Machine Learning with Applications 6 (2021) 100099

Contents lists available at ScienceDirect

Machine Learning with Applications

journal homepage: www.elsevier.com/locate/mlwa

Machine learning and statistical approach in modeling and optimization of surface roughness in wire electrical discharge machining

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ARTICLE INFO

Keywords:
Artificial neural network
Support vector machine
Response surface methodology
Genetic algorithm
WEDM
Surface roughness

ABSTRACT

The current work implements machine learning techniques such as artificial neural network (ANN), support vector machine (SVM), and genetic algorithm (GA) to model and optimize the surface roughness during wire electrical discharge machining (WEDM) of Inconel 718. For this, surface roughness values were obtained from real-time WEDM experiments conducted under the different levels of control factors such as pulse on time, pulse off time, peak current, servo voltage, and wire feed rate. The optimum ANN model architecture was identified as 5-10-10-1 and SVM parameters were tuned with the help of the grid search technique. The ANN and SVM models' predictions were compared with response surface methodology (RSM) predictions and performance was evaluated based on correlation coefficient (*R-value*) between experimental and model predictions. The SVM predictions were accurate among all the models studied, as determined from the *R-value* of 0.99998 with experimental results and the least mean absolute percentage error (MAPE) of 0.0347%. Further, the GA approach was implemented using the developed RSM equation as the fitness function and led to 61.31% improvement in the surface roughness. The proposed SVM and GA approach would help quick and high accurate prediction and optimization of surface roughness during WEDM of Inconel 718.

1. Introduction

Inconel 718 is one of the highly preferred nickel-based superalloys due to some of its imperative advantages, such as displaying resistance against thermal fatigue, high resistance to corrosion, high melting temperatures, low density, etc. Inconel 718 finds wide applications in aerospace, power generation, jet engines, gas turbine operations, and automotive high-temperature applications due to superior properties (Movahedi et al., 2020). The high strain hardening behavior leads to improper machining by traditional methods cause several implications like rapid tool wear, burr formation, improper surface finish, formation of snarled, and ribbon chips. To overcome these limitations, an unconventional machining process WEDM has been projected as an alternative method for conventional machining (Sharma et al., 2018).

WEDM process is effective in machining hard to cut materials like hardened steels and ceramics into precise and complex geometric profiles with high tolerance (Sanchez et al., 2006, 2007). Even though the WEDM approach is one of the leading unconventional machining methods, investigations on the process performance are still unknown. Further, the understanding of the process has been complex due to its intricacy, stochastic nature, and involvement of scads of parameters such as electrode feed rate, duty factor, peak current, pulse on time, voltage, wire tension, pulse off time, and dielectric flow rate, etc. (Ramakrishnan & Karunamoorthy, 2008). Novel algorithms have been developed for modeling WEDM process parameters and understanding the significance of each input variables on response values (Rakesh Chaudhari et al., 2019). In addition to various approaches, describing the relationship between process parameters and outputs through data-based machine learning approach is found to be highly beneficial due to their capability to yield greater efficiency in very less time (Paturi et al., 2021).

Computational techniques such as ANN, SVM, GA, etc., have become very popular in process modeling and optimization due to their great prediction capability with a high degree of accuracy. These techniques promise to expedite more acceptable results than statistical methods and are highly reliable for improving the process efficiency. They can approximate any function with a high-dimensional system and are flexible in simulating nonlinear behavior datasets (Otchere et al., 2021). Many researchers have explored the computational techniques in conventional machining methods (turning Gupta et al., 2015;

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https://doi.org/10.1016/j.mlwa.2021.100099
Received 3 May 2021; Received in revised form 12 June 2021; Accepted 25 June 2021
Available online 30 June 2021

Table 1
WEDM experimental setting parameters and their levels.

Parameter/ level	Pulse on time (μs)	Pulse off time (μs)	Peak current (A)	Servo voltage (V)	Wire feed rate (m/min)
1	100	50	10	30	3
2	105	55	15	40	6
3	110	60	20	50	9

Paturi et al., 2020, grinding Yang & Yu, 2012, milling Yeganefar et al., 2019, and welding Tian & Luo, 2020), bio-medical (Kaur & Kumari, 2019; Maltarollo et al., 2019), bio-mechanical (Reddy et al., 2021), construction (Wang et al., 2017), business management (Maita et al., 2015), energy resources (Gonçalves et al., 2011; Majumder & Saha, 2016; Peter & Raglend, 2017), food analysis (Zareef et al., 2020), environmental application (Li et al., 2018; Mohaptra et al., 2016; Narayana et al., 2021), etc.

In a study (Sivanaga Malleswara Rao et al., 2017), both SVM and ANN techniques were employed to model the WEDM parameters. The study demonstrated that the SVM results were substantial and were in good agreement with experiment values compared to ANN model predictions. GA and ANN techniques were implemented to optimize the input parameters and model the material removal rate (MRR) and surface roughness of TiB_2 nanocomposite ceramic in the WEDM process (Amini et al., 2011). ANN was implemented to model and predict the relationship between the process inputs and output responses in WEDM of Inconel 718 (Yusoff et al., 2018). The SVM method was exercised to estimate the height of the workpiece for reciprocated traveling WEDM (Huang et al., 2018). The SVM algorithm is integrated with a CNC system to optimize the machining conditions, and the verification results estimated height with an error of less than 2 mm. ANN and multi-GA methods were implemented to optimize the machining performance in WEDM of Ti-48Al-4Cr (Yusoff et al., 2019). In another study, gray relational analysis and SVM technique were utilized to model the process variables and predict the MRR and surface roughness characteristics during WEDM on superalloy Udimet-L605 (Nain et al., 2017). Similarly, the WEDM process parameters were optimized using gray relational analysis combined with GA and optimal results were generated (Varun & Venkaiah, 2015). ANN was employed to model and predict the surface roughness and acoustic emission (AE) signals while machining titanium material in WEDM. It is concluded that the ANN model trained with 70% datasets exhibited a good correlation with experimental values (Jain et al., 2017). GA was successfully implemented to optimize the kerf width of Ti6Al4V alloy in WEDM as a function of heat treatment (Altug et al., 2015). The back propagation neural network (BPNN) model was opted to model and predict the process parameters in WEDM of pure tungsten and concluded that the output response was closely matched with the experimental results (Chen et al., 2010). To investigate precision on machining holes by WEDM on aluminum 6061, GA was employed to yield optimal results for optimizing the process parameters (Sunkara et al., 2020).

From the literature review presented, the studies were not found to be comprehensive, and a very limited amount of research has been reported highlighting the suitable model to implement in WEDM of Inconel 718. Therefore, this study focuses on a comparative approach of ANN, SVM and GA discretely to obtain the most precise model to predict and optimize the surface roughness. The ANN and SVM models' predictions are compared with the RSM model results to demonstrate each model efficiency. Finally, the responses of all the models are analyzed based on *R-value* and MAPE.

