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Applications of Machine Learning to Friction Stir Welding Process Optimization

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ABSTRACT

Machine learning (ML) is a branch of artificial intelligent which involve the study and development of algorithm for computer to learn from data. A computational method used in machine learning to learn or get directly information from data without relying on a prearranged model equation. The applications of ML applied in the domains of all industries. In the field of manufacturing the ability of ML approach is utilized to predict the failure before occurrence. FSW and FSSW is an advanced form of friction welding and it is a solid state joining technique which is mostly used to weld the dissimilar alloys. FSW, FSSW has become a dominant joining method in aero-space, railway and ship building industries. It observed that the number of applications of machine learning increased in FSW, FSSW process which sheared the Machine-learning approaches like, artificial Neural Network (ANN), Regression model (RSM), Support Vector Machine (SVM) and Adaptive Neuro-Fuzzy Inference System (ANFIS). The main purpose of this study is to review and summarize the emerging research work of machine learning techniques in FSW and FSSW. Previous researchers demonstrate that the Machine Learning applications applied to predict the response of FSW and FSSW process. The prediction in error percentage in result of ANN and RSM model in overall is less than 5%. In comparison between ANN/RSM the obtain result shows that ANN is provide better and accurate than RSM. In application of SVM algorithm the prediction accuracy found 100% for training and testing process.

Keywords: Machine learning; Artificial Neural Network; Support Vector Machine; ANFIS; Response Surface Methodology

INTRODUCTION

Machine Learning (ML) is a branch of Artificial Intelligent. It is an approach, which allows computers to do which comes naturally from human, learn from experience. As the number of samples for learning increase, performance of algorithm adaptively improves (Alpaydin, 2004). ML firstly gained concentration after (Arthur, 1959) published his paper "Some Studies in ML Using the Game of Checkers". Since then, ML continuously flourish in the field of research but also it grew with more divers. In the field of smart manufacturing ML has capability to solve problems of NP-complete nature (Lászlo Monostori, Jozsef Homyak, Csaba Egresits, 1998). ML has ability to learn and adapt changes therefore no need to predict and provide solution for all situation (Alpaydin, 2010).The major strength of ML to learn from and adapting automatically to changing environment (Lu, 1990; Simon, 1983).The major factors that enhanced the capability and accelerated the applications of ML i.e. Advances in Computing (Hardware), Advances in Algorithms (Software), New generation of Machine Learning algorithms, Deep Learning and Reinforcement Learning, Advances in Sensor Technology (Data), High-performance and cheap sensors, Large amounts of data (Pokutta, 2016)

Since 2006, deep learning emerged as expeditiously growing research field which explore the performance in a wide range of areas like machine translation, image segmentation, speech recognition, and object recognition. Deep learning began from ANN which is branch of a ML. Most deep learning methods implies the neural network architecture that why some time represented as deep neural network. Deep learning exploit the technique of multiple non-linear processing layers for supervised or unsupervised and tries to learn from hierarchical description of data. The application of deep learning is available in all industries from automated driven to medical devices (Deng, 2014). (Wuest, Weimer, Irgens, & Thoben, 2016) distinguished the supervised and unsupervised ML algorithm. SVM found good for most manufacturing applications because of mostly manufacturing application provide labeled data. In manufacturing the SVMs is most commonly used algorithm in supervised machine learning. ML is a powerful tool and its value will enhance more in the coming days. ML is finding applications in every field systems some commercially available fields of study are face recognition, image processing, manufacturing, and medical and in many more areas.

