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Original Article

Modeling and optimization of surface roughness in single point incremental forming process

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ABSTRACT

Single point incremental forming (SPIF) is a novel and potential process for sheet metal prototyping and low volume production applications. This article is focuses on the development of predictive models for surface roughness estimation in SPIF process. Surface roughness in SPIF has been modeled using three different techniques namely, Artificial Neural Networks (ANN), Support Vector Regression (SVR) and Genetic Programming (GP). In the development of these predictive models, tool diameter, step depth, wall angle, feed rate and lubricant type have been considered as model variables. Arithmetic mean surface roughness (R_a) and maximum peak to valley height (R_z) are used as response variables to assess the surface roughness of incrementally formed parts. The data required to generate, compare and evaluate the proposed models have been obtained from SPIF experiments performed on Computer Numerical Control (CNC) milling machine using Box–Behnken design. The developed models are having satisfactory goodness of fit in predicting the surface roughness. Further, the GP model has been used for optimization of R_a and R_z using genetic algorithm. The optimum process parameters for minimum surface roughness in SPIF have been obtained and validated with the experiments and found highly satisfactory results within 10% error.

1. Introduction

Incremental sheet forming is a potential process used for sheet metal prototyping and low volume production applications. This process requires very simple tooling and can be carried out by CNC milling machine. Tool diameter, step depth, feed rate, spindle speed, friction, wall angle and tool path are some of the important process parameters that affect the mechanics of forming process. More processing time and less geometrical accuracy over conventional processes are some of the limitations of this process [1]. A schematic diagram of Incremental Sheet Forming (ISF) has been shown in Fig. 1.

In ISF, the sheet is pressed locally by a hemi-spherical headed tool. The motion of the tool is controlled along a proper trajectory to get the required shape. During the motion of the tool over the sheet, friction between tool and sheet plays a very vital role. In dry conditions, friction between tool and sheet is

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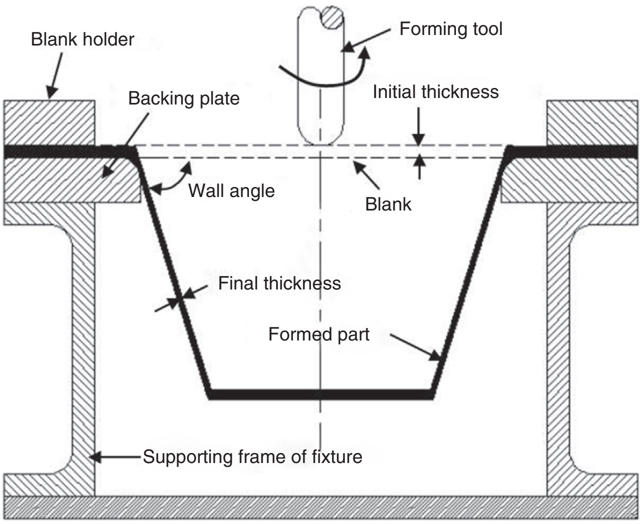

Fig. 1 – Schematic representation of SPIF process.

very high and thus it leads to galling and poor surface finish. It may also lead to premature failure of the part. Some kind of lubrication is very essential to minimize the friction and to get a good quality part. The surface quality of the part is also affected by other parameters such as tool diameter, wall angle, step depth, feed rate and sheet material.

Some researchers made an effort to develop analytical and empirical models to understand the effect of process parameters on surface roughness. Hagan and Jeswiet [2] conducted experiments to study the effect of spindle speed and step depth on mean surface roughness, RMS roughness, maximum profile height and mean peak to valley height. They proposed an empirical model to calculate the peak to valley height of incrementally formed components. Bhattacharya et al. [3] studied the effect of process parameters on formability and surface roughness of Al 5052 material by forming truncated conical and pyramidal frustums respectively. They developed the empirical equations for maximum formable wall angle and surface finish as a function of process parameters. Durante et al. [4] developed the analytical models for average roughness, maximum roughness and mean spacing between the profile peaks as a function of tool radius, wall angle and step depth. They also validated the models by creating pyramidal components with AA7075 T0 material.

The literature study reveals that very few studies have been done on development of analytical and empirical models for evaluation of surface quality in incremental forming. On the other hand, the machine learning techniques became very popular in the recent past in developing the most efficient predictive models in manufacturing [5–9]. These techniques are capable of providing better results than the analytical methods due to their capability of learning nonlinear behavior. But, no literature is available on the application of machine learning techniques to predict the surface roughness of parts formed in incremental forming. Thus, the aim of this study is to develop the mathematical models that relate the surface roughness with different process parameters in incremental forming. For this, three different machine learning techniques, namely, Artificial Neural Networks (ANN), Support Vector Regression (SVR) and Genetic Programming (GP) have been used. This study compares the results obtained from these three modeling methodologies. Further, the process was optimized for minimum surface roughness using Genetic Algorithm (GA). The minimum surface roughness values with corresponding optimum process parameters are reported in the subsequent sections and validated with experiments.

