Karbala International Journal of Modern Science

Volume 6 | Issue 2 Article 8

A Support Vector Machine-based Prediction Model for Electrochemical Machining Process

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Recommended Citation
Agarwal, Subham Mr.; Dandge, Shruti Sudhakar Ms.; and Chakraborty, Shankar Prof. (2020) "A Support Vector Machine-based Prediction Model for Electrochemical Machining Process," *Karbala International Journal of Modern Science*: Vol. 6 : Iss. 2 , Article 8.
Available at: https://doi.org/10.33640/2405-609X.1508

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Abstract

Manufacturing of quality products is one of the core measures to address competitiveness in industries. Hence, it is always necessary to accomplish quality prediction at early stages of a manufacturing process to attain high quality products at the minimum possible cost. To achieve this goal, the past researchers have developed and investigated the applications of different intelligent techniques for their effective deployment at various stages of manufacturing processes. In this paper, support vector machine (SVM), a supervised learning system based on a novel artificial intelligence paradigm, is employed for prediction of three responses, like material removal rate, surface roughness and radial overcut during an electrochemical machining (ECM) operation. Gaussian radial basis kernel function is adopted in this algorithm to provide higher prediction accuracy. Regression analyses are also carried out to validate the effectiveness of these prediction models. The SVM-based results show good agreement between the experimental and predicted response values as compared to linear and quadratic models. Among the four ECM process parameters, i.e. applied voltage, tool feed rate, electrolyte concentration and percentage of reinforcement of B_4C particles in the metal matrix, tool feed rate is identified having the maximum influence on the considered responses.

Keywords

ECM process; SVM; Kernel function; Prediction; Response

1. Introduction

Electrochemical machining (ECM) is one of the most potential and useful non-traditional machining processes which possesses the capability to generate complex and intricate shapes on diverse hard, tough and high strength materials. Nowadays, varieties of machining operations, like grinding, turning, drilling, deburring etc. can be effectively carried out using ECM process. This process works on the principle of the Faraday's law of electrolysis in which material is removed from the workpiece by anodic dissolution of the electrolyte. It consists of two electrodes, connected to high voltage power supply, and a very small gap is maintained between them separated by an electrolyte for efficient exchange of ions, causing removal of material from the workpiece. In this process, the material removal mechanism is based on electrolysis where metals are released from the workpiece atom by atom. Controlled anodic electrochemical dissolution takes place in the electrolyte in which tool acts as a cathode and workpiece as an anode while applying a voltage between the tool and the workpiece. The electrolyte is forced to pass at a high velocity through the gap between the electrodes and material is removed during this continuous dissolution process [1,2]. The ECM process can machine components with no burr formation and no residual stress generation. It has longer tool life with almost no tool wear, higher material removal rate (MRR), and achievement of good surface quality and higher dimensional accuracy of the machined components. Thus, it provides an effective and economical solution for machining of high strength materials having complex geometries which are not possible to be machined by the conventional machining processes [3]. As in this process, the machining performance does not depend on the hardness of the workpiece materials, it can thus be effectively applied for machining of any hard material. On the contrary, it has higher machining cost and lack of eco-friendliness, and it causes corrosion to the machining set-up. The performance of an ECM process is often characterized by its various outputs (responses), like MRR, surface roughness (SR), radial overcut (ROC) etc. which are usually influenced by its different control parameters, such as applied voltage, electrolyte concentration and flow rate, inter-electrode gap, tool feed rate etc. In recent years, it has also received significant attention in machining of micro-components [4].

Like all other machining processes, in an ECM process, its varied input parameters also interact between themselves and influence its outputs. These interrelations between the ECM process parameters and responses can be efficiently studied with the development of a suitable model based on the experimental observations. Models usually involve a set of independent parameters and fitting a model helps in determining the values of other dependant parameters. Due to complex stochastic material removal mechanism of the ECM process and possible interactions between the considered process parameters and responses, it has now become an essential task to develop an accurate and reliable model based on which the responses of an ECM process can be efficiently predicted so as to enhance quality of the machined components. It would finally help the concerned process engineers to envisage the responses for a given set of ECM process parameters.

2. Literature review

The past researchers have already proposed diverse methodologies for predicting the performance of the ECM processes, and investigating the complex interrelationships between the input parameters and responses. Ashokan et al. [5] applied artificial neural network (ANN) and grey relation analysis (GRA) for modeling and multi-objective optimization of an ECM process, while considering applied voltage, current, electrolyte flow rate and inter-electrode gap as the machining parameters, and MRR and SR as the responses. It was concluded that ANN would result in better prediction of the responses with respect to percentage deviation between the training and testing datasets. Senthilkumar et al. [6] studied the effects of electrolyte concentration, applied voltage, tool feed rate and electrolyte flow rate on MRR and SR, and developed a mathematical model for prediction of MRR and SR during ECM operation on LM25 Al/10% SiC_p composites. Based on Taguchi's L_{27} experimental design plan, Senthil Kumar and Sivasubramanian [7] examined the influences of applied voltage, electrolyte concentration, electrode feed rate and amount of reinforcement on MRR while performing ECM operation on aluminum A356/SiC_p metal matrix