2. Experimental procedure

The WEDM experimental setup consists of a workpiece mounting table, wire-driven section, dielectric fluid supply unit, and machining power supply with computer-controlled pulse spark generator. The brass wire of 250 μm diameter is used as the electrode. In all the experiments, de-ionized water is used as the di-electric medium. The wire electrode under constant tension is drawn over a wire drum which rotates in both directions. The dielectric medium temperature and flushing pressure are set at 27 °C and 12 kg/cm^2 respectively. In WEDM experiments, Inconel 718 workpiece of 200 mm × 100 mm × 10 mm dimension is used. To measure the surface roughness (Ra) of WEDM specimens, Mitutoyo talysurf profile meter was used. Surface roughness measurements were repeated three times on each specimen, then the average of these measurements was considered as surface roughness. The WEDM experimental setup and fabricated specimens of the work are presented in Fig. 1.

Table 2
Experimentally measured surface roughness results.

Exp. No.	Pulse on time (μs)	Pulse off time (μs)	Peak current (A)	Servo voltage (V)	Wire feed rate (m/min)	Surface roughness (μm)	Surface roughness in VDI scale (CH)
1	100	50	10	30	3	0.853	19
2	100	50	10	30	6	0.838	18
3	100	50	10	30	9	0.828	18
4	105	55	10	40	3	0.898	19
5	105	55	10	40	6	0.964	20
6	105	55	10	40	9	1.013	20
7	110	60	10	50	3	0.906	19
8	110	60	10	50	6	0.805	18
9	110	60	10	50	9	0.694	17
10	105	60	15	30	3	1.847	25
11	105	60	15	30	6	2.052	26
12	105	60	15	30	9	2.281	27
13	110	50	15	40	3	1.846	25
14	110	50	15	40	6	2.051	26
15	110	50	15	40	9	2.274	27
16	100	55	15	50	3	2.031	26
17	100	55	15	50	6	1.676	24
18	100	55	15	50	9	1.343	23
19	110	55	20	30	3	1.560	24
20	110	55	20	30	6	1.736	25
21	110	55	20	30	9	2.223	27
22	100	60	20	40	3	2.120	27
23	100	60	20	40	6	1.941	26
24	100	60	20	40	9	1.983	26
25	105	50	20	50	3	1.670	24
26	105	50	20	50	6	1.767	25
27	105	50	20	50	9	1.893	26

To estimate the influence of WEDM process parameters, i.e., pulse on time, pulse off time, peak current, servo voltage, and wire feed rate, on the machined surface quality (surface roughness), their different levels were used (Table 1). The L_{27} orthogonal array is utilized in the plan of WEDM experiments. The experimentally obtained surface roughness results are shown in Table 2. Also, surface roughness values are converted into VDI scale for better understanding of the obtained surface texture on the workpiece.

3. Modeling approach

3.1. ANN modeling

A multilayer feedforward neural network was used to model the measured surface roughness in WEDM of Inconel 718. MATLAB neural network toolbox has been utilized for the purpose and data was

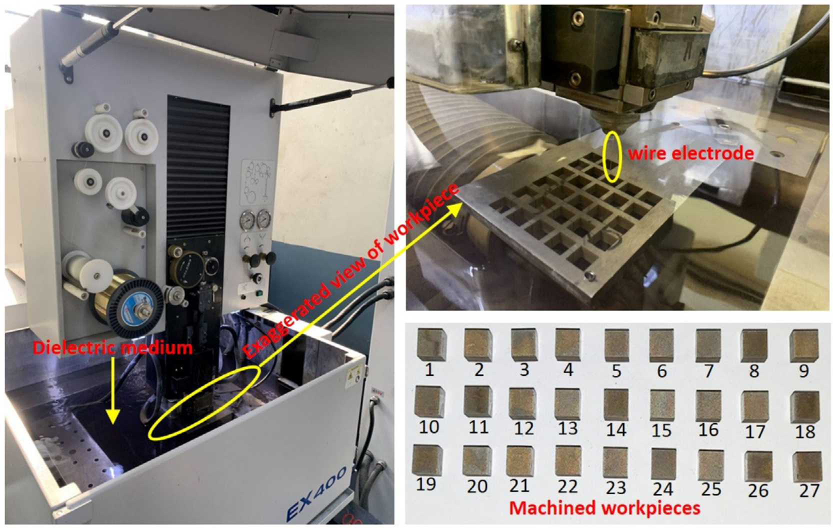

Fig. 1. WEDM experimental setup and fabricated workpieces.

separated in the ratio of 5:1:1 for training, testing, and validation respectively. Data was supplied in the form of two different matrices i.e., inputs and targets for training the neural network model. Backpropagation algorithm with Levenberg–Marquardt (*trainlm)* as a training function is chosen for the network. Hyperbolic tangent sigmoid function (*tansig*) was considered an activation function for all the layers to develop nonlinear relations between independent and dependent parameters. WEDM process parameters such as pulse on time, pulse off time, peak current, servo voltage, and wire feed rate were taken as inputs, with the output being surface roughness. An optimal neural network architecture was designed based on the statistical parameters of average error (AE) and mean sum squared error (MSE) between predicted and target values. AE and MSE calculations were performed using Eqs. (1) and (2) respectively.

$$AE = \frac{1}{N}\sum_{i=1}^{N}\left(\left|t_i - td_i\right|\right) \tag{1}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2 \tag{2}$$

where, t_i is the experimental data, td_i is the ANN predicted data, and N denotes the total datasets.

3.2. SVM modeling

Support vector regression modeling of surface roughness was carried out by implementing Libsvm MATLAB interface (Chang & Lin, 2011). SVM is highly sensitive to hyperplane parameters such as kernel function, epsilon, box constraint, and gamma, it is essential to determine the optimum hyperplane parameters before modeling. Fig. 2 demonstrates the generalized view of the support vector regression nonlinear model. The graph (Fig. 2) clearly depicts the main objective of the SVM model i.e., to obtain the maximum number of points within the range of epsilon (ε) using optimal hyperplane parameters. Therefore, initially, grid search was performed using python programming to avoid modeling drawbacks such as overfitting and underfitting of data. Different ranges of hyperplane parameters that were opted for selecting the best parameters are given in Table 3. In grid search, experimental data was divided into training and testing data in the size of 70% and 30%, respectively. Data was trained with different hyperplane parameters during grid search and prediction errors were observed. The model that resulted in the least MSE during training, and testing has opted. Finally, SVM modeling was performed with the best and optimal parameters, and surface roughness was predicted.

