Selection of optimal hot extrusion processing parameters for AA6061 using fuzzy AHP and TOPSIS

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Abstract: The need for improving the various material processing techniques for aluminium alloys has been felt due to their applications in various key industries. Due to ease of formability and low cost of aluminium alloys, extrusion has gained great popularity in recent years. Since the improper selection of processing parameters leads to poor quality and quantity, in the present work, an attempt was made to simulate hot direct extrusion of AA6061 alloy using DEFORM-3D, and the results were analysed using a hybrid multi-criteria decision making technique, a combined fuzzy AHP and TOPSIS approach to select the optimal combination of hot extrusion processing parameters. AHP is used to prioritise the evaluation criteria and the TOPSIS method used to rank the process parameters combination based on the simulation results.

Keywords: hot extrusion; simulation; processing parameters; MCDM; fuzzy AHP; TOPSIS.

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Biographical notes: Sarojini Jajimoggala is an Associate Professor in Mechanical Engineering at the Gitam Institute of Technology, GITAM, Visakhapatnam, Andhra Pradesh, India, where she has been teaching for the past 16 years. Prior to this, she worked as an Assistant Professor in the GMRIT, Rajam for one year. She received her BTech, ME and PhD in Mechanical Engineering from the Andhra University. She has published 18 papers in international and national journals of repute. Her areas of interest are optimisation techniques, hybrid MCDM techniques, metal matrix composites and maintenance decision models. She is an associate member of the Institute of Engineers. She has authored one book with S. Chand and Company Pvt. Ltd., one monograph with Lambert Publications Pvt. Ltd. and two book chapters with IGI Global.

1 Introduction

Extrusion is one of the secondary metals forming process that is used for transforming the cast structure of an ingot into a useful product of required size and shape. Aluminium is the most commonly used material due its easily deformable property. AA6061 is a material which is widely utilised for the development of aircraft structures, for example, wings and fuselages, yacht development incorporating little utility water crafts in ship building businesses, automobile parts like wheel spacers, foodstuffs and beverages in packaging industries. Since the product quality and yield mainly depends on the processing parameters of the manufacturing process, in most of the cases, the extrusion process parameters are selected on the basis of experience and the trial runs which is both costly and waste production time. Hence, most of the present research works in manufacturing are inclined towards the selection of optimal combination of parameters.

Process parameters optimisation is carried out in different manufacturing processes, some of which include wire electrical discharge machining (Kulkarni and Kulkarni, 2018), hot-wire laser welding (Yang et al., 2018), forming parts by direct laser fabrication of YCF101 alloy (Yu et al., 2018), friction stir welding (DurgaPrasad and Kirankumar, 2018), etc. Arif et al. (2001) experimentally studied the interrelationships among various extrusion process parameters in a direct extrusion of AA6063. Duan et al. (2004) used Taguchi-based FEM analysis to study the influence of processing variables on the surface cracks of extruded aluminium alloy products. Chen et al. (2008) studied the impact of processing control parameters on AA7075alloy tube extrusion of multi-hole through indirect extrusion using FEA. The optimum processing control parameters are evaluated by the method of Taguchi method. Hongjun et al. (2009) conducted FEM simulations for direct extrusion to study the effect of die angles on wrought Mg extrusions and thereby to obtain a optimum cone shaped die.

Lebaal et al. (2010) presented a new optimisation methodology for the design of coat-hanger dies. Two approaches are presented to optimise the velocities distribution across the die exit. In the first approach, the optimal shape of a coat hanger die can be predicted; in the second approach, the temperature of regulation can be optimised. To predict the temperature profiles at the exit of the induction heater and die for direct extrusion of Al6060 alloy, Carmine et al. (2010) developed two three layered artificial neural networks. Cunsheng et al. (2012) optimised the aluminium alloy extrusion process based on Taguchi's method with S/N analysis to study the effect of process parameters on profile exit temperature of industrially extruded 6063 aluminium alloy. Hu (2013) studied the effects of extrusion process and its process parameters on evolutions of microstructures for magnesium alloy using the DEFORM software. Temperature and strain evolution for deformation varying with initial billet temperatures has been explored. Salcedo et al. (2013), in their study, FEM simulations of the isothermal forging of an AA5083 previously deformed by ECAE were carried out to determine the total equivalent plastic strain, the damage and the forces required to carry out the isothermal forging of this nano-structured aluminium alloy. Mohammed (2013) developed an optimisation model to minimise the scrap produced by different dies in an aluminium industry. Bressana et al. (2015) performed hot extrusion of AA6351 using finite element method and reports on velocity field is obtained from FVM using FORGE 2008. Sharififar and Akbari Mousavi (2015) accomplished an optimisation for process of hot extrusion to generate rectangular waveguides using FEM simulations.

