Optimal Process Parameters in ECMAP of Al−3% Mg Alloy Strips

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Abstract: Equal channel angular pressing (ECAP) is one of the most appealing severe plastic deformation (SPD) methods. The proposed equal channel multi angular pressing (ECMAP) process enhances the efficiency of traditional ECAP technique with decreasing the process time. In this study, a complete investigation was done by the design of experiment (DOE) by compound Taguchi-Grey technique. FEM was applied by ABAQUS software in order to achieve responses of proposed Taguchi tests. Die geometrical parameters together with an important process parameter were selected as input factors and strain characteristics and also, required process load were selected as responses. The relationships between responses and input factors were obtained by regression analysis. Then, an analysis of variance (ANOVA) was used to determine the influence of each input factor on responses. ANOVA analysis revealed that FC with contribution percentage of 87.21% has the most influential factor on RPL. Furthermore, it was inferred that among input factors, φ_1 with contribution percentage of 94.57% has the most effect on the PEEQ. Finally, a multi objective optimization study was done by grey relational analysis. It was concluded that among all input factors, die channel angle, friction coefficient (FC), and die corner angle with contribution percentages of 42.30%, 26.08% and 14.84% are the first, second and third most influential factors on objectives, respectively.

Keywords: ANOVA, Equal Channel Multi Angular Pressing, Optimization, Taguchi-Grey

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Biographical notes: Peyman Mashhadi Keshtiban received his PhD in Mechanical Engineering (Manufacturing Engineering) from University of Tabriz in 2016. He is currently Assistant Professor at the Faculty of Mechanical Engineering, Urmia University of Technology, Urmia, Iran. His current research interest includes the optimization of different manufacturing techniques especially metal forming methods. He did some studies on various SPD methods and focuses on Equal channel angular pressing (ECAP) as the most popular technique among SPD methods. In order to enhance the efficiency and related speed of the subjected method, he introduced a novel method namely Equal Chanel Multi Angular pressing process (ECMAP). Three severe plastic deformations happen by just one pass of the designed die.

1 INTRODUCTION

Hall-petch equation indicates the fact that the strength of polycrystalline metals depends on the grain size. "Eq. (1)" demonstrates that decreasing the average diameter of material grain leads to enhancing strength.

$$\sigma_y = \sigma_0 + K_y d^{-1/2} \tag{1}$$

In this equation, d is the grain diameter of average size, σ_y is the yield stress, σ_0 is the reference yield stress and K_y is the yield constant [1]. In order to transform the coarse-grained material to ultra-fine grained material, it is necessary to produce higher dislocation density that was obtained from applying too much strain. This process is done by SPD techniques that exert intense deformation to material without changing the initial geometry. ECAP is one of the most appealing SPD methods and the proposed ECMAP process enhances the efficiency of traditional ECAP technique with decreasing the process time. In order to raise the process efficiency, it is necessary to optimize the effective process parameters.

Previous studies reveal that four different types of optimization were done to optimize the ECAP process. The first types of optimization works were done completely with FEM simulations. The series of numerical simulations were carried out by altering effective parameters and comparisons were performed between the results of different FEM analysis [2-5]. Aour et al. [2] considered the effects of input parameters on the strain homogeneity of thermoplastic polymer in the ECAP process. Back pressure, die geometrical parameters, process temperature, ram speed and process repetitions numbers were selected as the input parameters of FE simulations. The second types of optimization studies were done by experimental works. Several experimental works were done with various amounts of input parameters and the results for key parameters were extracted [6-9]. Purcek et al [6] experimentally studied the various existed routes in the ECAP process and investigated the effects of routes and aging on the electrical conductivity, ductility and strength of produced samples. The third types of ECAP optimization articles are the combination of both previous types e.g. FEM and experimental works [10-12]. Sordi et al [10] investigated die geometrical parameters effects on the process load, die corner gap and strain homogeneity of produced final samples by both FEM and experiments. It was inferred that die outer corner radius and die channel angle have an inverse effect on process load and the amount of corner gap depends on the deformation homogeneity. The fourth and last types of ECAP optimization works are the application of optimization methods besides numerical simulations or practical works [13-15]. The optimization methods seldom were applied to ECAP works. Fereshteh-Saniee et al [13] used the neural network, FE and genetic algorithm to optimize the ECAP process. The magnitude and the amount of PEEQ were selected as objectives and die geometrical parameters were considered as input variables. It was inferred that, by adjusting some geometrical parameters, the dead metal region and buckling probability can be controlled. Wang et al [14] used grey theory as an optimization technique in the ECAP process. Die geometrical parameters were selected as input variables and strain homogeneity, maximum damage value and deformation uniformity were considered as output variables. It was observed that the damage is small and the material refining can be done by optimized values of geometrical parameters. Also, Keshtiban et al [15] used grey relational analysis to optimize the ECMAP process of pure Al. Die structure was considered as input variables and strain inhomogeneity and process load were selected as objectives. It was observed that the die channel angle is the most effective parameter between die geometrical parameters.

Regression analysis with the aim of extracting the relationship between input and output variables, analysis of variance to obtain the contribution percentage of input parameters on output parameters along with grey relational analysis for process optimization in the ECMAP process of strip-type parts has not been done by researchers before. Thus, in this study, a complete investigation was done by DOE with compound Taguchi-grey technique. FEM was applied by ABAQUS software in order to achieve responses of proposed Taguchi tests. Die geometrical parameters together with an important process parameter were selected as input factors and strain inhomogeneity index (SII), equivalent plastic strain (PEEQ) and required process load (RPL) were selected as responses. The relationships between responses and input factors were obtained by regression analysis. Then, an analysis of variance (ANOVA) was used to determine the influence of each input factor on responses. Finally, multi objective optimization was done by grey relational analysis.

2 FINITE ELEMENT, EXPERIMENTAL AND OPTIMIZATION PROCEDURES

2.1. Finite Element and Experimental Procedures

The numerical analysis is an attractive technique capable of predicting the mechanical and thermal behavior of processed material. This analysis saves money and time that would be necessary to carry out the extensive experiments. At this present study, in order to simulate the process, ABAQUS was used as the FE software [16]. Die schematic and related geometrical parameters were depicted in "Fig. 1".

