Support Vector Regression approach for prediction of delamination at entry and exit during drilling of GFRP Composites

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Abstract. The demand for Composites in the modern era have increased immensely due to its vast applications and superior properties over conventional materials. Glass Fibre Reinforced Plastic (GFRP) is one of the economic alternative to conventional engineering materials due to its high specific modulus of elasticity, high specific strength, good corrosion resistance, high fatigue strength and lightweight. Components made out from GFRP composites are usually near net shaped and require holes for assembly integration. Drilling is an important process as concentrated forces can cause major damage to the composite. Drilling of GFRP causes various damage such as thermal degradation, fibre breakage, matrix cracking and delamination. A substantial damage is caused by delamination which can occur both on the entry and exit sides of the composite, exit side delamination considered more severe. Therefore, selection of proper process parameters during drilling operation is very much essential. In the present work, a support vector regression (SVR) model is developed to predict the delamination at entry and exit during the drilling of GFRP composites. The model is developed based on the data obtained from experimentation. The model accuracy is evaluated by the three performance criteria including root mean square error (RMSE), Nash–Sutcliffe efficiency co-efficient (E) and co-efficient of determination (R2). The model provides an inexpensive and time saving alternative to study the delamination at entry and exit of the GFRP composite actual drilling operation.

1 Introduction

In the recent years, conventional materials have been replaced by Composites due to its wide range of applications and excellent properties. Composites have high stiffness to density ratio which provide greater strength at lighter weights. Generally used in structural components, Composite materials such as Glass fiber reinforced polymer (GFRP) have great structural properties such as high strength to weight ratio, high fracture toughness, high specific modulus of elasticity, high fatigue strength and are lightweight materials. They have a low

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co-efficient of thermal expansion, which helps to provide dimensional stability. They are also good dampers and can reduce vibrations and noise. Due to these superior and unique properties, GFRP composites are used worldwide in automobile, aerospace and marine sectors. Hence, machining of these composites have become very important as a result of its widening range of applications[1-2]. Drilling is one of the most usual machining operations out of all the machining operations carried out on the composite. Components made out of GFRP composites are near net shaped and require holes for assembly integration. The drilling of GFRP composites are different than traditional materials because of its non homogenous and anisotropic properties. Drilling process and tool parameters play an important role in determining the quality of holes. Drilling is an important process as concentrated forces can cause major damage to the composite [3]. Hence, selection of proper process parameter such as, the spindle speed, drill diameter, feed rate of the machining operation is very much essential. Drilling of GFRP Composites triggers various damages such as delamination, fibre breakage, spalling, thermal degradation and matrix cracking. Out of these, a substantial damage is caused by delamination that can occur at the entry side as well as the exit sides of the composite. Exit side delamination is inspected to be critical. Drilling induced delamination can be reduced by optimizing the process parameters by various optimization techniques.

2 Literature review

Chadha et al. [4] analyzed various cutting parameters on delamination during the drilling of GFRP Composites. They investigated various parameters such as feed, cutting speed to study the delamination on the composite during the machining process. Design of Experiments were conducted using Taguchi's technique and analysis of variance was used to gain minimization of delamination controlled by the drilling parameters and the number of layers .Anand et al. [5] have investigated and optimized the process parameters during the drilling of hybrid glass fiber reinforced polymer using multi response optimization techniques such as grey relational analysis, regression analysis, fuzzy logic and Artificial Neural Network models. Thakur et al. [6] have optimized the drilling parameters using multi-objective optimization techniques during machining of CFRP Composites taking into consideration the delamination and material removal rate as the response parameters. Ramesh et al. [7] investigated the hole quality during drilling of thick non laminated Glass Fiber Reinforced Plastic Composite rods utilizing coated tungsten carbide twisted drill bit.They measured the ovality of the hole using Coordinate Measuring Machine. Solati et al. [8] investigated the surface quality and mechanical properties during CO_2 laser drilling of Glass Fiber Reinforced Composite. Shunmugesh et al. [9] optimized the process parameters in drilling of GFRP Composites with the help of Grey Relational Analysis along with fuzzy logic system considering input parameters as Cutting speed, feed rate and drill bit diameter and delamination and surface roughness as response parameter. Desikan and Jenarthanan [10] minimized the surface roughness during the drilling of Resin Hybrid GFRP Composite. Bhat et al. [11] have worked on various machining parameters during the drilling of a GFRP Composite mainly focusing on the feed and speed and the specimen thickness.For optimizing the parameters they have used TOPSIS for developing performance index and optimize it.S-ANOVA i.e stepwise analysis of variance have also been used to investigate the significance of the output parameters. Among other input parameters, specimen thickness was the most remarkable factor affecting the performance index. Increase in specimen thickness was worsening the surface roughness and peel up delamination. Kilickap [12] have done a similar analysis on the delamination occuring on drilling of GFRP Composites using Taguchi Method and analysis of variance for the minimization of delamination of the composites.