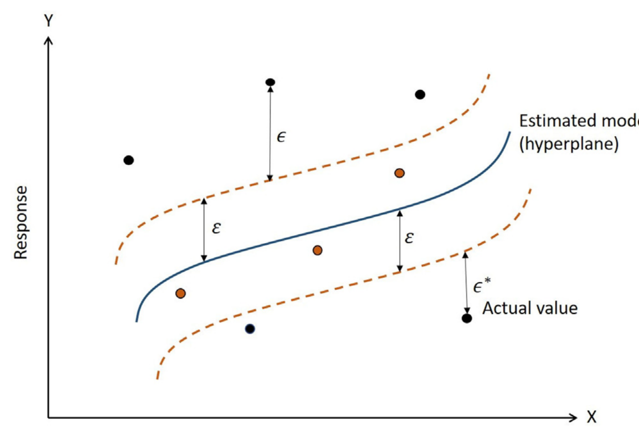

Fig. 2. Generalized view of SVM regression non-linear model.

Table 3
SVM initial conditions opted for performing grid search.

Hyperplane parameters	Conditions	Optimum parameters
C	1,10,100,1000	10
Epsilon	0.01,0.001,0.0001	0.01
Degree	3,4,5	3
Gamma	‘auto’, ‘scale.’	0.2
Kernel function	‘linear’,’poly’,’rbf’,’sigmoid’	‘rbf’

3.3. RSM modeling

To develop a relation between input and output parameters in a mathematical equation, a statistical tool, response surface methodology (RSM) was utilized. The WEDM process parameters and respective surface roughness were given as factors to the RSM model. The mathematical equation through which RSM modeling is performed is shown in Eq. (3). Moreover, analysis of variance (ANOVA) was performed to understand the influence of input parameters (pulse on time, pulse off time, peak current, servo voltage, and wire feed rate) on surface roughness. The percentage contribution of different factors in surface roughness variation was calculated, through which the most affecting parameter was determined. Performance of developed regression model was assessed based on correlation coefficient (R-value) between predicted and experimental results.

$$y_1 = \beta_0 + \beta_1 x_{11} + \beta_2 x_{12} + \cdots \beta_k x_{1k} + \in \tag{3}$$

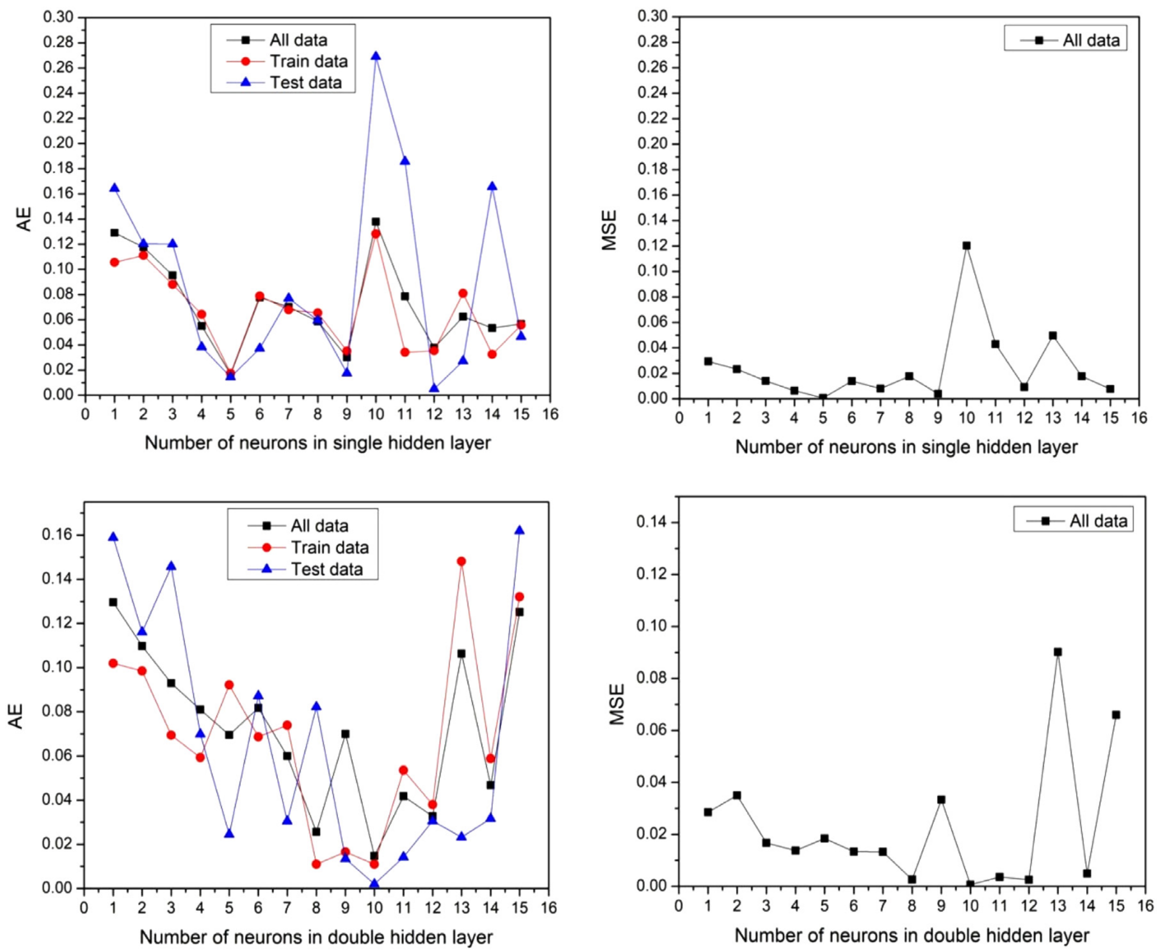

Fig. 3. AE and MSE against varying neurons in single hidden and double hidden layer.

where, y refers to response, x_{11}, x_{12}, …..x_{1k} refers to factors, β_1, β_2, ….β_k refers to coefficients, ∈ refers to error.

3.4. Optimization using genetic algorithm (GA)

To find the optimal input parameters, it is highly essential to improve the response value. In the present work, GA was employed to determine the optimum process parameters in WEDM of Inconel 718 at which minimum surface roughness is noticed. Optim toolbox from the MATLAB software has been utilized for GA optimization. The developed RSM model is used as a fitness function with variables as a pulse on time, pulse off time, peak current, servo voltage, wire feed rate, and surface roughness as response. The lower and upper bounds of variables were selected according to the experimental data. Population type, population size, number of generations, and type of function opted for GA optimization are given in Table 4. Optimization was carried out until the average change in the fitness value is less than the desired tolerance. Finally, the optimized process parameters and surface roughness at those conditions were obtained. Response value calculated at optimum conditions was compared with the experimental results.

Table 4
Conditions adopted in GA optimization.

Parameters	Conditions
Population size	50
Population type	Double vector
Number of generations	500
Selection function	Stochastic uniform
Lower bounds	(100 50 10 30 3)
Upper bounds	(110 60 20 50 9)

4. Results and discussion

Present work is designed to predict the surface roughness of Inconel 718 and examine the effect of WEDM process parameters on the surface roughness. The data shown in Table 2 were used to evaluate, model, and interpret the surface roughness using ANN, SVM and statistical RSM techniques. Surface roughness is accurately predicted using ANN and SVM methods and GA has been successfully implemented to determine the optimal WEDM process parameters. Combined effects of WEDM process parameters on the surface roughness are depicted by generating 3D surface plots and contour plots. Finally, ANN, SVM and RSM model efficacy was analyzed by comparing the model predictions with the experimental results.

4.1. ANN model predictions

Optimum neural network architecture was selected based on AE and MSE of train data, test data, and all data sets. With a different number of neurons and layers, the model was trained, tested, validated, and respective error at each neuron was calculated. Fig. 3 depicts AE and MSE at a different number of neurons in single and double hidden layers. From Fig. 3, it is observed that a neural network with ten neurons in two hidden layers has shown a minimum AE and MSE of 0.001968 and 5.02E−06 respectively for test data. Similarly, AE and MSE have also observed to very less for train data and all data compared to other

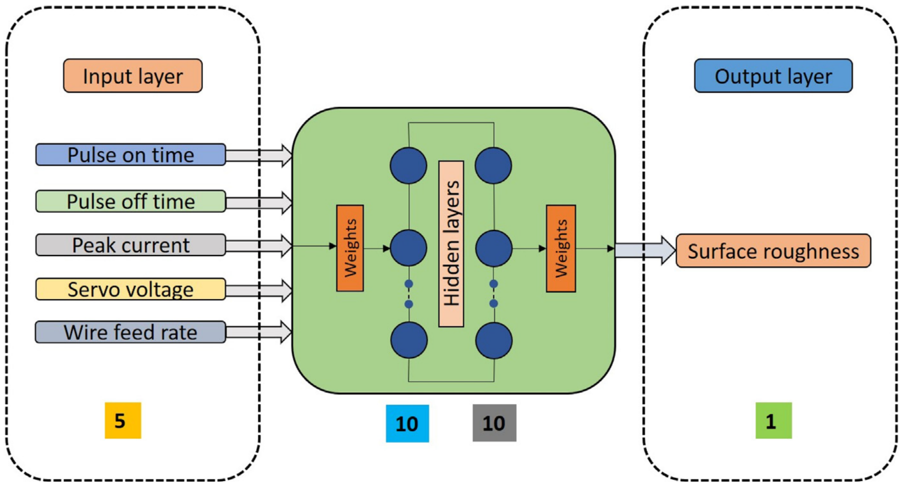

Fig. 4. Optimum neural network architecture with 5-10-10-1 topology.

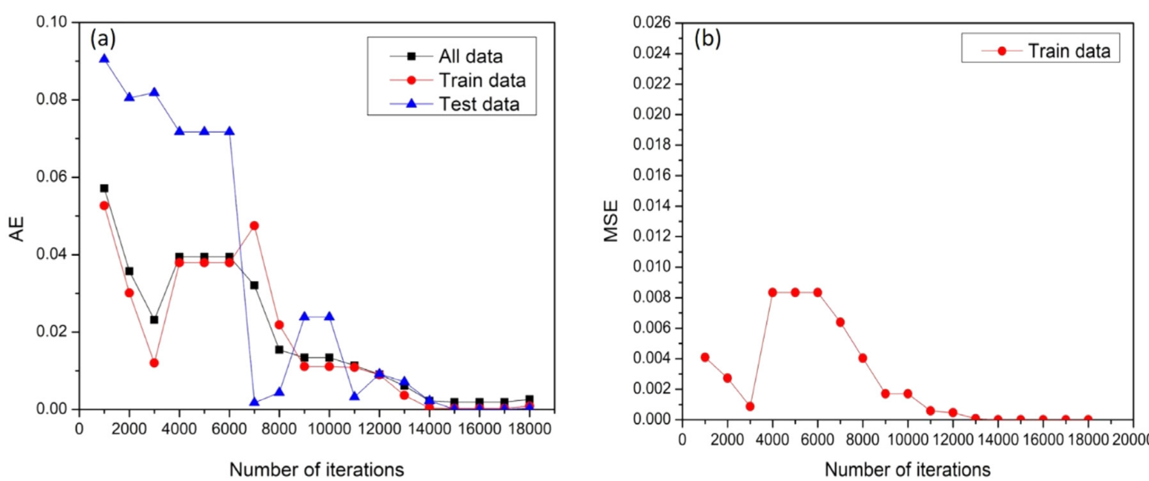

Fig. 5. AE and MSE variation against number of iterations.

neural network architectures. Thus, a neural network model with 5-10-10-1 topology was opted for predicting the surface roughness. A schematic view of developed optimum ANN architecture is given in Fig. 4.

Later, to avoid overtraining of the developed ANN model, it was again trained with several iterations. AE and MSE at a different number of iterations were calculated to observe the performance of the model. AE and MSE variation against the number of iterations are shown in Fig. 5. From Fig. 5, it is noticed that AE and MSE of train data, test data, and all data have found to be minimum at 14 000 iterations and are approximately constant up to 17 000 iterations and started increasing suddenly at 18 000 iterations. Hence, the training was stopped at 17 000 iterations, and respective AE values of train data, test data, and all data are 0.000324, 0.000049, and 0.001893.

Finally, the ANN model performance was evaluated based on the *R-value* by comparing predicted and actual values. Fig. 6 presents the correlation graph obtained for the developed ANN model. From Fig. 6, it is understood that the *R-value* of training, test, and validation data have been found to be 0.9998, 0.99932, and 1, respectively, indicating greater accuracy of the ANN model. *R-value* of 0.99988 for all data suggests a significant agreement between ANN predicted values and experimentally measured surface roughness results.

4.2. SVM model predictions

Grid search was utilized for determining the optimal hyperplane parameters. Conditions given in Table 3 were used as hyperplane parameters for performing grid search. With 70% datasets, the model was trained to estimate the best parameters that result in low MSE and high *R-value*. Through grid search, it was found that model with hyperplane parameters; C = 10, epsilon = 0.01, gamma = 0.2, and kernel = ‘rbf’, has shown *R-value* of 0.9999 for train data and 0.99983 for test data. Thus, hyperplane parameters were optimized to find a perfect fit for the model.

With optimized conditions, the SVM model was implemented using libsvm MATLAB interface. Initially, the data was converted into sparse data to avoid zero elements and accelerate the process. The SVM model was trained until the maximum number of support vectors are obtained. At 30th iteration, the model has 27 support vectors, demonstrating the model’s significant accuracy. Hence, training has been stopped at 30th iteration, and the trained model was used for predicting the surface roughness.

