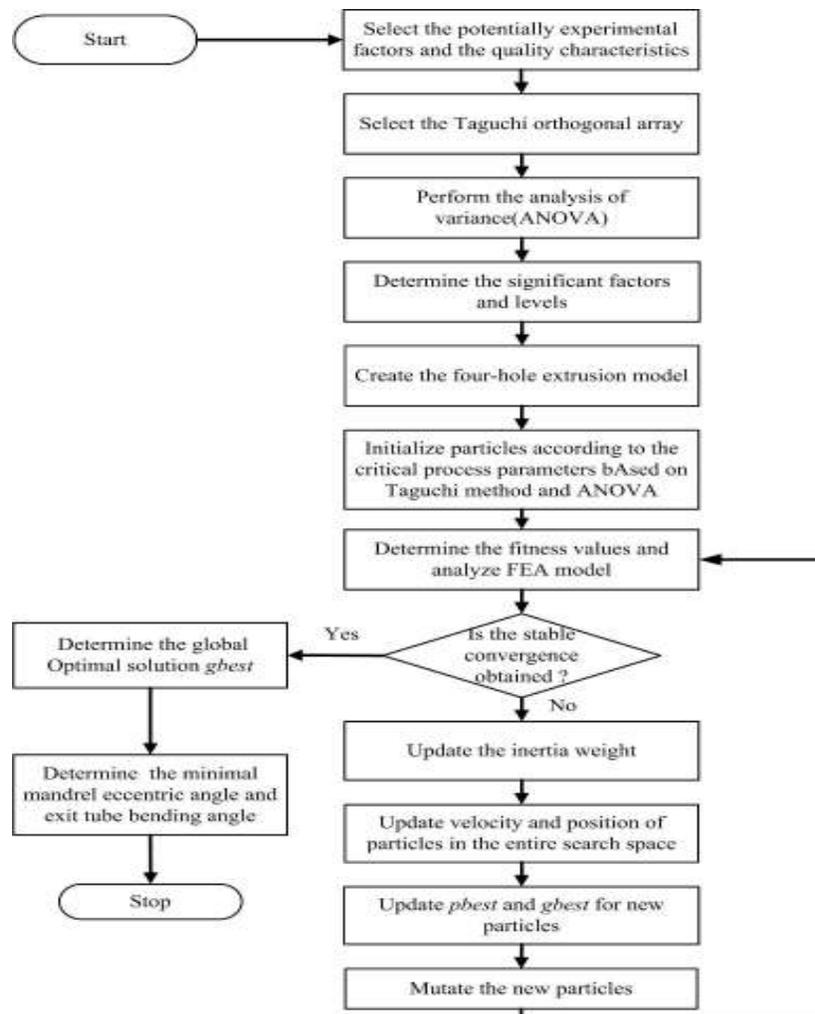


Fig. 2: Flow chart of the Taguchi experimental planning, ANOVA and Taguchi-based MPSO algorithm

eccentricity angle and exit tube bending angle calculated using the S/N formulation.

- Step 5:** Determine the most important process parameters V , e , T and μ influencing the mandrel eccentricity angle and exit tube bending angle.
- Step 6:** Initialize particles that represent the initial random combination of the significant process parameter conditions. Specify the ranges of parameter conditions between the upper and low limits according to the results of the Taguchi method and ANOVA.
- Step 7:** Compute the update position and velocity of the particles in each iteration using MATLAB and the Eq. (5)-(7).
- Step 8:** Implement the real-code mutation operator used in Eq. (8) to avoid early convergence and find the global optimal solutions in Taguchi-based MPSO algorithm.
- Step 9:** Create and analyze the FEA models to determine the mandrel eccentricity angle and exit tube bending angle for each iteration.
- Step 10:** Compute the values of the fitness function in Eq. (3).
- Step 11:** Determine whether the mandrel eccentricity angle and exit tube bending angle are at the minimal value by accessing the fitness value. If yes, then stop iterating and proceed to the next step. If no, return to Step 7.
- Step 12:** Determine the optimal process parameter values of the minimal mandrel eccentricity angle and exit tube bending angle.
- Step 13:** Stop computing and iterating.

