

Monitoring of Weld Quality in Friction Stir Welding Based on Spindle Speed and Motor Current Signals

Bipul Das, Sukhomay Pal and Swarup Bag

Abstract The process of friction stir welding passed more than two decades since its invention in the year 1991 in TWI, UK. It involves complex physics and has not been explored fully to understand its physical behavior. Due to the lack of precise mathematical modeling and too many influencing factors that govern the welding process, difficulty arises in direct monitoring of the process based on the process parameters only. Moreover, the influencing parameters are so correlated that the effect of one on the weld quality cannot be isolated from the others for effective monitoring of the process. Thus, a need is realized to develop different methods for the efficacious monitoring of the process with the acquired signals during welding for better control over the outcome of the process. In this study, effectiveness of spindle speed and main motor current signals is investigated for the development of tools which will lead to real-time weld quality prediction.

Keywords Monitoring · Friction stir welding · Signal · Neural network · Weld quality · Prediction

1 Introduction

Friction stir welding (FSW) is a solid-state joining process which results in joining of two metals either similar or dissimilar without melting any one of them. FSW as a welding process is quite new in the community, but still reached a diversified use

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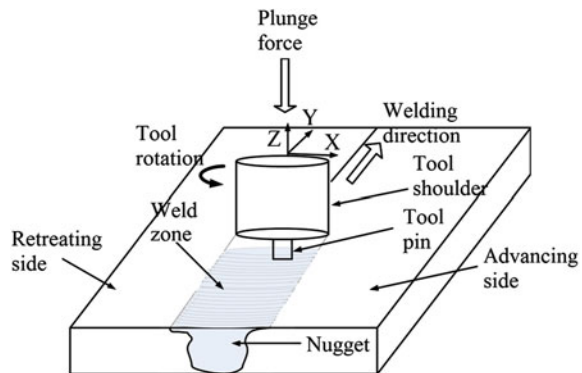
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in the field of automobile, railway, shipbuilding, and aerospace industries to name a few. The abilities of the process which help this to penetrate in so many industrial applications are successful welding of difficult-to-weld materials such as aluminum and magnesium, lightweight applications (as no filler materials are required to achieve the welding), environment friendly (as it does not emit any fume), more flexibility in welding of workpieces of different thicknesses, less power consumption as compared to other conventional, and advance welding processes. Different weld configurations are possible with FSW process as in other welding processes such as butt, lap, T-joint, and fillet joint.

As mentioned, the joining in case of FSW is achieved without melting of the parent materials. The process of FSW is schematically shown in Fig. 1. Here, a rotating tool is first plunged in the line of joining between the two workpiece materials which are held together tightly by fixtures. During plunging, first the tool pin is plunged completely into the material and once the pin plunging is over; shoulder of the tool is plunged into the workpiece. The depth through which the shoulder penetrates the material is called as the plunging depth. The tool is kept in this position for a certain time, and this period is referred as the dwell time. After this, the tool is traversed along the line of joining and retracted back once the welding is over. Tool used in FSW process consists of a pin, shoulder, and shank for holding. Different pin profiles can be used in FSW process such as straight cylindrical, cylindrical threaded, and taper threaded. Schematic of a typical straight cylindrical tool is shown in Fig. 2a. Tool in FSW performs two primary functions: (a) localized heating and (b) material flow. In the initial stage of pin plunge, the heating is a result from the friction between the pin and workpiece. Some additional heating results from deformation of materials. The friction between workpiece and shoulder results in the highest component of heating for the plasticization of the material. The shoulder also provides the confinement for the heated volume to be retained in the welding zone beneath the tool shoulder. The second function of the tool is to stir and move the plasticized material around the tool. Pin facilitates the stirring of the material around the tool and moves the material for proper mixing.

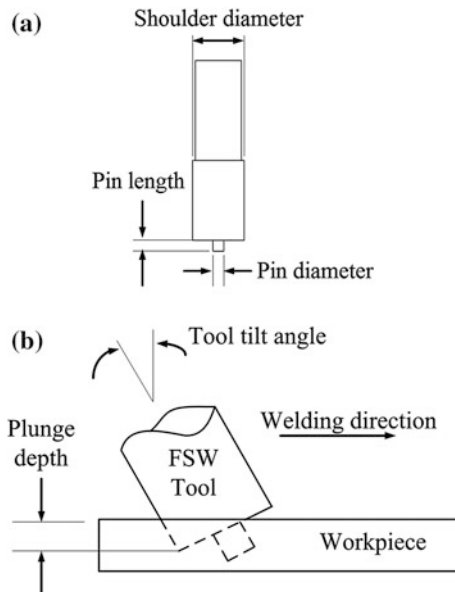
Fig. 1 Schematic representation of FSW process



FSW process involves many process parameters which influences the weld quality. The two most influencing process parameters are tool rotational speed (TRS) and welding speed (WS) (Mishra and Ma 2005). The key idea of joining in FSW process lies in severe plasticization of the workpiece material. The major component of heating for the plasticization of material is achieved from the frictional heat generated due to the friction between the rotating tool and workpiece material. This heat is again aided by the adiabatic heat generated due to plastic deformation of the material because of the stirring action of the rotating tool (Mishra and Ma 2005). The rotating tool mixes the plasticized material around the tool. Traversing of the tool distributed the plasticized material behind the tool and carried the heat for the plasticization of the material ahead the tool pin as the tool progresses along the joining line. The material gets solidified during cooling leading to the bond formation in FSW. Thus, it is evident that TRS and WS are most influencing process parameters. Apart from these two parameters, shoulder diameter of the tool, pin length, pin diameter, tool tilt angle, and plunging depth are few process parameters which also play an important role in the joining process of FSW, and all the mentioned parameters can be seen in Fig. 2a, b.