Venkatesh and Venkatesan (2015) used Taguchi's technique for conducting the hot extrusion experiments of SiC/Al 6061 composite. Ram speed, temperature of the billet and a friction between the die and the billet were considered as the process variables and the extrusion force as the response variable. Analysis of variance (ANOVA) is used to determine the significant factor to influence the response. Barbara et al. (2015) used multi objective optimisation for the extrusion of AA7003. In his study, neural networks were used for various response parameters. Ramya and Sreedevi (2016) employed Taguhci's L16 design to simulate hot extrusion process of 6061 aluminium alloy for each set of extrusion variables via finite element analysis solver. ANOVA was adopted to check the significance of input variables on the output responses and the optimal parameters were determined using Taguchi method. Singh et al. (2016) focused on the detailed investigation on the development of Nylon6-Al-Al_2O_3-based alternative fused deposition modelling (FDM) process feedstock filament (in lieu of commercial acrylonitrile butadiene styrene filament) by optimising the process parameters of single-screw extruder (such as composition, mean barrel temperature and die temperature) in terms of responses (tensile strength and diameter deviation) using response surface methodology. Yu et al. (2017) employed FEM simulation to investigate the influence of temperature, extrusion speed and friction coefficient on the extrusion load and deformation resistance, but have little influence on strain and strain rate. Das et al. (2017) had carried out an optimisation process for situ processing control parameters for attaining greater properties of mechanical by Taguchi's orthogonal array and GRA. Gagliardi et al. (2017) used 12 geometric variables of die with standard porthole for extruding profiles by circular section, the entire investigation is done using the technique of Taguchi's (OA) with the GRA and results were highlighted by ANOVA technique. Kitayama et al. (2018) performed numerical and experimental investigation in plastic injection moulding for the process parameters optimisation using multi-criteria decision making.

Most of the previous research works were focused on developing the model for optimal process parameters for different manufacturing environments using various single response optimisation techniques, but very few attempts have been made towards the multi-response optimisation for the selection of optimal hot extrusion process parameters. Hence, in the present work, hot extrusion process is simulated using DEFORM-3D software. Processing parameters friction coefficient (lubrication), ram speed and cone half angle (CHA) are varied during simulation for a constant extrusion ratio. Extrusion load, exit temperature of extrudate, damage factor and displacement in extrusion direction are recorded for each simulation experimental run.

From the past literature, it is also observed that all the criteria were treated with equal priority weights, which is not acceptable for a specific application. Hence, in the present work, a multi-criteria decision making technique is used to treat the criteria with different priority weights in the evaluation of optimal process parameters. Since 1990, MCDM techniques have been grown and got developed as a part of operations research. These techniques provide the combination of mathematical and computational tools for the subjective evaluation of decision makers' (DM) performance criteria to support strategic decisions in different areas. Mardani et al. (2015), in his review article, concludes that hybrid FMCDM and fuzzy AHP are ranked in first and second methods in use for are the various applications in four main fields: engineering, management and business, science and technology. Hybrid MCDM has been widely used by the authors for various applications namely for prioritisation of project risk (Amelian et al., 2016), for equipment prioritisation (Jajimoggala et al., 2010), for project selection (Amiri, 2010), for supplier evaluation (Jajimoggala et al., 2011b), for maintenance decision making (Jajimoggala et al., 2011a; Panchal and Kumar, 2017), for spare parts criticality evaluation (Jajimoggala et al., 2012), for material selection (Jajimoggala and Karri, 2013), for the evaluation of combination of individual pre-purchase internet information channels (Khatwani and Das, 2016), for blind spot reduction in heavy vehicles (Vincent et al., 2017), for the effective utilisation of quality cost analysis in manufacturing firms (Sailaja et al., 2018), etc. and it is also observed from the past literature that there is no work in which evaluation of optimal process parameters using MCDM technique.

Technique for order of preference by similarity to ideal solution (TOPSIS) is the simple and well known (Yadav et al., 2018) classical MCDM technique developed (Hwang and Yoon, 1981) for ranking the possible alternative solutions using Euclidean distances. This technique is based on the concept that optimal solution is always nearest from the positive ideal alternative solution and also farthest from negative ideal one. Out of the various numerous criterion priority weight calculation procedures, AHP has some advantages. One of the most important advantages of the AHP is based on pairwise comparison. In order to handle the uncertainty and vagueness of the experts' opinion, fuzzy sets theory (Zadeh, 1965) was used while making pairwise comparisons. FAHP embeds the fuzzy theory to basic AHP developed by Saaty (1980). To reduce the complexity in the calculations of more number of pairwise comparison matrices in FAHP, TOPSIS can be coupled with FAHP (Raut et al., 2011; Kabir and Hasin, 2013; Keshavarz et al., 2014; Zarook et al., 2015; Amini et al., 2016; Keshteli and Davoodvandi, 2017) to rank the alternatives. Hence, the present study proposes a combined fuzzy AHP and TOPSIS methodology for evaluating and selecting optimal set of hot extrusion process parameters for best quality and yield of the products. Fuzzy AHP is used to evaluate criteria weights and the TOPSIS is used to rank the simulation experiment alternatives.

