On applying interval fuzzy model to fault detection and isolation for nonlinear input-output systems with uncertain parameters

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***Abstract*— This paper presents an application of the interval fuzzy model (INFUMO) in fault detection and isolation for a class of processes with uncertain interval-type parameters. Confidence data bands for the process input-output pairs are approximated using a fuzzy model with interval parameters. The approximation, based on linear programming, employs l_∞-norm as the modelling error measure. Arbitrary sets of identification input signals can be used due to the application of low-pass filtering when obtaining the confidence bands. Using a combination of INFUMOs makes it possible to devise a fault-isolation scheme based on the given incidence matrix. Simulation results of a fault detection and isolation for a two-tank system are provided, which illustrate the relevance of the proposed FDI method.**

I. Introduction

Fault detection and isolation (FDI) problem is not new in the research world; in fact, FDI for linear systems has been extensively studied since the mid-seventies, and during that period a lot of powerful methods have been developed. A thorough review of the FDI methods is given in survey papers [4], [6], and [7]. However, if the monitored system is strongly nonlinear the use of the linear approaches is limited. Many industrial systems indeed exhibit nonlinear behaviour, therefore it is somehow expected that nonlinear FDI methods will play a significant role in practical applications. Recently, observer-based approaches [5], and different forms of artificial-intelligence applications (fuzzy models [2] and neural networks [9]) have been proposed. Most of the above-mentioned methods are based on a *decoupling* framework, where the modelling uncertainty and all possible faults can be decoupled through various residual formation and calculation. However, the modelling uncertainty is often unstructured, which makes it difficult to achieve exact decoupling between faults and modelling errors. In addition, some problems taking into consideration the input-output representation of systems as well as the design of the corresponding nonlinear observers are still open. Furthermore, in industrial applications simple and robust solutions are often sought to tackle process-monitoring problems.

In this paper a fault detection and isolation problem in nonlinear input-output systems with unstructured interval-type uncertainties is addressed. In [13] a FDI method using nonlinear adaptive fault estimators for dealing with a similar system type was given. The presented approach is based on the use of the interval fuzzy model (INFUMO). As was introduced in [10], by applying a Takagi-Sugeno-type [8] fuzzy model with interval parameters, one is able to approximate the upper and lower boundaries of the domain of functions that result from an uncertain system. The INFUMO is therefore intended for robust modelling purposes; on the other hand, studies show it can be used in fault detection as well. The novelty lies in defining of confidence bands over finite sets of input and output measurements in which the effects of unknown process inputs are already included. Moreover, it will be shown that by data pre-processing the INFUMO parameter-optimization problem will be significantly reduced. By calculating the normalized distance of the system output from the boundary model outputs, a numerical fault measure is obtained. The main idea of the proposed approach is to use the INFUMOs in an FDI system as residual generators, and combine the INFUMO outputs for the purpose of fault isolation. Due to data pre-processing, the decision stage is robust to the effects of system disturbances.

The paper presents an application of the INFUMO in fault detection and isolation for the two-tank system with interval-type uncertain parameters. The FDI problem was split into two steps. In the former step the INFUMOs along with data pre-processing and low-pass filtering were introduced into the fault detection scheme. In the latter the combination of residuals was used in the fault-isolation stage. In its final part the paper gives some outlines of the possible future work.

II. Using the fuzzy interval model in fault detection and isolation

A. Preliminaries

Let the nonlinear process be given in a general form as follows:

$$\begin{aligned} \dot{x}(t) &= \sigma(x,u,t) + \eta(x,u,t) + \phi(x,u,t) \\ y(t) &= \gamma(x,u,t) + \rho(x,u,t) \end{aligned} \qquad (1)$$

where $x \in \mathbb{R}^n$ is the state vector of the system, $u \in \mathbb{R}$ is the system input, $y \in \mathbb{R}^m$ denotes the system output, $\eta : \mathbb{R}^n \times \mathbb{R} \times \mathbb{R}^+ \rightarrow \mathbb{R}^n$ and $\rho : \mathbb{R}^n \times \mathbb{R} \times \mathbb{R}^+ \rightarrow \mathbb{R}^m$ represent the effects of the modelling uncertainties and disturbances on the system states and outputs, $\phi \in \mathbb{R}^n \times \mathbb{R} \times \mathbb{R}^+ \rightarrow \mathbb{R}^n$ denotes the fault function, and $\sigma : \mathbb{R}^n \times \mathbb{R} \times \mathbb{R}^+ \rightarrow \mathbb{R}^n$ and $\gamma : \mathbb{R}^n \times \mathbb{R} \times \mathbb{R}^+ \rightarrow \mathbb{R}^m$ are the nonlinear functions of the state vector, the input, and time, respectively. Throughout the paper the following assumptions will be made:

