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Perpetual Learning Framework based on Type-2 Fuzzy Logic System for a Complex Manufacturing Process

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Abstract: This paper introduces a perpetual type-2 Neuro-Fuzzy modelling structure for continuous learning and its application to the complex thermo-mechanical metal process of steel Friction Stir Welding (FSW). The 'perpetual' property refers to the capability of the proposed system to continuously learn from new process data, in an incremental learning fashion. This is particularly important in industrial/manufacturing processes, as it eliminates the need to retrain the model in the presence of new data, or in the case of any process drift. The proposed structure evolves through incremental, hybrid (supervised/unsupervised) learning, and accommodates new sample data in a continuous fashion. The human-like information capture paradigm of granular computing is used along with an interval type-2 neural-fuzzy system to develop a modelling structure that is tolerant to the uncertainty in the manufacturing data (common challenge in industrial/manufacturing data). The proposed method relies on the creation of new fuzzy rules which are updated and optimised during the incremental learning process. An iterative pruning strategy in the model is then employed to remove any redundant rules, as a result of the incremental learning process. The rule growing/pruning strategy is used to guarantee that the proposed structure can be used in a perpetual learning mode. It is demonstrated that the proposed structure can effectively learn complex dynamics of input-output data in an adaptive way and maintain good predictive performance in the metal processing case study of steel FSW using real manufacturing data.

Keywords: perpetual learning, incremental learning, fuzzy neural networks, granular computing, type-2 fuzzy systems, friction stir welding, metal processing.

1. INTRODUCTION

Data-driven computational intelligence (DDCI) models have gathered much pace and popularity due to the rapid growth in computing power and the availability of extensive data and information in modern industrial processes. Common DDCI paradigms that are often employed to describe complex processes and solve engineering problems include, but not limited to, neural networks (NN) (Bishop, 2006), fuzzy rule-based systems (FRBS) (Jang and Sun, 1996), and evolutionary and genetic algorithms (GAs) (Yang et al., 2003). In contrast to other DDCI methodologies, fuzzy rule-based systems offer good level of transparency and simplicity in their structure. Recently, studies on type-2 fuzzy logic systems (FLSs) have attracted much attention (Bustince Sola et al., 2015; Mendel, 2015) due to their capacity to capture uncertainty in the input linguistic variables (an extra degree of freedom compared to Type-1 sets). In addition, Type-2 FLSs appear to be more promising compared to their type-1 counterparts in handling uncertainties such as those associated with noisy data and different word meanings. Thus, type-2 fuzzy sets allow for better capture of uncertainties in rule-based systems.

The development of a type-2 FLS generally involves two learning phases, the structure learning phase and the parameter learning phase. These two phases are often carried out sequentially; the structure learning phase is used to construct the initial structure of fuzzy rules and then the parameter learning phase is used to tune the parameters of each rule. One characteristic of this modelling scheme is that it is suitable when sufficient amount of data is collected and used to train the model. From the two learning phases, the constructed rule-based system has a fixed structure with the desired accuracy. However, the model with a fixed structure cannot always perform well each time new data become available due to different characteristics of a complex system under different input conditions. This is often found in industrial/manufacturing processes, where when new data are available one has to redevelop and retrain the model, to accommodate the new data/information. To improve the performance of a model when new data are available, there are two general strategies. The first strategy is to develop an entirely new modelling paradigm considering the specific features of the new data, which are not considered by the 'old' model. In this case, it is required to develop a new model by following the two learning phases in order to cover the new input data patterns, which have not seen by the original model. However, in reality, developing a new model often requires significant effort and it is over-dependent on expert knowledge. The second strategy relates to modifying (adapting) the existing model. This is usually achieved via a

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two-step strategy: expanding the structure of the existing model by generating new rules to accommodate the new data without significantly disrupting the existing model and in the second step further fine-tune and/or prune the model.

