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ORIGINAL CONTRIBUTION

Monitoring of Friction Stir Welding Process using Main Spindle Motor Current

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Abstract The present work aims at demonstrating the different avenue for indirect monitoring of friction stir welding process which is hardly attempted. Information contained in the current signal of the main spindle motor is extracted in terms of four statistical features. These features along with tool rotational speed, welding speed and shoulder diameter are combined with support vector machine for the prediction of ultimate tensile strength of the joints. The parameters of the support vector machine are optimized using grid search method. The prediction performance of the model is tested for inputs which contain process parameters with and without signal features. The performance of the developed support vector regression models are compared with well accepted multi-layer feed forward neural network trained with back propagation algorithm and radial basis function neural network developed for the prediction of ultimate tensile strength of the welded joints. The analysis leads to the observations that inclusion of signal features to these models improve the prediction accuracy by an appreciable amount. Among the developed models, support vector machine outperform in modeling ultimate tensile strength of the welds compared to neural network models.

Keywords Monitoring · Support vector machine · Neural network · Strength prediction · Current signal

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Introduction

Friction stir welding process (FSW) found its implementation in many industrial applications [1, 2]; surely necessity arises in developing different techniques for monitoring the outcome of the process in terms of quality of the welded joints. But only few researchers had attempted monitoring of FSW process [3]. A mathematical model was proposed by Mehta, et al [4] for real time measurement of traverse force and torque in terms of input current and power from the spindle and feed motors in order to monitor the FSW process. Acoustic emission signals were analyzed to study the effect of pin profiles on FSW process by Subramanian, et al [5] and boiled down to a conclusion that square pin profile adds more towards the strength of the joints.

Modeling of weld quality has become significant nowadays to offer better control over the process. Different approaches had been evolved for predicting the weld quality. Support vector machine (SVM) learning technique for classification as well as prediction in different welding processes has been attempted by researchers. Prediction of residual stresses in gas tungsten arc welding of dissimilar metals was attempted by Na, et al [6] using SVR models. They found that the SVR models are highly accurate in predicting the experimental results. Classification of defective and defect free welds was attempted by Wang, et al [7] from the X-ray image features of line welds. It was presented that SVM accurately classify the defective features and the defect free features. Application of SVM in material design was demonstrated in the work by Lu, et al [8]. Electric resistance of material, thickness control of semiconductor film were attempted to predict using SVM models and concluded that the developed models can be effective in material designing. Apart from the SVM approach, researchers mostly used artificial neural network (ANN) models for prediction of weld qualities in FSW and other processes [9–11].

From the aforementioned literature survey, it is realized that prediction of weld quality in FSW process was targeted by few researchers, and most of them considered only process parameters in their prediction mechanisms. For the complex process like FSW, where precise physics based formulation is lacking and the outcome of the process is governed by too many influencing factors, depending solely on selective process parameters for the development of more accurate monitoring system for strength prediction will not suffice. Inclusion of current signal features to the monitoring systems will surely enhance the accuracy. To demonstrate this, in the current research work, prediction of weld quality in terms of UTS values is proposed using main spindle motor current signal features. Time domain statistical features namely, root mean square (RMS), skewness, variance and kurtosis are computed from the signals and presented to SVR model developed for the prediction of UTS of the welds. The prediction performances of the SVR models are compared with the ANN models.

Experimental Procedures

In the present work, two aluminum alloy (AA1100) plates with dimension of 160 × 110 × 6 mm are used as the workpiece material to perform the FSW operation in butt joint configuration. The composition and mechanical properties of base material is shown in Table 1. After the welding, the welded samples are cut into specific dimensions provided in ASTM E8 manual for tensile testing. The tensile test is performed using a universal testing machine. A converted milling machine developed indigenously for friction stir welding process, is used in the research work. The welding setup has a three phase ac induction motor (maximum current rating of 19 A, 440 V supply voltage and 50 Hz) responsible for tool rotational speed. Current signals from main spindle motor are acquired using a Hall Effect current transducer. All the signals are acquired using a high speed data acquisition system at a sampling rate of 10 kHz.

In FSW process, tool rotational speed and welding speed are the two most influencing process parameters responsible for rate of heat generation and mixing of the material [1]. Apart from these two parameters, shoulder diameter also plays an important role in FSW process [4]. Therefore, these three parameters are considered to study the FSW process behaviour. All these process parameters are chosen at four levels and a full factorial design method is used to obtain the design matrix. The levels of each parameter are listed in Table 2. A total of 4^3, that is, 64 experimental runs are obtained from the full factorial design. The design matrix is shown in Table 3 with responses. Experiments are performed randomly to reduce bias or experimental error. Straight cylindrical tool pin profile is used in all the experiments with fixed pin length of 5.7 mm, pin diameter of 6 mm and plunge depth of 0.06 mm.

