SI-ENGINE AIR-INTAKE SYSTEM DIAGNOSIS BY AUTOMATIC FDI DESIGN

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Abstract: Because of environmentally based legislative regulations, diagnosis of automotive engines has become increasingly important. In the design of diagnosis systems, it is important to strive for optimum performance and at the same time, minimize the amount of engineering work required. Therefore, it is desirable to have a highly automated design procedure, in which diagnosis performance is optimized. It is discussed how a diagnosis system for the air-intake system of an SI-engine, can be constructed with the help of automated tools. In particular the problem of residual and threshold selection is addressed. For this a fully automatic algorithm is proposed and it is experimentally shown that the algorithm successfully manage to generate a well functioning diagnosis system.

Keywords: fault diagnosis, fault detection, fault isolation, automotive, modeling

1. INTRODUCTION

In the field of automotive engines, environmentally based legislative regulations such as OBDII (On Board Diagnostics II) and EOBD (European On Board Diagnostics) specifies hard requirements on the performance of the FDI (Fault Detection and Isolation) system. This makes the area a challenging application for model based FDI. In (Nyberg and Nielsen, 1997b), a model based FDI system is constructed for the air intake system of a spark-ignition (SI) engine. In the present work it is discussed how a similar FDI system can be designed automatically.

Model based FDI has received much attention during the last decade, see for example the survey (Patton, 1994). Because of several reasons discussed in (Nyberg and Nielsen, 1997b), it is appealing to approach the diagnosis of the SI-engine air-intake system with model based techniques. Model based FDI for automotive engine diagnosis in general, has been studied in several works, see the survey in (Nyberg and Nielsen, 1997b).

When constructing a model based FDI system for automotive engines, it is desirable to strive for an optimum performance and at the same time minimize the amount of engineering work required. Automotive engines are rarely designed from scratch but often subject to small changes, e.g. for every new model year. Then usually also the diagnosis system needs to be changed. Since this may happen quite often and a car manufacturer typically has many different engine models in production, it is important for the car manufacturers that FDI systems can be reconstructed with minimal amount of work involved.

For manufacturers of independent FDI systems, to be used in independent repair-shops, the situation is even more critical. They need to design FDI systems for a large amount of different car brands and models. This makes it necessary to find procedures such that FDI systems can be constructed with very limited amount of work.

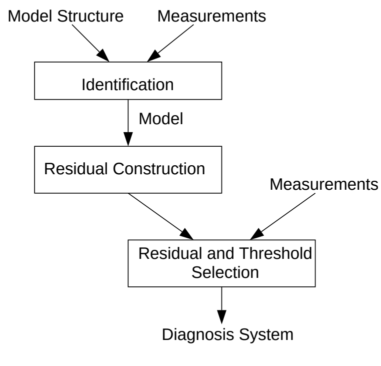

Fig. 1. The process of constructing a FDI system.

Thus the problem of designing FDI systems systematically with minimal amount of work involved, is the motivation for this paper, in which we demonstrate the use of an automated procedure to construct an FDI system for the air-intake system of the SI-engine. In Figure 1, the flow-chart for the process of constructing a model based FDI system is shown. The first part is to construct the model, in which at least parameter identification is possible to automatize. The model construction is described in Section 3. Then from the model, residual generators need to be constructed, which is discussed in Section 4. The last step is to select residual generators to be included and also to select thresholds. This can be treated by a residual and threshold selection (RTS) algorithm that was proposed in (Nyberg and Nielsen, 1997a). In Section 6 an extended version of this algorithm is described and in Section 7, it is applied to the construction of the FDI system for the air-intake system. The resulting FDI system is experimentally evaluated in Section 8.

2. EXPERIMENTAL SETUP

The engine is a 2.3 liter 4 cylinder SAAB production engine mounted in a test bench together with a Schenk “DYNAS NT 85” AC dynamometer. The measured variables are the same as the ones used for engine control. A schematic picture of the whole engine is shown in Figure 2.

