

Multiple Characterisation Modelling of Friction Stir Welding Using a Genetic Multi-objective Data-driven Fuzzy Modelling Approach

Qian Zhang, Mahdi Mahfouf, George Panoutsos

Department of Automatic Control and Systems
Engineering

The University of Sheffield
Sheffield, UK

{qian.zhang, m.mahfouf, g.panoutsos}@sheffield.ac.uk

Kathryn Beamish, Ian Norris

TWI Ltd

Cambridge, UK

{kathryn.beamish, ian.norris}@twi.co.uk

Abstract—Friction Stir Welding (FSW) is a relatively new solid-state joining technique, which is versatile, environment friendly, and energy and time efficient. For a comprehensive understanding of the effects of process conditions, such as tool rotation speed and traverse speed, on characterisations of welded materials, it is essential to establish prediction models for different aspects of the materials' behaviours. Because of the high complexity of the FSW process, it is often difficult to derive accurate and yet transparent enough mathematical models. In such a situation, a systematic data-driven fuzzy modelling approach is developed and implemented in this paper to model FSW behaviour relating to AA5083 aluminium alloy, consisting of microstructural features, mechanical properties, as well as overall weld quality. This methodology allows constructing transparent fuzzy models considering both accuracy and interpretability attributes of fuzzy systems. The elicited models proved to be accurate, interpretable and robust and can be further applied to facilitate the optimal design of process parameters, with the aim of finding the optimal combinations of process parameters to achieve desired welding properties.

Keywords—friction stir welding; aluminium alloy; mechanical property; microstructure; weld quality; fuzzy; modelling; multi-objective; NSGA-II

I. INTRODUCTION

Friction Stir Welding (FSW) is a practical solid-state joining technique, which was invented at The Welding Institute (TWI), UK in 1991 [1]. It was initially developed for welding aluminium alloys, and nowadays has been extended to be implemented in a variety of materials, including magnesium alloys [2], steels [3], copper alloys [4], titanium alloys [5], etc.

In a standard FSW process, a non-consumable rotating tool with a shoulder and a pin is inserted into the abutting edges of two rigidly clamped plates to be joined, as shown in Fig. 1 [6]. The tool moves along the joint line of the butting surfaces while the shoulder makes firm contact with the top surface of the work-piece. With the tool rotation, heat generated by friction between the tool and the work-piece softens the material being welded. Severe plastic deformation and flow of this plasticised metal occurs as the tool is rotating and

travelling along the welding direction. Material is transported from the front of the tool to the trailing edge where it is forged into a joint.

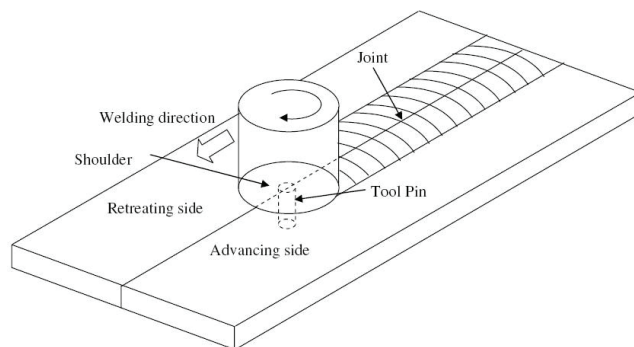


Figure 1. A schematic drawing of friction stir welding [6].

The FSW process involves intense plastic deformation and complex thermo-mechanical processes, which result in recrystallisation and development of texture within and around the stirred zone [7]. A typical cross-section of the FSW joint consists of three distinct zones, stirred (nugget) zone, Thermo-Mechanically Affected Zone (TMAZ), and Heat-Affected zone (HAZ), which can be identified in Fig. 2 [7].

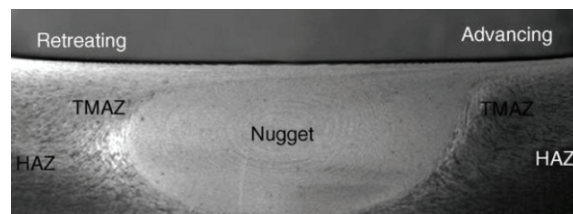


Figure 2. A cross-section macrograph of FSW showing various microstructural zones [7].

During the FSW process, the material undergoes intense plastic deformation at elevated temperature, resulting in generation of fine and equiaxed recrystallised grains [8]. This fine microstructure produces good mechanical properties for the welded material. In addition, FSW demonstrates its

versatility as it is able to weld dissimilar alloys and dissimilar composites [9], for various types of joints, such as butt joints, lap joints, fillet joints, etc. FSW is also considered to be a “green” technology due to its energy efficiency and environment friendliness [7]. Compared to conventional welding methods, FSW consumes considerably less energy and it does not need shielding gas or flux, thereby making the process environmentally friendly. Since its invention in 1991 [1], FSW has found widespread applications in diverse industries, for example, aerospace, shipbuilding, automotive and railway industries [10].

For a comprehensive understanding of the effects of process conditions, such as tool rotation speed and traverse speed, on characterisations of welded materials, it is essential to construct accurate and reliable prediction models. Because of the high complexity of the FSW process, it is often ‘tricky’ to derive practical physical models. In such a situation, a systematic data-driven fuzzy modelling strategy is developed in this paper to elicit adequate prediction models based on experimental data, which include the micro-structural features, mechanical properties, as well as overall weld quality relating to AA5083 aluminium alloy.

Compared with analytically based methods, fuzzy systems are simpler in structure and easier to apply. They are capable of learning from data without needing much prior knowledge about the materials and processing [11], [12]. Fuzzy models are also convenient when combined with optimisation techniques to identify the input parameters that will provide a desirable behaviour profile [13], [14]. On the other hand, compared with black-box modelling approaches, such as Artificial Neural Networks (ANNs), fuzzy systems have transparent characteristics and the relationships between inputs and outputs are more interpretable, because of their use of descriptive language, such as linguistic ‘IF-THEN’ rules.