Simultaneously, the model’s accuracy was calculated in terms of MSE and *R-value*. It has been found that the SVM model has shown an MSE of 5.70734e−06 and an *R-value* of 0.999985 for all data, indicating excellent prediction capability of the developed model. A correlation graph plotted between actual values and SVM predicted values are presented in Fig. 7.

4.3. RSM model predictions

The RSM model for surface roughness measured in WEDM of Inconel 718 was established based on experimentally data. With all the

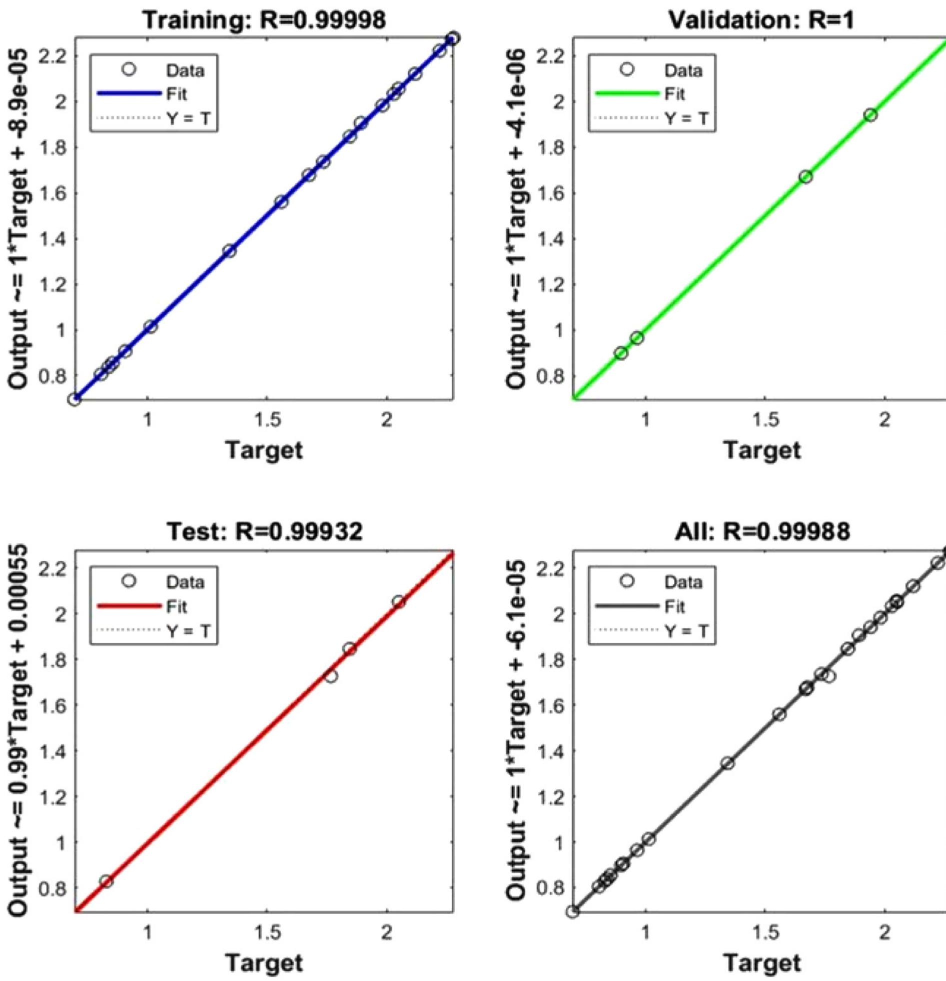

Fig. 6. Correlation between experimental results and ANN model predictions.

five independent parameters and their interactions, a second order polynomial equation has been derived. The developed RSM equation showing the relationship between surface roughness and different input parameters such as pulse on time, pulse off time, peak current, servo voltage, and wire feed rate is presented in Eq. (4). The developed RSM model depicts an accurate mathematical relation which can be used for predicting surface roughness with the aid of known coefficients.

$$\begin{aligned} Ra = & -17.8 + 0.443A - 0.406B + 0.7460C + 0.1624D \\ & - 0.751E - 0.00236A^2 + 0.00391B^2 - 0.02247C^2 - 0.001765D^2 \\ & + 0.00372E^2 + 0.00961A \times E - 0.00301B \times E \\ & + 0.00484C \times E - 0.004858D \times E \end{aligned} \tag{4}$$

where, A refers to pulse on time, B refers to pulse off time, C refers to peak current, D refers to servo voltage, and E refers to wire feed rate.

4.3.1. ANOVA for surface roughness

Analysis of variance (ANOVA) has been found to be the best tool for interpreting the data and determining the behavior of response value concerning input variables. In the present study, the WEDM experimental results were analyzed using ANOVA with 95% confidence level. The results of ANOVA for the measured surface roughness are presented in Table 5. The last column of the table indicates the percentage contribution (P) of each input factor in the total variation of surface roughness value. From Table 5, it can be observed that the peak current has the highest percentage contribution compared to other input parameters, indicating it is the most influencing parameter in surface roughness variation. The influence of different input parameters on surface roughness is as follows: peak current (60.21%), servo voltage (1.49%), wire feed rate (0.46%), pulse on time (0.16%), and pulse off time (0.27%). Moreover, from the *P-test* values of input variables in Table 5, it is perceived that the peak current is highly significant parameter with p value less than α i.e., 0.05. Thus, it can be clearly understood from the ANOVA results that a small change in peak current

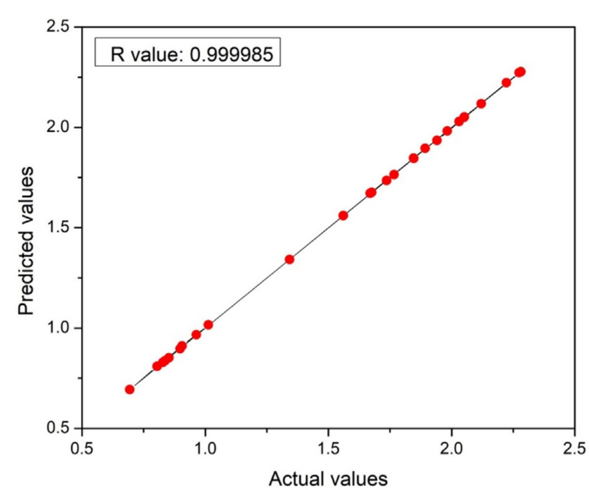

Fig. 7. Correlation between experimental results and SVM model predictions.