https://doi.org/10.33640/2405-609X.1508

composites. A back propagation-based ANN model was also proposed to predict the values of MRR. Acharya et al. [8] developed response surface methodology (RSM)-based regression models for prediction of MRR and SR values during ECM operation of super alloys. Non-dominated sorting genetic algorithm-II (NSGA-II) was later employed to optimize the machining performance of the said process. Abuzied et al. [9] presented an ANN-based model for prediction of SR and MRR in an ECM process. During controlled ECM operation, Senthilkumar et al. [10] analyzed the influences of electrolyte flow rate and concentration, applied voltage and tool feed rate on MRR and SR using RSM-based models. Later, NSGA-II technique was implemented to maximize MRR and minimize SR for the considered process. Rao and Padmanabhan [11] developed RSM-based models to study the relationships between electrode feed rate, applied voltage, electrolyte concentration and percentage of reinforcement, and SR and ROC during ECM operation of Al−Si/B_4C composites. Teimouri and Sohrabpoor [12] adopted a neuro-fuzzy inference system to develop the corresponding predictive models for MRR and SR in an ECM operation. The cuckoo search algorithm was later utilized to optimize the considered process. Kasdekar and Parashar [13] employed Box-Behnken and ANN-based prediction models for MRR during ECM operation of AA6061/Cu−SiC/graphite T6 composite materials. The prediction performance of those two models was subsequently compared. Taking into account applied voltage, feed rate, electrolyte flow rate and electrolyte concentration, Mehrvar et al. [14] endeavored to explore their effects on MRR and SR in an ECM process. Differential evolution algorithm was later employed to optimize the considered responses. Kasdekar et al. [15] developed a multilayer perceptron model with back propagation algorithm using voltage, feed rate, electrolyte concentration and type of the electrode material as the input parameters for prediction of MRR during ECM operation on AA6061 T6 aluminum alloys.

In ECM processes, the literature has mainly been flooded with the development of RSM-based regression models correlating various input parameters with the responses. Those models were optimized using different evolutionary algorithms to determine the optimal combinations of various process parameters for enhanced machining performance with better response values. On the other hand, applications of ANN (mostly back propagation feed forward type) have also been proposed by the past researchers to predict the responses for the ECM processes. Few applications of support vector machine (SVM) for prediction of the operational performance of different machining/manufacturing processes have been found in the literature. Zhang et al. [16] developed hybrid models for predicting processing time and electrode wear rate in a micro-electrical discharge machining process based on SVM using the Gaussian kernel function. Chou et al. [17] proposed the applications of SVM and radial basis function neural network (RBFNN) techniques for wafer quality prediction in a semiconductor manufacturing process. It was reported that SVM approach would result in better prediction accuracy than RBFNN technique. Xu et al. [18] developed a least square SVM (LSSVM) model with RBF to investigate the effects of electrochemical mechanical polishing parameters on SR properties of bearing rollers. It was concluded that the adopted model would be suitable for prediction of different surface characteristics with minimum mean absolute percentage error (MAPE). Nayak and Tripathy [19] applied multi-layer feed forward neural network (MFNN) and LSSVM techniques to predict MRR and SR values in an ECM process. Based on mean square error (MSE) values, it was propounded that LSSVM with RBF kernel function would outperform MFNN approach with respect to prediction accuracy. In an electrical discharge machining process, Aich and Banerjee [20] applied SVM algorithm to predict MRR and SR while attaining the minimum MAPE values of the training dataset at different combinations of the SVM parameters. Particle swarm optimization technique was finally employed to determine the optimal SVM parameter combinations for achieving better prediction performance. While conducting experimental runs in an abrasive water jet machining process using borosilicate glass as the work material, Aich et al. [21] presented the application of a SVM-based learning model for effective prediction of various responses of the considered process. Using SVM, Lu et al. [22] developed prediction models for envisaging SR characteristics in different machining processes. Artificial bee colony algorithm was further utilized to increase prediction accuracy and decrease parameter adjustment time of the adopted model. The derived results were finally compared with those as obtained from the other popular evolutionary algorithms.

Thus, it can be observed that statistical methods and artificial intelligence techniques are the suitable approaches for development of predictive models for envisaging the complex material removal behavior of varied machining processes. Among different artificial intelligence techniques, ANNs with different architectures and complexities have become popular amongst the researchers for studying the inherent relationships between input parameters and responses in diverse machining processes. But, ANNs usually suffer from several disadvantages, like hardware dependency, problem in determining the appropriate network architecture, unexplained behavior of the network, long learning time, over-fitting of data etc. While overcoming these disadvantages of ANNs, it may be worthwhile to explore the feasibility of SVM in understanding the relationships between the input parameters and outputs, and predicting the response values for different machining processes. It has also been noticed from the literature review that there is immense scarcity of the applications of SVM as an effective prediction tool in the domain of ECM processes. In an ECM process, random fluctuations in the responses are quite obvious due to its stochastic behavior. These random variations in the experimental results can be effectively absorbed with particular tolerance value for intelligent prediction. The application of SVM can be a smart solution for dealing with the complex behavior of ECM process while predicting the corresponding response values. Thus, in this paper, an attempt is put forward to efficiently predict three responses of an ECM process, i.e. MRR, SR and ROC while taking into account applied voltage, tool feed rate, electrolyte concentration and percentage of reinforcement of B_4C particles in the metal matrix as the input parameters of the said process. The prediction performance of SVM is later validated with that of regression method-based analyses. The anticipated response values are also compared with the actual experimental results which proves high prediction accuracy of the adopted SVM algorithm.