Advancing side and retreating side are the two most frequently used terms associated with FSW process. The side of the weld where the tool rotation direction is in the similar sense with the tool traversing direction is called the advancing side. The side of the weld where the tool rotation direction is in the opposite sense of the tool traverse direction is called the retreating side. These two can be seen in Fig. 1. Threadgill (2007) had reported on standardization of language used to describe FSW process. He proposed a few terms for the microstructural classification of friction stir welded sample.

Fig. 2 a Typical straight cylindrical FSW tool, b process parameters associated with tool



Nugget zone: Frictional heating and intense plastic deformation during the FSW results in generation of a recrystallized fine-grained microstructure within the stirred zone. This zone is usually referred to as nugget zone or dynamically recrystallized zone. In this zone, recrystallization occurs as the temperature reaches a critical value above which the material crosses critical dislocation density for recrystallization. Depending on process parameters, tool geometry, temperature, and thermal conductivity of the workpiece, material shape and the nugget size can vary. In the literature, two types of nugget shapes were reported. Basin-shaped nugget that widens near the upper surface and the other is the elliptical nugget. The interface between the recrystallized nugget zone and the parent material is relatively diffused in the retreating side of the tool, but quite sharp on advancing side of the tool (James et al. 1999).

Thermo-mechanically affected zone (TMAZ): This zone is the transition zone between the nugget zone and the base metal. TMAZ is characterized by highly deformed structure. Although TMAZ underwent plastic deformation, recrystallization does not occur in this zone due to insufficient deformation strain. It was revealed that the grains in the TMAZ usually contain a high density of subboundaries (Sato et al. 1999).

Heat-affected zone (HAZ): Beyond TMAZ, there is a HAZ. This zone experiences a thermal cycle but does not undergo any plastic deformation, and the grain structure is same as the base metal.

The process of FSW is governed by too many process parameters. The choices of combination of different process parameters need to be explored through proper investigation to find the effects on the weld quality. Researchers have reported different combinations of process parameter settings over different materials for better yielding of joint quality in terms of ultimate tensile strength (UTS), yield strength (YS), percentage elongation (E), and microhardness values of the welded joints. The variation of UTS of 7075-T6 aluminum alloy-welded joints with TRS was found in the work by Rezaei et al. (2011). With the increase in the TRS, UTS and YS were found to increase up to a certain speed and then decreases as the TRS increases. Liu et al. (2013) varied the WS keeping the TRS fixed and defined a parameter named the revolutionary pitch (WS/TRS). UTS, YS, and E were reported to increase with the increase in the revolutionary pitch and then decrease after a certain value of the same. Similar reporting on the variation of weld quality in FSW process can be found in the related works by different researchers (Li and Liu 2013; Lim et al. 2004; D'Urso et al. 2009; Kamp et al. 2009; Buffa et al. 2013; Hamilton et al. 2012; Miyazawa et al. 2012). Researchers have presented the effect of various process parameters over the quality of the weld, but none has reported on the inconsistency of the weld quality over the same range of process parameters. So a complex process like FSW may not be effectively monitored using the process parameters. This leads to the exploration of different indirect methods for the monitoring of the FSW process, and mostly preference is based on the signals acquired during the process.

In indirect monitoring methods, the process is monitored through the observation of different influencing process parameters to predict their effects on the process.

Signals related to different process parameters or the overall process could be capable of yielding more relevant information for the monitoring of the process. The use of force signals for monitoring FSW process was reported by different researchers (Yang et al. 2008; Boldsaikhan et al. 2009; Fleming et al. 2008; Gibson et al. 2014; Ramulu et al. 2013). In all the cases, force dynamometers were used for the acquisition of the force signals to correlate the behavior of these signals with the process parameters. In these research works, it is observed that Fourier transformation (FT) was the signal processing technique used for extracting the signal features. Acoustic emission signals were acquired by a few researchers (Chen et al. 2003; Huang and Kovacevic 2011; Zeng et al. 2006; Yen et al. 2013) using acoustic emission sensors where the signal features were used for the monitoring of the process. Wavelet transformation (WT) was the signal processing technique used by Chen et al. (2003) to characterize the acquired acoustic emission signal during FSW process.

The question might arise at this point if acquisition of signal be sufficient enough for developing an efficient monitoring system. The answer to this is obvious not because signal as a whole cannot be used for monitoring of the system. Relevant information from the signal needs to be presented to systems which may be capable of predicting some output in an understandable way for realistic justification and to develop decision models for the process. Modeling of FSW process for the prediction of different weld characteristics was attempted by many researchers. The most widely used tool is the artificial neural network (ANN) modeling. Okuyucu et al. (2007) developed a single-hidden layer ANN for the prediction of hardness, E, YS and UTS with TRS and WS as the two input parameters. Prediction capabilities of ANN were compared with the response surface method by Lakshminarayanan and Balasubramanian (2009) for the prediction of tensile strength using three process parameters and signal features acquired from the force signals. Mechanical and microstructural properties of friction stir welded joints were predicted by Buffa et al. (2012) using ANN.

The above survey reveals that mostly force signals and/or acoustic emission signals were acquired in FSW process monitoring and ANN was the most popular method among researchers for the modeling of FSW process. Apart from these signals, other signals may also be used for effective monitoring of FSW process. The principle of FSW operation lies in the plunging of a rotating tool into the workpiece material, and once the suitable plasticization and heat requirement is achieved, the tool is traversed with a suitable speed for the welding. If the rotation as well as traversing phenomena of the tool can be captured through signals, the signals will give more direct information as compared to other signals which need some advanced signal processing techniques before implementing it to any prediction mechanism.

