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Use of machine learning algorithm for the better prediction of SR peculiarities of WEDM of Nimonic-90 superalloy

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ABSTRACT

Purpose: With the end goal to fulfil stringent structural shape of the component in aeronautics industry, machining of Nimonic-90 super alloy turns out to be exceptionally troublesome and costly by customary procedures, for example, milling, grinding, turning, etc. For that reason, the manufacture and design engineer worked on contactless machining process like EDM and WEDM. Based on previous studies, it has been observed that rare research work has been published pertaining to the use of machine learning in manufacturing. Therefore the current research work proposed the use of SVM, GP and ANN methods to evaluate the WEDM of Nimonic-90.

Design/methodology/approach: The experiments have been performed on the WEDM considering five process variables. The Taguchi L 18 mixed type array is used to formulate the experimental plan. The surface roughness is checked by using surface contact profilometre. The evolutionary algorithms like SVM, GP and ANN approaches have been used to evaluate the SR of WEDM of Nimonic-90 super alloy.

Findings: The entire models present the significant results for the better prediction of SR peculiarities of WEDM of Nimonic-90 superalloy. The GP PUK kernel model is dominating the entire model.

Research limitations/implications: The investigation was carried for the Nimonic-90 super alloy is selected as a work material.

Practical implications: The results of this study provide an opportunity to conduct contactless processing superalloy Nimonic-90. At the same time, this contactless process is much cheaper, faster and more accurate.

Originality/value: An experimental work has been reported on the WEDM of Udimet-L605 and use of advance machine learning algorithm and optimization approaches like SVM, and GRA is recommended. A study on WEDM of Inconel 625 has been explored and optimized the process using Taguchi coupled with grey relational approach.

The applicability of some evolutionary algorithm like random forest, M5P, and SVM also tested to evaluate the WEDM of Udimet-L605.The fuzzy- inference and BP-ANN approached is used to evaluate the WEDM process. The multi-objective optimization using ratio analysis approach has been utilized to evaluate the WEDM of high carbon & chromium steel. But this current research work proposed the use of SVM, GP and ANN methods to evaluate the WEDM of Nimonic-90.

Keywords: Support vector machine, Gaussian process, Artificial neural networking, WEDM

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METHODOLOGY OF RESEARCH, ANALYSIS AND MODELLING

1. Introduction

To create effective complex technical products, it is very important to reliably predict the accuracy of manufacturing and long-term operation of these products [1,2]. Therefore, at present, methods of numerical modeling [3,4] and machine learning algorithm [5] are widely used in different scientific fields.

In particular, WITH the end goal to fulfill stringent structural shape of the component in aeronautics industry, machining of Nimonic-90 super alloy turns out to be exceptionally troublesome and costly by customary procedures, for example, milling, grinding, turning, etc. Issues that are most of the time experienced in machining super alloy by usual methods are large amount of heat generation, flank wear fracture, quick tool wear ensuing changes of work material qualities [6,7]. For that reason, the manufacture and design engineer worked on contactless machining process like EDM and WEDM. Others reason is the properties of super alloy material like high strength hardness and tendency to form built-up edge etc. are responsible to create the difficulty in machiningNimonic-90. Hence, there is a requirement to explore the machinability of Nimonic-90 using WEDM process and also required to evaluate the machining process using some evolutionary algorithm.

