Sensitivity Analysis of GFRP Composite Drilling Parameters and Genetic Algorithm-Based Optimisation

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ABSTRACT

In this article, a genetic algorithm (GA) is used for optimizing a metamodel of surface roughness (Ra) in drilling glass-fibre reinforced plastic (GFRP) composites. A response surface methodology (RSM)-based three levels (-1, 0, 1) design of experiments is used for developing the metamodel. Analysis of variance (ANOVA) is undertaken to determine the importance of each process parameter in the developed metamodel. Subsequently, after detailed metamodel adequacy checks, the insignificant terms are dropped to make the established metamodel more rigorous and make accurate predictions. A sensitivity analysis of the independent variables on the output response helps in determining the most influential parameters. It is observed that f is the most crucial parameter, followed by the t and D. The optimization results depict that the Ra increases as the f increases and a minor value of drill diameter is the most appropriate to attain minimum surface roughness. Finally, a robustness test of the predicted GA solution is carried out.

KEYWORDS

Box-Behnken Design, Drilling, GA, GFRP, RSM, Sensitivity Analysis

1. INTRODUCTION

During the last two decades, the growth in the use of laminated composites has been unprecedented. In developed countries, composite industry has thrived tremendously. For example, in US a 6.3% growth in 2014 was seen which translated as $8.2billion in value and 5.5 billion pounds as annual shipment (Mallick, 2007). Due to properties like high strength to weight ratio and lighter in weight, composites have been the ideal choice for replacement of conventional materials available in market where weight is an influential factor (Kalita, Ramachandran, Raichurkar, Mokal, & Haldar, 2016). Critical structures like aircraft like Boeing and Airbus are predominantly made up of composites. Composite have shown its own contribution in engineering applications as it come a long way (Stewart, 2009). Composites have now become an essential part of everyday life like bicycle, tennis racket, car bumpers etc. In making some of the components drilling is often used to serve some functional requirements. One of the problem associated with drilling of composite is delamination (Behera, Ghadai, Kalita, & Banerjee, 2016) (Tibadia, et al., 2018). The surface roughness of the drilled hole becomes another concern where minuscule tolerance is required.

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El-Sonbaty et al. (El-Sonbaty, Khashaba, & Machaly, 2004) reported that surface roughness could be minimized by using high fiber volume fraction and a higher cutting speed while drilling GFR epoxy composite. However, their research was limited to traditional high-speed twist drills. To determine and estimate the thrust force and the surface roughness in penetrating CFRP laminates, Tsao and Hocheng (Tsao & Hocheng, 2008) made use of Taguchi method and ANN. Palanikumar et al. (Palanikumar, Srinivasan, Rajagopal, & Latha, 2016) used RSM design of experiments to develop a numerical model for thrust force. They sought to reduce the thrust force to reduce delamination. Hansda and Banerjee (Hansda & Banerjee, 2014) to study the consequences of some process parameters on delamination aspect and surface roughness executed a Grey Relational analysis on glass fiber-reinforced polyester composite. They concluded feed rate to be the most significant parameter in drilling composites. To simultaneously forecast the delamination and the roughness of the surface in GFRP composites, Behera et al. (Behera, Ghadai, Kalita, & Banerjee, 2016) used an artificial neural network. Azmi and co-workers (Tan, Azmi, & Muhammad, 2016) (Nasir, Azmi, & Khalil, 2015) has made some valuable contribution to the understanding of the process parameters involved in drilling composite laminates. Tan et al. (Tan, Azmi, & Muhammad, 2016) reported feed rate to be the most dominant of parameters influencing the surface roughness of a drilled composite. Srinivasan et al. (Srinivasan, Palanikumar, Rajagopal, & Latha, 2017) too indicated that feed rate is the most influential parameter in delamination of composites. Jani et al. (Jani, Kumar, Khan, & Kumar, 2016) suggested that use of natural fibers can help in reducing delamination damages. Debnath et al. (Debnath, Sisodia, Kumar, & Singh, 2016) developed a new drill bit design to reduce such damages. Ramprasath and Jayabal (Ramprasath & Jayabal, 2016) investigated the impact behavior of bio filler-based composites.

Parameter optimization is used as a tool to monitor and distinguished the different parameters or factors involved in any processes. However, to validate the results experimentation is needed and the results produces should statistically significant. RSM is perhaps the most preferred ones for metamodels because it does not require more trails and can compare to a full factorial design. However, developing a statistically significant metamodel is a much easier task as compared to searching a 3-or-more factor domain for maximizing or minimizing an output response. It is practically impossible to perform experiments for all possible combinations to determine an optimum parameter setting. GA, which is computer-based search algorithm suitable for optimizing a variety of functions. Kalita and co-workers have used GA for optimization of laser marking process (Kalita, Shivakoti, & Ghadai, Optimizing process parameters for laser beam micro-marking using genetic algorithm and particle swarm optimization, 2017), EDM process optimization (Ragavendran, Ghadai, Bhoi, Ramachandran, & Kalita, 2018), PECVD optimization (Ghadai & Kalita, 2020), hole quality optimization of composite (K.Kalita, Mallick, Bhoi, & Ghadai, 2018), composite laminate ply-angle optimization (Kalita, Dey, Haldar, & Gao, Optimizing frequencies of skew composite laminates with metaheuristic algorithms, 2020) etc. Acherjee et al. used a cuckoo search and chicken swarm optimization algorithm to carry out ultrasonic machining process optimization (Acherjee, Maity, & Kuar, Ultrasonic Machining Process Optimization by Cuckoo Search and Chicken Swarm Optimization Algorithms, 2020) and a flower pollination algorithm for optimization of electrochemical machining process (Acherjee, Maity, & Kuar, Optimization of Corelated and Conflicting Responses of ECM Process Using Flower Pollination Algorithm, 2020).

It is worth noting that there is still some lacuna which presents an excellent scope for future investigations in drilling FRP composites, despite the existence of exemplary contributions in the field. Drilling of chopped GFRP laminates is one of the essential areas where little work has been done. Hence in the present study, an attempt is made for drilling of polyester composite reinforced to and find the optimal parametric combination.