2 Sensors and Signals During Friction Stir Welding

The necessity of incorporating signals for the efficient monitoring of the process is realized from the above paragraphs. The need of selection of suitable sensors for acquiring signals comes into picture. The question that needs to be answered is how many sensors will be sufficient for the development of efficient monitoring system. This can be seen in the context of a number of influencing parameters that need to be monitored during the process. The more is the number of sensors, the more will be the sensor data, i.e., signals, but all the acquired signals may not be useful for monitoring the process. Signals should contain some worthy information regarding the process and then only they will be useful for further analysis. The discussion regarding signals and sensors will be restricted to those signals which will be presented herewith. Different possible signals and related sensors were outlined in the earlier section of this article. Apart from those signals, a few other signals can also be acquired during the FSW process; the features of which can be effectively correlated with the physical outcome of the process.

The FSW process is governed by mainly the rotational speed of the tool. If this parameter can be monitored, it is expected to provide more straightforward information for monitoring the overall process output. The current signal from the main spindle motor which is responsible for the rotation of the tool is one of the signals which were not considered by researchers. For the acquisition of this signal, Hall effect current transducers are mostly used as these kind of sensors are not affected by the change in the ambient conditions and produce output independent of rate of detected field, which leads to less noisy signals. The other signal that can be acquired is the current signal from the motor which is responsible for the traversing of the tool. As WS also plays an important role in obtaining a competent welding, monitoring this parameter is also expected to enhance the monitoring of the overall process. TRS can also be monitored in terms of signals through rotational speed-detecting sensors which can be an effective addition to the monitoring of the TRS along with the main spindle motor current. Voltage signal is another solution for the monitoring of both TRS and WS from the respective motors.

The data from the sensors need to be stored for further processing, and for this purpose, data acquisition system is required. The prime objective of any data acquisition system is to convert the analog input signals to digital input signals and to store them for further processing. That is why sometimes data acquisition systems are also referred as analog-to-digital converter. The selection of data acquisition system depends on the output signal type from the sensors. In signal acquisition, sampling rate or sampling frequency is a crucial parameter. Analog-to-digital converter converts an analog signal into stream of digital numbers, each representing the analog signal's amplitude, at a moment in time. Each number is called a 'sample.' The number of sample per second is called as the 'sampling rate,' measured in samples per second. This sampling rate or sampling frequency has to be selected based on the frequency of the signals to be acquired. According to Nyquist–Shannon theorem, the sampling frequency of the signals should be at least

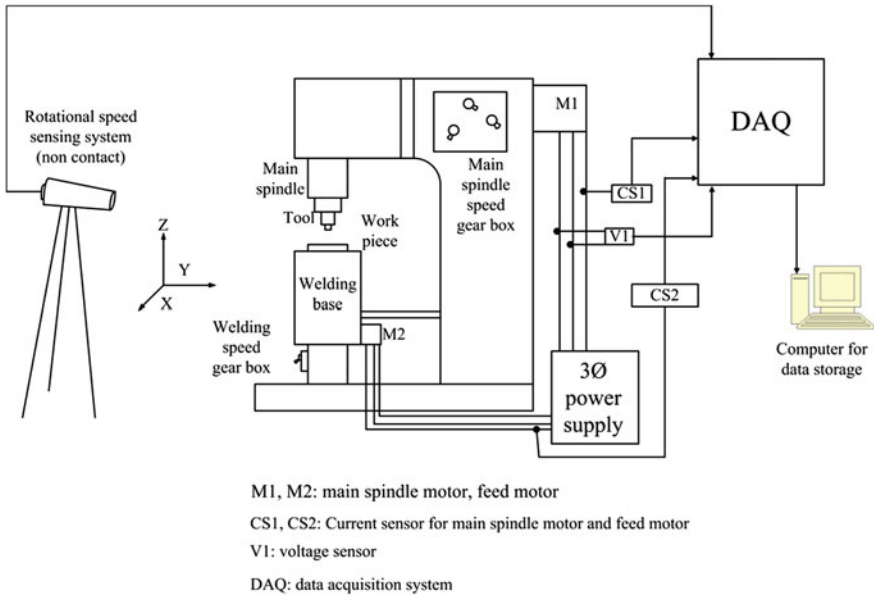


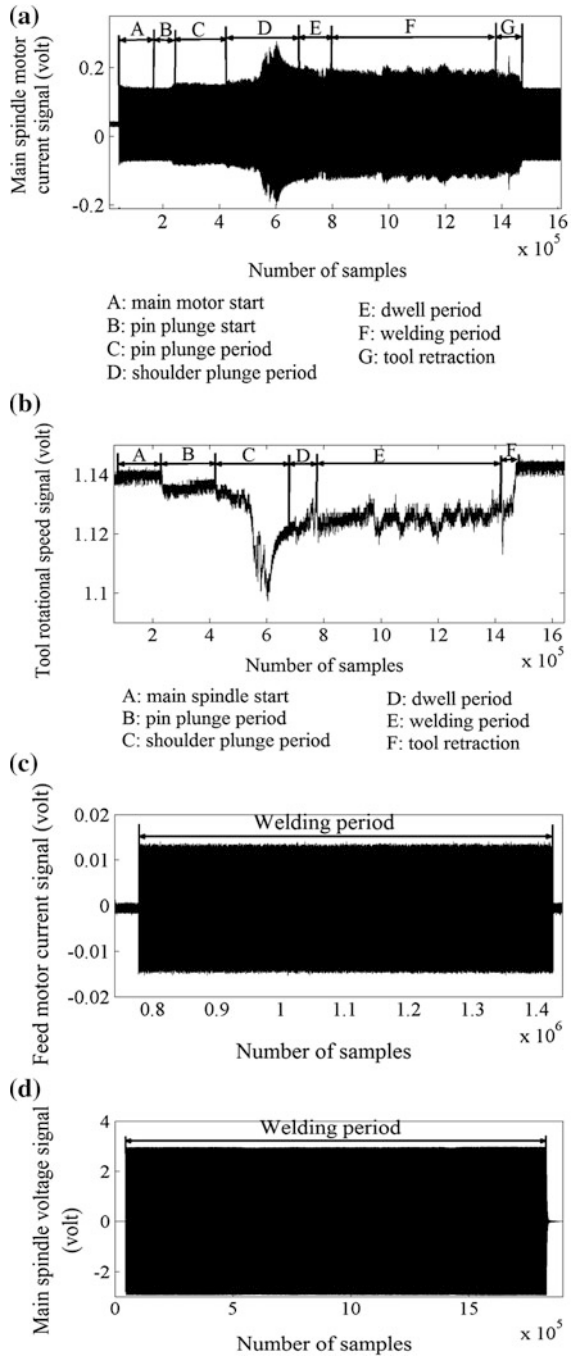
Fig. 3 Arrangement of different sensors in FSW process