In this paper, the research study is focused on the idea of offline incremental learning in which additional knowledge is added to the model based on the second strategy. In the proposed learning strategy, the modelling structure is designed to learn from an initial database (via an appropriate learning/optimisation algorithm) but at the same time incrementally adapt to new data when these are available without deteriorating the core model knowledge acquired from the initial database. Additional system's features include the system's ability to interact with the environment in a perpetual mode and having an open structure in which the system has the ability to add and remove rules (knowledge maintenance). Several methods have been developed so far to demonstrate some of the aspects of incremental learning (Kasabov, 2015; Kasabov and Song, 2002; Panoutsos and Mahfouf, 2008). However, all of them use type-1 fuzzy logic systems. In the field of type-2 fuzzy logic systems, several models have been proposed to incrementally optimise the parameters of the model (Juang and Chen, 2014; Juang and Tsao, 2008; Lin et al., 2014). However, all these models are used for online structure learning for time varying data. To our knowledge, no pervious incremental type-2 neural fuzzy systems for offline learning have been reported. In this study, we present a new perpetual (incremental) learning framework that is based on granular computing interval type-2 neural fuzzy systems (GrC-IT2-FLSs). By using such a modelling framework, it is possible to achieve good modelling performance and at the same time good system transparency (interpretability). An iterative rule pruning mechanism is used as the main feature that removes the redundant fuzzy rules after each incremental step, which allows the model to be used in a lifelong learning mode. The proposed methodology is tested against a real-industrial problem. The prediction of spindle peak torque of Friction Stir Welding of steel is investigated. Such manufacturing process involves highly complex databases, containing data with high uncertainty (measurement noise, operator errors, etc.) and non-linear dynamics (complex thermo-mechanical behaviour) as well as sparse data (due to constraints on the process conditions).

The rest of the paper is organised as follows: Section 2 presents the theoretical background of the systematic modelling framework of Interval type-2 Neural-Fuzzy (NF) systems developed via an information granulation process, and the process under investigation. Section 3, the main contribution of this paper: the perpetual learning framework based on rule growing and pruning strategies that are proposed to be used in the learning architecture. In Section 4, a case study is presented based on the complex manufacturing process of FSW. Finally, conclusions with respect to the whole research study are drawn in Section 5.

2. BACKGROUND THEORY AND PROCESS UNDER INVESTIGATION

2.1 Interval Type-2 Radial Basis Function Neural Network

Type2-Fuzzy Logic System (T2-FLSs) are similar to a Type1-Fuzzy Logic Systems (T1-FLSs), which are characterised by linguistic IF…THEN rules, however their premise and consequent sets are Type-2 Fuzzy Sets. A type-2 fuzzy set (T2-FSs) has a membership function (MF) that is itself a fuzzy set in [0, 1], unlike a normal fuzzy set (T1-FS) where the membership function includes a crisp number in [0, 1]. T2-FLSs take advantage of the extra degree of freedom to better handle uncertainties associated in the input space (Mendel, 2007). In this paper, we use IT2-FLSs to minimise the computational effort and produce a real-time capable system (Mendel, 2001).

The Interval Type-2 Radial Basis Function Neural Network (IT2-RBF-NN) proposed in this study has a similar structure to the structure used in (Baraka et al., 2015; Rubio-Solis and Panoutsos, 2015) (as shown in Fig. 1), however, the initial structure of the network is taken from type-2 fuzzy Gaussian mixture model (Zeng et al., 2008). The consequent part of each fuzzy rule is of the Mamdani type model, each of which has the following linguistic IF...THEN form:

$$\boldsymbol{Rule_i}: \boldsymbol{IF}\ x_1\ is\ \tilde{A}_1^i\ and, \dots, and\ x_d\ is\ \tilde{A}_d^i, \boldsymbol{THEN}\ y\ is\ \tilde{B}_1^i \quad (1)$$

Where $x_1, \dots, x_d$, are the input vectors, $\tilde{A}_1^i, \dots, \tilde{A}_d^i$ are the interval type-2 fuzzy sets, $i = 1, \dots, M$, M is the number of rules, i is the index of the rules. The mathematical description of the IT2-RBF-NN is provided below:

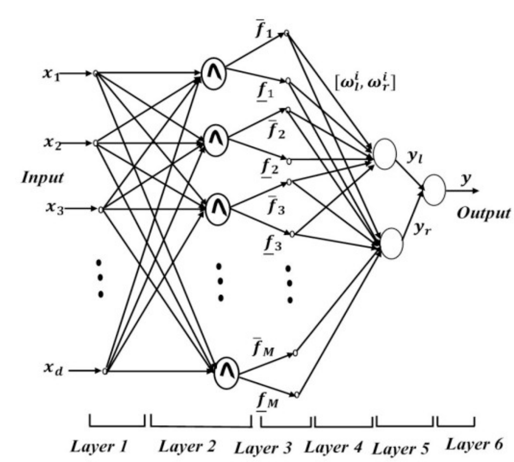

Fig. 1. IT2-RBF-NN general structure

The first layer only transmits the current input values $\vec{x} = [x_1, \dots, x_d] \in R^d$, to the next layer directly without performing any computation. The second layer uses an interval type-2 MF to perform the fuzzification process in order to produce the upper and lower intervals $[\underline{\mu}_{\tilde{A}_j^i}, \overline{\mu}_{\tilde{A}_j^i}]$. With the choice of a Gaussian primary MF having fixed mean m_j^i and uncertain standard deviation that the value in the interval $\sigma_j^i \in [\sigma_{j1}^i, \sigma_{j2}^i]$ can be stated as