2. MATERIALS AND METHODS

2.1 Experimental Details

Composite polyester strengthened with sliced fiberglass is taken as the work material in the present investigation. Hand layup technique is used for the preparation of the composite laminates. For hardening methyl ethyl ketone peroxide is used in the polyester matrix, reinforced by an E-glass, chopped strand mat. Dimension of 150 mm × 150 mm are used in the experiment. The laminates had a fiberglass which had a volume of 0.33, Barcol hardness of 40.6 and tensile strength 700 kg/cm^2. Taper shank twist drills (High-speed steel) of Addison & Co. Ltd., India. The diameter of the twist drill were 10 mm, 12 mm and 14 mm of M2 Grade are used. A Taylor Hobson Precision Surtronic 3+ Roughness checker is primarily used to establish the extent of the roughness of the surface on the penetrated surfaces. The surface roughness average $\left(R_a\right)$ is considered as the surface roughness parameter. The work material surface finish is quantified with a 0.8 mm length cut-off. The R_a for every test are obtained from the Taly-profile software integrated with the machine. The average of three readings is taken as the process response.

2.2 Metamodeling

Response surface methodology (RSM) develops a metamodel of lowing form.

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i \, x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} \beta_{ij} x_i x_j + \sum_{i=1}^{n} \beta_{ii} x_i^2 + \varepsilon \tag{1}$$

In the present study, the RSM design by Box-Behnken method (BBD) is used (Pal, 2012) (Vikas Kumar Singh, 2017). Moreover, the number of design points needed for a BBD design is far less than 3^k factorial designs, thereby significantly reducing experimental cost and time. In this particular case concerning four input parameters, only 29 design points are necessary. To find the effect of surface roughness four parameters were cahanged. These parameters were material thickness (t), drill diameter (D), spindle speed (N) and feed rate (f). The parameters is coded with different levels (-1, 0 and 1). Table 1 and shows the input parameters and their levels considered. Box-Behnken RSM is designed for 29 experimental trials as shown in Table 2. Further, randomising the 29 experimental trials (design points), allow each trial to become an equal participant in the study (Kalita, Dey, & Haldar, Search for accurate RSM metamodels for structural engineering, 2019).

Table 1. Process parameters and levels considered

Factors		Levels		
Symbol	Unit	-1	0	1
Material thickness (t)	mm	8	12	16
Drill diameter (D)	mm	10	12	14
Spindle speed (N)	rpm	400	800	1100
Feed rate (f)	mm/rev	0.1	0.175	0.275

Table 2. Design matrix and experimental values

Trial No.	Material Thickness, t (mm)	Drill diameter, D (mm)	Spindle Speed, N (rpm)	Feed rate, f (mm/rev)	Av. surface roughness, R_a (μm)
1	8	10	800	0.175	3.947
2	16	10	800	0.175	4.227
3	8	14	800	0.175	4.253
4	16	14	800	0.175	5.173
5	12	12	400	0.100	3.567
6	12	12	1100	0.100	3.98
7	12	12	400	0.275	4.353
8	12	12	1100	0.275	4.563
9	8	12	800	0.100	3.703
10	16	12	800	0.100	3.553
11	8	12	800	0.275	4.297
12	16	12	800	0.275	4.817
13	12	10	400	0.175	3.907
14	12	14	400	0.175	4.513
15	12	10	1100	0.175	3.753
16	12	14	1100	0.175	5.023
17	8	12	400	0.175	3.653
18	16	12	400	0.175	4.561
19	8	12	1100	0.175	4.083
20	16	12	1100	0.175	4.457
21	12	10	800	0.100	3.437
22	12	14	800	0.100	3.673
23	12	10	800	0.275	4.280
24	12	14	800	0.275	4.204
25	12	12	800	0.175	4.171
26	12	12	800	0.175	4.171
27	12	12	800	0.175	4.171
28	12	12	800	0.175	4.171
29	12	12	800	0.175	4.171

2.3 Genetic Algorithm

The metamodel generated by using the Box-Behnken method is then optimised using a genetic algorithm (GA). GA are efficient for optimal combinations of parameters and predicting outcomes. This will provide good and robust solutions which are highly rated according to certain fitness criteria. So, it pursues global fitness and avoids local optima. It works on Darwin's principle of natural selection (Goldberg, 2006). GA is different from traditional search optimisation in three distinct ways. First, they search and explore parallel from a population of points and in that case, it is not confined in local optima. Second, rather than directly optimising the parameters, GA works on chromosomes which are an encrypted version of potential solution parameters. Thirdly GA makes use of the fitness score which is acquired from objective functions without any artificial over-engineered black box mathematics (Kalita, Dey, & Haldar, Robust genetically optimized skew laminates, 2019). The GA is implemented as per the following flowchart presented in figure 1.