3. Support vector machine

The SVM is a useful soft computing tool based on statistical learning theory which has been extensively utilized for classification, regression, pattern recognition, dependency estimation, forecasting and constructing intelligent machines [23]. The concept of SVM was proposed by Vapnik [24] mainly for classification tasks, but later, it was also adopted to deal with regression problems (support vector regression (SVR)) with the inclusion of a loss function with a specific distance measure [25]. The application of SVM is based on construction of a separating hyperplane to maximize the margin between two datasets according to their classes which have been previously mapped to a high dimensional space [24]. To determine the margin, two parallel hyperplanes are established on each side of the separating hyperplane. An optimal separation is achieved by the hyperplane which has the largest distance to the neighboring data points of the both classes as larger margin leads to better generalization error of the classifier. The SVM can be established while assigning a few numbers of parameters, like kernel function, loss function, regularization parameter etc., which makes it more suitable for adoption in manufacturing environment. Moderate sets of training data are sufficient to effectively train this algorithm. This feature of SVM is highly useful for its deployment in real time machining operations where collection of huge set of experimental data is practically impossible due to involvement of higher machining time and related cost. It has excellent generalization property, minimal adjusting parameters, no requirement to search out the best architecture and less chance of producing over-fitted model.

The SVR develops a linear model when all the related input variables have been mapped into a higher dimensional feature space while applying some non-linear mapping (based on reproduction of kernels). Let, a set of training data $\{(x_1,y_1)\ (x_2,y_2),\ \ldots\ (x_N,y_N)\}$ is employed for model development in a d-dimensional input space ($x \in R^d$). It is supposed that both the training and testing datasets are independent, disjoint and identically distributed. The basic objective is to identify a model from the hypothesis space which would be closest to the underlying target function. The linear target function in the feature space can be expressed as:

$$f(\boldsymbol{x}) = \boldsymbol{w}\cdot\boldsymbol{x} + b \tag{1}$$

where $(\cdot)$ is the dot product in the vector space, and **w** and b are the parameter vectors of the function. If the input parameters do not have any linear relation to the output (non-linear model), they can then be mapped to the feature space $\Phi(x_i)$ from high dimensional input space through kernel functions. In most of the model development techniques, data are fitted based on the least training error calculation to determine the unknown weight vectors related with the training data. Hence, there is always an attempt to fit all the data as close as the expected model. In SVR, an insensitive zone around the estimated function is implemented. This zone usually takes into consideration the variations within the allowable tolerances mentioned with the outputs. Using Vapnik's ϵ-insensitive approach, a flexible tube with a specific radius is symmetrically formed around the estimated function so that the absolute values of errors less than a certain threshold ϵ are ignored for both above and below the estimate. The radius of this hypertube thus controls the complexity of the learning process. With the increment of this radius, the model would tend to be more flat being incapable to unfold the unseen variations in the outputs. On the contrary, lower radius would make the model more complicated. The outliers around this hypertube are known as the support vectors. In order to utilize SVR for model fitting, a regularization parameter is introduced to penalize those support vectors and the points inside the insensitive zone are considered having zero loss (penalty). In SVR, the learning task is transformed to the minimization of the error function defined through ϵ-insensitive loss function which controls the accuracy of the regressor. Thus, for effective model fitting, selection of the appropriate values of regularization parameter (C), radius of the insensitive tube (ϵ) and kernel function is most important. The computational complexity of SVR does not depend on the dimensionality of the input space. Additionally, it has excellent generalization capability with high prediction accuracy.

Let L($\mathbf{y}$) be the loss function introduced to penalize over-fitting of the model based on a set of training data points. Amongst various types of loss functions, ϵ-insensitive loss function is mostly preferred for performing the process modeling.

$$\mathrm{L}(y_i, f(x_i)) = \left|y_{i,\mathrm{experimental}} - f(x_i)\right| - \epsilon, \text{if} \left|y_{i,\mathrm{experimental}} - f(x_i)\right| \geq \epsilon = 0, \text{if} \left|y_{i,\mathrm{experimental}} - f(x_i)\right| < \epsilon \tag{2}$$

The concept of kernel function K (x_i,$\boldsymbol{x}$) provides a way to deal with the problem of dimensionality, enabling the operations to be performed in the feature space instead of potentially high dimensional input space. Gaussian radial basis function (GRBF) with σ standard deviation has better potentiality in solving problems in the higher dimensional input space.

$$\mathrm{K}(x_i, x) = \exp\left(-\left\|x_i - \mathbf{x}\right\|^2 \Big/ 2\sigma^2\right) \tag{3}$$

This problem can be efficiently solved using standard dualization principle based on the Lagrange multipliers (α_i, α_i*). The appropriate support vectors can be easily identified from the difference between the Lagrange multipliers (α_i, α_i*). Smaller values (close to zero) highlight the points inside the insensitive hypertube and the non-zero values indicate the elements in support vector group. Thus, the weight vector $\mathbf{w}$ can be estimated as follows [26,27]:

$$\mathrm{w} = \sum_{i=1(1)N} \left(\alpha_i - \alpha_i^*\right) \varphi(\mathrm{x_i}) \tag{4}$$

Thus, the final model with the optimal combination of C, ϵ and σ can be presented as below:

$$f(x) = \sum_{i=1(1)N} \left(\alpha_i - \alpha_i^*\right) \mathrm{K}(x_i, \mathbf{x}) + b \left| \begin{matrix} C_{\mathrm{optimal}} \\ \epsilon_{\mathrm{optimal}} \\ \sigma_{\mathrm{optimal}} \end{matrix} \right. \tag{5}$$

4. SVM for an ECM process

Rao and Padmanabhan [28] conducted 27 experiments on LM6 Al/B_4C metal matrix composites using an ECM set-up (Metatech make). A copper tool having circular cross section and 12 mm diameter with a central hole was utilized during the experiments. The flow rate of NaCl electrolyte was kept as 10 l/min and a steady inter-electrode gap of 0.5 mm was maintained during the experiment runs. While performing all the experimental runs, values of the four ECM process parameters, i.e. applied voltage (AV) (in V), tool feed rate (FR) (in mm/min), concentration of the electrolyte (EC) (in g/l) and percentage of reinforcement of B_4C particles in the metal matrix (PC) (in Wt%) were varied at three different levels and the corresponding responses, i.e. MRR (in g/min), SR (μm) and ROC (in mm) were measured. Table 1 shows the detailed experimental plan along with the response values. These ECM process parameters are treated here as the inputs to the SVM algorithm for effective prediction of the corresponding response values. The MRR is the amount of material removed from the workpiece surface at unit machining time during the ECM operation, and it is the most important response characterizing the productivity and efficiency of an ECM process. On the other hand, SR basically symbolizes the surface quality of a machined component. It is quantified by the deviations in the direction of the normal of a machined surface from its ideal form. If there are large deviations, the surface is rough; otherwise, it is smooth. The ROC is the absolute deviation between the diameters of the machined hole and initial tool. Among these responses, MRR is the only beneficial quality characteristic requiring its higher value. On the contrary, lower values are always required for SR and ROC (non-beneficial quality characteristics). The initial dataset containing 27 experimental runs of the ECM process is adopted here to test the performance of the SVM algorithm. On the other hand, another 500 experimental trials are simulated for training this

Table 1
Experimental plan and measured responses [28].

Exp. No.	Applied voltage	Tool feed rate	Electrolyte concentration	Percentage of reinforcement	MRR	SR	ROC
1	12	0.2	10	2.5	0.268	4.948	0.96
2	12	0.2	20	5	0.335	5.002	0.94
3	12	0.2	30	7.5	0.227	4.591	0.79
4	12	0.6	10	2.5	0.353	4.92	0.75
5	12	0.6	20	5	0.448	4.498	0.65
6	12	0.6	30	7.5	0.42	4.725	0.8
7	12	1.0	10	2.5	0.689	4.555	0.67
8	12	1.0	20	5	0.545	4.356	0.64
9	12	1.0	30	7.5	0.703	4.232	0.65
10	16	0.2	10	5	0.321	4.882	0.91
11	16	0.2	20	7.5	0.329	4.823	0.94
12	16	0.2	30	2.5	0.488	4.254	1.05
13	16	0.6	10	5	0.379	4.54	0.76
14	16	0.6	20	7.5	0.302	4.431	0.69
15	16	0.6	30	2.5	0.583	3.998	0.99
16	16	1.0	10	5	0.615	4.274	0.75
17	16	1.0	20	7.5	0.619	4.346	0.7
18	16	1.0	30	2.5	0.812	3.598	0.93
19	20	0.2	10	7.5	0.282	5.472	0.91
20	20	0.2	20	2.5	0.599	4.797	1.1
21	20	0.2	30	5	0.603	4.64	1.16
22	20	0.6	10	7.5	0.526	5.214	0.85
23	20	0.6	20	2.5	0.688	4.897	1.03
24	20	0.6	30	5	0.732	4.531	1.08
25	20	1.0	10	7.5	0.688	5.002	0.64
26	20	1.0	20	2.5	0.887	4.389	0.99
27	20	1.0	30	5	0.944	3.989	1

algorithm. These additional runs are simulated in such way that all the process parameter settings and responses must range within their extreme (minimum and maximum) values.