2. Experimental setup and process parameters

Incremental forming experiments were performed on BRIDGEPORT HARDINGE 3-axis CNC milling machine with Fanuc controller. The machine has a maximum spindle speed of 8000 rpm and a drive motor of 15 kW. It has a maximum stroke length of 600 mm × 540 mm × 540 mm in x, y and z directions respectively. The tool path required to form different part geometries was generated with Pro-Manufacturing software and has been transferred to the machine through RS-232 port. Fig. 2 shows the experimental setup of incremental forming process.

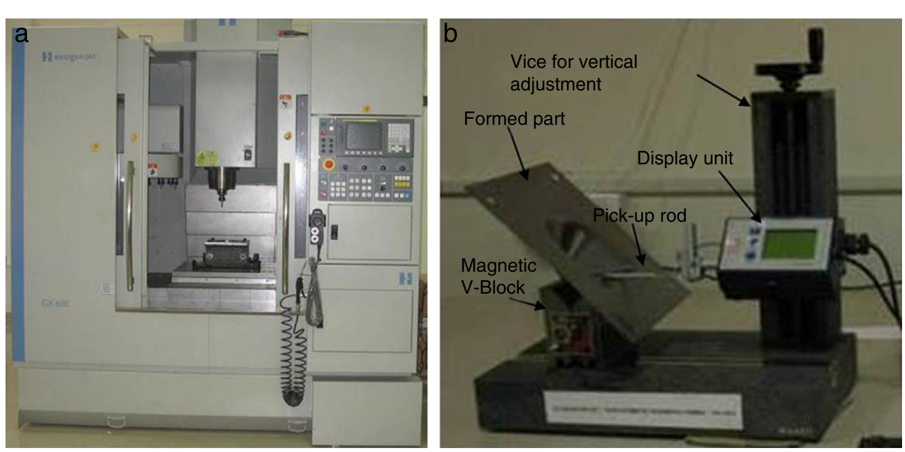

Fig. 2 – Experimental setup for single point incremental forming (a) CNC milling machine with fixture (b) formed part geometry for surface roughness measurement.

Table 1 – Chemical composition of EDD steel.

Element	Weight percent
Carbon	0.044
Silicon	0.78
Manganese	0.17
Sulphur	0.01
Phosphorous	0.01
Chromium	0.024
Tin	0.005
Copper	0.021
Nickel	0.051
Molybdenum	0.025

Table 2 – Physical and mechanical properties of EDD steel.

Density (kg/m^3)	7800
Youngs modulus (in GPa)	200
Poissons ratio	0.29
Yield strength (in MPa)	206
Ultimate strength (in MPa)	337
% Elongation	43
Strength coefficient (in MPa)	560
Strain hardening exponent	0.23
Limiting dome height (in mm)	13.65

2.1. *Blank material and forming tools*

In this work, Extra Deep Drawing (EDD) steel sheets were used as blank material. This material is widely used in automotive industry due to its better formability, strength and dent resistance. EDD steel is typically found in door inners, dash panels, body side inners and floor pans with spare tire tubs. The blanks of 250 mm × 250 mm × 1 mm size were used to form the required shape under different forming conditions. The chemical composition of the blank material is given in Table 1, while the physical and mechanical properties are given in Table 2. The initial roughness of the blank was 0.88 μm. The forming tools were made with EN 36 material and were heat treated to 60 HRC. The tools were polished with different grades of 1600 sianor b abrasive papers for fine finish. The initial roughness of forming tool was found to be 0.218 μm. Tools of 6 mm, 10 mm and 14 mm diameter were used for the experimental work. Three different lubricants were used to minimize the friction between the tool-sheet interfaces. These are canola oil, SAE-40 oil and mixture of canola and MoS_2. Canola oil is derived from natural canola seeds and is an environmental friendly lubricant. SAE-40 is a heavy viscous oil used in engines to provide necessary lubrication. It possesses good resistance to lubricant breakdown caused at high temperature. Third lubricant is prepared by 5% (w/v) of molybdenum disulphide (MoS_2) powder of particle size 100 μm or less in canola oil.

2.2. *Process parameters and experimental design*

Design of Experiments (DOE) methods enables the designer to decide the optimum number of experiments to study the effect of process parameters on the output. The DOE technique has significant effect on accuracy and cost of the experiments. In the present work, Box–Behnken design was used to study the effect of feed rate, tool diameter, step depth, wall angle and lubrication on surface roughness. This design is highly economical when the number of factors is more than four. In this design each parameter is varied over three levels and recommends total 46 experiments with different combination of process parameters. The process parameters and their factor levels are shown in Table 3.