Analysis of Current Signal

In this study, four statistical features namely RMS, skewness, kurtosis and variance of current signal are computed and listed in Table 3 to analyze the signal in time domain. The magnified view of signals acquired during Exp. No. 36 and Exp. No 45 are shown in Fig. 1. It is to note that, these two experiments correspond to minimum and maximum UTS, respectively, and performed against same tool rotational speed. But from the figure, the difference in the current signal magnitude for these two cases can be clearly seen and is supported by the change in different statistical domain features tabulated in Table 3. This entails the fact that the process parameters may go inconsistent in the presence of other unknown influencing factors, the cumulative effects of which will bring some change in the process and thus in the weld quality. Therefore, monitoring based on signal feature will provide a rich way for the evaluation of the process performance.

The variation of UTS with the statistics domain features are explored in this study to check for existence of correlation between computed features and UTS. From the investigation it is observed that all the statistical features follow an increasing trend with the increase in the UTS. It manifests that there is intelligible correlation between these

Table 1 Composition and mechanical properties of AA1100

Mechanical properties	Chemical composition, weight %
	Al: 99.3
UTS, MPa = 119.8	Si: 0.2
Yield strength, MPa = 106	Zn: 0.2
Percentage elongation: 17.1	Fe: 0.2
	Cu: 0.1

Table 2 Levels of process parameters

Process parameters	Level 1	Level 2	Level 3	Level 4
Tool rotational speed (TRS), rev/min	600	815	1100	1500
Welding speed (WS), mm/min	36	63	98	132
Shoulder diameter (SD), mm	16	20	24	28

Table 3 Design matrix with responses

Exp. no.	Process parameters			Statistical features of the signal				UTS, MPa
	TRS, rev/min	WS, mm/min	SD, mm	RMS $\times 10^{-2}$	Variance $\times 10^{-3}$	Skewness $\times 10^{-3}$	Kurtosis	
1	600	36	16	7.92	5.03	1.82	1.51	94.05
2	600	36	20	7.73	4.47	2.01	1.54	85.87
3	600	36	24	8.13	5.22	5.25	1.56	78.56
4	600	36	28	7.66	4.39	2.59	1.64	65.69
5	600	63	16	7.79	4.83	6.14	1.52	88.42
6	600	63	20	6.70	4.49	3.98	1.56	84.64
7	600	63	24	8.44	5.76	5.16	1.56	88.12
8	600	63	28	7.91	4.75	1.58	1.93	71.88
9	600	98	16	7.52	4.43	1.72	1.53	82.45
10	600	98	20	8.05	4.82	1.77	1.55	85.24
11	600	98	24	8.15	5.27	3.72	1.56	73.60
12	600	98	28	8.46	5.71	1.02	1.82	67.55
13	600	132	16	7.72	4.71	3.54	1.54	95.89
14	600	132	20	7.96	4.95	9.30	1.57	81.89
15	600	132	24	8.35	5.59	3.71	1.56	81.95
16	600	132	28	9.22	7.17	1.45	1.71	84.09
17	815	36	16	7.86	4.95	1.79	1.52	92.00
18	815	36	20	7.88	4.69	0.01	1.53	77.34
19	815	36	24	8.23	5.43	4.40	1.54	85.48
20	815	36	28	8.54	5.65	1.23	1.57	80.33
21	815	63	16	8.15	5.41	6.05	1.53	94.63
22	815	63	20	7.76	4.44	1.21	1.53	78.22
23	815	63	24	8.25	5.43	1.04	1.55	83.13
24	815	63	28	8.35	5.36	0.06	1.74	78.48
25	815	98	16	7.96	5.09	1.11	1.54	73.87
26	815	98	20	8.00	4.85	6.72	1.54	77.90
27	815	98	24	8.55	5.96	1.02	1.58	87.86
28	815	98	28	8.03	4.85	1.71	1.66	65.74
29	815	132	16	8.06	5.25	1.78	1.54	88.05
30	815	132	20	8.21	5.17	7.56	1.54	75.15
31	815	132	24	8.78	6.41	3.52	1.55	92.62
32	815	132	28	8.51	5.67	8.22	1.79	77.83
33	1100	36	16	7.96	5.04	1.18	1.53	74.54
34	1100	36	20	7.39	5.46	2.03	1.54	83.45
35	1100	36	24	8.97	6.76	7.50	1.54	76.30
36	1100	36	28	8.90	6.29	1.16	1.59	51.15
37	1100	63	16	7.96	5.02	1.31	1.58	91.86
38	1100	63	20	8.48	5.48	1.94	1.56	82.69
39	1100	63	24	8.89	6.60	2.86	1.54	89.91
40	1100	63	28	9.32	7.08	4.67	1.58	76.12
41	1100	98	16	7.81	4.80	9.32	1.55	81.41
42	1100	98	20	8.61	5.60	0.05	1.55	77.86
43	1100	98	24	8.85	6.54	3.52	1.56	75.35
44	1100	98	28	8.98	6.56	2.29	1.67	79.28
45	1100	132	16	8.30	5.65	2.68	1.58	95.95
46	1100	132	20	8.37	5.39	7.36	1.57	77.55
47	1100	132	24	8.78	6.41	3.52	1.55	63.91
48	1100	132	28	8.87	6.41	1.36	1.79	77.86
49	1500	36	16	8.75	6.39	1.74	1.53	88.42
50	1500	36	20	8.49	5.48	5.37	1.54	64.95
51	1500	36	24	9.20	7.16	1.35	1.63	92.22
52	1500	36	28	8.95	6.55	6.54	1.58	81.08
53	1500	63	16	8.93	6.68	1.01	1.53	92.59
54	1500	63	20	9.18	6.73	2.40	1.54	81.65

