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PROBABILISTIC FAULT DIAGNOSIS FOR NONLINEAR STOCHASTIC SYSTEMS

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ABSTRACT
The paper focuses on fault detection and isolation (FDI) in stochastic nonlinear systems using Bayesian statistics. The main concept of this approach leans on a probabilistic model, which estimates the occurrences of faults by probabilities. The methodology consists in probabilistic mapping of the measured data into a fault variable, which acts as an indicator of considered modes of the systems. One of the main advantages of the proposed FDI approach is the ability to perform real-time supervised training by which the parameters of the fault probability table are updated in real time. The suggested methodology is very simple for numerical calculations and enables one to include heuristic knowledge about the faults. The practical aspects of the proposed FDI algorithm were successfully tested in real time using a laboratory heating system.
Keywords: fault diagnosis, nonlinear system, probabilistic model

1. INTRODUCTION
The design of reliable systems is one of the key objectives in engineering. A monitoring system, which is used to detect faults and diagnose their location and significance in a system, is called a fault diagnosis system [1]. The safety of processes can be greatly enhanced through the detection and isolation of the changes indicative of modifications in the process performances. The problem of fault detection and isolation consists in detecting and isolating faults in a physical system by monitoring its inputs and outputs. Quantitative model-based FDI methods rely on the comparison of available measurements of the system with prior information represented by the mathematical model [8]. The mathematical model is not easy to obtain in practice from physical relationships or even it is impossible to derive it for complex and uncertain systems, e.g. [1]. However the most FDI techniques are impossible without the model implementation.
To overcome this difficulty it is desirable to design FDI methodology based on a “universal” model technique, which can be used to obtain an approximate representation of any non-linear system. Neural networks, as well-known powerful tools for handling non-linear problems, have been successfully applied to non-linear system FDI problems, e.g. [8]. An alternative FDI approach based on Bayesian identification technique seems to be a promising tool, because it can automatically extract the system features from historical training data [6]. The main concept of this methodology is a probabilistic model, which describes the system in the form of conditional probabilities or probability distributions. The advantage of this approach is that it may be applied to both non-linear and linear systems. Moreover, the learning can be carried out on-line. This paper acquaints with a concept of the real-time fault detection and isolation approach based on Bayesian statistics [7]. The methodology consists in probabilistic mapping of the measured data into a fault variable, which acts as an indicator of the considered modes of the system [3, 4, 5]. One of the main advantages of the proposed FDI approach is the ability to perform real-time supervised training by which the parameters of the fault probability table are updated in real time.

2. PROBABILISTIC APPROACH TO THE FDI

Let us assume that we have a stochastic non-linear dynamic system, where we want to detect a finite number N_f of known faults. We set up a random variable f to serve as a pointer of faults, $f_t \in S_f$, $S_f \equiv \{0,1,\ldots,N_f\}$, which detects the faults at the discrete time $t \in t^*$, $t^* \equiv \{1,2,\ldots,\overline{t}\}$, $\overline{t}$ is a natural number. If $f_t = 0$ the stochastic system at the time t is without faults. The sequence of discretized data observed at the discrete time t is denoted as D_t and the sequence of all data from the beginning of observation up to the discrete time instant t is denoted by $D^{(t)} \equiv \{D_1, D_2, \ldots, D_t\}$.

In a real case we may rely only on analytical redundancy, which is contained in the available measurements of the system and in the prior information about it. As the considered system is uncertain and the measured data are affected by noise the concept of probability is used for the FDI.

We will assume that the information about the particular faults is contained in the observed data vector x_t, $x_t \in S_x$, where S_x is the set of possible observed data vectors with μ_x elements that may contain the finite number of inputs and outputs. From this point of view, our aim is to determine $p(f_t \mid x_t)$ at discrete time $t \in t^*$, where $p(.|.)$ denotes a conditional probability mass (density) function. Since the probability mass function $p(f_t \mid x_t)$ is not available, we have to use the parametrized time-invariant model. This model defines the set of probability mass functions $p(f_t \mid x_t, \Theta)$, for $t \in t^*$, where the parameter Θ is the fault probability table, which determines the relationship between observed data and faults.

The matrix Θ may be estimated using Bayesian statistics where the probability is interpreted as a subjective measure of one unit of the statistician's belief distributed over the set of values which random variable could possibly take. With this approach using the natural conditions of control [7], we can determine the posterior probability density function $p(\Theta \mid D^{(t)}, f^{(t)})$ conditioned by the observed data and information about faults.

