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ORIGINAL ARTICLE

Optimization of processing parameters and surface roughness of metallic sheets plastically deformed by incremental forming process

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Abstract
Single point incremental sheet forming (SPIF) is a process of manufacturing parts that leads to low prices of manufactured parts and high productivity. However, surface finish and forming time are responses that still need to be optimized to get better surface quality and less forming time. In the present paper, two techniques, the Taguchi grey relational analysis (TG) and response surface methodology (RSM), are combined together in order to get an optimal combination of several process parameters, such as the step increment, the feed rate, the rotation speed, the lubricant, and the sheet material. The cost function takes into account the response parameters such as the forming time, the axial, and the radial force, as well as the surface roughness in the sheet plane. The obtained results of this combination of techniques predict the grey relational grade by an empirical model that could be used in further experiments. Furthermore, the analysis of variance (ANOVA) for the grey relational grade is conducted to obtain the best levels of input process parameters.

Keywords SPIF · RSM · TG · DOE · ANOVA

1 Introduction

The single point incremental sheet forming (SPIF) is a recent technology for manufacturing sheet parts considered as a rapid prototyping process. The principle of this process is to deform locally and successively a blank sheet using a hemispherical tool following a tool path which controlled by a 3-axis CNC machine. This process is used in many areas to manufacture parts for small series and prototypes, and it covers various fields such as biomedical, aeronautics and micromechanical applications. In previous studies [1–4], two classes of incremental sheet forming processes have been presented. SPIF has attracted the interest of several researchers worldwide [5–7]. Several authors have chosen this technique for its simplicity and rapidity for applications. It optimizes the forming components served to stamp sheets, which leads to cost reductions [8, 9]. Some authors like Kim et al. [10] have studied the effect of tool geometries on formability and they have shown that the best formability is achieved by an optimal tool diameter of about 10 mm, which results in using a hemispherical tool in this work with a 10-mm diameter.

In the above studies, many techniques have been used for multi-response optimization. The most commonly taken methods include the response surface methodology, the fuzzy logic, the relational analysis, and the artificial neural networks [11–13]. For the present work, the response surface methodology is chosen, which is applied to explore the relationships between the input variables and the responses resulting from an experiment, i.e., to propose an analytical equation of responses taking into account uncertainty, hazards and error. It is used to study the interaction effect of input factors on response parameters. It determines, as well, the optimal combination to get the best performance characteristic. For a different manufacturing process, the impact of various process parameters on surface roughness has been studied by a lot of authors [14–16]. However, it has not been treated well in the forming process. Among the small number of authors,

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who have worked on the piece roughness formed by SPIF, Kurra et al. [17] analyzed the impact of multiple factors on the surface roughness and the forming time using the Box-Behnken design. They optimized the process by minimizing the response values using the NSGA-II algorithm and they found that the response parameters could be improved by the NSGA-II algorithm. Moreover, they identified the most significant factors that would influence the surface roughness and the manufacturing time. Several authors have utilized a Taguchi L18 orthogonal array and have determined the levels of the studied factors to find the optimal response parameters combining two techniques: the response surface methodology and the grey relational analysis [18, 19]. In many other studies [18, 20], there have been more than one response parameter. Some authors have sought to optimize multi-responses at one time using a grey relational grade. Raju et al. [20] employed a hybrid optimization technique in the SPIF of copper sheets to determine an optimal combination of input process parameters, where they combined the response surface methodology and the grey relational grade. In addition, they developed an empirical model that predicted the grey relational analysis. Moreover, they utilized the Analysis of Variance (ANOVA) to determine the dominant parameter. Mulay et al. [21] conducted an experimental investigation in which they studied the effect of such process parameters (feed rate, step increment, tool diameter, and sheet thickness) on surface roughness and formability by using the Box Behnken design with the response surface methodology. Many authors have used the grey relational analysis and ANOVA analysis for the grey relational grade in order to reach the optimal combination parameters [22–24]. For example, Selvarajana et al. [25] designed the experiments using the Taguchi orthogonal array. They determined the optimal input process parameters via the grey relational coefficient. Then, they identified the significant parameters by the analysis of variance. Sarraji et al. [11] identified the significant factors that affected the forming time in the negative incremental sheet forming using the Taguchi method with the Design of Experiments (DOE) and the ANOVA analysis. Ambrogio et al. [26] used the same type of material and showed with the ANOVA analysis that the thickness had an impact on the shape accuracy and the formability of produced parts. Kurra et al. [27] studied the effect of different process parameters of single point incremental sheet forming on thickness

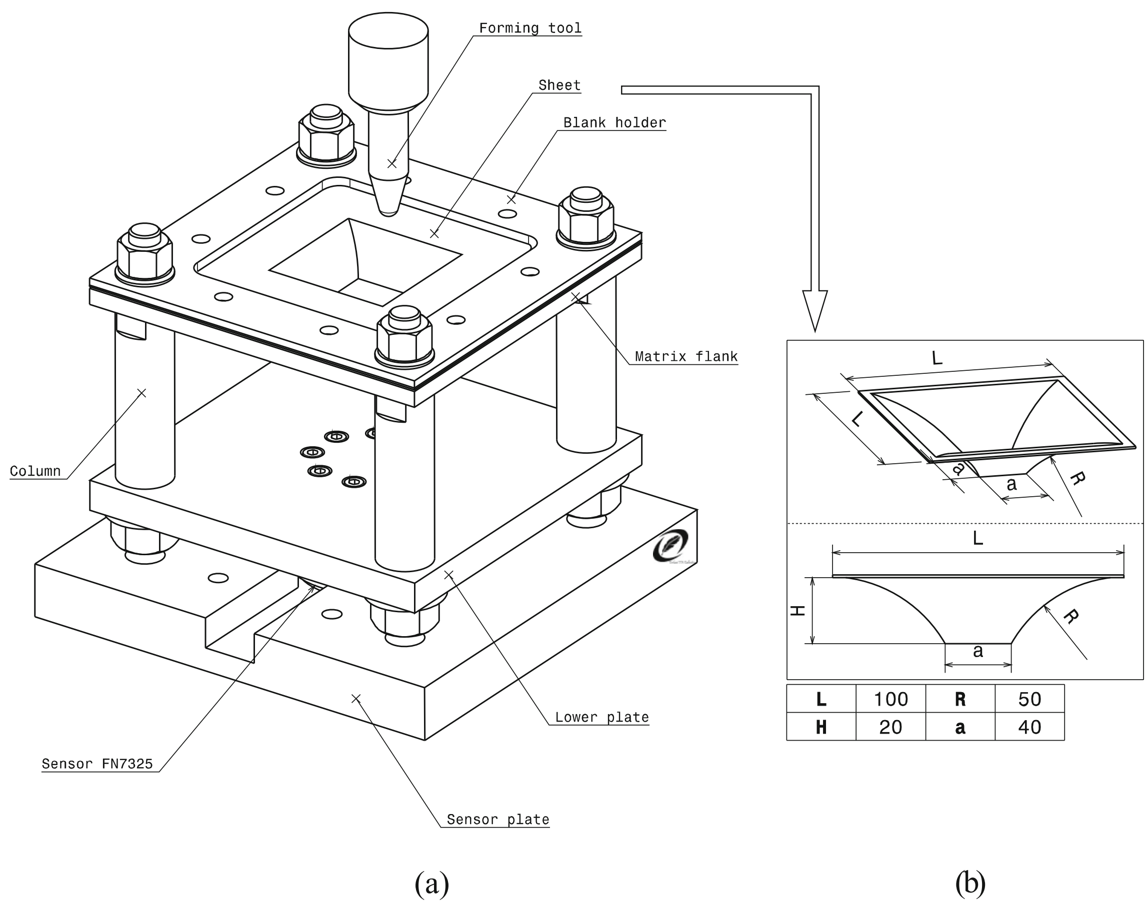


Fig. 1 (a) Experimental apparatus (b) Proposed geometry

Table 1 Mechanical and hardening properties of the specimen materials

Material	Mechanical properties				Hardening low of Swift		
	Young's modulus (MPa)	Yield strength (MPa)	Ultimate strength (MPa)	Poisson ratio ν	K (MPa)	ε_0	*n*
AA 1050	69,000	28	170	0.33	705	0.018	0.28
DC01	210,000	173	311	0.35	619	0.003	0.24
CuBe2	120,000	33.3	220	0.31	515	0.002	0.41

distribution and maximum wall angle using the Taguchi orthogonal arrays. Thus, Pandivelan et al. [28] carried out an L9 orthogonal array with the design of experiment in order to determine the optimal combination of process parameters for improving the formability of produced sheets. Adalarasan et al. [29] applied the grey Taguchi in an L18 array and utilized the response surface methodology to predict the optimal condition process.

Little work has studied the effect of input process factors on output parameters. The response surface methodology has been used with the Taguchi L18 grey relational analysis to determine the optimal response factors for the experimentation process. Thus, in this paper, an optimization of the multiple-responses for SPIF is performed utilizing the grey relational grade with the response surface methodology. Therefore, the output parameters to be optimized are the forming forces in two directions, the forming time, and the surface roughness in two directions.

2 Materials and methods

2.1 Experimental work

In the present work, the blank sheets are cut in a square shape with 200 mm × 200 mm and a thickness of about 1 mm. The experiments are carried out on a 3-axis Heindenhein CNC machine as shown in Fig. 1(a). The experimental device is fixed on the machine table. In order to form a sheet metal to the desired shapes with complex geometries using a SPIF process, the desired shape is designed and developed by CAD/CAM software (Catia V5). In this part, the tool path is defined, where the step increment is introduced. For all experiments, a truncated pyramid with a circular generatrix is chosen to be manufactured increment by increment using a hemispherical tool with 10 mm diameter, as shown in Fig. 1(a). The large and small bases of this pyramid are square bases with respective values: L = 100 mm and a = 40 mm, as depicted in Fig. 1(b). Then, the height of the pyramid is H = 20 mm and the radius of the generatrix is R = 50 mm. The specimen materials used for the experimentation are AA1050, DC01, and Cu-Be2. The mechanical properties and the hardening low of Swift for these materials are illustrated in Table 1.

During the experiments, three types of lubricants are used to minimize the friction between the tool and the sheet. In Table 2, are summarized the chemical properties of used lubricants.

The input process parameters are the sheet material, the spindle speed, the feed rate, the step increment, and the lubrication. DOE, with three levels, is performed with an L18 orthogonal array, as presented in Tables 3 and 4. The output responses are the forming time, the axial force (Fa), the radial force (Fr), and the surface roughness (Ra) in two directions: 0° and 45°, regarding the forming direction, defined by Ra $_{\mathrm{DIR0}}$ and Ra $_{\mathrm{DIR45}}$. The methodology used in this work is illustrated in Fig. 2, as follows:

i. Identification of input process parameters and their levels and the response parameters to be optimized,
ii. Achievement of test campaigns based on adopted DOE,
iii. Computation of S-N ratio of each response parameter,
iv. Normalization of each response,

Table 2 Chemical properties of used lubricant

Designation	Lubricant	Density (g/l)	Viscosity at 40 °C (Cst)
Oil 1	Oil Jelt	0.93	136
Oil 2	Slide Oil	0.894	100
Oil 3	88% Water +12% Oil	0.891	–

Table 3 Factors and levels of L 18 array

N°	Factors		Levels		
	Factors	Notations	1	2	3
1	Materials	A	AA1050	DC01	Cu Be2
2	Rotation speed (tr/mn)	B	500	1000	1500
3	Feed rate (mm/mn)	C	300	600	900
4	Step depth (mm)	D	0.25	0.50	0.75
5	Lubricant	E	Oil 1	Oil 2	Oil 3

Table 4 Input process parameter values and response values

N°	Factors					Response values				
	A	*B*	*C*	*D*	*E*	*Fa(N)*	*Fr(N)*	*Ra* $_{DIR0}$ (µm)	*Ra* $_{DIR45}$ (µm)	Forming time (s)
1	1	1	1	1	1	656.28	0.50	2.60	3.10	59.26
2	1	2	2	2	2	842.71	11.47	2.80	3.23	16.23
3	1	3	3	3	3	911.71	9.63	2.20	1.90	7.83
4	2	1	1	2	2	3021.63	20.70	7.20	7.10	30.63
5	2	2	2	3	3	3071.01	6.53	3.40	3.90	12.05
6	2	3	3	1	1	1696.26	7.16	5.00	3.40	21.86
7	3	1	2	1	3	1797.39	2.84	1.10	1.10	31.48
8	3	2	3	2	1	1976.27	7.04	1.28	1.14	11.85
9	3	3	1	3	2	1550.36	30.97	1.60	1.60	20.40
10	1	1	3	3	2	995.791	1.19	1.25	1.12	7.96
11	1	2	1	1	3	793.98	14.28	1.76	1.51	59.28
12	1	3	2	2	1	907.787	7.69	1.32	1.21	16.21
13	2	1	2	3	1	3331.01	23.75	1.95	2.00	11.20
14	2	2	3	1	2	2591.95	6.46	1.77	1.80	21.88
15	2	3	1	2	3	1676.11	3.39	3.76	3.40	15.31
16	3	1	3	2	3	2242.11	2.63	3.99	4.81	11.48
17	3	2	1	3	1	1704.38	20.10	1.60	1.97	20.48
18	3	3	2	1	2	1815.98	4.30	3.51	4.59	31.00

v. Calculation of grey relational coefficients from normalized values for each output process parameter and the computation of grey relational grade,

vi. Performance of variance ANOVA analysis and determination of contour plots, main effects plot and interaction plots between input processes, thanks to Minitab 18 software,

vii. Selection of optimal levels of input factors.

2.2 3D altimeter

The obtained forming surfaces are not perfectly smooth. After the incremental forming process, they present micro geometric defaults. As a consequence, for analyzing and measuring roughness, a 3D altimeter is used, as it is observed in Fig. 3. This device constitutes an optical metrology tool that makes it possible to study the specimen surface topography. Indeed, it is utilized to establish relationships between surface states, micro dimensions, coatings, and functionality and qualities expected of a product.

In this work, the roughness measurements are taken on the inside of the test piece along the x-axis in two directions: 0° and 45°, as shown in Fig. 4. The programmed measuring area is 4 mm × 4 mm, defined by (a), (b), (c), and (d) in the same figure. The test parameters are performed as dimensions area, pitch, and speed. The sensor is focused on the specimen. After that, the laser probe for the sensor comes into contact with the supporting surface for measurement. It sweeps the entire surface step by step according to the parameters set by collecting the roughness parameters.

2.3 Methods

To make the best of process parameters, the signal-to-noise S-N is computed [25, 30]. In this research, all responses need to be minimized using the smaller-is- the- best equation. Therefore, the formulae used to determine the *SN_Ratio* for the forming time, the forming forces, and the surface roughness is presented in Eq. (1):

$$SN\_Ratio = -10\log_{10}\frac{1}{N}\sum_{i=1}^{n} x_{ij}^2 \tag{1}$$

where x_{ij} is the observed response value in the i^{th} test, i is the response value in the j^{th} trial, and j correspond to the number of experiments. To normalize the S_N ratio for the experimental results [30], eq. (2) is used to minimize the performance characteristics:

$$X_{ij} = \frac{\max\left(x_{ij}, i=1,2,\ldots,n\right)-x_{ij}}{\max\left(x_{ij}, i=1,2,\ldots,n\right)-x_{ij}-\min\left(x_{ij}, i=1,2,\ldots,n\right)-x_{ij}}\, x\mathrm{SN\_Ratio} \tag{2}$$

where X_{ij} is the normalized value of x_{ij}.

The grey relational coefficient of each experiment that illustrates the relationship between the best and normalized

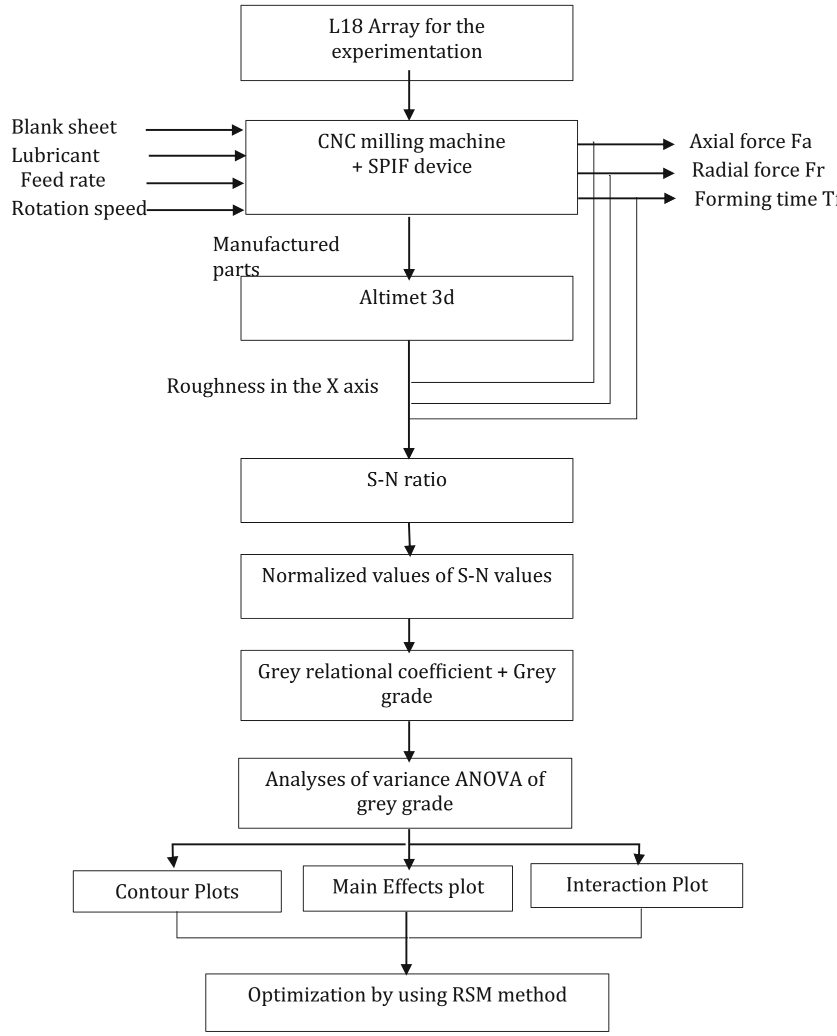


Fig. 2 Used methodology

values of the *SN_Ratio* [25] using eq. (3) is calculated as follows:

$$\beta_{ij} = \frac{\Delta\min - \Phi\Delta\max}{\Delta_{0\ j}(z) + \Phi\Delta\max} \qquad (3)$$
$$\Delta_{0\ j}(z) = \left|X_0(z) - X_j(z)\right|$$

where β_{ij} is the grey relational coefficient, $\Delta_{0\ j}$is the deviation sequence between the reference sequence and the comparability sequence Δmin and Δmax are the smallest and largest values of the deviation sequence, and $\Phi$is the distinguishing coefficient chosen in the meantime [0, 1].