SIMULATION RESULTS AND DISCUSSION

S/N ratio from Taguchi method: Table 1 shows that eight potential factors were studied in this research and

Table 1: Factor and levels selection of OA $L_{18}(2^1 \times 3^7)$

Factor	Level 1	Level 2	Level 3
A Billet thickness (BT)	50	70	
B Extrusion velocity (V)	0.1	0.3	0.5
C Four-hole eccentricity ratio (e)	0.35	0.4	0.45
D Billet temperature (T)	300	450	600
E Friction coefficient(μ)	0.12	0.25	0.3
F Hole diameter (D)	13	14.125	16
G Tube thickness (t)	1.5	2.25	3
H Hole's draft angle (A)	1	2	3

three levels of each factor were considered except Factor A. The setting range values of control factors were equally divided into two (Factor A) and three levels (Factors B-H), respectively. Simulations were carried out as per OA $L_{18}(2^1 \times 3^7)$ using the DEFORMTM software. The sum of the mandrel eccentricity angle α and exit tube bending angle β were converted into the S/N ratios. The S/N ratio (Table 2) of each experimental run consisting of the $|\alpha| + |\beta|$ was calculated according to Eq. (1). Figure 3 shows the S/N ratio response diagram of each factor. The highest S/N ratio for each process parameter gave the optimal process conditions, which correspond to a billet thickness of 50 mm (level 1), a extrusion velocity of 0.3 mm/s. (level 2), a four-hole eccentricity ratio of 0.45 (level 3), a billet temperature of 600°C (level 3), a friction coefficient of 0.25 (level 2), a hole diameter of 16 mm (Level 3), a tube thickness of 2.25 mm (level 2) and a hole's draft angle of 2° (level 2).

ANOVA results: The aim of the ANOVA method is to evaluate the significant ratios percentage of the process parameters affecting the mandrel eccentricity angle and exit tube bending angle. Table 3 shows the raw results of ANOVA data. The data indicate that the F-values of Factor B, Factor C, Factor D and Factor E were all greater than $F_{0.01, 2, 20}$, which were 5.53 at the 99%

Table 2: $L_{18}(2^1 \times 3^7)$ orthogonal array and their S/N ratio results

Exp	A	B	C	D	E	F	G	H	$ \alpha $	$ \beta $	$ \alpha + \beta $	S/N(dB)
1	1	1	1	1	1	1	1	1	0.21	9.11	9.32	-36.645
2	1	1	2	2	2	2	2	2	0.51	9.60	10.11	-35.417
3	1	1	3	3	3	3	3	3	0.05	1.91	1.96	-39.432
4	1	2	1	1	2	2	3	3	0.30	7.81	8.11	-36.839
5	1	2	2	2	3	3	1	1	0.41	8.98	9.39	-36.022
6	1	2	3	3	1	1	2	2	0.04	1.67	1.71	-39.473
7	1	3	1	2	1	3	2	3	0.27	13.59	13.86	-34.555
8	1	3	2	3	2	1	3	1	0.19	10.54	10.73	-36.160
9	1	3	3	1	3	2	1	2	0.36	0.29	0.65	-39.095
10	2	1	1	3	3	2	2	1	0.04	16.04	16.08	-34.414
11	2	1	2	1	1	3	3	2	0.43	11.04	11.47	-35.087
12	2	1	3	2	2	1	1	3	1.88	13.64	15.52	-22.316
13	2	2	1	2	3	1	3	2	0.14	8.17	8.31	-37.211
14	2	2	2	3	1	2	1	3	0.33	3.81	4.14	-38.115
15	2	2	3	1	2	3	2	1	0.40	5.48	5.88	-37.364
16	2	3	1	3	2	3	1	2	0.54	8.05	8.59	-36.028
17	2	3	2	1	3	1	2	3	0.94	5.73	6.67	-35.511
18	2	3	3	2	1	2	3	1	0.51	9.60	10.11	-35.418
Average												-35.834