2 Simulation of hot direct extrusion using DEFORM-3D

The geometry of the workpiece and the tooling were designed in CATIA. Figure 1 represents the typical meshed profile of billet of diameter of 50 mm and length of 50 mm. For die and ram, H13 chromium hot-work steel is used as material. Figure 2 and Figure 3 represent die modelling in CATIA and simulation of hot extrusion process in DEFORM-3D, respectively. Die outlet diameter is taken as 20 mm. This gives us the extrusion ratio of 25:4. Both die inlet and outlet diameters were fixed based on trial extrusion experiments in DEFORM-3D. Tool temperature is taken as 30°C.

Simulations are performed by varying ram speed, CHA and friction coefficient with extrusion load, exit temperature of the extruded product, damage factor and displacement in extrusion direction as the determining factors. Two varieties of lubricants with friction coefficients as 0.1 and 0.2 are considered. Without lubrication, friction coefficient of 0.3 is considered between the die material and AA6063. Ram speed is varied between 1 mm/s to 5 mm/s with an increment of 2 mm/s. CHAs considered are 35°, 40° and 45°. All these parameters were fixed based on the past literature.

Figure 1 Meshed profile of billet (see online version for colours)

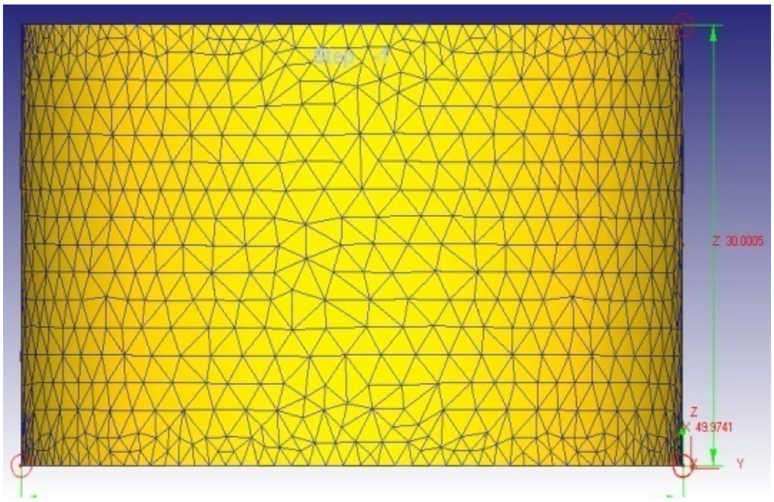


Figure 2 Modelling of die (see online version for colours)

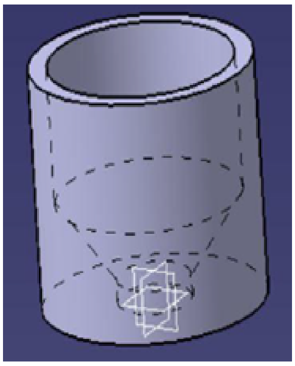


Figure 3 Simulation of extrusion (see online version for colours)

3 Applications of hybrid MCDM methodology for the selection of optimal extrusion process parameters combination

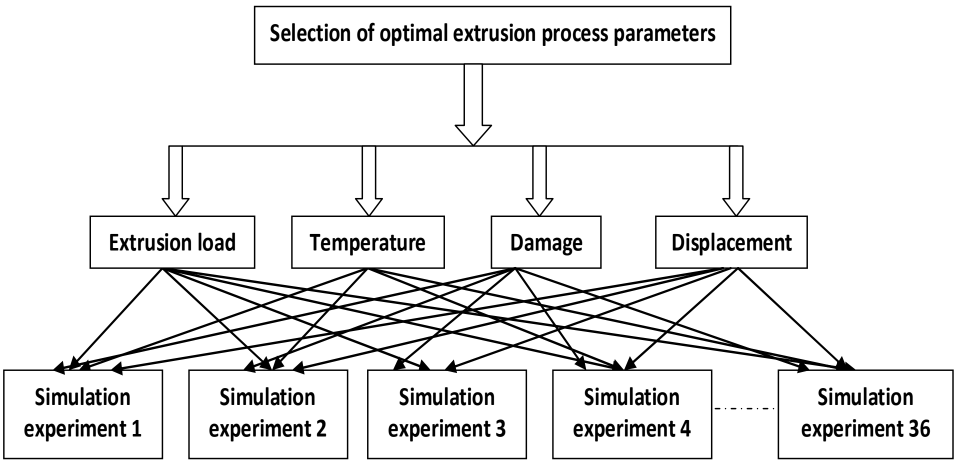
In order to select the optimal combination of hot extrusion process parameters, the results obtained from the 36 simulation experiments are considered. All the experiments are ranked and optimal process parameters are selected using a user friendly two stage decision support hybrid MCDM technique. In this, the different evaluation criteria are prioritised using fuzzy AHP in the first stage and all the possible decision alternatives were ranked using TOPSIS methodology.

