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Interval Type-2 Fuzzy Logic Adaptive Modelling for Human Operators Undergoing Mental Stress

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Abstract: This paper presents a modelling design framework and results for human participants undergoing mental stress. A mental stressful scenario is achieved while participants perform operations in a simulated control process on an automation-enhanced Cabin Air Management System simulator. Recordings from a previous experiment using psychophysiological markers (Heart Rate Variability and Task Load Index) as inputs with an output performance marker (Time In Range) were used for offline modelling training and validation. Interval Type-2 Fuzzy Logic (IT2FL) architecture optimized with Genetic Algorithms and with an efficient type-reduction algorithm, was selected as the modelling technique. Results demonstrate the ability of IT2FL systems to cope with an additional level of uncertainty and to adapt to important input-output relation changes on validation of the model. These results surpass performance in validation of a type 1 Mamdani Fuzzy Logic system constructed and validated previously in a similar fashion. The constructed model provides an adequate framework that can be used for the prevention of operator breakdown.

Keywords: fuzzy modelling; interval type 2 fuzzy logic modelling; ergonomics; mental workload; genetic algorithms.

1. INTRODUCTION

Psychophysiology is a field that identifies and studies the human body's electrochemical changes normally originated in neurons, muscles and gland cells; in other words it is the study of physical and mental states in response to stimuli. Recordings taken from the body surface should provide meaningful responses to stressful events (Stern, Ray and Quigley 2001). These signals should enable one to identify certain bodily functions that respond to the environment, e.g., stimuli in the form of mental or physical stressors, for instance.

Automation systems represent the archest rival to manual controls as they can perform similar tasks better and faster than any human can do. However, these are designed for specific scenarios but cannot challenge the cognitive capabilities of a human when presented with an unseen situation, i.e. they lack generalising features. Ergonomics, which is born from the use of biological and behavioural sciences for the design of machines and human – machine systems (HMS), focuses in the study of the human normally centric to an automation system that needs to be monitored to ensure 'optimal' as well as safe operations.

When safety is critical for a HMS, operators continually adjust and adapt for the dynamic process under control (Meshkati 2003). Decision on which tasks should be allocated to the human and which should be automated in order to avoid threats to safety and reliability is becoming increasingly complex as well as crucial with increasing demands, complex environments and potential operator stress and fatigue (Hancock and Desmond 2001).

The advantages of HMS are acknowledged in many developments such as those reported by Billings (1996). In these systems, both human and machine are ergonomically analysed for dynamic and effective allocation of tasks (Hancock 2007). The identification of the criteria which should drive this allocation is not a trivial exercise, although the detection of high risk operational function states (OFS) should prevent operator breakdown and as a result should avoid potential catastrophe.

As far as the HMS interaction framework is concerned, the issue of measurements is of prime importance. Two questions arise: 1. Are we measuring what we think we are measuring? 2. Can we access (non-invasively) measurements that have never been accessed before? As far as the first question is concerned, one should expect some measurements to represent the direct measurements rather than the measurements themselves. The second question should represent an incremental exercise which coincides with developments in hardware technologies by means of new sensors and integrated electronics. For instance, mental stress has been proven to correlate with cardiovascular bodily responses such as Heart Rate Variability (HRV) (Akselrod *et. al.* 1981, Vincent, Craik and Furedy 1996, Kuriyagawa and Kageyama 1999) as well as cognitive processes such as planning strategies and attention, reasoning, problem solving and decision making (Royall *et. al*. 2002, Shallice 2005). These cognitive demands are assumed to be facilitated by the activity in the prefrontal cortex of the brain, where frontal midline theta activity and "task load index" (TLI) (Gevins 1997, Gevins 2003, Luu and Posner 2003) relate to mental stress in complex task environments (Smith *et. al.* 2001, Lorenz and Parasuraman 2003, Hockey *et. al.* 2009).

In a previous experimental setup, recordings of HRV and TLI were found to correlate sufficiently with performance measured in terms of Time in Range (TIR), a performance measurement in the automation-enhanced Cabin Air Management System (aCAMS) simulation model (Ting *et. al.* 2008; 2010). With this set of data previously acquired for ten healthy participants, modelling was performed utilising Interval Type 2 Fuzzy Logic (IT2FL) with the efficient Enhanced Iterative Algorithm with Stop Condition (EIASC) type reduction algorithm. Parameters were optimized via a Genetic Algorithm (GA) and compared with previously designed models represented by type 1 fuzzy logic models optimized in a similar fashion.