As already mentioned, this paper deals with the development of SVM-based models for effective prediction of three responses, i.e. MRR, SR and ROC in an ECM process using R-Studio (Version 1.1463) software. Based on the training data sets, three models are fitted through the learning process of SVM for the three responses. The effectiveness and prediction accuracy of the SVM would mainly depend on the optimal values of three free parameters, i.e. generalization constant (C), insensitive parameter (ϵ) and standard deviation for GRBF (σ). When applying the SVM for the considered ECM process, it is the first task to identify the most effective kernel function. The SVM algorithm can construct varieties of learning machines while adopting different kernel functions. Each of these kernel functions has its own specialized applicability. The GRBF is employed here due to its global acceptability and better potentiality to deal with higher dimensional input space. It has minimum hypermeters that greatly reduce the complexity of the prediction model than the other polynomial kernel functions. Grid search plots are the simplest approaches to determine the optimal values of these three parameters. The lower and upper limits in the search space are set by the user to find out the corresponding values of the considered parameters with maximum accuracy. Here, the search intervals for parameters ϵ and C are set as [0 1] and [1 1000] respectively. The grid search with 10 k-fold validation with the training dataset is performed to optimize these parameters. The optimal values of ϵ, C and σ are provided in Table 2.

Now, using the optimal values of ϵ, C and σ, the corresponding SVM-based prediction models are developed so that the performance of these models

Table 2
Optimal values of SVM parameters.

Response	ϵ	C	σ
MRR	0.0625	16	0.14057
SR	0.2500	8	0.15355
ROC	0.1250	32	0.14057

with respect to prediction accuracy can be fairly validated. After training these models using the considered dataset, their performance results are provided in Table 3. The SVM attempts to search out the best line (the line that results in the largest margin between two classes) that separates two classes. The points that lie on these margins are the support vectors. The problem can be formulated so as to find out the maximum-margin hyperplane that only considers these support vectors. The optimal hyperplane is obtained by comparing the maximum number of support vectors in its margins among all other hyperplanes proposed at the time of grid searching iterations. While performing the search for MRR response, the maximum-margin hyperplane is obtained with 281 support vectors. Likewise for SR, the maximum-margin hyperplane is derived with 20 support vectors and for ROC, the maximum-margin hyperplane is formed with 148 support vectors. It can be clearly noticed from Table 3 that the SVM model for MRR with the maximum number of support vectors has the minimum training error of 0.004762. It has also the minimum cross validation error of 0.000277. In Fig. 1, the flowchart depicting the procedural steps for the application of SVM algorithm for prediction of the ECM process responses is presented.

Table 3
Performance results of the SVM models.

Response	Number of support vectors	Training error	Cross validation error
MRR	281	0.004762	0.000277
SR	20	0.049243	0.0467
ROC	148	0.008615	0.000303

Now, in order to validate the applicability and potentiality of these SVM-based models for predicting the values of three responses in the considered ECM process, two sets of regression equations are subsequently developed using MINITAB (Version 17) software. The first set of equations deals with linear regression models for the three responses and the other set of equations is for second order (quadratic) regression models. These regression equations are provided in Tables 4 and 5 respectively. It can be observed that applied voltage and tool feed rate are the two most significant ECM process parameters influencing all the three responses, followed by electrolyte concentration and percentage of reinforcement of B_4C particles in the metal matrix. Higher R^2 values signify the superiority of the quadratic regression models over the linear models in depicting the relationships between the ECM process parameters and responses.

Based on these developed regression models, values of the three responses are now envisaged for all the 27 experimental runs. In Tables 6–8, values of MRR, SR and ROC as predicted using the linear regression model, quadratic regression model and SVM are respectively compared. It can be interestingly revealed that the predicted response values based on SVM-based models are quite closer to the actual

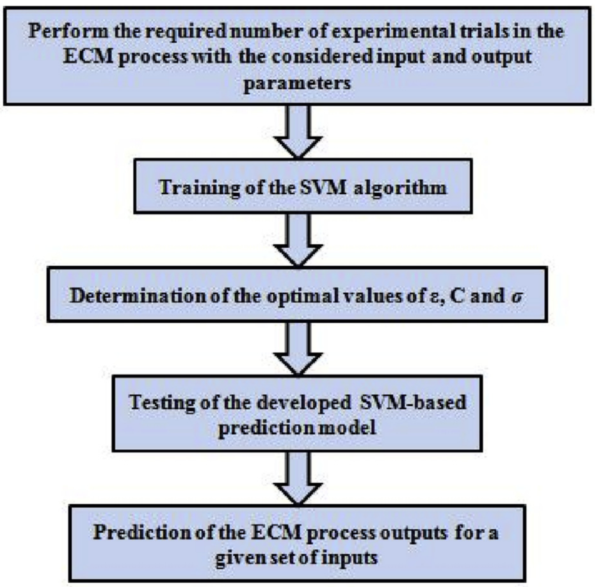


Fig. 1. Flowchart for SVM-based prediction model.

Table 4
Linear regression models for the ECM process.

Response	Linear model	R^2 (%)
MRR	MRR = −0.1705 + 0.02724 × AV + 0.4236 × FR + 0.00773 × EC − 0.02824 × PC	90.67
SR	SR = 4.889 + 0.0179 × AV − 0.704 × FR − 0.02297 × EC + 0.0594 × PC	73.73
ROC	ROC = 0.6166 + 0.02653 × AV − 0.2486 × FR + 0.00694 × EC − 0.03333 × PC	89.09

Table 5
Quadratic regression models for the ECM process.