two times of the frequency of the signals to be acquired (Shannon 1998). Mathematically, if a signal is having a frequency of f_s , then sampling frequency should be $F_s \geq 2 f_s$, where F_s is the sampling frequency as per the theorem to avoid aliasing error. A typical arrangement of different sensors with the FSW system is shown as line diagram in Fig. 3. Figure 4a–d shows typical main spindle motor current signal, TRS signal, feed motor current signal, and main spindle motor voltage signal acquired during FSW process under same operating condition.

3 Analysis of the Signals

In the process of FSW, there are four significant stages which make this process completely different from others. First is the plunging of the rotating tool in which initially the tool pin is plunged completely, and then, the shoulder is plunged up to a distance called as the plunge depth. Then, after a defined period called as the dwell time, the tool is traversed along the joining line to achieve the welding. Once the welding is over, the rotating tool is retracted back. All these stages carry notable information for successful and competent welding in FSW process. So, if these stages can be captured through some signals, then it would be of more importance to analyze the process as a whole for desired output as anomaly in any of these stages will surely affect the joining process and the quality of the weld will deteriorate.

Fig. 4 Signals acquired during friction stir welding **a** main spindle motor current signal, **b** tool rotational speed signal, **c** feed motor current signal, and **d** voltage signal



As shown in Fig. 4a, main spindle motor current signal has the potential to encapsulate the significant stages during FSW process both in trend and magnitude of the signal. As the motor starts, it draws more current. This can be seen in the figure as a sudden rise on the signal amplitude. The amplitude of the signal increases further when there is a contact between the rotating tool and the rigidly clamped material which is due to the resistance offered by the workpiece material to the rotating spindle. To maintain the same rotational speed, main spindle motor draws more current resulting in increasing magnitude of the current signal. This increasing trend in the amplitude of the signal continues, and a sharp rise in the amplitude of the signal can be noticed where amplitude of the signal grows to maximum. This is because of the shoulder penetration to the material which offered more resistance as compared to the tool pin due to the size difference between the pin and the shoulder of the tool. Rotation of the tool introduces rubbing action between the shoulder material and workpiece material which aid toward the generation of frictional heat, causing the material softening, and plasticization. As the plasticization increases, resistance offered by the material decreases and this drop in resistance can be noticed as a drop in signal amplitude in main spindle motor current signal. During dwell period, the signal comes to a stable position and during welding maintains more or less the same level of amplitude as in dwell period. When the tool is retracted back after the welding, the resistance decreases gradually and this gradual change can be seen as a gradual drop in current amplitude to the level of starting current value.

The above analysis holds good for the TRS signal too where all these significant stages were effectively seen both in signal amplitude and trend of the signal. In Fig. 4b where TRS signal is shown, during the welding period, some irregular drops in the signal can be noticed in the trend as well as magnitude of the signal. More interestingly, these trends were also retained by the main spindle motor current signal as shown in Fig. 4a. These trends of the signals give a clear indication that there must be some oddity in the process during welding, which were effectively captured by these two signals. Thus, the analysis of signals would provide more useful information regarding the process and monitoring, by which a better and precise control can be gained over the process. It is surprising to observe that the main spindle motor voltage signal, even though it is acquired from the same main spindle motor, does not reflect any of the significant stages during welding. The probable reason could be that voltage signal is acquired between two phases of the motor, which is supposed to be at a fixed value as the supply voltage. It is not quite astonishing that the significant stages involved in the FSW process were not captured by the feed motor current signal as this motor is switched on only during the welding period, so any prior physical change cannot be expected here. Even though it is anticipated that the abruptions as seen in main spindle motor current signal and TRS signal during the period of welding will be enfolded by feed motor current signal, no such concluding remarks could be made by simply looking at the signal as in other two signals. The aforementioned analysis appraised the capability of different signals acquired during FSW process other than those being considered by different researchers to explore a new avenue for the monitoring of the process.

4 Monitoring of FSW Process

Monitoring in a generic way can be defined as the procedure of observation of some physical process or phenomenon and recording some valuable information through which the performance of the process is evaluated periodically or continuously and the output from it is predicted. Thus, this involves two crucial steps: one is recording of valuable information through observation, and the other one is the estimation or prediction of the output. Monitoring in case of FSW process can be implemented for the process output prediction. The output from the process can be represented in terms of the quality of the welds. Quality of the welds relates to the strength of the welds and hardness distribution of the welds as compared to the base material properties. To have better control over the outcome of the process, the monitoring should be very effective to note every possible change in the process. As mentioned in the earlier section, signals can effectively detect changes occurred in the FSW process over time which gives a clear indication that monitoring for the prediction of weld quality in FSW can be achieved with signals acquired during FSW process. Moreover, acquired signals give a more direct representation of the physical process. Since signals are sampled over time, time information of the signals can play an important role in detecting any unusual event at some point of time occurred during the process, which will undoubtedly enhance the monitoring process.