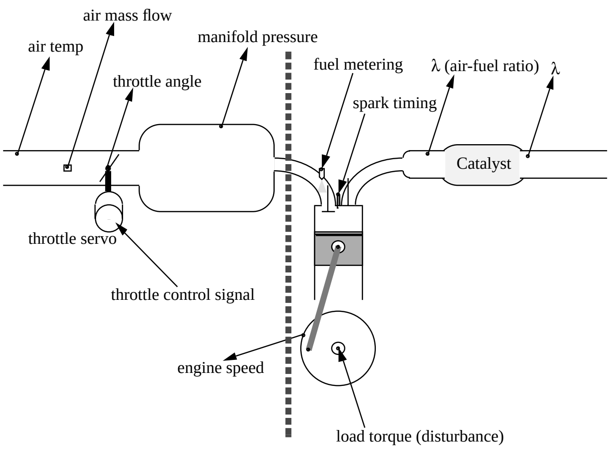

Fig. 2. The basic SI-engine.

The part of the SI-engine, that is considered to be the air-intake system, is everything to the left of the dashed line in Figure 2. When studying the air intake system, also the engine speed must be taken into account because it affects the amount of air that is drawn into the engine.

3. MODEL CONSTRUCTION

The SI-engine is a non-linear plant and it has been indicated in several works by different authors (see survey in (Nyberg and Nielsen, 1997b)), that FDI based on a linear model is not sufficient for the engine application. This motivates the choice of a non-linear model in this work.

For the purpose of FDI, a simple and accurate model is desirable. In the air-intake system application there is no need for extremely fast fault detection, therefore a so called *mean value model* is chosen. This means that no within cycle variations are covered by the model.

The model of the air-intake system is continuous, and has one state which is the manifold pressure. The air dynamics is derived from the ideal gas law.

The process inputs are the throttle control signal u, and the engine speed n. The outputs are throttle angle sensor α_s, air-mass flow sensor $\dot{m}_s$, and manifold pressure sensor p_s. The faults are modeled as additive faults. The equations describing the fault-free model can be written as

$$\dot{p} = \frac{RT_{man}}{V_{man}}(\dot{m}_{th} - \dot{m}_{ac}) \quad (1)$$

$$\dot{m}_{th} = f(p, \alpha) \quad (2)$$

$$\dot{m}_{ac} = g(p, n) \quad (3)$$

where p is the manifold pressure, R the gas constant, T_{man} the manifold air temperature, V_{man} the manifold volume, $\dot{m}_{th}$ the air-mass flow past the throttle, $\dot{m}_{ac}$ the air-mass flow out from the manifold into the cylinders, α the throttle angle, and n the engine speed.

The model consists of a physical part, (1), and a black box part, the functions (2) and (3). Even if variations in ambient pressure and temperature do affect the system, they are here assumed to be constant. The identification of the static functions f and g, and the constant V_{man}, is described in (Nyberg and Nielsen, 1997b). Except for selection of model structure, the model construction can be considered to be automatic since the identification is usually performed by computerized automatic tools.

4. RESIDUAL GENERATION

The inputs to the FDI system, and therefore also the residual generators, are $\dot{m}_s$, α_s, p_s, and n. The components that are to be diagnosed are the throttle angle sensor, the air-mass flow meter, and the manifold pressure sensor. It is assumed that only one fault can occur at the same time.

How residual generation should be done in general is still an active research area but for classes of systems there exists systematic methods. For instance residual generators for linear system can be constructed with the method described in (Nyberg and Nielsen, 1997c). By using systematic methods a number of residual generators can be designed. In addition, many residual generators can be designed with an ad-hoc approach. Ad-hoc design is often necessary for non-linear systems because of the scarcity of design methods. Thus it is usually not difficult to design a large number of residual generators, but the lack of systematic methods for non-linear systems, makes it difficult to find general automatic design procedures.

It is not sure that all constructed residual generators perform satisfactory or it can be the case that several residuals perform very similarly or identically. Also the number of residual generators that can be designed is generally larger than what is needed to be able to detect and isolate the faults. All this results in a possibly large set of residuals that are candidates to be included in the final FDI system.

These residuals are denoted *base residuals* and the set of all base residuals is denoted $\mathcal{R}_{base}$.

4.1. Residual Generation for the Air-Intake System

The model of the air-intake system is non-linear. To not introduce unnecessary constraints, the design of residuals is not restricted to one method. Instead a combination of static relationships, non-linear diagnostic observers, and parity equations have been used to construct 12 base residuals of the type where an output is compared to an estimate of the output, or two estimates of the same output are compared. The computational form of these 12 base residuals are

$$
\begin{aligned}
r_1 &= m_s - \hat{\dot{m}}_1(a_s, p_s) \\
r_2 &= m_s - \hat{\dot{m}}_2(n, p_s) \\
r_3 &= p_s - \hat{p}_1(a_s, n, p_s) \\
r_4 &= m_s - \hat{\dot{m}}_3(a_s, n, \dot{m}_s) \\
r_5 &= p_s - \hat{p}_2(a_s, \dot{m}_s, n) \\
r_6 &= a_s - \hat{a}_1(u, a_s, \dot{m}_s, p_s) \\
r_7 &= m_s - \hat{\dot{m}}_4(a_s, n, p_s) \\
r_8 &= r_2 - r_1 = \hat{\dot{m}}_1(a_s, p_s) - \hat{\dot{m}}_2(n, p_s) \\
r_9 &= r_4 - r_2 = \hat{\dot{m}}_2(n, p_s) - \hat{\dot{m}}_3(a_s, n, \dot{m}_s) \\
r_{10} &= r_4 - r_1 = \hat{\dot{m}}_1(a_s, p_s) - \hat{\dot{m}}_3(a_s, n, \dot{m}_s) \\
r_{11} &= r_3 - r_5 = \hat{p}_2(a_s, \dot{m}_s, n) - \hat{p}_1(a_s, n, p_s) \\
r_{12} &= a_s - \hat{a}_2(\dot{m}_s, p_s)
\end{aligned}
$$

where $\hat{\dot{m}}_i$, $\hat{a}_i$, and $\hat{p}_i$ are different estimates of the output signals.

The 12 base residuals form a set of structured residuals. Different residuals are sensitive to different faults. This can be seen by studying the equations of the residuals and is summarized in Figure 3, which contains the *residual structure*.

	α_s	$\dot{m}_s$	p_s
r_1	1	1	1
r_2	0	1	1
r_3	1	0	1
r_4	1	1	0
r_5	1	1	1
r_6	1	1	1
r_7	1	1	1
r_8	0	1	1
r_9	1	1	1
r_{10}	1	1	1
r_{11}	1	1	1
r_{12}	1	1	1

Fig. 3. The residual structure of the base residuals.

5. DON'T CARE IN THE RESIDUAL STRUCTURE

The algorithm described in the next section uses the concept of *don't care* (Nyberg and Nielsen, 1997b, Nyberg and Nielsen, 1997a). This section gives an introduction to this concept.

Don't care, X, is an alternative to *ones* and *zeros* in the residual structure. The meaning of an X, in the position for the i:th residual and the j:th fault, is that the fault decision should not take any notice about the value of residual i when deciding if fault j has occured. In most situations a residual is affected differently by different faults. This is the underlying reason why there is a need for *don't care*, or X, in the residual structure. Explicit examples of such cases are model uncertainty and non-linear physics.

For the FDI of the air-intake system, both model uncertainties and non-linear physics are present. An example of a non-linearity which enforces an X, is the fact that the air flow past the throttle is largely dependent on the manifold pressure for low air speeds but not dependent on the manifold pressure for supersonic air speed (Heywood, 1992). Supersonic air speed occurs for manifold pressures below 50 kPa.

For anything but small residual structures, it is difficult to see if a residual structure containing X's is strongly, weakly or not isolating. In (Nyberg, 1997), there are two theorems that can be used to determine if a residual structure containing X's is strongly or weakly isolating.

Introduction of X's will increase residual robustness and also the robustness of the complete system if done properly. When and how these X's should be introduced, can generally not be concluded by studying the equations describing how the residuals are computed. Instead measurements on the real process must be used. This is what is done in the RTS-algorithm described next.