2.3. *Surface roughness measurement*

Surface roughness is one of the important parameters to assess the product quality or surface quality. This factor has a significant effect on functionality as well as esthetic aspects of the product. The most commonly used parameter to quantify the surface roughness is arithmetic mean surface roughness value (R_a). R_a is the arithmetic average of the absolute values of the roughness profile ordinates or the integral of the absolute value of the roughness profile height over the evaluation length. Mathematically this can be described by the following relations.

$$R_a = \frac{1}{n}\sum_{i=1}^{n}\left|y_i\right| \tag{1}$$

$$R_a = \frac{1}{l}\int_0^l \left|y(x)\right| dx \tag{2}$$

Another important parameter to study the surface roughness of parts produced in incremental forming is the maximum peak-to-valley height (R_z) [2].

The roughness of formed parts was measured by Surtronic 25 instrument of Taylor Hobson make shown in Fig. 2b. Each measurement was repeated five times to improve the accuracy of measurement. The average value was reported as the surface roughness of the formed component. For all the measurements evaluation length is taken as 4 mm and cutoff length as 0.8 mm. Technical drawings of formed part geometry and forming tools are shown in Fig. 3.

Table 3 – Process parameters and their levels used in experimental work.

Level	Tool Diameter x_1 (in mm)	Step depth x_2 (in mm)	Wall angle x_3 (in deg.)	Feed rate x_4 (mm/min)	Lubricant (x_5)
−1	6	0.15	35	700	MoS_2 + Canola
0	10	0.3	45	900	Canola
1	14	0.45	55	1100	SAE

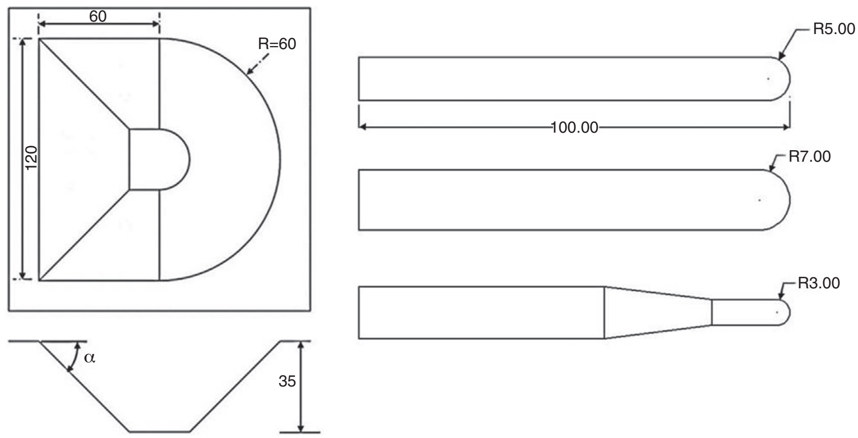

Fig. 3 – Experimental setup for surface roughness measurement.

3. Development of predictive models and optimization

3.1. Artificial neural networks

ANN became more popular in the recent past for development of predictive models [10–12]. This network will have three layers namely input layer, output layer and hidden layer. Hidden layer performs nonlinear mapping between input and output through a suitable basis function. In the present paper feed forward back propagation algorithm is used to model the surface roughness in incremental forming. During training phase this method uses gradient search technique to adjust the weights and to minimize the mean square error of the output. The proposed network is having five neurons in the input layer namely, tool diameter, step depth, wall angle, feed rate and lubricant. There are ten neurons in the hidden layer and two neurons in the output layer namely R_a and R_z. The architecture of this 5-10-2 network is shown in Fig. 4.

Hyperbolic tangent sigmoid basis function and linear basis functions are used at hidden layer and output layer respectively to map the output parameters. MATLAB ANN toolbox has been used for training, testing and validation. Based on the recommendations of Zhang et al. [13], 90% data has been used for training, 5% data has been used for testing and 5% data has been used for validation. The network has been trained using Levenberg–Marquardt function. The error between the ANN output and experimental output is calculated using mean square error performance function (MSE). Other parameters related to the network are summarized in Table 4.

3.2. Support vector regression

The concept of Support Vector Machines (SVM) was developed in early sixties by Vapnik and his co-workers [14]. The SVM framework was rooted in statistical learning theory and got successful results in optical character recognition and object recognition tasks. In the recent past this concept has been extended to regression and time series prediction and got good results [15,16]. Training set of SVR will have input vector (x_i) and output vector (y_i) and the relationship between input and output is constructed using a non linear function. The resultant regression model is given by the following equation.

$$f(x) = w^T\phi(x) + b \tag{3}$$

where w is the weight vector and b is the bias term. $f(x)$ varies at most ε from the target and is as flat as possible. If the deviation is more than ε the function is proportionately penalized with constant λ. The flattest of $f(x)$ is obtained by searching the smallest w. For this ε-SVR is formulated as the following equation.