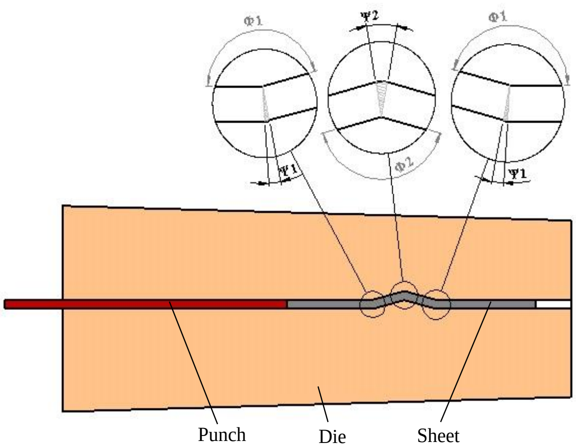


Fig. 1 Schematic of ECMAP.

It is evident that six angles explain all geometrical conditions in route C. Three angles are the die channel angles (Φ_i) and the other three are the die corner angles (ψ_i). The geometry of designed die revealed that three equal channel angular pressing occurs on each element of ECMAPed strips. Also, it should be noted that because of the symmetry in the inlet and outlet channels, three geometrical parameters were considered as the independent input parameters.

All die components were taken as rigid bodies and coulomb friction law was considered between all contacting surfaces. Since the products are in the strip type, the plane strain condition was considered for simulations [17]. Since the strain rate is not significant, the isothermal condition was assumed [18]. From the obtained stress-strain graphs from tension tests, constants of work hardening relationship extracted "Eq. (2)". The subjected equation was set on the strength coefficient (k) of 432.46 GPa, strain hardening exponent (n) of 0.3506 and yield stress (y) of 100 MPa. Both die and punch were considered as rigid bodies and punch velocity was supposed to be 0.5 mm/s.

$$\sigma = k\,\varepsilon^n + y \tag{2}$$

The commercially 5754 aluminum alloy with a chemical composition of (wt%) 0.085 Si, 0.247 Fe, 0.138 Mn, 2.828 Mg, 0.011 Cu and balance Al was cut into rectangular strips of 60 mm× 20 mm× 3 mm in size. All samples were cut by wire-cut machine from 3 mm sheet (thickness). The FE simulation with subjected geometry was calibrated with experimental tests in our previous works [19], [20].

2.2. Taguchi Method

With the aim of higher efficiency and with the aim of lowering production cost, adequate DOE should be selected. Taguchi method is one of the most popular and economical DOE methods that was used in this study.

Process parameters and die geometrical parameters were selected as input variables in three levels ("Table 1") and strain characteristics and RPL were assumed as objectives. From the number of inspected variables and related levels, Taguchi L9 orthogonal array was selected ("Table 2"). Mono-objective optimization was done by Taguchi method to find the conditions that both RPL and SII of products are minimized but the value of generated PEEQ is maximized.

Table 1 Control variables and their levels.

Code	Control Parameters	Level 1	Level 2	Level 3
A	FC	0.05	0.075	0.1
B	Ψ_1	0	10	20
C	Ψ_2	0	10	20
D	Φ_1	150	155	160

Table 2 Taguchi L9 orthogonal array.

Set No.	FC	Ψ_1	Ψ_2	Φ_1
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

3 RESULTS AND DISCUSSION

3.1. Regression Analysis

The relationship between dependent and independent variables were achieved by regression analysis. Two equations usually are used to achieve the subjected relationship ("Eqs. (3-4)"). "Eq. (3)" shows the general form of first degree polynomial between each objective and input variables. "Eq. (4)" can be used when interactions between input parameters have a high effect on objectives.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + e \tag{3}$$

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<}^{k} \sum_{j=2}^{k} \beta_{i,j} x_i x_j + e \tag{4}$$

Where □ is the coefficient of each term, *K* is the number of each independent variable and e is the related error.
The accuracy check of first degree model was done by R^2 ratio with "Eq. (5)".

$$R^2 = 1 - \frac{\text{Sum squared error (SSE)}}{\text{Sum squared total (SST)}} \quad (5)$$

In this study, all die geometrical angles (Ψ_1, Ψ_2, Φ_1) and FC were supposed to be input parameters. RPL, SII and PEEQ were chosen as output parameters. Then, three first degree models were achieved for three outputs ("Eqs. (6-8)").

$$\begin{aligned} RPL &= 9972.26 + 233847\,FC + 172.424\,\Psi_1 - 1414.37\,\Psi_2 - 106.255\,\Phi_1 - 3159.19\\ &FC\times\Psi_1 + 15508.8\,FC\times\Psi_2 + 27.31\,\Psi_1\times\Psi_2 \quad (6)\\ S &= 3212.43 \quad R^2 = 97.38\% \quad R^2(adj) = 79.05\% \end{aligned}$$

$$\begin{aligned} SII &= -1.09852 - 2.52608\,FC - 0.00512536\,\Psi_1 - 0.025631\,\Psi_2 + 0.00902844\,\Phi_1 + 0.0706627\,FC\times\Psi_1\\ &+ 0.27223\,FC\times\Psi_2 + 0.00061223\,\Psi_1\times\Psi_2 \quad (7)\\ S &= 0.0165325 \quad R^2 = 97.84\% \quad R^2(adj) = 82.73\% \end{aligned}$$

$$\begin{aligned} PEEQ &= 9.22821 - 5.20087\,FC - 0.0380555\,\Psi_1 - 0.012077\,\Psi_2 - 0.0500078\,\Phi_1 + 0.534139\,FC\times\Psi_1\\ &+ 0.167859\,FC\times\Psi_2 + 0.000341509\,\Psi_1\times\Psi_2 \quad (8)\\ S &= 0.0133653 \quad R^2 = 99.98\% \quad R^2(adj) = 99.80\% \end{aligned}$$

SSE values for RPL, SII and PEEQ are 10319675, 0.0002733 and 0.000179 respectively. Also, SST values for mentioned parameters are 394072258, 0.0126591 and 0.723940, correspondingly. R^2 values were calculated by "Eq. (5)". "Fig. 2" illustrates the simulated and predicted conditions for "Eqs. (6-8)", respectively. It can be inferred that the subjected equations for RPL, PEEQ and SII are suitable for prediction.