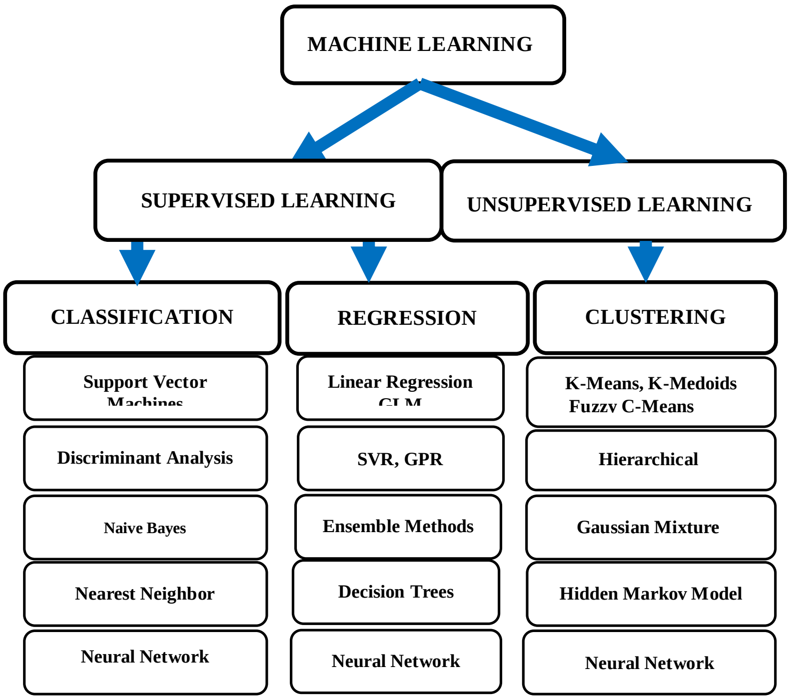

FIGURE 1. Machine Learning Techniques

Recently many authors applied ML techniques in manufacturing (Alpaydin, 2010; Dingli, 2012; Gordon & Sohal, 2001; Pham & Afify, 2005; Shiang & Nagaraj, 2011; Susto et al., 2015; Thomas, Byard, & Evans, 2012). The following are the major advantages of ML in manufacturing: ML technique in manufacturing systems provide an improved quality control optimization (Apt, Weiss, & Grout, 1993) Handling of high-dimensional, multi variate data, extract implicit relationships within large data sets in a complicated, dynamic, and anarchic environment (Köksal, Batmaz, & Testik, 2011; Rostami, Dantan, & Homri, 2015; Yang & Trewn, 2004) improve understanding of expertise to arrange powerful tools for constant improvement of complex process (Lászlo Monostori, Jozsef Homyak, Csaba Egresits, 1998; Pham & Afify, 2005). Only those ML algorithm are applicable in manufacturing which are able to handle high dimensional data. The usability of application of algorithms enhanced due to ML program. The main benefit of ML algorithm to find formerly anonymous implicit expertise and point out implicit connection in data (Alpaydin, 2010; Bar-or, Schuster, & Wolff, 2005; Do, Lenca, Lallich, & Pham, 2010).

(Rasmussen, 2004) provided the general presentation on Gaussian process regression models and focused on the role of the stochastic process and how to define a distribution over function. Supervised learning in the form of regression (continuous output) and classification (discrete output) is an important part of statistics and ML, either for data analysis or sub goal of complex problems. (Verma, Gupta, & Misra, 2018) presented the methodologies of machine learning approaches, Gaussian process regression (GPR), SVM, and MLR for UTS of FSW joint to investigate the incongruity between the predicted and experimented outcomes.

The applications of ML can be enforced in the domains of all industries. ML approaches implemented in procedural compliance, documentation of process and orientation, risk and quality frameworks of manufacturing industry. The ML also used in cloud computing, data science and in IoT. The ability of ML to predict the failure before occurrence is a useful feature and some manufacturing firms already using in production to minimize the financial losses, as well as risk loss (Kashyap, 2017). (Yucesan, Gul, & Celik, 2018) explored the furniture manufacturing industry in Turkey, by applying an Auto regression Integrated Moving Average with external variables (ARIMAX) model develop to predict total monthly sales of furniture product of a manufacture. (Malviya & Pratihar, 2011) utilized particle swarm optimization (PSO) method for the tuning of neural network by using both front and back mappings of metal inert gas (MIG) welding process. (Mian et al., 2005) worked on dissimilar material, especially solid-state welding techniques, which can escape many of the issues such as excessive heat input, fume generation, cracking, and indigent joint properties that are commonly confront when compare with fusion welding. While aluminum and steel are not compatible during fusion welding, FSW is consider most convenient joining method for various alloys as well as for the combinations of dissimilar metals.

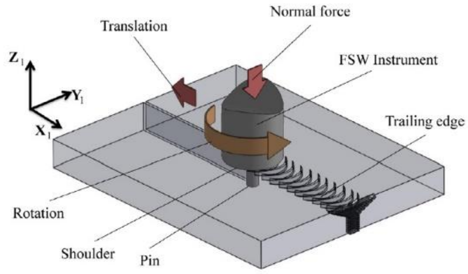

FIGURE 2. Model of FSW (Nataliia, Erik, Igor, & Klaus, 2019)

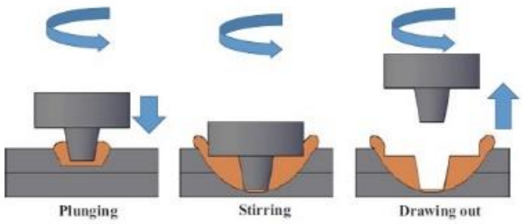

FIGURE 3. Schematic illustration of FSSW process

Currently, FSSW consider an alternate method to resistance spot welding (RSW) due to the meaningful energy and cost savings. Comparatively to the process of resistance spot welding, FSSW had created huge interest in automotive manufacturing industry (Abdullah & Hussein, 2018). The demand of lightweight materials like aluminum alloys are getting more attractions in the field of automotive, shipbuilding, aerospace, transport, military and many other industries because of extensive features, like high formability, high strength to weight ratio and better corrosion resistance. However comparatively to ferrous alloys the joining method of aluminum alloy and other light weight alloys are difficult by conventional processes due to their high thermal conductivity, hydrogen solubility, high thermal expansion and aluminum oxide formation (Verma et al., 2018). (Nourani, Milani, & Yannacopoulos, 2011) the forthright and computationally effective methodology for optimizing the FSW process parameters of 6061 aluminum alloy. The achieved results confirm that the method can be successfully used for minimizing both the HAZ distance to the weld line and peak temperature. (Shuangsheng, Xingwei, Shude, & Zhitao, 2012) applied the SVR network based on linear kernel function, polynomial kernel, RBF and Sigmoid. Mechanical properties model for welded joint built to use SVR network and make assumption. A comparison done between the prediction based SVR result and on ANFIS. The obtained results marks that the anticipated precision relay on SVR with radial RBF gave higher value than the other three kernel functions and that depend on ANFIS.