The proposed fuzzy modelling methodology allows to generate fuzzy models considering not only accuracy (precision) but also transparency (interpretability) of fuzzy systems via applying multi-objective optimisation techniques. As a result, a set of so-called ‘Pareto-optimal’ [15] models, in terms of different accuracy and interpretability levels, are constructed, which provide a wide range of choices for practitioners or users. In this paper, a hierarchical optimisation structure is proposed to improve the modelling efficiency, where two learning methods are systematically combined in order to improve various attributes of fuzzy systems: One multi-objective optimisation algorithm, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [16], is used to optimise the model’s structure; Based on a fixed model structure, the other single-objective learning paradigm, the Gradient Descent (GD) method is employed to improve the model’s parameters.

The remaining parts of this paper are organised as follows. Section II introduces the proposed modelling framework. Section III presents the experimental studies on modelling the FSW-related properties in detail. Finally, conclusions in relation to the whole study are drawn in Section IV.

II. THE MODELLING METHODOLOGY

A. Introduction to fuzzy systems

Fuzzy rule-based systems are viewed as robust ‘universal approximators’ capable of performing nonlinear mappings between inputs and outputs. It is an approach that allows a system to be represented using a descriptive language (linguistic ‘IF-THEN’ rules), which can easily be understood and explained by humans to allow them to gain a deeper insight into uncertain, complex and ill-defined systems.

Generally, a fuzzy system consists of four fundamental components: fuzzy rule-base, fuzzy inference engine, fuzzifier and defuzzifier. Fig. 3 shows the diagram of a fuzzy system. The central part of a fuzzy system is the knowledge-base (rule-base) consisting of the fuzzy rules. A fuzzy rule is an IF-THEN statement in which some words are characterised by continuous membership functions. Specifically, the fuzzy rule-base comprises the following fuzzy rules:

Rule_{*l*}: IF x_1 is A_1^l AND ... AND x_n is A_n^l , THEN y is B^l ,

where $l = 1, 2, \dots, m$; m is the number of rules in the fuzzy rule-base; A_i^l and B^l are fuzzy sets in $U_i \subset R$ and $V \subset R$, respectively, and $\mathbf{x} = (x_1, x_2, \dots, x_n)^T \in U$ and $y \in V$ are the input and output (linguistic) variables of the fuzzy system, respectively.

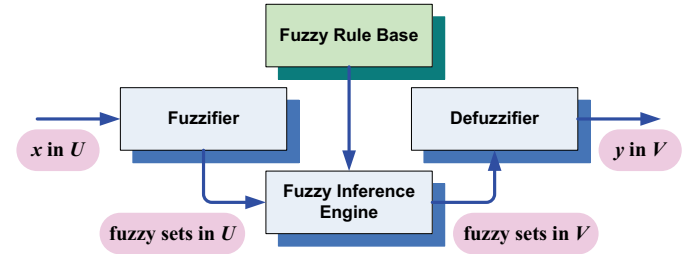


Figure 3. Basic configuration of fuzzy systems.

The fuzzifier is defined as a mapping from a real-valued point $\mathbf{x}^* \in U \subset R^l$ to a fuzzy set A^* in U . Normally, three types of fuzzifiers are used, which are singleton fuzzifier, Gaussian fuzzifier and triangular fuzzifier. They correspond to three types of fuzzy sets with different shapes of membership functions. In a fuzzy inference engine, fuzzy logic principles direct how to employ the fuzzy rules into a mapping from an input fuzzy set A^* to an output fuzzy set B^* . The defuzzifier is a mapping from the output fuzzy set B^* in $V \subset R$ to a real-valued point $y^* \in V$. Conceptually, the purpose of the defuzzifier is to specify a point in V that best represents B^* . Three widely used defuzzifiers are centre of gravity defuzzifier, centre average defuzzifier and maximum defuzzifier [17].

Fuzzy modelling is a systems modelling approach with fuzzy rule-based systems. In most of the fuzzy modelling methods, the fuzzy inference engine and the defuzzifier are predefined. Thus, the primary work is to generate appropriate fuzzy sets and right fuzzy rules.

B. A hierarchical multi-objective fuzzy modelling approach

Generally, data-driven fuzzy modelling can be viewed as a two-step process. The first step aims to generate a ‘crude’

approximation of the fuzzy model. The second step consists of optimising the initial fuzzy rules and fuzzy sets to lead to a final 'optimised' fuzzy model.

For the first step, it can be achieved via two different methods: the grid-partitioning based method or the clustering based method. For the first method, the grid-partitioning defines a number of evenly distributed fuzzy sets for each variable. These fuzzy sets are shared by all the fuzzy rules. The main disadvantage of this method, in its basic version, lies in the large number of generated fuzzy rules when dealing with a high-dimensional modelling problem. In contrast, the second method employs data clustering information to define fuzzy sets. The fuzzy sets are not shared by all the rules, but each set is only mapped into one particular fuzzy rule. In this method, each fuzzy rule is associated to one cluster. In this paper, the clustering based method is employed, which includes a previously developed high-performance clustering algorithm, an agglomerative complete-link clustering algorithm [18].

For the second step, the main learning and optimisation techniques include linear least squares, gradient descent methods, neuro-fuzzy training methods, and some evolutionary optimisation techniques (evolutionary fuzzy systems). Compared with the fuzzy systems using other learning techniques, evolutionary fuzzy systems are able to realise improvements on not only the parameters but also the structure of the fuzzy systems. Moreover, multi-objective optimisation techniques within the evolutionary computation can prove very helpful in studying the trade-off between the accuracy and the interpretability of fuzzy systems. Some recent works in the literature [19], [20] have employed multi-objective optimisation techniques to tackle the trade-off issue of fuzzy models, while most of them were carried out based on grid-partitioning-type fuzzy sets.

In the previously proposed modelling approach [18], [21], a multi-objective optimisation algorithm was used to improve fuzzy models' structure and tune their parameters at the same time. This method would use relatively more calculation and would take longer to converge, where a large number of decision variables need to be adjusted and optimised simultaneously.

In this paper, a hierarchical optimisation structure is proposed, where two learning techniques conduct sequentially and iteratively to improve the different aspects of fuzzy systems: the multi-objective optimisation algorithm NSGA-II [16] is mainly employed to optimise the model's structure; while the gradient descent method is employed to improve the model's parameters. The NSGA-II algorithm has been demonstrated as one of the most efficient algorithms for multi-objective optimisation on a number of benchmark problems and applications. Two of the most important features in NSGA-II lie in its fast non-dominated sorting procedure and an elitist strategy. The detailed implementation procedure can be found in [16]. Gradient descent is a first-order optimisation algorithm that can quickly find a local minimum of a function. It has widely been employed in fuzzy modelling for tuning the membership functions [17] and shown to perform efficiently in improving the accuracy of fuzzy models.

Fig. 4 illustrates the proposed fuzzy modelling approach. This approach will be referred to throughout as a Fast Hierarchical Multi-Objective Fuzzy Modelling (FHMO-FM) approach. It can be divided into several components and the execution steps can be described as follows:

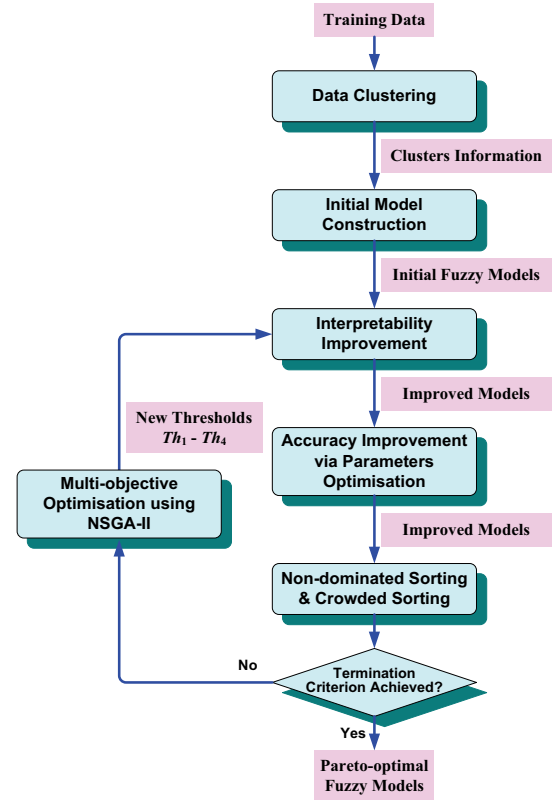


Figure 4. The flow chart of the proposed fuzzy modelling approach.

1. Data clustering: A modified agglomerative complete-link clustering algorithm [18] is employed to process training data in order to obtain the information relating to clusters. This algorithm has been shown to be more efficient and perform better than other well-known clustering algorithms, such as the fuzzy c-means (FCM) clustering algorithm [22].

2. Initial model construction: The information that these clusters provide is then used to construct an initial fuzzy model. In this approach, one cluster corresponds directly to one fuzzy rule; the centres of membership functions are defined using the information of their corresponding clusters' centre positions; other parameters relating to the membership functions are defined under the principle that one membership function must cover all the training data, which are included in its corresponding cluster. More details about this step have been introduced in [11].

3. Interpretability improvement: The fuzzy system is improved in structure, including the variation of the fuzzy rules and fuzzy sets, considering the interpretability issue. This task can be achieved using a four-step operation, including (1) removing redundant fuzzy rules, (2) merging similar fuzzy rules, (3) removing redundant fuzzy sets and (4) merging similar fuzzy sets. These four steps are controlled by 4

threshold parameters, $Th_1 - Th_4$. The details relating to the whole operation have been explained in [18], [21].

4. Accuracy improvement: The fuzzy models are improved by the gradient descent method [17] in terms of accuracy based on a fixed modelling structure.

5. Non-dominated sorting and crowed sorting: The non-dominated fuzzy models with a good diversity are found using the non-dominated sorting and crowed sorting mechanism, which are introduced in the algorithm NSGA-II [16].

6. Termination check: If the termination criterion is achieved, the modelling process is stopped and the final Pareto-optimal solutions are obtained; if not, all the modelling and performance information are passed to the algorithm NSGA-II. Normally, the termination criteria are designed so that the number of function evaluations achieves a predefined value.

7. Multi-objective optimisation using NSGA-II: The algorithm generates new control parameters ($Th_1 - Th_4$) for interpretability improvement based on the multi-objective optimisation strategy, then return to Step 3. It should be noted that the structure of a fuzzy model is not directly coded into the optimisation procedure, but is rather varied and optimised via controlling the thresholds. The accuracy of a fuzzy model can be evaluated using the Root Mean Square Error (RMSE) index, which is described as follows:

$$RMSE = \sqrt{\frac{\sum_{l=1}^N (y_l^m - y_l^p)^2}{N}} \quad (1)$$

where y_l^m is the measured output data and y_l^p is the predicted output data, $l = 1, 2, \dots, N$; N is the total number of data. The interpretability of a fuzzy model is affected by the number of fuzzy rules ($Nrule$), the number of fuzzy sets ($Nset$) and the total length of fuzzy rules ($Lrule$). To normalise these two objectives and make them similar and comparable in scale, they are formulated as follows:

$$\text{Objective 1: } \frac{RMSE}{RMSE_l} \quad (2)$$

$$\text{Objective 2: } \frac{Nrule}{Nrule_l} + \frac{Nset}{Nset_l} + \frac{Lrule}{Lrule_l} \quad (3)$$

where $RMSE_l$ is the root mean square error of the fuzzy model that is not optimised using the multi-objective optimisation mechanism; $Nrule_l$, $Nset_l$ and $Lrule_l$ represent the number of fuzzy rules, the number of fuzzy sets and the total rule length of this fuzzy model, respectively.

In the next section, this method will be further applied to predict the multiple properties for the friction stir welded materials. In those experiments, the initial number of clusters was set to 9, which means that the initial fuzzy model was generated using 9 rules. For the NSGA-II algorithm, the population size and the archive size were set to be 50 and the number of generation was set to be 200. Every single experiment was carried out over 20 runs. Only one set of typical results out of the 20 runs is selected and shown in the following paragraphs.

III. EXPERIMENTAL STUDIES

AA5083 is a non-heat treatable aluminium alloy that has excellent corrosion resistance and weldability combined with good strength and formability [23]. In this paper, 5.8 mm AA5083 plates were friction stir processed using the MX-Triflute™ tool [24].

For FSW, two independent variables are used to control the process: tool Rotation Speed (RS) (rpm) in clockwise or counter-clockwise direction and Forward Movement per revolution (FM) (mm/rev) along the line of joint. The rotation of tool results in stirring and mixing of material around the rotating pin and the translation of tool moves the stirred material from the front to the back of the pin. Normally, a higher tool rotation speed generates higher temperature because of higher friction heating and results in more intense stirring and mixing of material. In this work, the welds were conducted at five different tool rotation speeds, typically between 200 and 600 rpm and five different traverse feed rates of 0.6, 0.8, 1.0, 1.2, and 1.4 mm/rev.

A. Mechanical properties

First, all the welds being tested for tensile properties at room temperature, including Yield Strength (YS), Ultimate Tensile Strength (UTS), Reduction Of Area (ROA) and elongation, where a two-dimensional Digital Image Correlation (DIC) system (LaVision 2D system running a 2MP monochrome camera) was used for data acquisition and displacement measurements. For each weld profile, 5 separate specimens were produced and tested. Based on these testing data, the intelligent modelling approach is then employed to construct the prediction models for the above mechanical properties.

Tensile specimens were machined from the nugget zone in transverse orientation to the weld. It should be emphasized that the strength obtained in the transverse tensile test represents the weakest region of the weld and the observed ductility is an average strain over the gage length including various zones.

In these tensile tests, failures mainly occurred as shear fracture in the HAZ (see Fig. 5 (a)), because the HAZ has the lowest strength due to significantly coarsened precipitates and the development of the Precipitate-Free Zones (PFZs) [7]. For the welds with defects, failures may also occur in the nugget zone (see Fig. 5 (b)), where porosity voids are produced.

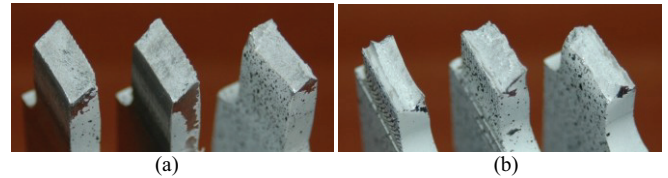


Figure 5. Fracture surfaces of tensile specimens: fracture occurring in the (a) HAZ and (b) nugget zone.

In the following case relating to the yield strength, 16 data were used for training and 4 data were used for final testing. Fig. 6 demonstrates the trade-offs among the Pareto-optimal models respect to the multiple objectives and various criteria, including the Root Mean Square Error (RMSE), the number of

fuzzy rules, the number of fuzzy sets and the total length of fuzzy rules.

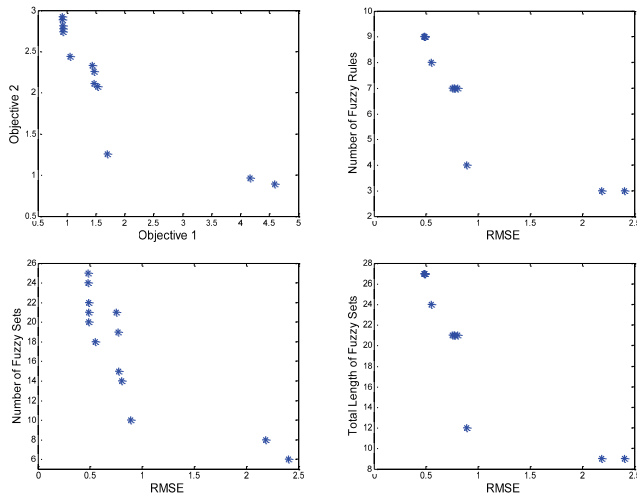


Figure 6. The performance of one set of optimised Pareto-optimal fuzzy models for the yield strength modelling problem.

Table I includes the main parameters of three optimised fuzzy models, which are selected from all the Pareto-optimal models and with 9, 7 and 4 rules respectively. Fig. 7 shows the prediction performance of these models. It can be seen that, for these optimised models, more fuzzy rules and more parameters will bring more accuracy while the models with fewer fuzzy rules and parameters are simpler in structure and easier to understand.

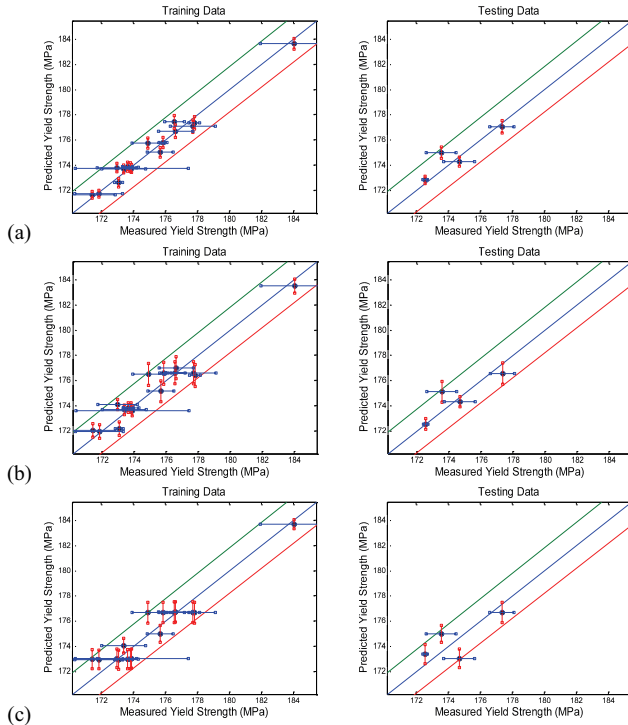


Figure 7. The yield strength models' predicted outputs versus measured outputs (with +1% and -1% error bands): (a) an optimised model with 9 rules, (b) an optimised model with 7 rules, and (c) an optimised model with 4 rules.