The grey relational grade G_z is computed by eq. (4) [30]. It is the average of the grey relational coefficients in each trial:

$$G_z = \frac{1}{m}\sum_{i=1}^{m}\beta_{ij} \qquad (4)$$

where β_{ij} is the grey relational coefficients, m is the number of performance characteristics.

3 Results and discussion

The experiments were carried out according to the run order for the design of experiment. The arithmetical mean roughness profile is determined for all trials. From the obtained results of roughness in Table 4, Ra is very important in case of mild steel DC01 as material sheet. A slight variation in surface roughness was observed between the copper and aluminum sheets obtained by the SPIF process.

The optimization problem is a multi-objective. It consists to minimize the forming time, the roughness Ra $_{\mathrm{DIR0}}$ and Ra $_{\mathrm{DIR45}}$, the axial forces and radial forces. The determination of the objectives makes possible to determine the best combination of levels for factors.

Table 5 presents the computed *SN_Ratio* and the normalized *SN_Ratio* of the response values. The deviation sequences, the grey relational coefficients, the grey grade and the rank of each experience are provided in Table 6. The grey relational grade varies from 0.397 to 0.939. The highest grey relational grade implies that the

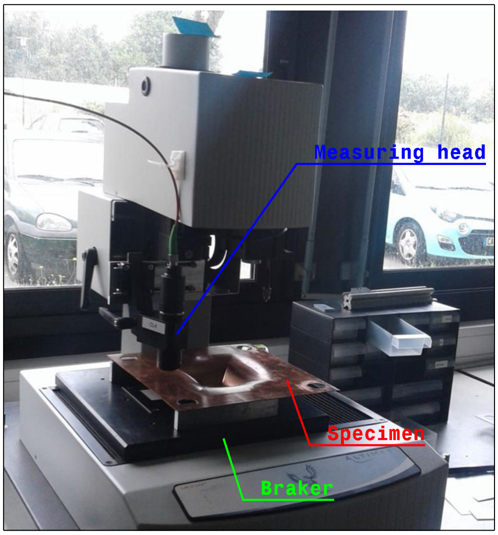


Fig. 3 3D altimeter

corresponding experimental result is closer to the ideal normalized value. In other words, for a good grey relational quality, better will be the multiple performance characteristics. The highest grey grade corresponds to the 10 th trial where the sheet material is aluminum, the feed rate is 900 mm/min, the rotation speed is 500 rpm, the step increment is 0.75 and the lubricant is Oil2. Experiment N° 12 has the second highest value of the grey grade for the same material.

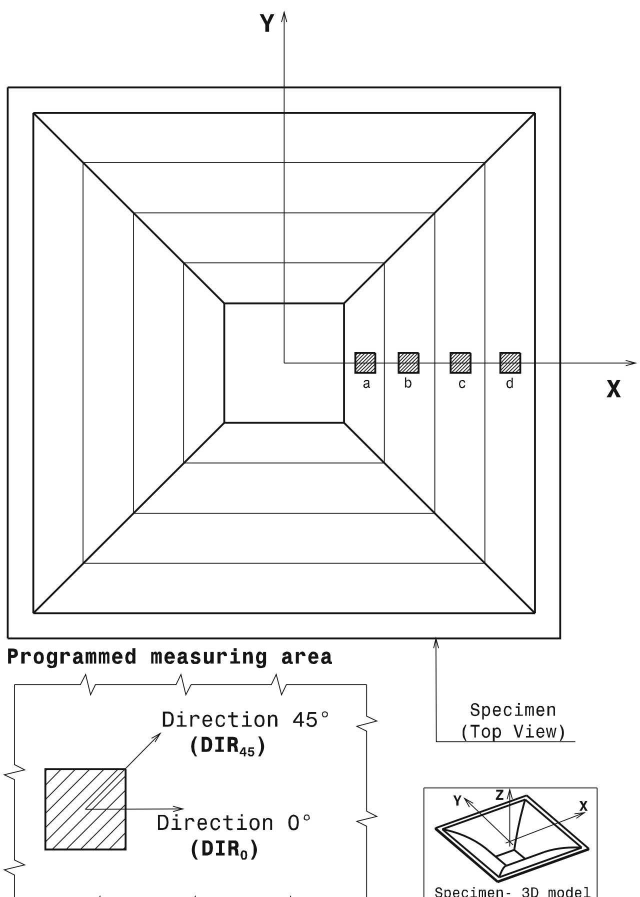


Fig. 4 Roughness programmed measuring area

To identify the significant input process parameters, ANOVA is conducted. The confidence level in ANOVA is about 95%. Table 7 shows the Sum of Square (SS), the Mean Square (MS), the F value and the *P* value of each factor for the grey relational grade. The F value is equal to the MS of each factor divided by the MS of the error and the *P* value. Furthermore, the MS of each factor Adj MS is obtained by dividing the Adj SS by a degree of freedom for each factor. Afterwards, the percentage contribution for each parameter is illustrated in Table 7. Else, Table 5 illustrates the results of the analysis ANOVA for the grey relational grade. It consists to study the significant factors that affect the grade. The significant parameters that affect the performance are presented too in the Pareto chart in Fig. 5.

We can deduce that the material sheet (A) and the lubricant (E), as well as the interactions (B)*(C), (B)*(D), (A)*(D) and (E)*(E), are statistically significant factors. They affect the performance characteristics "Grey relational grade". They pass through the line reference. It indicates that the *P* value of the material sheet and the lubricant are smaller than 0.005. As a result, these terms are the most important terms on the quality of the relational gray rank. They have a percentage contribution in of 15.79% for the interaction (B) * (C), 6.22% for the factor (A), 0.12% for the lubricant (E), 16.21% for the interaction (B)* (D), 1.68% for the interaction (A) * (D), and 5.64% for the interaction (E) * (E).

