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Evolutionary algorithm-based design of a fuzzy TBF predictive model and TSK fuzzy anti-sway crane control system ☆

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ABSTRACT

The efficiency of material handling system requires an automation on the different levels of control and supervision to keep availability of the material handling devices for fast, safety and precise transferring materials, as well as to reduce the maintenance cost, which is involved by enhancing the productivity of manufacturing process. In this paper, evolutionary-based algorithm for fuzzy logic-based data-driven predictive model of time between failures (TBF) and adaptive crane control system design is proposed. The heuristic searching strategy combining the arithmetical crossover, uniform and non-uniform mutation and deletion/insertion mutation is developed for optimizing the rules base (RB) and tuning the triangular-shaped membership functions to increase the efficiency and accuracy of a fuzzy rule-based system (FRBS). The evolutionary algorithm (EA) was employed to design a fuzzy predictive model based on the historical data of operational states monitored between the failures of the laboratory scaled overhead traveling crane electronic equipment. The fuzzy predictive model of TBF was implemented in the supervisory system created for supporting decision-making process through forecasting upcoming failure and delivering the user-defined maintenance strategies. The effectiveness of EA was also verified through designing a Takagi–Sugeno–Kang (TSK) fuzzy controller in the anti-sway crane control system.

1. Introduction

The hybrid soft computing techniques combining fuzzy logic, artificial neural network (ANN) and EAs find applications in many areas concerning the classification and control problems. A data-driven FRBS can be optimized using different techniques and their combinations. The heuristic searching strategies based on the EAs and fuzzy clustering techniques, as well as their combination with the ANN, are useful for reducing the complexity of a FRBS, adjusting the RB to the patterns hidden in a training data set and tuning the parameters and shapes of membership functions to increase the accuracy of a fuzzy model. Generally, the two approaches for the rules selection problem using genetic algorithm (GA) are proposed in the literature, called Pittsburgh (Smith, 1980; De Jong et al., 1993) and Michigan (Holland and Reitman, 1978), which differ with a chromosome coding method. In the Pittsburgh approach an individual that represents the whole RB and a genetic fuzzy system (GFS) aims to improve the individuals genomes, while the Michigan method based on a single rule per individual consists in optimizing the all population representing the RB. One kind of Michigan method is an iterative procedure (Venturini, 1993; Gonzalez and Perez, 1999; Cordon and Herrera, 2000) in which a GA is switched in consecutive iterations producing each time a new rule added to the RB. Many examples of GFS-based applications are quoted by Cordon et al. (2004), Ishibuchi (2007) and Herrera (2008).

Nowadays, controlling system availability, on-line monitoring operational state and proactive–predictive maintenance are key factors in industry (Monin et al., 2011). Fuzzy logic-based fault identification, supervision and diagnosis in industrial processes are reported in many scientific works. A model of the process behavior employed for abnormal states identification can be created based on the expert knowledge and formulated as a linguistic model (Kiupel and Frank, 1993) or derived from the historical data using for example fuzzy clustering methods (Kempowsky et al., 2006; Jyoti and Singh, 2011; Botia et al., 2013). Data-driven fuzzy model of remaining useful life (RUL) in the nuclear power plant is proposed by Zio and Di Maio (2010). Neuro-fuzzy approaches for failure detection and prediction of electrical machines and engines are described by e.g. Ye et al. (2001), Hammer et al. (2004), and Palmero (2005). The fuzzy logic-based model that used to identify and compensate the aileron and differential elevator failures in the F-16 aircraft control scheme is described

Abbreviations: ANN, artificial neural network; EA, evolutionary algorithm; FRBS, fuzzy rule-based system; GA, genetic algorithm; GFS, genetic fuzzy system; MISO, multi input, single output; PPM, pole placement method; RB, rules base; RMSE, root mean square error; RUL, remaining useful life; TBF, time between failure; TSK, Takagi–Sugeno–Kang fuzzy inference system

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Nomenclature

$A_j^{(i)}$	fuzzy set on the variable x_i universe of discourse, where $i=1, 2, \ldots, n$, $j=1, 2, \ldots, r_i$, and r_i is the number of fuzzy sets defined for x_i
$a_j^{(i)}$	parameter of the triangular membership function
$\mu_{A_j^{(i)}}(x_i)$	membership function
$R\hat{U}L$	estimated remaining useful life
$T\hat{B}F$	estimated time between failure
τ_k	fuzzy singleton determined on the fuzzy system output variable universe of discourse, where $k=1, 2, \ldots, N$, and N is the number of fuzzy rules
w_k	fuzzy rule activation degree (weight of a rule)
z	uniformly distributed random number in the interval [0, 1]

