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Model Fusion via a Master Fuzzy System with Special Application to Engineering Materials

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Abstract: To improve the modelling performance, one should either propose new modelling methodologies or make the best of existing models. In this paper, the study is concentrated on the latter solution, where a structure-free modelling paradigm is proposed to combine various modelling techniques in 'symbiosis' using a 'master fuzzy system'. This approach is shown to be able to include the advantages of different modelling techniques altogether by minimising efforts relating optimisation of final structure. The proposed approach is then successfully applied to predict machining induced residual stresses for aerospace alloy components as well as mechanical properties of heat-treated alloy steels.

Keywords: Fuzzy modelling, Prediction problems, Material, Mechanical properties, Steel

1. INTRODUCTION

In order to describe various physical and social systems in nature, different models and their associated modelling methodologies have been developed. To improve the performance of a model, there are two general strategies. The first strategy is to develop an entirely new modelling paradigm considering the specific features of an object system, which are not coped with by 'old' methods. The second strategy relates to making the best of existing modelling paradigms. This is usually achieved via two ways: further optimisation or systematic combination with other types of models.

In this paper, the research study is focused on the idea of systematic combination of various models. In reality, one single modelling paradigm cannot always perform well due to different systems, or different characteristics of a complex system under different situations. In this case, the combination of various models may cover a wider range of model formulations and provides a more flexible modelling structure. On the other hand, when given a modelling problem without any preliminary knowledge about it, it is very difficult to choose the most appropriate modelling approach before extensive experiments. In this situation, the systematic combination strategy will automatically find a suitable structure, whereby adequate modelling methods will be employed most while inadequate ones will be adjusted to affect the few.

To achieve a sophisticated combination of different types of models, a linear combination is far from enough. In this paper, a fuzzy rule-based system is designed as a high-level master system to handle the cooperation of low-level sub-models, since fuzzy systems are inherently non-linear topologies which are known to be universal approximators and can deal with the curse of dimensionality effectively.

The following sections in the paper are organised as follows. Section 2 introduces the proposed modelling paradigm in details. In Section 3, the new approach is validated using some industrial problems, which aim at modelling machining induced residual stresses in aluminium alloy components and mechanical properties of alloy steels. Finally, Section 4 concludes this paper.

2. THE PROPOSED PARADIGM FOR COMBINING VARIOUS MODELLING METHODOLOGIES

2.1 Introduction to fuzzy systems

Fuzzy rule-based systems are viewed as robust 'universal approximators' capable of performing non-linear 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: a fuzzy rule-base, a fuzzy inference engine, fuzzifiers, and defuzzifiers. The central part of a fuzzy system is the knowledge-base (rule-base) consisting of fuzzy rules. A fuzzy rule is an IF-THEN statement in which some words are characterised by continuous membership functions. Specifically, a fuzzy rule-base comprises the following fuzzy rules:

Rule$_l$: IF x_1 is A_1^l AND … AND x_i is A_i^l, THEN y is B^l,
where $l = 1, 2, …, N_c$; N_c 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 $\boldsymbol{x} = (x_1, x_2, \ldots, x_i)^T \in U$ and $y \in V$ are the input and output (linguistic) variables of the fuzzy system, respectively.

The fuzzifier is defined as a mapping from a real-valued point $x^* \in U \subset R^n$ to a fuzzy set A^* in U. 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^* (Wang 1997).

Generally, when constructing a fuzzy system, the fuzzy inference engine and the defuzzifiers are predefined. Thus, the primary work will be centred around the idea of generating appropriate fuzzifiers (fuzzy sets) and an appropriate fuzzy rule-base.

2.2 Master fuzzy systems

In order to handle the combination of different modelling techniques, a singleton fuzzy system, which is referred to as 'master fuzzy system', is designed. As shown in Fig. 1, it includes a range of pre-developed sub-models, a master fuzzy rule-base, a fuzzy inference engine, etc. When a set of inputs are imported to the master fuzzy system, the master fuzzy rules will first 'decide' which sub-model(s) should be used in this particular circumstance; the fuzzy inference engine will then process the given inputs and the activated sub-models to produce a final predicted output.