$$\min \frac{1}{2} w^T.w + \lambda \sum_{i}^{l} (\xi_i + \xi_i^*) \tag{4}$$

Subjected to

$$\begin{aligned} & y_i - (w^T\phi(x) + b) \le \varepsilon + \xi_i \\ & (w^T\phi(x) + b) - y_i \le \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \ge 0 \end{aligned} \tag{5}$$

ξ_i, ξ_i^* are slack variables, everything above ε is captured in ξ_i and everything below ε is captured in ξ_i^*. This ε-insensitive loss function is defined as follows:

$$\begin{aligned} & |\xi|_\varepsilon = 0 \quad ; \quad \text{if} \quad \left|f(x) - y\right| < \varepsilon \\ & \left|f(x) - y\right| - \varepsilon \quad ; \quad \text{otherwise} \end{aligned} \tag{6}$$

Table 4 – ANN control parameters.

Parameters for ANN	
No of hidden layers	1
Size of hidden layer	10
Training function	Levenberg–Marquardt
Performance function	SSE
Training samples	90%
Testing samples	5%
Validation samples	5%

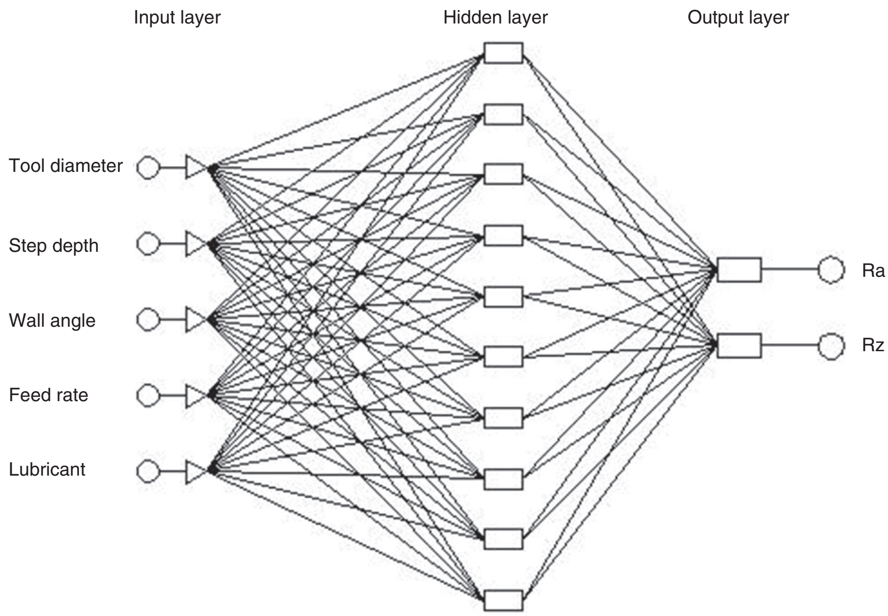

Fig. 4 – ANN architecture for surface roughness modeling in SPIF.

SVR model with an allowable error ε is shown in Fig. 5. In this figure, the data points, which are falling on the margin lines, are called support vectors, the points within the tube are called remaining set and outside the tube are called error set. Increasing the insensitive region ε, increases the error percentage in the model.

Online SVR toolbox developed by Parrella [17] has been used to model the surface roughness in incremental forming. The training set X is the combined vector of all five input parameters (step depth, tool diameter, feed rate, wall angle and lubricant) and the training set Y is the response parameters (mean surface roughness and peak to valley height). Forty six input-output pairs are used for training SVR. Kernel type, cost function, ε value and other constants used for training are given in Table 5. SVR trains the data one by one by adding each sample to the function if and only if the Karush–Kuhn–Tucker (KKT) conditions are verified. If the KKT conditions are verified the sample is added, or else the sample is stabilized using the stabilization technique. The stabilization technique changes the SVR parameters such as cost function and ε to optimize the values.

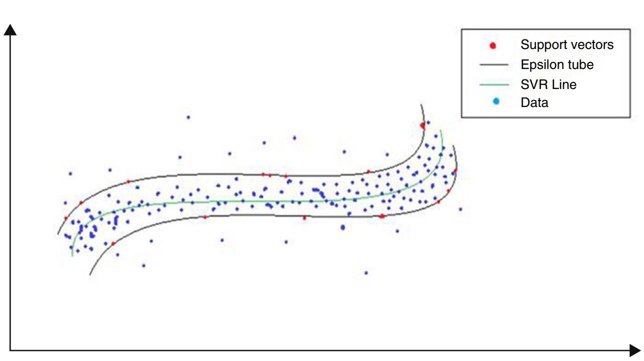

Fig. 5 – Non linear regression with ε-insensitive function.

Table 5 – SVR control parameters.