A lot of research work is highlighted by many researchers pertaining to the machining of super alloy using conventional and wire-cut electric discharge machining (WEDM). An investigation has been done on WEDM of Inconel X-750 and evaluated the cutting speed and surface roughness traits [8].The grey relational analysis approach has been proposed to find the optimal parameter of turning and boaring operation on 15-5PH stainless steel [9].The grey relational approach has been applied to optimize the EDM of M2-tool steel in presence and absence of dielectric fluid [10].The regression modeling approaches have been used to ascertain the relation amid the process variables and response variables of WEDM of Udimet-L605 [11]. An experimental work has been reported on the WEDM of Udimet-L605 and use of advance machine learning algorithm and optimization approaches like SVM, and GRA is recommended [12]. The behavior of different grade of Inconel 718, 625 and Monel 400 super alloy is discussed during hot turning operation [13]. The machinability of Inconel 600 super alloy has been explored during WEDM and optimized the process variables using grey relational approach [14]. A study on WEDM of Inconel 625 has been explored and optimized the process using Taguchi coupled with grey relational approach [15]. An investigation has been made for the MRR and SR in WEDM of Inconel 800 [16]. The applicability of some evolutionary algorithm like random forest,M5P, and SVM also tested to evaluate the WEDM of Udimet-L605 [17-20].The fuzzy-inference and BP-ANN approached is used to evaluate the WEDM process [21]. The multi-objective optimization using ratio analysis approach has been utilized to evaluate the WEDM of high carbon & chromium steel [22].

Based on previous studies, it has been observed that rare research work has been published pertaining to the use of machine learning in manufacturing. The current research work proposed the use of SVM, GP and ANN methods to evaluate the WEDM of Nimonic-90.

2. Materials and methods. Experimental details and methodology

The nimonic-90 super alloy is selected as a work material. Two different types of wire like plain brass wire and zinc coated brass wire have been used for cutting the workpiece material. The experiments have been performed on the WEDM considering five process variables. The Taguchi L 18 mixed type array is used to formulate the experimental plan. Therefore, total 18 experiments have been performed. The surface roughness is checked by using surface contact profilometre.

The evolutionary algorithms like SVM, GP and ANN approaches have been used to evaluate the SR of WEDM of Nimonic-90 super alloy. The data is divided into training and testing set. Training set consists of 66.66 % data whereas testing set is consisting of 33.33% data as shown in Table 1. The performance variables like CC and RMSE are used to check the consistency of the each model. The scattering plot for the train and test data, validation and errors plot are also used to observe the behavior of each model.

Table 1.
Experimental and prediction outcome of entire models for the SR

Sr. No.	Ton (μs)	Toff (μs)	IP (A)	WT (gm)	SV	Exp. SR	SRGP Poly	SR GP PUK	SR GP RBF	SR SVM	SR SVM	SR SVM	SR ANN
Training													
1	1	1	1	1	1	2.300	2.507	2.300	2.347	2.300	2.302	2.343	2.306
2	1	1	2	2	2	2.050	2.046	2.050	2.012	2.048	2.050	2.342	2.060
3	1	2	1	1	2	2.650	2.528	2.650	2.533	2.358	2.648	2.378	2.649
4	1	2	2	2	3	1.980	2.068	1.980	2.061	2.105	1.981	2.377	2.005
5	1	3	1	2	1	3.000	3.216	3.000	3.069	3.036	2.999	2.448	3.001
6	1	3	2	3	2	2.850	2.756	2.850	2.808	2.783	2.850	2.448	2.873
7	2	1	1	3	3	2.100	2.148	2.100	2.095	2.166	2.101	2.342	2.111
8	2	1	2	1	1	2.320	2.373	2.320	2.312	2.318	2.321	2.342	2.359
9	2	2	1	2	3	2.360	2.397	2.360	2.404	2.358	2.361	2.377	2.387
10	2	2	2	3	1	2.860	2.832	2.860	2.867	2.862	2.858	2.413	2.901
11	2	3	1	3	2	3.180	3.085	3.180	3.141	3.037	3.178	2.448	3.176
12	2	3	2	1	3	2.430	2.415	2.430	2.431	2.432	2.431	2.413	2.486
Testing													
1	1	1	3	3	3	1.200	1.586	2.438	1.563	1.795	2.446	2.343	1.612
2	1	2	3	3	1	2.500	2.503	2.513	2.604	2.609	2.520	2.412	2.472
3	1	3	3	1	3	2.020	2.085	2.460	2.068	2.179	2.467	2.412	2.194
4	2	1	3	2	2	2.120	1.912	2.469	1.927	2.065	2.476	2.343	1.826
5	2	2	3	1	2	2.220	2.162	2.471	2.179	2.257	2.478	2.378	2.106
6	2	3	3	2	1	2.520	2.850	2.536	2.979	2.936	2.542	2.447	2.680