5 Feature Extraction from Signals

Signals are some sensor data collected with a specific sampling frequency and for a finite period of time and cannot fetch any useful information on their own. The information contained in signals should be presented in a comprehensive way to work for any monitoring system based on signals. Most primitive threshold values from signals can be obtained, and a database can be maintained through rigorous experimentation for the evaluation of the process. Thresholds can be either amplitude of the signals or the frequency of the signals. With this approach, difficulty arises when unknown operating conditions arrive for which database is not available to compare with. To handle such cases, different techniques need to be implemented in order to extract most salient and informative quantities referred as features from the signal.

Features from a signal can be extracted in different context as well as depending on the requirement and roughly can be categorized as follows: (i) features in the time domain of a signal which is about computing average values, the shape of enveloping signal, changes in signal levels such as increments or decrements, crest factor (ratio of peak to the root mean square value of the signal), and polynomial approximation of the signal. These quantities can reveal overall information of the

signals and can be computed with lesser efforts. (ii) Frequency domain where spectral features were computed from a signal: Typical features in this category can be total power level of a signal and the power in different spectral bands. The advantage of frequency-domain approach is that it has the ability to render information that is not possible with time-domain approach such as a signal can have multiple frequency components more likely due to the presence of the noise which cannot be observed in time-domain approach. This has the disadvantage that time information of the signal is lost once converted to frequency domain which is essential for detecting the occurrence of some undesired event in the process. For the frequency-domain analysis of signals, most widely used technique is FT, where the transformation of signals from time to frequency domain is achieved using a very well-known algorithm called the fast Fourier transformation (FFT). Short-time FT was the advancement proposed to this method for the elimination of the drawback of losing time information of the signal, but it too suffers from other limitations of fixed window size, etc. (iii) Features in the statistical domain which is applicable to time-, frequency-, and time–frequency-domain approaches: This domain includes features such as root mean square, variance, skewness, kurtosis, coefficients of a time series model used to describe the measured signal (autoregressive, moving average, autoregressive moving average, etc.), and cross-correlation with a measuring cut, etc. (iv) Features in time–frequency domain of the signal are exclusively performed using WT and are more robust and flexible in feature extraction from a signal by retaining its time information with frequency content.

The difficulties faced in FFT during signal analysis were eliminated by the introduction of WT of signals. Wavelet analysis has been proved to be more flexible and robust method for signal processing of non-stationary signals due to the characteristics of the wavelet basis function as irregular, asymmetric, and of finite time length. Wavelet transform of a signal is a function of two parameters, namely time and scale, the latter being a key point of the WT. WT is a technique of extracting coefficients comparing the original signal with the wavelet basis functions. These wavelet basis functions were called as the mother wavelets. The mother wavelet is contracted or dilated by changing the scale parameters. This variation in the scale parameter not only changes the central frequency of the signals but also the window length. In WT, a signal is split into two parts: approximation which contains low-frequency, high-scale components, and details which contain high-frequency, low-scale components. The approximation part is again split into two new approximations and details, and the process is repeated. Schematic representation of WT of a signal is shown in Fig. 5 up to third level of decomposition. In WT, as the approximation part is only split for further approximation and details. This does not guaranty that it will lead to effective features extraction from the signals as details part might also contain some valuable information. Another form of WT is the wavelet packet transformation. In wavelet packet transformation, both the approximation and details part are split into further approximation and details, which give a more rich way of analyzing a signal. This

Fig. 5 Third-level wavelet transformation of a sine wave corrupted with white noise

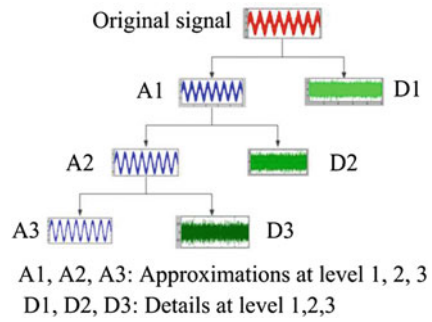
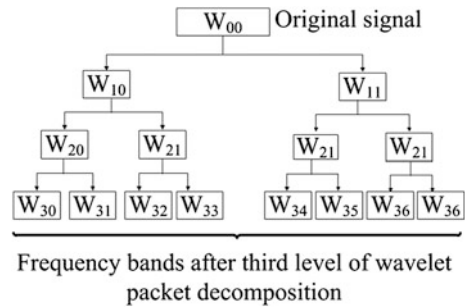


Fig. 6 Schematic of wavelet packet tree at third level of decomposition



generates a tree composed of different nodes at the end of the final level of decomposition where each node represents a particular frequency band of the signals. Schematically, a three-level wavelet packet tree is shown in Fig. 6.

6 Correlation of Process Parameters with Signal Features

Signal features to be used for monitoring of the process should have some correlation with the process parameters, as an indication that any change in the physical behavior of the process is reflected through the extracted features. Figure 7a–d shows the variation of four statistical domain features, namely root mean square, variance, skewness, and kurtosis of the TRS signal, and the TRS and variation with WS are shown in Fig. 8a–d. The variation of signal features with the TRS shows an increasing trend. However, similar conclusive remarks cannot be drawn for the variation of the statistical features with WS. The reason behind this could be that these features were extracted from TRS signal, where the effect of WS is obviously less as compared to TRS. The variation as depicted by the figures intimates a vivid indication of definite correlation between signal features and process parameters. This information conveyed through the above analysis reveal that signal features can be effectively incorporated in monitoring of FSW process.

