Process Parameter Sensitivity in Magnetic Pulse Welding: An Artificial Neural Network approach

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Abstract

Magnetic pulse welding (MPW), a solid-state impact welding technique provides the ability to join a wide array of material combinations, whilst introducing little to no heat to the system and preserving the base metal microstructure. Impact velocity is one of the key criteria which determines the weldability of the joint during MPW. Experimental measurement of impact velocity in MPW across wide-ranging parameters is expensive and time-consuming. Therefore, guidelines for process selection and knowledge of relative influence of parameters on impact velocity is limited. This study presents the applicability of coupling finite element method (FEM) and artificial neural network (ANN) modelling to perform sensitivity analysis of MPW. The welding process was simulated using FEM, and multilayer modular feedforward networks based on the results from finite element simulations were developed. The results of the present study revealed that the coil cross-sectional area and turns primarily governed the process, followed by the voltage. The relative sensitivity of the parameters remained independent of the material combination. Inclusion of shop floor applicable process parameters suggests that the developed ANN models can substantially narrow down experimental runs and simultaneously act as a decision support tool for end users.

Keywords

Magnetic pulse welding, Impact velocity, Artificial neural network, Finite element method, Sensitivity analysis.

1 Introduction

The use of advanced and high-strength dissimilar material pairs in automobile, defense and aerospace sectors has seen a significant growth in the recent past owing to the continually growing demands for sophisticated and versatile products and equipment. However, subsequent development of joining technologies for these disparate material pairs has been gradual. Although, techniques like friction stir welding (Mastanaiah et al. 2016), electron beam welding (Mastanaiah et al. 2018), etc., have been quite successful for dissimilar material joining, yet there exist inherent issues that need to be resolved. Solid-state welding techniques facilitate joint formation at low temperatures and often very quickly, usually within microseconds (Stern and Aizenshtein, 2002). Examples include explosive welding (Blazynski, 1983), magnetic pulse welding (MPW) (Spitz and Shribman, 2001) , vaporizing foil actuator welding (Vivek et al., 2013), cold welding, and diffusion welding. These processes involve reduced formation of brittle intermetallic compounds, and thereby keep the material properties intact. Among the solid-state processes, the MPW is one of the most environmentally friendly methods for joining dissimilar materials, wherein electromagnetic forces impact one metal on to another to form a solid-state cold weld (Kapil and Sharma, 2015a).

The weldability of the joint in MPW is decided by a host of parameters among which impact velocity and impact angle are of prime importance (Kore et al., 2010). Based on these two criteria's, several weldability windows have been developed by researchers for different material classes. These windows provide the lower and upper limits of the impact velocity and angle, provide an idea of the jetting, as well give an understanding of the interface state (melting/intermetallic compound formation) (Kapil and Sharma, 2015a). This study focuses on one of the weldability criterion i.e., impact velocity and conducts a comprehensive assessment of its influence on the weldability. The impact velocity, i.e., the velocity at which the mating members collide, is directly influenced by a host of parameters, including electrical (voltage, capacitance, frequency, inductance, and resistance), coil (turns, length, and cross-sectional area), geometrical (air gap), and material properties. The interrelation between these parameters is crucial for the design of process selection guidelines; however, capturing multi-parameter interaction requires a significant number of experiments and producing many electromagnetic coils. Additionally, experimental determination of impact velocity (e.g., photon Doppler velocimetry (Johnson et al., 2009) for a wide-ranging set of parameters entails considerable workforce, monetary resources, and technicality. The graphical representation to understand the effect of process parameters has a limitation of depicting the effect of up to two parameters. For a multi-variable, multi-parameter process such as MPW, where the interaction of parameters affects the process, the graphical representation method does not appear feasible. Studies that can quickly and economically relate the parameter interaction, predict the impact velocity, and enable the user to realize the relative significance of the parameters lack in the literature.

Scaling the MPW process for actual shop floor applications requires the development of robust and accurate predictive models to narrow down the number of trial experiments without missing significant parameters. While finite element model (FEM) development is a solution, the execution of developed models consumes lot of time and computer resources. The artificial neural network (ANN) can model the input-output relations of complex systems and then be used to predict, explore data patterns, map, optimize and control (Paturi and Cheruku, 2020). ANN models rely on the formation and generalization of large input datasets. Once the model is trained, validated, and tested, it can effectively and quickly map a wide array of process inputs and outputs. The use of ANN in modelling the fusion welding processes like arc (Sharma 2016) and laser (Kochar et al., 2019) is prevalent, however, there is no reported literature on predictive model development in MPW using neural networks.

The present study uses the FEM and ANN for virtual experimentation to reduce, if not eliminate, process optimization experiments significantly. The larger goal is to develop a model capable of predicting impact velocity and reveal the relative significance of the parameters through sensitivity analysis, particularly for MPW of dissimilar alloys. The issue is whether it is possible to have a clear idea regarding the ability of the process parameters to influence the impact velocity, independently or depending on the combination of materials to be welded. With a clear understanding, the high cost of process development mainly because of the manufacture of several electromagnetic coils can be significantly reduced. The approach presented is the first of its kind, and, to the authors' best knowledge, no prior literature on sensitivity analysis in the MPW has been published.

2 Materials and Methods

Two different material pairs, i.e., pure Al-SS 304 and AA 2219-SS 321, were chosen for investigation. The properties and the geometry of the selected material pairs are presented in **Table 1** and **Figs. 1(a) and (b)**, respectively. **Fig. 2** depicts the methodology employed in this study. The FEM was used to predict the impact velocity for various combinations of process parameters, namely voltage, capacitance, frequency, inductance, resistance, coil turns/length/cross-sectional area, and air gap. The FEM runs were conducted based on the orthogonal arrays using the aforementioned parameters. **Table 2** presents the details of the FEM, for further details on the FEM utilized in this study, the authors' previous work can be referred to (Kapil and Sharma, 2015b). The developed orthogonal array and the numerically computed impact velocities (by the FEM) are then fed as input to a multilayer modular neural network. The optimum network architecture was reached upon after several iterations with different network topologies, the selection based on the smallest cross-validation mean-squared error between outputs of ANN and input dataset obtained from the FEM.

	Physical properties		Mechanical properties				Plastic properties (Cowper-Symonds Model)	
	Density (Kg/m^3)	Speed of sound (m/s)	Bulk modulus (GPa)	Shear modulus (GPa)	Poisson's ratio	Modulus of elasticity (GPa)	m	P (s^{-1})
Pure Al	2700	5305	76	26.2	0.33	70	0.25	6500
AA 2219	2700	5100	76	26	0.33	73		
SS 304	8033	4211	142.5	77.5	0.29	193	0.28	996
SS 321	8027	5130	120	90	0.29	193		

Table 1: *Material properties*

Mesh	Type	User-controlled			
	Element Size	Flyer tube-Extremely fine, Remaining Geometry-Fine			
	Element Size parameters	Maximum element size (mm)	Minimum element size (mm)	Maximum element growth rate	Curvature factor
		2	0.004	1.1	0.2
Contact pair	Contact pressure method	Augmented Lagrangian			
	Penalty factor	Penalty factor control		Tuned for	
		Preset		Speed	
Solver (Time dependent)	Direct solver used	Multifrontal massively parallel sparse direct solver (MUMPS)			
	Time stepping	Method	Steps taken by solver	Maximum step (µs)	Event tolerance
		BDF	Free	0.1	0.01

Table 2: *FEM properties*

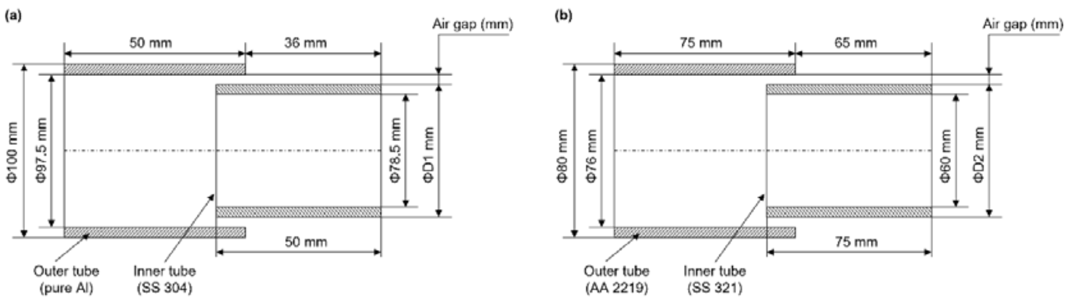

Figure 1: *(a) and (b) Configuration of flyer and base tubes for different air gaps for the selected material pairs. (Schematic not drawn to scale).*

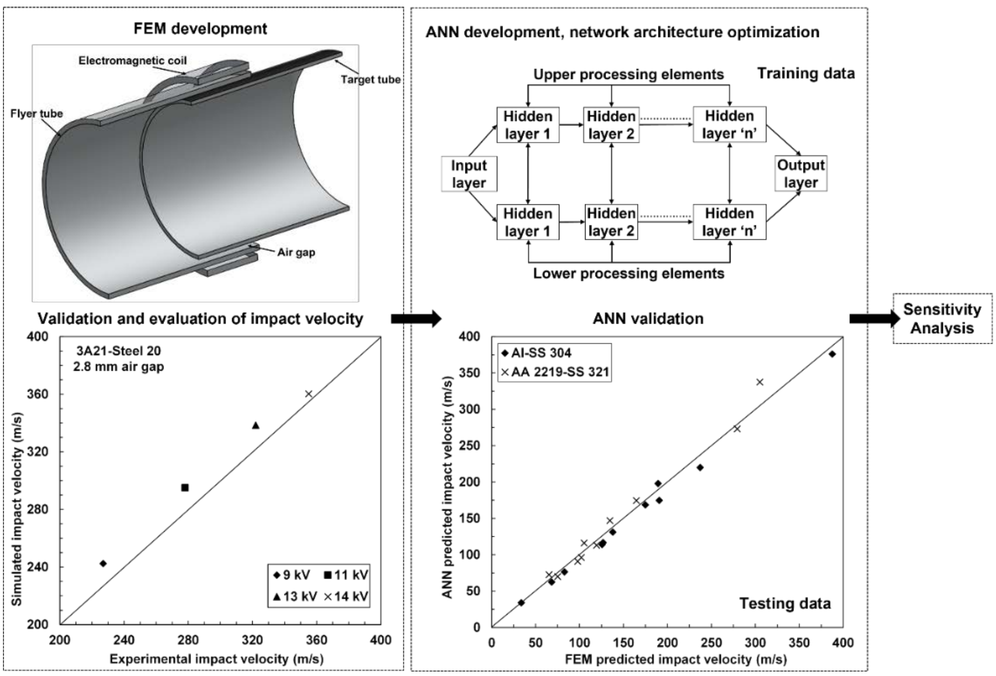

Figure 2: *Flow chart depicting the methodology employed for model development and validation and performing sensitivity analysis.*

Table 3 lists the parameters of the optimized neural networks. The input data for the neural network were randomly divided into three sets, i.e., training, cross-validation, and test data. The optimized network was validated using the test data (Fig. 2), which allowed for comparison of impact velocities predicted by FEM and the neural network. To further establish the predictability of the developed neural network, the general trend of impact velocity with variation in process parameters was checked and compared with known trends from literature (for Al-SS 304 pair). For this exercise, the velocity was calculated for random values of selected process parameters, with the calculation being performed with the best weights obtained during training step of the network development. The variation of the velocity with each parameter was done by generating random values of the considered parameter and keeping all the other parameters at their mid values.

The trained and tested network was then utilized to perform a sensitivity analysis. A multidimensional domain representing the group of process parameters can be expressed in terms of K patterns. Every pattern represents a combination of process parameters, with at least one process parameter having a different value. Thus, for K^{th} pattern, sensitivity due to i^{th} input can be defined as (Sharma et al., 2007):

$$S_{i,k} = \left(\frac{\partial y_k}{\partial x_i}\right) \tag{1}$$

The overall sensitivity of i^{th} input is given as follows:

$$S_i = \sqrt{\frac{\sum_{k=1}^{K}\left(S_{i,k}\right)^2}{K}} \tag{2}$$

The inputs and outputs were normalized (between 0 and 1) to account for the difference in the dimensionality of the different inputs.

Transfer function		Sigmoid Axon			
Learning algorithm		Levenberg–Marquardt			
Data classification (%)		Training	Cross-validation		Test
		70	15		15
ANN topology		Al-SS 304		AA 2219-SS 321	
	Upper layer	8-6-4		12-8-8-6	
	Lower layer	6-4-4		6-5-4-4	

Table 3: *Neural network parameters*

3 Results and Discussions

The FEM was validated by comparing the simulated impact velocities with the experimental values available in the literature (Desai et al., 2010; Xu et al., 2013). Fig. 2 shows a close agreement between the impact velocities obtained from the simulations and the experimental values. A comparison of the impact velocities computed by the ANN and the FEM is depicted in Fig. 2. Most of the data lie on the bisector or in its vicinity, which presents a good correlation between FEM data and output predicted by the ANN. For both the material pairs, the percentage error in prediction is within the ± 10% range.

Figs. 3 (a) to (i) show the general trend of impact velocity with process parameters predicted by the developed ANN. For all the considered process parameters, the neural network predicts variation in impact velocity with change in process parameters that matched with the trends observed in literature. Details regarding the change of the impact velocity with process parameters in MPW have been well explained in literature and thus have not been reiterated in this study (Kapil and Sharma, 2015a; Kapil, 2015). The developed model could accurately predict the impact velocity not only for a single case, but over a wide range of parameters, giving confidence in the model developed in this work.

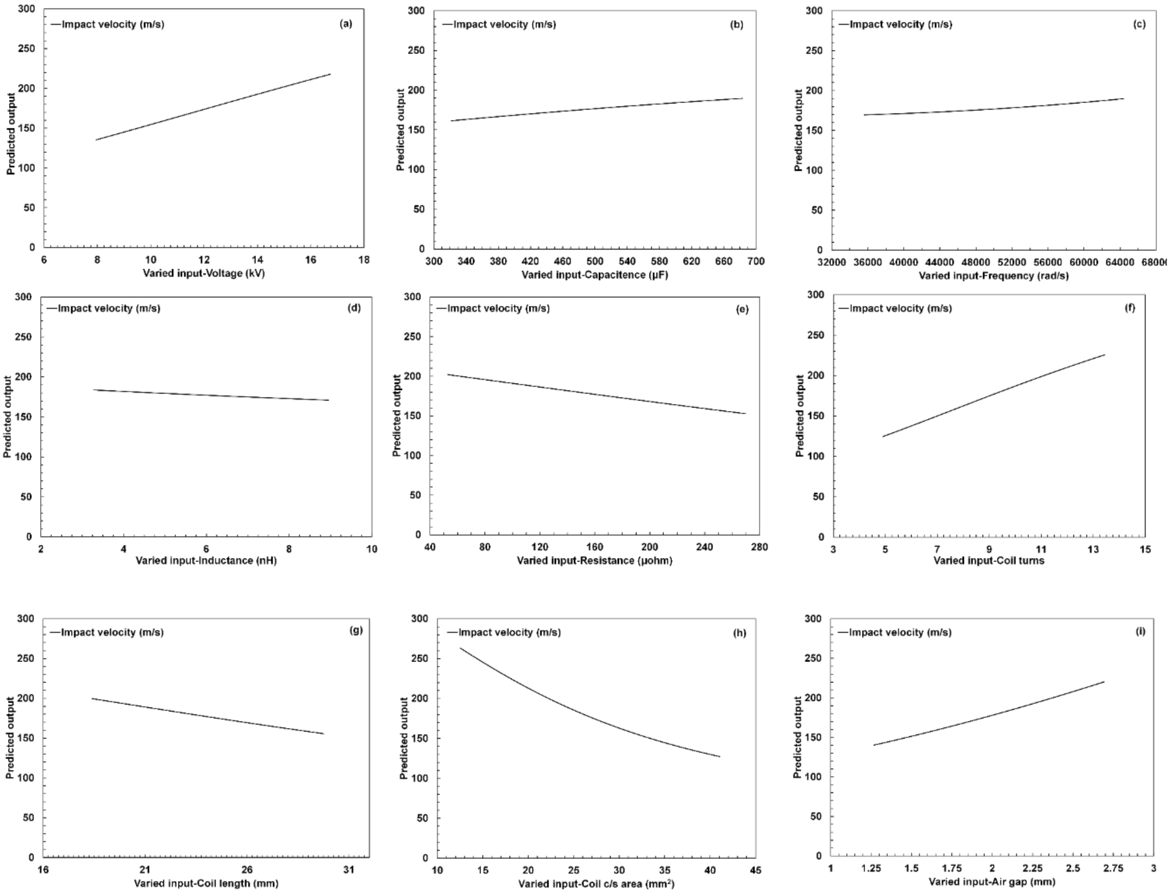

Figure 3: *(a) to (i) General trend of impact velocity with process parameters predicted by the ANN (Al-SS 304 material pair).*

Fig. 4 shows how sensitive each parameter is towards the impact velocity, which, as mentioned before, plays a decisive role in attaining a successful joint in MPW. For both material pairs, the coil cross-sectional area and turns (coil parameters) most significantly affected the process, followed by the operating voltage (electrical parameter) and the air gap (geometrical parameter) (also observed in Figs. 3(h), (f), (a) and (i) respectively). It can also be observed that the sensitivity was almost independent of the material combination employed. These observations are significant, as coil design strategies and guidelines have received limited attention in MPW.

The results of neural network, developed herein can be utilized to identify optimized coil parameters for a variety of materials employed, preventing the physical need to produce many coils. Although the operating voltage is significant, electromagnetic coils are damaged or fatigued when higher voltages are employed, limiting the operable voltage range. In similar lines, the air gap, despite having a relatively high significance, has limited variability (ideally 1.5-3 mm (Kapil and Sharma, 2015a). Thus, coil design and its use with the conjunction of a field shaper (not considered in this study) provide higher flexibility to the user to frame process design guidelines. The lower significance of other electrical parameters (capacitance, frequency, resistance, and inductance) makes them less preferable to change, which is rather good. These parameters are fixed for a particular machine and would require substantial monetary resources to introduce variability.

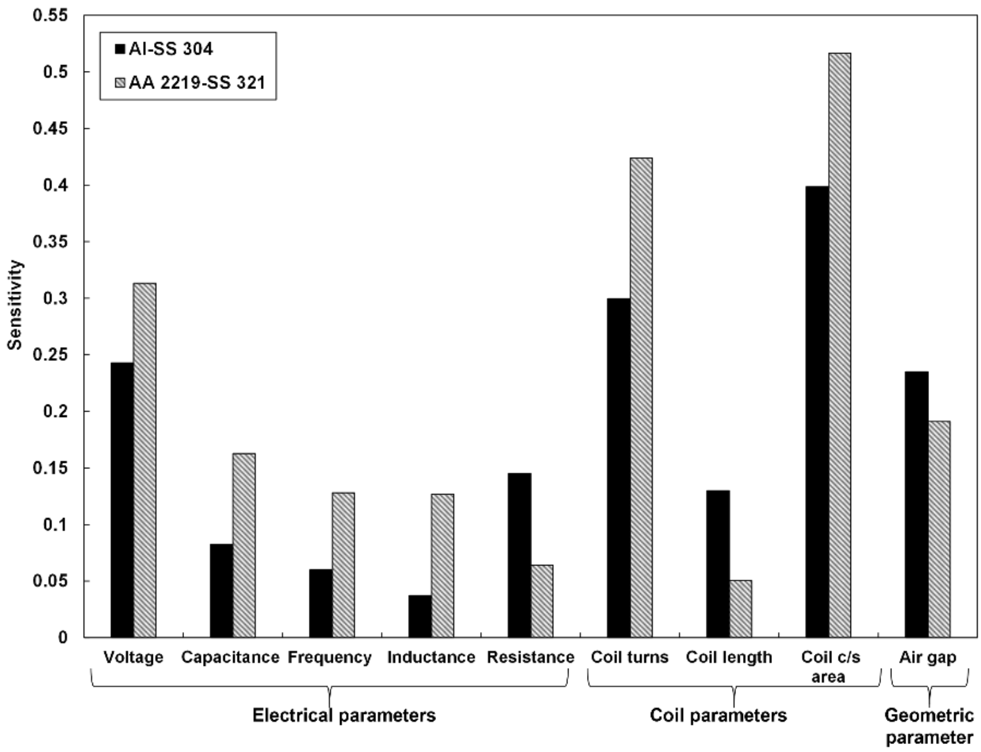

Figure 4: *Sensitivity of impact velocity with process parameters.*

Once the parameters are filtered to introduce variability, the ANN could be used to inverse model to obtain the range of process parameters that yield feasible impact velocity as follows:

$$1.2 * V_{threshold} < Impact\ velocity < 1.2 * V_{threshold} \quad (3)$$

where $V_{threshold}$ is the threshold impact velocity below which the welding does not occur, and V_{damage} is the velocity at which damage occurs, as observed from the FEM simulations.

$V_{threshold}$ is calculated using the speed of sound, material density, bulk modulus, shear modulus and the tensile yield stress of flyer and base materials (Kore et al., 2010; Botros, and Groves, 1980; Blazynski, 1983). The factor 1.2 ensures impact velocity remains sufficiently above the threshold while 0.8 compensates overprediction in impact velocity due to neglecting the compression of air between the colliding members.

Although the focus of this study is limited to sensitivity analysis of process parameters based on impact velocity, the developed neural network can be extended to include other important criteria like impact angle, effective plastic strain, and shear stress, and thereby perform a multi-criterion, multi-parameter sensitivity analysis in future. The methodology employed in this study can also be extended for development of multi-criteria weldability windows. The parameter interaction can be analysed in more detail to exploit neural network modelling as a decision-making tool in MPW.

4 Conclusions

1. Finite element model coupled with modular artificial neural network is an effective tool to analyze process sensitivity over a wide range of parameters for complex multi-variable manufacturing operations like magnetic pulse welding of dissimilar materials. Concurrently, the range of feasible impact velocity and corresponding process parameters can be obtained by inverse modelling.
2. The order of predominance of the process parameters is established. The coil cross-sectional area and turns have the most significant effect on the impact velocity followed by the working voltage and air gap. The low order sensitivity of machine-specific electrical parameters makes the capital investment in a new welding machine to change the process parameter ranges the less preferred.
3. The order of sensitivity to the individual parameters remained the same for the different material pairs used, meaning that the process and material effects can be isolated.

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