However limited research work has been carried out for developing predictive tool for various responses during drilling of GFRP composites. Hence, in the present work, a support vector regression (SVR) model is developed to predict the delamination at entry and exit during the drilling of GFRP composites. The model is developed based on the data obtained from experimentation. A set of four important input parameters such as cutting speed, feed, depth of cut and degree of orientation is chosen to conduct the drilling operation of GFRP Composite. The model accuracy is evaluated by the three performance criteria including root mean square error (RMSE), Nash–Sutcliffe efficiency co-efficient (E) and co-efficient of determination (R^2).

3 Proposed Methodology

Support Vector Regression (SVR) is a well known artificial intelligence method which invokes generalization ability in models.It allows the usage of several kernel functions.The origin of SVR is Support Vector Machines (SVM) introduced Vapnik.It is a learning method with a theoretical root in the framework of statistical learning theory.On unseen data,SVM can have good generalization ability with proper training.SVM was originally developed to solve classification problems which was later extended to solve regression problems, also known as Support Vector Regression (SVR).There are several advantages of SVR as compared to neural networks.Firstly, training for SVR results in a global optimum as it is formulated as a convex quadratic optimization problem.There are fewer tuning parameters in SVR than in neural networks.As compared to the neural networks, the design and training of SVR models is much more straightforward and systematic.SVR formulates models based only on the data obtained from the system unlike regression analysis which is void of statistical assumptions such as model structure assumption, error dependency, etc.The framework is derived from structural risk minimization(SRM) principle which is a modification of empirical risk minimization principle and minimizes an upper bound on the expected risk.The input decision space is transformed to the higher dimensional space by the hyperspace function which implies that the nonlinear regression problem is converted to a linear regression problem when the decision space is transformed.Numerous hyperspace functions can be used for this transformation [14].

SVR model is formulated based on the data, $\left(x_i, y_i\right)_{i=1}^{N} \in R^m \times R$, where xi is the input process parameter and yi is the actual value of the process.The SVR model is given by,

$$y = v(x) = \sum_{i=1}^{N} j_i \beta_i(x) + d = j^T \rho(x) + d \tag{1}$$

Where the function ρ(x) is a space converted into higher dimensional space, and

$$j = \left[j_1 \, j_2 \cdots j_N\right]^h \quad \text{and} \quad \beta = \left[\beta_1 \, \beta_2 \cdots \beta_N\right]^h$$

The hyperspace function is projected in the higher dimensional space .The nonlinear regression model β(x) is converted to a linear regression model in the higher dimensional space.The kernel function chosen learns and minimizes the regulated risk function (L).The parameters support vector weight (j) and bias (d) are estimated which minimizes the regulated risk function.

$$L(j) = \frac{1}{2} j^T j + \lambda \sum_{i=1}^{N} |y_i - v(x)|_e \tag{2}$$

$$where \quad |y_i - v(x)|_e = \begin{cases} 0, & if \ |y_i - v(x)| < \varepsilon \\ |y_i - v(x)| - \varepsilon, & otherwise \end{cases}$$

The regularization parameter (λ) determines the optimum balance between the weight vector norm and the approximation error.The approximation error is decreased by increasing λ, or decreasing weight vector norm, .This can cause over fitting of model or may not even guarantee the high generalization ability of the model.If the predicted values of the model v(x) lies within the defined tolerance value ε, the loss function is zero and for the points outside ε, the loss function is the absolute of the difference between the values predicted by the model and tolerance level ε.Supports vectors are the points on the margin lines with those outside are called error set.