3.1 Identifying criteria for the selection of optimal extrusion process parameters

In the evaluation of optimal hot extrusion process parameters combination, an objective, unbiased decision is very hard to reach given the numerous criteria that need to be carefully considered and examined. Nominal group technique (NGT) (Delbecq et al., 1975) is used to determine the set of evaluation criteria. Four potential evaluation criteria are determined as follows:

- temperature: extrusion exit temperature
- extrusion load: minimum load required to perform extrusion
- damage: the amount of deviation from the desired
- displacement: displacement in the extrusion direction (yield of the product).

Figure 4 The decision hierarchy



3.2 Structuring the AHP model hierarchically (goal, factors and alternatives)

The AHP model formed by the factors determined in the first step is shown in Figure 4. AHP model is consisted of three levels. The goal and the evaluation criteria are represented in the first and second levels, respectively and are connected with a single directional arrow in the AHP model. The third level represents various possible alternate simulation extrusion experiments at different process parameter combinations which are to be ranked.

3.3 Determining the priority weights of the criteria

In this step, priority weights of the criteria under consideration which take part in the second level of AHP model are calculated. Five different pairwise comparison matrices are prepared from the decision committee opinions and the Saaty's scale given in Table 1. For example, the question "How important is temperature when it is compared with damage?" and the answer 'weak importance', to this linguistic scale, corresponding triangular fuzzy number (1, 3, 5) is used in the relevant cell of pairwise comparison matrix. In the similar manner, all the pairwise comparison matrices are prepared. These matrices are analysed with Chang's (1996) extent analysis and obtained triangular fuzzy numbers are defuzzified using centre of area method proposed by Chou and Chang (2008) to obtain the crisp priority weights. In similar way, priority weights are calculated for all the fuzzy pairwise comparison matrices given by five different DM in Tables 2 to 6. The overall priority matrix is shown in Table 7. The order of priority weights of the criteria considered is as follows:

Displacement > Extusion load > Temperature > Damage

Table 1 Linguistic variables describing weights of the criteria and values of ratings

Linguistic scale for importance	*Fuzzy numbers for fuzzy AHP*	*Membership function $\mu_M(x)$*	*Domain*	*Triangular fuzzy number (l, m, u)*
Just equal				(1, 1, 1)
Equal importance	$\tilde{1}$			
Weak importance of one over another	$\tilde{3}$	$3 - x/3 - 1$	$1 \le x \le 3$	(1, 1, 3)
		$x - 1/3 - 1$	$1 \le x \le 3$	(1, 3, 5)
Essential or strong importance	$\tilde{5}$	$5 - x/5 - 3$	$3 \le x \le 5$	(3, 5, 7)
		$x - 3/5 - 3$	$3 \le x \le 5$	
Very strong importance	$\tilde{7}$	$7 - x/7 - 5$	$5 \le x \le 7$	(5, 7, 9)
		$x - 7/7 - 5$	$5 \le x \le 7$	
Extremely preferred	$\tilde{9}$	$9 - x/9 - 7$	$7 \le x \le 9$	(7, 9, 9)
		$x - 9/9 - 7$	$7 \le x \le 9$	

where

$$\mu_M(x) = \begin{cases} (x-l)/(m-l) & l \le x \le m \\ (u-x)/(u-m) & m \le x \le u \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Table 2 Pairwise comparison matrix

DM1	*Temperature*	*Extrusion load*	*Damage*	*Displacement*	*Weights*
Temperature	(1, 1, 1)	(1/5, 1/3, 1)	(1/9, 1/7, 1/5)	(1/9, 1/9, 1/7)	0.0432
Extrusion load	(5, 7, 9)	(1, 1, 1)	(1, 3, 5)	(1/5, 1/3, 1)	0.2727
Damage	(1, 3, 5)	(1/5, 1/3, 1)	(1, 1, 1)	(1/9, 1/7, 1/5)	0.1039
Displacement	(7, 9, 9)	(5, 7, 9)	(1, 3, 5)	(1, 1, 1)	0.5727

Table 3 Pairwise comparison matrix

DM2	*Temperature*	*Extrusion load*	*Damage*	*Displacement*	*Weights*
Temperature	(1, 1, 1)	(1/7, 1/5, 1/3)	(1/5, 1/3, 1)	(1, 1, 3)	0.1135
Extrusion load	(1, 3, 5)	(1, 1, 1)	(1/3, 1, 1)	(7, 9, 9)	0.3508
Damage	(1/3, 1, 1)	(1/9, 1/9, 1/7)	(1, 1, 1)	(1/9, 1/9, 1/7)	0.0513
Displacement	(3, 5, 7)	(7, 9, 9)	(1, 1, 3)	(1, 1, 1)	0.4791

