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Evolving model identification for process monitoring and prediction of non-linear systems

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ABSTRACT

This paper tackles the problem of model identification for monitoring of non-linear processes using evolving fuzzy models. To ensure a high production quality and to match the economic requirements, industrial processes are becoming increasingly complicated in both their structure and their degree of automation. Therefore, evolving systems, because of their data-driven and adaptive nature, appear to be a useful tool for modeling such complex and non-linear processes. In this paper the identification of evolving cloud-based fuzzy models is treated for process monitoring purposes. Moreover, the evolving part of the algorithm was improved with the inclusion of some new cloud-management mechanisms. To evaluate the proposed method two different processes, but both complex and non-linear, were used. The first one is a simulated Tennessee Eastman benchmark process model, while the second one is a real water-chiller plant.

1. Introduction

In general, modern industrial processes are typical dynamic systems with complex structures and frequently operating under a variety of environmental conditions. For successful and optimal operation of any process, it is important to detect, or even better, to predict undesired events as early as possible. Due to this, model-based methods play a crucial rule in the field of process monitoring and fault detection (Isermann, 1984). These methods can be used for measurable signals prediction and for non-measurable parameters estimation. The method proposed in this paper is used for both, prediction of measured signals and for estimation of non-measurable parameters (performance production indicators, pPIs).

The methods of process monitoring and fault diagnosis can be classified into three general categories: methods based on mathematical/physical knowledge of the process; statistical data-driven methods; and data-driven model-based methods.

The methods based on the mathematical/physical knowledge of the process have been successfully applied in different industrial applications (Isermann, 2004; Gertler, 1998; Venkatasubramanian et al., 2003b; Campos-Delgado and Espinoza-Trejo, 2011; Huang et al., 2012; He et al., 2013). This type of methods use an *a priori* knowledge based on fundamental understanding of the physics of the process. Beside their wide-range usage (Isermann, 2011), the methods have several disadvantages. They are limited to linear models and in some cases to very specific nonlinear models (using linear approximation). Other problems are disturbance simplification, parameter drifts, *a priori* estimation of classification errors, adaptability to varying process' conditions, etc.

Due to the information revolution and data expansion new data-driven techniques have been investigated and developed. Data-based schemes for system monitoring mainly concentrate on the data collected from the processes. Statistical approaches (Qin, 2003) use this data to extract the knowledge and to detect the faults. Principle component analysis (PCA) (Li et al., 2000; Gertler and Cao, 2004; Chen et al., 2016) and partial least squares (PLS) (Li et al., 2010; Zhang et al., 2010; Chen et al., 2016) are two basic techniques. More recently, independent component analysis (ICA) (Zhang and Qin, 2008; Tsai et al., 2013) has received a lot of attention and has seen great success in practice and (Venkatasubramanian et al., 2003a; Yin et al., 2014) have provided a review of the basic statistical data-driven approaches for process monitoring. In general, statistical data-based schemes can effectively monitor only the industrial processes when they operate under stationary conditions (Yin et al., 2014). However, this type of methods are not suitable to handle the complex process dynamics under changing environmental conditions.

The applicability of statistical data-based methods can be improved by considering the system dynamics (Chapter 3 in Simani et al. (2003)). Fault detection methods which combine the data-driven with model-based approaches, have been presented by Precup et al. (2015). As

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dynamic models are required, the evolving-based identification methods play an important role (Lughofer, 2011, 2015). In this case the process model is not known *a priori* but is identified recursively from the data streams. Furthermore, the acquired model could be used for the prediction of the future system behavior.

The evolving methods can be divided into different categories according to their structure, ability of learning, level of autonomous adapting, etc. In the field of fault detection and process monitoring, most of the evolving methods use Takagi–Sugeno (Takagi and Sugeno, 1985) type of fuzzy structure to construct the process model (Lughofer and Guardiola, 2008; Chivala et al., 2010; Petković et al., 2012; Lemos et al., 2013; El-Koujok et al., 2014; Dovžan et al., 2015). In this methods the membership function (in a form of data clusters) usually follow the Gaussian distribution using a predefined distance measure.

By introducing the new simplest form of fuzzy system (Angelov and Yager, 2011), named AnYa, a new branch of evolving methods have been developed. AnYa fuzzy system uses a non-parametric (cloud-based) antecedent part which does not require any explicit definition of the membership function or even *a prior* assumption of its form. The membership functions and the evolving mechanisms are based on the relative density of the current data according to the existing clouds. The data clouds represent sets of previous data points with similar properties. Contrary to the clusters, clouds do not have any boundaries and they directly and exactly represent all previous data samples. More information about differences between the data clouds and the clusters can be found in (Angelov and Yager, 2011).

The AnYa based methods (Angelov et al., 2013; Costa et al., 2013; Rosa et al., 2014) use local and global density to evolve the structure, while the methods in (Škrjanc et al., 2014; Blažič et al., 2014) use just local density with simple threshold to evolve the structure. The proposed method in this paper represents an extension of the latter methods with introducing new evolving mechanisms.

Based on the AnYa fuzzy system a fault detection method was proposed by Costa et al. (2014a, b, 2015) which uses a recursive density estimation to detect novelty in a statistical manner (without including any dynamics of the process into the model).