6. THE RESIDUAL AND THRESHOLD SELECTION ALGORITHM

Following is a description of an extended version of an algorithm that was proposed in (Nyberg and Nielsen, 1997a) and (Nyberg, 1997). Given the set $\mathcal{R}_{base}$ of base residuals and a set $\mathcal{M}$ of arbitrary measurement series, the goal is to find a residual structure and fix thresholds such that optimal performance is obtained with respect to each of the measurements series. Depending on what fault situation that is present in the measurement series, the term *optimal* has different meanings. Therefore the set $\mathcal{M}$ is divided into three disjunct subsets corresponding to different fault sizes. $\mathcal{M}_{ff}$ is the set of fault-free measurements, $\mathcal{M}_{small}$ are the measurements with a *small fault* present, and $\mathcal{M}_{real}$ are the measurements with a *real fault* present.

For the fault-free measurements $\mathcal{M}_{ff}$, the goal is to minimize the probability of false alarm. For the measurements in $\mathcal{M}_{real}$, with a *real fault* present, the goal is to minimize the probability of missed detection and also the probability of mis-isolation. For the measurements in $\mathcal{M}_{small}$, with a *small fault* present, we decide that it is acceptable to both detect and not detect these faults, so the goal becomes to minimize the probability of mis-isolation. It is assumed that detection (and isolation) of faults is performed by matching residual behavior with columns in the residual structure.

Compared to the original algorithm, there is no limit of how many measurement series that can be used as an input to the algorithm. This implies that it is not necessary to fix any specific fault size, i.e. arbitrary many different fault sizes can be used in the measurement data. In addition, the original algorithm constrained the residual structures obtained to be strongly isolating. In the extended version, this constraint is relaxed and to still guarantee good isolation performance, the optimization is performed with respect to also isolation requirements.

The RTS algorithm is fully automatic and it has been implemented in Matlab. Following is a description of the algorithm, which is here separated into four steps. First *residual candidates* are generated, then thresholds are selected and finally, residual structures, consisting of subsets of residual candidates, are selected. More detailed information, e.g. regarding optimality, can be found in (Nyberg, 1997).

INPUT: The input to the algorithm is $< \mathcal{R}_{base}, \mathcal{M} >$.

STEP 1: Generate Residual Candidates

To lower the computational load in the search among residual structures, in step 3 and 4, it is desirable to have few residual candidates. Therefore, the correlation coefficients between the different base residuals are computed and for each pair of highly correlated base residuals, only the best one is allowed to generate residual candidates.

Then from each of the remaining base residuals $r_k \in \mathcal{R}_{base}$, n_k residual candidates are generated by introducing *don't care* in different combinations. When introducing X's, different strategies are possible. One that makes sense, and therefore used here, is to only allow *ones* to be replaced by X's.

For a each base residual, the goal is to generate residual candidates such that the probabilities of false alarm and missed detection are minimized. These probabilities are dependent on the current state (condition) of the system and in particular the fault situation. For the system condition present during the measurement $m_l \in \mathcal{M}$, let λ_{il} be the event that base residual i fires. Then for a fault free measurement $m_l \in \mathcal{M}_{ff}$, λ_{il} denotes the event false alarm. Now define $\lambda_{il}^0 = \lambda_{il}^C$, $\lambda_{il}^1 = \lambda_{il}$, and s_{ij} to be the entry in the residual structure corresponding to the i:the residual and j:th fault. Then it follows that for a *real-fault* measurement $m_l \in \mathcal{M}_{real}$, in which fault j is present, $\lambda_{il}^{s_{ij}C}$ is the event that residual i do not fire in accordance with the residual structure. In other words, $\lambda_{il}^{s_{ij}C}$ is the event *missed detection* if residual i is designed to respond to fault j, and the event *false alarm* if residual i is designed to not respond to fault j.