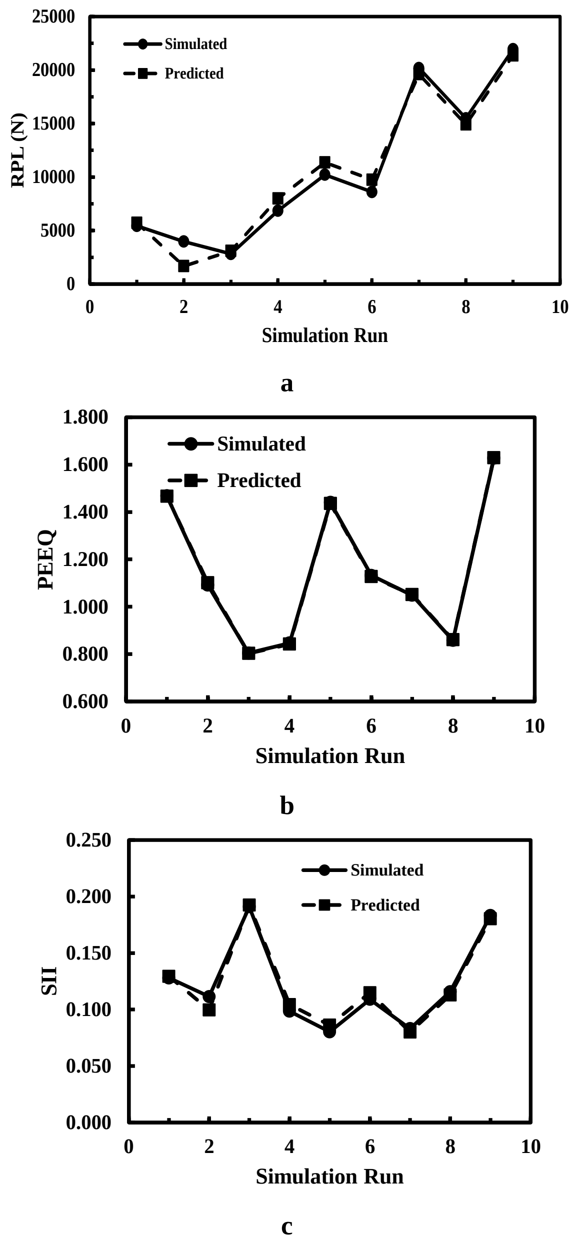


Fig. 2 Comparison of measured-predicted values for: (a): RPL, (b): PEEQ and (c): SII.

3.2. S/N Ratio Analysis

Signal to noise (S/N) ratio was used to determine the effects of uncontrollable factors on optimum parameters. This ratio represents the sensitivity of the investigated parameter to environmental effects that could not be controlled. The higher S/N ratio shows that controllable parameters have more effectiveness. The term "Signal" indicates a desirable effect for each output and the term "Noise" shows unfavorable effects on outputs. The process objectives indicate the optimization of S/N ratios procedure. When the objective for the special variable is "the smaller is better", "Eq. (9)" is used. Also, "Eq. (10)" is used when the aim is "larger is better". In this study "Eq. (9)" was used to obtain the minimum amounts of both RPL and SII. Also, "Eq. (10)" was used to achieve the maximum value of PEEQ.

$$S/N = -10\log_{10}\left[\frac{1}{n}\left(\sum_{i=1}^{n} y_i^2\right)\right] \quad (9)$$

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

Where y_i is the measured response in *i*th simulation and *n* is the repetition number of simulations. "Table 3" lists simulation results and calculated S/N ratios.

Table 3 The simulation and S/N results.

Set No.	RPL (N)		PEEQ		SII	
	Result	*S/N* (dB)	Result	*S/N* (dB)	Result	*S/N* (dB)
1	5440.210	-74.7123	1.468	3.33565	0.128	17.8579
2	3971.015	-71.9780	1.091	0.75856	0.111	19.0566
3	2812.474	-68.9818	0.804	-1.89419	0.191	14.3834
4	6853.245	-76.7179	0.847	-1.44452	0.099	20.1272
5	10220.606	-80.1895	1.440	3.16930	0.080	21.9042
6	8606.246	-78.6963	1.132	1.07539	0.109	19.2493
7	20190.186	-86.1028	1.049	0.41314	0.083	21.6115
8	15493.606	-83.8031	0.858	-1.32943	0.116	18.7275
9	21948.377	-86.8280	1.627	4.22846	0.183	14.7383

Main effects plots for all objectives were illustrated in “Figs. (3-5)”. The highest values of S/N ratios indicate the favorable levels that were shown by red circles. Higher deviation form horizontal lines show more effectiveness of parameters on responses.

It is inferred from “Fig. 3” that the optimum levels for RPL are A1B3C3D3. This means that optimum values of parameters are as follows: FC= 0.05, Ψ_1=20°, Ψ_2=20°, and Φ_1 = 160°. Also, it is concluded that compared with other parameters, FC effects more on RPL than other parameters.

“Fig. 4” depicts that the optimum levels for inhomogeneity index are A2B2C3D2. So, for obtaining optimum condition, FC, Ψ_1, Ψ_2 and Φ_1 should be set on 0.075, 10°, 20° and 155°, respectively. Also, it can be concluded that Ψ_2 has less effect on inhomogeneity. Also, “Fig. 5” reveals S/N ratios for PEEQ. From this figure it is evident that, the best levels for subjected variables are A3B3C2D1, correspondingly. In this case the values of FC, Ψ_1, Ψ_2 and Φ_1 are 1, 20°, 10° and 150°, respectively. Moreover, Φ_1 is the most effective parameter when PEEQ is selected as a response parameter.