Table 3 continued

Exp. no.	Process parameters			Statistical features of the signal				UTS, MPa
	TRS, rev/min	WS, mm/min	SD, mm	RMS $\times 10^{-2}$	Variance $\times 10^{-3}$	Skewness $\times 10^{-3}$	Kurtosis	
55	1500	63	24	9.39	7.53	3.85	1.54	88.92
56	1500	63	28	8.67	6.09	1.82	1.62	68.57
57	1500	98	16	8.93	6.68	1.95	1.54	71.38
58	1500	98	20	8.71	5.97	1.12	1.57	77.17
59	1500	98	24	9.19	7.18	7.23	1.56	87.12
60	1500	98	28	9.49	7.60	2.41	1.65	81.81
61	1500	132	16	8.99	6.81	3.36	1.54	80.29
62	1500	132	20	8.52	5.70	1.91	1.63	83.93
63	1500	132	24	9.19	7.16	1.33	1.56	59.12
64	1500	132	28	8.96	6.46	1.32	1.61	83.64

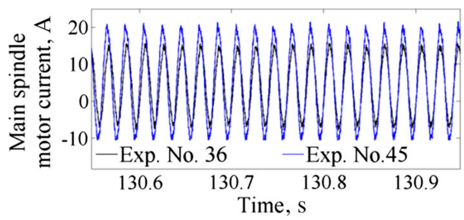

Fig. 1 Magnified view of main spindle motor current signal

signal features and the strength of the welded joints. So, these signal features along with the process parameters are used in the input space of the SVR model as well as ANN models for predicting UTS of the joints.

Modelling of UTS using SVM

SVMs are very specific class of algorithm characterized by usage of kernels, absence of local minima, sparseness of the solution and capacity controlled by acting on margin or on support vectors, etc. As the same way with classification approach there is motivation to seek and optimize the generalization bounds for support vector regression (SVR). The detail of the SVR is out of the scope of this article and can be found in relative technical article [12]. SVM generalization performance (estimation accuracy) depends on setting of meta parameters C, ε and kernel parameter (γ). Different algorithms are available for hyperparameter optimization and grid search algorithm is one of those [13, 14]. For SVMs, C and γ are the two hyperparameter that need to be optimized and initialized in pairs. Grid search trains a SVM with each pair (C, γ) in the Cartesian product of these two sets and evaluate their performance on held-out validation set. Finally the grid search outputs the settings that achieved highest score in the validation procedure.