2.1. Support vector machine

Support Vector Machines (SVM) is a regression and classification approach which is originate from statically learning theory [23]. The SVMs classification techniques depend on the standard of ideal division of classes. In the event that the classes are divisible: this strategy chooses, from among the endless number of linear classifiers, the one that limit the generalization error, Along these lines, the chosen hyper plane will be one that leaves the most extreme edge between the two classes, where edge is characterized as the total of the separations of the hyper plane from the nearest purpose of the two classes [23]. On the off chance that the two classes are non-distinct: this strategy endeavor to discover the hyper plane that augments the edge and in the meantime limits an amount corresponding to the quantity of misclassification errors. The trade- off among edge and misclassification error is controlled by a positive steady that must be picked previously. This method of structuring SVMs can be reached out to take into account non-straight choice surfaces. It very well may be accomplished by anticipating the first arrangement of factors into a higher dimensional element space and figuring a straight characterization issue in the element space [23]. The support vector machines can be connected to regression issues and can be figured as clarified in this manner.

2.2. Gaussian process

The Gaussian (GP) models depend on the presumption that nearby observations ought to pass on data about one another. They indicate an earlier specifically over function space. Therefore, the GP is a natural generalization distribution whose covariance is a matrix and mean is a vector. The Gaussian method is based upon the function whereas distribution relies upon the vector. Due to earlier information pertaining to the function, the validation is not necessary for speculation and Gaussian process regression model can comprehend the prescient distribution related to test input [24].

A Gaussian procedure is characterized as an accumulation of arbitrary factors, any limited number which has a joint multivariate Gaussian distribution. The n number of pairs ($x_i \times y_i$) have been made through the ($\chi \times \gamma$) which indicates the input and output data domain, correspondingly. It is assumed that $y \subseteq R$, accordingly the GP on χ is uttered by mean function μ: $\chi \rightarrow R$ and covariance function κ: $\chi \times \chi \rightarrow R$.

2.3. Back-propagation artificial neural network

The back-propagation artificial neural system (BP-ANN) is widely drawn in for numerical prescience and grouping. It is manufactured with quantities of handling components and includes three essential layers, for example, the information layer, hidden layer and output layer correspondingly. The channel in the midst of the layer is used to make the weight relationship in the midst of the hubs. Each node is similar to biological neuron and performs mostly two tasks. It has done the total of the information values and weight related with each interaction. Further, this summation is yielded over activation function f to make the result. By giving the weight, the system creates a result which is existed close to the watched target result as symbolized in condition (1).

$$y_j = \sum W_{ij} x_i \tag{1}$$

3. Results and discussion

The Table 2 demonstrates that all the models present the significant result for the training and testing results of SR of WEDM of Nimonic-90 super alloy. Total seven models have been formulated. The GP PUK model revealed significant result against the others models due to having the highest value of CC and lowest value of RMSE for the training data set of SR as shown in Table 2. The scattering plot for the training outcome of entire model also confirmed the significance of the GP PUK kernel as revealed in Figure 1. The Figure 2 also confirmed that GP PUK model is showing the better results in comparison to the others model.

The feebleness of model is actually relies upon the testing outcome of the models. The performance order of the model is changed for the testing results. The GP poly kernel model is dominating the all models as revealed in Table 2 and Figures 1, 3 and 4. GP poly kernel model demonstrates the highest value of CC and lowest value of RMSE in comparison to the others model as shown in Table 2.

The scattering plot for testing result of the SR also confirmed that the predicted value of SR are scattering closely to the agreement line as revealed in Figure 1. The validation plot also confirmed that GP Poly kernel model presents the significant prediction results for the SR against the others model as confirmed by Figure 3.