4 Experimentation

In the present work, the drilling operations were performed on CNC milling machine [MAXMILL 3 axis CNC machine with FANUC Oi Mate MC Controller, Model No. CNC 2000EG]. The work material used for the present investigation is GFRP (Glass fibre reinforced plastic composite) made by filament winding processes. E-glass fibre is used in composites and is randomly orientated. Carbide drill bits having coating of TiAlN supplied by WIDIA is used. Drill size of 6,8, 10 and 12 mm diameter are used for the investigation. Experiments were performed using Taguchi's L_{16} orthogonal array considering three input parameters with four different levels as present in Table 1. Delamination at entry and exit and surface rough are considered as the performance measures during the present work.

Table 1: Input parameters with their levels

Input variables	Unit	Symbol	Levels			
			Level I	Level II	Level III	Level IV
Cutting speed	mm	A	850	1050	1250	1450
Feed	mm/min	B	100	150	200	250
Driil bit size	mm	C	6	8	10	12

During drilling of GFRP composites delamination is an important factor, which affects the drilled components.Delamination at entry as well as exit side the laminate was measured using magnified photographs obtained through microscope (radial instrument with Samsung camera setup, 10-X magnification). The delamination factor (Fd) may be calculated from the ratio of the maximum diameter of the delamination(Dmax) of the delamination zone to the drill diameter(D), as shown in following equation:
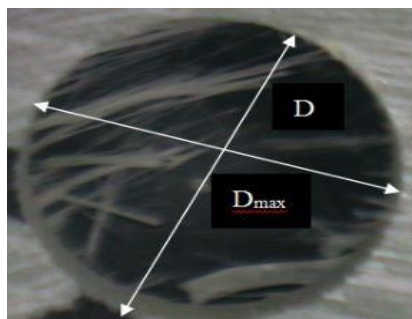
Delamination Factor= Dmax/D

Fig. 1: Delamination in GFRP

Drilling operations have been carried out using Taguchi's L16 experimental design on different composite samples for assessing performance characteristics such entry delamination factor and exit delamination factor and surface roughness as presented in Table .2.

Table 2: Experimental Results

Expt no.	Speed (rpm)	Feed (mm/min)	Drill bit size (mm)	Delamination factor at entry	Delamination factor at exit
1	850	100	6	1.096	1.35
2	850	150	8	1.02	1.26
3	850	200	10	1.069	1.34
4	850	250	12	1.079	1.82
5	1050	100	8	1.106	1.108
6	1050	150	6	1.105	1.108
7	1050	200	12	1.14	1.2
8	1050	250	10	1.095	1.098
9	1250	100	10	1.09	1.091
10	1250	150	12	1.113	1.118
11	1250	200	6	1.12	1.135
12	1250	250	8	1.028	1.112
13	1450	100	12	1.081	1.088
14	1450	150	10	1.076	1.086
15	1450	200	8	1.087	1.091
16	1450	250	6	1.089	1.094

5 Results and Discussions

The experiments are conducted and the response values are calculated as shown in Table 2. Then normalization of raw data is carried out to obtain values between 0 and 1 for expressing all data in a common scale. A support vector regression method is used to develop the model for the prediction of delamination at entry and exit during drilling of GFRP composites. In this model, out of Sixteen experimental data, approximately 75% are used for training and approximately 25% data for testing. LS-SVM toolbox built for MATLAB is used for the model development. The kernel function plays an important role in learning the hyperspace from the training data in SVR. There are lot of kernel function are available. However, in this work, RBF kernel function is chosen since it is more compact and well known for its shorter training process and imparting high generalization ability to the model. In order to make an SVR model (with Gaussian RBF kernel), we need two tuning parameters: λ is the regularization parameter, determining the trade-off between the traing error minimization and smoothness and σ_{sv}^2 is the squared variance. The parameters λ and σ of the radial basis function are determined using a combination of coupled simulated annealing (CSA) and a grid search method. Firstly the CSA determines the good initial values of λ and σ, and then these are passed to the grid search method which uses cross-validation to fine tune the parameters.