Based on the recent studies the popularity to study the machine learning technique in FSW process is increasing. Now researchers are implementing these ML techniques in FSW/FSSW processes to forsee the actual and predicted response of the process parameters. The main purpose of this review paper is to gather all the implemented and suggested approaches in one platform.

Artificial Neural Network (ANN)

Neural Network (NN) technology is substantial branch of statistical ML and repeatedly been implemented in various kinds of prediction tasks. (Kutsurelis, 1998) ANN inspired by natural NN. ANN is a computer program that develop to obtain information in a similar manner like human brain. Artificial intelligence, is a combination of neural networks which developed due to research on cognitive talent and machinery design. The ability of ANNs to resolve forecasting problems bring appreciable research attention because ANN substantially beat previous implemented techniques for anticipating based on non-linear input variables. (Ekici & Aksoy, 2009; Kandananond, 2011; Li, Hu, Liu, & Xue, 2015; Mena, Rodríguez, Castilla, & Arahal, 2014; Qamar & Khosravi, 2015) ANNs are intensely favorable at modeling the nonlinearities in data of many fields and have theoretically provable ability with arbitrary precision to approximate complex functions.

(Bennell & Sutcliffe, 2003) ANN is a tool that commonly used for prediction and categorization in data processing that is inspired from the attribute of biological neuron system that learns by experience. It has many features that make him attractive for problems such as pricing option which has the capability to develop a nonlinear model relationship that do not depend on the restrictive assumption implied in parametric approach, nor does depended on the specification of theory that connects the price of underlying assets to the price of option. The successful implementation of ANN models considered when it has ability to learn a lesson from the provided data and use in new one. The ANNs model strength lies in relationship between the input and output variables that may be complex and difficult to get from mathematical formulation. (Staub, Karaman, Kaya, Karapınar, & Güven, 2015) explore the features that ANN are the most important tool to solve the complex nonlinear problems. ANN modify their own values and they have the ability to adapt themselves for the exact solution of the problem. During the training process, ANNs are able to create the desire response.

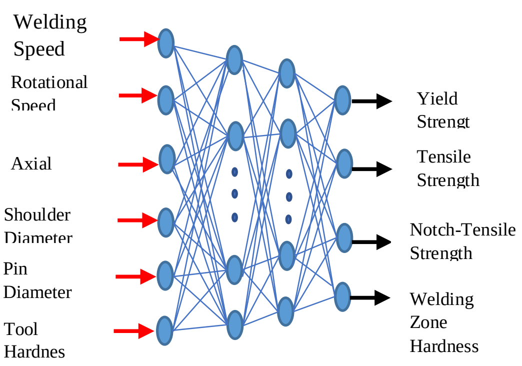

FIGURE 4. A conceptual Structure of ANN model

(Yousif, Daws, & Kazem, 2008) implemented the ANN to predict the correlation for the analysis and simulation between the FSW parameters of aluminum plates and mechanical properties. Two different training algorithms of NN utilized in this study: 1) Gradient descent with momentum algorithm: 2) Levenberg-Marquardt (LM) algorithm. The obtain result exhibit that the recommended ANN (LM) algorithm shows better performance than other because it implies 2nd order Taylor series instead of 1st order approximation as with gradient descent algorithm. (Maleki, 2015) investigated the modeling of FSW effective parameters on thirty AA-7075-T6 specimens by using ANN. The network established on back propagation (BP) algorithm. In this study, the TRS, TS, axial force, pin diameter, shoulder diameter and tool hardness considered as input parameters of ANN. On the other hand, TS, YS, and welding zone hardness, notch tensile strength used as outcome of NN see figure 4 . The acquired result demonstrate that the forecast hardness values of welding zone, notch tensile strength, TS and YS have the least mean relative error (MRE). The connection of anticipated result and the experimental results shows that the ANN modeling is very effective for FSW parameters.

TABLE 1. Applications of ANN techniques to various FSW and FSSW processes

Author	Material	DOE	Process	Models	Input parameters	Output	Remarks
(Vaira Vignesh & Padmanaban , 2018)	AA1100	FCC composite design with five level variation	FSW	ANN (LM) algorithm with feed forward model	TRS (rpm), WS (mm/s) and shoulder diameter (mm)	TS,	• The error Percentage prediction found to be low in ANN, developed model. • The overall model interaction coefficient is 0.8214 • Which shows closeness in relationship between the FSW process parameters and in TS.
(Wakchaure, Thakur, Gadakh, & Kumar, 2018)	AA 6082-T6	Taguchi based GRA	FSW	ANN	TRS, WS and tilt angle	TS and impact strength	• The hybrid Taguchi GRA of ANN Method provides grey relation grade 0.508. • Hybrid Taguchi GRA is 9.70% higher than traditional analysis of Taguchi grey.
(Kurtulmu & Kiraz, 2018)	high-density polyethylene (HDPE) sheets	x	FSSW	Feed forward back propagation ANN model	TRS (rpm), PD (mm), DT (s)	lap-shear fracture load (N)	• Outputs ANN models compared with the actual values. • Best prediction performance achieved with 100% training set and 20 neurons in the hidden layer.
(Ranjith, Giridharan, & Senthil, 2017)	AA2014 T651 and AA6063 T651	x	FSW	ANN with (LM) algorithm	Pin Diameter (mm), Tool (mm), Geometer, Tool Offset	TS	• The based on ANN model optimized process parameter are 7mm pin diameter and 4 degree tilt angle. • Better TS exhibits when tool is offset towards advancing side. • ANN predict the TS with an accuracy of 98% with 2% error.

(Dehabadi, Ghorbanpour, & Azimi, 2016)	AA6061	x	FSW	ANN model with Two feed forward (BP)	Threads, tool tilt angle , and welding distance from centerline	Vickers micro hardness	• For training and test data sets Mean absolute percentage error (MAPE) did not exceed from 5.4% and 7.48%, respectively. • In MAPE training process the both predict values for ANNs were less than 4.83% • Mathematical modeling techniques i.e ANN can save time, material, costs, and results in optimized designs.
(Anand, Barik, Tamilmannan, & Sathiya, 2015)	Incoloy 800H	x	FSW	ANN based on (BBPNN), (IBPNN), (QPNN), (LMNN) and (GANN)	Heating pressure (HP), heating time (HT), upsetting pressure (UP) and upsetting time (UT)	TS, micro hardness(H) and burn off length (BOL)	• GANN process urged for keeping both forward and reverse mappings. • The averages RMSE of training, testing and validation data are 0.9628,1.2148 and 1.2196 respectively • The RMSE for validation data is 1.2196, the coefficient of determination is 0.9899 and the R^2 is 0.9978.
(Paoletti, Lambiase, & Di Ilio, 2015)	Polycarbonate sheets	x	FSSW	ANN composed by three layers	plunge rate, TRS, and DT	plunging force (Fmax), torque (Cmax), temperature (Tmax), heat resistance (Fr) of joint	• Strong correlation is observed between experimental results and ANN predicted values. • Result confirmed by low values of the Mean Absolute Errors (MAE). • which is ~2% for Fmax, ~3% for Cmax and ~5% for Fr.
(Ghetiya & Patel, 2014)	AA8014	x	FSW	ANN with (BP) algorithm	TRS (rpm), WS (mm/s), and PD (mm)	TS	• The measured and anticipated values almost close to each other. • Overall R^2 value for training, validation and testing is bigger than 0.99. • ANN design 4-8-1 has less than 3% error between experiment and predicted result.
(Shojaeefard, Behnagh, Akbari, Givi, & Farhani, 2013)	AA7075-O / AA5083-O	x	FSW	(ANNs) feed forward NN with BP algorithm and multi objective particle swarm optimization (MOPSO)	TRS (rpm), WS (mm/s)	UTS and hardness	• ANN disclose a better interaction between the predicted data and the acquire data • Linear regression analysis is performed to obtain the R^2 among the experimental and anticipated values. • The R^2 result for UTS and hardness at training and testing were respectively as 0.999 and 0.9916 and 0.9799 and 0.9891.
(Manvatkar, Arora, De, & DebRoy, 2012)	AA 7075	L50 Taguchi array and CCD design	FSW	ANN	TRS, TS, pin radius, tool shoulder, axial force, pin length.	Total torque, WS, peak temperature, bending stress and Max	• The uncertainties in prediction of ANN models alter from 2.5% for peak temperature and 7.5% for torque, Max shear stress and traverse force.

						shear stress	• Bending stress within the training data range vary up to 12%. • Training data sets values are exceeding when calculated in range up to 20%. • The maximum prediction value of uncertainties for peak temperature is 4%. • Maximum shear stress and torque has 12%, traverse force 15% and 20% for the bending stress.
(Buffa, Fratini, & Micari, 2012)	Ti–6Al–4V titanium alloy	x	FSW	ANN and multi objective optimization	TRS (rpm), WS (mm/min), Tilt angle, PD (mm)	Microstructure, and Micro hardness	• Two different neural network trained under different process parameters for the calculation of post weld micro hardness and microstructure. • A delightful agreement found for the prediction of micro hardness • An excellent prediction capability of neural network achieved regarded to microstructure.
(Okuyucu, Kurt, & Arcaklioglu, 2007)	Hot rolled aluminum plates	x	FSW	ANN (BP) algorithm with numerical technique (SCG) and (LM)	TRS (rpm), WS (mm/s)	Hardness (HV), Weld metal, %Elongation, YS, TS	• The RMS error values for Hardness of HAZ, weld metal, %EL, yield Strength, TS are 0.0115, 0.0064, 0.0566, 0.0253, and 0.018 respectively. • The R^2 values are bigger than 0.99 except elongation that is 0.985

The application of ANN in manufacturing used like cold forging to predict the flow stress during hot deformation, for tool wear, for machining behavior prediction and manufacturing process optimization along with other process (Ghetiya & Patel, 2014). (Tansel, Demetgul, Okuyucu, & Yapici, 2010) proposed FSW operation by using ANNs and choose the optimal tool rotational speed and feed rate by using genetic algorithm. The selection of GONNS for modeling the stir welding process founded a viable option for optimal solutions. (Shojaeefard, Akbari, & Asadi, 2014) conduct the ANN analysis to model the correlation between the tool parameters (pin and shoulder diameter) and heat-affected zone, thermal, and strain value in the weld zone. (Fratini, Buffa, & Palmeri, 2009) linked ANN to a finite element model (FEM) and predicted the average grain size values of butt, lap and T type FSW joints. (Jayaraman, Sivasubramanian, Balasubramanian, & Lakshminarayanan, 2008) ANN modelling predicted the TS of A356 alloy which is a high strength Aluminum.

(Tansel et al., 2010) applied genetically optimized neural network system (GONNS) to evaluate the optimal operation condition of FSW process. The characteristics of FSW operation by using ANNS and the selection of parameters like optimal TRS and TS proposed by using Genetic algorithm (GA). Only one ANN model assigned for five performance parameters of welding zone, TS, YS, elongation, weld metal hardness and hardness of HAZ. The input were same for five ANNs (TRS and TS). The error estimation of the ANNs were superior to average 0.5%. (Boldsaikhan, Corwin, Logar, & Arbegast, 2011) introduced a real-time novel technique to detect the wormhole imperfection in FSW in a nondestructive method. In a way by utilizing the discrete Fourier transformation and the multilayer neural network to figure out the provided feedback forces by welding method. By trial and error a near optimum neural network value achieved. A classified testing result of 95% achieved with 60 input unit by optimum neural network, with 9 hidden units, and one output unit. A validation of experiment conducted to proof the generality of NN to characterize the weld quality. The suggested algorithm spent about 0.01 s on a 2700 MHz machine. (Khourshid, El-Kassas, & Sabry, 2015) investigated the mechanical properties to show the feasibility of FSW of Al 6061 on pipe. To conclude the TS, the %EL and hardness of FSW weld of AA6061 aluminum ANN and RSM implanted. The obtained results of ANN and RSM model proved prosperous in term of settlement with experimental result ratio of 93.5% and 90%.

ANFIS Modeling

The acronym ANFIS derives its name from adaptive neuro-fuzzy inference system. By Utilizing a provided input/output data set, the toolbox function ANFIS build a fuzzy inference system (FIS) whose function membership framework are tuned by utilizing only a back propagation (BP) algorithm or merger with a least squares type of method. This adaptation of fuzzy systems allow him learn from the data they are modeling. The ANFIS learning method works similarly as neural networks. Fuzzy modeling method obtained from neuro-adaptive learning technique to learn information about a data set (Jang, 1993). Fuzzy modeling is established on Fuzzy implications and interpretation are one of the most important field in Fuzzy system approach. The Fuzzy model build on input-output data that classified into two things, first is mathematical tool to show a model system and the second is identification method. The Fuzzy implication depend on input space of a Fuzzy partition. A linear input-output relation formed in each Fuzzy subspace. A fuzzy meddling system apply fuzzy if-then rules which can model the qualitative aspects of human expertise and analysis processes without exploit accurate quantitative investigation. First time Fuzzy modeling is systematically explore by (Takagi & Sugeno, 1985).

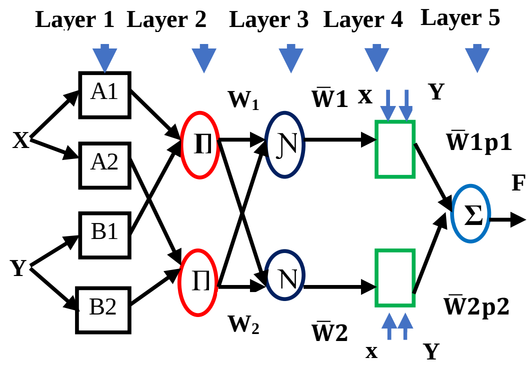

FIGURE 5. ANFIS design model of two input rules

(Babajanzade Roshan et al., 2013) tested the various arrangement of ANFIS model for each response (TS, YS, and hardness). Mechanical properties of FSW process predicted by two stage of ANFIS model, training and testing. The obtained structural model shown in figure, model that has a broad number of MFs shows overfitting and not be able to develop the ambitious value of root mean square error (RMSE). In the accuracy of ANFIS model the influential factor that affect is the class of membership function. It can conclude that a good relationship established between the predicted value of ANFIS and experimental value.

TABLE 2. Applications of ANFIS techniques to various Friction Stir Welding processes

Author	Material	DOE	Process	Models	Input parameters	Output	Remarks
(Shanavas & Dhas, 2018)	AA 5052 H32	CCCD with 4 factors, 5 levels	FSW	Fuzzy logic model with four stages and RSM	Tool pin geometry, TRS, WS, and tool tilt angle.	Weld quality	• Fuzzy model anticipate an acceptable output with less than 4% error. • Regression model foresee the outcome less than 7%. • The obtained result shows calculated F-ratio value is higher than tabulated F-ratio at 95% confidence level reveals that model is adequate.
(Barath, Vaira Vignesh, & Padmanaban, 2018)	AA2024-AA7075	X	FSW	Sugeno-Fuzzy logic mechanism uses ANFIS	TRS and WS	TS	• The ANFIS is trained by utilizing the training data in Sugeno inference system. • For the experimental data 80% is used for training and testing and remaining used for testing and validation. • The ANFIS model demonstrate that TRS of 1050 rpm and WS of 15 mm/min^{-1} are highly influential parameters in FSW to generate optimum heat for grain refinement getting peak TS.