This work is organised as follows. Section 2 gives a brief overview of the previous experimental setup as well as a brief description of the automation-enhanced Cabin Air Management System. In section 3 all steps followed in the modelling phase are described. Finally, sections 4 and 5 deal with results and conclusions respectively.

2. EXPERIMENTAL SETUP

For the experimental setup the automation-enhanced Cabin Air Management System (aCAMS) simulator (Fig. 1), was used to provide a means of major mental demands on the operator's mental resources (Ting *et. al.* 2008; 2010). The objective was to manually control an increasing and decreasing number of key system parameters of breathable air quality. Nine consecutive 15-minute task periods were applied in cyclic-loading manner increasing and decreasing manual control in a stepwise form for two sessions. The experiment provided a means of inducing mental workload and allowing detection of near breakdown periods as well as recovery ones. (Ting *et. al.* 2008; 2010)

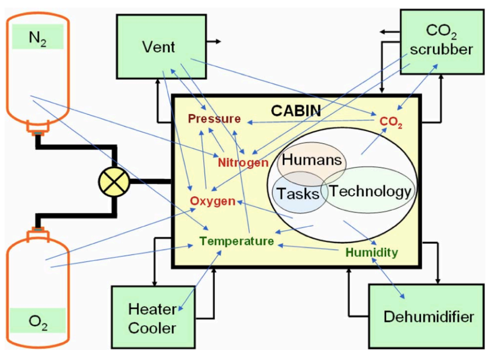

Fig. 1. aCAMS model with interacting subsystems (Ting *et. al.* 2010).

In terms of psychophysiological markers used, Electro-cardiographic (ECG) and Electro-encephalographic (EEG) measurements were recorded. The Active Two System by BioSemi was used for acquisition. Ocular artifact (EOG) detection was also recorded for correction of EEG. More information on the experimental setup can be found in: (Ting *et. al.* 2008; 2010).

3. MODELLING

3.1 Inputs and Output description

As inputs to the system, Heart Rate Variability (ECG) and Task Load Index (EEG) were selected. HRV can be represented by two indicators, HRV1 and HRV2. HRV1 represents the 0.1-Hz component in the heart rate (HR) signal. It was calculated by averaging the power spectrum of the HR signal collected in a 7.5 min period in the frequency range from 0.07 to 0.14 Hz. HRV2 is the ratio between the standard deviation over the mean value of the HR signal in the same period. TLI is based on presence of high levels of brain theta activity at frontal midline sites accompanied with attenuation of alpha power in parietal sites (Gevins and Smith 1999). This indicator reflects fatigue or strategic disengagement from the tasks at hand. (Ting *et. al.* 2008; 2010)

In previous experiments in the Human Performance Laboratory of the University of Sheffield (Nickel, Roberts and Hockey 2006, Ting *et. al.* 2008; 2010), HRV1 and TLI2 were found to correlate better in the modelling procedures and for this reason, were used as inputs for a type 1 fuzzy logic system model.

Time in Range (TIR) output for the model denotes the current performance state in the aCAMS. It represents the time during which the variables (oxygen, carbon dioxide, humidity, pressure, temperature, etc.) remain in their normal range. It is given in percentage.

3.2 General Rule-Base

In (Ting *et. al.* 2008; 2010) two categories of type 1 fuzzy modelling techniques were selected for analysis, namely, Mamdani (MFLS) and Takagi-Sugeno (T-SFLS). These two models were tuned via hybrid learning in an ANFIS configuration and with the use of GA. Results demonstrated an improved performance in both training and validation (session 1 and session 2 respectively) for a "hand-crafted" rule base MFLS optimized with GA. Based on these previous results, the elicited "hand-crafted" general rule-base was selected for use with the IT2FLS modelling. The term "general" acknowledges a subjacent uniform response in all participants, meaning that inputs (HRV1, TLI2) were related to the output (TIR) in a similar fashion. This relationship information in terms of linguistic variables was poured into the rule-base shown in Table 1.

Table 1. General rule base

TLI2 \ HRV1	S	M	B	VB
S		H	VH	VH
M	N		H	VH
B	L	N		
VB	L	L		

In Table 1, S, M, B, VB stand for input linguistic levels small, medium, big and very big respectively. Output TIR linguistic levels L, N, H and VH stand for low, neutral, high and very high respectively.

3.3 Interval Type-2 Fuzzy Logic modelling

Zadeh devised fuzzy sets in 1965 and type 2 fuzzy sets (T2 FS) in 1975 (Zadeh 1975). Type 1 fuzzy sets (T1 FS) such as the MFLS previously designed (Ting *et. al.* 2008; 2010), have limited capabilities to directly handle data uncertainties. A T1 FS has a grade of membership that is crisp, whereas a T2 FS has grades of membership that are fuzzy (Mendel, John and Liu 2006, Mendel 2007). T2 FS are useful in circumstances where it is difficult to determine the exact membership grade for an input, instead, they give each input mapped into one or two membership functions not one but a collection of possible or uncertain grades of membership with different weights (second membership) associated with them. Since T2 FS are unpractical and difficult to compute, an Interval Type 2 Fuzzy Logic System (IT2FLS) comes to be when all weights (second memberships) associated with each possible grade of membership for a corresponding input is equal to one. In this manner, an IT2FLS is completely defined by a sketch that is called a footprint of uncertainty (FOU). The FOU depicts an area of a collection of infinite (in a continuous space) T1 membership functions whose union defines the IT2FLS membership function at hand. This way it is easy to visualize the additional dimension of uncertainty for each input.

A FOU is bounded by a lower and an upper membership functions (LMF and UMF). IT2FLS are computationally simple to implement since only two values are computed throughout the inference. This way, uncertainties are retained and presented in the output, which is a type-reduced set (Wang and Mahfouf 2012).

In an IT2FLS model inputs can have FOU with two very common shapes as can be observed in Fig. 2. The first shape corresponds to a fixed variance with an uncertain mean (Fig. 2a), second shape is the opposite, having a fixed mean with an uncertain variance (Fig. 2b). A third shape could also exist, where uncertainty exists in the maximum level of membership of the LMF as depicted by the discontinuous line in Fig. 2b.

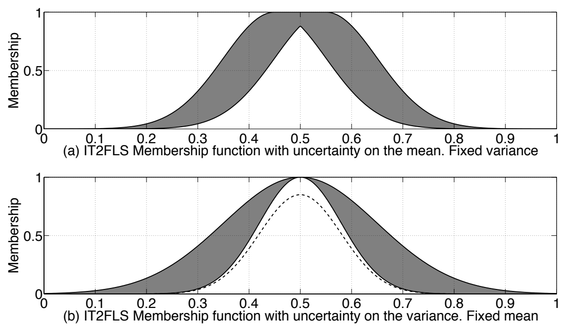

Fig. 2. Gaussian IT2FL Membership functions. (a) IT2FL MF with fixed variance. (b) IT2FL MF with fixed mean.

Although IT2FLS are very similar in essence to a T1 fuzzy logic system (T1FLS), the T1 simple defuzzification process becomes a two-phase type-reduction and defuzzification system for IT2FLS. In Fig. 3 the structure of an IT2FLS is observed.

The type-reduction process in an IT2FLS is the most important block (Fig. 3), and is the more computationally intensive of all. This block reduces the resulting IT2FLS into a T1 interval output set characterised by its left and right endpoints. The defuzzifier block is normally implemented by a mathematical mean when crisp outputs are required (Wang and Mahfouf 2012).

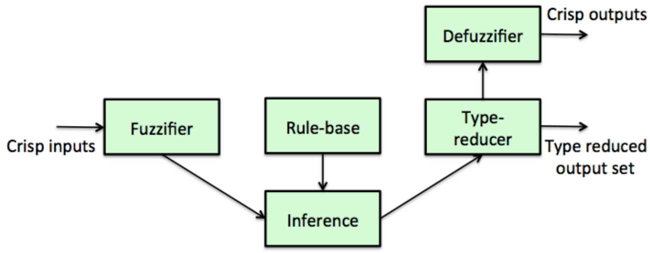

Fig. 3. Structure of an IT2FLS.

The most popular type-reduction algorithm is the Karnik-Mendel Algorithm (Mendel 2007), but it is also the most computationally intensive. Since the final aim of this modelling project is the construction of an adaptive control system for the HMS, a more computationally efficient alternative was implemented to simplify a future real-time construction. The Enhanced Iterative Algorithm with Stop Condition (EIASC) was selected (Wu and Nie 2011).

