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STRUCTURAL MODELING AND FUZZY-LOGIC BASED DIAGNOSIS OF A SHIP PROPULSION BENCHMARK

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Abstract: An analysis of structural model of a ship propulsion benchmark leads to identifying the subsystems with inherent redundant information. For a nonlinear part of the system, a Fuzzy logic based FD algorithm with adaptive threshold is employed. The results illustrate the applicability of structural analysis as well as fuzzy observer.

Keywords: Structural analysis, Fuzzy logic, Fuzzy observer, fault detection, adaptive threshold, Ship benchmark.

1. INTRODUCTION

In complex systems, continued operation of various subsystems has both economic and safety implications. The primary objective of Fault-Tolerant Control (FTC) systems is to handle faults and discrepancies by accommodating for them whenever they occur. Detection and Isolation of abnormal situations are thus the first stages for FTC. The issue of obtaining information about various parameters and signals, which have to be monitored for fault detection purposes, becomes a rigorous task with the growing number of subsystems. The structural approach (Cassar *et al.*, 1994); (Declerck and Staroswiecki, 1991), presented in this paper, constitutes a general framework for providing information when the system becomes complex. The main objective of applying the structural approach is to identify the subsystems with inherent redundant information. The methodology of this approach is illustrated on the ship propulsion benchmark. The redundant information has to be analyzed by using an appropriate FD algorithm. The paper illustrates the procedure of constructing a fuzzy observer (for a part of the system) in order to generate a residual. An Fuzzy adaptive observer is used to handle the changes in the plants dynamic. Two faults in this subsystem is considered and the isolation possibilities are discussed.

2. BUILDING THE STRUCTURAL MODEL

Consider the system S as a set of components $\bigcup_{i=1}^{m} \mathsf{C}_i$, each imposing a relation f_i between a set of variables and parameters $z_j, j = 1, .., n$ i.e.

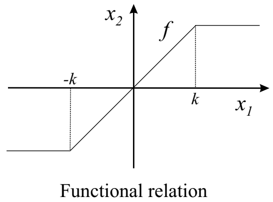

Fig. 1. Calculability property for a nonlinear relation.

$$f_i(z_1, .., z_p) = 0, \qquad 1 < p \leq n \tag{1}$$

where f_i can represent a dynamic, static, linear, or non-linear relation. These relations are also called constraints as the value of an involved variable can not change independent of the other involved variables (Cassar *et al.*, 1994) (also see (Declerck and Staroswiecki, 1991) and (Blanke *et al.*, 2000 (to appear))). The system's structural model is represented by the set of constraints $\mathcal{F} = \{f_1, f_2, \cdots, f_m\}$ and the set of variables $\mathcal{Z} = \mathcal{K} \cup \mathcal{X} = \{z_1, z_2, \cdots, z_n\}$. $\mathcal{X}$ is the set of unknown variables and $\mathcal{K} = \mathcal{U} \cup \mathcal{P} \cup \mathcal{Y}$ is the set of known variables/parameters i.e. input/reference signals ($\mathcal{U}$), known constant/parameters ($\mathcal{P}$), and measured signals ($\mathcal{Y}$). Before defining the structural model of the system, it is important to address the calculability property that is illustrated by following simple example:

Example 1. The function f in Fig. 1 represents a surjective mapping from x_1 onto x_2. This mapping is not bijective, i.e. the values for the variable x_2 are always calculable for given values of x_1, but the inverse is not always possible.

The calculability property is defined by the following definition:

Definition 2. **Calculability:** Let $z_j, j = 1, \cdots, p, \cdots, n$ be variables that are related through a constraint f_i, e.g. $f_i(z_1, \cdots, z_p, \cdots, z_n) = 0$. The variable z_p is calculable if its value can be determined through the constraint f_i under the condition that the values of the other variables $z_j, j = 1, \cdots, n, j \neq p$ are known.

Using the following notation, the structural model is defined:

Notation: Since all elements in $\mathcal{K}$ are known they can be assumed to stem from an information source. This source is denoted by K, hence $\mathcal{Z} = \mathcal{X} \bigcup K$.

Definition 3. The structure graph of the system is a bipartite directed graph $\big((K \bigcup \mathcal{F} \bigcup \mathcal{X}), (K \bigcup \mathcal{F} \bigcup \mathcal{X}), \mathcal{A}\big)$ where the elements in the set of $\mathcal{A} \subset (K \bigcup \mathcal{F} \bigcup \mathcal{X}), (K \bigcup \mathcal{F} \bigcup \mathcal{X})$ are defined by:

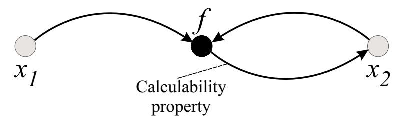

Fig. 2. bipartite directed graph model of ex. 1.

$$\begin{cases} a_{ij} = (f_i, x_j) = 1 & \text{iff } f_i \text{ applies to } x_j, \\ a^*_{ij} = (x_i, f_j) = 1 & \text{iff } x_i \text{ is calculable through } f_j \\ kf_i = (K, f_j) = 1 & \text{iff } f_j \text{ applies on a known var.} \\ 0 & \text{Otherwise.} \end{cases} \tag{2}$$

The corresponding incidence matrix $\mathbf{I_{md}}$ is shown below

$$\mathbf{I_{md}} = \begin{bmatrix} 0 & \begin{bmatrix} kf_1 & \cdots & kf_m \end{bmatrix} & \mathbf{0} \\ \begin{bmatrix} kf_1 \\ \vdots \\ kf_m \end{bmatrix} & \mathbf{0} & \begin{bmatrix} a_{11} & \cdots & a_{1|\mathcal{X}|} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{m|\mathcal{X}|} \end{bmatrix} \\ \mathbf{0} & \begin{bmatrix} a^*_{11} & \cdots & a^*_{1m} \\ \vdots & \ddots & \vdots \\ a^*_{|\mathcal{X}|1} & \cdots & a^*_{|\mathcal{X}|m} \end{bmatrix} & \mathbf{0} \end{bmatrix} \tag{3}$$

that in the compact form can be written as:

$$\begin{array}{c c} & \begin{matrix} K & \mathcal{F} & \mathcal{X} \end{matrix} \\ \begin{matrix} K \\ \mathcal{F} \\ \mathcal{X} \end{matrix} & \begin{bmatrix} 0 & \mathbf{KF} & \mathbf{0} \\ \mathbf{KF}^T & \mathbf{0} & \mathbf{A} \\ \mathbf{0} & \mathbf{A}^* & \mathbf{0} \end{bmatrix} \end{array} = \mathbf{I_{md}} \tag{4}$$

where $a_{ij}, a^*_{ij}, kf_i \in \{0, 1\}$ in $\mathbf{I_md}$ represents the elements in $\mathcal{A}$. Figure 2 shows the bipartite directed graph model of example 1. The constraint in the example is:

$$f(x_1, x_2) = 0$$

with $K = \{\}$, $\mathcal{Z} = \{x_1, x_2\}$, $\mathcal{F} = \{f\}$ and

$$\mathbf{I_md} = \begin{array}{c c} & \begin{matrix} K & f & x_1 & x_2 \end{matrix} \\ \begin{matrix} K \\ f \\ x_1 \\ x_2 \end{matrix} & \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \end{array}$$

The ultimate aim of representing the system in terms of a structured graph is to obtain knowledge about the parts/subsystems with inherent redundant information that exists within the system. These parts can be analyzed in detail and the redundant information can then be used for FDI as well as fault accommodation purposes. By applying matching on the obtained structured graph one can decompose the system into parts with redundant information and parts with no redundant information (see (Declerck and Staroswiecki, 1991), (Blanke *et al.*, 2000 (to appear)) for more details).

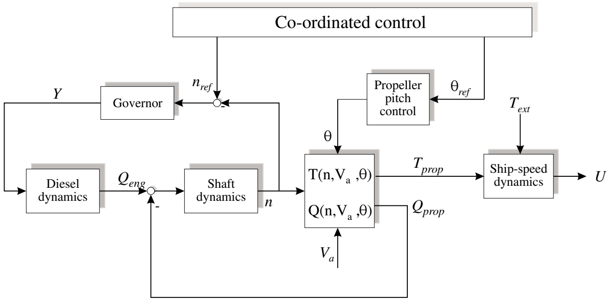

Fig. 3. Diagram of the ship propulsion system.

3. SHIP BENCHMARK

The ship benchmark is described in (Izadi-Zamanabadi and Blanke, 1998) and (Izadi-Zamanabadi and Blanke, 1999). An outline of the propulsion system is shown in Fig. 3 To exemplify the described method in previous section only the torque related equations are mentioned below:

$$
\begin{array}{ll}
\mathsf{C}_1: f_1(\theta,\theta_m)=0: & \theta=\theta_m \\
\mathsf{C}_2: f_2(n,n_m)=0: & n=n_m \\
\mathsf{C}_3: f_3(Y,Y_m)=0: & Y=Y_m \\
\mathsf{C}_4: f_4(k_y,K_y)=0: & k_y=K_y \\
\mathsf{C}_5: f_5(Y,k_y,Q_{eng})=0: & Q_{eng}+\tau_c\dot{Q}_{eng}=k_yY \\
\mathsf{C}_6: f_6(Q_{eng},Q_{prop},\dot{n})=0: & I_m\dot{n}=Q_{eng}-Q_{Prop} \\
\mathsf{C}_7: f_7(\dot{n},n)=0: & n=\int\dot{n}+n_0 \\
\mathsf{C}_8: f_8(n,\theta,U,Q_{prop})=0: & Table^* \\
\mathsf{C}_9: f_9(U,U_m)=0: & U=U_m
\end{array}
\tag{5}
$$

θ is propeller pitch, n and U denote shaft and ship speed, Y is the fuel index, K_y is the engine gain, and Q_{eng} and Q_{prop} are the engine and propeller developed torque. the data in the $Table^*$ can be approximated by the following bilinear relation (Blanke, 1981):

$$Q_{prop}=Q_{nn}(\theta)|n|n+Q_{nU}(\theta)|n|U(1-w)$$

w is the wake fraction parameter. The structured system is $\mathsf{S}=\bigcup_{i=1}^{9}\mathsf{C}_i$, $\mathcal{F}=\mathcal{F}_{\mathcal{X}}=\{f_1,f_2,\cdots,f_9\}$, $\mathcal{K}=\{\theta_m,n_m,Y_m,U_m,K_y\}$, $\mathcal{X}=\{U,\theta,n,Y,k_y,U,Q_{prop},Q_{eng}\}$, and $\mathcal{Z}=\mathcal{K}\bigcup\mathcal{X}$. The measurement noise is disregarded here, hence $\theta_m=\theta$ and $n=n_m$ and $\cdots$.
By performing the matching on the complete system three subsystems with inherent redundant information are obtained. These subsystems are: the pitch propeller control loop (Fig. 4 a)), the subsystem involving the thrust equation and the ship speed dynamics (Fig. 4b)), and the subsystem involving the torque equation (Fig. 4c)). A detailed example of how to perform the matching can be found in (Izadi-Zamanabadi, 1999) and (Blanke *et al.*, 2000 (to appear)). It appears that all defined faults in (Izadi-Zamanabadi and Blanke, 1999) are covered by these subsystems, hence it should be possible to detect and isolate these faults. If a fault is not covered by any of the subsystems that are obtained by matching, then the fault is neither detectable nor isolable. The following section deals with designing a FDI algorithm in order to detect faults in the shaft speed (Δn) and the engine gain (Δk_y) under the assumption that the propeller pitch measurements are not faulty.

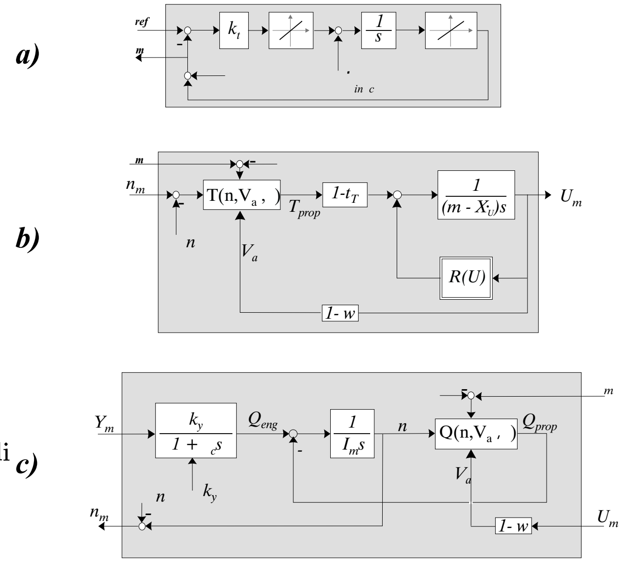

Fig. 4. The parts of the system with (possible) redundant information. Each part corresponds to one over-determined subsystem obtained by structural analysis approach.

4. FAULT DETECTION WITH FUZZY OBSERVER

The structural analysis, described in the previous section, enables the designer to identify the parts of the system that have inherent redundant information. The next step would be to manipulate this information for FDI purposes. This is done by employing a Fuzzy observer in this section. In the following, the architecture of an Adaptive Neuro-Fuzzy Inference system (ANFIS) is briefly described.

4.1 *A Neuro-Fuzzy model*

For simplicity assume a system with two inputs, u_1 and u_2, and one output, y. Let U_1 and U_2 be the *universe of discourse* (the range) for u_1 and u_2. A Fuzzy set A_1 in the universe of discourse U_1 is defined as a set of ordered pairs:

$$A_1=\{(u_1,\mu_{A_1}(u_1)) \quad | \quad u_1\in U_1\}$$

where $\mu(u_1)$ is called the membership function (MF) of u_1 in A_1. A trapezoidal MF is defined by the following function in the simulations:

$$
\begin{aligned}
\mu(x) &= f(x,a,b,c,d) \\
&= \max\big(\min(\frac{x-a}{b-a},1,\frac{d-x}{d-c}),0\big)
\end{aligned}
$$

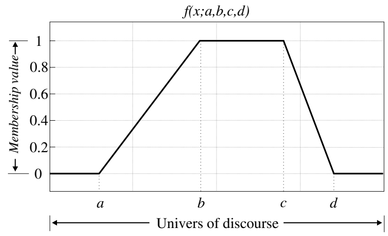

Fig. 5. The trapezoidal membership function.

The parameters a, b, c, and d are shown in Figure 5. Assume a first order Sugeno type of rule base with the following two rules.

$$\begin{aligned} &\text{IF } u_1 \text{ is } A_1 \text{ AND } u_2 \text{ is } B_1 \text{ THEN} \\ &\quad y_1 = c_{11}u_1 + c_{12}u_2 + c_{10} \\ &\text{IF } u_1 \text{ is } A_2 \text{ AND } u_2 \text{ is } B_2 \text{ THEN} \\ &\quad y_1 = c_{21}u_1 + c_{22}u_2 + c_{20} \end{aligned}$$

Let the firing strengths of the rules be denoted by α_1 and α_2 respectively, for the given values of the input signal u_1 and u_2, the overall rule output is computed as a weighted average.

$$y = \frac{\alpha_1 y_1 + \alpha_2 y_2}{\alpha_1 + \alpha_2} = \bar{\alpha}_1 y_1 + \bar{\alpha}_2 y_2$$

where α_1 and α_2 are the firing level of their corresponding rules.

4.2 *Choice of the model (input and output)*

The focus in this subsection is on the (torque) subsystem, which dynamics is shown in Fig. 4c).The figure shows clearly the inputs and the outputs for the fuzzy model. The next step for building the fuzzy model is to determine those signals that influence the actual output directly, i.e. the fuzzy model structure. By choosing an appropriate number of signals one avoid an oversized model with its corresponding heavy computation time. An oversized model would also have ineffectual rules, that are not excited during the identification stage. The model structure may be known a priori, for instance through the knowledge of a human expert, or it can be obtained by using different methods. In one method, the model can be chosen based on the estimation error achieved by different models and different time delays. In other methods the statistical property (covariance, correlation) of the signals are used to determine the number of needed signals. The method in this section, is based on the linearized version of the sub-system, and also knowledge about the intended use of the model. The method is described in the following.

Linearizing the shaft speed dynamics around an operational point, when the quadratic approximation of the propeller torque is used (see (Izadi-

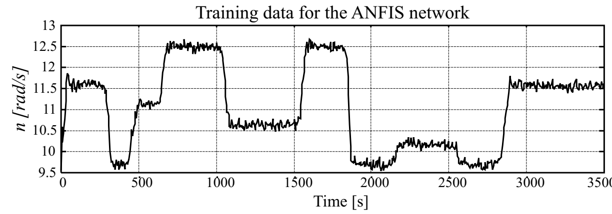

Fig. 6. Training data for the Adaptive Neuro-fuzzy Inference System (ANFIS) network.

Zamanabadi and Blanke, 1998)), results in the following transfer function:

$$n(s) = \frac{k_n}{1 + \tau_n s}\big(k_y Y(s) + b_u U(s) + b_\theta \theta(s)\big)$$

where k_n, τ_n, b_u and b_θ are the parameters whose values depend on the systems operating point. By discretizing the transfer function and performing simple manipulations, following model was obtained:

$$\begin{aligned} n(k+1) = f\big(&Y(k), Y(k-1), \theta(k), \theta(k-1), \\ &U(k), U(k-1)\big) \end{aligned}$$

Further analysis showed that since the dynamics of the ship speed was much slower that the shaft speed, it was sufficient to only use $U(k)$ and omit $U(k-1)$ from the model. Removing this signal also resulted in significant reduction in learning time. The final model was chosen to be:

$$n(k+1) = f\big(Y(k), Y(k-1), \theta(k), \theta(k-1), U(k)\big)$$

4.3 *Training result*

In order to use the fuzzy model one needs to specify its inference system for training. Available knowledge can be used to define the membership functions parameters and shape. An alternative method is to define number and type of the membership functions and use a program, such as programs in the Fuzzy logic Tool-box in MATLAB™ , to automatically generate the optimal fuzzy inference system based on the training data. The second option was used here, as training data were available. In this context, one should notice that it is also important to choose the correct number of membership functions for each input. Choosing too few membership functions results in insensitivity of the model to the systems dynamics, while choosing too many results in an oversized model that becomes actually over-sensitive to the signals. By testing the system with various number and type of membership functions, the "best" structure was found. This structure of the Fuzzy observer is shown in table 4.3. Training data is obtained from a simulation model of a Danish ferry's propulsion system, wherein the tables of real data from the sea trial are incorporated

(Izadi-Zamanabadi and Blanke, 1998). The output signal for the training data is shown in Fig. 6.

Table 1. The structure of the fuzzy model. Membership functions are denoted by **MF**.

Signal	Nr. of MF	Type of MF
$\theta_m(k)$	2	Trapezoidal
$\theta_m(k-1)$	2	Trapezoidal
$U_m(k)$	2	Trapezoidal
$Y_m(k)$	3	Trapezoidal
$Y_m(k-1)$	3	Trapezoidal

4.4 *An adaptive threshold*

A Fuzzy based approach, which is used for robust threshold selection for fault detection, has been described in (Frank, 1996). The adaptive threshold consists of a predefined (but constant) value, T_{F0}, and an adaptive term, ΔT_F, which is determined by heuristic knowledge. The threshold is determined by:

$$T_F(y,u) = T_{F0} + \Delta T_F(y,u)$$

The term T_{F0} represents an optimal threshold for the nominal process. The adaptive term, $\Delta T_F(y,u)$ incorporates the effect of modeling errors and uncertainties. For the benchmark, the change in the dynamics is mainly responsible for the modeling error. This can adequately be addressed by representing the adaptive part as a function of rate change in the reference signals for the propeller pitch and the shaft speed, hence $\Delta T_F(\Delta n_{\text{ref}}/\Delta T, \Delta\theta_{\text{ref}}/\Delta T)$. In the "*Economy*" operational mode of the plant, since the change in the reference signals are obtained simultaneously, it is sufficient to use one of the reference signals. Taking this into account and using the fact that the reference signal for the propeller pitch is additionally affected by the overload module, it is appropriate to choose the adaptive part as a function of rate of change in pitch reference signal.The threshold is hence determine by:

$$T_F(\Delta\theta_{\text{ref}}/\Delta T) = T_{F0} + \Delta T_F(\Delta\theta_{\text{ref}}/\Delta T) \quad (6)$$

The first term T_{F0}, is determined by considering the obtained residual in the non-faulty situation and where the rate change in pitch reference is equal zero:

$$T_{F0} > \max\left(abs(\epsilon_n(k))\right), \qquad k \in [0 \cdots N]$$
$$\textit{and} \qquad \frac{\Delta\theta_{\text{ref}}}{\Delta T} = 0,$$

The time period is $[T_0 \cdots T_N]$. For this residual the following two simple rules are used:

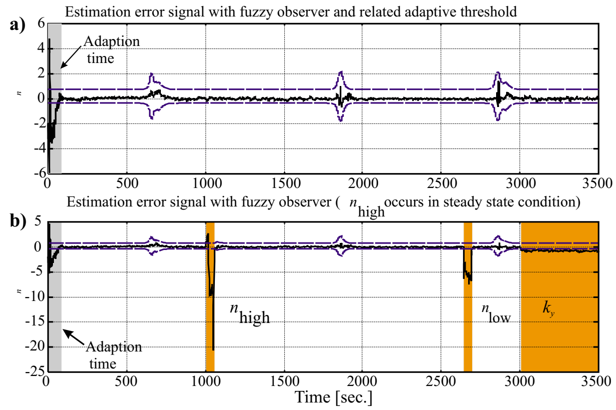

Fig. 7. Estimation error signal for the shaft speed when a fuzzy observer is used. a) non-faulty case and b) faulty case where Δn_{high} occurs in the steady state conditions.

IF $\dfrac{\Delta\theta_{\text{ref}}}{\Delta T}$ is Positive_Big THEN ΔT_F is Positive_Big

IF $\dfrac{\Delta\theta_{\text{ref}}}{\Delta T}$ is Negative_Big THEN ΔT_F is Negative_Big

The fuzzy sets, labeled by the linguistic variables "Positive_Big" and "Negative_Big", are represented by trapezoidal membership functions.

4.4.0.1. *remarks* The number of fuzzy rules can vary and it is up to the designer to decide how many rules is needed. In the benchmark case, two rules were found to be sufficient to generate the adaptive threshold. It was, however, necessary to filter the output of the fuzzy rules in order to obtain a smooth behavior. The filter is a low-pass filter with the transfer function: $H(s) = \frac{0.1}{s+0.1}$.

4.5 *Simulation results*

The shaft speed error signal is shown in Figure 7 a), for the non-faulty case. Simulation results show that the error signal changes slightly during the transitional situations when the dynamics of the system is activated. The observations were used during the design and implementation of the fuzzy adaptive threshold. The constant term T_{F0} in Equation 6 is set to $T_{F0} = 0.55$ for the positive threshold and $T_{F0} = -0.35$ for the negative threshold.

Figure 7 b) shows the error signal for the faulty case when Δn_{high} occurs in the steady state conditions. It should be noticed that during the initial start of the fuzzy observer, the calculated error exceeds the threshold as it is shown by the dark gray areas in Figures 7 a) and b). This "adaption time" period should be incorporated in the related FDI module in order to avoid false detection situations.

4.6 *Fault isolation*

Analyzing various simulation results, reveals that it is possible to isolate gain and shaft speed faults from this single residual under certain assumptions and knowledge about the possible/probable occurrence of different faults. This is discussed in the following.

The simulation showed that when the gain fault Δk_y occurs, the mean value of the residual/error signal becomes negative. Hence, when the residual exceeds the positive threshold one can immediately conclude that the shaft speed measurements instrument has failed to function. Additional analysis showed that this case occurs when the shaft speed measurement fails high, i.e. Δn_{high} occurs.

It is quite difficult to isolate Δn_{low} from Δk_y as the occurrence of each results in a drop of the residual value bellow the negative threshold value. In order to distinguish these two cases from each other, one should consider the magnitude of the residual as well as the probability of a gain fault that is bigger than %20 of the nominal gain. The probability of a situation when two or more cylinders drop out simultaneously due to failure is very small and can be neglected. Under the assumption that $\Delta k_y < \%20 k_{yc}$, i.e. at most one cylinder is out of function, the simulations show that the magnitude of the residual in the case when Δn_{low} occurs is much bigger than the case when Δk_y occurs. This feature can appropriately be used to distinguish and isolate these two faults.

The discussion above is solely based on the assumption that only one residual is available. Generating an additional residual would enhance the isolation ability greatly. Consequently, another isolation strategy needs to be adopted.

5. CONCLUSION

The structural approach is presented and applied to the ship propulsion benchmark. Well-defined di-graph theory is employed in this approach which allows developing a software tool that can fully support design engineers. One of the main advantages of this approach is that even course information available on the system (qualitative, quantitative, rules) can be used during all the design phases. Detailed informations are, hence, not necessary to find the monitorable part (overdetermined part) of the system. However, detailed information is needed to compute the residuals.

The (Neuro)Fuzzy observer, which follows the principle of black-box modeling were applied. The prerequisite is having sufficient amount of data for learning the observer. The structure of the observer was then specified. Due to the sensitivity of the fuzzy model/observer to a change in dynamics of the plant, it was necessary to design an adaptive threshold. A Fuzzy adaptive threshold was designed to accommodate for this. It was shown that fault detection and isolation was possible when knowledge about the system behavior in faulty situation, impact of faults on the residuals, and the magnitude of faults are available.
The results underline the importance of gaining detailed knowledge about the system dynamics and its behavior both in the normal as well as the faulty situations. It was shown that it is possible to detect and isolate the specified faults when detailed knowledge is available.

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