To find the optimum network parameters, the value of C is varied in the range of 1 to 100 in steps of 1. Whereas, γ and ε values are varied in the range of 0.01 to 0.1 in steps of 0.01. From the grid search method, optimum set of C and γ are found to be 90 and 0.06, respectively, when the input space of the model contains signal features along with the process parameters. On the otherhand, optimum set of C and γ values for the model when the input space contains only the process parameters are 60 and 0.07, respectively. Optimum values of ε are found to be 0.03 and 0.06 for the models, respectively. The models are trained using 57 data sets and remaining 7 data sets are used for testing the developed models. Prediction performance of the developed models are shown in Fig. 2. Output predictions of the developed models for the testing cases are listed in Table 4. From the table it is observed that absolute average percentage error of 2.15 and 6.03 are obtained from the models. Moreover, it is demonstrated that inclusion of signal features in the model input space, increases the prediction accuracy by 64% which indicates that signal features in the input space of the model can be quite effective to accurately predict the quality of the weld. The prediction performance of the SVR model is compared with perfomance obtained from ANN models to find the better candidate for accurate prediction of weld quality.

Modelling of UTS using ANN

In this work, a standard multi-layer feed forward neural network trained using back propagation algorithm; known as back propagation neural network (BPNN) and a radial basis function neural network (RBFNN) are developed to model the UTS of the welded samples. Computer programs for ANN models are developed using the C programming language. As neural networks are prone to overfitting the data, validation datasets are used to monitor the behaviour of the network so that it does not move towards overfitting [15, 16]. In general, it is found that around 15% of datasets are used for validation, 10% are used for testing the developed neural network model [17]. Remaining datasets

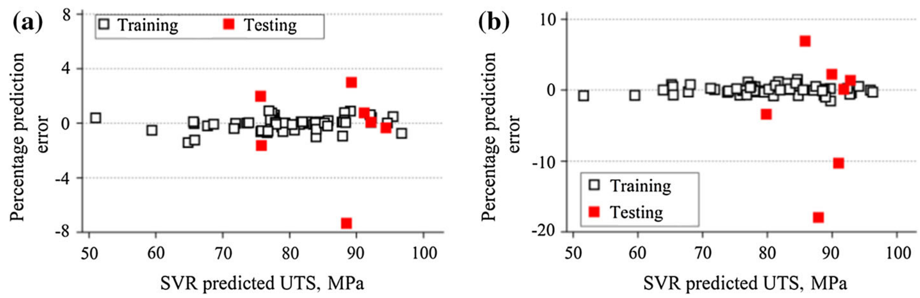

Fig. 2 Performance of support vector regression model **a** with signal features **b** without signal features

Table 4 Performance of support vector regression models

Exp. no.	Actual UTS, MPa	Predicted UTS, MPa			
		Without signal features	Error, %	With signal features	Error, %
33	74.54	87.87	−17.88	75.77	−1.65
58	77.17	79.83	−3.44	75.64	1.98
1	94.05	92.82	1.31	94.38	−0.35
17	92	89.95	2.23	89.25	2.98
37	91.86	91.79	0.08	91.16	0.71
51	92.22	85.82	6.93	92.15	0.08
9	82.45	90.99	−10.36	88.50	−7.33
Average absolute percentage error			6.03		2.15

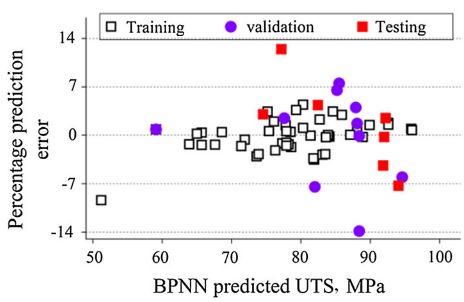

Fig. 3 Prediction performance of BPNN model

are used for training the network. Among the full factorial datasets, 47 and 10 patterns are selected randomly for training and validating the models, respectively. Data set used for testing the SVR model is used for testing the developed neural networks.

The prediction performance of BPNN model depends on the architecture of the network, learning rate (η) and momentum coefficient (α). The number of neurons in the hidden layer is varied from 5 to 39 in steps of 1. Learning rate is varied in between 0.1 to 1 in the steps of 0.04 and momentum coefficient is varied in between 0.01 to 1 in the steps of 0.04. Initial weight values are chosen randomly between ± 0.9 and the bias values at the input layer is taken as 0 and that for hidden and output layer as 1.0 respectively. All the inputs and output variables are normalized between 0.1 and 0.9 which ensures that the back propagation algorithm does not drive some of the connections weights to infinity and thus slow down the training [18, 19]. The activation functions for both the hidden and output layers neurons are log-sigmoid. The objective of the training is to minimize the mean square error (MSE) by updating the weights through gradient descent method [18].