Table 4 Pairwise comparison matrix

DM3	*Temperature*	*Extrusion load*	*Damage*	*Displacement*	*Weights*
Temperature	(1, 1, 1)	(1/7, 1/5, 1/3)	(1/9, 1/7, 1/5)	(1/3, 1, 1)	0.0709
Extrusion load	(3, 5, 7)	(1, 1, 1)	(1/3, 1, 1)	(1, 3, 5)	0.335
Damage	(1, 1, 3)	(1/5, 1/3, 1)	(1, 1, 1)	(1/5, 1/3, 1)	0.1504
Displacement	(5, 7, 9)	(1, 1, 3)	(1, 3, 5)	(1, 1, 1)	0.4374

Table 5 Pairwise comparison matrix

DM4	*Temperature*	*Extrusion load*	*Damage*	*Displacement*	*Weights*
Temperature	(1, 1, 1)	(1/5, 1/3, 1)	(1/5, 1/3, 1)	(1/7, 1/5, 1/3)	0.0849
Extrusion load	(1, 3, 5)	(1, 1, 1)	(1, 1, 3)	(1/3, 1, 1)	0.2559
Damage	(1, 3, 5)	(1/3, 1, 1)	(1, 1, 1)	(1/5, 1/3, 1)	0.1917
Displacement	(3, 5, 7)	(1, 1, 3)	(1, 3, 5)	(1, 1, 1)	0.4095

Table 6 Pairwise comparison matrix

DM5	*Temperature*	*Extrusion load*	*Damage*	*Displacement*	*Weights*
Temperature	(1, 1, 1)	(1/9, 1/7, 1/5)	(1/9, 1/7, 1/5)	(1/9, 1/9, 1/7)	0.0373
Extrusion load	(5, 7, 9)	(1, 1, 1)	(1, 1, 3)	(1/3, 1, 1)	0.297
Damage	(5, 7, 9)	(1/3, 1, 1)	(1, 1, 1)	(1/5, 1/3, 1)	0.2216
Displacement	(7, 9, 9)	(1, 1, 3)	(1, 3, 5)	(1, 1, 1)	0.4441

Table 7 Overall priority weights of the evaluation criteria

Criteria	*Temperature*	*Extrusion load*	*Damage*	*Displacement*
Priority weights	0.1929	0.3001	0.1278	0.4654

Table 8 Decision matrix

Simulation expt. no.	*Process parameters*			*Exit temperature in °C*	*Extrusion load (N)*	*Displacement (mm)*	*Damage (%)*
	COF	*Speed*	*CHA*				
1	0.1	1	30	347	373,132	108.5	1.12
2	0.1	1	35	358	353,995	120.4	0.789
3	0.1	1	40	366	369,799	129.8	0.622
4	0.1	1	45	375	367,720	137.2	1.64
5	0.1	3	30	406	311,628	108.7	1.39
6	0.1	3	35	305	409,773	120.5	2.51
7	0.1	3	40	304	407,820	129.9	0.612
8	0.1	3	45	310	394,291	137.8	1.42
9	0.1	5	30	384	342,734	108.1	1.06
10	0.1	5	35	397	316,736	120.6	1.1
11	0.1	5	40	405	349,422	129.5	0.683
12	0.1	5	45	415	335,214	136.4	0.973
13	0.2	1	30	385	306,906	109.8	1.85
14	0.2	1	35	397	306,486	121.4	2.76
15	0.2	1	40	406	311,628	131	1.39
16	0.2	1	45	415	332,708	137.9	1.1
17	0.2	3	30	348	323,280	107.2	1.22
18	0.2	3	35	357	347,660	120.7	1.35
19	0.2	3	40	367	344,984	131.8	1.16
20	0.2	3	45	375	342,836	136.6	1.54
21	0.2	5	30	295	392,783	108.8	0.729
22	0.2	5	35	406	311,628	131	1.39
23	0.2	5	40	304	378,981	129.6	0.812
24	0.2	5	45	309	384,006	137.1	1.22
25	0.3	1	30	348	333,611	110.2	0.528
26	0.3	1	35	356	322,645	121.8	1.78
27	0.3	1	40	367	384,021	132	0.413
28	0.3	1	45	375	335,176	137	0.845
29	0.3	3	30	384	301,249	110.1	1.5
30	0.3	3	35	395	308,619	121.7	1.98
31	0.3	3	40	407	368,576	131.5	0.685
32	0.3	3	45	416	369,711	138	0.896
33	0.3	5	30	295	351,133	131	1.39
34	0.3	5	35	302	385,309	123.2	1.74
35	0.3	5	40	304	368,576	130.7	0.927
36	0.3	5	45	307	369,711	135.3	2.44

3.4 Preparing decision matrix

In this step, the decision matrix is prepared from the simulation results. Table 8 represents the decision matrix. In this, criteria extrusion load, temperature and damage are assumed to be cost criteria and displacement is assumed to be benefit criteria.