Response	Quadratic model	R^2 (%)
MRR	MRR = 0.766−0.0884 × AV − 0.031 × FR + 0.00486 × EC + 0.0056 × PC + 0.00361 × AV^2 + 0.379 × FR^2 + 0.000072361 × EC^2 − 0.00339 × PC^2	95.08
SR	SR = 9.98−0.642 × AV + 0.159 × FR − 0.0063 × EC − 0.0101 × PC + 0.02068 × AV^2 − 0.668 × FR^2 − 0.00545 × EC^2 + 0.0164 × PC^2	94.22
ROC	ROC = 0.799 + 0.0076 × AV − 0.469 × FR + 0.00050 × EC − 0.0031 × PC + 0.00059 × AV^2 + 0.184 × FR^2 + 0.000161 × EC^2 − 0.00302 × PC^2	90.51

experimental observations as compared to linear and quadratic regression models.

In Table 9, the prediction performance of the linear regression model, quadratic regression model and SVM model is compared with the actual experimental observations with respect to R^2 and root mean square error (RMSE) values. Based on these results, it can be concluded that for all the considered responses, the SVM-based prediction models outperform the other regression models with respect to maximum R^2 and minimum RMSE values. Thus, it can be unveiled that SVM can be employed as an efficient tool for predicting the quality characteristics of the machined components during any machining operation.

Table 6
Predicted values of MRR using regression analyses and SVM.

Exp. No.	AV	FR	EC	PC	Experimental	Linear regression	Quadratic regression	SVM
1	12	0.2	10	2.5	0.268	0.3108	0.282613	0.280279
2	12	0.2	20	5	0.335	0.3175	0.30325	0.363658
3	12	0.2	30	7.5	0.227	0.3242	0.295913	0.251172
4	12	0.6	10	2.5	0.353	0.48024	0.391493	0.374552
5	12	0.6	20	5	0.448	0.48694	0.41213	0.460211
6	12	0.6	30	7.5	0.42	0.49364	0.404793	0.432215
7	12	1.0	10	2.5	0.689	0.64968	0.621653	0.70131
8	12	1.0	20	5	0.545	0.65638	0.64229	0.57836
9	12	1.0	30	7.5	0.703	0.66308	0.634953	0.71528
10	16	0.2	10	5	0.321	0.34916	0.28377	0.33101
11	16	0.2	20	7.5	0.329	0.35586	0.262033	0.3343
12	16	0.2	30	2.5	0.488	0.57436	0.488133	0.50029
13	16	0.6	10	5	0.379	0.5186	0.39265	0.39122
14	16	0.6	20	7.5	0.302	0.5253	0.370913	0.33068
15	16	0.6	30	2.5	0.583	0.7438	0.597013	0.59523
16	16	1.0	10	5	0.615	0.68804	0.62281	0.62724
17	16	1.0	20	7.5	0.619	0.69474	0.601073	0.63084
18	16	1.0	30	2.5	0.812	0.91324	0.827173	0.81132
19	20	0.2	10	7.5	0.282	0.38752	0.358073	0.29436
20	20	0.2	20	2.5	0.599	0.60602	0.569773	0.60929
21	20	0.2	30	5	0.603	0.61272	0.60481	0.6093
22	20	0.6	10	7.5	0.526	0.55696	0.466953	0.5257
23	20	0.6	20	2.5	0.688	0.77546	0.678653	0.70024
24	20	0.6	30	5	0.732	0.78216	0.71369	0.74428
25	20	1.0	10	7.5	0.688	0.7264	0.697113	0.70024
26	20	1.0	20	2.5	0.887	0.9449	0.908813	0.89273
27	20	1.0	30	5	0.944	0.9516	0.94385	0.95622

Table 7
Predicted values of SR using regression analyses and SVM.

Exp. No.	AV	FR	EC	PC	Experimental	Linear regression	Quadratic regression	SVM
1	12	0.2	10	2.5	4.948	4.8818	5.21875	5.025122
2	12	0.2	20	5	5.002	4.8006	5.2745	4.900699
3	12	0.2	30	7.5	4.591	4.7194	5.42625	4.692491
4	12	0.6	10	2.5	4.92	4.6002	5.06859	4.818579
5	12	0.6	20	5	4.498	4.519	5.12434	4.599409
6	12	0.6	30	7.5	4.725	4.4378	5.27609	4.623488
7	12	1.0	10	2.5	4.555	4.3186	4.70467	4.568086
8	12	1.0	20	5	4.356	4.2374	4.76042	4.254431
9	12	1.0	30	7.5	4.232	4.1562	4.91217	4.333455
10	16	0.2	10	5	4.882	5.1019	5.24916	4.9349
11	16	0.2	20	7.5	4.823	5.0207	5.50991	4.800759
12	16	0.2	30	2.5	4.254	4.494	4.40491	4.355366
13	16	0.6	10	5	4.54	4.8203	5.099	4.641145
14	16	0.6	20	7.5	4.431	4.7391	5.35975	4.532416
15	16	0.6	30	2.5	3.998	4.2124	4.25475	4.008566
16	16	1.0	10	5	4.274	4.5387	4.73508	4.375348
17	16	1.0	20	7.5	4.346	4.4575	4.99583	4.244467
18	16	1.0	30	2.5	3.598	3.9308	3.89083	3.699541
19	20	0.2	10	7.5	5.472	5.322	6.14633	5.370803
20	20	0.2	20	2.5	4.797	4.7953	5.15033	4.898431
21	20	0.2	30	5	4.64	4.7141	5.09708	4.695756
22	20	0.6	10	7.5	5.214	5.0404	5.99617	5.198132
23	20	0.6	20	2.5	4.897	4.5137	5.00017	4.795556
24	20	0.6	30	5	4.531	4.4325	4.94692	4.429595
25	20	1.0	10	7.5	5.002	4.7588	5.63225	4.900715
26	20	1.0	20	2.5	4.389	4.2321	4.63625	4.490256
27	20	1.0	30	5	3.989	4.1509	4.583	4.09052

Table 8
Predicted values of ROC using regression analyses and SVM.