Fig. 7 Variation of **a** RMS, **b** variance, **c** skewness, and **d** kurtosis with tool rotational speed

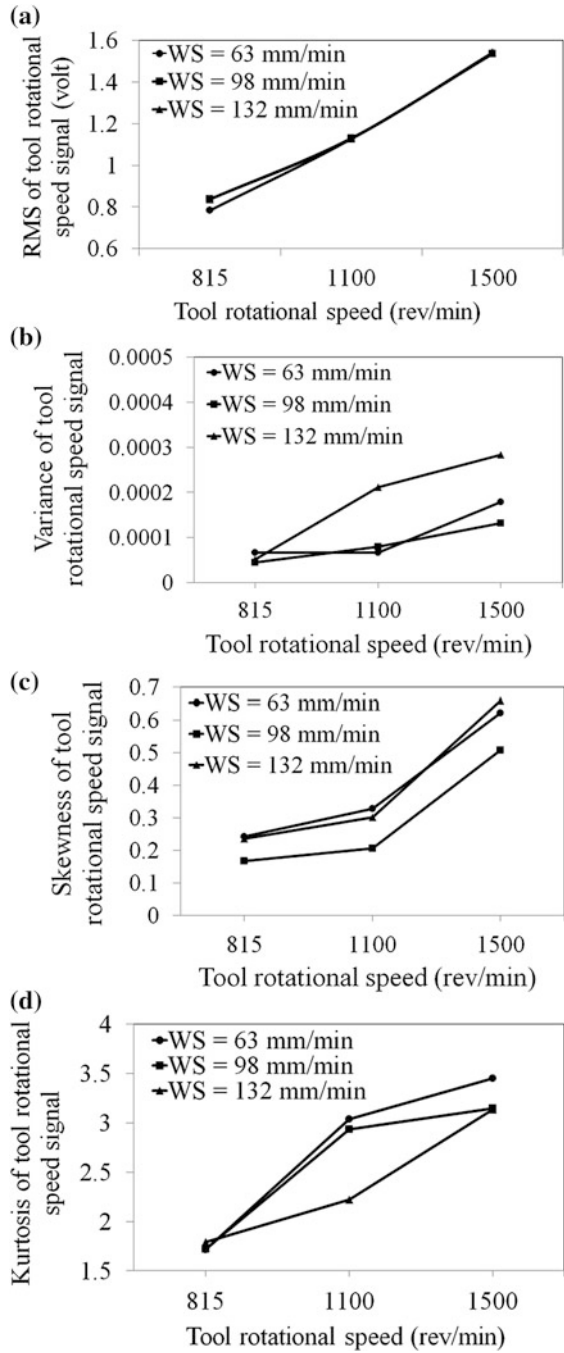
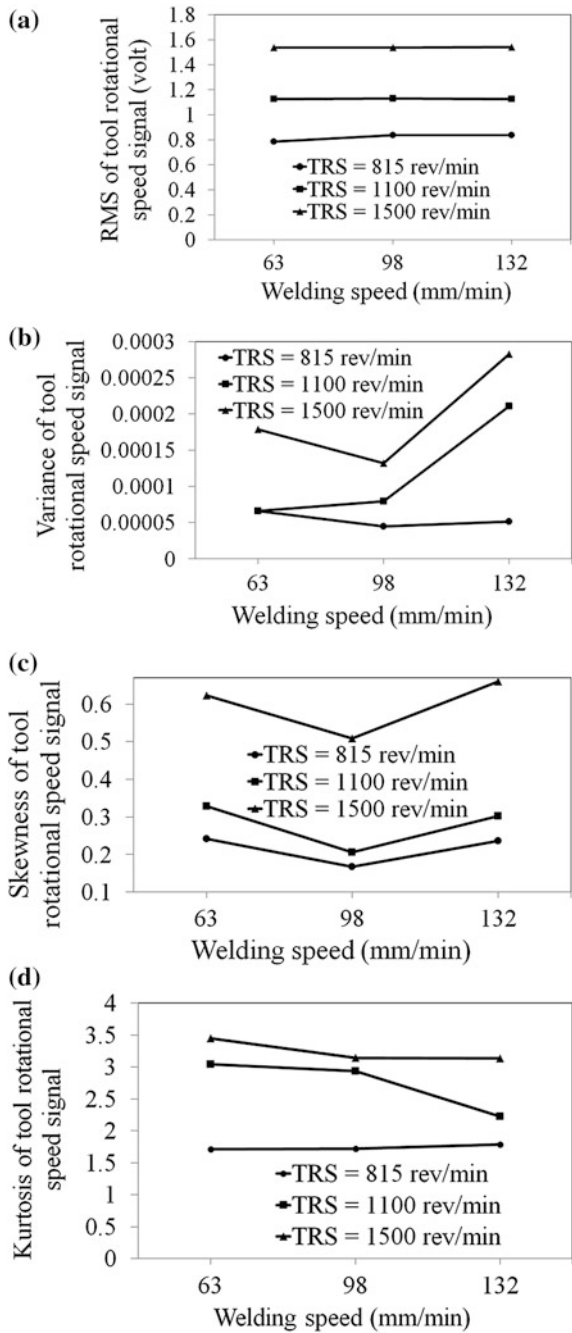


Fig. 8 Variation of **a** RMS, **b** variance, **c** skewness, and **d** kurtosis with welding speed