by Kwong et al. (1995). Diao and Passino (2001) combined the fuzzy logic and ANN to design the direct and indirect fault-tolerant control scheme of an aircraft turbine engine. Lo et al. (2009) applied a GA for designing the fuzzy model of aircraft behavior to identify the actuators failures. The GFS was applied by Parashant and Ganguli (2007) to solve a problem of on-line structural health monitoring of composite helicopter rotor blades. Weiss (1999) studied the problem of failure prediction in telecommunication equipment employing a GFS to obtain the relationships between sequences of occurrences leading to a specific event. Kim and Kim (1997) proposed the two-stage genetic-based design method of fuzzy predictor for estimating the chaotic and non-stationary time series. In the first step the GA is used to determine the coarse RB by optimizing the compatibility of fuzzy partitions to training data. In the next stage the membership functions are tuned to minimize the root mean square error (RMSE). The Pittsburgh-based simple genetic algorithm (SGA) based approach to optimize FRBS for predicting the wind speed and electrical power produced at a wind park is presented by Damousis et al. (2004). They used a binary coded GA to tune the fixed number of fuzzy sets. Zanaganeh et al. (2009) propose the design of a fuzzy predictive model through the subtractive fuzzy clustering-based selection of the RB combining with the GA employed to optimize the parameters of subtractive clustering algorithm and ANN used to tune the parameters of rules antecedents and conclusions. The other approaches to obtain a data-driven fuzzy predictive model are based on the genetic programming adapted to optimize fuzzy wavelet-network (Kisi and Shiri, 2011) or TSK-type fuzzy wavelet-network optimized in the consecutive steps using principal components analysis, GA and backpropagation algorithm applied, respectively, for the input variables and rules reducing, and wavelet network coefficients tuning (Ning et al., 2006).

In general, the revised methods of GA-based optimization of data-driven fuzzy predictive models can be classified into evolutionary strategies used only for tuning the parameters of fuzzy model with the assumed number of fuzzy rules or sets, and hybrid approaches combining the soft computing techniques utilized for fuzzy model designing in consecutive stages of classification of the historical data, RB optimization and membership functions and/or rules conclusions' parameter tuning. Hence, the second approach relies on realizing separately the procedures of determining the suitable set of predictive patterns represented by the fuzzy if–then relations and next optimizing the parameters of fuzzy rules premises and conclusions. In this paper the real-coded Pittsburgh-type EA is proposed to design a FRBS through the reproduction operations developed based on the arithmetical crossover, uniform and non-uniform mutation, and genes deletion/insertion mutation ensuring diversity of genome sizes, as well as diversity of the rules antecedents and conclusions parameters space. The heuristic searching strategy was developed for optimizing the RB and tuning the triangular-shaped membership functions. The performances of the EA were verified in two different applications addressed to the automated material handling systems:

(i) fuzzy predictive model of TBF of the laboratory scaled overhead crane electronic equipment, which was implemented in the supervisory and proactive maintenance system created on the laboratory stand for supporting decision-making process through forecasting the upcoming failure and delivering the user-defined maintenance strategies,
(ii) fuzzy logic-based anti-sway crane control system design.

The paper also deals with the problem of designing an adaptive crane control system robustness for the variation of rope length and mass of a payload shifted by a crane. Cranes are a group of material handling devices which are used extensively for shifting all kinds of cargos in many manufacturing processes, construction industries, container terminals and shipping yards. The automation of crane operations is very important owing to necessity of ensuring the safety and efficiency of the transportation process, which is involved by the requirements of enhancing the productivity of manufacturing processes. Those requirements motivate scientists and engineers to develop and implement solutions for crane control system which face up to the following problem: transfer a payload as fast as possible from point to point and precise positioning at a final point with the reduction of sway of a payload suspended at the end of a rope. The soft computing techniques, especially fuzzy logic, are widely employed to the considered problem which involves to implement the adaptive methods owing to the nonlinearity of a system under consideration including the rope length and mass of a payload variation. Some examples of a fuzzy logic-based anti-sway crane control system are based on the linguistic models extracted from the expert knowledge (Benhidjeb and Gissinger, 1995; Mahfouf et al., 2000). Trabia et al. (2008) propose the Mamdani-type fuzzy controllers of crane position and sway angle of a payload, and the method based on the inverse dynamic for calculating the ranges of fuzzy controllers' input intervals within which the membership functions were distributed. Kijima et al. (1995) employed the GA to tune the triangular-shaped membership functions according to the objective function, which has been specified based on the control performances evaluated during simulation. Liu et al. (2002) proposed the two fuzzy controllers of crane position and sway angle with singleton-type rules output optimized during the simulation by GA according to the cost function including the settle time, position error and sway angle of a payload. Chang (2007) developed a two-input (position error and sway angle) fuzzy controller with Gaussian-shaped input membership functions and output fuzzy singletons, both, tuned on-line using gradient technique. Some researchers (e.g. Kang et al., 1999; Oh et al., 2004; Sadati and Hooshmand, 2006; Smoczek and Szpytko, 2008) take an advantage of the simplicity of a TSK-type fuzzy controller (Takagi and Sugeno, 1985; Sugeno and Kang, 1988) applying it for interpolating gains of linear controllers. Oh et al. (2004) estimated scaling factors of the fuzzy PID controller using a hard c-means fuzzy clustering method and ANN. Sadati and Hooshmand (2006) utilized a fuzzy c-means technique to select the operating points of fuzzy scheduler used in tower crane control. Smoczek and Szpytko (2010, 2012a) propose the iterative and GA-based procedures for a TSK controller design based on the interval analysis of closed-loop control characteristic polynomial coefficients.

The other examples of soft computing approaches to crane control problem are based on the neurocontrollers on-line tuned