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Improved fault detection employing hybrid memetic fuzzy modeling and adaptive filters

Francisco Serdio[a], Edwin Lughofer[a,*], Alexandru-Ciprian Zavoianu[a], Kurt Pichler[b], Markus Pichler[b], Thomas Buchegger[b], Hajrudin Efendic[c]

[a] Department of Knowledge-Based Mathematical Systems, Johannes Kepler University Linz, Austria
[b] Austrian Competence Center of Mechatronics, Linz, Austria
[c] Institute for Design and Control of Mechatronical Systems, Johannes Kepler University Linz, Austria

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ABSTRACT

We propose an *improved fault detection (FD) scheme* based on residual signals extracted on-line from system models identified from high-dimensional measurement data recorded in multi-sensor networks. The system models are designed for an all-coverage approach and comprise linear and non-linear approximation functions representing the interrelations and dependencies among the measurement variables. The residuals obtained by comparing observed versus predicted values (i.e., the predictions achieved by the system models) are normalized subject to the uncertainty of the models and are supervised by an incrementally adaptive statistical tolerance band. Upon violation of this tolerance band, a fault alarm is triggered. The improved FD methods comes with two the main novelty aspects: (1) the development of an enhanced optimization scheme for fuzzy systems training which builds upon the SparseFIS (*Sparse Fuzzy Inference Systems*) approach and enhances it by embedding genetic operators for escaping local minima $\longrightarrow$ a *hybrid memetic (sparse) fuzzy modeling* approach, termed as *GenSparseFIS*. (2) The design and application of *adaptive filters* on the residual signals, over time, in a sliding-window based incremental/decremental manner to smoothen the signals and to reduce the false positive rates. This gives us the freedom to tighten the tolerance band and thus to increase fault detection rates by holding the same level of false positives. In the results section, we verify that this increase is statistically significant in the case of adaptive filters when applying the proposed concepts onto four real-world scenarios (three different ones from rolling mills, one from engine test benches). The hybridization of sparse fuzzy inference systems with genetic algorithms led to the generation of more high quality models that can in turn be used in the FD process as residual generators. The new hybrid sparse memetic modeling approach also achieved fuzzy systems leading to higher fault detection rates for some scenarios.

1. Introduction

1.1. Motivation and state-of-the-art

The fault detection and identification component within modern industrial systems is of decisive importance. Several goals are pursued by the development and installation of such components. While some goals are product-related, placing the focus on the assurance of high quality items/parts at the end of the production chain [19], some others are production-related, mainly aiming for minimal operational downtime due to maintenance, degradation or failures inside the system [11,51]. In the ideal case, a zero-defect strategy is pursued in order to exclude any bad production parts, thus saving costs and time-intensive posteriori checks. Human-related factors are vital as well especially within active human-machine interaction scenarios [46], as operators could be injured when a system suffers from any malfunction not properly addressed [2,38].

In former times, systems were supervised manually, inducing high efforts for operators working with the system. Present-day industrial systems are larger and more complex, with many different setups, different production types and throughput, usually equipped with multi-sensor networks [32] to supervise as many

* Corresponding author.
E-mail addresses: francisco.serdio@jku.at (F. Serdio), edwin.lughofer@jku.at (E. Lughofer), ciprian.zavoianu@jku.at (A.-C. Zavoianu), kurt.pichler@lcm.at (K. Pichler), markus.pichler@lcm.at (M. Pichler), thomas.buchegger@lcm.at (T. Buchegger), hajrudin.efendic@gmx.at (H. Efendic).

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system variables as possible at different positions of the production chain [13]. This makes modern industrial systems very unlikely candidates for a manual monitoring context.

During the last decades, several techniques were used to achieve fully automatic fault detection and identification:

(i) differential equations, modeling physical laws within the systems [17,29]
(ii) fault models based on physics of the failure [35] and
(iii) fault models based on expert knowledge from experienced operators of the system [67].

All aforementioned techniques, even when successful, are mainly bounded by their (high) development effort (e.g., huge physical and mathematical derivations and proofs), whereas at the same time they may be limited by boundary conditions for specific system behaviors or only applicable for particular systems setups/variants. Small changes in these setups or other types of processes in the system often require a complete redesign and mathematical re-derivation of the physical-based or state-space based models (again requiring significant manual effort). In the end, all of the techniques used are based on modeling dependencies and interrelations among the system variables.