They have an important effect on the grey relational grade. We consider also that the model has an impact on the grey relational grade results. For that reason, we applied a full quadratic response surface model for the grey grade via Minitab software in order to analyze the experimental results. The model will have the following form (Eq. (5)):

$$\text{Grey } grade = a_0 + \sum_{i=1}^{k} a_i X_i + \sum_{i=1}^{k} a_{ii} X_i^2 + \sum_{ij}^{k} a_{ij} X_i X_j \tag{5}$$

Where k, the number of factors; a_i,a_{ii}, a_{ij}, regression coefficients; X_i, X_i^2, and X_iX_j represent respectively the linear effect of factors, the quadratic effect of factors, and the linear effect by linear for the interaction of factors.

The predicted GRG regression equation for this experimentation is as follows. It contains linear factors, square factors, and an interaction between 2 factors:

Table 5 S-N ratio and normalized S-N ratio of the response values

N°	S- N values					Normalized values				
	Fa(N)	Fr(N)	Ra_{DIR0} (μm)	Ra_{DIR45} (μm)	Forming time (s)	Fa(N)	Fr(N)	Ra_{DIR0} (μm)	Ra_{DIR45} (μm)	Forming time (s)
1	−56.3418	6.0206	−8.29947	−9.82723	−35.4552	1	1	0.754098	0.666667	0
2	−58.5136	−21.1913	−8.94316	−10.1841	−24.2064	0.092361	0.639974	0.721311	0.645	0.836671
3	−59.1971	−19.6725	−6.84845	−5.57507	−17.8752	0.904504	0.700361	0.819672	0.866667	1
4	−69.6048	−26.3194	−17.1466	−17.0252	−29.7229	0.115667	0.337053	0	0	0.556679
5	−69.7456	−16.2983	−10.6296	−11.8213	−21.6197	0.097206	0.8021	0.622951	0.533333	0.917947
6	−64.5898	−17.0983	−13.9794	−10.6296	−26.793	0.611184	0.781424	0.360656	0.616667	0.727202
7	−65.0928	−9.06637	−0.82785	−0.82785	−29.9607	0.573375	0.923203	1	1	0.540152
8	−65.9169	−16.9515	−2.1442	−1.1381	−21.4744	0.506497	0.785363	0.970492	0.993333	0.921836
9	−63.8087	−29.8188	−4.0824	−4.0824	−26.1926	0.665732	0	0.918033	0.916667	0.75559
10	−59.9634	−1.51094	−1.94515	−0.98436	−18.0183	0.873069	0.977355	0.975246	0.996667	0.997472
11	−57.9963	−23.417	−4.94965	−3.59678	−35.4582	0.948518	0.53003	0.890492	0.931167	−0.00039
12	−59.1597	−17.7185	−2.44432	−1.69867	−24.1957	0.905971	0.76403	0.963115	0.980667	0.83706
13	−70.4515	−27.5133	−5.80069	−6.04662	−20.9844	0	0.236954	0.860656	0.849	0.934474
14	−68.2725	−16.2047	−4.98397	−5.14397	−26.8009	0.276313	0.804398	0.889344	0.882	0.726813
15	−64.4861	−10.604	−11.5038	−10.6525	−23.6995	0.618718	0.905153	0.563934	0.615167	0.85456
16	−67.0131	−8.39911	−12.0325	−13.6429	−21.1988	0.407107	0.930095	0.525246	0.381667	0.92903
17	−64.6313	−26.0639	−4.08783	−5.89373	−26.2266	0.608148	0.356744	0.917869	0.854833	0.754035
18	−65.1822	−12.6694	−10.9259	−13.2363	−29.8272	0.566425	0.875287	0.603607	0.418333	0.549485

Table 6 Deviation sequences, grey relational coefficients and the grey grade

Deviation sequences					Grey relational coefficient						
Fa(N)	Fr(N)	Ra_{DIR0} (μm)	Ra_{DIR45} (μm)	Forming time (s)	Fa(N)	Fr(N)	Ra_{DIR0} (μm)	Ra_{DIR45} (μm)	Forming time (s)	Grey relational grade	Rank
0	0	0.245902	0.333333	1	1	1	0.67033	0.6	0.333333	0.720733	6
0.907639	0.360026	0.278689	0.355	0.163329	0.355205	0.581378	0.642105	0.584795	0.753774	0.583451	15
0.095496	0.299639	0.180328	0.133333	0	0.839636	0.625282	0.73494	0.789474	1	0.797866	4
0.884333	0.662947	1	1	0.443321	0.361185	0.429942	0.333333	0.333333	0.530042	0.397567	18
0.902794	0.1979	0.377049	0.466667	0.082053	0.356432	0.716435	0.570093	0.517241	0.859028	0.603846	14
0.388816	0.218576	0.639344	0.383333	0.272798	0.562546	0.695821	0.438849	0.566038	0.647	0.582051	16
0.426625	0.076797	0	0	0.459848	0.539592	0.866856	1	1	0.520916	0.785473	5
0.493503	0.214637	0.029508	0.006667	0.078164	0.50327	0.699656	0.944272	0.986842	0.864806	0.799769	3
0.334268	1	0.081967	0.083333	0.24441	0.599328	0.333333	0.859155	0.857143	0.671673	0.664126	9
0.126931	0.022645	0.024754	0.003333	0.002528	0.797536	0.956672	0.952827	0.993377	0.99497	0.939076	1
0.051482	0.46997	0.109508	0.068833	1.000389	0.906647	0.51548	0.820334	0.878992	0.333247	0.69094	7
0.094029	0.23597	0.036885	0.019333	0.16294	0.84171	0.679376	0.931298	0.962773	0.754216	0.833874	2
1	0.763046	0.139344	0.151	0.065526	0.333333	0.395869	0.782051	0.768049	0.884133	0.632687	13
0.723687	0.195602	0.110656	0.118	0.273187	0.408601	0.718802	0.818792	0.809061	0.646674	0.680386	8
0.381282	0.094847	0.436066	0.384833	0.14544	0.567355	0.840552	0.534151	0.565078	0.774665	0.65636	11
0.592893	0.069905	0.474754	0.618333	0.07097	0.457501	0.877339	0.51295	0.447094	0.875702	0.634117	12
0.391852	0.643256	0.082131	0.145167	0.245965	0.560631	0.437347	0.858913	0.774994	0.670272	0.660432	10
0.433575	0.124713	0.396393	0.581667	0.450515	0.535575	0.800368	0.557791	0.46225	0.52603	0.576403	17

Table 7 Analysis of variance for grey relational grade

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F value	*P* value
Regression	14	0.244565	96.80%	0.244565	0.017469	6.48	0.075
Linear	5	0.057023	22.57%	0.106485	0.021297	7.89	0.060
A	1	0.016539	6.55%	0.063783	0.063783	23.64	0.017
B	1	0.000000	0.00%	0.003867	0.003867	1.43	0.317
C	1	0.034454	13.64%	0.001203	0.001203	0.45	0.552
D	1	0.005720	2.26%	0.006374	0.006374	2.36	0.222
E	1	0.000309	0.12%	0.050119	0.050119	18.58	0.023
Square	3	0.091272	36.12%	0.062107	0.020702	7.67	0.064
*A*A*	1	0.069406	27.47%	0.000009	0.000009	0.00	0.956
*D*D*	1	0.007621	3.02%	0.010230	0.010230	3.79	0.147
*E*E*	1	0.014244	5.64%	0.029480	0.029480	10.93	0.046
Interaction	6	0.096270	38.10%	0.096270	0.016045	5.95	0.086
*A*B*	1	0.002294	0.91%	0.002229	0.002229	0.83	0.430
*A*D*	1	0.004254	1.68%	0.042291	0.042291	15.68	0.029
*A*E*	1	0.002319	0.92%	0.019714	0.019714	7.31	0.074
*B*C*	1	0.039891	15.79%	0.081335	0.081335	30.15	0.012
*B*D*	1	0.040957	16.21%	0.046192	0.046192	17.12	0.026
*B*E*	1	0.006555	2.59%	0.006555	0.006555	2.43	0.217
Error	3	0.008093	3.20%	0.008093	0.002698		
Total	17	0.252658	100.00%				

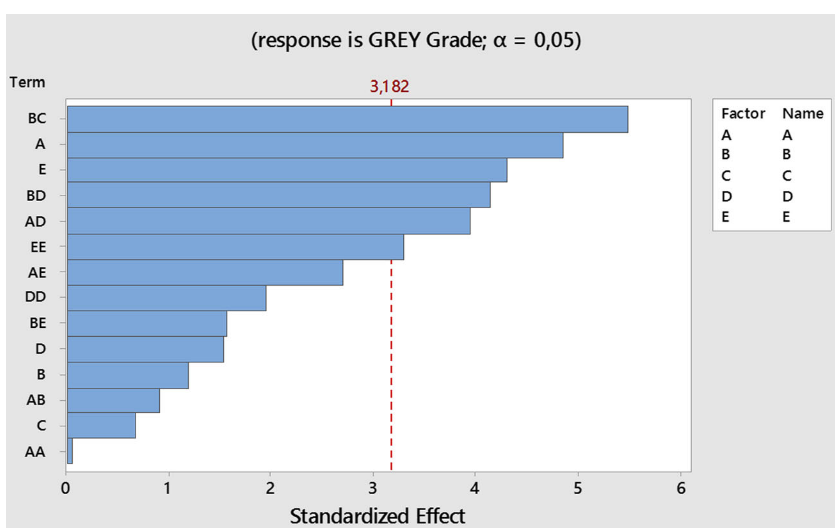
DF degree of freedom, *Seq SS* sequential sums of squares, *Adj SS* adjusted sums of squares, *Adj MS* adjusted mean squares

$$\text{Grey} = \text{Grey} = 0.728 + 0.268\,\text{A} + 0.083\,\text{B} + 0.3745\,\text{C}–0.290\,\text{D}–0.371\,\text{E} + 0.0022\,\text{A*A} + +0.0633\,\text{D*D} + 0.1306\,\text{E*E} + 0.0356\,\text{A*B}–0.1408\,\text{A*D}–0.0805\,\text{A*E}–0.1796\,\text{B*C} + 0.1437\,\text{B*D}–0.0510\,\text{B*E} \quad (6)$$

In Fig. 6(a), the experimental GRG vs the number of the trials is plotted. Moreover, the experimental GRG Vs analytical GRG is plotted too in Fig. 6(b). It can be seen that the coefficient correlation is equal to 96.79%. Hence, the experimental GRG is in good correlation with the analytical one.

Using Minitab18 software, the main effect plot and the interaction plot of data means for the grey grade are depicted in Figs. 7 and 8. According to the ANOVA analysis, Fig. 7 shows the main effect segments of the grey relational grade, where the average horizontal line is the

Fig. 5 Pareto chart for the standardized effects



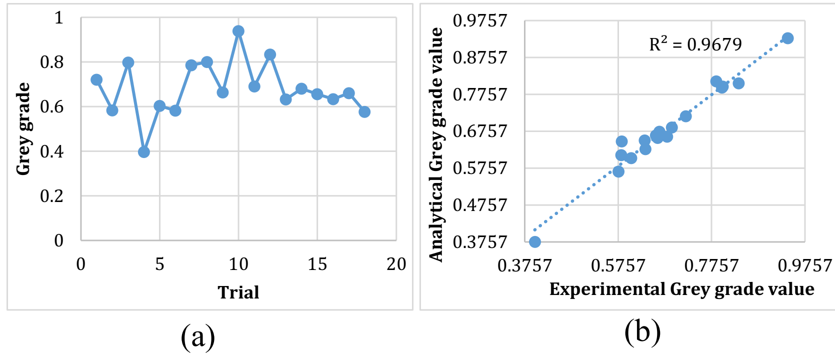


Fig. 6 (a) Grey relational grade vs trial; (b) analytical grey relational grade value vs experimental grey relational grade value

total average value of the gray relational grade. Based on the slope values, the importance of the input factors can be judged. If the line is horizontal, we deduce that the factor no longer has a main effect. In our case, all factors have major effects. But, the degree or intensity of each factor depends on the slopes. When the value of the slope is higher, the factor has a significant effect. So, the biggest is the gray relational grade, and the best is the performance characteristics. Then, the best combination of parameters levels optimizing simultaneously the performance characteristics "grey grade" is obtained at level 1 of sheet material and at the same level for rotation speed, the feed rate is at level 3 and at the same level for the step depth, the lubricant is at level 2. The maximum value of Grey grade is recorded to the factor A in which it presents the material sheet at the smaller level "1."

Using the method of Grade_ Taguchi, the best combination of factor levels that allows the simultaneous optimization of performance characteristics is as follows:

- Level 1 of the sheet material
- Level 1 of the rotation speed
- Level 3 of the feed rate
- Level 3 of the step depth
- Level 2 of Lubricant

The results of the optimal combination obtained by the Grade-Taguchi method are consistent with those obtained by the effects analysis with Minitab except for the level of factor E. Instead of having level 2, the factor E takes level 1 in the main effects graph.

The first highest interaction is noted between A and B, where A is the material sheet and B is the rotation speed. The second highest interaction is between the rotation speed and the lubricant. Regarding the main effect plot, all the input process parameters expect the feed rate has the same gait. It decreases and then it increases. There is a large and slight deviation by means of the grey grade GG of the material sheet and the feed rate, respectively. For the material sheet, it varies from 0.67 to 0.59.

Figure 9 presents the surface the surface plots of grey grade for different outputs. Figure 9(a) shows the surface plots of GG vs the material sheet and the other predictors and Fig. 9(b) shows the surface plots of grey grade vs lubricant and the other factors. For example, the highest GG values in Fig. 9(a) is obtained when A and B reach their lower values. The

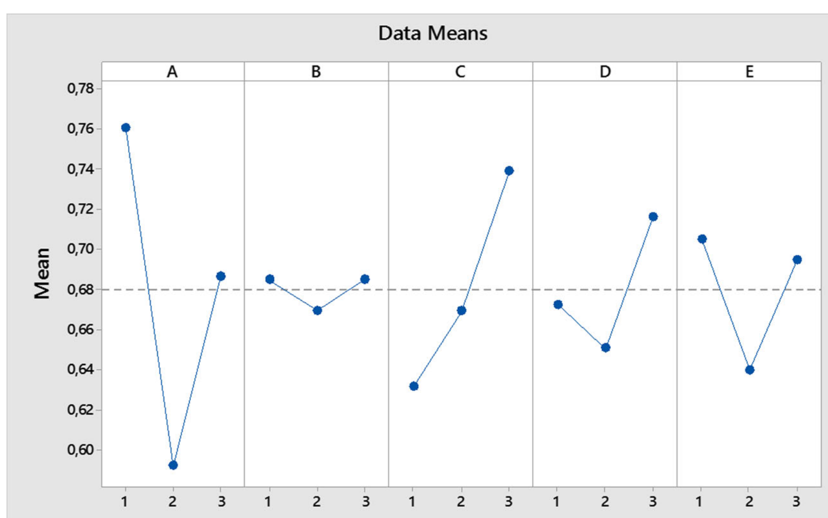


Fig. 7 Main effects plot for grey grade

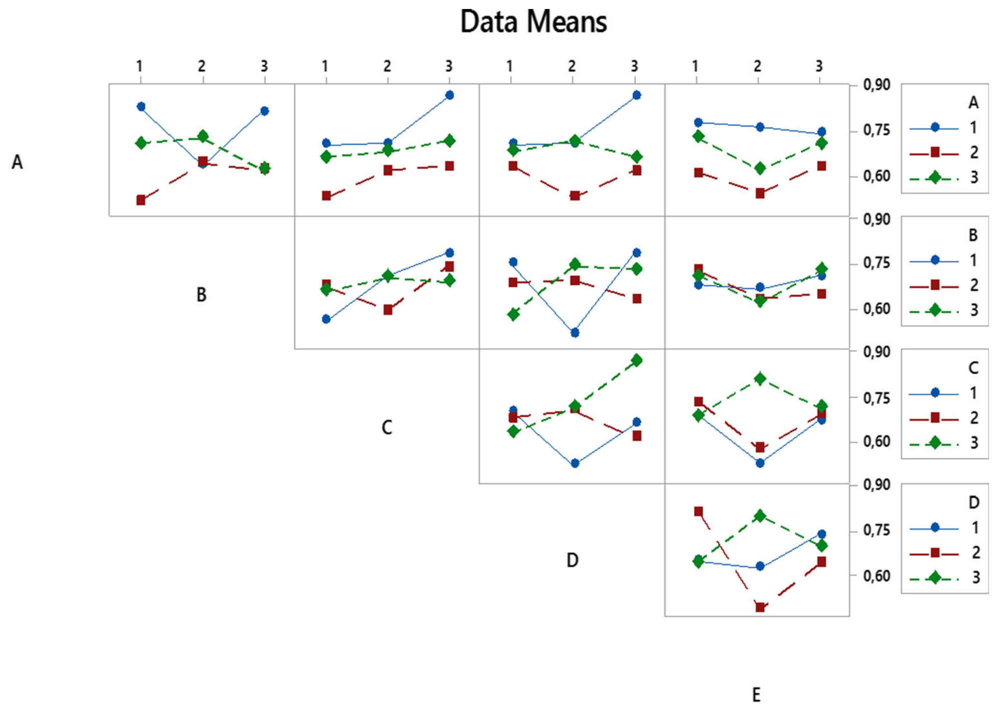


Fig. 8 Interaction plot for grey grade

other parameters, C, D, and E, are considered constant by Minitab18 software. Similarly, for the variation in the grey grade with respect to the lubricant and various input parameters is given in Fig. 9(b).

Thanks to the response optimizer, the combination of the input process parameters that optimize one or more responses is determined. In this work, the grey grade is the only chosen response to be optimized using Minitab 18. It should be maximized utilizing the desirability function approach. According to the desirability value, as illustrated in Fig. 10, the optimal levels of process parameters are a copper sheet, 500 rpm rotation speed, a 900 feed rate, a 0.25 mm step increment, and an oil 3 lubricant. In this case, the desirability is ideal. It is defined by the following formulae (Eq. (7)):

$$D(Y) = d(Y) = 1 \; if \; Y > T, \quad \begin{cases} \text{D : overall desirability} \\ \text{d : individual desirability} \\ \text{Y : response} \\ \text{T : target value} \end{cases} \tag{7}$$

The optimal values presented in red brackets are considered for the optimal combination.