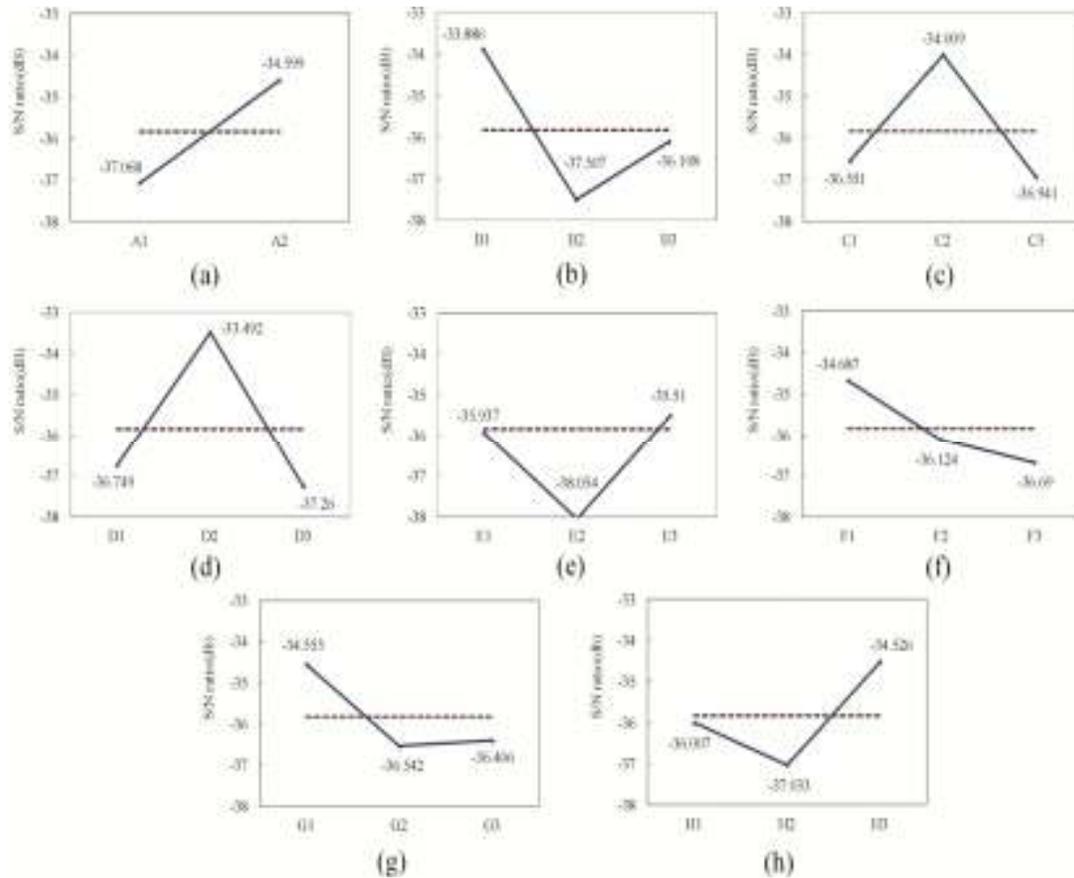


Fig. 3: Main effects plot for S-N ratios of $\alpha + \beta$ in Taguchi-based MPSO(The dotted lines represent the average vluesof S-N ratio)

Table 3: ANOVA table for responded raw data

Factor	DOF	SS	Variance	F-value	Confidence level	Contribution
A	1	110.604	110.604	1.280	<75%	0.99%
B	2	1429.393	714.696	8.504	>99.9%	12.90%
C	2	2057.293	1028.646	11.910	>99.9%	18.57%
D	2	2984.549	1492.274	17.279	>99.9%	26.94%
E	2	1447.873	723.936	8.382	>99.9%	13.06%
F	2	293.207	146.603	1.697	75%	2.64%
G	2	240.001	120.000	1.389	<75%	2.16%
H	2	834.365	417.182	4.830	95%-99%	7.53%
Error	20	1680.820	84.041			