	Parameters for SVR
Cost function	100
Epsilon	0.0001
Kernel type	RBF
Kernel parameter	30

3.3. *Genetic programming*

The terminology and principles of genetic programming is formulated by Koza [18]. It is an extension of Genetic Algorithms and proved to be an effective tool for modeling and regression [19,20]. In GP, the solution is represented in tree structure with terminal nodes and functional nodes. Terminal nodes represent input parameters or constants and functional nodes represent arithmetic operators and/or non linear functions. In surface roughness modeling the terminal set includes five input parameters (tool diameter, step depth, wall angle, feed rate and lubricant) and function set consists of + −, *, /. In the first step, GP generates initial population by randomly combining the terminal set and functional set for a given population size. Each generation is tested with appropriate performance measure, and subsequent generations are improved using genetic operators such as selection, crossover and mutation. In this paper, tournament selection was chosen, this method keeps only good individuals in the subsequent population. In the crossover operation, two of the fittest individuals are selected to be parents and selected parts of the parents are swapped. Mutation maintains the diversity of the population and prevents the solution from being trapped in a local minimum. In modeling the surface roughness, probabilities of mutation and cross over are set as 5% and 85% respectively. Number of generations is used as a criterion for termination. Various parameters defined for GP are shown in Table 6. GP is stochastic in nature, thus the operator has

Table 6 – GP control parameters.

Parameters for GP	
Population size	300
No of generations	50
Maximum genes	3
Maximum tree depth	6
Selection method	Tournament
Crossover probability	85%
Reproduction probability	10%
Mutation probability	5%
Fitness function	R-squared
Functions used	+, −, *, /

to make multiple runs with the given number of generation. Among all the runs the model with the best performance measure (highest R^2 value) is given by the following relations

$$R_a = \frac{0.03002 + 0.002x_5}{x_2} - \frac{0.03002x_3 + 13.5}{x_1} + \frac{1708x_2(x_2+1)}{{x_1}^3} - \frac{1314{x_2}^5(x_1+449.6)(x_4-691.6)}{{x_1}^4x_4} + 1.531 \quad (7)$$

$$R_z = 0.2623x_1 - \frac{0.2623x_3}{x_1} + \frac{1251(x_2+0.001x_5)}{{x_1}^2} - \frac{0.009966(x_2x_4-(x_4/x_1))(x_2x_4-(2x_4/x_1))}{{x_1}^3x_2} - 0.1457 \quad (8)$$

Subjected to constraints

$$\begin{aligned} &6 \le x_1 \le 14 \\ &0.15 \le x_2 \le 0.45 \\ &35 \le x_3 \le 55 \\ &700 \le x_4 \le 1100 \\ &-1 \le x_5 \le 1 \end{aligned} \quad (9)$$

3.4. *Optimization using genetic algorithm*

Genetic Algorithm (GA) is the most robust search algorithm with its concepts rooted in evolutionary theory. This technique was applied successfully in many fields and different variants of genetic algorithms have been developed subsequently. In this paper, the mathematical function generated using genetic programming for surface roughness prediction in SPIF has been used as an objective function for optimization using GA. The lower and upper limits of process parameters *viz.* tool diameter, step depth, wall angle, feed rate and lubricant are represented as two binary string functions called chromosomes. Initially, population of chromosomes is generated randomly between the upper and lower limits of the process parameters. In the present problem, population size is taken as 100. The binary data of the chromosomes is decoded using Eq. (10), and fitness of the individual is calculated using the fitness function (11). Based on the fitness value, parents are selected for generating the new population. The new population of the offspring was generated with a crossover probability of 80% and constraint dependent mutation function. This new population becomes the parents for the next generation. This process is continued till the specified termination criterion is satisfied.

$$x_i = x_i(L) + \frac{x_i(U) - x_i(L)}{2n-1} \quad (10)$$

where x_i is the decoded decimal value of process parameter, x_i (L) and x_i (U) are lower and upper limits of process parameters, n is the sub-string length.

$$f(x) = \frac{1}{1+R_a} \quad (11)$$

where $f(x)$ is the fitness function and R_a is the objective function.

Table 7 – Descriptive statistics of R^2 values.

Model	R^2		Adj. R^2	
	R_a	R_z	R_a	R_z
ANN	0.95494	0.976858	0.944699	0.971599
SVR	0.994896	0.993676	0.993736	0.992238
GP	0.946345	0.921008	0.934151	0.903056