Assumption 1: *The modelling uncertainties, represented by η and ρ in* (1)*, are unstructured unknown nonlinear*

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functions of x, u and t, but bounded by some known functionals [13], *i.e.,*

$$|\eta(x,u,t)| \leq \overline{\eta}(y,u,t),\ |\rho(x,u,t)| \leq \overline{\rho}(y,u,t),\\ \forall(x,y,u)\in\mathcal{X}\times\mathcal{Y}\times\mathcal{U},\ \forall t\geq 0 \tag{2}$$

where the bounding functions $\overline{\eta}(y,u,t)$ and $\overline{\rho}(y,u,t)$ are known and uniformly bounded. $\mathcal{X}\subset\mathbb{R}^n$ is some compact domain of interest, and $\mathcal{U}\subset\mathbb{R}$ and $\mathcal{Y}\subset\mathbb{R}$ are the compact sets of admissible inputs and outputs, respectively.

Assumption 2: *The output functions $y_i(t),\ i=1,\ldots,m$, when $\phi(x,u,t)=0$, are bounded by the following interval:*

$$y_i(t)\in\left[\underline{y}_i(t),\overline{y}_i(t)\right]\subset\mathcal{Y} \tag{3}$$

Assumption 1 characterizes the possible modelling uncertainties as unstructured but bounded by some constant or function, and Assumption 2 guarantees that in the absence of faults the bounds of the interval can be determined. As a consequence, a confidence bands of outputs guarantee that process outputs exhibiting normal behaviour are found in the intervals $\left[\underline{y}_i,\overline{y}_i\right]$. However, due to the unknown effect of the actual disturbance functions the exact bounds cannot be defined analytically. In the proposed approach, introducing the interval fuzzy model, the boundary responses will be obtained by a fuzzy function approximation of the bounds of a set of filtered input-output data that already comprises the effects of disturbances.

B. Derivation of an interval fuzzy model

A short description of the model derivation will be given, and for further information the reader is referred to [10].

A static fuzzy TS-type model [8] in affine form with one antecedent variable can be given as a set of rules

$$\mathbf{R}_\mathrm{j}:\ \textbf{if}\ x_p\ \textbf{is}\ \mathbf{A}_j,\ \textbf{then}\ y=\boldsymbol{\theta}_j^T\boldsymbol{x},\ j=1,\ldots,m \tag{4}$$

The variable x_p denotes the input or variable in premise, and variable y is the output of the model. The antecedent variable is connected with m fuzzy sets $\mathbf{A}_j$, and each fuzzy set $\mathbf{A}_j$ ($j=1,\ldots,m$) is associated with a real-valued function $\mu_{A_j}(x_p):\mathbb{R}\rightarrow[0,1]$, that produces a membership grade of the variable x_p with respect to the fuzzy set $\mathbf{A}_j$. The consequent vector is denoted $\boldsymbol{x}^T=[x_1,x_2,\ldots,x_n,1]$. As the output functions are in affine form, 1 was added to the vector $\boldsymbol{x}$. The system output is a linear combination of the consequent states, and $\boldsymbol{\theta}_j$ is a vector of fuzzy parameters. The system in Eq. (4) can be described in closed form

$$y=\boldsymbol{\beta}^T(x_p)\boldsymbol{\Theta}\boldsymbol{x}, \tag{5}$$

where $\boldsymbol{\Theta}^T=[\boldsymbol{\theta}_1,...,\boldsymbol{\theta}_m]$ denotes a coefficient matrix for the complete set of rules, and $\boldsymbol{\beta}^T(x_p)=[\beta_1(x_p),\ldots,\beta_m(x_p)]$ is a vector of normalized membership functions with elements that indicate the degree of fulfilment of the respective rule. Functions $\beta_j(x_p)$ can be defined as

$$\beta_j(x_p)=\frac{\mu_{A_j}(x_p)}{\sum_{j=1}^m\mu_{A_j}(x_p)},\ j=1,\ldots,m, \tag{6}$$

if the partition of unity is assumed.