*NOTE: At least 99% confidence

Table 4: Characteristics and parameter ranges of billet and die

Billet	Melting point	1604 -1660°C
	CTE, linear	8.60 $\mu\text{m}/\text{m}\cdot\text{C}$
	Hole diameter	16 mm
		0.30, 0.35, 0.40, 0.45,
	four-hole eccentricity ratio	0.50, 0.55, 0.60, 0.65
	Billet thickness	50 mm
	Billet temperature	150°C~900°C
	Friction coefficient	0.10~0.50
	Billet grid	40000
	Container diameter	100 mm
	Mandrel	50 mm
Die	Extrusion velocity	0.10~1.20 mm/s

confidence level. The larger the F -value and the contribution, the greater the effect on the performance characteristic due to the change of the process parameter. Therefore, the data in Table 3 show that the most significant effect was billet temperature D which F -value and contribution were 17.279 and 26.94%, respectively. The extrusion velocity B, four-hole eccentricity ratio C and friction coefficient E were more significant parameters of the minimal mandrel eccentricity and exit tube bending angles. Factor A, Factor F, Factor G and Factor H were not significant

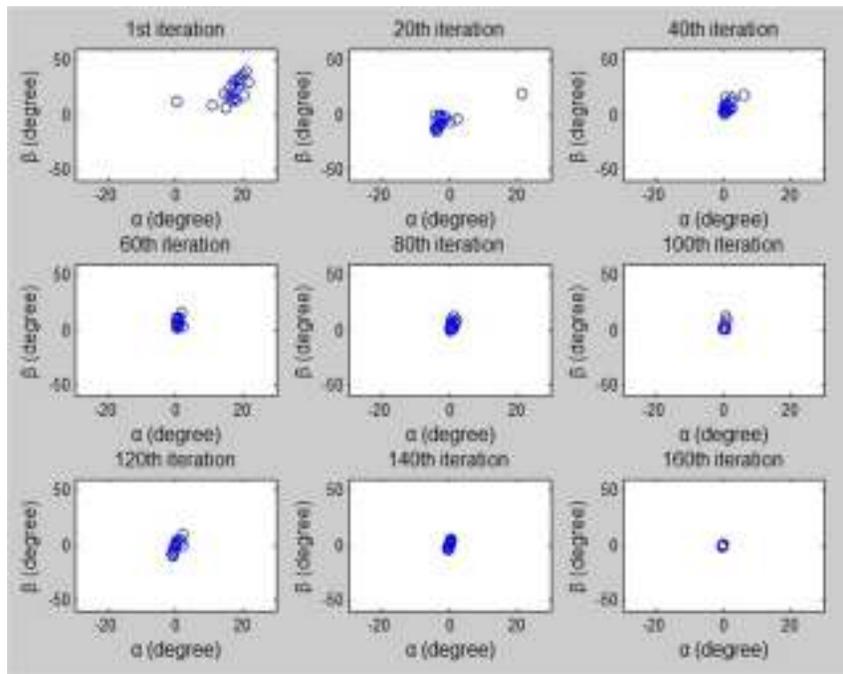


Fig. 4: Particle swarm evolution with dynamic inertia weigh in Taguchi-based MPSO through 160 iterations considering the entire search space (α in x-axis and β in y-axis)