From the measurement series provided as inputs to the RTS algorithm, the residual density functions can be estimated. Then from these, estimates of the probabilities of false alarm and missed detection, as a function of the threshold, can easily be obtained. Fault-free measurements $m_l \in \mathcal{M}_{ff}$ are used to estimate probabilities $P(\lambda_{il})$ and *real-fault* measurements $m_l \in \mathcal{M}_{real}$ are used to estimate probabilities $P(\lambda_{il}^{s_{ij}C})$. *Small-fault* measurements are not used at this stage since we are allowed to both detect and miss these faults.

It was mentioned above that introducing *don't care* will increase the robustness of the diagnosis system. This can readily be seen in how introduction of X's makes it possible to find a threshold such that the probabilities $P(\lambda_{il})$ and $P(\lambda_{il}^{s_{ij}C})$ get lowered. So by successively replacing *ones* in the residual structure with *zeros*, we generate residual candidates with probabilities of false alarm and missed detection that is lower than for the corresponding base residual. In general a base residual r_k that is sensitive to p_k faults can in this way generate $n_k = p_k - 1$ residual candidates. A more detailed discussion about how this is done can be found in (Nyberg and Nielsen, 1997a).

In spite of that X's have been introduced, the probability that the residual respond the way it shouldn't, can still be high for all threshold levels. In that case, the corresponding residual candidate is omitted. This means that in reality $n_k \le p_k - 1$.

Define $\mathcal{R}_{cand}$ to be the set of all residual candidate. Then the total number of residual candidates is $|\mathcal{R}_{cand}| = \sum_{k=1}^{|\mathcal{R}_{base}|} n_k$. In correspondence with the definition of $\lambda_{il}^{s_{ij}}$, we define $\Lambda_{il}^{s_{ij}}$ to be the event that *residual candidate* i responds in accordance with the residual structure. For compatibility with the X's, now present in the residual structure, we define $\Lambda_{il}^X = \Omega$, which means that $s_{ij} = X$ implies $P(\Lambda_{il}^{s_{ij}}) = 1$.

STEP 2: Find Thresholds

By using the probability estimates $\hat{P}(\Lambda_{il})$, $m_l \in \mathcal{M}_{ff}$, and $\hat{P}(\lambda_{il}^{s_{ij}C})$, $m_l \in \mathcal{M}_{real}$, optimal thresholds are chosen for all residual candidates individually. Let f_0 be defined to be the fault-free case and thus $s_{i0} = 0$. Then the optimal threshold for the i:th residual candidate can be expressed as

$$J_i = \arg\min_{J} \max_{m_l \in \mathcal{M}_{ff} \cup \mathcal{M}_{real}} \hat{P}\big(\Lambda_{il}^{s_{i,fault(l)}C}\big)$$

where $fault(l)$ is a function returning the fault present in measurement l. If more than one threshold minimizes the maximum probability estimate, the threshold J_i can be chosen as the mean value of all minimizing thresholds.

STEP 3: "Almost" Minimize Probability Bounds

In step 3 and step 4 of the RTS-algorithm, the goal is to minimize the probabilities of false alarm, missed detection, and mis-isolation for the complete FDI system. Here this means that all residual structures obtained from the RTS-algorithm must fulfill two requirements. The first is that bounds of these probabilities must be "almost" minimized. This is taken care of in step 3. The second requirement, which is treated by step 4, is that the residual structures obtained must be the "best ones".

Let $\mathcal{S}$ denote the set of all residual structures that are possible to form with the residual candidates in $\mathcal{R}_{cand}$. Then the number of elements in $\mathcal{S}$, i.e. the number of possible residual candidates, is $|\mathcal{S}| = 2^{|\mathcal{R}_{cand}|} - 1$. Because it is required that the faults are possible to isolate, it is only interesting to investigate the set of isolating structures, which is denoted $\mathcal{S}_{isol} \subseteq \mathcal{S}$.