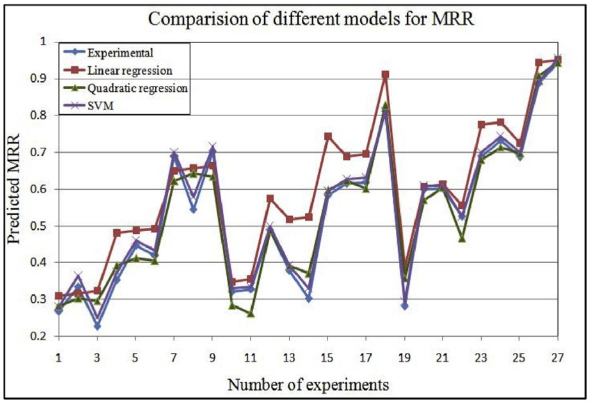
Exp. No.	AV	FR	EC	PC	Experimental	Linear regression	Quadratic regression	SVM
1	12	0.2	10	2.5	0.96	0.732515	0.883195	0.9779591
2	12	0.2	20	5	0.94	0.57979	0.87212	0.9597756
3	12	0.2	30	7.5	0.79	0.427065	0.855495	0.8097946
4	12	0.6	10	2.5	0.75	0.633075	0.754475	0.7455534
5	12	0.6	20	5	0.65	0.48035	0.7434	0.6697914
6	12	0.6	30	7.5	0.8	0.327625	0.726775	0.8131503
7	12	1.0	10	2.5	0.67	0.533635	0.684635	0.6897996
8	12	1.0	20	5	0.64	0.38091	0.67356	0.6597868
9	12	1.0	30	7.5	0.65	0.228185	0.656935	0.6697983
10	16	0.2	10	5	0.91	0.75531	0.9153	0.9289596
11	16	0.2	20	7.5	0.94	0.602585	0.866475	0.9490444
12	16	0.2	30	2.5	1.05	0.699835	1.118475	1.0698451
13	16	0.6	10	5	0.76	0.65587	0.78658	0.7660861
14	16	0.6	20	7.5	0.69	0.503145	0.737755	0.7098141
15	16	0.6	30	2.5	0.99	0.600395	0.989755	1.0098487
16	16	1.0	10	5	0.75	0.55643	0.71674	0.7564918
17	16	1.0	20	7.5	0.7	0.403705	0.667915	0.707678
18	16	1.0	30	2.5	0.93	0.500955	0.919915	0.9498055
19	20	0.2	10	7.5	0.91	0.778105	0.928535	0.9265004
20	20	0.2	20	2.5	1.1	0.875355	1.148335	1.1082601
21	20	0.2	30	5	1.16	0.72263	1.16946	1.1567052
22	20	0.6	10	7.5	0.85	0.678665	0.799815	0.8343884
23	20	0.6	20	2.5	1.03	0.775915	1.019615	1.0498376
24	20	0.6	30	5	1.08	0.62319	1.04074	1.0998425
25	20	1.0	10	7.5	0.64	0.579225	0.729975	0.6532017
26	20	1.0	20	2.5	0.99	0.676475	0.949775	1.0097725
27	20	1.0	30	5	1	0.52375	0.9709	1.0189854

Table 9
Comparison of different prediction models with actual experimental data.

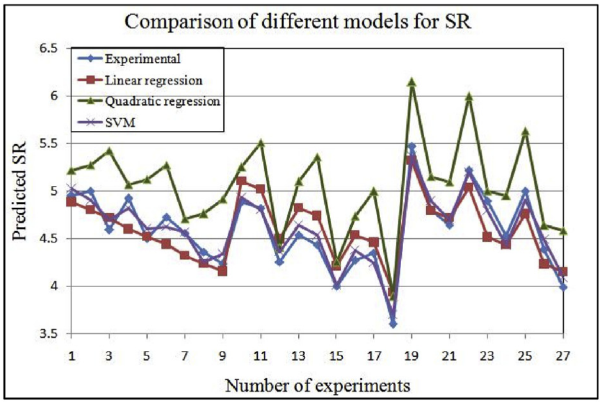
Response	Compared pair	R	R^2	RMSE
MRR	Actual vs. SVM	0.9993	0.9986	0.015
	Actual vs. Linear regression	0.9522	0.9067	0.087
	Actual vs. Quadratic regression	0.9751	0.9508	0.043
SR	Actual vs. SVM	0.9769	0.9543	0.09
	Actual vs. Linear regression	0.8479	0.7189	0.2112
	Actual vs. Quadratic regression	0.8846	0.7825	0.5163
ROC	Actual vs. SVM	0.9983	0.9966	0.0165
	Actual vs. Linear regression	0.6674	0.4454	0.3043
	Actual vs. Quadratic regression	0.9514	0.9052	0.4836

Fig. 2 graphically exhibits the relationships between the actual experimental observations and response values as predicted using the considered models. It can clearly be observed that for all the responses, the SVM model-based response values are the nearest to the observed values having minimum deviations.