The best network architecture from the optimization framework is found to be 7-21-1 with $\eta = 0.7$ and $\alpha = 0.41$ with signal features and the process parameters in the input space. The comparison between the actual UTS values and BPNN predicted UTS values are shown in Fig. 3. In the figure it is reflected that out of 64 number of patterns, only six predictions deviate from the $\pm 5\%$ error line and among which, only two are from the testing data set. The absolute average percentage error for the testing cases is 4.89.

Radial basis function neural networks are different than BPNN in the way that it has some special activation functions in the hidden layers called as the radial basis functions. Detail description of training algorithm is out of the scope of this article; interested readers may refer to the relevant technical article [20]. Number of hidden layer neurons is varied from 5 to 29 in steps of 1 to find out the optimal network structure. Learning rate for updating weights is varied in the interval of 0.1 to 1 and that for center updation and Gaussian functions spread updation were varied in the interval of 0.01 to 1 in steps of 0.04, respectively.

The best RBFNN is found to be 7-7-1 with 0.46, 0.05 and 0.05 as learning rate for weight, center and spread updating, respectively, with signal features along with the process parameters in the input space. In Fig. 4, comparison between the actual UTS and RBFNN predicted UTS is

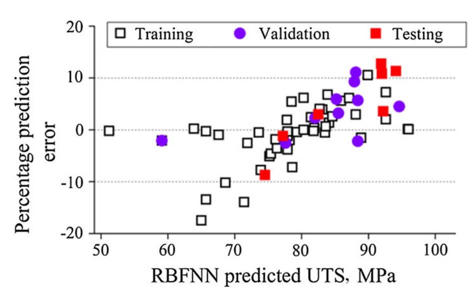

Fig. 4 Prediction performance of RBFNN model

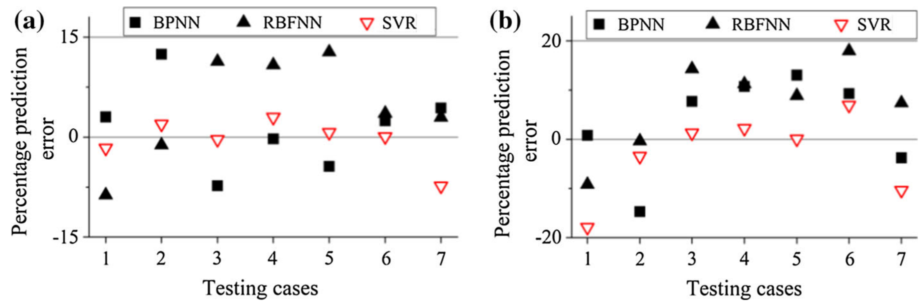

Fig. 5 Comparison of SVR and ANN model performance **a** with signal features **b** without signal features

shown. Compared to BPNN prediction, the prediction of RBFNN is inferior and out of 64 datasets, 23 predictions are out of ±5% error line. The absolute average percentage error for the testing cases is 7.33.

The prediction performance of SVR models with BPNN and RBFNN models developed in this research work is compared and comparative analysis is presented in Fig. 5. From the figure it is observed that, SVR model performance for prediction of UTS is better than ANN models. An improvement of 55% is experienced in SVR model prediction accuracy when compared with BPNN model predictions. When compared with RBFNN predictions, there is an improvement of 70% in prediction of SVR model. This implies that SVR models, coupled with current signal features can lead to more accurate predictions of UTS of friction stir welded joints and can be implemented in real time in-process monitoring of FSW process.

Conclusions

Main spindle motor current signal against each experiment is acquired and time domain features of the signal are computed. SVR and ANN models are developed for the prediction of UTS of the welded joints using the process parameters along with the extracted signal features. Prediction performances of the developed models are compared to find the best candidate for the accurate prediction of UTS of the joints. Following conclusions are drawn from this research work.

- Current signal of main spindle motor is a potential candidate for real time monitoring of FSW process.
- The performance of the SVR model is compared with the output from two ANN models. Among the developed models, SVR model yields better prediction accuracy as compared to developed neural network models. An increase of 55% in accuracy is observed for SVR prediction UTS compared to BPNN model prediction UTS for the case when input space of both the models contain the signal features along with the process parameters. Whereas, an increase of 70% in prediction accuracy is observed for SVR model when compared with the performance of RBFNN model.

The presented work can be modified towards the development of online monitoring techniques for FSW process to achieve accurate prediction of the joint strength without destroying the welded components. This will offer precise control over the process to get the desired output in terms of weld quality.

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