4. Results and discussion

The predictive models for arithmetic mean surface roughness and peak to valley height in SPIF have been developed as a function of tool diameter, step depth, wall angle, feed rate and lubricant type. Three different techniques, ANN, SVR and GP have been used to develop these models for the estimation of surface roughness. The validity of the models have been tested with correlation coefficient R^2 and *adj* R^2 values calculated using Eqs. (12) and (13). The R^2 values for R_a model with ANN, SVR and GP were found to be 0.954, 0.994 and 0.946, respectively. For the adequacy of model, R^2 value should be in between 0.8 to 1. The high R^2 (>0.94) values indicate that the developed models can be used to predict the surface roughness well. Among these three models, SVR model has better capability to predict the surface roughness followed by ANN and GP. Similar results were found for the predictive models developed for the estimation R_z. The estimated R^2 values for the responses R_a and R_z are summarized in Table 7. The predicted and experimental values of R_a and R_z with ANN, SVR and GP have been plotted as shown in Fig. 6. This figure shows a minimum variation between the experimental and predicted values with the three selected techniques for surface roughness modeling in SPIF.

$$R^2 = 1 - \frac{\sum_i (y_i - f_i)^2}{\sum (y_i - \bar{y})^2} \quad (12)$$

$$R^2_{adj} = 1 - \frac{(1-R^2)(n-1)}{n-p-1} \quad (13)$$

where y_i, f_i, and $\bar{y}$ are experimental, predicted and mean values of the surface roughness, respectively. n and p are sample size and number of predictors, respectively.

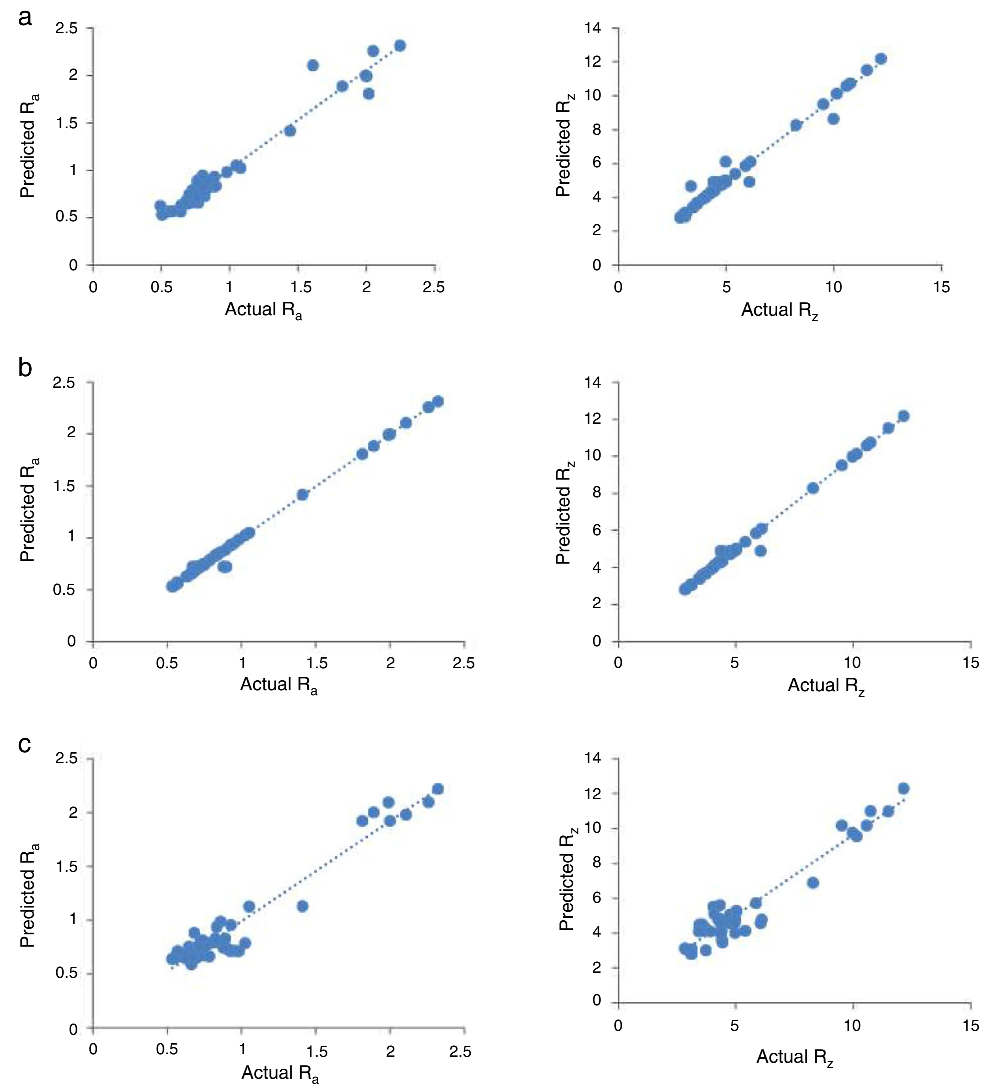

Fig. 6 – Predicted and actual values of R_a and R_z using (a) ANN (b) SVR and (c) GP.

Performances of these techniques have been evaluated by calculating the percentage of error between predicted and experimental values. The error in surface roughness parameters prediction with different techniques was shown in Fig. 7. The statistics of the errors with different modeling techniques have been summarized in Table 8. The error statistics reveals that the ANN and SVR techniques are having better performance over GP. Among ANN and SVR, the maximum error has occurred in ANN model. Further, the mean error in SVR was found to be less compared to ANN. Even though, the error statistics reveal that ANN and SVR have better performance than GP, the performance of GP cannot be underestimated. The positive aspect of GP is that it produces an explicit relationship between input and output parameters, whereas, ANN and SVR both are black box methods.

To test the goodness of fit with different modeling techniques, *t*-test, *F*-test and Levene's test are conducted. Results of hypothesis tests are given in Table 9. In all three modeling techniques (ANN, SVR and GP), the calculated *p*-value with three hypothesis tests are greater than 0.05. This indicates that there is no significant difference between experimental and predicted values using ANN, SVR and GP.

Following the development of predictive models, the process parameters in SPIF have been optimized for minimum surface roughness using GA toolbox in MATLAB. The objective function and constraints for the optimization problem has been given by Eqs. (11) and (12), respectively. In GA modeling, the lubricant was treated as a discrete variable with limits −1, 0 and 1. For the manufacturing simplicity the diameter of tool was also treated as a discrete variable with limits 6, 10 and 14. The optimum process parameters and minimum surface roughness values obtained from the model are given in Table 10. To verify the results obtained from the GA, the experiments have been performed with the optimum settings. The measured and estimated values of surface roughness parameters are shown in Fig. 8. The measured R_a and R_z values with these settings were found to be 0.4502 μm and 2.564 μm, respectively. The results shows that the optimum process parameters obtained from GA can be used to enhance the surface quality of parts produced in SPIF process.

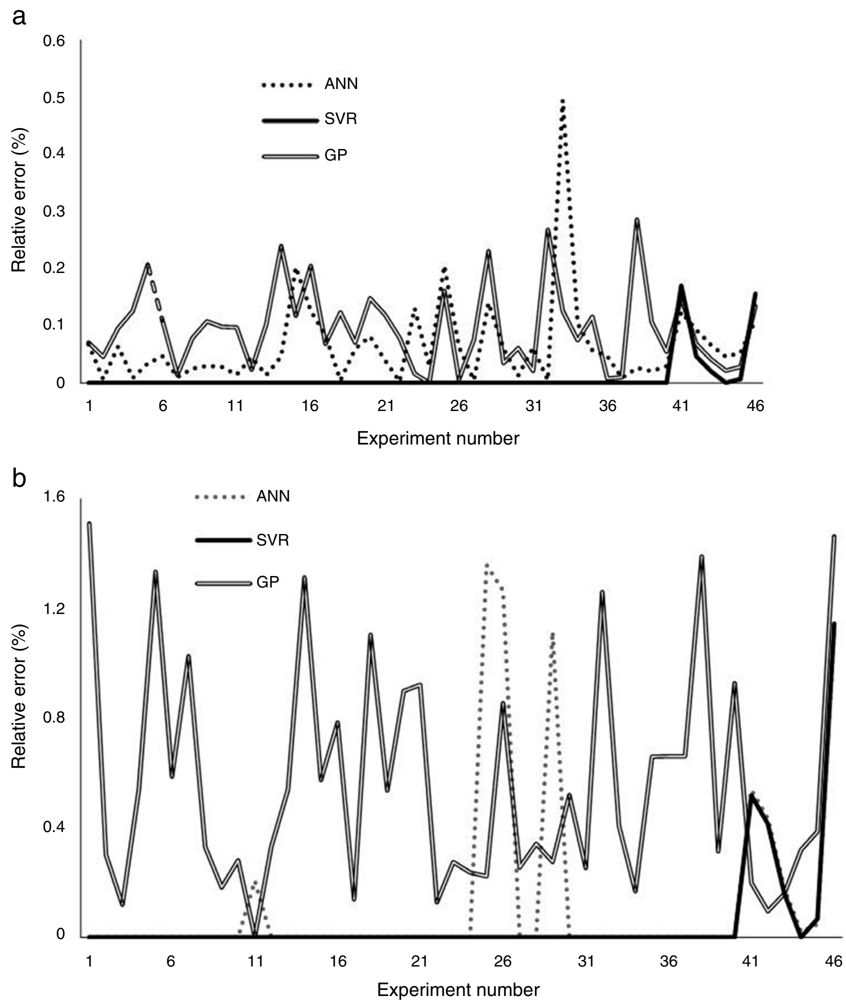

Fig. 7 – Relative percentage of error with different predictive modeling techniques in predicting (a) R_a and (b) R_z.

Table 8 – Error statistics with ANN, SVR and GP.