(Dewan, Huggett, Warren Liao, Wahab, & Okeil, 2016)	AA-2219-T87	X	FSW	ANN and ANFIS model with approach of leave-one-out cross-validation (LOO-CV)	TRS, WS,PD, and empirical force index (EFI)	UTS	• For the development of ANFIS and ANN all four input parameters were utilized and optimized and obtain result show that EFI has strong relation with UTS compared to others. • ANFIS predict better results than ANN in term of RMSE and MAPE 29.7 MPa and 7.7% in ANFIS model and 36.7 MPa and 10.09% in ANN model respectively.
(Babajanzade Roshan et al., 2013)	AA7075	CCD with 4 factor 5 levels	FSW	ANFIS with simulated annealing	TRS (rpm), WS (mm/s), Axial force (N), Tool pin geometry	TS, YS, and Hardness	• The prediction error for TS is 3.21% for single response and 2.24% for multi-response. • The prediction response for YS and Hardness for Single and multi-response are respectively.2.27% and 3.1% for single and 3% and 3.8% for multi-response.

(Satpathy, Mishra, & Sahoo, 2018) developed the regression model, ANN, and ANFIS to simulate and predict the joint strength of Ultrasonic metal welding USMW of Al-Cu sheets. The result of ANN and ANFIS investigation compared with outcome of regression analysis. The obtained average absolute error of TS for regression, ANN and ANFIS analysis are 0.47%, 0.15% and o.o7%. Similarly TP values varied respectively 1.89%, 0.61% and 0.22% for regression, ANN and ANFIS. So result conclude that the ANFIS predict most accurate result than ANN and regression. The obtained R2 result for TS values for regression, ANN and ANFIS are 91.47%, 99.30% and 99.98%. The R^2 values for TP results in ANFIS is 99.79% that more accurate than other two techniques. (Dewan, Huggett, Warren Liao, Wahab, & Okeil, 2016) developed an optimized ANFIS model to anticipate UTS of FSW joints. Total 1200 models developed by changing the quantity of membership function (MFs), types of MFs, and mixture of input parameter which are spindle speed, plunge depth, welding speed and empirical force index (EFI) by using MATLAB platform. An ANNs models was also develop for the comparison of UTS of FSW process. EFI founded a strong relation with UTS relative to other parameters. The predicted results of both models ANFIS and ANN with three input variables WS, PD, and EFI resulted as respectively in lowest RMSE 29.7 MPa and Mean Absolute percentage error (MAPE) of 7.7% in ANFIS model on the other hand in ANN model minimum Root mean square error (RMSE) is 36.7 MPa and MAPE is 10.09% which is larger than ANFIS model.

Regression model

Regression analysis is the most frequently used conventional prediction approach to recognize the connection between the dependent and independent variables. The cooperation between dependent variable and predictor variables is develop as a linear model in Eq. (1)

$$Y=\beta_0+\sum\beta_i X_i+ \varepsilon_i \quad (1)$$

In this formulation β_0 ….. β_p are the regression coefficients to be predicted according to scrutiny. To prevent multicollinearity problems, interrelationship between the predictors should be organized (the correlation coefficient of the descriptive variables should not surpass 0.7) (Anderson, Sweeney, & Williams, 2011). The last term ε, designate the random error and is attribute as the residual for examining the overall influence of the model and each regression coefficient. Error term is independently and normally distributed, with a mean of zero and a constant variance of σ2 (Douglas C. Montgomery & Vining, 2012). Regression models describe the relationship between the output values and one or more input values. The multiple regression model is a parametric model. There are many statistic and machine learning method to generate the result like, linear, generalized and nonlinear regression model, containing mixed effect model and stepwise models. The connection between the numeric predictor and continuous target approximates by simple linear regression by using straight line. Relationship between a set of P>1 predictors and a single continuous target approximates multiple regression modeling using a P-dimensional plane (Vardhan & Bayar, 2013). The main objective of regression model designing to select a best suitable regresses that can develop an accurate response variable. Regression Trees (RT) and ANN are ambitious techniques for modeling regression problems. MLR is a classic method that provide many advantages: simplicity, interpretability, chances of being accommodated over the transformations of the variables, and the performing of reasoning, supposing the hypothesis of normality, homoscedasticity and inter correlation between the error ε and the predictor variables (Chakraborty, Chakraborty, & Chattopadhyay, 2018). (Heidarzadeh, 2019) applied first time the RSM in partnership with electron back scattered microscopy (EBSD) and TEM to examine the influence of parameters on tensile properties of brass plate.