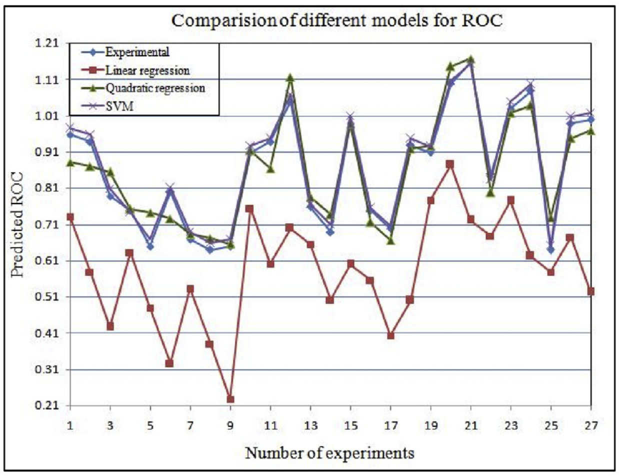
The SVM has already proved itself as an effective prediction model in the domain of data mining to



(a)



(b)



(c)

Fig. 2. Comparison between predicted and actual experimental data for three responses.

envisage the possible outcomes based on a set of input variables. In SVM, each model consists of a number of predictors, which are variables influencing the outcomes. It is an efficient tool for modeling of multi-dimensional problems where standard analytical/statistical approaches fail. If the values of its three free parameters, i.e. C, ϵ and σ are optimally chosen, it is supposed to provide robust prediction models while capturing small scale fluctuations in training as well as testing datasets. Other statistical approaches may have generalization property producing over-fitted models, but SVM minimizes the upper bound of the expected risk to minimize error in the training data. Thus, compared to statistical learning methodologies, SVM is devoid of four problems of efficiency of training, efficiency of testing, over-fitting and algorithm parameter tuning. As compared to other models, it can produce accurate predictions and are least affected by noisy data. In this paper, three SVM-based models are developed to accurately predict MRR, SR and ROC responses in an ECM process which would help the concerned process engineers to maintain the quality of the machined components. In Table 9, high R^2 values between the actual experimental data and SVM-based predicted values for all the three ECM responses validate the superiority of SVM over linear and quadratic regression-based models as employed for the prediction purpose.

While applying GRA technique, Rao and Padmanabhan [28] determined the optimal parametric mix for the considered ECM process parameters as applied voltage = 16 V, tool feed rate = 1.0 mm/min, concentration of the electrolyte = 30 g/l and reinforcement content = 5%. At that optimal setting, MRR, SR and ROC values were obtained as 0.798 g/min, 3.859 μm and 0.73 mm respectively. On the other hand, the corresponding responses were experimented as 0.268 g/min, 4.948 μm and 0.96 mm at the initial operating levels of the process parameters as applied voltage = 12 V, tool feed rate = 0.2 mm/min, concentration of the electrolyte = 10 g/l and reinforcement content = 2.5%. Table 10 exhibits the predicted values of the considered responses both at the initial and optimal operating levels using linear, quadratic and SVM-based models. It can be clearly revealed that the SVM-based model is perfectly able to anticipate better values of all the responses as compared to the observations of Rao and Padmanabhan [28].

Table 10
Prediction of the responses at the optimal operating levels.

Response	Method	Initial operating levels	Optimal operating levels
MRR	Linear	0.3108	0.84264
	Quadratic	0.28261	0.77761
	SVM	0.28028	0.85213
SR	Linear	4.8818	4.0793
	Quadratic	5.21875	4.17308
	SVM	5.02512	3.72361
ROC	Linear	0.73252	0.41763
	Quadratic	0.88320	0.85554
	SVM	0.97795	0.67256

5. Conclusions

This paper deals with the development of suitable SVM-based models for effective prediction of MRR, SR and ROC during an ECM operation on metal matrix composites. The relationships of applied voltage, tool feed rate, electrolyte concentration and percentage of reinforcement of B_4C particles in the metal matrix with the considered responses are examined based on linear and quadratic regression models. For successful prediction of the responses, Gaussian radial basis kernel function is considered in the SVM algorithm. Finally, the optimal values of C, ϵ and σ are identified. The prediction performances of SVM, linear regression and quadratic regression models are compared with the actual experimental data with respect to R^2 and RSME values. It can be revealed that SVM-based model has better prediction accuracy as compared to the other two regression-based models. The response values as envisaged using the developed SVM-based models closely match with the actual values. Thus, this model can be efficiently implemented to predict the quality characteristics of varied machining processes. Studying the influences of other kernel functions, and values ϵ, C, and σ on the prediction performance of the SVM algorithm for the considered ECM process may be treated as the future scope of this paper.

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