Response	Model	Count	Mean	SE Mean	Std Dev	Median	Minimum	Maximum
R_a	ANN	46	0.066	0.0119	0.0809	0.0465	0.0026	0.4949
	SVR	46	0.0088	0.00504	0.0341	0.0001	0.0001	0.1703
	GP	46	0.0944	0.0092	0.0630	0.0900	0.0013	0.2274
R_z	ANN	46	0.1366	0.0522	0.3541	0	0	1.3576
	SVR	46	0.0501	0.0283	0.1921	0.0001	0.0001	1.1436
	GP	46	0.5351	0.0660	0.4476	0.4315	0.0303	2.3015

Table 9 – Descriptive statistics of hypothesis tests.

95% CI	P-value					
	R_a			R_z		
	ANN	SVR	GP	ANN	SVR	GP
Mean paired *t*-test	0.479	0.296	0.930	0.753	0.93	0.994
Variane *F*-test	0.678	0.984	0.850	0.86	0.984	0.783
Levene's test	0.76	0.958	0.676	0.944	0.991	0.604

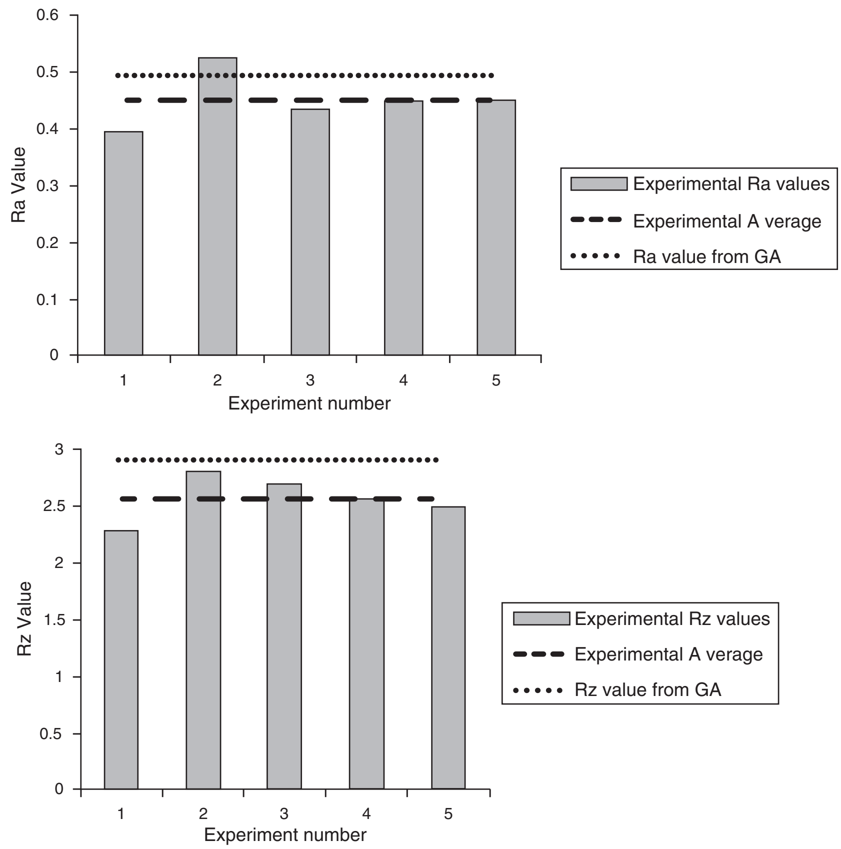

Fig. 8 – Experimental R_a and R_z values corresponding to optimum process parameters.

Table 10 – Optimum process parameters calculated using GA for minimum surface roughness.

Process parameter	Optimum process parameters for minimum	
	R_a	R_z
Tool diameter	10	10
Step depth	0.15	0.15
Wall angle	55	55
Feed rate	1100	700
Lubricant type	−1	−1

5. Conclusions

In this study, surface roughness of incrementally formed parts with EDD steel has been investigated under different forming conditions and predictive models have been developed by using ANN, SVR and GP. Adequacy of model is tested using hypothesis tests and performance is evaluated using R^2 value. The models developed using ANN and SVR are performing better than GP. However, GP produces explicit relationship between input and output variables. GP model is stochastic in nature, thus this model can be improved further by changing different parameters. Among ANN and SVR, SVR exhibited better performance in predicting R_a and R_z. The developed models using GP has been used for optimization using genetic algorithm with the objective of minimum surface roughness. The R_a and R_z values corresponding to optimum process parameters are found to be 0.4956 μm and 2.9 μm, respectively. For validation, experiments were conducted with optimum settings and the results were found to be in very good agreement with the predicted values by GA. The reported results are applicable only for EDD steel sheets within the specified range of process parameters. In this study the step depth and feed rate are restricted to 0.45 mm and 1100 mm/min, respectively. The future work focuses on studying the effect of high step depth and feed rates on surface roughness and formability of the sheet.

Conflicts of interest

The authors declare no conflicts of interest.

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