3.4 Optimization with Genetic Algorithms

Genetic Algorithms (GA) are computational algorithms that work in analogy to the way evolution and natural selection is thought to happen to life on Earth. They start with a random pool of possible parameter values for a fitness function to optimize. In a stepwise manner, the algorithm modifies (with evolution inspired operations) the population of individual solutions searching for an optimum (commonly minimum or maximum, depending on the fitness function).

For the modelling of a human operator undergoing a mentally stressful task, GA were used to optimize an IT2FLS model with the general rule base described in section 3.2. Thus, a general IT2FLS model shell was constructed. As described before, this shell takes two inputs, HRV1 and TLI2 with four membership functions each as can be observed in Table 1. Output for the model is TIR and has four overlapping levels as can be appreciated in Table 1 as well. This general shell was then optimized with a minimum square error function like:

$$MSE = \frac{1}{N}\sum_{k=1}^{N}[y(k) - y_M(k)]^2 \qquad (1)$$

Where $y(k)$ is the actual recorded output and $y_M(k)$ is the estimated IT2FLS output at sample instant k. The number of samples is N.

To respect the logic in the general rule base of section 3.2, initial ranges were defined for the parameters to optimize. Seven IT2FLS models were optimized with slightly different characteristics. Table 2 addresses these differences.

From Table 2 it is clear that IT2FLS models 1 to 3 have input MF similar to the one in Fig. 2b. All other models have membership functions similar to Fig. 2a.

Table 2. IT2FLS constructed models

IT2FLS Model	Uncertainty M	Uncertainty V	Uncertainty LM
No. 1	Fixed	Variable	1
No. 2	Fixed	Variable	Variable
No. 3	Fixed	Variable	Variable
No. 4	Variable	Fixed	-
No. 5	Variable	Fixed	-
No. 6	Variable	Fixed	-
No. 7	Variable	Fixed	-

(M mean; V variance; LM level of membership of LMF)

4. RESULTS

All model evaluations, comparisons and optimizations were performed in MatLab environment. GA Optimization was performed with the 'Optimization Graphical User Interface'. The IT2FLS model was programmed with the EIASC type-reduction algorithm (Wu and Nie 2011) inside the fitness function of MSE.

Following the optimization of the IT2FLS models described in Table 2, a comparison of their performance against a Mamdani T1 FLS was obtained (Ting *et. al.* 2010). The comparison included an overall MSE value and Correlation for training and validation data. Results in this paper show performances related to healthy participant two (P02) for a detailed analysis. Brief results are also presented for P03. In Fig. 4, recorded training and validation inputs and output for P02 can be observed. Validation inputs and output are observed in Fig. 5.

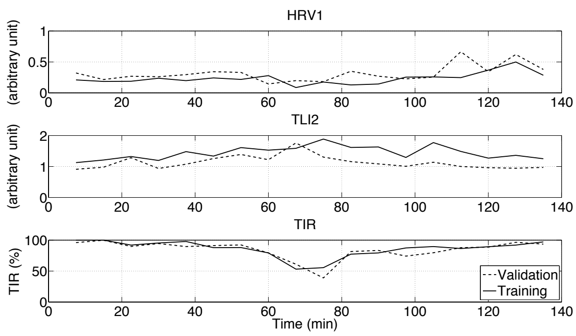

Fig. 4. Training and validation inputs (HRV1 and TLI2) and output (TIR) for P02. Experimentation session 1 and 2.

From Fig. 4 similar behaviours for training and validation can be observed in terms of shape of the curves. However, upon closer examination it should be noted that important variations exist. For example, it is clear that the minimum percentage value of the recorded output TIR in validation is smaller that the training one for similar input values.

Table 3 shows evaluation results for the different IT2FLS models constructed and optimized. In this table the previously designed and optimized MFLS evaluation is also shown for comparison purposes.