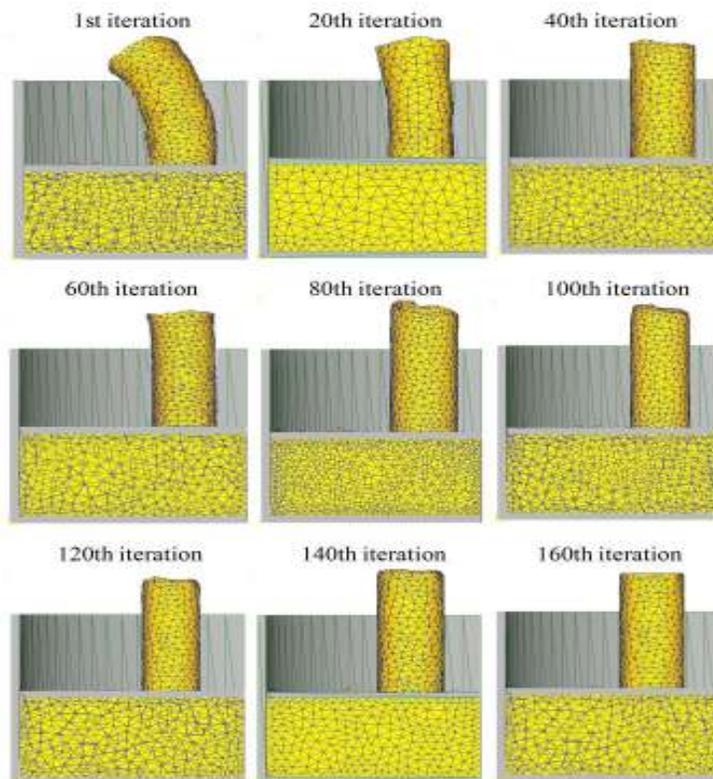


Fig. 5: FEM results through 160 iterations for Taguchi-based MPSO

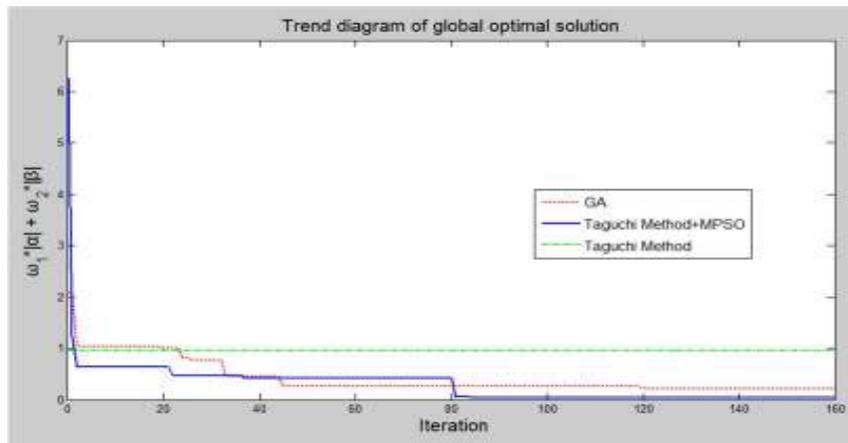


Fig. 6: Comparison of the optimal solutions by using Taguchi method, GA and Taguchi-based MPSO

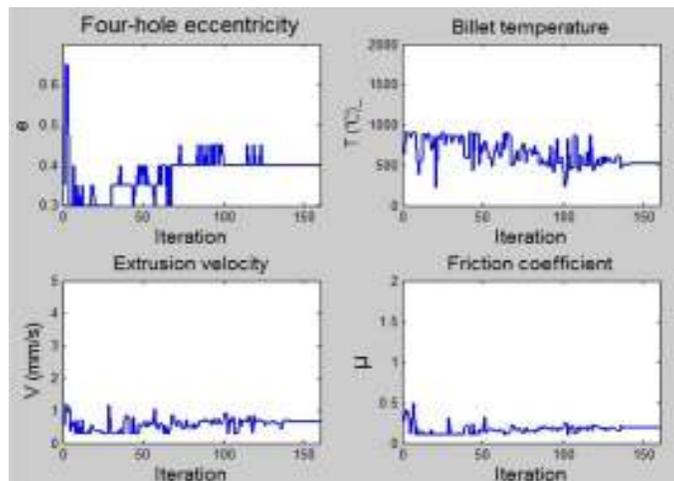


Fig. 7: The optimal values of the critical process parameters through 160 iterations

parameters for the minimal mandrel eccentricity angle and exit tube bending angle. Their F -values were less than $F_{0.01, 2, 20} = 5.53$. The F -value of Factor H was between 95% and 99%. It was greater than $F_{0.05, 2, 20} = 3.49$ but less than $F_{0.01, 2, 20} = 5.53$. Therefore, billet thickness A, hole diameter F, tube thickness G and hole's draft angle H were not significant parameters of the minimal mandrel eccentricity and exit tube bending angles at the 99% confidence level. In other words, billet thickness, hole diameter, tube thickness and hole's draft angle were excluded from the design variables of multi-hole extrusion.