A model parameter estimation using l_∞-norm as a criterion for the measure of the modelling error will be considered next. Let $\mathbf{C}\subset\mathbb{R}^{n+2}$ be a compact set and $\mathcal{G}=\{g:\mathbf{C}\rightarrow\mathbb{R}\}$ be a class of nonlinear functions. Let us assume that there exist the exact upper bound $\overline{g}$ and the exact lower bound $\underline{g}$ that satisfy the following conditions for an arbitrary $\varepsilon>0$ and for each $\boldsymbol{z}=[x_p\ \boldsymbol{x}^T]^T$:

$$\overline{g}(\boldsymbol{z})\geq\max_{g\in\mathcal{G}}g(\boldsymbol{z}),\ \exists g\in\mathcal{G}:\overline{g}(\boldsymbol{z})<g(\boldsymbol{z})+\varepsilon \tag{7}$$

$$\underline{g}(\boldsymbol{z})\leq\min_{g\in\mathcal{G}}g(\boldsymbol{z}),\ \exists g\in\mathcal{G}:\underline{g}(\boldsymbol{z})>g(\boldsymbol{z})+\varepsilon \tag{8}$$

Obtaining the bounds in Eqs. (7) and (8) would require an infinite amount of data; however, in this case we are limited to the finite set of measured output values $\mathbf{Y}=\{y_1,y_2,\ldots,y_N\}$ and the finite set of input data $\mathbf{Z}=\{z_1,z_2,\ldots,z_N\}$:

$$y_i=g(z_i),\ g\in\mathcal{G},z_i\in\mathbf{C}\subset\mathbb{R},y_i\in\mathbb{R},i=1,\ldots,N \tag{9}$$

Therefore, the upper and the lower boundary functions are approximated by fuzzy functions in the form given by Eq. (5). Extending the Stone-Weierstrass Theorem [11], there exist fuzzy systems $\overline{f}$ and $\underline{f}$ such that

$$0<\overline{f}(z_i)-g(z_i)<\varepsilon,\quad\forall i,\\ -\varepsilon<\underline{f}(z_i)-g(z_i)<0,\quad\forall i. \tag{10}$$

The main requirement when defining the band is that it is as narrow as possible, within the proposed constraints.

To estimate the optimal parameters of the proposed fuzzy function the minimization of the maximum modelling error ε in Eq. (10) over the whole input set $\mathbf{Z}$ is performed. This implies the *min-max* optimization method, and l_∞-norm is used as the modelling error measure, yielding

$$\min_{\underline{\boldsymbol{\Theta}}}\max_{z_i\in\mathbf{Z}}\left|y_i-\underline{f}(z_i)\right|\ \text{s.t.}\ y_i-\underline{f}(z_i)\geq 0,\\ \min_{\overline{\boldsymbol{\Theta}}}\max_{z_i\in\mathbf{Z}}\left|y_i-\overline{f}(z_i)\right|\ \text{s.t.}\ y_i-\overline{f}(z_i)\leq 0. \tag{11}$$

where $\underline{f}(z_i)=\boldsymbol{\beta}^T\underline{\boldsymbol{\Theta}}\boldsymbol{x}(z_i)$ and $\overline{f}(z_i)=\boldsymbol{\beta}^T\overline{\boldsymbol{\Theta}}\boldsymbol{x}(z_i)$. Note that the data are obtained by sampling different functions from $\mathcal{G}$ with arbitrary values of z_i. The solutions to both problems can be found by linear programming, because both problems can be viewed as linear programming problems, and this brings simplicity to the realization of the optimizing process.

C. Residual formation and fault-isolation scenario

The main idea of the fault-detection approach is to filter both the input and the output data, thus obtaining a confidence band of filtered input-output data pairs, approximate the band using the optimization procedure of the INFUMO, and connect as many INFUMOs as there are outputs in parallel to the process to get online estimations of the boundary outputs. For fault detection, the decision functions should consist of verifying that each measurement belongs to the corresponding confidence band. In order to provide quantitative information about the proximity of the measurements to the closest interval bound, distances were used, as presented in [3]. If a filtered output value $y_{fi}(t)$ belongs to the corresponding interval $\left[\underline{y}_{fi}(t), \overline{y}_{fi}(t)\right]$, and if the mean interval value is denoted $\tilde{y}_{fi}(t)$, the proposed distance is defined in the following way:

$$\begin{aligned} \text{if } y_{fi}(t) < \tilde{y}_{fi}(t),\ d(y_{fi}) &= \frac{y_{fi}(t) - \tilde{y}_{fi}(t)}{\underline{y}_{fi}(t) - \tilde{y}_{fi}(t)} \\ \text{if } y_{fi}(t) > \tilde{y}_{fi}(t),\ d(y_{fi}) &= \frac{y_{fi}(t) - \tilde{y}_{fi}(t)}{\overline{y}_{fi}(t) - \tilde{y}_{fi}(t)} \end{aligned} \tag{12}$$

The distance in (12) is zero when the measurement is equal to $\hat{y}_f$, and approaches the value 1 if the measurement is close to one of the interval bounds. A fault $f_i = 1$ is signalled every time $d(y_{fi})$ exceeds the value 1, and $f_i = 0$ otherwise. For fault isolation purposes the fault signals are characterized by an incidence matrix. The rows of this matrix belong to residuals and its columns are obtained in response to the particular faults. The structure is isolating if columns are different. In our case, a fault is characterized by a corresponding 3-digit binary number where fault signals f_i are the multiples of succesive powers of number 2 (2^{i-1}). Fig. 1 gives a schematic representation of the proposed fault-isolation system. The block denoted LPF represents a linear filter, and the distances are calculated in the DIST blocks, connected to the outputs of the INFUMOs. The output of the block denoted Fault isolation logic, f, is a sum of the products of the fault signals $f = f_1 \cdot 2^0 + f_2 \cdot 2^1 + f_3 \cdot 2^2$.

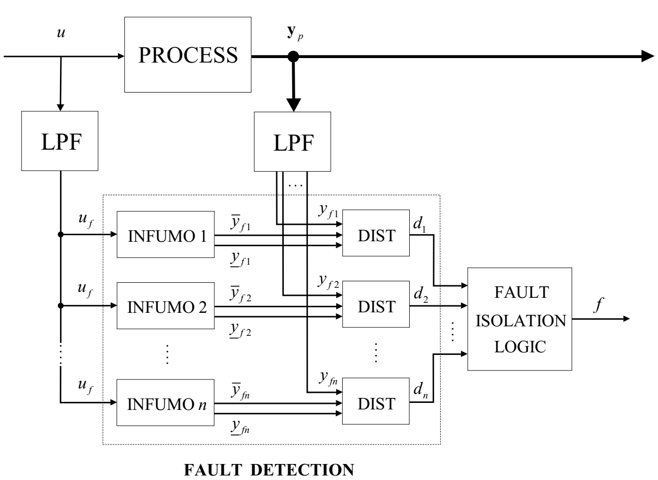

Fig. 1. Fault-isolation system using INFUMO models for FD

III. Simulation example

In this section the benefits of the proposed method will be illustrated by a simulation example. A well-known benchmark problem will be considered. It deals with a laboratory plant using two tanks with fluid flow, as was described in [12]. The two cylindrical tanks are identical, with a cross section $A_s = 0.0154$ m^2. The cross section of the connection pipe and the outlet pipe is $S_{p1} = S_{p2} = 3.6 \cdot 10^{-5}$ m^2, and the liquid levels in the two tanks are denoted h_1 and h_2, respectively. The plant-setup scheme is presented in Fig. 2. The supplying flow rates coming from an electric pump to tank 1 are denoted $q_1(t)$, and there is an outflow from tank 2 denoted $q_2(t)$. Using the mass balance equations and Toricelli's rule, the following equations are obtained:

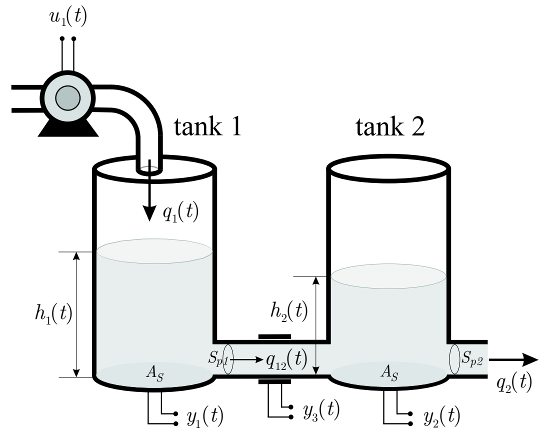

Fig. 2. Two-tank laboratory plant

$$\begin{aligned} \dot{h}_1 &= \frac{1}{A_s}\left(-K_{p1}\text{sign}(h_1 - h_2)\sqrt{2g|h_1 - h_2|} + q_1\right) \\ \dot{h}_2 &= \frac{1}{A_s}\left(K_{p1}\text{sign}(h_1 - h_2)\sqrt{2g|h_1 - h_2|} - K_{p2}\sqrt{2gh_2}\right) \end{aligned} \tag{13}$$

where $K_{p1} = a_1 S_{p1}$ and $K_{p2} = a_2 S_{p2}$ denote the outflow constants, and g is the gravity acceleration. Let $a_1 = a_2 = 1$ for the sake of simplicity.