Response surface methodology was used to indicate the simultaneous effects of two input factors on each response. 3D surface plots for RPL, SII and PEEQ according to input factors were indicated in “Figs. (6-8)”. “Fig. 6” reveals that higher FC values lead to an increase of RPL [19], [21].

On the contrary, the lower values of φ_1 cause to increase of RPL which was also reported by researchers [22]. It is evident from “Fig. 7” that, when Ψ_1 is more, SII will also be more. “Fig. 8” shows the influence of input factors on PEEQ. It is obvious that increasing $\Phi_1$leads to decreasing PEEQ. Also, it is inferred that FC, $\Psi_1$and Ψ_2 do not have a significant effect on PEEQ. The results are in good agreement with S/N results.

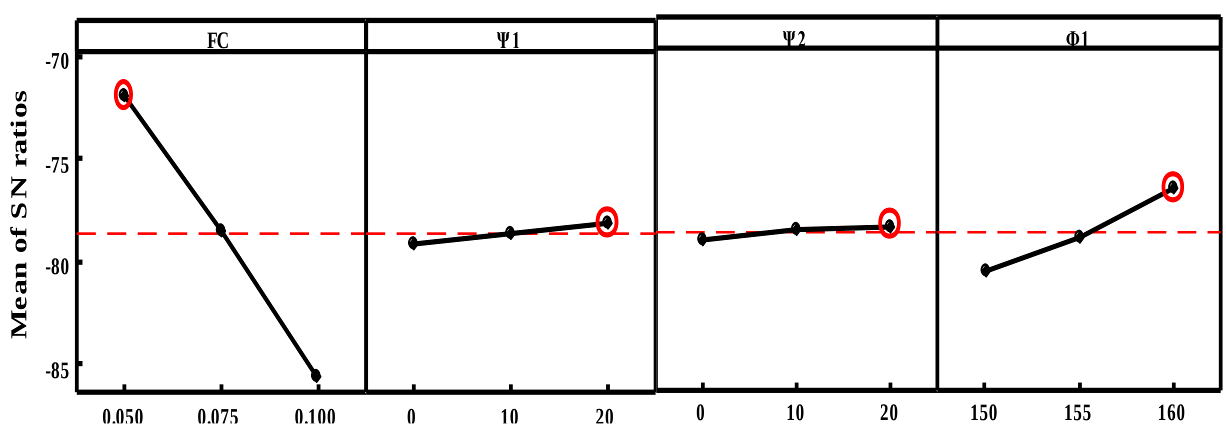


Fig. 3 Main effects plot of *S/N* ratios for RPL (N).

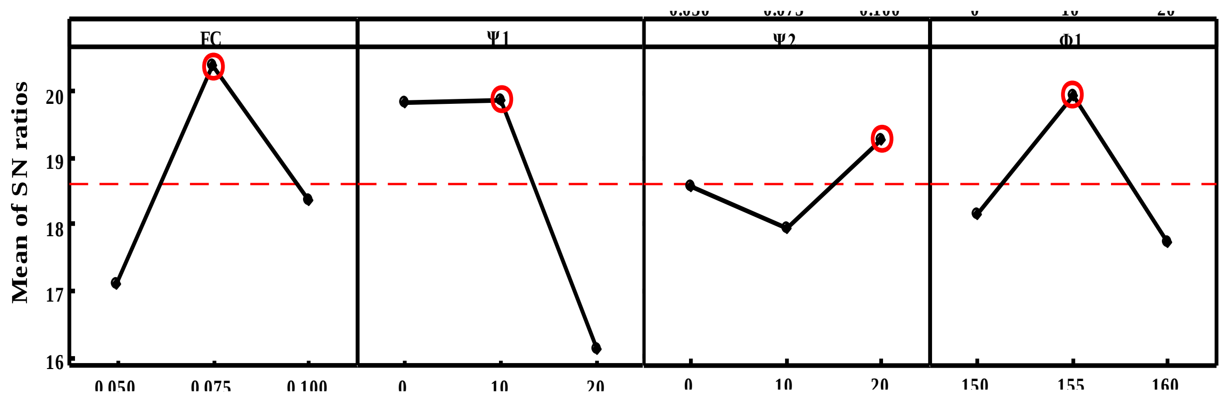


Fig. 4 Main effects plot of *S/N* ratios for SII.

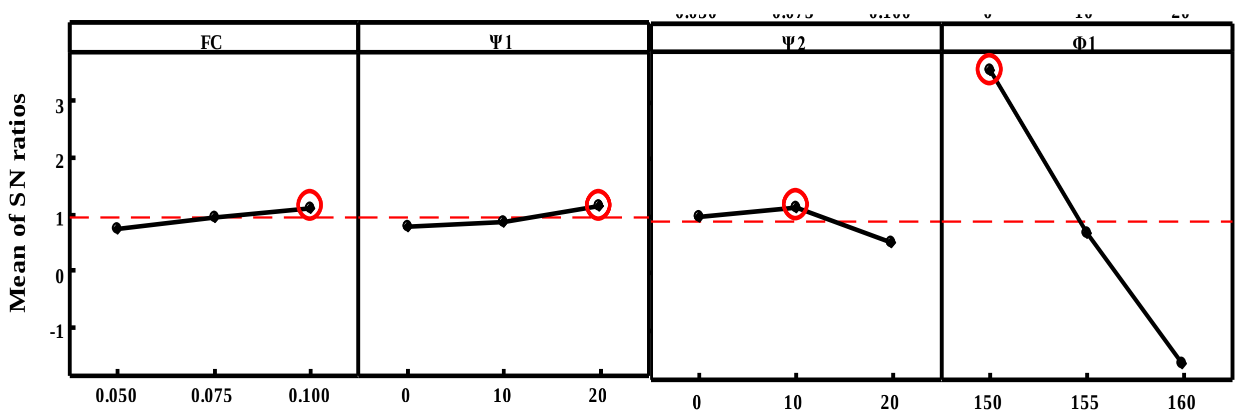
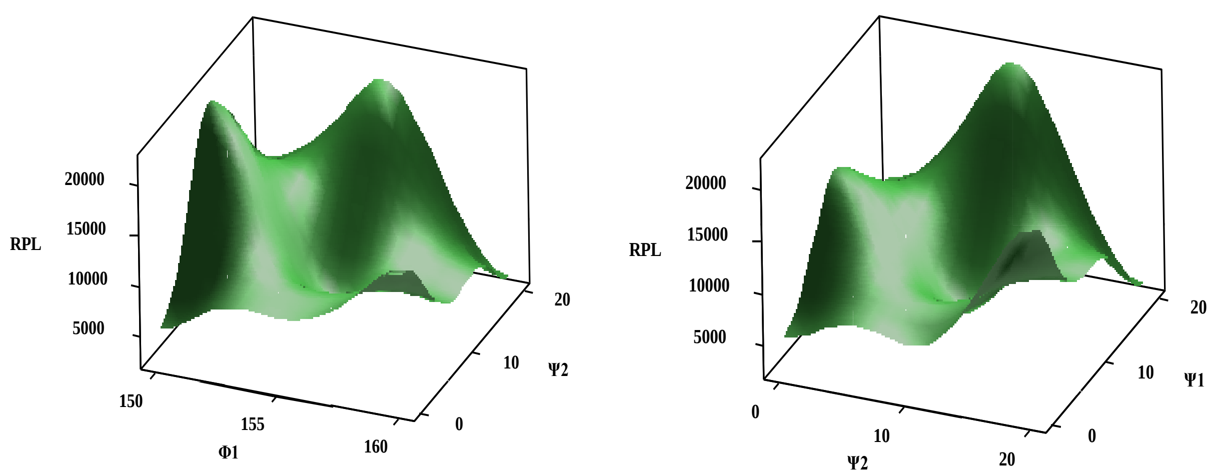