Once the model is developed, its accuracy is evaluated by three performance criteria including root mean square error (RMSE), Nash–Sutcliffe efficiency co-efficient (E) and coefficient of determination (R2). Root mean square error is a frequently used tool for evaluating the performance of the model which is calculated by using "Equation (3)". The individual difference between the actual values and predicted values are also called residuals.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(X_{obs,i} - X_{model,i}\right)^2}{n}} \tag{3}$$

where Xobs is observed values and Xmodel is modelled values.

Nash-Sutcliffe model efficiency coefficient (E) is also efficient to evaluate the performance of the model which is described by using "Equation (4)"

$$E = 1 - \frac{\sum_{i=1}^{n}(X_{obs,\ i} - X_{model,i})}{\sum_{i=1}^{n}(X_{obs,i} - \overline{X_{obs}})} \tag{4}$$

where Xobs is observed values and Xmodel is modelled values . Essentially, the closer the model efficiency is to 1, the more accurate the model is.

The co-efficient of determination (R2) is observed from the co-rrelation plot between the actual and predicted values.

The prediction accuracy of SVR model based on three performance criteria is shown in Table 5.1. Table 5.1 indicates that the model is predicting with reasonable accuracy as evident from three performance measures. However, RMSE (R) is greater (lower) for testing data compared to training data.

Table 3. Performance evaluation of the SVR model for delamination at exit

Training Stage			Testing stage		
RMSE	E	R^2	RMSE	E	R^2
0.0037	0.9998	0.9999	0.2721	0.8644	0.96037

A linear regression curve between actual and predicted value is shown in Fig. 2 for testing data. It is evident that co-efficient of determination (R2) for testing data is 0.96037, which is nearly equal to 1.
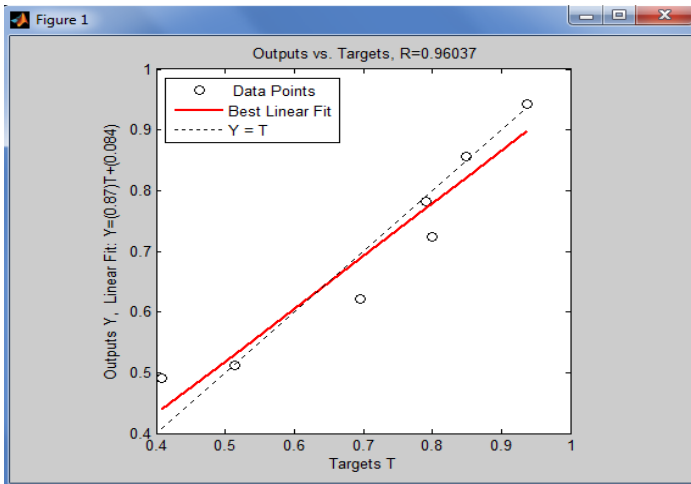

Fig. 2. Co-rrelation plot for testing data set in SVR model

6 Conclusion

Process modelling and optimization of the machining parameters are the two important issues in the field of manufacturing. Hence the experimental research work carried out in this study contributes to the generation of knowledge related to drilling of GFRP Composites. The Taguchi method seems to be an efficient methodology to find out the optimum cutting parameters for drilling operation as experiment was based on minimum number of trails conducted to obtain optimum setting for cutting parameters. Delamination is a major concern among the tool engineers while assembling complex parts using drilling operation. To

alleviate such problems, a simple but reliable predictive method using support vector machine has been proposed in this work.The model can efficiently produce a mapping relationship among three important process parameters with delamination at entry and exit. The method being simple and elegant, it can be easily used by tool engineers for prediction of delamination factor in real applications.

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