As for the residual related probabilities, the probabilities of false alarm, missed detection, and mis-isolation are dependent on the current state (condition) of the system and in particular the fault situation. For the system condition present during the fault-free measurement $m_l \in \mathcal{M}_{ff}$, let $P(\bar{B}^l_j(s))$ denote the probability of false alarm of fault j for a residual structure $s \in \mathcal{S}_{isol}$. Similarly, for $m_l \in \mathcal{M}_{real}$ let $P(\bar{A}^l_j(s))$ denote the probability of missed detection of fault j and for $m_l \in \mathcal{M}_{small}$ let $P(\bar{C}^l_{jk}(s))$ denote the probability of detecting fault k when fault j is present, i.e. mis-isolation.

Recall the definition of $\Lambda^{s_{ij}}_{il}(s)$, now as a function of the residual structure s with the index i referring to the i:th residual candidate in the residual structure s. This implies

$$\begin{array}{ll} P(\bar{B}^l_j(s)) = P\big(\bigcap_i \Lambda^{s_{ij}}_{il}(s)\big) & m_l \in \mathcal{M}_{ff} \\ P(\bar{A}^l_j(s)) = P\big(\big[\bigcap_i \Lambda^{s_{ij}}_{il}(s)\big]^C\big) & m_l \in \mathcal{M}_{real} \\ & fault(l) = j \\ P(\bar{C}^l_{jk}(s)) = P\big(\bigcap_i \Lambda^{s_{ik}}_{il}(s)\big) & m_l \in \mathcal{M}_{small} \\ & fault(l) = j \neq k \end{array}$$

To calculate the true values of these probabilities, the joint multi-dimensional density function would be needed. Unfortunately this density function is generally difficult to derive from the measurements $\mathcal{M}$, because a very large amount of data would be needed. However, it is possible to derive an upper bound of $P(\bar{B}^l_j(s))$ and $P(\bar{C}^l_{jk}(s))$, and both lower and upper bounds of $P(\bar{A}^l_j(s))$. The bounds are derived in (Nyberg and Nielsen, 1997a) and are

$$\begin{array}{c} P(\bar{B}^l_j(s)) \leq \min_i P(\Lambda^{s_{ij}}_{il}(s)) \\ \max_i P({\Lambda^{s_{ij}}_{il}}^C(s)) \leq P(\bar{A}^l_j(s)) \leq 1 - \prod_i P(\Lambda^{s_{ij}}_{il}(s)) \\ P(\bar{C}^l_{jk}(s)) \leq \min_i P(\Lambda^{s_{ik}}_{il}(s)) \end{array}$$

Note that in the definition of $P(\bar{C}^l_{jk}(s))$ we did not consider the case $m_l \in \mathcal{M}_{real}$, even if it would be possible to do so. The reason is that the lower bound of $P(\bar{A}^l_j(s))$ for $m_l \in \mathcal{M}_{real}$ is always less than the upper bound of $P(\bar{C}^l_{jk}(s))$ for $m_l \in \mathcal{M}_{real}$. Thus the lower bound of $P(\bar{A}^l_j(s))$, which is minimized, serves also as an upper bound of $P(\bar{C}^l_{jk}(s))$.

The idea is to minimize these bounds, but with estimated probabilities instead of true probabilities. Minimizing the bounds actually gives the same result as minimizing the true probabilities in some special cases. Let N be the number of faults. Then the number of bounds to $P(\bar{B}^l_j(s))$ is $N|\mathcal{M}_{ff}|$, the number of bounds to $P(\bar{A}^l_j(s))$ is $2|\mathcal{M}_{real}|$, and the number of bounds to $P(\bar{C}^l_{jk}(s))$ is $(N-1)|\mathcal{M}_{small}|$. Let $\mathcal{B}$ denote the set of all bounds. The bounds $b(s)$ in $\mathcal{B}$ are then functions of s only. The total number of bounds is

$$|\mathcal{B}| = N|\mathcal{M}_{ff}| + 2|\mathcal{M}_{real}| + (N-1)|\mathcal{M}_{small}| \quad (4)$$