Table 2.
Performance variables outcome of entire models

Training			Testing	
Model	CC	RMSE	CC	RMSE
GP Poly	0.9613	0.1069	0.8805	0.2270
GP Puk	1.0000	0.0000	0.8554	0.5646
GP RBF	0.9901	0.0533	0.8761	0.2565
SVM Poly	0.9654	0.1048	0.8605	0.3078
SVM PUK	1.0000	0.0013	0.8534	0.5695
SVM RBF	0.8529	0.3629	0.7016	0.5078
ANN	0.9989	0.0266	0.8582	0.2329

The error plot also have been plotted to confirm the dominancy of the GP model over the entire model. As revealed, GP poly kernel model have minimum error in comparison to the others model.

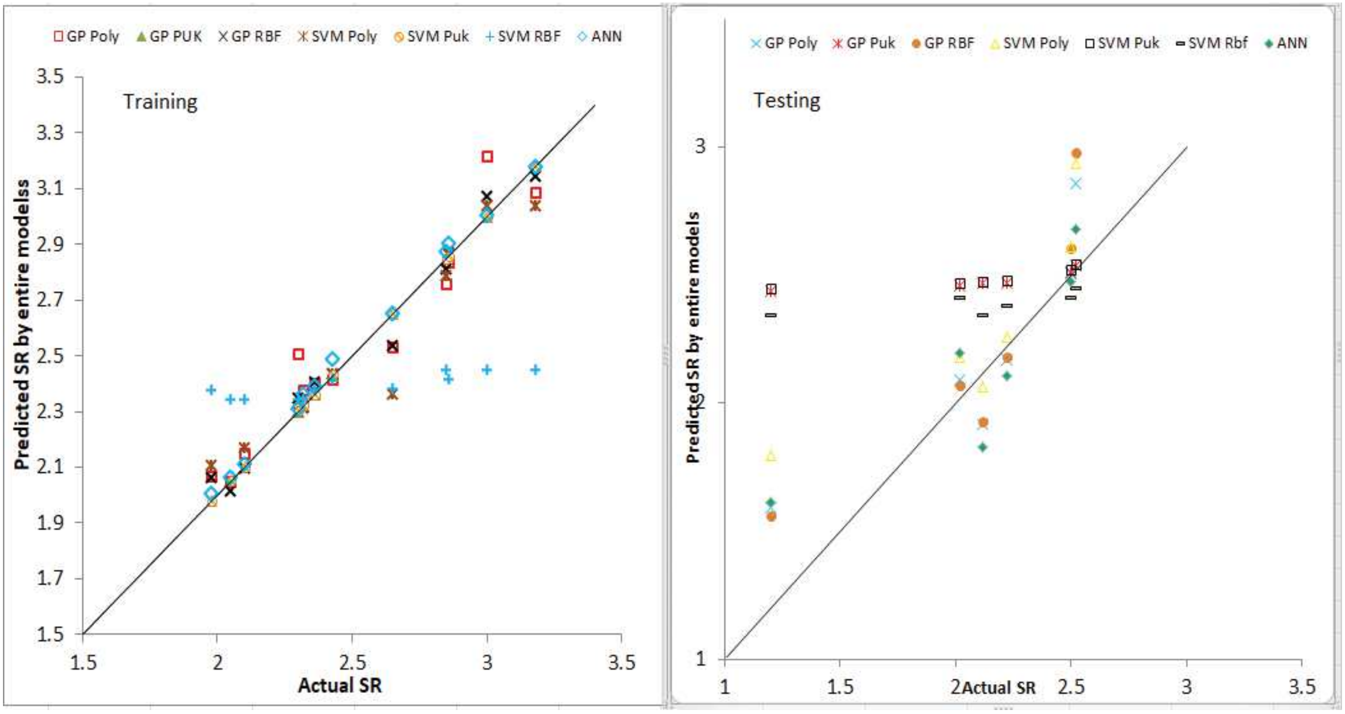

Fig. 1. Scattering plot for the train and test data outcome of entire model

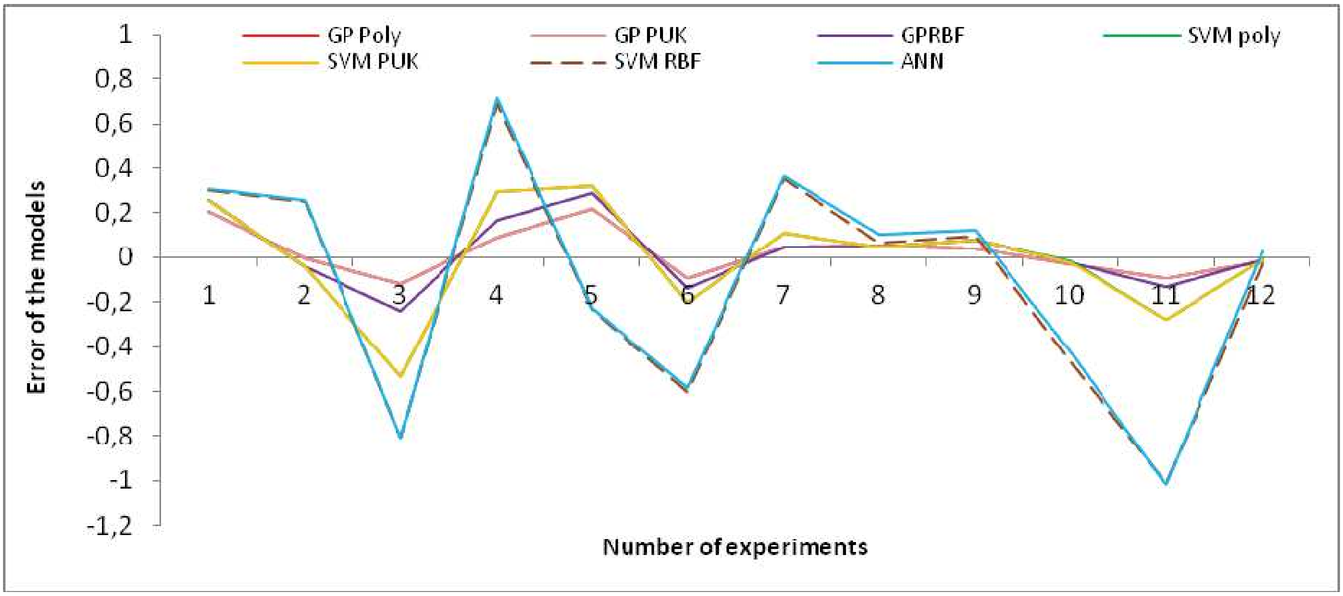

Fig. 2. Error plot for the training outcome of entire models

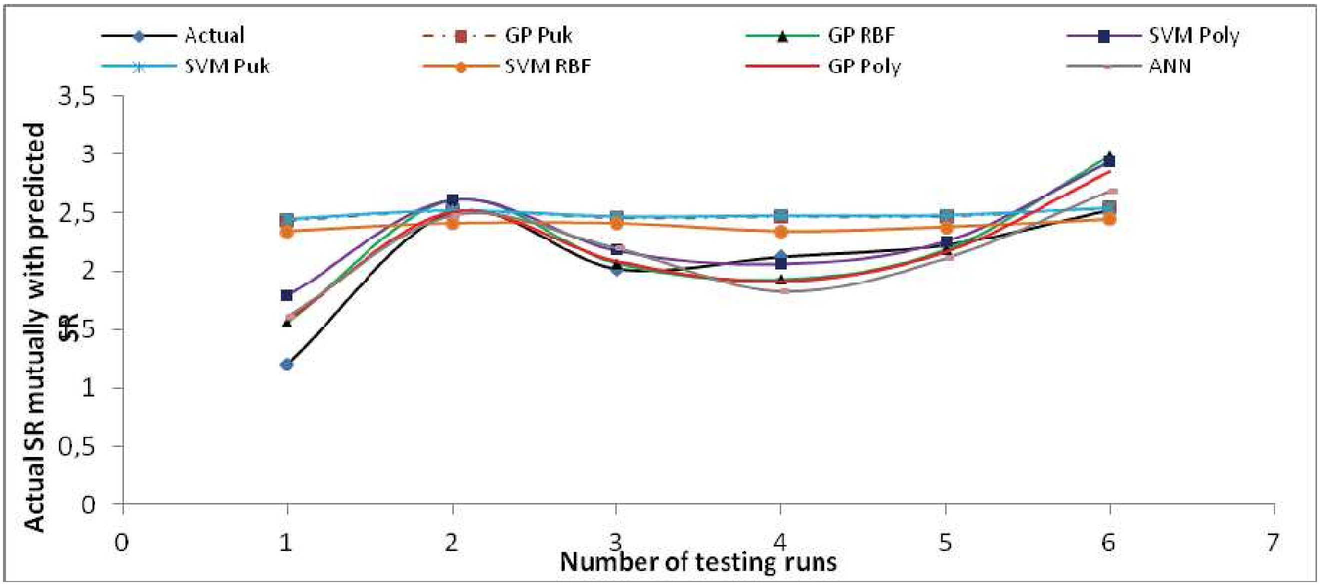

Fig. 3. Validation plot confirming the dominancy of GP Polly kernel model over the others model

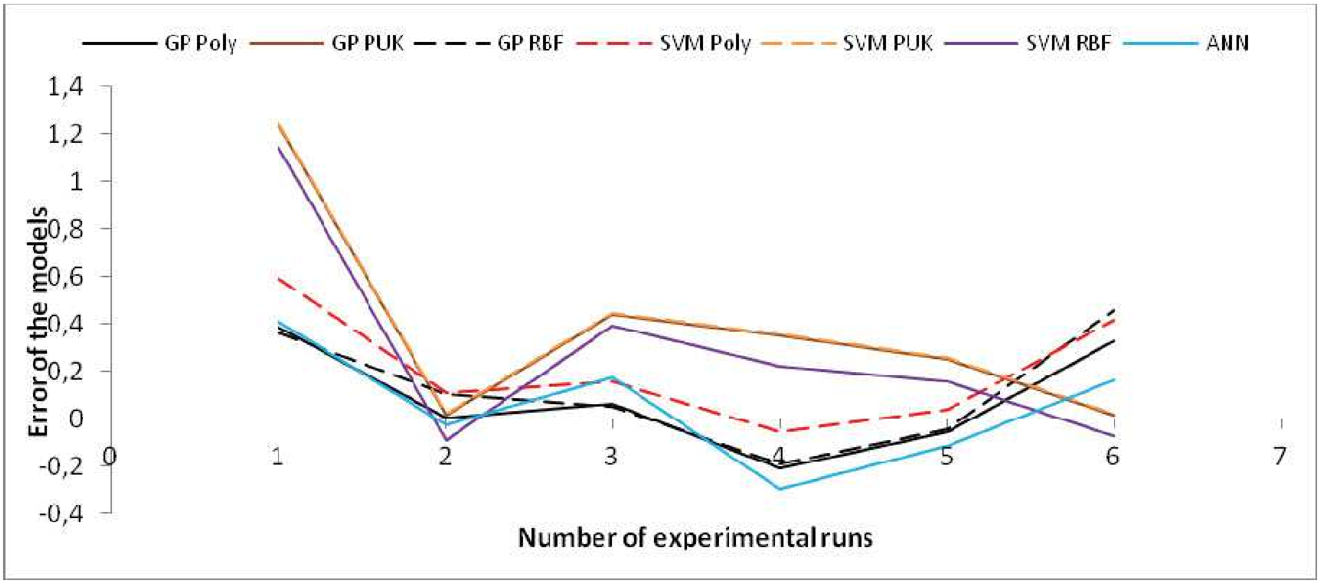

Fig. 4. Error plot for the testing outcome of the entire models

4. Conclusions

The entire models present the significant results for the better prediction of SR peculiarities of WEDM of Nimonic-90 superalloy. The GP PUK kernel model is dominating the entire model. The increasing order of the performance of the entire model is given as: SVM RBF < SVM PUK < GP PUK < ANN < SVM Poly < GP RBF < GP Poly.

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Additional information

The work was carried out within the framework of scientific studies of colleges and universities where the authors of this article work.

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