TABLE 3. Applications of RSM techniques to various FSW processes

Author	Material	DOE	Process	Models	Input parameters	Output	Remarks
(Jenarthanan, Varun Varma, & Krishna Manohar, 2018)	AA2014 and AA6061	Central-Composite method (CCD)	FSW	applying RSM	TRS (rpm), WS (mm/s), pin diameter	TS	• RSM validated by using confirmation test and error found within ± 5% • RSM is a power full tool in optimizing the FSW process parameters. • The difference between the predicted and experimental strength values are marginal± 5%. In modelling and optimizing process the RSM show better accuracy.
(Kadaganchi, Gankidi, & Gokhale, 2015)	AA 2014-T6.	CCD with four process parameter	FSW	RSM applied	TRS (rpm), WS (mm/s), Tilt angle, Tool pin profile	% EL, YS and UTS	• 2^{nd} order response surface fitting model by using analysis of variance. • Regression equation developed on experimental values of YS, UTS and %EL. • Developed model utilized to predict the response within ±10 % of experimental values at 95% confidence level.
(Elatharasan & Kumar, 2013)	AA 6061-T6	face-centered CCD design	FSW	RSM	TRS (rpm), WS (mm/s), Axial force (N)	UTS, TS, YS, and %EL	• The fitted quadratic model is applied to get the response. • UTS, YS, and %E effectively predict the joint at 95% confidence level
(Karthikeyan & Balasubramanian, 2010)	AA2024-T3	CCD rotatable four-factor, five-level factorial design	FSSW	RSM with	TRS (rpm), PD (mm), Plunge rate (mm/min), DT (s)	tensile shear fracture load (TSFL)	• 2^{nd} order polynomial equation used to response the model. • To predict the TSFL of joint an empirical relationship developed combine with welding parameters at 95% confidence level. • On TSFL plunge rate influence greater than PD, DT, and TRS.

(Elatharasan & Kumar, 2012) applied the quadratic model of RSM to evaluate the UTS, YS and displacement of FSW joint. Multi objective optimization by utilizing the RSM is a valuable method to enhance the FSW parameters to achieve optimum UTS, YS and displacement of a joint at 95% confidence level. (Srinivasa Rao & Ramanaiah, 2018) applied three factor central composite design with five level to construct a mathematical regression model for employing RSM. The importance of process parameters studied by implementing the RSM technique. The R^2 values of predicted model for hardness, UTS, %E, bending strength, and impact strength are respectively 83.90%, 95.47%, 86.47%, 90.73% and 93.78% which disclose a good combination between the response data and independent variables.

TABLE 4. Comparison of ANN/RSM techniques to various FSW processes

Author	Material	DOE	Process	Models	Input parameters	Output	Remarks
(M. Krishnan, Maniraj, Deepak, & Anganan, 2018)	AA6063 -T6 and A319.0	Three factor ,5 level (CCC) design	FSW	(ANNS) with (BP) algorithm and RSM applied	TRS (rpm), WS (mm/s), and axial force(N)	YS, UTS, %EL, and hardnes s	• ANN model cultivate to predict the exclusive input parameter and reciprocal effect like TS, and hardness. • Regression model developed on experimental value of YS, TS, %EL and hardness and develop model validated for 95% confidence level.
(Lakshminar ayan & Balasubram anian, 2009)	AA7039	Three factor, three level and (CCC) design	FSW	Compariso n of RSM and ANN Model	TRS (rpm), WS (mm/s), and axial force(N)	TS	• More robust and accurate model found ANN in evolution of TS values. • When compared ANN with the RSM. • The mean errors for ANN and RSM were 0.258, 847% and 0.769, 831% respectively
(Jayaraman et al., 2008)	Commer cial A356 aluminu m	Central composit e faced design (CCFD)	FSW	ANN with BP algorithm and RSM with cause and effect diagram	TRS (rpm), WS (mm/s), and axial force(N)	TS	• In comparison ANN model result are better and accurate than RSM. • ANN is good in estimating the tensile strength values. • The obtained R^2 value is 0.978398 of this model which is only 3% less of the total variation • The lower value of coefficient of variation (CV) is 2.556 which shows improvement in reliability and precision in experiment.

Support Vector Machine (SVM)

In many machine learning tasks SVM is used, such as object classification, pattern recognition and in time series prediction, also containing forecasting of energy consumption. SVR is a procedure for regressions in support vector machine (SVMs). SVMs worked on the principle of structural risk belittlement. SVM build up one or more hyperplanes in a high dimensional space. The purpose of SVR is diminish the probability of the model that produce from input data set which will create an error on an unseen data item. The objective is accomplished by finding a solution which, best generalizes the training examples. (Vapnik, 2000) SVM segregate the data points into two classes. Each data point apply to one of the two classes distinguished by a linear classifier with a hyper plane. The data points are separated into two classes by using various linear classifier. To obtain best classification between the two classes it is necessary to select the hyperplane with utmost margin. SVM classify the testing data points by choosing the hyperplane with maximum margin. That utmost margin hyperplane is persistent by a subset of data points called support vector. (Dong, Cao, & Eang, 2005) enforced SVM to forecast the energy utilization of buildings in a tropical region. The obtained result have coefficient of variance (CV) less than 3% and percentage error within 4%.

Figure 6 demonstrate the hyperplanes H1, H2, and H3 in which only H2 gain maximum margin. The p-1 dimensional hyperplanes that allocate vectors but only one hyperplane that can escalate the margin between two classes. Otherwise, the nearest hyperplane between sides of this hyperplane is maximized. Such hyperplane called maximum-margin hyperplane and recognize as the SVM classifier (Nguyen, 2017).

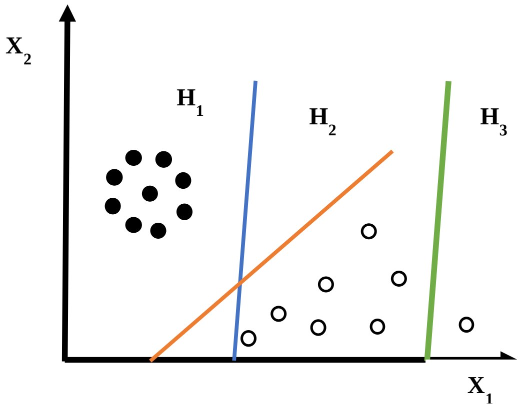

FIGURE 6. Separating Hyperplane Adapting from (Nguyen, 2017)

SVM are capable of handling immense dimensionality greater than1000 very well. However, accompanying concern like possible over-fitting has to be (Murty & Raghava, 2016; Widodo & Yang, 2007; Yang & Trewn, 2004) applied the SVM classification. Particularly the linear SVM which is perfectly appropriate to pledge with linearly separable classes. Based on linear discriminant function SVM is the most popular distributer. SVM is perfectly suitable for binary categorization. It extensively studied in data mining and in pattern recognition applications. Over the past three decades SVM turn into basic standard for classification due to exceptional software packages which developed consistently. (Cortes & Vapnik, 1995) explored the SVM classification problems for two group. The machine theoretically implement an idea: input vector non-linearly mapped to a very high dimension feature space. Decision surface assemble in this feature space. The immense generalization capability of the learning machine ensures by special characteristic of the decision surface. Previously SVM network carried out for limited condition where training data detached without any error. However, in this study the result extended to non-separable training data. Due to the extension, SVM consider as a new method of machine learning that is strong and comprehensive as neural networks.

TABLE 5. Application of SVM techniques to various FSW processes

Author	Material	DOE	Process	Models	Input parameters	Output	Remarks
(Armansyah & Astuti, 2018)	AA6061	X	FSW	SVM through Kernel function as pattern classification	TRS (rpm) and WS (mm/s)	TS (MPa)	• Performance evaluation and testation model developed for FSW. • Prediction accuracy for TS found 100% for training and testing system.
(Armansyah & Astuti, 2018)	AA5052-H112	X	FSSW	SVM through Kernel function as pattern classification	TRS (rpm), PD (mm), DT (s).	Shear Tensile load	• SVM classification is implemented for pattern classification and model development for system model. • The training and testing process of FSSW joint result found with 100% accuracy.
(Bhat, Kumari, Dutta, Pal, & Pal, 2015)	AA1100	X	FSW	SVM classification technique using Gaussian and polynomial kernel	TRS (rpm), WS (mm/s), and PD(mm)	Energy, Variance and Entropy	• In comparison Gaussian kernel provide higher accuracy than polynomial kernel. • The obtain result classifying with Gaussian and polynomial kernel with good and defective weld with 99% and 97% accuracy.

(Fleming et al., 2007) worked on fault detection in FSW. Fault such as tool misalignment and excessive flash can reduce the weld quality of the weld. SVM based method implemented to identifies the presence of gaps and determine the gap depth. The predicted result accuracy found 100% for each training and testing system, either for low TSor high TS class which demonstrates the effectiveness and accuracy of this technique that can be implemented in a variety of other FSW fault detection scenarios. (Zhu Lingyun, Cao Changxiu, Wu Wei, & Xu Xiaoling, 2003) applied a new method of computation intelligent using SVM to envision the bond welding quality. To develop SVM Classifier a

RBF picked as kernel function. The weld quality of the FSW joints by SVM classifier is completely feasible. The new method perform exceptional than traditional assessment methods with benefit of low cost, better efficiency and simple implementation on line. In precise prediction and generalization the SVM classifier proved with better result than RBF neural networks. This technique provides a novel approach for evaluation of nondestructive characteristic of friction welding joints

DISCUSSION AND CONCLUSION

Machine learning is a waste field which is implemented in every field some commercially available fields of study are face recognition, image processing, manufacturing, and medical and in many more areas. Mostly in the application of ANN algorithm in FSW process parameters the major material that used is aluminum 5xxx, 6xxx and 7xxx series. The design of experimented (DOE) technique applied by few author which shows a lack of systematical approach in process parameters. The error percentage in prediction the result in ANN and RSM methods is less than 5% in overall. In case of comparison between RSM/ANN it found that the ANN is more robust and accurate than RSM. The result prediction accuracy in training and testing in SVM is 100% approximately in all present cases. In machine learning popularity the SVM technique overtook the ANN technique. In comparison between the regression model and ANFIS it found that ANFIS is more suitable in prediction the output with error percentage less than 4%. In manufacturing the most commonly used algorithm in supervised machine learning is SVMs.

In this study, an attempt made to highlights all the machine-learning approaches that recently implemented in FSW process to predict the response of the process parameters. The recent work on machine learning algorithms, which implemented in FSW and FSSW process parameter are ANNS, ANFIS, Regression model, and SVM classification. During this study found that the Deep Learning has not yet been applied to FSW or FSSW. There is much scope and gap of research available in the application of ANFIS and SVM method to apply in FSW or FSSW process parameters. In the knowledge of prescribed work that there is much need of implementation in machine learning techniques to predict the behavior of process parameters in FSW or FSSW.

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