To validate the optimal combination of input parameters, a test is carried out using the optimal forming process. The estimated value of GRG and the obtained one from the experiment are 1.2864 and 1.3174, respectively. The improvement in the grey grade is equal to 2.4%. Consequently, the results are validated, and the used optimization and the developed equation of GRG can be used in further experimentation with respect to the input parameters.

4 Conclusions

This work combines two methods Taguchi grey relational analysis and the response surface methodology in which an optimization of multi-response parameters are made by computing the grey relational grade. By the analysis taken from the obtained results, some conclusions are illustrated in the following:

- The experiment N °10 has the greatest value of the grey relational grade when the sheet material is aluminum, the rotation speed is 500 rpm, the feed rate is 900 mm/min, the step depth is 0.75 mm, and the lubricant is Oil 2. The levels of this experiment are close to the best performance in the SPIF process by utilizing a hybrid optimization.
- The coefficient correlation and the adjusted one are in harmony and consistency in the prediction of GRG.
- Based on the ANOVA analysis, the material sheet and the lubricant are the most significant factors that affect the surface roughness, the forming forces, and the manufacturing time.
- The main effect plots show that the high main effect for grey grade is obtained with the material sheet at level 1.
- With the desirability approach, an optimal parameter condition of the SPIF process is obtained when the sheet material is copper, the rotation speed is 500 rpm, the feed rate

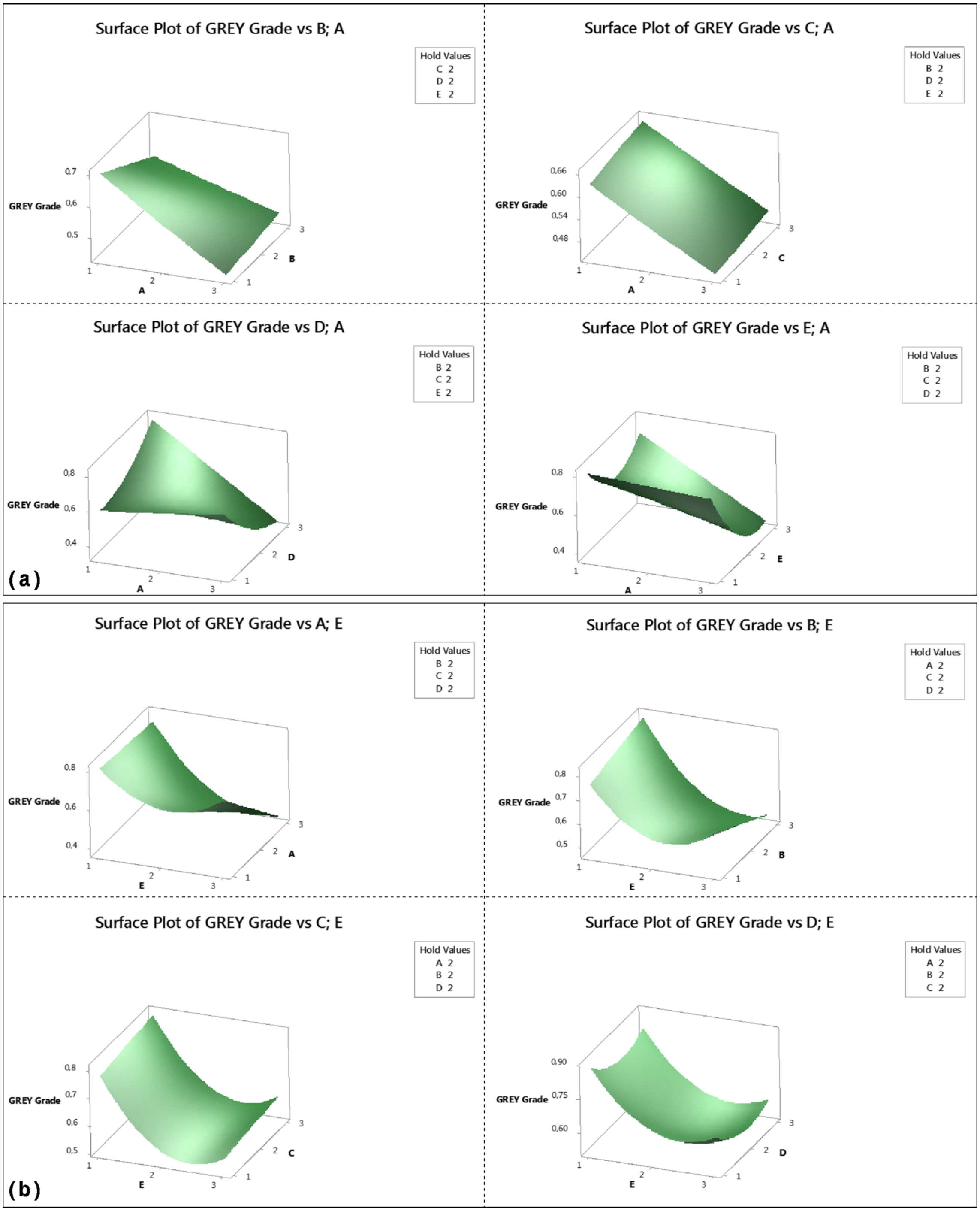
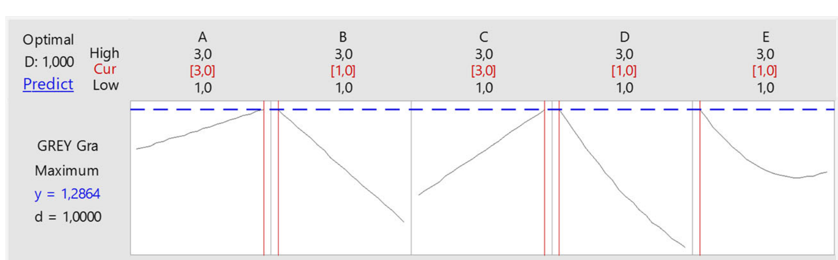


Fig. 9 (a) Surface plots of grey grade vs material sheet and various input factors; (b) Surface plots of grey grade vs lubricant and various input factors

Fig. 10 Optimization plot of grey grade using response optimizer



is 900 mm/min, the step increment is 0.25 mm and the lubricant is Oil 1. This combination will offer good results for the surface roughness, the axial and radial forces, and the forming time.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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