The optimization goal is to find the residual structure for which the bounds are minimized. All bounds are generally not minimized by the same residual structure. This problem could be solved by minimizing some weighted sum of all bounds. However this would lead to that some bounds might get quite large. Instead, the strategy adopted here is to replace the minimization with a constraint that for a residual structure, all bounds must be "almost minimized". Generally this does not give one residual structure but a set of residual structures. Thus let $\mathcal{S}_{min}(\epsilon) \subseteq \mathcal{S}_{isol}$ be the set of residual structures for which all the bounds $\mathcal{B}$ are "almost minimized". Formally $\mathcal{S}_{min}(\epsilon)$ is defined as

$$\mathcal{S}_{min}(\epsilon) = \{s \mid \max_{b(s) \in \mathcal{B}} \big(b(s) - \min_{\sigma} b(\sigma)\big) \leq \epsilon\}$$

The number of residual structures obtained in $\mathcal{S}_{min}(\epsilon)$ is dependant on the value of ϵ. A value $\epsilon = 0$, can result in that no residual structures are obtained. Therefore we find the minimal value of ϵ for which $\mathcal{S}_{min}(\epsilon) \neq \emptyset$, i.e.

$$\epsilon_{min} = \min_{\mathcal{S}_{min}(\epsilon) \neq \emptyset} \epsilon$$

Then $\mathcal{S}_\epsilon$ is defined as $\mathcal{S}_\epsilon = \mathcal{S}_{min}(\epsilon_{min})$.

STEP 4: Find Optimal Set of Residual Structures
Because ϵ_{min} is minimal, we know that in the set $\mathcal{S}_\epsilon$, there is no residual structure for which the values of all bounds $\mathcal{B}$ are strictly less than for *any* other residual structure in $\mathcal{S}_\epsilon$. There may however be many pairs of residual structures s_1 and s_2 such that $\forall b \in \mathcal{B}\ b(s_1) \leq b(s_2)$. By omitting the worst residual structure of all such pairs, we are left with a set $\mathcal{S}_{opt}$ that can be expressed as

$$\mathcal{S}_{opt} = \{\sigma \mid \forall s \in \mathcal{S}_\epsilon([\forall b \in \mathcal{B} \quad b(s) \leq b(\sigma)] \Rightarrow s \equiv \sigma)\}$$

OUTPUT: The output from the RTS-algorithm is the residual candidates $\mathcal{R}_{cand}$ with corresponding thresholds and the residual structures $\mathcal{S}_{opt}$. Thus for each element in $\mathcal{S}_{opt}$ we have a complete FDI system with residuals, thresholds and a residual structure including X's.

7. THE APPLICATION OF THE RTS ALGORITHM TO THE AIR-INTAKE FDI

In this section, the RTS-algorithm is applied to the 12 base residuals constructed in Section 4.

INPUT: Measurement data were collected during a one minute fault-free test cycle, see (Nyberg and Nielsen, 1997b). All faults were added to fault-free measurements and constant bias faults were chosen. The fault sizes were ±2%, ±4%, and ±6% for the α-fault, ±2.5%, ±5%, and ±7.5% for the $\dot{m}$-fault, and ±2%, ±4%, and ±6% for the p-fault. For each sensor, the two smallest fault sizes are considered to be *small faults* and rest of the four fault sizes are considered to be *real faults*. In addition there were one fault-free measurement. Thus the input

$< \mathcal{R}_{base}, \mathcal{M} >$ consists of 12 base residuals, and a total number of 19 one minute measurements.

STEP 1 and STEP 2: From studying the correlation coefficients, it is concluded that base residuals 1 and 7 are highly correlated, $C(r_1, r_7) = 0.99$, and also base residuals 5 and 11, $C(r_5, r_{11}) = 0.99$. Therefore base residuals 7 and 11 are omitted.

X's are introduced and residuals candidates for which the lowest probability that they will signal false alarm or miss a fault, is higher than 0.2, are omitted. After this, there are 14 residual candidates left, i.e. $|\mathcal{R}_{cand}| = 14$.