Hence, in order to reduce manual experts'/operators' efforts, automatic extraction of these dependencies in multi-sensor systems using either data-driven methods, machine learning methods or/and fusion methods has been maturing and spreading during the last years [32,64]. This approach led to the so called *data-driven System Identification based fault detection (FD)*, where the learnt models are known as System Identification (SysID) models [41,49,68] and reflect higher-dimensional relations between the considered variables. The System Identification models are then used as monitoring reference for the nominal, fault-free situation of the system. Opposed to univariate time-series based monitoring, they are able to express more complex faults and also to process variables showing a more discontinuous (but fault-free) signal behavior [62]. In contrast to other data-driven FD techniques that rely on (1) the supervision of anomaly behavior directly in the recorded measurements [10], (2) frequency-based analysis of measurement signals [6,53] or (3) autoregressive moving average models [75], SysID models do not require any re-occurring (typical) patterns representing the fault-free cases in the signals and thus are applicable to a wider range of measurement signals.

By simply checking the residuals, i.e. the differences between predictions and observations, obtained from the SysID models, any form of *violations of the interrelations between the system variables* can be found and thus significant deviations to the nominal condition of the system within variable/feature space can be elicited (raising fault alarms) [2,24]. In this sense, such approaches are also termed as *residual-based FD* and can be applied in a *fully unsupervised manner*. This has also significant advantages over approaches employing classifiers for a direct mapping of system states to particular type of faults [4,51]: the faults either need to be known and clearly defined (i.e., fault signatures), usually based on expert knowledge [1], or simulated and recorded at the system, which may be time-intensive and in some cases even impossible (e.g. consider a leakage in an emission gas pipe) [2].

Hence, residual-based FI based on data-driven SysID models for condition monitoring enjoyed a large attraction during the last years. Some examples are [38,66,49,34] and especially our long-term previous research [62,64,65], using several types of regression models such as regularized linear regression types, partial least squares, a genetic version of Box–Cox models [5], as well as fuzzy systems automatically extracted from historical process data using a training technique termed as *SparseFIS* (short for *Sparse Fuzzy Inference Systems*) [44]. The latter have been essential

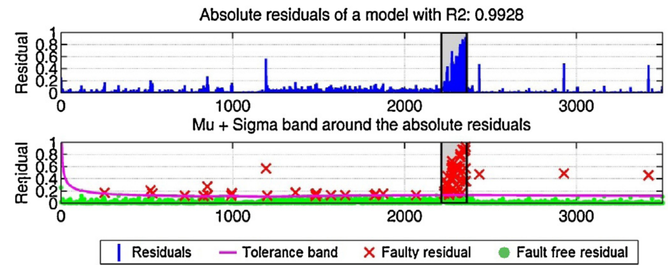

Fig. 1. Original residual signal with and without the tolerance band: several distinct peaks appearing over the tolerance band are detected as false positives (false alarms).

for guaranteeing models with high predictive quality, especially in case of significant non-linearities contained in the system. From our previous research (where we successfully benchmarked our methods with several related state-of-the-art methods in data-driven FD), we identified two major shortcomings, which potentially lead to a non-optimal FD performance and thus are going to be addressed by this work.

Poorly modeled variables. Even when fuzzy systems are proven to be universal approximators [8], the learning algorithm is based on a deterministic optimization method, which, under certain circumstances (initial start values, etc.), might get trapped in local optima (due to the nature of the embedded projected gradient descent steps). When this occurs, one could end up with low quality models not suitable for FD purposes due to unreliable predictions. This in turn leads to variables for which the FD approach might fail to detect faults happening therein.

Noisy residual signals. One important aspect about FDI systems is the trust of its users. This trust could be compromised when the system exhibits an unacceptable ratio of false positives (FPs). FPs are alarms indicating that a problem is occurring inside the system under monitoring, when, however, the system is healthy and properly working. When the cost of FPs is critical, the user might even switch off the FDI system. There are several reasons for a significant amount of FPs:

(i) The system under supervision is affected by a significant non-stationary dynamic environment [59], and the models are statically conceived and never adapted for new system behaviors.
(ii) There is uncertainty in the system, and the creation (training) of the model(s) did not addressed it properly, so the training was not optimal but sub-optimal.
(iii) The noise in the system is highly affecting the smoothness of the on-line data, thus affecting the model outputs and the tracking of the residuals.
(iv) The input space is highly non linear and the models experience impulsive noise in the nonlinearities, affecting the model outputs and the tracking of the residuals.

Fig. 1 underlines the problematic by showing a typical (unsmoothed) residual signal from a (noisy) real-world scenario we observed in the past.

1.2. Our approach

The current approach builds upon our preliminary work in [62,64] (see also Section 2 below for the overall SysID-based FD framework) tries to alleviate the aforementioned shortcomings and to boost fault detection rates for low fault positive rates. Thereby, we propose two major improvements: