OPTIMIZING GAS TURBINE GENERATOR DATA IN UNCERTAIN ENVIRONMENTS: A FUZZY APPROACH

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ABSTRACT

This paper describes the use of a new kind of fuzzy logic system namely, a Takagi-Sugeno-Kang (TSK)-based interval type-2 intuitionistic fuzzy logic inference approach with artificial neural network learning for the prediction of electricity generation of a gas turbine engine. Fuzzy logic systems have been used widely to solve many real world application problems because they are found to be universal approximators. The gradient descent algorithm is used for the optimization of the parameters of the interval type-2 intuitionistic fuzzy logic system membership and non-membership functions. The capability to optimize the parameters of the fuzzy logic systems increases performance and robustness of the engine and leads to increased engine production and reliability thereby reducing system cost and mitigating environmental risks. In this study, we investigate the performance of an industrial power plant gas turbine used in oil fields to produce power especially for plants that are far away on oil fields and offshore sites where there is no possibility to connect to the general electricity network. Analysis of the gas turbine data is carried out using two types of fuzzy logic systems. Specifically, we evaluate the performance of interval type-2 intuitionistic fuzzy logic system, a fuzzy logic system that enables hesitation with fuzzy membership and non-membership functions with the classical interval type-2 fuzzy logic system (with no hesitation) and compare results. The root mean squared error is used as the performance metric and comparison made between actual data and predicted values. Results of analysis demonstrate how promising the combined method of intuitionistic interval type-2 fuzzy logic systems with hesitation indices is as compared to the classical interval type-2 fuzzy logic system with no hesitation in this application domain.

INTRODUCTION

Fuzzy sets, popularly known as type-1 fuzzy sets (T1FSs) first proposed by Zadeh (1965) has found usefulness in many real life application domains. However, because the type-1 fuzzy set membership functions are precise, they are not able to cope with many real life problems. Another generalization of fuzzy set, also by Zadeh (1975), called the type-2 fuzzy sets (T2FSs) have membership functions that are fuzzy thereby able to cope with problems in many uncertain environments better than their type-1 counterparts. Nevertheless, the traditional fuzzy sets (T1FS and T2FS) are defined using only the membership functions with non-membership taken to be the complement of the membership functions. It is however rarely the case that non-membership functions are complementary sets. Atanassov (1986) defined a new kind of set, the so-called intuitionistic fuzzy set (IFS) defined by membership and non-membership functions. Similar to the traditional T1 fuzzy sets, we argue that the type-1 IFS may not handle the amount of uncertainty inherent in many real world applications as their single membership and non-membership functions cannot incorporate information from diverse sources simultaneously. In other words, Atanassov-intuitionistic fuzzy logic systems (IFLSs) are useful for defining an uncertain term from a single point of view. To tackle this problem, Atanassov and Gargov (1989) extended the concept of IFS to interval valued IFSs (IVIFS) which is a generalization of the notion of IFS in the sense of IVFS (a special case of IT2FS).For IVFS, the membership and non-membership functions are fuzzy and according to Bustince *et al.* (2015), IVFS cannot easily be used to model other concepts such as type-1 FS, interval valued FS, multi-FS and multi-interval FS. The capability to model these concepts according to Bustince *et al.* (2015) is only possible with IT2FS. Based on this premise, Eyoh *et al.* (2016) developed an enhanced IT2FLS otherwise known as interval type-2 intuitionistic fuzzy logic system (IT2IFLS) utilizing interval type-2 intuitionistic fuzzy sets (IT2IFSs) in the rule base, with the aim of handling uncertainty well and able to model other concepts better than the more specific IVIFS.In this paper, we adopt two fuzzy logic approaches to analyze the gas turbine engine data. To the best knowledge of the authors, this is the first study where the two fuzzy logic approaches namely interval type-2 intuitionistic fuzzy logic (IT2IFL) and interval type-2 fuzzy logic (IT2FL) systems are used in the analysis of gas turbine engine data with the aim of improving system performance and reducing environmental risks.

DEFINITIONS

Definition 1. An IT2FS is specified by a footprint of uncertainty delineated by a lower membership function, $\underline{\mu}_{\tilde{A}}(x, u)$ and an upper membership function, $\bar{\mu}_{\tilde{A}}(x, u)$ for all $x \in X$.

$$\tilde{A} = \{((x, u), \underline{\mu}_{\tilde{A}}(x, u), \bar{\mu}_{\tilde{A}}(x, u)) \mid \forall x \in X, \forall u \in J_x[0,1]\} \tag{1}$$

Where, $\underline{\mu}_{\tilde{A}}(x, u) = 1$ and $\bar{\mu}_{\tilde{A}}(x, u) = 1$. Thus the IT2FS can also be expressed as:

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} 1/(x, u) \qquad J_x \in [0,1] \tag{2}$$

or

$$\tilde{A} = \sum_{x \in X} \sum_{u \in J_x} 1/(x, u) \qquad J_x \in [0,1] \tag{3}$$

Where$\int$ and $\sum$ represent the union of all admissible points in a continuous and discrete universe of discourse respectively. A fuzzy logic system that utilizesIT2FS in its antecedent and/or consequent parts of the rule is referred to as interval type-2 fuzzy logic system(IT2FLS). The final output of an IT2FLS-TSK is computed as follows (Mendel *et al.,* 2014):

$$y = \frac{(1-\beta)\sum_{k=1}^{M} f_k y_k}{\sum_{k=1}^{M} \underline{f_k^{\mu}}} + \frac{\beta \sum_{k=1}^{M} \overline{f_k} y_k}{\sum_{k=1}^{M} \overline{f_k}} \tag{4}$$

where$\underline{f_k}$ and $\overline{f_k}$ are the lower and upper firing strength of the rules.