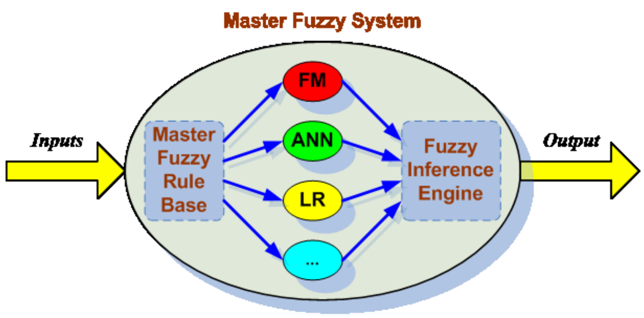

Fig. 1. The diagram of the master fuzzy system.

The master fuzzy rules are as follows:

Rule R_n: IF x_1 is A_1^n AND … AND x_m is A_m^n, THEN y is Y^n (Y_{FM}, Y_{ANN}, Y_{LR}, *etc.*),

where R_n is the label of the nth fuzzy rule; $\boldsymbol{x} = [x_1, x_2, \ldots, x_m]^T \in U_1 \times U_2 \times \ldots \times U_m$ are input linguistic variables, m is the number of inputs; A_i^n are the antecedent fuzzy sets of the universes of discourse U_i, where $i = 1, 2, \ldots, m$; $y \in V$ is the output linguistic variable; Y^n is chosen from Y_{FM}, Y_{ANN}, Y_{LR}, etc., which are the predicted results using various sub-models, such as the Fuzzy Models (FM) (Jang et al. 1997; Cordon et al. 2001), the Artificial Neural Network (ANN) (Haykin 1999) models, the Linear Regression (LR) (Montgomery et al. 2006) models, etc.

Fig. 2 shows an example of a two-dimensional modelling problem. In this example, the modelling space is divided into several parts. For every part, the most appropriate systems model(s) is (are) assigned. If a master fuzzy rule is used to describe the situation of the upper right sub-space in Fig. 2, then the master fuzzy rule will be as follows:

IF x_1 is *big* and x_2 is *big*, THEN y is Y_{ANN},

where Y_{ANN} is the predicted result using the neural-network sub-model.

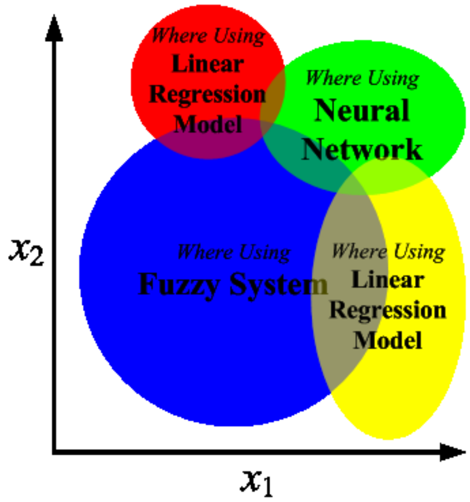

Fig. 2. An example of employing various methods in one modelling problem.

2.3 An approach of generating master fuzzy systems

The development of the proposed master fuzzy system can be broadly divided into the following two stages:

1. Constructing several separate data-driven models using different modelling strategies, such as fuzzy modelling, artificial neural network, and linear regression. All these models work as sub-models of the whole modelling framework and they share the same training, validation, and testing data sets.
2. Constructing the 'master fuzzy system'.

For the second stage, one hierarchical clustering algorithm (Zhang & Mahfouf 2007b, 2008) is employed. The obtained cluster information is first used to define the fuzzy sets of the master fuzzy system and then used to elicit the related master fuzzy rules. The details of the whole modelling process can be described as follows:

1. **Obtaining cluster information**: One should divide the input data of the training set into a set of clusters (sub-space) $\boldsymbol{C}_n$ ($n = 1, 2, \ldots, N_c$, N_c is the number of clusters) using a clustering algorithm. For every cluster (sub-space), the input data included in it are $\{\boldsymbol{p}^{n1}, \boldsymbol{p}^{n2}, \ldots, \boldsymbol{p}^{n(NDn)}\}$, where $\boldsymbol{p}^{nj} = [x_1^{nj}, x_2^{nj}, \ldots, x_D^{nj}]^T$, $j = 1, 2, \ldots, NDn$, NDn is the number of data in the nth cluster. For these input data, their corresponding output data are $\{y^{n1}, y^{n2}, \ldots, y^{n(NDn)}\}$.

2. **Defining fuzzy sets**: For every master fuzzy rule, the parameters of the fuzzy sets A_i^n ($n = 1, 2, \ldots, N_c$; $i = 1, 2, \ldots, D$; D is the number of inputs) are obtained using the following method:

   If Gaussian functions are used as the membership functions, i.e.

$$\mu_{A_i^n}(x) = \exp\left(-\frac{(x-c_i^n)^2}{{\sigma_i^n}^2}\right), \quad (1)$$

then c_i^n can be calculated using the equation

$$c_i^n = \sum_{j=1}^{NDn} x_i^{nj} \Big/ NDn \quad . \quad (2)$$

The idea behind this is that the centres of clusters are the centres of membership functions.

σ_i^n can be calculated using the following equation (Zhang 2008):

$$\sigma_i^n = \frac{\max_j (x_i^{nj} - c_i^n)}{\sqrt{-\ln(Th)}}, \quad (3)$$

where j = 1, 2, …, NDn, Th is a threshold value. This equation emanates from the principle that the membership function should cover all the data contained in its corresponding cluster. In other words, for every data included in one cluster, its membership degree should be high enough to ensure the data maps into this rule. Based on this requirement, the membership parameter σ_i^n is designed to satisfy the following equation:

$$\min_j\left(\mu_{A_i^n}(x_i^{nj})\right) = \min_j\left(\exp\left(-\frac{(x_i^{nj}-c_i^n)^2}{(\sigma_i^n)^2}\right)\right) = Th, \quad (4)$$

where j = 1, 2, …, NDn. This equation means that, for all the data included in the nth cluster, the membership degrees are higher than a threshold Th. The value of Th can be set to 0.5 without any loss of generality. Equation (4) can be rewritten in the form of Equation (3).

3. **Generating the fuzzy rules**: One master fuzzy rule corresponds to one data cluster. The consequent part of each rule is determined using the following methodology:

   For every cluster (sub-space), the sum of the absolute prediction errors of each modelling method is first calculated. For instance, for the nth cluster, the absolute error sum of the fuzzy sub-model can be described as follows:

$$s_{FM}^n = \sum_{j=1}^{NDn} \left| y^{nj} - y_{FM}^{nj} \right|, \quad (5)$$

   where y_{FM}^{nj} is the predicted output using the fuzzy sub-model corresponding to the input data $\boldsymbol{p}^{nj}$.

   The output of the sub-model, which has the minimum value of the absolute error sum, is then set as the output of the relevant fuzzy rule. For instance, for the nth fuzzy rule:

   R_n: IF x_1 is A_1^n AND … AND x_D is A_D^n, THEN y is Y^n.

   Y^n is calculated using the following method

$$Y^n = \begin{cases} Y_{FM}, if \ \min(s_{FM}^n, s_{ANN}^n, s_{LR}^n) = s_{FM}^n \\ Y_{ANN}, if \ \min(s_{FM}^n, s_{ANN}^n, s_{LR}^n) = s_{ANN}^n \\ Y_{LR}, if \ \min(s_{FM}^n, s_{ANN}^n, s_{LR}^n) = s_{LR}^n \end{cases}, \quad (6)$$

   where s_{FM}^n, s_{ANN}^n and s_{LR}^n are the sum of the absolute errors of the fuzzy sub-model, the neural-network sub-model, and the linear-regression sub-model based on the data of the nth cluster, respectively.