Table 3. MFLS and IT2FLS comparison for P02

P02	MSE Training	MSE Validation	CORRELATION Training	CORRELATION Validation
MFLS	**14.2252**	**163.2577**	**0.9626**	**0.5372**
IT2FLS No. 1	17.8987	100.1359	0.948	0.8247
IT2FLS No. 2	**32.2605**	79.5631	**0.9119**	0.8636
IT2FLS No. 3	24.8446	70.8343	0.9518	0.8191
IT2FLS No. 4	17.7692	72.7647	0.9515	0.8399
IT2FLS No. 5	20.4289	102.2802	0.9375	0.7915
IT2FLS No. 6	28.4322	56.6657	0.913	0.8659
IT2FLS No. 7	26.2394	**51.1363**	0.9198	**0.8872**

From Table 3 it can be observed that training and validation MSE for models designed with IT2FLS models are able to cope with unseen data with a smaller error, which is to be expected given that T2 FS systems achieve an additional level of uncertainty. Between the different IT2FLS models, which have in some cases uncertainty on variance and in other cases uncertainty on mean (see Table 2), no important difference can be observed. It is clear that there is a trade-off with this added uncertainty since errors are bigger in training. This is also expectable since additional uncertainty makes the model less prone to over fitting training data.

Continuing with the comparison between the MFLS model and the IT2FLS models, Figs. 5 through 12 show fuzzy membership functions as well as estimated and recorded TIR outputs for selected best performance IT2FLS models and for the MFLS.

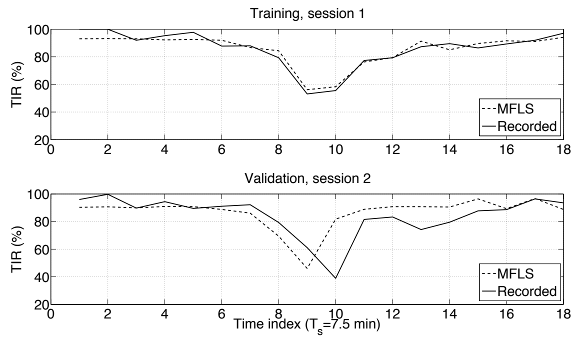

Fig. 5. Estimated and recorded TIR for MFLS. Training and Validation.

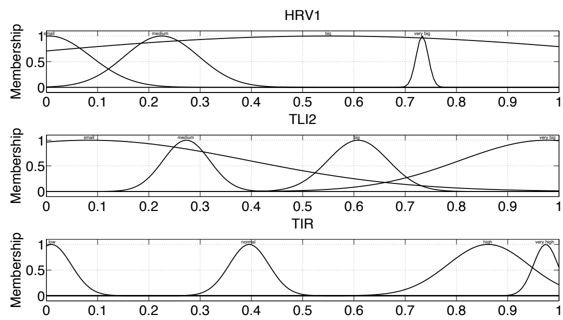

Fig. 6. Input (HRV1 and TLI2) and output (TIR) membership functions. MFLS model.

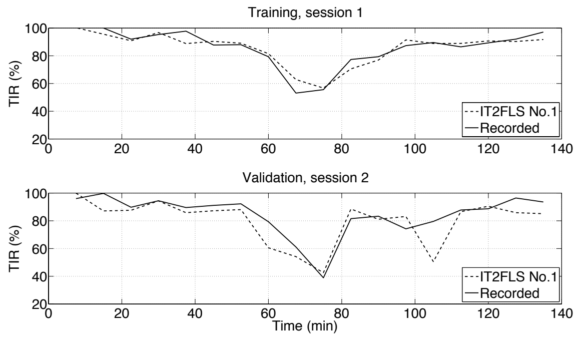

Fig. 7. Estimated and recorded TIR for IT2FLS No.1. Training and Validation.

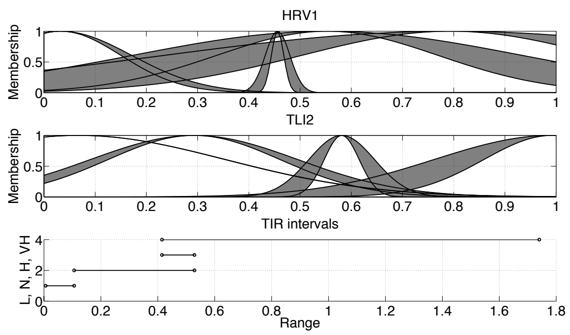

Fig. 8. Input (HRV1 and TLI2) and output (TIR) membership functions. IT2FLS No.1 model.