Fig. 5 Main effects plot of *S/N* ratios for PEEQ.

a b



c d

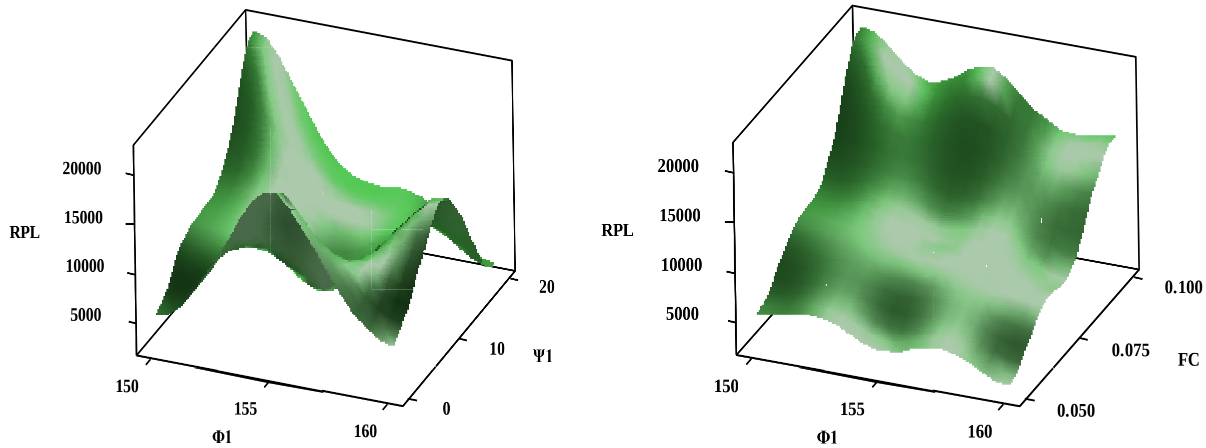


Fig. 6 3D surface plots for the effects of factors on RPL(N).

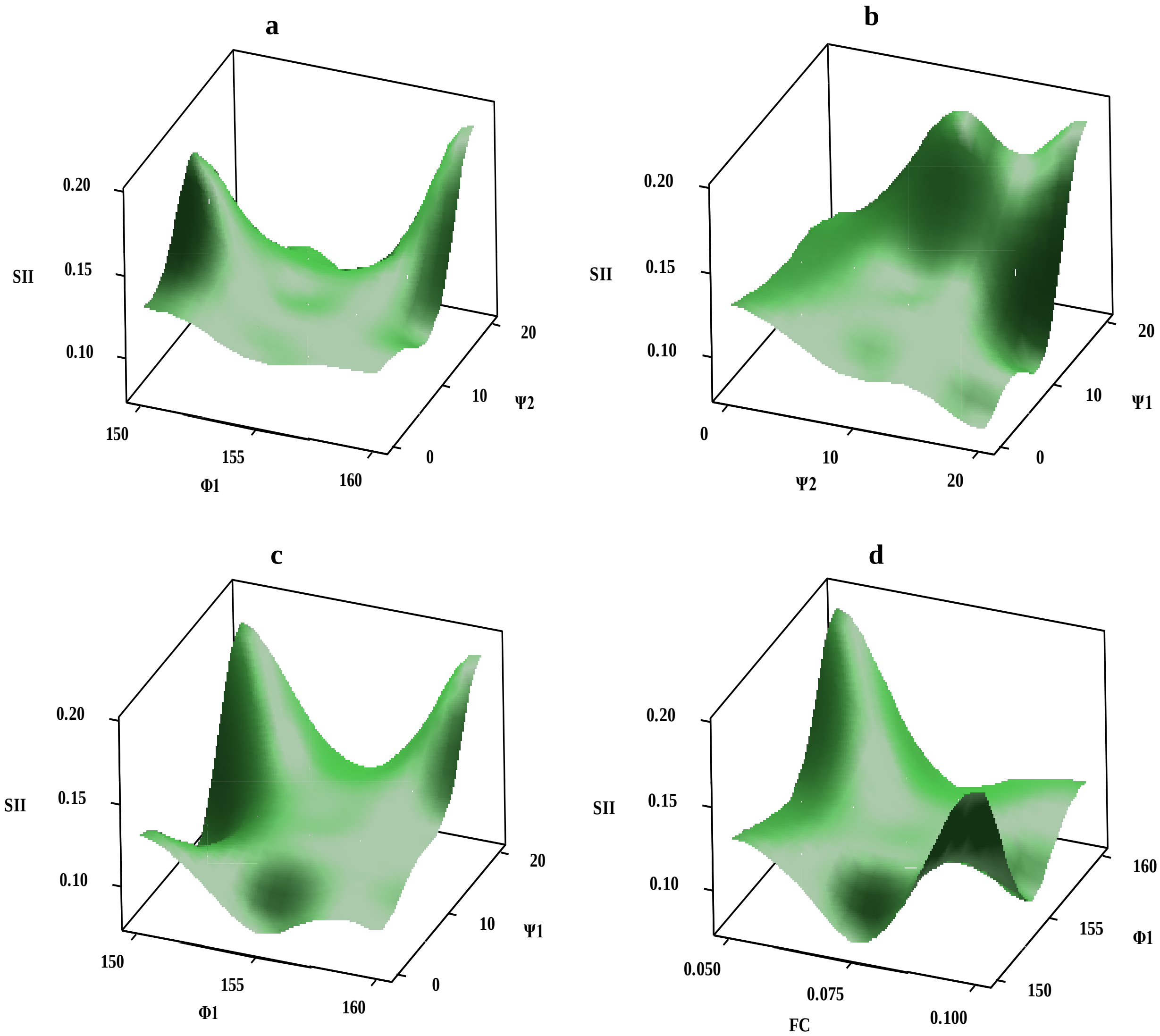


Fig. 7 3D surface plots for the effects of factors on SII.

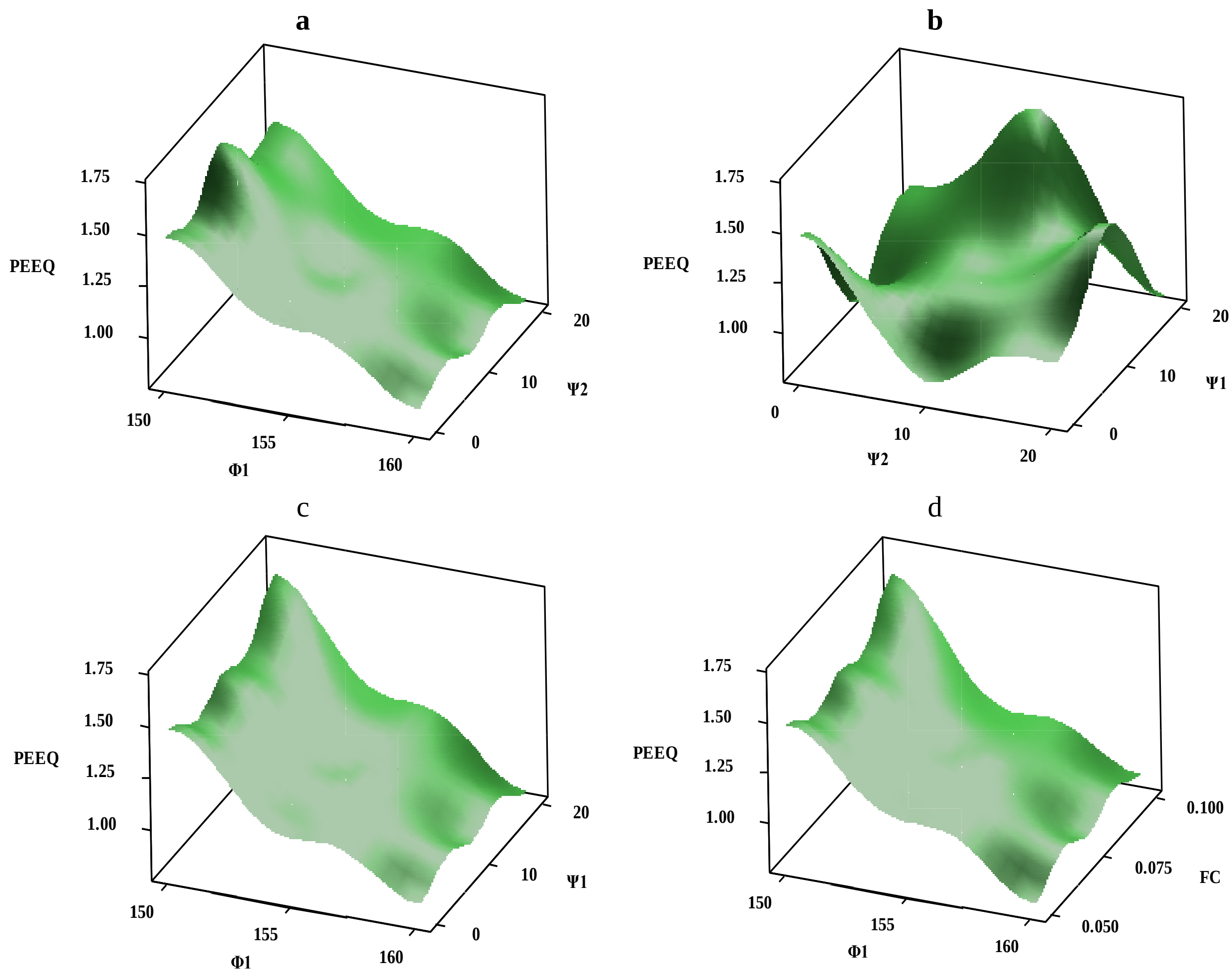


Fig. 8 3D surface plots for the effects of factors on PEEQ.

3.3. ANOVA

ANOVA is one of the important statistical methods for analysis of factors effectiveness when just one response is considered. The values for contribution reveal the effectiveness of each parameter on responses. ANOVA results for three responses were listed on “Tables (4-6)”. “Table 4” shows the effectiveness amounts of all input parameters on RPL. FC has more effect on load by the effectiveness of 87.21%[23]. The ANOVA analysis indicates that other parameters have less influence. Also, analysis of this table reveals that, the value of P for FC is less than 0.05, so this factor has physical and statistical importance. The level of confidence is 95% for analyses (The significance level is 5%).

Table 4 ANOVA results for RPL (N).

Factors	DF	Seq SS	Adj SS	Adj MS	F	P	Contribution (%)
FC	1	343654865	343654865	343654865	61.94	0.001	87.21
Ψ_1	1	130082	130082	130082	0.02	0.886	0.03
Ψ_2	1	2260998	2260998	2260998	0.41	0.558	0.57
Φ_1	1	25833203	25833203	25833203	4.66	0.097	6.56
Error	4	22193110	22193110	5548278			5.63
Total	8	394072258					100

"Table 5" shows the ANOVA results for SII as a response. It can be inferred that, Ψ_1 has more contribution than others with the effectiveness of 39.69%. Also, FC has 3.07% effectiveness as the second influential factor.

The effectiveness of input factors on PEEQ was shown in "Table 6". It is obvious that, the highest value belongs to Φ_1 with 94.57% of contribution. Also, with the zero P value, Φ_1 has physical and statistical importance on PEEQ.

Table 5 ANOVA results for SII.

Factors	DF	Seq SS	Adj SS	Adj MS	F	P	Contribution (%)
FC	1	0.000388	0.000388	0.000388	0.22	0.667	3.07
Ψ_1	1	0.005024	0.005024	0.005024	2.79	0.17	39.69
Ψ_2	1	0	0	0	0	0.989	0.00
Φ_1	1	0.000031	0.000031	0.000031	0.02	0.902	0.24
Error	4	0.007215	0.007215	0.001804			57.00
Total	8	0.012659					100

Table 6 ANOVA results for PEEQ.

Factors	DF	Seq SS	Adj SS	Adj MS	F	P	Contribution (%)
FC	1	0.00484	0.00484	0.00484	0.83	0.414	0.67
Ψ_1	1	0.00662	0.00662	0.00662	1.13	0.347	0.91
Ψ_2	1	0.00453	0.00453	0.00453	0.78	0.428	0.63
Φ_1	1	0.68461	0.68461	0.68461	117.34	0	94.57
Error	4	0.02334	0.02334	0.00583			3.22
Total	8	0.72394					100

3.4. Grey Multi Objective Optimization

Multi objective optimization was done by grey relational analysis and all objectives were considered simultaneously here. Optimum values for levels of die geometrical parameters and FC obtained for different conditions of objectives: minimum values for RPL and SII and maximum values for PEEQ.

3.4.1. Grey relational generating

Objective parameters should be normalized firstly ("Table 7") and then grey relational coefficient and grey relational grade were calculated, subsequently. Based on the type of the optimization, normalizing of parameters will be done by "Eqs. (11-12)" [24].
For objective parameters:
When the objective is the minimum value, "Eq. (11)":

$$X_i^*(k) = 1 - \frac{\max X_i^0(k) - X_i^0(k)}{\max X_i^0(k) - \min X_i^0(k)} \tag{11}$$

Also, when the objective is the maximum value, "Eq. (12)" will be used.

$$X_i^*(k) = 1 - \frac{X_i^0(k) - \min X_i^0(k)}{\max X_i^0(k) - \min X_i^0(k)} \tag{12}$$

Where X^*_i (k) is the value of the parameter after generation, X^0 is the preferred value, max X^0_i (k) and min X^0_i (k) denote the maximum and minimum value of X^0_i (k), respectively [25]. In this study, the optimum condition for both SII and RPL occurs in minimum value therefore, "Eq. (11)" was employed. Also, "Eq. (12)" was used to find the maximum value of PEEQ.

3.4.2. Grey relational coefficient

Grey relational coefficient calculated for each objective parameter by "Eq. (13)" and results are listed in "Table 7". This coefficient is the number between zero and one. For each objective parameter, grey relational coefficient demonstrates the amount of closeness from optimum value [26-27].

$$\xi_i(k) = \frac{\Delta_{\min} + \xi\Delta_{\max}}{\Delta_{0i}(k) + \xi\Delta_{\max}} \tag{13}$$

In which $\Delta_{\min}$ and $\Delta_{\max}$ reveal the minimum and maximum difference between values after grey analysis correspondingly, Δ_{0i} (k) demonstrates data value for *i*th response and *k*th test after grey analysis and $\xi_i(k)$ is the grey relational coefficient. Each parameter in "Eq. (13)" can be calculated from "Eqs. (14-16)".

$$\Delta_{0i}(k) = \left\| X_0^*(k) - X_i^*(k) \right\| \tag{14}$$

$$\Delta_{\max} = \max\max \left\| X_0^*(k) - X_i^*(k) \right\| \tag{15}$$

$$\Delta_{\min} = \min\min \left\| X_0^*(k) - X_i^*(k) \right\| \tag{16}$$

Grey relational coefficient is a number between zero and one as stated by [28] and optimal grey coefficients are usually selected as average (0.33).

3.4.3. Grey relational grade

Line with the values computed for obtaining grey relational coefficient for each objective, grey relational grade were calculated from "Eq. 17" [29].

$$\gamma_i = \frac{1}{m} \sum_{i=1}^{m} \omega_i \xi_{ij} \tag{17}$$

$$\sum_{i=1}^{m} \omega_i = 1 \tag{18}$$

Where ω_i is the weight percent of a parameter. γ_i is the grey relational grade for the *i*th experiment. The values of grey relational grade were listed in "Table 7".

Both "Table 7 & Fig. 9" show that the optimal condition occurs at simulation number 5. In this simulation, the grey relational grade equal to one, so optimization suggests that the geometry for this experiment is the best for achieving the minimum RPL and SII but, maximum PEEQ.

Table 7 Normalized simulation results, Grey relational coefficients, Grade and its order.