3.5 Evaluating weighted normalised decision matrix

The decision matrix is normalised via equation (2) and the results are shown in Table 9.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=}^{m} \sum_{j=1}^{n} x_{ij}^2}} \tag{2}$$

Then, weighted normalised decision matrix is determined using equation (3). The results are shown in Table 10.

$$v_{ij} = w_{ij} * r_{ij} \qquad \text{for } i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, m \tag{3}$$

3.6 Ranking of simulation experiments based on closeness coefficient

From the weighted normalised values, positive ideal solution (PIS) and negative ideal solution (NIS) are determined using equations (4) to (5).

$$\text{PIS} = \left\{v_i^+, \ldots, v_n^+\right\} \text{ where } v_j^+ = \left\{\max\left(v_{ij}\right) \in J; \min\left(v_{ij}\right) \text{ if } j \in J'\right\} \tag{4}$$

$$\text{NIS} = \left\{v_i^-, \ldots, v_n^-\right\} \text{ where } v_j^* = \left\{\min\left(v_{ij}\right) \in J; \max\left(v_{ij}\right) \text{ if } j \in J'\right\} \tag{5}$$

The relative closeness coefficient (CC) to the ideal solution is calculated in the last step. The relative closeness to the PIS and the NIS D^+ and D^- are calculated using equations (6) and (7), respectively. Equation (8) is used to calculate CC. Table 11 summarises the results.

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_j^+ - v_{ij}\right)^2} \qquad \text{for } i = 1, 2, \ldots, m \tag{6}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_j^- - v_{ij}\right)^2} \qquad \text{for } i = 1, 2, \ldots, m \tag{7}$$

$$CC_i = \frac{D_i^-}{\left(D_i^+ + D_i^-\right)},\ 0 < C_i^+ < 1 \qquad \text{for } i = 1, 2, \ldots, m \tag{8}$$

The higher the closeness means the better the criticality rank (CR), so the relative closeness to the ideal solution of the alternatives can be substituted as follows: Expt. no. 11 > Expt. no. 35 > Expt. no. 3 > Expt. no. 12 > Expt. no. 36 > Expt. no. 23 > Expt. no. 27 > Expt. no. 4 > Expt. no. 31 > … Experiment 11 is defined as the most optimal process parameter combination.

Table 9 Normalised decision matrix

Simulation expt. no.	*Exit temperature in °C*	*Extrusion load (N)*	*Displacement (mm)*	*Damage (%)*
1	0.1592	0.1768	0.1458	0.1875
2	0.1643	0.1677	0.1611	0.2475
3	0.1679	0.1752	0.1741	0.0856
4	0.1720	0.1742	0.1827	0.112
5	0.1863	0.1476	0.1735	0.1737
6	0.1399	0.1941	0.1631	0.2175
7	0.1395	0.1932	0.1731	0.1158
8	0.1422	0.1868	0.1792	0.305
9	0.1762	0.1623	0.1459	0.066
10	0.1822	0.1500	0.1613	0.2225
11	0.1859	0.1655	0.1748	0.0516
12	0.1904	0.1588	0.1814	0.1056
13	0.1766	0.1454	0.1454	0.2312
14	0.1821	0.1452	0.1607	0.345
15	0.1863	0.1476	0.1735	0.1737
16	0.1904	0.1576	0.1826	0.1375
17	0.1597	0.1531	0.1419	0.1525
18	0.1638	0.1647	0.1598	0.1687
19	0.1684	0.1634	0.1745	0.145
20	0.1720	0.16244	0.1809	0.1925
21	0.1353	0.1861	0.1441	0.0911
22	0.1863	0.1476	0.1735	0.1737
23	0.1395	0.1795	0.1716	0.1015
24	0.1418	0.1819	0.1815	0.1525
25	0.1597	0.1580	0.1439	0.1737
26	0.1633	0.1528	0.1596	0.3137
27	0.1684	0.1819	0.1720	0.0765
28	0.1720	0.1588	0.1825	0.1775
29	0.1762	0.1427	0.1437	0.14
30	0.1812	0.1462	0.1594	0.0986
31	0.1867	0.1746	0.1719	0.0777
32	0.1909	0.1751	0.1817	0.205
33	0.1353	0.1663	0.1431	0.1325
34	0.1385	0.1825	0.1597	0.1375
35	0.1395	0.1746	0.1715	0.0853
36	0.1408	0.1751	0.1806	0.1216