For the purpose of process monitoring in this paper we propose an improved evolving fuzzy model based on AnYa fuzzy system. This method uses the ability of evolving the fuzzy structure to cope with changing environmental conditions. On the other hand an NARX model is used to deal with the process dynamics. This is the main advantage over the existing process monitoring methods based on AnYa fuzzy system (Costa et al., 2015; Precup et al., 2015). The new evolving mechanisms are able to protect from addition of new clouds (rules) based on outliers. Moreover, a new mechanism for removing the "less active" and the "less informative" clouds is introduced. The *activity* is a property of the cloud and it is defined as a relative number of data samples associated with a particular cloud from its creation. On the other hand, the second removing mechanism deletes the clouds that has obtained less information and are less active in comparison with the other clouds.

The proposed cloud-based model, as a tool for estimation of the non-measurable parameters, is tested on a simulated input/output data acquired from the Tennessee Eastman (TE) (Downs and Vogel, 1993) benchmark process model. The non-measured production objectives of the systems are defined through the production performance indicators (pPIs), namely, *Cost*, *Production* and *Quality* (Glavan et al., 2012). The models for these three pPIs are identified with the proposed fuzzy-cloud-based method and the results are compared with the eFuMo identification tool proposed by Dovžan et al. (2012, 2015) and with the NNSYSID neural network tool (Norgaard et al., 2000). The main goal is to monitor the process by detecting potential undesired future trends based on the estimated production performance indicators.

A practical example to test the usability of the proposed method is a real water-chiller plant (WCP) located in a local factory. The proposed method is used as a model identification tool for undesired events prediction. Using the real data, two variables are identified: the WCP's power production and the factory's power consumption. The goal of monitoring these indicators is to predict the future behavior of the system in order to prevent unnecessary short-time start-ups of the water chillers. This can improve the overall efficiency of the whole system.

The paper is organized as follows. In Section 2 the cloud-based identification method is presented, while in Section 3 an improved evolving mechanism for adding and removing clouds is presented. Section 4 introduces the experimental results for a Tennessee Eastman process, while in Section 5 the practical results for a water chiller plant are presented. Finally, in Section 6, the main ideas and results are summarized.

2. Cloud-based identification of a dynamic system

2.1. Fuzzy-rule-based model

Fuzzy systems are general approximation tools for the modeling of non-linear dynamic processes. In this paper we use a fuzzy-rule-based system with a non-parametric antecedent part presented by Angelov and Yager (2011). The main difference is the simplified antecedent part that relies on the data relative density. The rule-based form of the ith rule is defined as:

$$\mathcal{R}^i : \text{IF} \quad (\boldsymbol{x}_f \sim X^i) \quad \text{THEN} \quad y^i = f^i(\boldsymbol{x}_f) \tag{1}$$

where the data sample (regression vector) $\boldsymbol{x}_f(k) = [y(k-1), \ldots, y(k-n_a), u(k-1), \ldots, u(k-n_b)]$ includes the delayed system inputs and outputs . The operator $\sim$ is linguistically expressed as '*is associated with*', which means that the current data $\boldsymbol{x}_f$ is related to one of the existing clouds X^i according to the membership degree (the normalized relative density of the data). The input and output orders are denoted as n_a and n_b, respectively. Note that the input $u(k)$ does not have an immediate influence on the output $y(k)$. The partial NARX model of the ith rule is defined as:

$$f^i(k) = {\theta^i}^T \boldsymbol{\psi}(k) \tag{2}$$

where the vector $\boldsymbol{\psi}(k) = \left[\boldsymbol{x}_f, 1\right]^T$ consists of the regression vector $\boldsymbol{x}_f$ (used for partitioning the data space) to which we usually add a regressor 1. The vector of parameters for the ith cloud (rule) is denoted as $\boldsymbol{\theta}^i = \left[a_1^i, \ldots, a_{n_a}^i, b_1^i, \ldots, b_{n_b}^i, r^i\right]^T$. Once we have declared all the parameter vectors $\boldsymbol{\theta}^i$ for each cloud ($i = 1, \ldots, c$) we can define the output of the system in a compact matrix form:

$$y(k) = \sum_{j=1}^{c} \beta^j(\boldsymbol{x}_f) {\theta^j}^T \boldsymbol{\psi}(k) = \boldsymbol{\beta}^T(\boldsymbol{x}_f) \boldsymbol{\Theta}^T \boldsymbol{\Psi}(k) \tag{3}$$

where c is the number of existing clouds [1] (fuzzy rules), $\boldsymbol{\beta}^T(\boldsymbol{x}_f) = \left[\beta^1, \beta^2, \ldots, \beta^c\right]$ is the vector of normalized relative densities determined between the current data $\boldsymbol{x}_f$ and all the existing clouds, and $\boldsymbol{\beta}^T$ will be discussed in the next subsection. The matrix $\boldsymbol{\Theta} = \left[\theta^1, \theta^2, \ldots, \theta^c\right] \in \mathbb{R}^{(1+n_a+n_b)\times c}$ contains the vectors of the parameters for all the existing clouds.

2.2. Identification of the antecedent part

In this subsection we will describe an identification method for the non-parametric antecedent part of the fuzzy-rule-based system AnYa (Angelov and Yager, 2011). The method starts with zero fuzzy rules (clouds) and the first cloud is initialized with the first data $\boldsymbol{x}_f$ received. For each of the following data the normalized relative densities β^i are calculated and then the current data is associated with one of the existing clouds (according to the maximum density β^i, where

[1] We use the term 'existing clouds' because this method is an evolving one and the number of clouds changes when some requirements are fulfilled.