Figure 1. Flowchart of the genetic algorithm

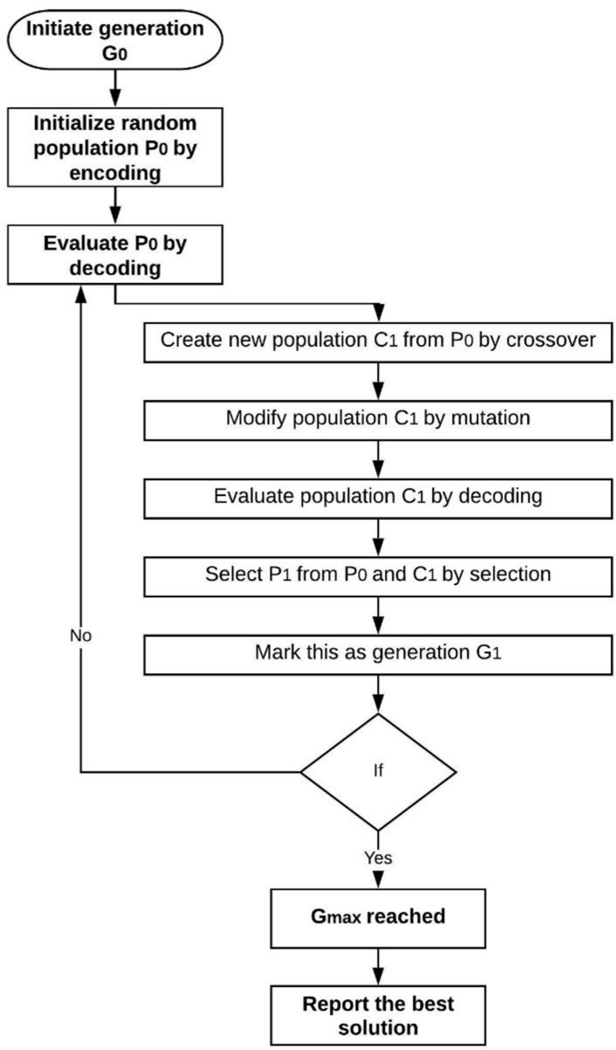


Table 3. ANOVA results for reduced second-order response surface model

Source	SS	df	MS	F Value	Prob > F
Model	4.1005	8	0.5126	10.4370	0.0000
Material thickness (t)	0.8013	1	0.8013	16.3160	0.0006
Drill diameter (D)	0.9009	1	0.9009	18.3448	0.0004
Spindle speed (N)	0.1343	1	0.1343	2.7340	0.1138
Feed rate (f)	1.7641	1	1.7641	35.9214	0.0000
tD	0.1024	1	0.1024	2.0851	0.1042
tN	0.0845	1	0.0845	1.7204	0.1045
tf	0.0861	1	0.0861	1.7540	0.1003
f^2	0.5463	1	0.5463	11.1241	0.0033
Residual	0.9822	20	0.0491		
Lack of Fit	0.9822	16	0.0614		
Std. Dev.	0.2216				
Mean	4.1666			R^2	80.68%
C.V. %	5.3186			Adj. R^2	72.95%
PRESS	2.2368			Adeq. Precision	12.4812

3. RESULTS & DISCUSSION

3.1 Analysis of the Metamodel

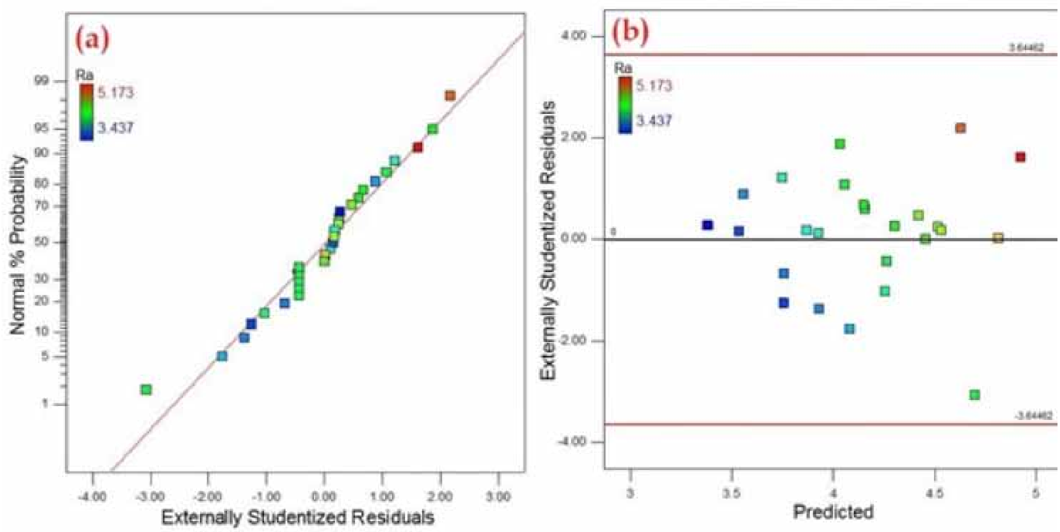
The experiments performed is based on the RSM design, which are used for fitting a metamodel. This will describe the average surface roughness in GFRP composites approximately. A standard statistical software package DESIGN-EXPERT™ is used for performing the regression analysis. Table 3 presents the Analysis of Variance (ANOVA) results for reduced second-order BBD metamodel for average surface roughness (for sake of brevity, the full ANOVA is not presented in the manuscript). The full second-order metamodel contained a number of insignificant terms and these are removed as per the p-value criteria. The values of "*Prob > F*" smaller than 0.0500 show that the terms of the metamodel are substantial. All terms having "*Prob > F*" greater than 0.1 indicate that they may not be significant and thus are removed to form the reduced second-order metamodel. The metamodel F-value of 10.44 infers the metamodel is noteworthy. This shows that there is only 0.01% opportunity that an F-value this great could happen due to noise. Thus, the following reduced second-order metamodel used,

$$R_a = 2.399699 - 0.174426t - 0.103000D + 0.001538N + 13.402897f + 0.020000tD - 0.000103tN + 0.416459tf - 37.382682f^2 \quad (2)$$

3.2 Metamodel Adequacy Check

Fig. 2 shows a normal probability plot for R_a. The studentized residuals are obtained by dividing the residual using an estimate of its standard deviation. It was observed that all the residual points are almost linear and follow straight line which means that the errors and distributed normally. However, there is no sign of clusters of residuals at one place this implies that the data does not consist of any ties which shows measuring resolution is adequate. It was also observed that there is no significant outliers as seen in the plot. Fig. 2 (b) shows the variation of predicted response versus the externally studentized residuals for average surface roughness. The data points of random scatter are shown in Fig. 2 (b) suggest that there is no violation of constant variance in the present metamodel which shows that the proposed metamodel is adequate. Fig. 3 shows the comparison of the predicted average surface roughness calculated using Eqn. 2 and the experimental output. The present metamodel predicts the R_a in the drilling of GFRP composites with very high accuracy. The variation in the predicted metamodel can be seen in trial no. 24 (11.5%). For other cases the metamodel is entirely accurate and overall average variation were found to be only 3.39%.