To get an input-output system that is similar to industrial processes the model will be modified in the following way. The input to the system is the electric-pump voltage $u_1(t)$ that produces the inlet flow

$$q_1(t) = K_u\big(1 + \nu_1(t)\big)u_1(t), \tag{14}$$

where K_u is the voltage-to-flow-conversion constant, and $\nu_1(t)$ denotes the inaccuracy of the conversion. The first two measurable output signals are the voltages of the pressure sensors, converting the fluid levels $h_1(t)$ and $h_2(t)$ in tanks 1 and 2 into the output voltages $y_1(t)$ and $y_2(t)$ according to the following equation:

$$\begin{aligned} y_1(t) &= K_{h1}\big(1 + \nu_2(t)\big)h_1(t) \\ y_2(t) &= K_{h2}\big(1 + \nu_3(t)\big)h_2(t), \end{aligned} \tag{15}$$

where K_{h1} and K_{h2} are the height-to-voltage-conversion constants, and $\nu_2(t)$ and $\nu_3(t)$ denote the inaccuracies of the conversion. The third output is the voltage $y_3(t)$ produced by a flow-meter mounted on the connection pipe. The flow $q_{12}(t)$ is transformed into voltage following the equation

$$y_3(t) = K_q\big(1 + \nu_4(t)\big)q_{12}(t), \tag{16}$$

where K_q and $\nu_4(t)$ are presented analogously as in (15). The values of the constants are $K_u = 8.8 \cdot 10^{-6}$ m^3/Vs, $K_q = 1.1364 \cdot 10^5$ Vs/m^3 and $K_{h1} = K_{h2} = 16.667$ V/m, and the upper bounds of the inaccuracies are $\overline{\nu}_1 = \overline{\nu}_2 = \overline{\nu}_3 = \overline{\nu}_4 = 0.03$.

The set of faults under consideration will follow the examples presented in [14] and [12], with the exception of three additional sensor faults that will serve as an efficiency test for the proposed fault-isolation system. The following faults will be considered:

- **Leakage in tank 1**. The leak is assumed to be circular in shape and of unknown radius r_1. As a consequence, the outflow rate of the unknown-size leak is $q_{f1} = a_1\pi(r_1)^2\sqrt{2gh_1}$.
- **Leakage in tank 2**. Analogously to the case of leakage in tank 1, the outflow rate is $q_{f2} = a_2\pi(r_2)^2\sqrt{2gh_2}$.
- **Offset in sensor 1**. A simple multiplicative sensor fault is assumed by letting the actual voltage value be described by $\bar{y}_1(t) = y_1(t) + (1 - K_{1off})y_1(t)$, where $y_1(t)$ is the voltage in the non-fault case, and $K_{1off} \in [0, 1]$ is the fault constant.
- **Offset in sensor 2**. Analogously to the case of the offset in sensor 1, the actual voltage is described by $\bar{y}_2(t) = y_2(t) + (1 - K_{2off})y_2(t)$.
- **Offset in sensor 3**. Analogously to the previous cases, the actual voltage is described by $\bar{y}_3(t) = y_3(t) + (1 - K_{3off})y_3(t)$.

With reference to the given INFUMO identification procedure, a confidence band of input-output data must be defined. This band will also include all unexpected output deviations due to parameter uncertainties. A set of 20 experiments was carried out. The inputs and associated signals from the first output are shown in Fig. 3, and the associated signals from the other two outputs are presented in Fig. 4. For the sake of brevity, only the first, the second, and the last data sets are presented. One of the major benefits of the interval fuzzy model identification, shown in Fig. 3, is that the input signals can be arbitrary.

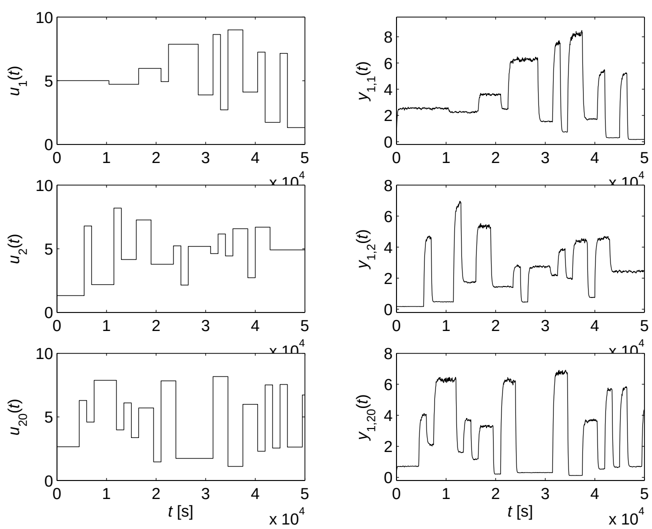

Fig. 3. The inputs and first output signals: the first, the second, and the last experiment

The input and output signals are lead through a low-pass filter (LPF) whose structure was chosen as a simple first-order system, represented by the transfer function $G_f = 1/(T_f s + 1)$. The optimal design of the LPF time constant was not considered in this study. The cut-off frequency ω_f was chosen according to the absolute values of the Fourier transforms of the output signals. Hence, the filter time constant was defined as $T_f = 1/\omega_f = 800$ s. This way three compact sets of measurements that represent steady-state system behaviours are obtained. They can be seen as approximations of static input-output mapping areas. Plots in Fig. 5 present the areas.