7 Correlation of Process Output with Signal Features

For any monitoring system, the goal is to observe the performance of the system to achieve desired output through better control over the process. For FSW process, the output from the process is the quality of the welds in terms of tensile strengths and hardness distribution as compared to the base material properties. It is inevitable that process parameters will surely have influence over these outputs from the process. But the question is whether the extracted signal features will have definite correlation with these outputs or not. Until and unless signal features show some correlation with the process output, it would be difficult for any modeling system to predict the process output using the signal features. Figure 9a–d shows the variation of UTS with the four statistical domain features already mentioned in the earlier section. UTS of the welds shows an increasing trend up to a certain value of the signal features of the TRS signal, but after a certain value, it decreases dramatically. This could be explained as with the increase in the rotational speed of the tool, heat input to the material increases and the material undergoes more plasticization. Thus, even at a low WS, material extrusion increases and the welds could not reach to a perfect condition required for joining the workpiece material, which leads to deterioration of the weld quality. Thus, presence of correlation between the signal feature and process output from FSW process is proved and can be implemented in modeling of the process.

8 Modeling of Weld Quality

Different approaches have been tested and effectively implemented by researchers for the efficient modeling of the FSW process for the prediction of different weld quality. Regression analysis (Jayaraman et al. 2009; Mohanty et al. 2012; Rajakumar et al. 2011a), response surface methodology (Lakshminarayanan and Balasubramanian 2009; Elatharasan and Kumar 2012; Palanivel and Mathews 2012; Rajakumar et al. 2011b), and ANN (Ocuycu et al. 2007; Boldsaikhan et al. 2011; Ghetiya and Patel 2014; Chiteka 2014; Fahd 2014; Shojaeefard et al. 2013; Tansel et al. 2010; Rezgui et al. 2013) are different tools used for the modeling of weld strength. Among these, ANN was mostly used because of its robustness and flexibility in modeling complex processes where precise mathematical formulation is not available as FSW process.

ANN is data-driven modeling technique, which is more robust in mapping any input–output relationship without much simplification and precise mathematical formulation. It can be considered as nonlinear statistical data modeling tool. Various types of neural network are in use such as feed-forward neural network, recurrent neural network, stochastic neural network, and modular neural network. The most widely used neural network is multilayer feed-forward neural network. In Fig. 10, typical multilayer feed-forward neural network architecture is shown. The

Fig. 9 Variation of ultimate tensile strength with **a** RMS, **b** variance, **c** skewness, and **d** kurtosis

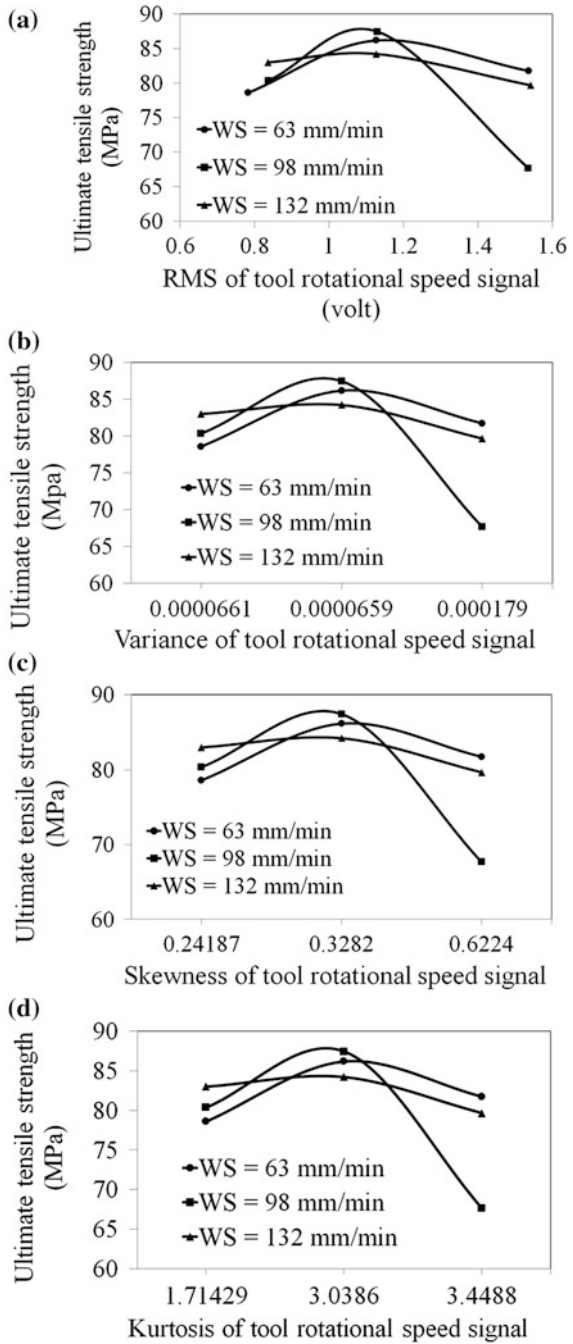
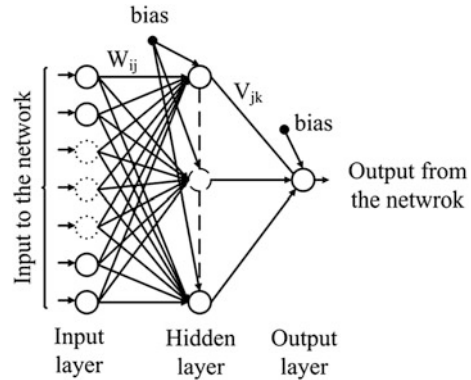


Fig. 10 Schematic representation of multilayer feed-forward neural network with single output and single hidden layer



input and output layer neurons are connected to hidden layer neurons through some weights. The universal approximation theorem of neural networks states that a standard multilayer feed-forward neural network with a single hidden layer containing a finite number of neurons with arbitrary activation function is a universal approximator (Hornik 1991). Each working unit of a neural network is called as the neuron, and it is activated through some functions called as the activation function. This function maps the data from one space to other by some nonlinear mapping. Linear, log-sigmoid, and tan-sigmoid are some activation functions; among them, log-sigmoid is the most popular activation function. Neural network helps in predicting output where input space data are not well correlated and cannot be mapped linearly and where some precise mathematical relationship does not exist between the input and output variables.