Optimization parameter values using MPSO algorithm: Based on Eq. (5)-(8), we set $c_1 = c_2 = 2$ and the initial weight $\psi = 0.9$. Since n is conducted in the space of 4 critical design variables, t is an integral value within the range [1, 4] in Eq. (8). As shown in Fig. 4, a

swarm with 20 particles based on each particle's position representing a candidate solution and consisting of a combination of four critical process parameters can be used to explore the solution space based on the results of Taguchi method and ANOVA. Table 4 shows the critical parameter ranges of the Ti-6Al-4V titanium alloy material. The MPSO algorithm determined the optimal solution of α and β through 160 iterations. As shown in Fig. 4, the swarm values trended toward consistency as the number of iterations increased. At the 160th iteration, the maximal and the minimal values of α were almost the same and β demonstrated the same results. The calculations of 160 iterations obtained a solution with the optimal parameter combination based on $\min |\alpha|$ and $\min |\beta|$ for the multi-hole tube extrusion process.

Figure 5 illustrates the FE modeling through 160 iterations. It was necessary to update the FEA models in each iteration because α and β values needed to be

Table 5: Comparison of Taguchi method, GA and Taguchi-based MPSO results for process parameters, minimal mandrel eccentric and exit tube bending angles

Methods	Extrusion velocity (mm/s)	Eccentric ratio	Billet temperature (°C)	Friction coefficient	A (degree)	B (degree)
Taguchi method	0.3	0.45	600.00	0.25	0.40	1.67
GA	0.61	0.35	480.03	0.17	0.30	0.13
Taguchi-based MPSO	0.67	0.40	517.65	0.19	0.03	0.03

calculated. Figure 6 shows that the Taguchi-based MPSO algorithm has relatively good convergence performance and greatly improved its global search capability without losing its fast convergence property.

Figure 7 shows the convergent values of the critical process parameters for min $|\alpha|$ and min $|\beta|$ after 160 iterations. Table 5 shows the comparison of the Taguchi method, GA and Taguchi-based MPSO. From the comparison between Taguchi method and Taguchi-based MPSO algorithm at the 160th generation, the minimal mandrel eccentricity α was reduced from 0.40° to 0.03° and the exit tube bending angle β was reduced from 1.67° to 0.03° . These results show that the Taguchi-based MPSO algorithm can efficiently achieve the optimal process parameters design to greatly decrease the mandrel eccentricity and exit tube bending angles of the multi-hole extruded parts.

CONCLUSION

This study proposes a Taguchi-based MPSO algorithm to search for the appropriate values of the critical process parameters of the multi-hole extrusion process. The Taguchi method and ANOVA are utilized to investigate the optimal set of process parameters for the minimal mandrel eccentricity and exit tube bending angles. In doing so, the $L_{18}(2^1 \times 3^7)$ OA used in the Taguchi method utilized S/N ratios to determine the levels of critical process parameters and ANOVA gave the significance degree of the each process parameter. As shown in Table 3, the billet temperature was statistically significant and the hole position had the second degree of importance.

The MPSO algorithm mainly allowed the search to avoid premature convergence to reduce the risk of falling into a local optimal solution and to search for a global optimal solution. Taguchi-based MPSO performed better than the Taguchi method or the GA. The minimal mandrel eccentricity and exit tube bending angles were greatly reduced in the results of the Taguchi-based MPSO algorithm, showing that it can be successfully used to find the optimal parameter design in the multi-hole extrusion process. The results demonstrate that the proposed methods can act as a predictive tool of the process conditions arising from the multi-hole extrusion process and will be extended to other process conditions for the various manufacturing methods.

ACKNOWLEDGMENT

The authors are grateful to the National Science Council of Taiwan for sponsoring this research study.

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