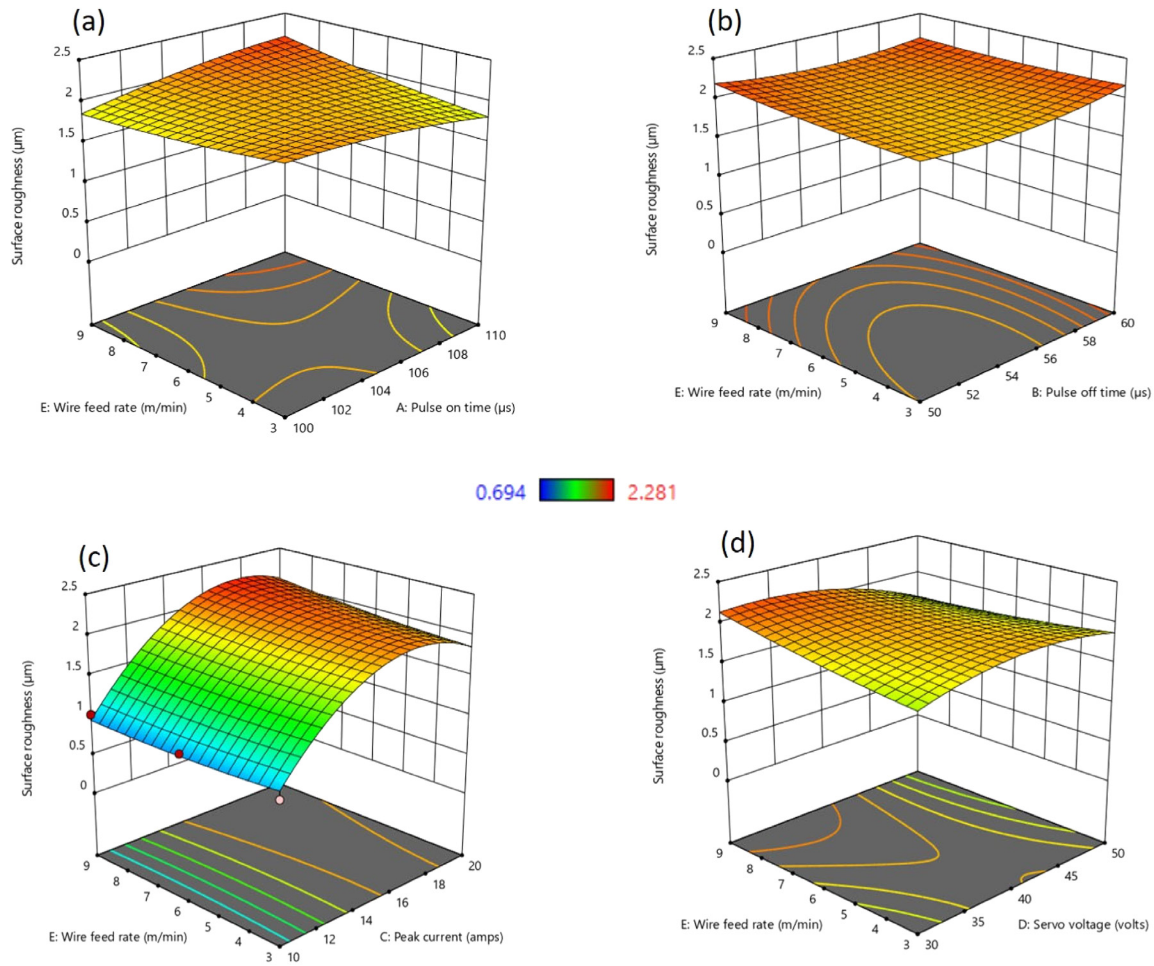

Fig. 8. 3D surface roughness plot surface roughness against WEDM parameters.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

leads to a significant difference in the surface roughness value, whereas the change in pulse on time has a negligible effect.

4.4. Parametric modeling

Surface roughness variation concerning different process parameters of WEDM is given in Fig. 8. Fig. 8 depicts the flat surface plot with constant color, indicating that change in wire feed rate, pulse on time, and pulse off time has minimal effect on surface roughness. From Fig. 8, it is also observed that change in wire feed rate led to a decrease in surface roughness value with less variation, whereas the difference in peak current resulted in higher variation with both increment and decrement of surface roughness values at different conditions. Moreover, contour plots presented in Fig. 9 depicts 2D visualization of surface roughness variation regarding process parameters. Fig. 9(a) indicate significantly less variation of surface roughness concerning pulse on time. Similarly, from Fig. 9(b), negligible change in surface roughness is observed with regard to pulse off time. Fig. 9(c) demonstrates the significant change in surface roughness against peak current as it is the most affecting parameter on surface roughness. Fig. 9(d) shows that change in servo voltage has a considerable effect on surface roughness value since it is the second most influencing parameter after peak current. Besides, from the ANOVA table, 3D surface plots, and contour plots, it can be perceived that any interaction involving peak current led to high variation in surface roughness value followed by servo voltage.

The correlation between RSM predicted values and experimental results is presented in Fig. 10. From Fig. 10, it is observed that the majority of RSM predicated values lie on the regression line with an overall *R-value* of 0.9873. Thus, RSM model has been found to be reasonable in establishing a relationship between surface roughness and WEDM process parameters but, compared to ANN and SVM models, it has less prediction capability.

4.5. Process optimization using GA

The developed RSM equation has been used as a fitness function in GA optimization. GA conditions given in Table 4 have opted for process optimization. Level 1 factors of process parameters were taken as lower bounds, and level 3 factors were considered upper bounds for GA optimization. The optimization was carried out until the average change in the fitness value is less than the desired tolerance. At the 126th iteration, the optimization has been terminated, and the best fitness objective value i.e., surface roughness, is 0.2685. The optimum conditions at which the minimum surface roughness is observed are pulse on-time = 100, pulse off time = 55.384, servo voltage = 10, peak current = 50, and wire feed rate = 9.

Fig. 11(a) presents the variation of fitness value at different generations. Between the 100 and 150th generation, the best fitness value of 0.2685 is observed. Importance of each individual variables that led to minimal surface roughness are given in Fig. 11(b). From Fig. 11(b), it is understood that at level 1 factors of pulse on-time and servo voltage, level 3 factors of peak current and wire feed rate, and pulse off time of 55.384, the best response value has been obtained. There is a greater improvement in the surface roughness value obtained through GA optimization compared to experimental results. The least surface roughness obtained through experiments was 0.694, whereas GA has