A network can be trained using supervised as well as unsupervised learning algorithm. For training of neural network, incremental mode of training and batch mode of training are the two methods for presenting the data to the network during training. For a large data set, batch mode is preferred over incremental mode of training. One of the notable limitations with neural network relies in its working principle. It works on minimizing the error function generated during the training of the network. Since for the minimization, gradient descent method is generally implemented, the chances of solution to get trapped in local minima are high. This can be reduced by selecting multiple starting solutions and adding momentum term. For the training of the network, one most important and essential parameter is learning rate which the user has to select. The more is the value of learning rate, the faster is the convergence, but the network may become unstable, and the lower is the value of learning rate, the slower is the convergence, but the network parameters might get overtrained. So a trade-off has to be maintained while selecting this parameter. Details of ANN can be found in an illustrative manner elsewhere (Haykin 1999). To develop an ANN model, the data set needs to be divided into training, validation, and testing before presenting it to the network. The training data set is used to train the network during which weights' values were updated through any of the methods as gradient descent, conjugate gradient descent,

Lavenberg–Marquardt back-propagation, or quasi-Newton method by minimizing the mean square error. Testing data set is presented to the network once the network is fully trained. Validation data set is used for avoiding the overfitting as neural networks are prone to overfit (Srivastava et al. 2014). The statistical features extracted from the signals acquired during FSW process show prominent correlation with the process output, so inclusion of these features will surely lead to more accurate prediction of the weld quality.

9 Case Study

To represent the usefulness of different signal features in the modeling of UTS of the joints, four statistical features computed from main spindle motor current signal were used and regression models were developed. A total of 64 data sets containing tool rotational speed (R), welding speed (W), and shoulder diameter (S) as process parameters and RMS, variance (V), kurtosis (K), and skewness (Sk) as the computed features were used to develop the regression models for modeling the UTS. Equation 1 involves all the process parameters and the computed signal features. Here, the goodness of fit obtained is 53.26. Equation 2 represents the UTS model considering only the process parameters which yield goodness of fit as 24.59, and Eq. 3 represents the UTS model considering the signal features only, which yield goodness of fit as 16.49. Though the goodness of fit by including process parameters and signal features together was less, this gives a clear indication that inclusion of the signal features in the regression model leads to the improvement of prediction accuracy of the developed models.

$$\begin{aligned}
 \text{UTS(MPa)} = & -1301.43 - 0.09 \times R - 3.68 \times W + 14.37 \times S + 9138.77 \\
 & \times \text{RMS} - 28,808.3 \times V + 1248.63 \times K - 34,358.8 \times \text{Sk} \\
 & - 0.00016 \times R \times W + 0.0027 \times R \times S - 2.260 \times R \times \text{RMS} \\
 & + 10.16 \times R \times V + 0.10 \times R \times K - 2.68 \times R \times \text{Sk} + 0.0027 \\
 & \times W \times S + 50.85 \times W \times \text{RMS} - 238.59 \times W \times V + 0.47 \\
 & \times W \times K + 25.40 \times W \times \text{Sk} + 319.56 \times S \times \text{RMS} - 2465 \\
 & \times S \times V - 20.75 \times S \times K - 129.19 \times S \times \text{Sk} + 288,955 \\
 & \times \text{RMS} \times V - 12,228.3 \times \text{RMS} \times K + 1.05594e + 006 \\
 & \times \text{RMS} \times \text{Sk} + 47,544.2 \times V \times K - 6.04652e + 006 \times V \\
 & \times \text{Sk} - 10,247.1 \times K \times \text{Sk}
 \end{aligned} \tag{1}$$

$$\begin{aligned}
 \text{UTS(MPa)} = & 131.8 - 0.02 \times R - 0.07 \times W - 2.45 \times S - 6.84264e - 005 \\
 & \times R \times W + 0.00105 \times R \times S + 0.0065 \times W \times S
 \end{aligned} \tag{2}$$

$$\begin{aligned}
 \text{UTS(MPa)} = & 731.50 - 8996.79 \times \text{RMS} + 32,004.3 \times V - 405.09 \times K \\
 & - 5784.49 \times Sk - 82,987.8 \times \text{RMS} \times V + 5266.47 \\
 & \times \text{RMS} \times K + 144,327 \times \text{RMS} \times Sk - 0795.5 \times V \\
 & \times K - 1.40944e + 006 \times V \times Sk + 1235.54 \times K \times Sk \quad (3)
 \end{aligned}$$

10 Conclusion

Possibilities of monitoring of FSW process with the acquired signals during welding were presented in this research work. The capability of main spindle motor current signal and TRS signal to capture significant stages involved in FSW process was demonstrated, which gives a clear notion that signals can be considered for effective monitoring of the system to achieve desired output through better control over the process. The correlation of four time-domain features extracted from TRS signal with the UTS of the welds reflects a vivid intimation that inclusion of signal features to modeling tools can yield more satisfactory results as compared to modeling only with the process parameters. At the end, ANN model is presented that can be implemented as strength prediction mechanism which will lead to more accurate prediction that will lead toward the development of tools for efficient prediction of real-time weld quality, which is always desired in any manufacturing process.

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