Figure 2. Normal probability plot (b) Residuals vs. predicted response



3.3 Sensitivity Analysis

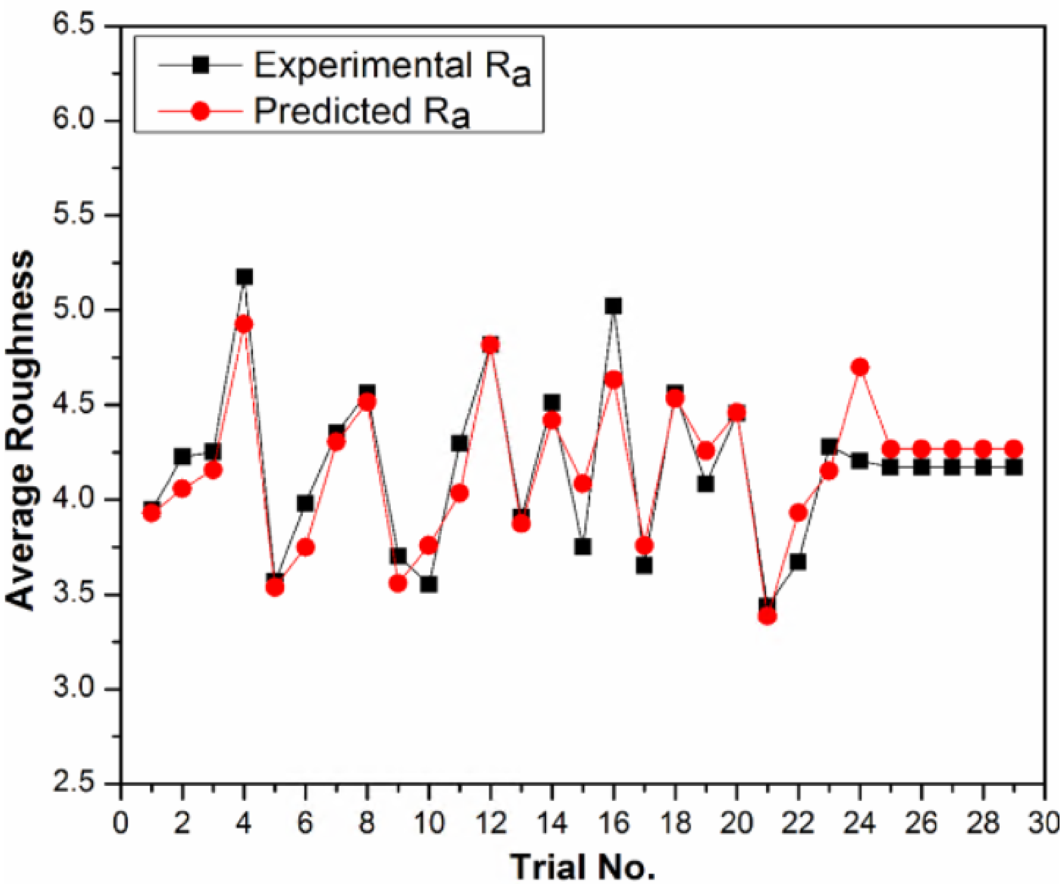
To understand the effect of for independent parameters on measured output response R_a, general sensitivity analysis were carried out. First order derivative was used calculating the sensitivity of a particluar input parameter, followed by calculation of sensitivity coefficients by varying the input parameter of interest within its range while maintaing the other two input parameters were kept at their repective mean levels.

$$\frac{dR_a}{dt} = -0.174426 + 0.02D - 0.000103N + 0.416459f \tag{3}$$

$$\frac{dR_a}{dD} = -0.103 + 0.02t \tag{4}$$

$$\frac{dR_a}{dN} = 0.001538 - 0.000103\ t \tag{5}$$

Figure 3. Comparison of the experimental and predicted results



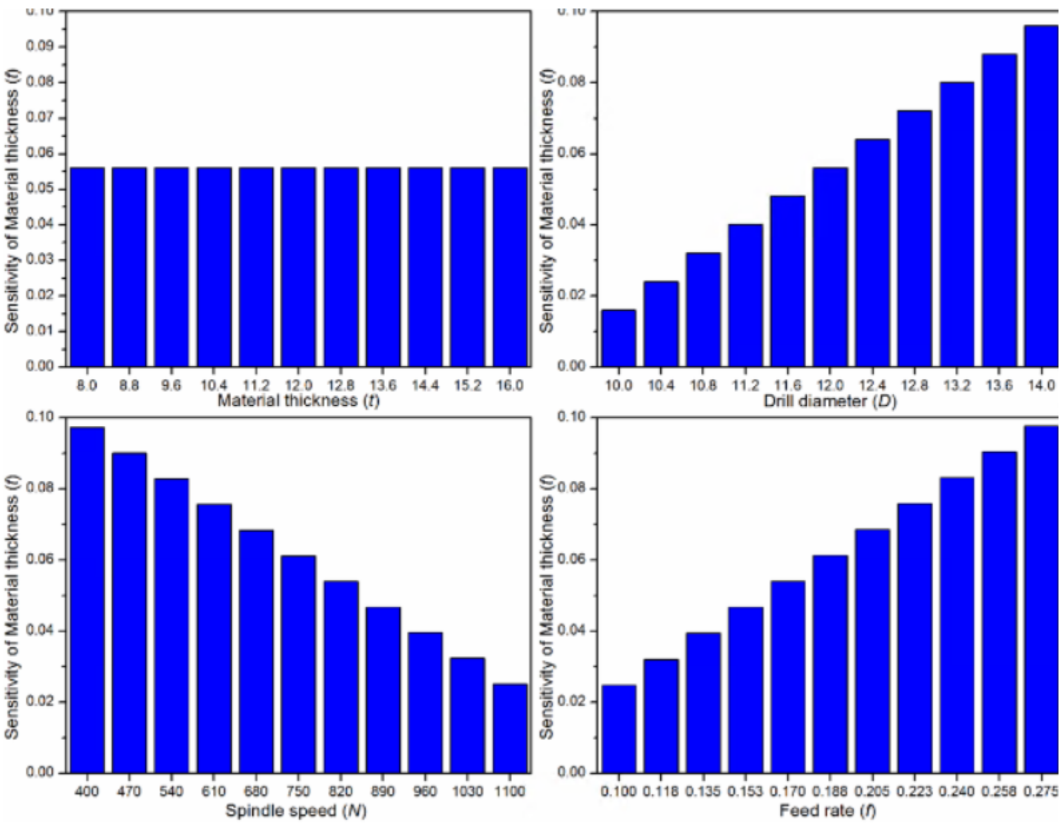
$$\frac{dR_a}{df} = 13.402897 + 0.416459\ t - 74.765364\ f \tag{6}$$

Fig. 4 represents the sensitivity of material thickness (t) to the surface roughness of the workpiece. The sensitivity indexes in Fig. 3 are calculated by using Eqn. 4. In Fig. 4(a), material thickness is varied within its range while keeping other parameters— D, N and f at their mean value. Similarly, by keeping other parameters constant at mean value and varying drill diameter (D) Fig 4(b) is obtained and so on. It can be observed that sensitivity of material thickness (t) to the surface roughness is always positive. In fig. 4(b), the sensitivity of material thickness (t) to the surface roughness with use of larger diameter drills. Similarly, increasing the f causes the sensitivity of t to the surface roughness to increase, while increasing the N causes the t to monotonically become less sensitive.