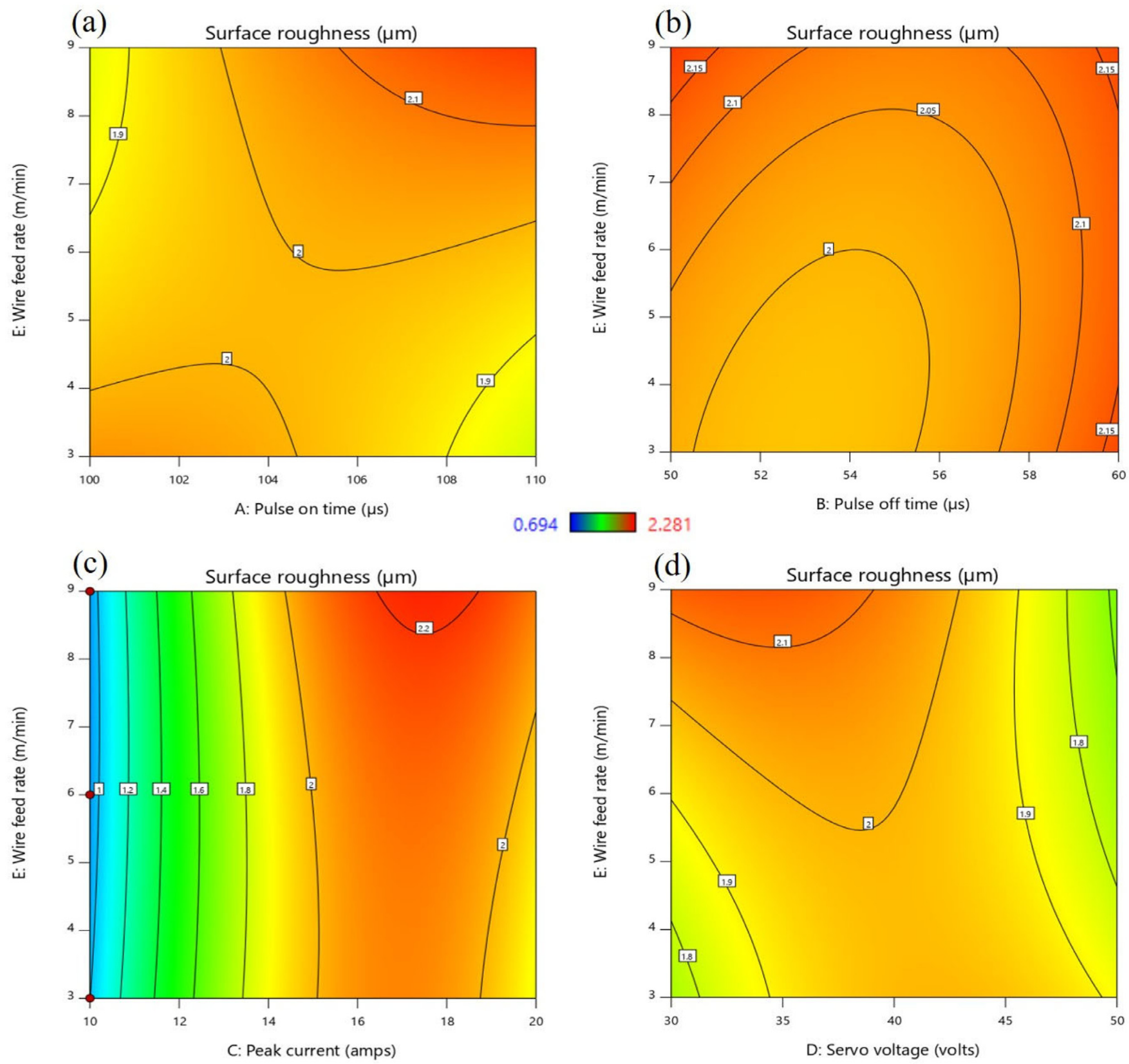

Fig. 9. Contour plots for surface roughness against WEDM parameters.

Table 5
ANOVA results for surface roughness.

Factors	Degrees of freedom	Sum of squares	Variance	Test F	Test P	PC (%)
A	1	0.0129	0.0129	1.6125	0.229	0.169144
B	1	0.0206	0.0206	2.5750	0.135	0.270021
C	1	4.59	4.59	573.75	< 0.0001	60.21059
D	1	0.1141	0.1141	14.2625	0.0027	1.495049
E	1	0.0356	0.0356	4.45	0.057	0.46712
AE	1	0.2491	0.2491	31.1375	0.0001	3.264707
BE	1	0.0244	0.0244	3.05	0.1072	0.319631
CE	1	0.0632	0.0632	7.9	0.0160	0.828496
DE	1	0.2549	0.2549	31.8625	0.0001	3.340672
A^2	1	0.0209	0.0209	2.6125	0.1331	0.27371
B^2	1	0.0574	0.0574	7.1750	0.0203	0.752593
C^2	1	1.89	1.89	236.25	< 0.0001	24.80528
D^2	1	0.1869	0.1869	23.3625	0.0004	2.449493
E^2	1	0.0067	0.0067	0.8375	0.3783	0.088242
Residual	12	0.0965	0.0080			1.265253
Total	26	7.63				100

given surface roughness of 0.2685, indicating a 61.31% improvement in the surface roughness. Hence, GA can be the best optimization tool to obtain better results during WEDM machining with optimum process conditions.

4.6. Comparison of ANN, SVM, and RSM model performance

The performance of the developed models used in the present study is compared based on correlation coefficient (*R-value*) and absolute percentage error (*Δ*). Absolute percentage error between predicted values and experimental results are calculated using Eq. (5). Table 6

Table 6
Comparison between experimental results and different model predictions.

S. No.	Experimental results	Model predictions			Absolute percentage error (Δ)		
		ANN	SVM	RSM	ANN	SVM	RSM
1	0.853	0.8548	0.8520	0.832167	0.215745	0.107143	2.442321
2	0.838	0.837393	0.838003	0.817333	0.072453	0.000299	2.466229
3	0.828	0.828559	0.828012	0.8695	0.067453	0.001418	5.012077
4	0.898	0.897042	0.897995	0.997583	0.106717	0.000596	11.08942
5	0.964	0.967183	0.964002	0.936	0.330165	0.000242	2.904564
6	1.013	1.015372	1.013005	0.941417	0.2342	0.000518	7.066436
7	0.906	0.911157	0.906008	0.887667	0.569193	0.000898	2.02351
8	0.805	0.809812	0.804979	0.779333	0.59773	0.002663	3.188447
9	0.694	0.694755	0.693393	0.738	0.108718	0.087487	6.340058
10	1.847	1.844856	1.846996	1.926	0.116066	0.00023	4.277206
11	2.052	2.052372	2.052002	2.03767	0.01815	8.57E−05	0.698343
12	2.281	2.280248	2.276998	2.21633	0.032947	0.175451	2.83516
13	1.846	1.846674	1.846001	1.8345	0.036515	5.17E−05	0.622969
14	2.051	2.056773	2.049904	2.03467	0.281477	0.053427	0.796197
15	2.274	2.272904	2.273946	2.30183	0.048187	0.002387	1.223835
16	2.031	2.033863	2.029032	1.93983	0.140971	0.096894	4.488922
17	1.676	1.677762	1.676019	1.661	0.105133	0.001157	0.894988
18	1.343	1.345138	1.342045	1.44917	0.159233	0.071105	7.905436
19	1.56	1.560037	1.560025	1.44392	0.002343	0.001634	7.441026
20	1.736	1.735264	1.736046	1.81733	0.042412	0.002651	4.684908
21	2.223	2.222397	2.223008	2.25775	0.027128	0.00036	1.563203
22	2.12	2.117912	2.121495	2.09792	0.09847	0.070538	1.041509
23	1.941	1.934971	1.941	1.99233	0.310626	1.15E−05	2.644513
24	1.983	1.982144	1.983009	1.95375	0.043143	0.000436	1.475038
25	1.67	1.671851	1.670002	1.77142	0.110862	0.000114	6.073054
26	1.767	1.726509	1.764921	1.75433	2.291486	0.117677	0.717035
27	1.893	1.906142	1.895702	1.80425	0.694268	0.142715	4.688325