Definition 2. An IT2IFS, $\tilde{A}^*$, is characterized by membership and non-membership bounding functions defined as $\{\bar{\mu}_{\tilde{A}^*}(x), \underline{\mu}_{\tilde{A}^*}(x)\}$ and $\{\bar{v}_{\tilde{A}^*}(x), \underline{v}_{\tilde{A}^*}(x)\}$ respectively for all $x \in X$ with constraints: $0 \leq \bar{\mu}_{\tilde{A}^*}(x) + \underline{v}_{\tilde{A}^*}(x) \leq 1$ and $0 \leq \underline{\mu}_{\tilde{A}^*}(x) + \bar{v}_{\tilde{A}^*}(x) \leq 1$ (Nguyen *et al.,* 2013).

Two IF-indices used in this study are the IF-index of center and IF-index of variance previously used in [9] and defined in this work as:

$$\pi_c(x) = \max(0, (1 - (\mu_{\tilde{A}^*}(x) + v_{\tilde{A}^*}(x))))$$

$$\overline{\pi}_{var}(x) = \max(0, (1 - (\bar{\mu}_{\tilde{A}^*}(x) + \underline{v}_{\tilde{A}^*}(x))))$$

$$\underline{\pi}_{var}(x) = \max(0, (1 - (\underline{\mu}_{\tilde{A}^*}(x) + \bar{v}_{\tilde{A}^*}(x))))$$

Such that: $0 \leq \pi_c(x) \leq 1$ and $0 \leq \pi_{var}(x) \leq 1$

A fuzzy logic system that utilizes IT2IFS in the antecedent and/or consequent parts of the rule base is referred to as IT2IFLS. The main purpose of this work is to predict the performance of gas turbine generator data using the newly developed IT2IFLS. Interested readers are referred to (Eyoh *et al.,* 2016, Eyoh *et al.,* 2017a, Eyoh *et al.,* 2017b, Eyoh *et al.,* 2018a, and Eyoh *et al.,* 2018b)for detailed description of the system. The IT2IFLS-TSK consists of the intuitionistic fuzzifier, intuitionistic rule base, intuitionistic fuzzy inference engine and intuitionistic output processing.

The output of an IT2IFLS-TSK is as follows:

$$y = \frac{(1-\beta)\sum_{k=1}^{M}(\underline{f_k^{\mu}}+\overline{f_k^{\mu}})y_k^{\mu}}{\sum_{k=1}^{M}\underline{f_k^{\mu}}+\sum_{k=1}^{M}\overline{f_k^{\mu}}} + \frac{\beta\sum_{k=1}^{M}(\underline{f_k^{v}}+\overline{f_k^{v}})y_k^{v}}{\sum_{k=1}^{M}\underline{f_k^{v}}+\sum_{k=1}^{M}\overline{f_k^{v}}} \quad (5)$$

is a weighted average of each IF-THEN rule's output and as such do not require any defuzzification procedure.

where $\underline{f_k^{\mu}}$, $\overline{f_k^{\mu}}$, $\underline{f_k^{v}}$, $\overline{f_k^{v}}$, are the lower membership, upper membership, lower non-membership and upper non-membership firing strengths respectively. In this study, the implication operator employed is the "prod" t-norm.

COMPUTATIONAL APPROACH

Parameter Update Rule

In this study, we employ the gradient descent (GD) algorithm to tune the parameters of the two models under investigation. The GD searches through the solution space to find a function that has the lowest possible cost. The cost function for a single output is defined as:

$$E = \frac{1}{2}(y^{\alpha} - y)^2$$

where$y^{\alpha}$is the actual output and y is the model point. The generic parameter update rule using GD is as follows:

$$\theta_{ik}(t + 1) = \theta_{ik}(t) - \gamma \frac{\delta E}{\delta \theta_{ik}} \quad (6)$$

where γ is the learning rate(step size) that must be carefully chosen as a large value may lead to instability, and small value on the other hand may lead to a slow learning process. The parameterθ is the generic parameter to be tuned. The learning rate and IF-indices for this study are fixed.

Simulation Example

In order to evaluate the performance of the two models, a real world gas turbine generator data is utilized. The dataset is split into the training set and the test set in the ratio 70:30. The performance criterion adopted is the RMSE defined as:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y^{\alpha} - y)^2} \quad (8)$$

wherey^{α} denotes the actual output and y is the output of the model. N is the number of testing data points. The data for the analysis have been normalized to a small range of [0,1]. Table 1 shows the prediction results of the traditional IT2FLS and intuitionistic IT2FLS.

Table 1: Summary of Prediction Results

Model	No. of Parameter	Rules	RMSE	
			Train	0.1785
IT2FLS	184	16	Test	0.0940
IT2IFLS			Train	0.1645
	192	16	Test	0.0893

DISCUSSION AND CONCLUSION

From the simulation results, it is shown that IT2IFLS (with hesitation indices) outperforms the traditional IT2FLS (without hesitation indices). This could be as a result of the additional parameters provided by the non-membership function and hesitancy degrees incorporated into the traditional IT2FLS to obtain IT2IFLS. In the future, we intend to enhance the capability of the models by hybridizing the training apparatus with derivative-free algorithms such as Simulated Annealing (SA) and Particle Swarm Optimization (PSO) algorithms.

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