Table 10 Weighted normalised decision matrix

Simulation expt. no.	*Exit temperature in °C*	*Extrusion load (N)*	*Displacement (mm)*	*Damage (%)*
1	0.0307	0.0530	0.0678	0.0239
2	0.0316	0.0503	0.0750	0.0316
3	0.0324	0.0525	0.0810	0.0109
4	0.0331	0.0522	0.0850	0.0143
5	0.0359	0.0443	0.0807	0.0221
6	0.0270	0.0582	0.0759	0.0277
7	0.0269	0.0579	0.0805	0.0147
8	0.0274	0.0560	0.0834	0.0389
9	0.0339	0.0487	0.0679	0.0084
10	0.0351	0.0450	0.0750	0.0284
11	0.0358	0.0496	0.0813	0.0065
12	0.0367	0.0476	0.0844	0.0134
13	0.0340	0.0436	0.0676	0.0295
14	0.0351	0.0435	0.0748	0.0440
15	0.0359	0.0443	0.0807	0.0221
16	0.0367	0.0473	0.0850	0.0175
17	0.0308	0.0459	0.0660	0.0194
18	0.0316	0.0494	0.0744	0.0215
19	0.0324	0.0490	0.0812	0.0185
20	0.0331	0.0487	0.0842	0.0245
21	0.0261	0.0558	0.0670	0.0116
22	0.0359	0.0443	0.0807	0.0221
23	0.0269	0.0538	0.0798	0.0129
24	0.0273	0.0546	0.0845	0.0194
25	0.0308	0.0474	0.0670	0.0221
26	0.0315	0.0458	0.0742	0.0400
27	0.0324	0.0546	0.0800	0.0097
28	0.0331	0.0476	0.0849	0.0226
29	0.0339	0.0428	0.0668	0.0178
30	0.0349	0.0438	0.0742	0.0125
31	0.0360	0.0524	0.0800	0.0099
32	0.0368	0.0525	0.0845	0.0261
33	0.0261	0.0499	0.0664	0.0169
34	0.0267	0.0547	0.0743	0.0175
35	0.0269	0.0524	0.0798	0.0109
36	0.0271	0.0525	0.0840	0.0155

Table 11 The results

Simulation expt. no. i	*Process parameters*			D_i^+	D_i^-	$CC_i = \frac{D^-}{(D^+ + D^-)}$	CR_i
	COF	*Speed*	*CHA*				
1	0.1	1	30	0.02688	0.02173	0.44702621	30
2	0.1	1	35	0.02853	0.018005	0.386912	33
3	*0.1*	*1*	*40*	*0.013016*	*0.037059*	*0.740061743*	*3*
4	*0.1*	*1*	*45*	*0.014105*	*0.035982*	*0.71839519*	*8*
5	0.1	3	30	0.018989	0.029817	0.610928618	17
6	0.1	3	35	0.027764	0.021423	0.435536931	31
7	0.1	3	40	0.017828	0.034122	0.656821168	13
8	0.1	3	45	0.035021	0.02047	0.36888952	34
9	0.1	5	30	0.019847	0.037036	0.651091892	14
10	0.1	5	35	0.025734	0.02244	0.465810807	29
11	*0.1*	*5*	*40*	*0.012467*	*0.041374*	*0.768447128*	*1*
12	*0.1*	*5*	*45*	*0.013569*	*0.037206*	*0.73276392*	*4*
13	0.2	1	30	0.029874	0.020858	0.411142983	32
14	0.2	1	35	0.039879	0.01718	0.301094501	36
15	0.2	1	40	0.018989	0.029817	0.610928618	17
16	0.2	1	45	0.01591	0.034356	0.683486269	11
17	0.2	3	30	0.023627	0.028139	0.543580393	26
18	0.2	3	35	0.020276	0.026098	0.562775073	25
19	0.2	3	40	0.015365	0.0314	0.671435543	12
20	0.2	3	45	0.020236	0.028486	0.584662595	22
21	0.2	5	30	0.022778	0.034243	0.600533136	21
22	0.2	5	35	0.018989	0.029817	0.610928618	17
23	*0.2*	*5*	*40*	*0.013791*	*0.035708*	*0.721388506*	*6*
24	0.2	5	45	0.0175	0.03236	0.649008259	15
25	0.3	1	30	0.024751	0.025152	0.504016995	28
26	0.3	1	35	0.035711	0.016274	0.313056922	35
27	*0.3*	*1*	*40*	*0.014635*	*0.037465*	*0.719100866*	*7*
28	0.3	1	45	0.018216	0.030643	0.627172671	16
29	0.3	3	30	0.022806	0.030531	0.572414265	24
30	0.3	3	35	0.015271	0.035587	0.699736253	10
31	*0.3*	*3*	*40*	*0.015055*	*0.037333*	*0.712627978*	*9*
32	0.3	3	45	0.024359	0.026345	0.519582022	27
33	0.3	5	30	0.022286	0.030347	0.576575243	23
34	0.3	5	35	0.019457	0.029737	0.604490984	20
35	*0.3*	*5*	*40*	*0.011761*	*0.037693*	*0.76218465*	*2*
36	*0.3*	*5*	*45*	*0.013296*	*0.035542*	*0.727753975*	*5*