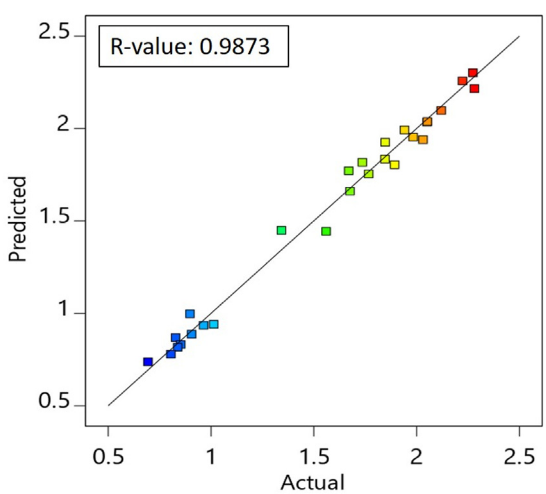

Fig. 10. Correlation between experimental results and RSM model predictions.

presents the calculated absolute percentage error of different models used in the present work.

$$\Delta = \left| \frac{Ra_{exp} - Ra_{pred}}{Ra_{exp}} \right| \times 100 \tag{5}$$

SVM has been found to be highly precise, with an *R-value* of 0.999985 and a maximum absolute percentage error of 0.142715% among all the techniques. Followingly, ANN and RSM have shown good accuracy with *R-values* of 0.9998 and 0.9873 with maximum absolute percentage error of 2.291% and 11.089%, respectively. Moreover, MAPE presented in Table 7 indicates high accuracy of SVM with 0.0347% followed by ANN and RSM with 0.2541% and 3.577% respectively. Hence, it is well understood that SVM model has the better prediction capability compared to ANN and RSM models and can the best option for modeling complex WEDM process.

Table 7
Efficacy of ANN, SVM and RSM model.

S. No.	Model	R-value	MAPE	Δ_{max}
1	ANN	0.9998	0.2541%	2.291%
2	SVM	0.9999	0.0347%	0.1427%
3	RSM	0.9873	3.577%	11.089%

5. Conclusion

In this work, an experimental and computational analysis for WEDM of Inconel 718 has been presented. The surface roughness values against different levels of control factors were measured by conducting WEDM experiments. Later, WEDM process was modeled, and surface roughness is predicted using SVM, ANN and RSM models. In addition, GA was employed to find the optimum parameters in WEDM process. The important conclusions are summarized below:

- The prediction capability of machine learning techniques (SVM and ANN) was found to be very accurate when compared to statistical RSM model. The MAPE between model predictions and experimental data is very low for SVM model (0.0347%) followed by ANN model (0.2541%) and RSM model (3.577%).
- A high *R-value* (99.9985%) of SVM model demonstrates that the developed model presents a significant harmony between model predictions and experimental results. Thus, the machine learning approach can analyze and model the WEDM process effectively and become a possible alternative to time consuming and expensive experiments.
- Optimal values of input parameters determined using GA led to better surface finish. An improvement of 61.31% in surface roughness value was observed after GA optimization. GA has found to be highly effective in optimizing the WEDM process parameters and yielding superior surface roughness with the aid of given fitness function.
- ANOVA explored the effect of process inputs and demonstrated that among all inputs, peak current has a significant impact on the output surface roughness with a percentage contribution of 60.21%.

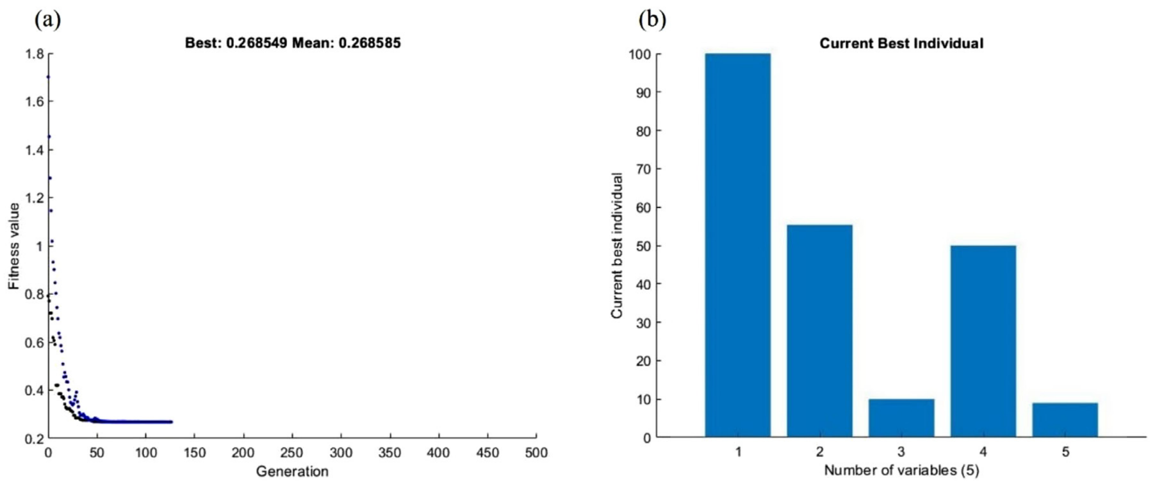

Fig. 11. **(a)** Fitness value against number of generations, and **(b)** optimized input variables.

CRediT authorship contribution statement

Uma Maheshwera Reddy Paturi: Conceptualization, Writing - review & editing. **Suryapavan Cheruku:** Software, Writing - original draft. **Venkat Phani Kumar Pasunuri:** Validation. **Sriteja Salike:** Investigation. **N.S. Reddy:** Methodology, Supervision. **Srija Cheruku:** Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The authors wish to thank the reviewers and the Editors for their productive comments which significantly improved in the quality of this research paper. Also, N.S. Reddy acknowledges YSJ and AJR for the inspiration.

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