Experiment Number	Normalized simulation results			Grey relational coefficient			Grade	Order
	RPL (N)	PEEQ	SII	RPL (N)	PEEQ	SII		
1	0.1373	0.1932	0.4324	0.7845	0.7213	0.5362	0.6807	2
2	0.0605	0.6513	0.2793	0.8920	0.4343	0.6416	0.6560	3
3	0.0000	1.0000	1.0000	1.0000	0.3333	0.3333	0.5556	8
4	0.2112	0.9478	0.1712	0.7031	0.3454	0.7450	0.5978	4
5	0.3871	0.2272	0.0000	0.5636	0.6876	1.0000	0.7504	1
6	0.3028	0.6015	0.2613	0.6228	0.4539	0.6568	0.5779	5
7	0.9081	0.7023	0.0270	0.3551	0.4159	0.9487	0.5732	6
8	0.6627	0.9344	0.3243	0.4300	0.3486	0.6066	0.4617	9
9	1.0000	0.0000	0.9279	0.3333	1.0000	0.3502	0.5612	7

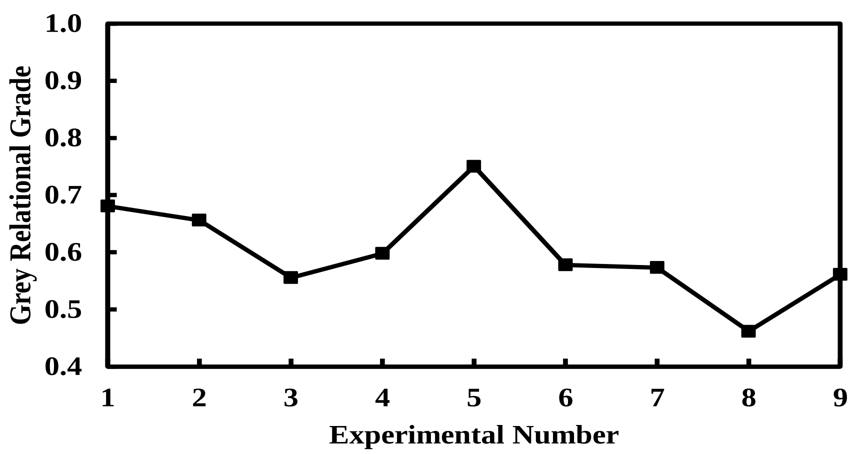


Fig. 9 Grey relational grade.

It is inferred from "Fig. 9" that the best result belongs to the set number 5. Since the highest value for the grey relational grade is better so "Eq. (12)" was used for S/N analysis. The optimum values were shown with circles in "Fig. 10". Then, it is evident that the optimum levels are A3B3C1D3. This means that to reach the optimum results, FC, Ψ_1, Ψ_2 and Φ_1 should be 0.1, 20°, 0° and 160°, correspondingly.

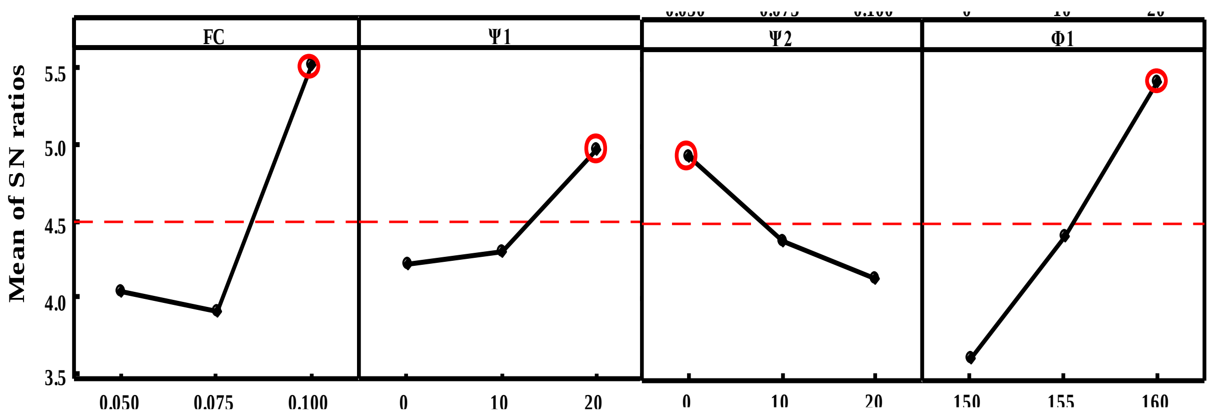


Fig. 10 Main effects plot of S/N ratios for the grey relational grade.

ANOVA analysis was done and results were listed on "Table 8". The contributions of FC, Ψ_1, Ψ_2 and Φ_1 have 26.08%, 7.33%, 7.51% and 42.3%, respectively. Results show that both FC and Φ_1 have more effects on grey grade. The level of confidence is 95% for analyses (The significance level is 5%).

Table 8 ANOVA: Analysis of Variance for grey.

Factors	DF	Seq SS	Adj SS	Adj MS	F	P	Contribution (%)
FC	1	0.014622	0.014622	0.014622	6.22	0.067	26.08
Ψ_1	1	0.004108	0.004108	0.004108	1.75	0.257	7.33
Ψ_2	1	0.004208	0.004208	0.004208	1.79	0.252	7.51
Φ_1	1	0.023713	0.023713	0.023713	10.08	0.034	42.30
Error	4	0.009408	0.009408	0.002352			16.78
Total	8	0.05606					100

4 CONCLUSION

ECMAP process optimization in the production of ultrafine grained Al alloy was discussed in this study. A complete investigation was done by DOE with compound Taguchi-Grey technique. Die geometrical parameters and friction coefficient were considered as input factors and strain characteristics and required process load set as response factors. The following results obtained:

1- Achieved relations for regression analysis shows that objectives can be predicted with good accuracy.

2- S/N and ANOVA analysis revealed that FC with contribution percentage of 87.21% has the most influential factor on RPL. Also, it was achieved that all input factors have effect on SII. Furthermore, it was inferred that among input factors, $\Phi_1$with contribution percentage of 94.57% has the most effect on the PEEQ.

3- The results of response surface methodology revealed that higher $\Phi_1$values lead to lower RPL and PEEQ. Also, higher FC causes higher RPL.

4- Grey relational analysis was used as optimization method and the 5th set with Φ_1 of 150° and FC of 0.075 is the best one among simulations.

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