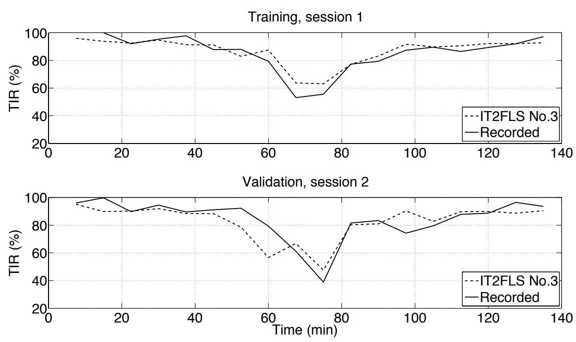

Fig. 9. Estimated and recorded TIR for IT2FLS No.3. Training and Validation.

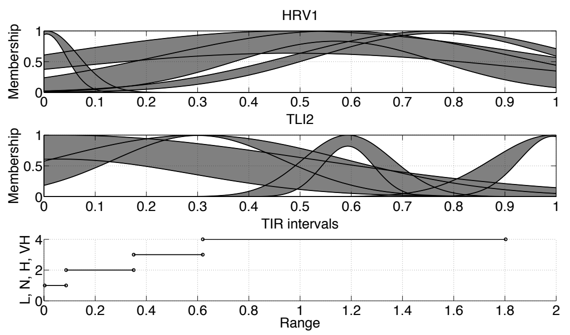

Fig. 10. Input (HRV1 and TLI2) and output (TIR) membership functions. IT2FLS No.3 model.

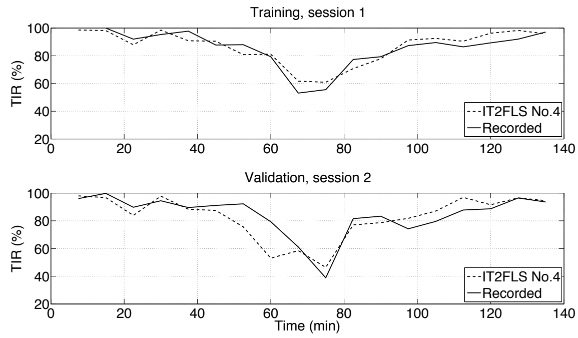

Fig. 11. Estimated and recorded TIR for IT2FLS No.4. Training and Validation.

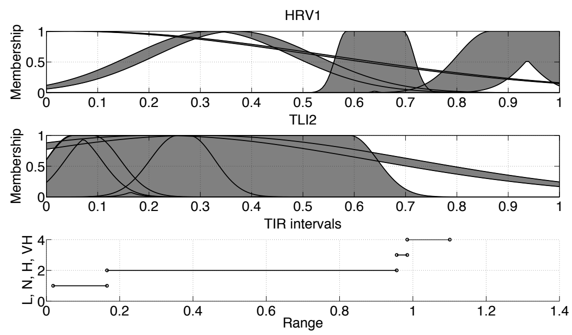

Fig. 12. Input (HRV1 and TLI2) and output (TIR) membership functions. IT2FLS No.4 model.

From inspection of the MF of the several models in Figs. 6, 8, 10 and 12, it can be observed that there is no similarity in their shapes. However, analysing TIR outputs in Figs. 5, 7, 9 and 11 there are not big differences for training data. In terms of validation it is easy to observe better performance in the T2 FS models.

Table 4 presents a comparison for a MFLS and an IT2FLS for P03.

Table 4. MFLS and IT2FLS comparison for P03

P03	MSE		CORRELATION	
	Training	Validation	Training	Validation
MFLS	17.8571	216.8081	0.9746	0.1353
IT2FLS	93.6097	71.5312	0.8551	0.6115

From Table 4, similar results than the ones in Table 3 can be observed. Validation values are improved, but there is a trade-off with training.

5. CONCLUSIONS

The presented work addresses a modelling framework with IT2FLS models optimized using Genetic Algorithms (GA). Type-reduction of the IT2FLS is performed with the EIASC computationally efficient algorithm. Models for different participants in the experiment share a common rule-base, obtained from a previous close inspection among relationships between the inputs, HRV1 and TLI2, and the output, TIR. Working with this assumption, IT2FLS models were optimized and demonstrated their ability to use an additional level of uncertainty to map inputs with output. When compared with a previously trained MFLS, IT2FLS showed a more **generalising** feature in validation with unseen data. However, there was a trade-off in the training fitting results. For this paper, a simple mean was utilised as the defuzzification process to produce crisp outputs. Future work is planned to address a more effective way of obtaining crisp outputs.

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