Fig. 5 illustrates the sensitivity of drill diameter (D) to the surface roughness of the workpiece calculated using Eqn. 5. Despite being positive in all the cases, the sensitivity of drill diameter (D) is unaffected by changes in D, N and f. However, progressively increasing the material thickness (t), positively enhances the sensitivity of D to R_a .

Fig. 6 depicts the sensitivity of N to the R_a of the workpiece calculated using Eqn. 6. Like the earlier case, the increase or decrease in D, N and f does not affect the sensitivity of N to R_a . But

Figure 4. Sensitivity of material thickness (t) on surface roughness



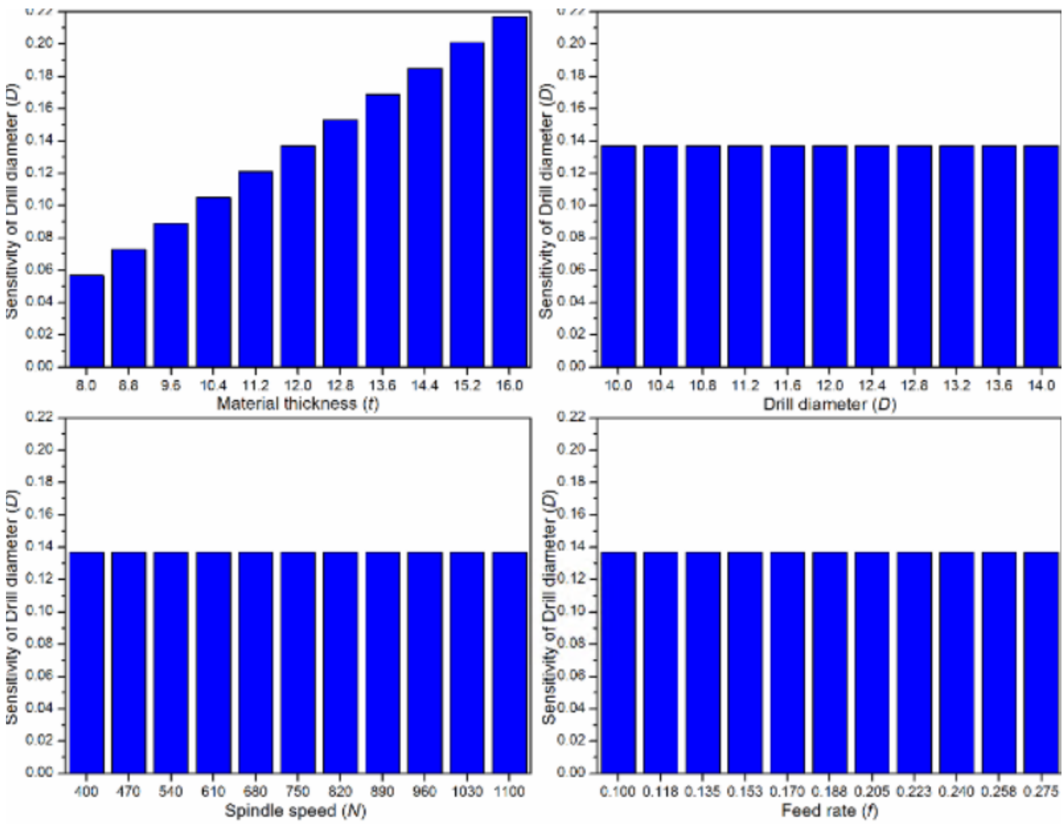
when the material thickness (t) is progressively increased, the sensitivity of N to the R_a gradually decreases from positive to negative.

Fig. 7 illustrates the sensitivity of f to R_a of the workpiece calculated using Eqn. 7. The sensitivity of f to R_a seems to be unaffected by variations in D and N. Increasing t causes the sensitivity of f to R_a to increase. However, it gradually decreases from being positively sensitive to become increasingly negatively sensitive as the feed rate (f) is increased.

3.4 Interaction Effect of the Parameters

Making use of metamodel, the consequences of the procedure parameters on the average roughness of the surface is investigated. Fig. 8, 9 and 10 shows the interaction effect of the terms '*tD*', '*tN*' and '*tf*' on surface roughness. f is the utmost crucial parameter in the drilling process and then the material thickness (t) and drill diameter (D). Hansda and Banerjee (Hansda & Banerjee, 2014) has also reported f to be the most significant parameter involved in the drilling of composite laminates. The optimisation results depicted that the roughness of the surface parameters increased as f increased and a minor value of drill diameter is the most appropriate to attain minimum surface roughness. Tan el al. (Tan, Azmi, & Muhammad, 2016) in their work has also found the feed rate to be most important among the considered parameters. However, they had considered spindle speed and tool geometry as the other parameters as opposed to this work where t, N and D are considered. Further, the investigations show that with an increase in spindle speed the R_a intensifies. This is primarily because with increased

Figure 5. Sensitivity of drill diameter (D) on surface roughness



spindle speed the generated forces also increase which in turn drills the laminate smoothly thereby reducing the surface roughness.

3.5 Predicting the Optimal Process Parameters by GA

Empirical equation (Eqn. 2) for R_a in the drilling of GFRP composites formed is used as the objective function for optimization using a genetic algorithm. A FORTRAN code has been compiled for executing the GA. The variables— t, f, N and D are coded in the binary string. String length of each of the four variables is taken as 4. Crossover rate of 90% and mutation rate of 2% is fixed. An initial population of 100 arbitrary individuals is generated, and the iterations are allowed to take place for 100 generation. Multiple re-runs of the algorithm with independent seeds is carried out. The problem is formulated as an optimization problem where the goal is to minimize R_a.