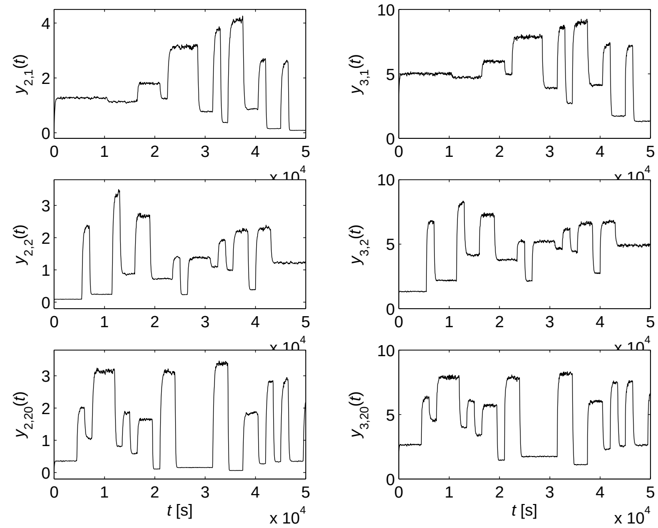

Fig. 4. The second and the third output signals: the first, the second, and the last experiment

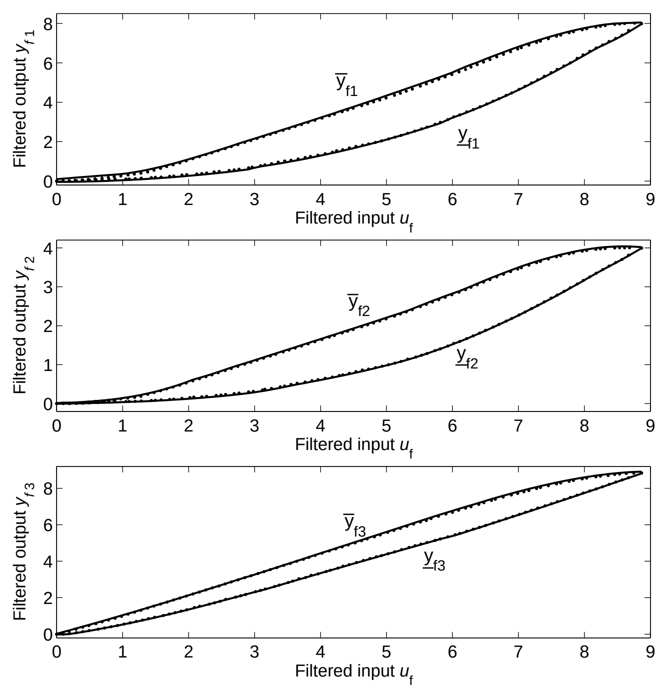

Fig. 5. Set of filtered input-output data with boundary points and boundary INFUMO functions for the first, second and third outputs

To avoid the problems with optimization convergence due to vast amount of input-output data, a simple data-reduction method was performed to determine the boundary points. The range of input measurements was divided into subspaces of equal length that was chosen in accordance to the subspace with the highest data density. In each subspace the extremal points were determined. Due to space limitations only the resulting sets of boundary points are shown in the plots of figure 5. These data were used as the training data set for the INFUMO identification. Static INFUMOs were employed. This brings additional reduction of the number of fuzzy parameters to be optimized. The membership functions of the INFUMO antecedent variables were of triangular shape and arranged using grid partitioning [1]. According to the data-area shape, it was sufficient to use 4 fuzzy subsets for the upper and lower fuzzy functions. The membership functions are presented in figure 6.