4. **Improving accuracy**: Based on a fixed rule-base, the master fuzzy system is improved in terms of accuracy by optimising the parameters of membership functions. In this paper, the related work is carried out by using a salient nature-inspired optimisation algorithm, Reduced Space Searching Algorithm (RSSA) (Zhang & Mahfouf 2007a, 2010).

3. EXPERIMENTAL STUDIES

In order to validate the effectiveness of the proposed modelling paradigm, the associated strategy was applied to two industrial problems, the prediction of machining induced residual stresses in aerospace alloy components and the prediction of a mechanical property of alloy steels, i.e. Ultimate Tensile Strength (UTS).

In the following experiments, the sub-models consist of one fuzzy system, one neural network, and one linear-regression model. The fuzzy sub-model is a Takagi-Sugeno-Kang (TSK) fuzzy system (Takagi & Sugeno 1985), which is generated using a subtractive clustering method (Chiu 1994) and trained using a hybrid learning algorithm introduced in (Jang 1993). The neural-network sub-model is a feed-forward back-propagation network (Haykin 1999). For the optimisation algorithm RSSA, the configuration of parameters is inspired from suggestions included in (Zhang & Mahfouf 2010): $C_1 = D/2 + 8$, $C_2 = 1$, $K = 0.5$, $m = 20$, where D is the dimension of the optimisation problem; the variation operator works as a combination of the one-dimensional variation strategy (with the 50% probability of usage) and the multi-dimensional variation strategy (with the 50% probability of usage). The Root Mean Square Error (RMSE) index works as the performance index of modelling accuracy.

3.1 Prediction of machining induced residual stresses

In material engineering and mechanical engineering, the residual stresses induced during shaping and machining play an important role in determining the integrity and durability of metal components (British Energy Generation Ltd. 2006). Their combination with primary loads contributes to changes in the operating performance of mechanical parts. Tensile residual stresses enhance the likelihood of fatigue, fracture and corrosion induced failures. Conversely, compressive residual stresses are often introduced by shot-peening and burnishing to enhance structural integrity and durability (McClung 2007).

Metal removal by machining operations such as milling and drilling induces residual stresses in the near surface region. These stresses are highly dependent on the machining parameters and cannot be accurately described using mathematical models because of the high complexity of the processes. Our research programme proposes to investigate manufacturing induced part distortion in aerospace alloy components, where the prediction of machining induced residual stresses is conducted using the systems modelling approach introduced in this paper. Fig. 3 shows a predicted part distortion under residual stresses (Boumaiza et al.) using finite element modelling combined with the developed prediction models (Zhang et al. 2009, 2011).

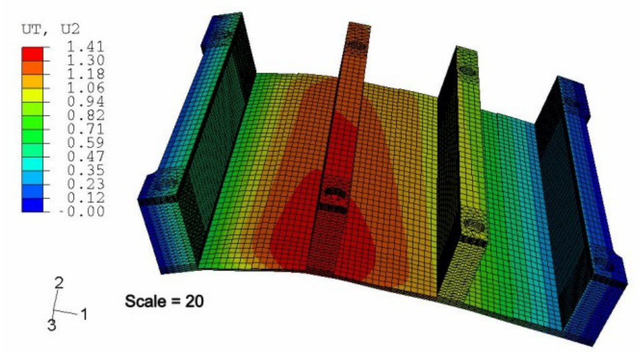

Fig. 3. Part distortion of a machined component under residual stresses (Boumaiza et al. 2010).

In the following case, the proposed approach was applied to predict the surface and near-surface residual stresses (up to 250 μm in depth) in aerospace aluminium parts, where experimental tests were conducted by the Institute of Production Engineering and Machine Tools (IFW), the University of Hannover using the X-ray diffraction measurements.

In this case, 194 residual stress data were used for training and 49 data were used for final testing. System inputs include the profiles of machining parameters, i.e. cutting speed, feed per tooth, feed velocity, as well as coolant medium and measurement depth. The residual stress in the longitudinal rolling direction of the original aluminium billet is the modelling target.

In the following experiments, the fuzzy sub-model includes 20 fuzzy rules, the neural-network sub-model includes a hidden layer of 5 neurons, and the master fuzzy system includes 50 rules. The maximum number of function evaluation for RSSA was set to 5,000.

The experiment was carried out over 20 runs. Table 1 includes the main parameters of the final integrated model as well as three sub-models. One set of results out of the 20 runs is selected and shown as follows. Fig. 4 shows the predicted outputs versus the measured outputs of the obtained model and different sub-models based on the testing data. It can be observed that the proposed modelling approach can successfully combine other modelling techniques and the integrated model outperforms any of the sub-models.

Table 1. Training and testing errors for the prediction of the machining induced residual stress

	RMSE of training (mean ± std)	*RMSE* of testing (mean ± std)
Fuzzy Sub-model	21.2384 ± 3.2833	31.5351 ± 3.4091
Neural-network Sub-model	17.0670 ± 1.7436	27.1175 ± 3.6044
Linear-regression Sub-model	84.6009 ± 40.7627	105.5339 ± 13.4400
Integrated model	13.4949 ± 0.9315	22.8968 ± 2.0986

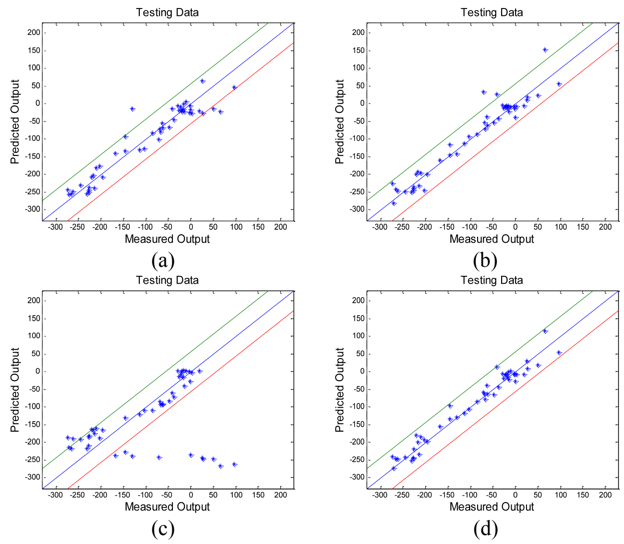

Fig. 4. The residual stress models' predicted outputs versus measured outputs based on the testing data: (a) the fuzzy sub-model, (b) the neural-network sub-model, (c) the linear-regression sub-model, and (d) the integrated model.

By using the generated model, residual stress curves can also be obtained. These are achieved by plotting one input variable, measurement depth, against the output, residual stress, while keeping other input variables constant. Fig. 5 shows both the predicted curves and the measured data. It allows us to observe the fact, in another way, that the integrated model predicts the residual stress more accurately than the sub-models.

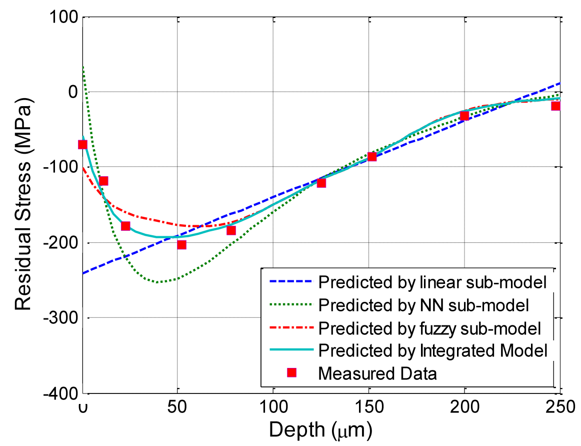

Fig. 5. The predictive residual stress curves and measured data.