Table 12 Sensitivity analysis results

Expt. no.	*Process parameters*			*CR*	*CR12*	*CR13*	*CR14*	*CR23*	*CR24*	*CR34*	*CR (equal weights)*
	COF	*Speed*	*CHA*								
1	0.1	1	30	30	30	31	28	24	29	27	27
2	0.1	1	35	33	33	32	33	33	33	33	33
3	*0.1*	*1*	*40*	*3*	*4*	*6*	*4*	*9*	*3*	*6*	*5*
4	0.1	1	45	8	8	11	10	14	9	11	11
5	0.1	3	30	17	22	15	22	27	20	23	22
6	0.1	3	35	31	29	33	30	23	31	30	30
7	0.1	3	40	13	6	26	12	6	13	12	13
8	0.1	3	45	34	32	36	34	31	34	34	34
9	0.1	5	30	14	16	4	7	11	10	2	4
10	0.1	5	35	29	31	28	31	32	30	31	31
11	*0.1*	*5*	*40*	*1*	*7*	*2*	*1*	*13*	*1*	*1*	*2*
12	0.1	5	45	4	11	3	8	21	5	10	10
13	0.2	1	30	32	34	29	32	30	32	32	32
14	0.2	1	35	36	36	34	36	36	36	36	36
15	0.2	1	40	17	22	15	22	27	20	23	22
16	0.2	1	45	11	17	7	14	25	12	15	16
17	0.2	3	30	26	26	18	20	12	24	19	20
18	0.2	3	35	25	21	22	21	20	25	21	21
19	0.2	3	40	12	12	12	16	16	14	18	17
20	0.2	3	45	22	20	27	27	26	26	28	28
21	0.2	5	30	21	15	21	11	4	15	7	8
22	0.2	5	35	17	22	15	22	27	20	23	22
23	*0.2*	*5*	*40*	*6*	*2*	*13*	*6*	*2*	*8*	*9*	*7*
24	0.2	5	45	28	27	23	26	18	27	22	25
25	0.3	1	30	28	27	23	26	18	27	22	25
26	0.3	1	35	35	35	35	35	35	35	35	35
27	*0.3*	*1*	*40*	*7*	*5*	*14*	*2*	*10*	*6*	*3*	*3*
28	0.3	1	45	16	18	20	25	22	23	26	26
29	0.3	3	30	24	25	9	19	19	19	17	18
30	0.3	3	35	10	14	1	9	15	7	8	9
31	0.3	3	40	9	10	8	5	17	4	4	6
32	0.3	3	45	27	28	30	29	34	28	29	29
33	0.3	5	30	23	19	19	17	5	18	14	14
34	0.3	5	35	20	13	25	15	7	17	16	15
35	*0.3*	*5*	*40*	*2*	*1*	*5*	*3*	*1*	*2*	*5*	*1*
36	0.3	5	45	5	3	10	13	3	11	13	12

4 Sensitivity analysis

Sensitivity analysis is carried out for getting accurate results. Sensitivity analysis is conducted to explore the influence of criteria in determining the experiment priority. It is done by swapping criterion's weights with one another, then calculating new CR for each criteria weight interchanging. So, seven different calculations are formed and different names are given for each calculation as follows: calculations CR12, CR13, CR14, CR23, CR24, CR34 and CR (equal weights). For example, CR13 means CR of experiment when criterion 1's and criterion 3's weights have interchanged and CR (equal) means all the criterion were given equal priority weights. Table 12 summarises new CR values of the experiment alternatives, when the weights have interchanged among various criterions. From the results, it is observed that in most of the cases though the weights have been interchanged, experiments nos.: 3, 11, 23, 27 and 35, conducted at CHA = 400 are in the top ten ranks. Hence, it can be concluded that cone angle is the most influencing parameter among the three parameters. Ram speed and friction coefficients occupy second and third positions, respectively.

5 Conclusions

The present work demonstrates and establishes the flow of the simulation of hot *direct* extrusion process using DEFORM-3D followed by hybrid MCDM technique for the selection of optimal hot extrusion process parameters. Simulation is carried out by varying the process parameters and the results of 36 simulations are considered with respect to output criteria. Four main criteria, load (C1), temperature (C2), max. principal stress (C3) and displacement (C4) are chosen by using expert interview. Then, priority weights were derived using *fuzzy* AHP and order of significance of criteria are found to be Displacement > Extrusion load > Temperature > Damage. Based on the priority weights, all the simulation experiments considered were sorted using TOPSIS. From the results (Table 11), it is observed that for a given COF and ram speed, experiments conducted with 400 and 450 CHA have better ranks. As the ram speed is increasing, the results are good since at high ram speeds heat loss during extrusion is minimum thereby less pressure is required to extrude. As the friction coefficient is increasing, poor ranks are obtained. Hence, it can be concluded that optimal hot extrusion process parameters combination is COF = 0.1, ram speed = 5 mm/sec and CHA = 400.

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