STEP 3 and STEP 4: It follows that $|\mathcal{S}| = 2^{14} = 16384$, and from a search in $\mathcal{S}$ that $|\mathcal{S}_{isol}| = 12032$. From (4) we know that $|\mathcal{B}| = 39$. Then from a search in $\mathcal{S}_{isol}$ it follows that $|\mathcal{S}_{\epsilon}| = 256$ and $|\mathcal{S}_{opt}| = 18$. Of these 18 residual structures, there are 4 structures having 5 residuals, 8 having 6 residuals, 5 having 7 residuals, and 1 having 8 residuals. Three of these residual structures can be seen in Figure 4.

	f_1	f_2	f_3
r_1	1	X	X
r_2	0	1	1
r_3	1	0	1
r_4	1	1	0
r_8	1	0	X

	f_1	f_2	f_3
r_1	1	X	X
r_2	0	1	1
r_3	1	0	1
r_3	1	0	X
r_4	1	1	0

	f_α	$f_{\dot{m}}$	f_p
r_1	1	1	X
r_1	1	X	X
r_2	0	1	1
r_3	1	0	1
r_8	1	0	X

Fig. 4. Three examples of residual structures.

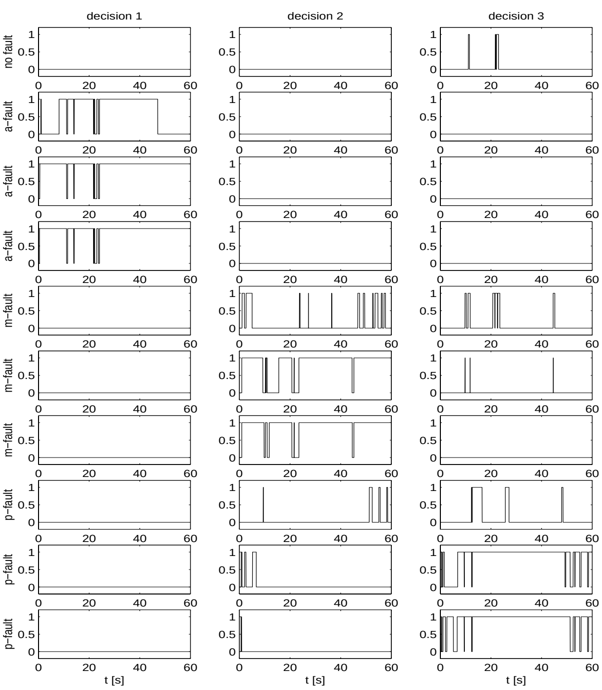

Fig. 5. Confirmation of the FDI design for the cases no fault, α-, $\dot{m}$-, and p-fault respectively.

8. CONFIRMATION OF THE DESIGN

For the final selection in a real application, a residual structure with 5 residuals should be the best choice. This is to minimize the FDI system complexity and computational load.

To confirm the design, the leftmost residual structure in Figure 4 is chosen. In Figure 5, each column contains plots of the fault decision for the three faults respectively. Each row of plots corresponds to a measurement with a specific fault situation (indicated to the left in the plot).

It is clear that the RTS algorithm successfully manage to generate a FDI system for the air-intake system of the engine. However in the first row, it can be seen that there are some false alarms. Rows 2, 5, and 8, corresponds to measurements with *small faults* present and we see some mis-isolations. Rows 3, 4, 6, 7, 9, and 10 corresponds to measurements with *real faults* present and we see some miss detections and mis-isolations. Thus the performance is not perfect but we should remember that the fault sizes used in $\mathcal{M}_{real}$ are comparably small for this application. If better performance, in terms of less false alarms etc., is required, then the smallest faults in $\mathcal{M}_{real}$ must be moved to $\mathcal{M}_{small}$.

9. CONCLUSIONS

The problem of automatic FDI design, with application to automotive engines, has been investigated. An FDI system for the air-intake system of an SI-engine is constructed. The complete design chain has been covered, including model construction, residual generator design, selection of thresholds, and design of residual structure.

The last two design stages were performed by the fully automatic residual and threshold selection (RTS) algorithm. The RTS algorithm uses arbitrary measurement series and minimizes probabilities of false alarm, missed detection, and mis-isolation.

The resulting diagnosis system is experimentally validated and it is shown that good performance is obtained.

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