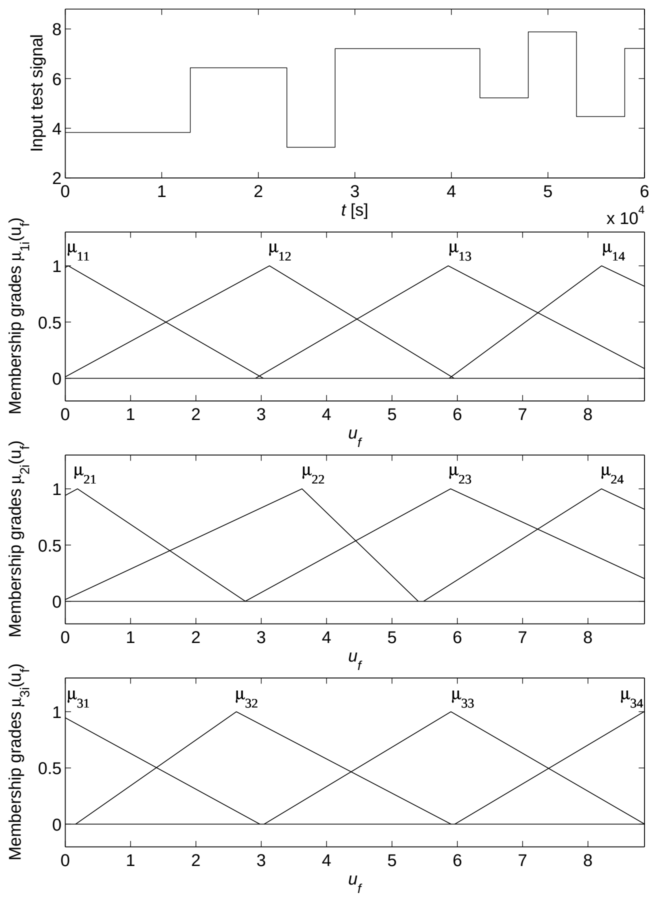

Fig. 6. Input test signal and membership-function arrangement for the INFUMOs

The parameters were optimized using the proposed INFUMO optimization algorithm in (11). The resulting boundary functions can be seen in figure 5. It is evident that the *min-max* optimization gave satisfactory results in approximating the given area.

To realize a fault-isolation system, the INFUMOs are connected to the process in parallel, as shown in Fig. 1. In the test experiment a leakage of $r_1 = 2 \cdot 10^{-3}$ m in tank 1 is assumed to occur in the time period $t_{leak1} = 10000 - 15000$ s, a leakage of $r_2 = 2 \cdot 10^{-3}$ m in tank 2 at $t_{leak2} = 20000 - 25000$ s, a 20% offset in sensor 1 ($K_{1off} = 0.2$) at $t_{1off} = 30000 - 35000$ s, a 20% offset in sensor 2 ($K_{2off} = 0.2$) at $t_{2off} = 40000 - 45000$ s, and a 20% offset in sensor 3 ($K_{3off} = 0.2$) at $t_{3off} = 50000 - 55000$ s, respectively. The input test signal is presented in the upper plot of Fig. 6. According to the fault signals from the DIST blocks, the incidence matrix was defined as given in Table I.

TABLE I
INCIDENCE MATRIX FOR THE SET OF FAULTS

Fault	Leak 1	Leak 2	Offset 1	Offset 2	Offset 3
f_1	1	1	1	0	0
f_2	1	1	0	1	0
f_3	1	0	0	0	1
f	7	3	1	2	4

The results of the test are presented in figures 7 to 9. The upper diagrams demonstrate the distance-calculation, and in the lower diagrams the filtered process outputs y_{fi} and the INFUMO boundary functions $\overline{y}_{fi}$, $\underline{y}_{fi}$ are shown.

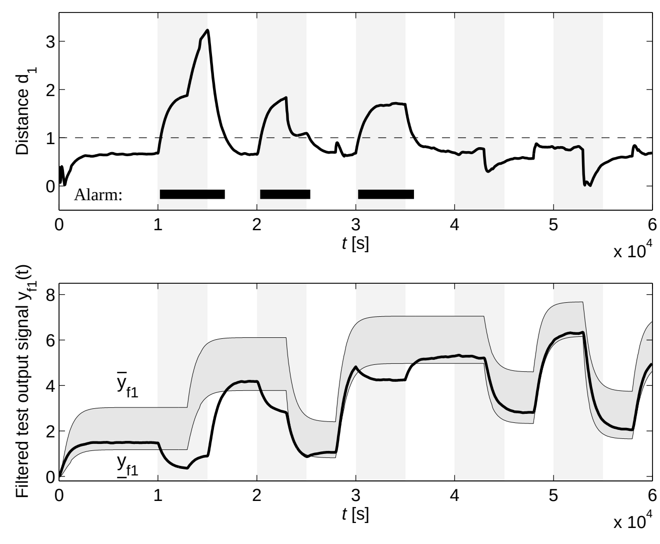

Fig. 7. Results of the fault detection with INFUMO1

The proposed FD system using the INFUMOs successfully tracks the filtered output crossings of the permitted bands. In the shaded areas, faults are declared with a reasonably small time delay, depending on the time constant of the proposed low-pass filter. The result of the fault-isolation system is presented in 10.

It can be seen that the FDI system successfully tracks and characterizes all the faults from the given set.

IV. CONCLUSION

A novel approach of the fault detection and isolation for a class of nonlinear input-output systems was presented. The interval fuzzy model (INFUMO), formerly used in robust identification of nonlinear functions, was applied in the residual generation stage of the FDI. The benefit is to

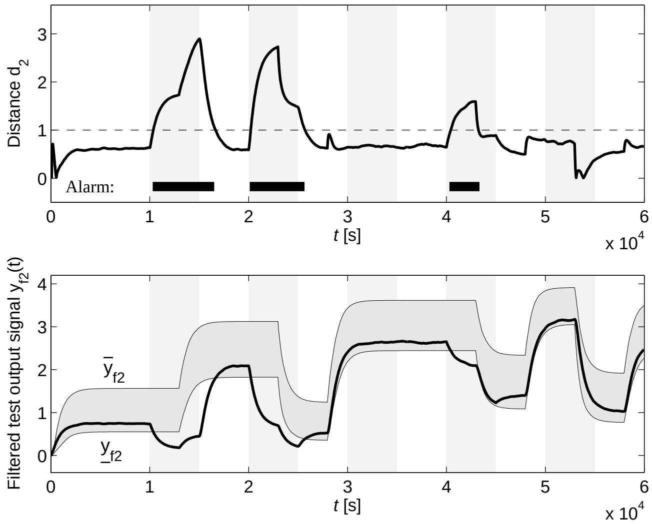

Fig. 8. Results of the fault detection with INFUMO2

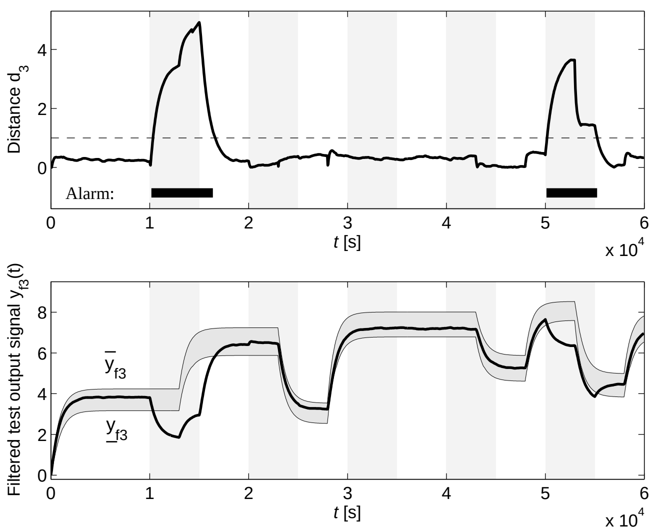

Fig. 9. Results of the fault detection with INFUMO3

be able to model a family of system responses from the confidence band, already including the effects of uncertainties, that is based only on the input-output data. Applying low-pass filtering when obtaining the input-output data set makes it possible to use relatively simple fuzzy structure of the INFUMO, without any significant loss in FD-stage efficiency. The presented example illustrates that by using the INFUMO-based approach, faults can be successfully isolated, even though only a limited amount of the input-output data is available.

Investigating the performance changes resulting from different choices of filter structure, applying the proposed method on a broader range of systems, and investigating possible extensions to frequency-based methods and fault-tolerant control deserves further attention. In addition, the results of the simulated example demonstrate the quality of performance coupled with simplicity of application, which is very important from the application point of view.

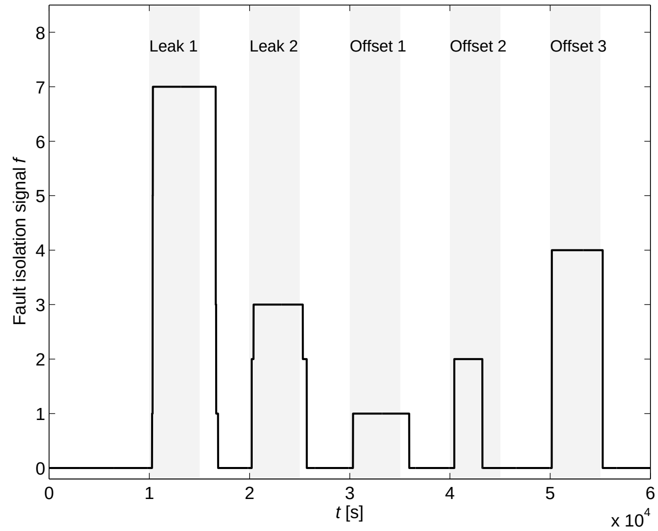

Fig. 10. Results of the fault isolation with a bank of INFUMOs

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