i.e. minimize average surface roughness, with the limits,

$8 \leq t \leq 16$

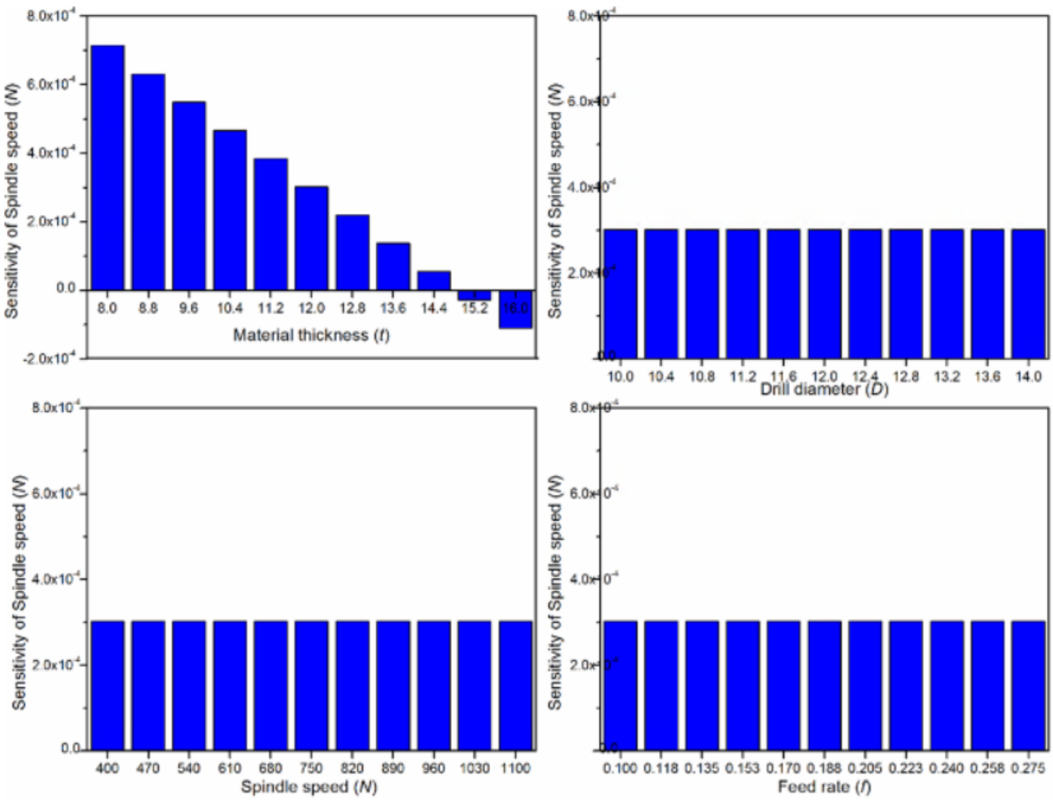
$10 \leq D \leq 14$

$400 \leq N \leq 1100$

$0.1 \leq f \leq 0.275$

Fig. 11 shows the performance of the GA across the generations. The optimal process parameters are found in generation 21 and are reported in Table 4 along with the predicted maximum average surface roughness.

Figure 6. Sensitivity of spindle speed (N) on surface roughness



3.6 Robustness of the Optimal Solution

In this section, the robustness of the predicted optimal solution is critically analysed. Since there is an inherent uncertainty associated with traditional machining processes, it is important to analyse the robustness of the predicted optimal process parameters. This will provide an understanding of the effect of unwanted human or operational errors that may creep in during the machining process. The percentage variation of the response with respect to optimum at ±5% of the optimum process parameters is plotted in Fig. 12. It is seen that the variation in the predicted response is about ±3%. Further, it should be noted that while considering the ±5% uncertainty in parameters the bounds of the process parameters discussed in section 3.5 are not followed. This is why even better values than the predicted optimal solution obtained in section 3.5 is seen in Fig. 12.

Figure 7. Sensitivity of feed rate (f) on surface roughness

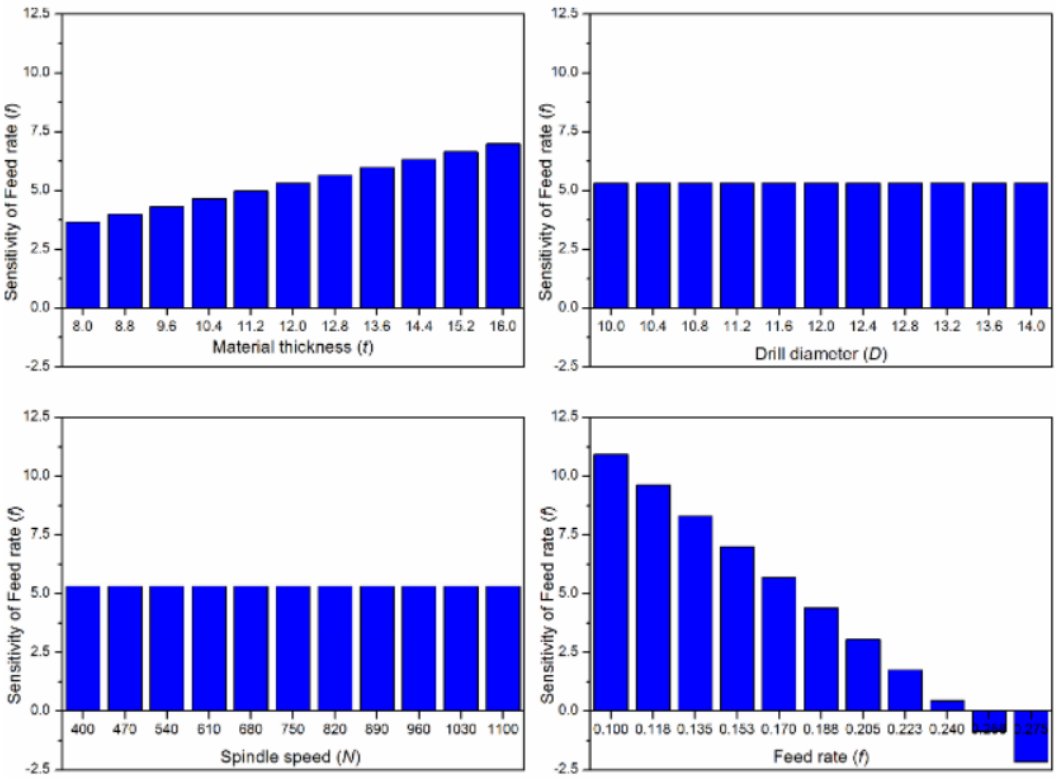


Figure 8. Interaction effect of thickness (t) and drill diameter (d) on average surface roughness

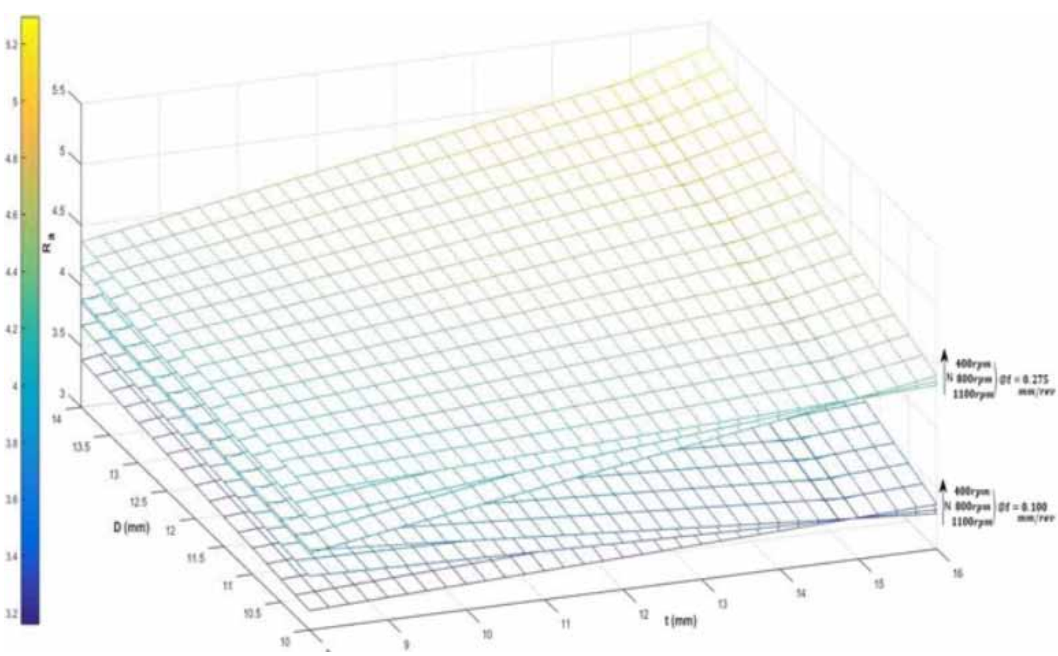


Figure 9. Interaction effect of thickness (t) and Spindle speed (N) on average surface roughness

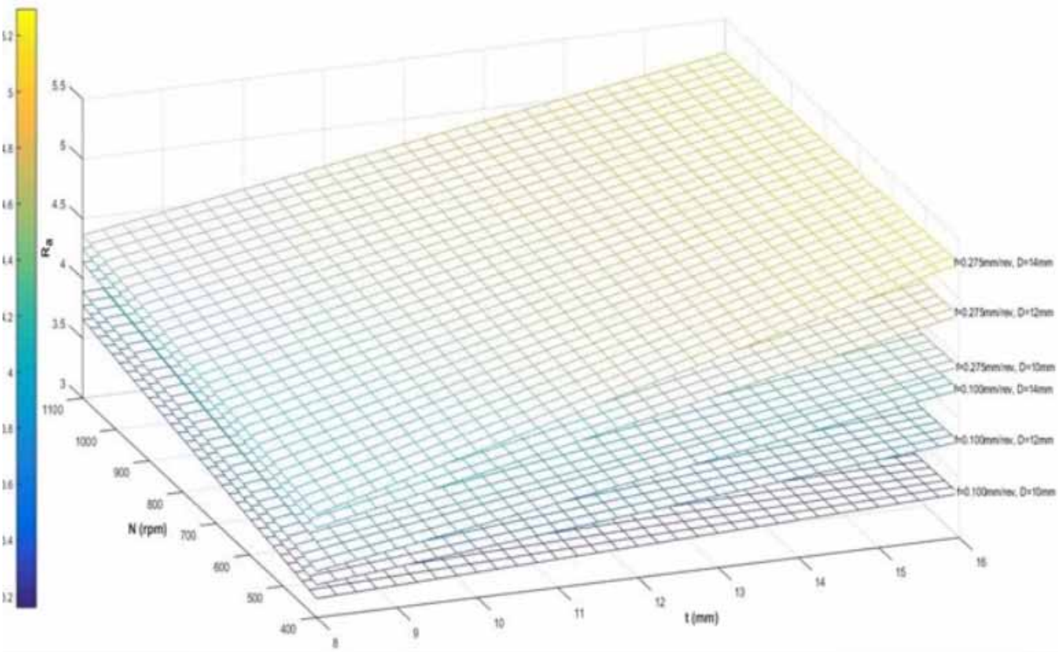


Figure 10. Interaction effect of thickness (t) and feed rate (f) on average surface roughness seen.

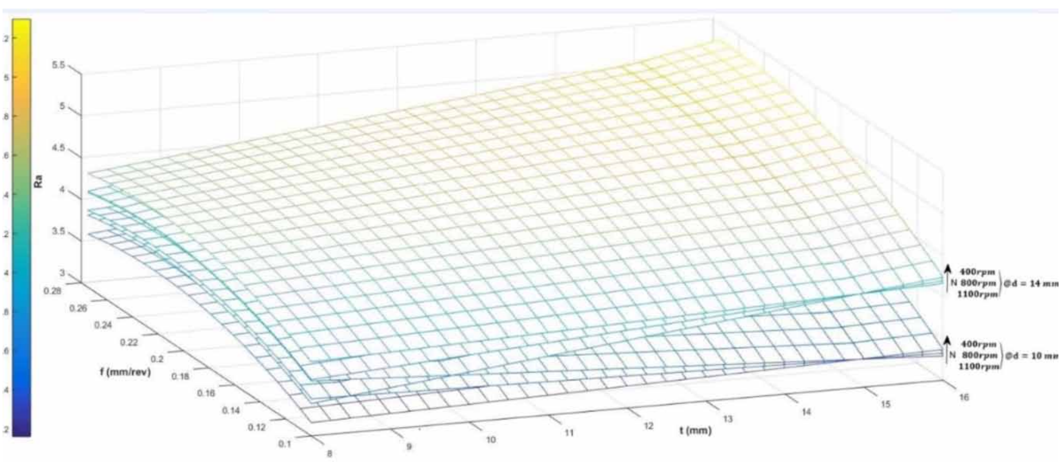


Figure 11. Performance of the GA across 100 generations

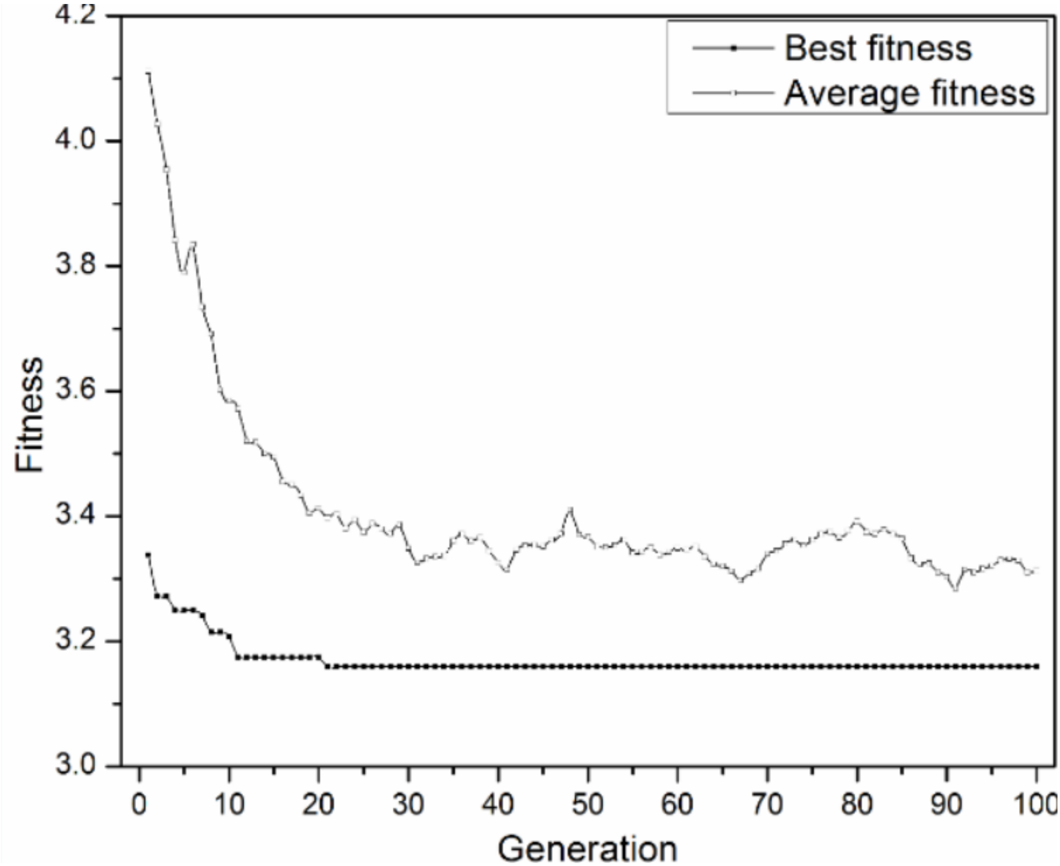
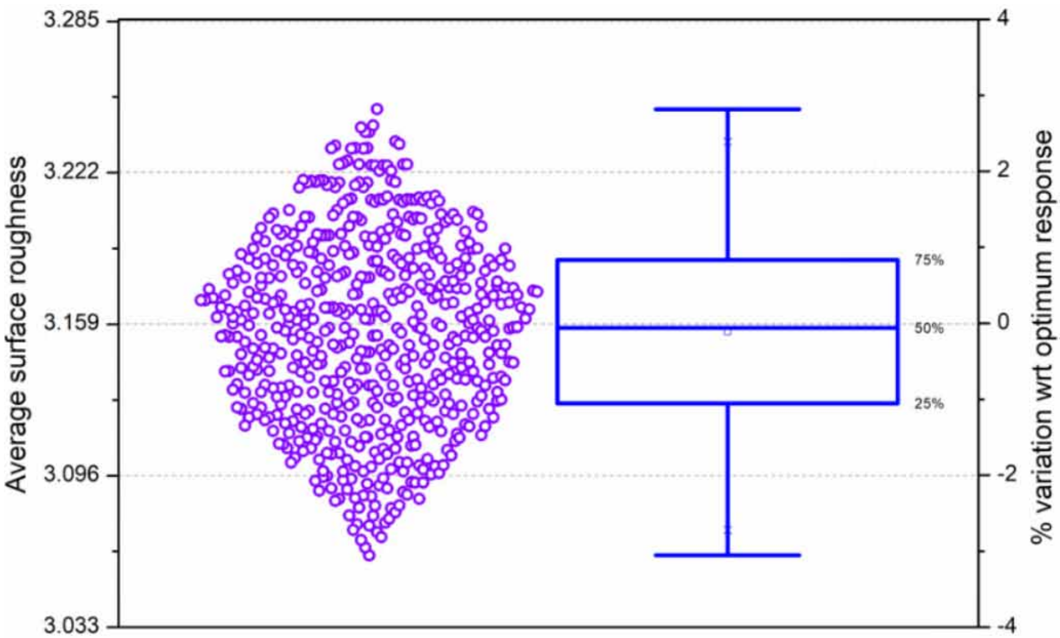


Table 4. Optimum parameters predicted by genetic algorithm

Material Thickness, t (mm)	Drill diameter, D (mm)	Spindle Speed, N (rpm)	Feed rate, f (mm/rev)	Average surface roughness, R_a (µm)
8	10	400	0.1	3.1596

Figure 12. Variation in the predicted solutions by considering ±5% uncertainty in the optimized process parameters.



4. CONCLUSION

Based on the experimentation on GFRP composite laminates and the statistical analysis performed the following conclusion can be drawn-

- The experimental data are in close proximity (overall variation less than 4%) with the RSM predictions, which indicate that the generated empirical equation is useful in predicting the response.
- Feed rate (f) is the most vital parameter in the drilling process followed by the material thickness (t) and finally drill diameter (D).
- The optimization results showed that the surface roughness parameters increased as the feed rate increased and a smaller value of drill diameter is vital for the minimum surface roughness.
- The genetic algorithm suggests that low parameter settings are better equipped in reducing the surface roughness.
- A comprehensive assessment of the robustness of the solution by considering $\pm 5\%$ variation in optimized process parameters shows that the predicted solution varies only $\pm 3\%$ with respect to the predicted optimal response.

Thus, this approach can be used as a reliable predictive analysis and optimization tool, which would, in turn, lead to a significant increase in efficiency and productivity.

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