To provide more information about the above models, Fig. 6 shows 3 master fuzzy rules out of the rule-base. It should also be noted that, in this experiment, the sub-models were not well optimised, while the integrated model shows a clear improvement in accuracy performance. This means that the proposed method can save a lot of time and effort used in models' training and optimisation.

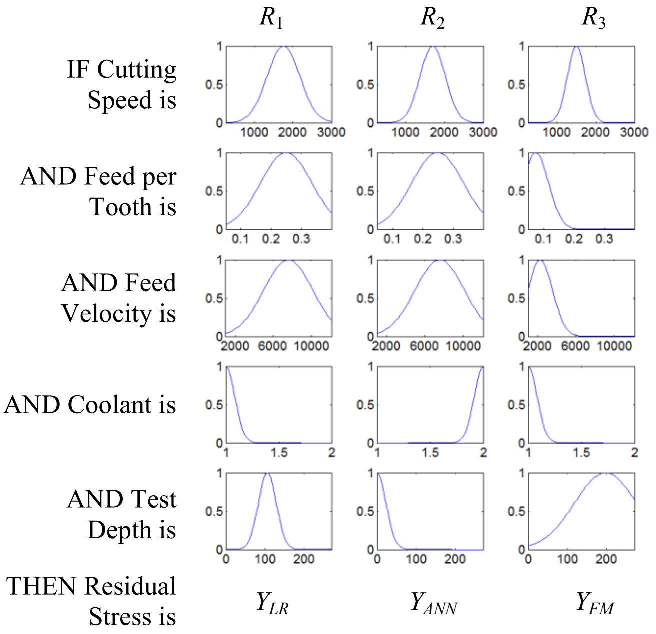

Fig. 6. Master fuzzy rules of the residual stress model.

3.2 Prediction of mechanical properties

In material engineering, it is essential to establish accurate and reliable mechanical property prediction models for materials design and development. But it may be 'tricky' to precisely describe the behaviour of mechanical properties using mathematical models alone due to the complexity of materials' chemical composites and their underlying physical processing mechanisms, such as hot rolling and heat treatment.

One typical mechanical property that one may be interested in is Ultimate Tensile Strength (UTS) (Zhang & Mahfouf 2007b, 2011), which is obtained via an engineering tension test and represents a measure of the maximum load that a material can withstand. In the following experiments, all the data are provided by Tata Steel Europe.

In this case, 3760 UTS data were used for data-driven modelling. 60% of the data were used for training, 20% of them were used for validation, and the remaining 20% were used for final testing. These UTS data include 15 inputs and one output, which is considered to be a high-dimensional problem for modelling purposes. The inputs consist of the weight percentages for the chemical composites, namely Carbon (C), Silica (Si), Manganese (Mn), Sulphur (S), Chromium (Cr), Molybdenum (Mo), Nickel (Ni), Aluminium (Al), and Vanadium (V), the test depth, the size and site where the processing of the alloy steel took place, the cooling medium, as well as the hardening and tempering temperatures.

In the experiment, the fuzzy sub-model includes 8 fuzzy rules, the neural-network sub-model includes a hidden layer of 5 neurons, and the master fuzzy system includes 50 rules. The maximum number of function evaluation for RSSA was set to 1,000.

The experiment was repeated 20 times. Table 2 shows the performance index values of the final integrated model as well as the sub-models. One of the 20 models is selected and shown in the following figures. Fig. 7 shows the prediction performance of the elicited models based on the testing data.