Using the probability density function $p(\Theta \mid D^{(t)}, f^{(t)})$ and under the previous mentioned assumptions we may derive:

$$p(f_{t+1} = \varphi \mid x_{t+1} = \xi, D^{(t)}, f^{(t)}) = \frac{n_{\xi,\varphi}(t)}{\sum_{\varphi_p=0}^{N_f} n_{\xi,\varphi_p}(t)}, \tag{1}$$

where $n_{\xi,\varphi}(t)$ is the number of events $f_\tau = \varphi, x_\tau = \xi$ for $\tau \in \{1,2,\ldots,t\}$, see [4, 5].

According to formula (1) the data $D^{(t)}, f^{(t)}$ must be available for the probability estimation of the particular possible values of the random variable f_{t+1}. But the true values of the quantities $f^{(t)}$ are known only for the discrete time $\tau = 1,2,\ldots,t_r$, where t_r is the time of the last observed training sample $(t_r < t)$, which we can use for the parameter Θ estimation. Therefore instead of formula (1) for the estimation of f_t at discrete time $t > t_r$ formula (2) may be used for $t = t_r + 1, t_r + 2, \ldots, \overline{t}$:

$$p(f_{t+1} = \varphi \mid x_{t+1} = \xi, D^{(t_r)}, f^{(t_r)}) = \frac{n_{\xi,\varphi}(t_r)}{\sum_{\varphi_p=0}^{N_f} n_{\xi,\varphi_p}(t_r)}. \tag{2}$$

Further improvement of the fault diagnosis can be done for faults with time duration lasting longer than n sampling periods, when $f_{t+1} = f_{t+2} = \ldots = f_{t+n}$. At least n probability distributions $p(f_\tau \mid x_\tau, D^{(t_r)}, f^{(t_r)})$, $\tau = t+1, t+2, \ldots, t+n$ can be used for the fault diagnosis in this case, e.g. by the application of the arithmetic or geometric means of these probability functions.

From numerical point of view, this approach to fault diagnosis is very simple but the dimension of the sufficient statistic $n(t) = \left[n_{x,f}(t)\right]$, $x \in S_x$, $f \in S_f$ is extremely large even for small cardinality of data-value sets of f_t and x_t, $t \in t^*$. To overcome the above-mentioned drawback the approximation of the Markov chain-based prediction algorithm (see [2]) was adapted for the estimation

$p(f_{t+1} \mid x_{t+1} = \xi, D^{(t_r)}, f^{(t_r)})$, where $\xi \notin S_x^{(t_r)}$, $S_x^{(t_r)}$ is the set of the observed data vectors x_τ, $\tau = 1, 2, \ldots, t_r$ see [4, 5].

3. LABORATORY APPLICATION

This suggested way of fault diagnosis was tested on a laboratory heating system (Fig.1) designed and built by the Centre for Applied Cybernetics at Czech Technical University in Prague.

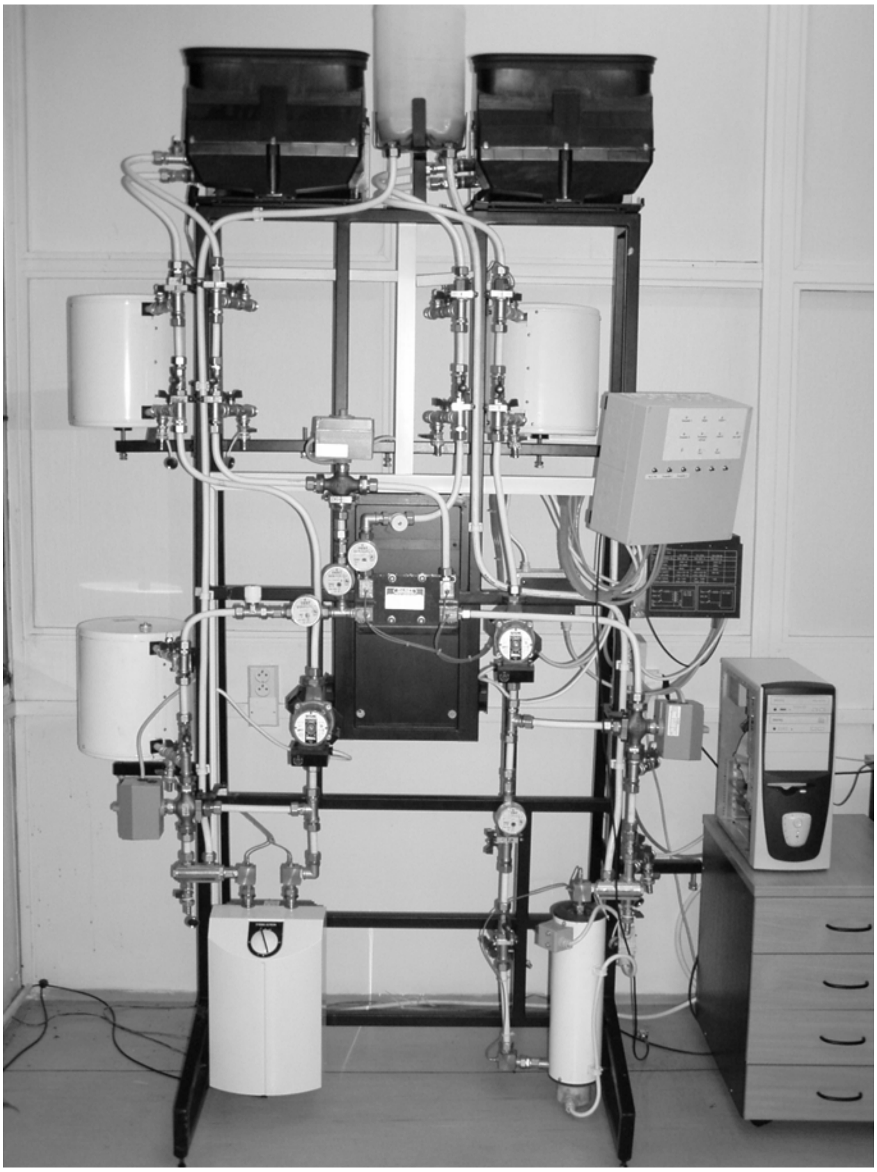

Figure 1. A photograph of the laboratory heating system

The system consists of two closed independent heating circuits, in which the water is the heat transfer medium. Both the circuits are equipped with a heater, cooler, pump and valves, by which the heat transfer within the circuit can be controlled. The heat can also be transferred between the circuits through a multi-plate heat exchanger. From the temperatures measured in the right circuit, only the three temperatures were chosen to monitor the behaviour of the system. Besides temperatures, the control signal assigning the performance of the right heater was used as an input for fault detection.
Several possible modes of the system behaviour were taken into consideration (e.g. the changes of the heads of the pumps, the performances of the coolers and the heaters, the setting of the opening of the valves etc.). Fig.2 displays the obtained results of the mentioned fault diagnosis for one experiment,

where it was detected 7 faults ($N_f = 7$) and the faultless state of the system ($f_t = 0$). One can see the good matching between the real fault evolution (Line 1) and the fault estimation (Line 2).

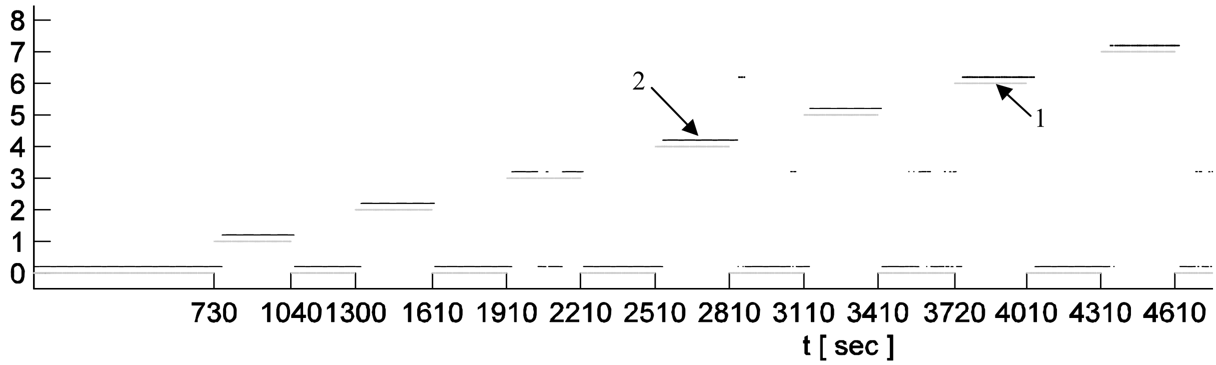

Figure 2. Courses of the real fault evaluation and the fault estimation

4. CONCLUSION

This paper informs about the proposed methodology for real-time fault diagnosis of stochastic nonlinear dynamic systems. The proposed methodology consists in probabilistic mapping of the measured data into a fault variable that acts as an indicator of the considered modes of the system. The methodology was successfully tested on a laboratory heating plant. The experimental results confirmed the promising properties of the underlying theory and related algorithms and the ability to perform real-time supervised training by which the parameters of the fault probability table are updated in real time.

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