TABLE I. MAIN PARAMETERS OF SOME OBTAINED YIELD STRENGTH MODELS

Fuzzy model	Number of fuzzy sets for each variable	Rule length of each fuzzy rule	RMSE of training	RMSE of testing
Yield strength model with 9 rules	Inputs: [6; 7] Output: 9	[3; 3; 3; 3; 3; 3; 3; 3; 3]	0.4846	0.7676
Yield strength model with 7 rules	Inputs: [6; 7] Output: 6	[3; 3; 3; 3; 3; 3; 3]	0.7707	0.8878
Yield strength model with 4 rules	Inputs: [3; 4] Output: 3	[3; 3; 3; 3]	0.8901	1.2190

To provide more details about the obtained fuzzy models, Fig. 8 shows the fuzzy rule-base of the 4-fuzzy-rule model. For these fuzzy rules, they can be rewritten as the following approximate linguistic rules using the linguistic hedges approach [25]:

R₁: IF *RS* is *medium small* AND *FM* is *medium large*, THEN *YS* is *small*.

R₂: IF *RS* is *small* AND *FM* is *large*, THEN *YS* is *large*.

R₃: IF *RS* is *large* AND *FM* is *small*, THEN *YS* is *small*.

R₄: IF *RS* is *large* AND *FM* is *medium*, THEN *YS* is *medium*.

By inspecting these linguistic rules, one can understand more about the system's behaviour.

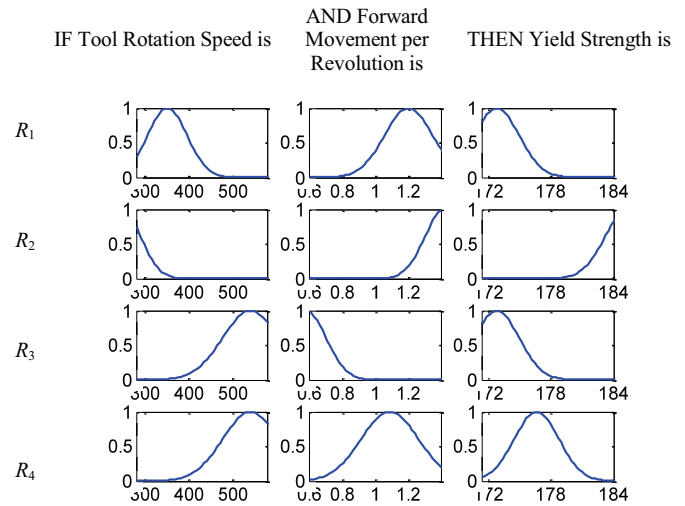


Figure 8. The rule-base of the 4-rule yield strength model.

To verify the physical interpretation of the obtained model, Fig. 9 shows three-dimensional response surfaces of the obtained models. From these surfaces, it can be seen that the models with more fuzzy rules can catch more details from the training data. It can also be observed that, with increasing forward movement per revolution, the yield strength tends to increase. This trend is considered to be consistent with the expected behaviour from the knowledge experts.

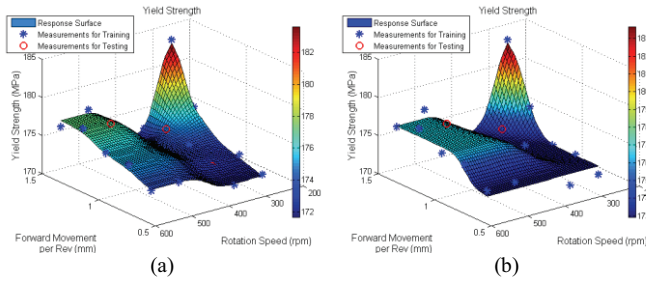


Figure 9. Response surfaces of the yield strength models: (a) the 9-rule model and (b) the 4-rule model.

B. Weld quality

Common defects in friction stir welds include porosity and surface defects [6]. To evaluate the quality of welds, three independent tests were conducted, including a bend test, a surface inspection, and a cross-section inspection. Based on these tests, four sub-indexes are designed to express the various aspects relating to the weld quality, i.e. the face flaws and root flaws in the bend test, the flaws on the surface, and the flaws within the cross-section. The values of such sub-indexes are integers from 0 to 3, where 0 means free from identifiable flaws and 3 represents complete failure or significant number of voids. By summing these sub-indexes together, an overall Weld Quality index (WQ) is obtained to represent the general situation for weld quality, whose value could be from 0 to 12 (0: excellent quality).

In this case, 20 overall weld quality index data were employed in the training phase and the remaining 5 data were used for testing. Fig. 10 demonstrates the trade-offs respect to the multiple criteria within these Pareto-optimal fuzzy models. It can be observed that these Pareto-optimal models exhibit fuzzy sets pattern behaviour, which means that they provide a wider choice of different solutions to users.

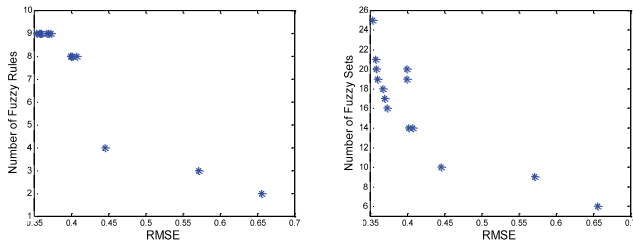


Figure 10. The performance of one set of optimised Pareto-optimal fuzzy models for the weld quality modelling problem.

Table II includes the main parameters of three optimised fuzzy models, which are selected from all the Pareto-optimal models and with 9, 8 and 4 rules respectively. Fig. 11 shows the prediction performance of these models. It can be seen that, for these optimised models, more rules and more parameters will bring more accuracy while the models with fewer rules and parameters are simpler in structure and easier to understand (interpret).

Fig. 12 shows the 3-D response surfaces of these models. From it, one can observe that, at a constant rotational speed, an increase in the travel speed favours the formation of wormhole

defects. This shows a consistency with the phenomena reported in other literatures [6], [26].

TABLE II. MAIN PARAMETERS OF SOME OBTAINED WELD QUALITY MODELS

Fuzzy model	Number of fuzzy sets for each variable	Rule length of each fuzzy rule	RMSE of training	RMSE of testing
Weld quality model with 9 rules	Inputs: [5; 7] Output: 6	[3; 3; 3; 3; 3; 3; 3; 3]	0.3751	0.3047
Weld quality model with 8 rules	Inputs: [4; 6] Output: 6	[3; 3; 3; 3; 3; 3; 3]	0.3993	0.3313
Weld quality model with 4 rules	Inputs: [5; 4] Output: 5	[3; 3; 3; 3; 3]	0.4452	0.5165

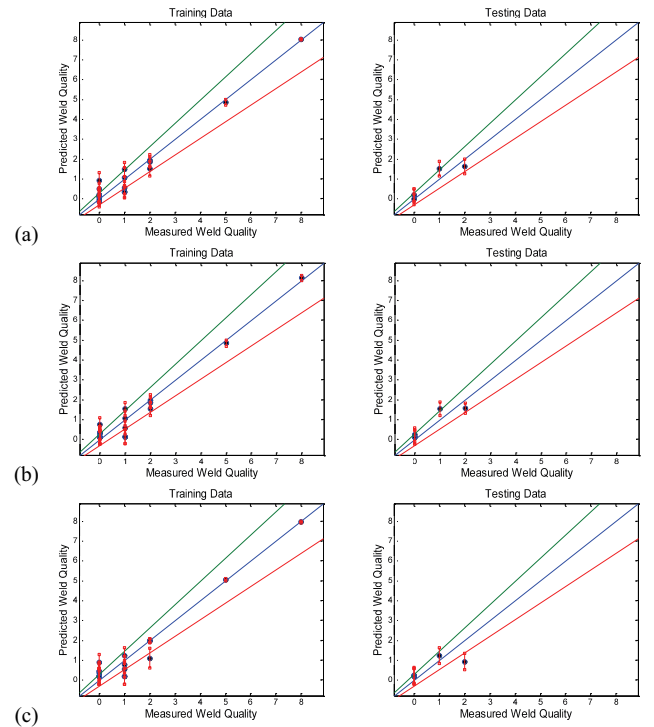


Figure 11. The weld quality models' predicted outputs versus measured outputs (with +10% and -10% error bands): (a) an optimised model with 9 rules, (b) an optimised model with 8 rules, and (c) an optimised model with 4 rules.

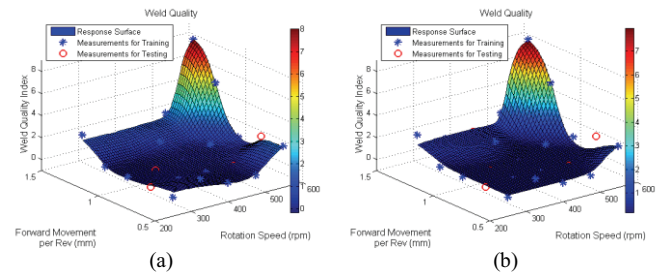


Figure 12. Response surfaces of the weld quality models: (a) the 9-rule model, (b) the 8-rule model, and (c) the 4-rule model.

For more details about these Pareto-optimal models, Fig. 13 shows the rule-base of the 4-rule fuzzy model. It can be further represented as the following approximate linguistic rules using the linguistic hedges approach [25]:

R_1 : IF RS is *medium small* AND FM is *large*, THEN WQ is *medium small*.

R_2 : IF RS is *more or less medium large* AND FM is *medium small*, THEN WQ is *small*.

R_3 : IF RS is *very large* AND FM is *small*, THEN WQ is *medium small*.

R_4 : IF RS is *very large* AND FM is *large*, THEN WQ is *more or less large*.

It is clear that such linguistic fuzzy rules allow for a better insight into the FSW process.

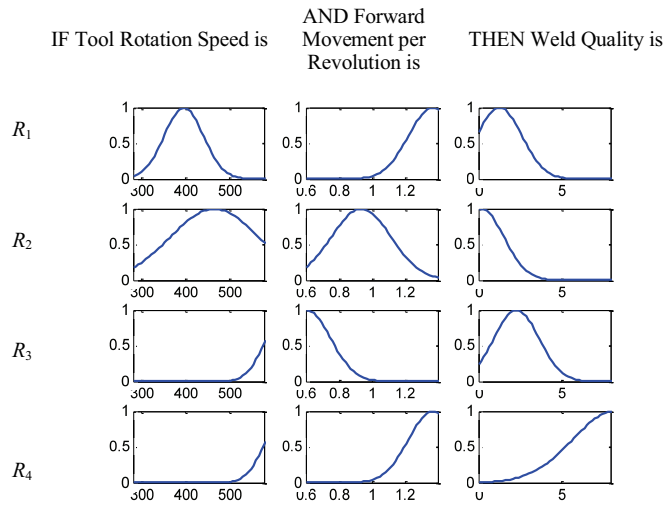


Figure 13. The rule-base of the 4-rule weld quality model.

C. Grain size

The FSW process results in significant micro-structural evolution, including grain size, grain boundary character, dissolution and coarsening of precipitates, breakup and redistribution of dispersoids, and texture [7]. In this paper, Average Grain Size (AGS) in the nugget zone is studied. Fig. 14 shows the micrographs of the pre-weld and post-weld materials, where one can identify different grain sizes.

In this experiment, 20 data points were used for training and 5 data points were reserved for testing. Fig. 15 shows the trade-offs among the multiple criteria within the non-dominated fuzzy solutions.

Fig. 16 shows the prediction performance of the model with 5 fuzzy rules and its response surface is displayed in Fig. 17. This surface has been confirmed to indeed follow the expected behaviour as predicted by theory and by knowledge experts. It should also be noted that the elicited fuzzy models reveal good generalisation ability from the smooth input-output response surface.

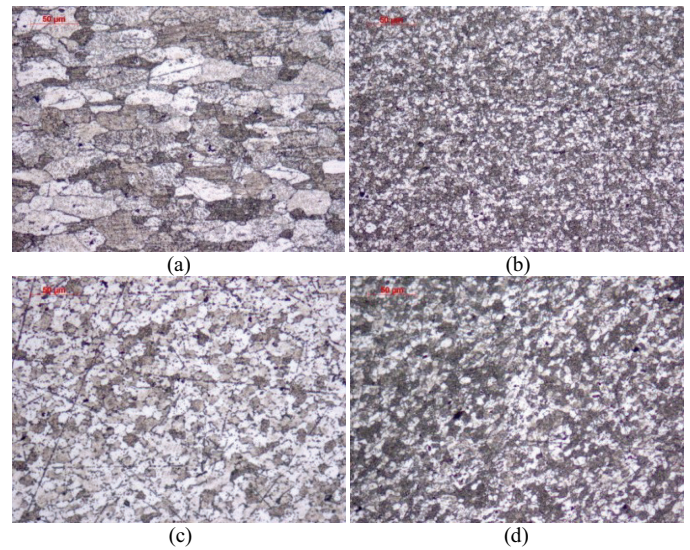


Figure 14. Micrographs of (a) the parent material, (b) the weld with $RS = 280$ rpm and $FM = 1.4$ mm/rev, (c) the weld with $RS = 580$ rpm and $FM = 0.6$ mm/rev, and (d) the weld with $RS = 580$ rpm and $FM = 1.4$ mm/rev.

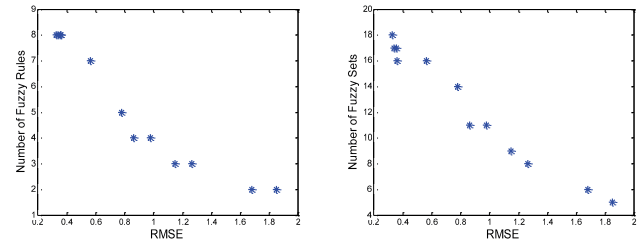


Figure 15. The performance of one set of optimised Pareto-optimal fuzzy models for the grain size modelling problem.

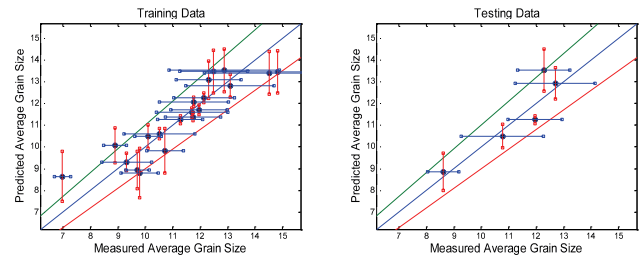


Figure 16. The 5-rule average grain size model's predicted outputs versus measured outputs (with +20% and -20% error bands).

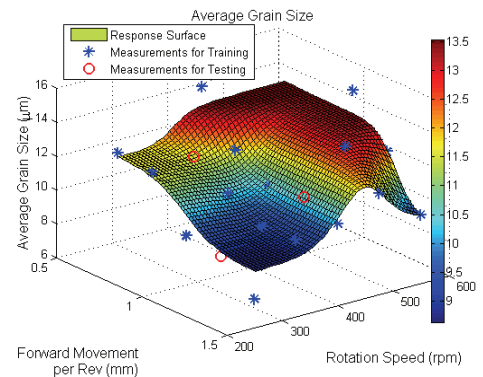


Figure 17. The response surface of the 5-rule average grain size model.

IV. CONCLUSION

In spite of the relatively short history of friction stir welding, it has found widespread applications in various industries. FSW can also lead to significant improvements in the mechanical properties of the welded materials (weld and parent material) over the more conventional welding techniques. However, the fundamental physical understanding about the process is still lacking, as the material flow and micro-structural evolution within the weld is very complex. To achieve a comprehensive understanding of the effects of process conditions on characterisations of welded materials, a systems modelling framework, FHMO-FM, was successfully applied in this paper within the context of predicting multiple properties for the FSW processed material, including mechanical properties, weld quality, and average grain size. In the derived modelling method, the multi-objective optimisation technique has been employed to improve both the accuracy and the interpretability attributes of fuzzy models, and a hierarchical optimisation structure, including two learning techniques (NSGA-II and gradient descent), has also been included to improve the modelling efficiency. In future, the developed models will be exploited to serve as the core module for 'reverse-engineering' designs that are able to suggest optimal process conditions (process routes) by taking into account a set of desired objectives relating to achieving structurally sound, defect free, and reliable welds.

REFERENCES

- [1] W.M. Thomas, E.D. Nicholas, J.C. Needham, M.G. Murch, P. Templesmith, and C.J. Dawes, G.B. Patent Application No. 9125978.8, December 1991.
- [2] N. Afrin, D.L. Chen, and M. Jahazi, "Microstructure and tensile properties of friction stir welded az31b magnesium alloy," *Materials Science and Engineering A*, vol. 472, pp. 179–186, 2008.
- [3] H. Fujii, L. Cui, N. Tsuji, M. Maeda, K. Nakata, and K. Nogi, "Friction stir welding of carbon steels," *Materials Science and Engineering A*, vol. 429, pp. 50–57, 2006.
- [4] T. Sakthivel and J. Mukhopadhyay, "Microstructure and mechanical properties of friction stir welded copper," *Journal of Materials Science*, vol. 42, pp. 8126–8129, 2007.
- [5] A.J. Ramirez and M.C. Juhas, "Microstructural evolution in Ti-6Al-4V friction stir welds," *Materials Science Forum*, vol. 426–432, pp. 2999–3004, 2003.
- [6] R. Nandan, T. DebRoy and H.K.D.H. Bhadeshia, "Recent advances in friction stir welding-process," *Weldment Structure and Properties, Progress in materials science*, vol. 53, pp. 980–1023, 2008.
- [7] R.S. Mishra and Z.Y. Ma, "Friction stir welding and processing," *Materials Science and Engineering R: Reports*, vol. 50, no. 1-2, pp. 1–78, 2005.
- [8] K.V. Jata and S.L. Semiatin, "Continuous dynamic recrystallization during friction stir welding of high strength aluminium alloys," *Scripta Materialia*, vol. 43, pp. 743–749, 2000.
- [9] L.E. Murr, Y. Li, E.A. Trillo, and J.C. McClure, "Fundamental issues and industrial applications of friction-stir welding," *Materials Technology*, vol. 15, no. 1, pp. 37–48, 2000.
- [10] W.M. Thomas and E.D. Nicholas, "Friction stir welding for the transportation industries," *Materials and Design*, vol. 18, pp. 269–273, 1997.
- [11] Q. Zhang and M. Mahfouf, "Fuzzy predictive modelling using hierarchical clustering and multi-objective optimisation for mechanical properties of alloy steels," in *Proceedings of the 12th IFAC symposium on automation in mining, mineral and metal processing*, 2007, DOI: 10.3182/20070821-3-CA-2919.00059.
- [12] Q. Zhang, M. Mahfouf, L. de Leon, S. Boumaiza, J.R. Yates, C. Pinna, and R.J. Greene, "Prediction of machining induced residual stresses in aluminium alloys using a hierarchical data-driven fuzzy modelling approach," in *Proceedings of the 13th IFAC workshop on automation in mining, mineral and metal industry*, 2009, DOI: 10.3182/20091014-3-CL-4011.00042.
- [13] Q. Zhang and M. Mahfouf, "A Modified PSO with a Dynamically Varying Population and Its Application to the Multi-Objective Optimal Design of Alloy Steels," in *Proceedings of the 2009 IEEE Congress on Evolutionary Computation*, pp. 3241–3248, 2009.
- [14] Q. Zhang and M. Mahfouf, "A nature-inspired multi-objective optimisation strategy based on a new reduced space searching algorithm - special application to the design of alloy steels," *Engineering applications of artificial intelligence*, vol. 23, no. 5, pp. 660–675, 2010.
- [15] C.A. Coello Coello and R.L. Becerra, "Evolutionary Multiobjective Optimization in Materials Science and Engineering," *Materials and Manufacturing Processes*, vol. 24, no. 2, pp. 119–129, 2009.
- [16] K. Deb, A. Pratap, and S. Agarwal, and T. Meyarivan, "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.
- [17] L.-X. Wang, *A course in fuzzy systems and control*. Englewood Cliffs, NJ: Prentice-Hall, 1997.
- [18] Q. Zhang and M. Mahfouf, "Mamdani-type fuzzy modelling via hierarchical clustering and multi-objective particle swarm optimisation (FM-HCPSO)," *International Journal of Computational Intelligence Research*, vol. 4, no. 4, pp. 314–328, 2008.
- [19] H. Ishibuchi and Y. Nojima, "Analysis of interpretability-accuracy tradeoff of fuzzy systems by multiobjective fuzzy genetics-based machine learning," *International Journal of Approximate Reasoning*, vol. 44, no. 1, pp. 4–31, 2007.
- [20] R. Alcalá, P. Ducange, F. Herrera, B. Lazzerini, and F. Marcelloni, "A multiobjective evolutionary approach to concurrently learn rule and data bases of linguistic fuzzy-rule-based systems," *IEEE Transactions on Fuzzy Systems*, vol. 17, no. 5, pp. 1106–1122, 2009.
- [21] Q. Zhang, and M. Mahfouf, "A hierarchical Mamdani-type fuzzy modelling approach with new training data selection and multi-objective optimisation mechanisms: A special application for the prediction of mechanical properties of alloy steels," *Applied Soft Computing*, vol. 11, no. 2, pp. 2419–2443, 2011.
- [22] Q. Zhang, *Nature-Inspired Multi-Objective Optimisation and Transparent Knowledge Discovery via Hierarchical Fuzzy Modelling*. PhD Thesis, The Department of Automatic Control and Systems Engineering, The University of Sheffield, UK, 2008.
- [23] E.A. El-Danaf, M.M. El-Rayes, and M.S. Soliman, "Friction stir processing: An effective technique to refine grain structure and enhance ductility," *Materials and Design*, vol. 31, pp. 1231–1236, 2010.
- [24] W.M. Thomas and M.F. Gittos, "Development of friction stir tools for the welding of thick (25mm) aluminium alloys," *TWI Members Report* 694/1999, December 1999.
- [25] L.A. Zadeh, "A fuzzy-set-theoretic interpretation of linguistic hedges," *Journal of Cybernetics*, vol. 2, pp. 4–34, 1972.
- [26] X. Long and S.K. Khanna, "Modelling of electrically enhanced friction stir welding process using finite element method," *Science and Technology of Welding and Joining*, vol. 10, pp. 482–487, 2005.