Table 2. Training and testing errors for the UTS prediction

	RMSE of training (mean ± std)	*RMSE* of testing (mean ± std)
Fuzzy Sub-model	35.5840 ± 0	42.4510 ± 0
Neural-network Sub-model	37.0458 ± 1.2144	40.4127 ± 0.8832
Linear-regression Sub-model	55.5079 ± 0	56.9017 ± 0
Integrated model	33.7989 ± 0.7481	38.4084 ± 0.6668

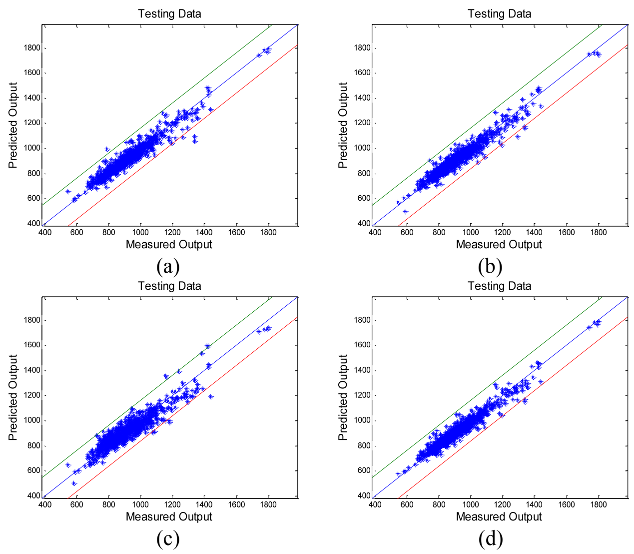

Fig. 7. The UTS models' predicted outputs versus measured outputs based on the testing data: (a) the fuzzy sub-model, (b) the neural-network sub-model, (c) the linear-regression sub-model, and (d) the integrated model.

Fig. 8 shows three-dimensional response surfaces of the obtained UTS model. These surfaces are achieved by plotting two varying input variables against the output while keeping other input variables constant. The constant variables are set to the average values of the dominant steel grade, which is the 1%CrMo steel grade (Tenner 1999). It can be seen that the integrated model shows a combination of the sub-models' characters. This combination may correct any errors of mapping generated by the sub-models.

4. CONCLUSIONS

In this paper, a new structure-free modelling paradigm was proposed by systematically combining various modelling techniques. This new approach does not rely on a fixed modelling structure and can include the advantages of different modelling techniques. It does not need the involved sub-models to be optimised, which can save a lot of time and effort used in training and optimisation. The proposed approach has been successfully applied for eliciting the prediction models for machining induced residual stresses and mechanical properties of alloys. In future, the paradigm can be further enhanced via the introduction of a heuristic learning mechanism when generating master fuzzy rules. By doing so, not only accuracy but reliability can also be considered in the control of sub-models' fusion.

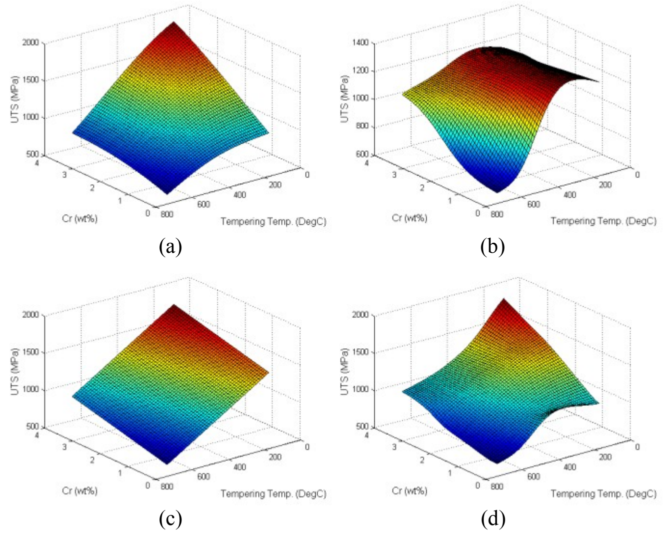

Fig. 8. The UTS models' response surfaces: (a) the fuzzy sub-model, (b) the neural-network sub-model, (c) the linear-regression sub-model, and (d) the integrated model.

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