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Robust optimization of ANFIS based on a new modified GA

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ABSTRACT

Adaptive Network-based Fuzzy Inference Systems (ANFIS) is one of the most well-known predictions modeling technique utilized to find the superlative relationship between input and output parameters in different processes. Training the adaptive modeling parameters in ANFIS is still a challengeable problem which has been recently considered by researchers. Hybridizing of a robust optimization algorithm with ANFIS as its training algorithm provides a scope to improve the effectiveness of membership functions and fuzzy rules in the model. In this paper, a new Modified Genetic Algorithm (MGA) by using a new type of population is proposed to optimize the modeling parameters for membership functions and fuzzy rules in ANFIS. As well, a case study on a machining process is considered to illustrate the robustness of the proposed training technique in prediction of machining performances. The prediction results have demonstrated the superiority of the presented hybrid ANFIS–MGA in term of prediction accuracy (with 97.74%) over the other techniques such as hybridization of ANFIS with Genetic Algorithm (GA), Taguchi-GA, Hybrid Learning algorithm (HL), Leave-One-Out Cross-Validation (LOO-CV), Particle Swarm Optimization (PSO) and Grid Partition method (GP), as well as RBFN and basic Grid Partition Method (GPM). In addition, an attempt is done to specify the effectiveness of different improvement rates on the prediction result and measuring the number of function evaluations required. The comparison result reveals that MGA with improvement rate 0.8 raises the convergence speed and accuracy of the prediction results compared to GA.

1. Introduction

Modeling techniques are classified into mechanistic and empirical. Mechanistic models such as regression require complex physical understanding of the modeling process [3,47]. Also there are not enough suitable explicit models for the various processes [4]. Thus, empirical models such as artificial neural network (ANN) and fuzzy logic (FL) are commonly employed by many processes [27].

ANN is the most common empirical techniques applied for modeling. On the other hand, FL also plays an important role in input–output and in-process parameter relationship modeling [33] to describe human thinking and reasoning in a mathematical framework [34]. As well, integration of ANN and FL or adaptive network-based fuzzy inference systems (ANFIS) is considered efficiently as a modeling technique. ANFIS is a hybrid technique which integrates the advantage of learning in ANN and employing a set of fuzzy if–then rules with appropriate membership functions to generate input–output pairs with high degree of accuracy [18,24,2,32]. In the recent years, ANFIS system is widely employed to produce non-linear models of processes to determine the input–output relationship. As well, the authors Cus et al. [6] and Mukherjee and Ray [33] observed that ANFIS technique is an effective means of control in complex manufacturing process.

Although, ANFIS is a robust modeling technique in various applications, but it has some disadvantages of artificiality, randomness and irregularity [48] and needs to be trained to work successfully. Consequently, an effective training algorithm is applied to find optimal values of adaptive modeling parameters. The main problem discussed is complexity of training membership functions' parameters (premise parameters) and fuzzy rules' parameters (consequent parameters). So they become very important parameters in training process [38]. The basic and most usual training algorithm is based on gradient descent (GD), while calculation of that in each step of training is difficult and the use of chain rule may cause trapping into local minimum [18,21].

In the recent years, some affords have been done to find optimal value for modeling parameters in order to decline training error and increase the modeling accuracy such as Li et al. [23]. Genetic algorithm (GA) is an optimization technique which has been employed effectively by the previous researchers to determine optimal values of modeling parameters [16] and improve the

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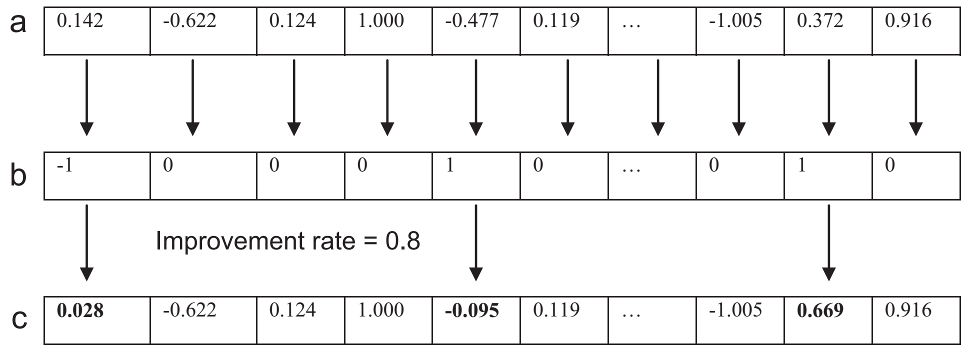

Fig. 1. New solution generation process. (a) Current solution, and (b) experience chromosomes, and (c) the new solution.

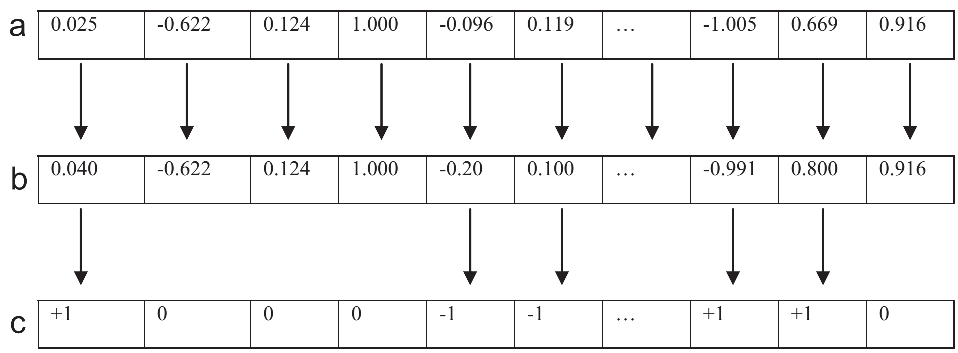

Fig. 2. New experience generation process. (a) Current solution, (b) new (optimal) solution, and (c) new experience chromosomes.

training accuracy performance [21]. The researchers, Rangajanardhaa and Rao [36], Carrano et al. [5], Wei and Cheng [42], and Wang et al. [41] employed GA as a training algorithm to increase the accuracy of ANFIS and minimize the prediction error during training and testing of the network. As well, Wei [43] utilized ANFIS–GA model for Stock market forecasting. In addition, Ho et al. [15] applied a new modified GA based on Taguchi method as ANFIS training algorithm. Also, [37] developed a training algorithm for ANFIS based on HL which is the integration of least squares and back propagation gradient descent methods. Furthermore, LOO-CV approach was employed by Dong and Wang [11] for training a prediction model based on ANFIS. As well, Sharkawy [37] developed radial basis function neural networks to get the best prediction accuracy for a process. Moreover, Yang et al. [44,45] presented the Grid Partition Method (GPM) to integrate the advantages of GA and genetic programming in ANFIS training.

In this paper, a new modified GA is employed as ANFIS training algorithm to estimate the most suitable membership function and fuzzy rules for the model and find the best prediction model by improving prediction accuracy. An experimental dataset on a machining process is considered as a test case in this study to show the effectiveness of proposed hybrid modeling technique (ANFIS–GA). Additionally, the prediction results of the proposed model are compared with several techniques considered in the literature. Moreover, some results are given to show the performance of various MGA factors on prediction error.

2. ANFIS training

The basic architecture of ANFIS consists of five layers [20] with different functions. Two layers in the model include adaptive parameters while the parameters considered in the others are fixed. Adaptive parameters are classified into premise and consequent parameters. Premise parameters in the model are related to the membership functions determined in the first layer [18] such as Gaussian function (see Eq. (1)).

$$\mu_i(x) = e^{\frac{-(x-c_i)^2}{2a_i^2}} \tag{1}$$

where a_i and c_i are the premise parameters. By changing the values of these parameters, the Gaussian functions diverge consequently [18]. The number of membership functions in this layer depends on the number of linguistic terms defied for inputs. Therefore, the total number of premise parameters for Gaussian function is calculated as follows:

$$\text{Total number of memebership functions}(m) = \sum_{i=1}^{n} L_i \tag{2}$$

$$\text{Total number of premise parameters} = m*2 \tag{3}$$

where n and L_i denote the number of inputs and linguistic terms of ith input respectively.

In addition, consequent parameters are related to the fuzzy rules specified in the fourth layer. The ith fuzzy rule format for a network with two inputs is given as follows:

$$\text{Total number of fuzzy rules}(r) = \cup_{i=1}^{n} L_i \tag{4}$$

$$R_i: \text{ if } x_1 \text{ is } \alpha \text{ and } x_2 \text{ is } \beta \text{ then } f_i = (p_i x_1 + q_i x_2 + r_i) \tag{5}$$

$$f = \sum_{j=1}^{r} \overline{w}_i f_i \tag{6}$$

where p_i, q_i, and r_i are consequent parameters, α and β are linguistic terms, $\overline{w}_i$ is the normalized firing strength calculated in the third layer [18], and f is the output. As well, the total number of consequent parameters which needs to be optimized is calculated as follows:

$$\text{Total number of consequent parameters} = r*(n+1) \tag{7}$$

where n denotes the number of inputs.