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Iterative Multilayer Fault Diagnosis Approach for Complex Systems

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Abstract: - The trend to higher systems complexity while requiring enhanced reliability increases the interest in using model based fault diagnosis methods. As a sufficiently good modeling of complex plants can be very demanding or even impossible, data based methods are being widely used, but the computational time and the quality can still be too poor for reliable fault detection. In this paper, we propose an iterative multilayer approach, which is characterized by two elements: fault detection and fault isolation consist of sequentially triggered cascaded processes, whose speed and quality rely on dynamical modeling abilities. The presented methods have been developed in the framework of an industrial project in the field of engine test benches, from which examples are shown.

Key-Words: - Fault Detection, Fault Isolation, Data Based Modeling, Model-on-Demand, Process Monitoring

1 Introduction

Early fault diagnosis (FDI) is a critical issue for many industrial or commercial applications, especially for large measurement systems, as in process, steel or chemical industry, but also for specific components, as in the automobile industry. As FDI relies based on models, and models are often difficult to obtain, a substantial effort has been performed to obtain and to use automatically models for data plausibility (see *e.g.* [1,2]). This effort has been extended also to fault detection in the context of engine test benches, *e.g.* by [3,4], as well as fault isolation in large measurement systems *e.g.* by [5]. An important question is also the reliability of the modeling process. The robustness in modeling uncertainties is discussed i.e. in [6], where the authors addressed the problems of the measures of detectability as well as the determination of thresholds for fault detection and isolation.

Modern complex systems are characterized by a high number of measurement channels, and the measurement process itself produces a large amount of data, which are not likely to be analyzed in any other way than automatically. This, however, can be a very difficult task, due both to the unknown functional relationships as well as to the possibly insufficient data richness.

A key concern is the computational complexity which can be reduced if a systematic approach to modeling and fault diagnosis is adopted. If only simple models of the measurement system are used, the fault diagnosis system can become inefficient due to inability to detect smaller variances of observed variables. If the goal is to use only complex but very accurate models, the fault diagnosis can be very slow and unusable in real time. Therefore, there is a need to restrict the modeling and to use simple models at the beginning of the fault diagnosis process, and then to continuously increase the complexity of models in the next steps, until the acceptable trade-off between model complexity, computational performance and fault diagnosis results is reached.

This idea lies behind the work related in this paper in which we present a new approach which combines flexibility and efficiency. This consists first in processing the measurements to have a basic fault detection statement, whose quality is then improved iteratively building up models-on-demand with the available measurements. The proposed approach was proven in practice to be efficient and precise, flexible and capable of learning.

2 Problem Statement and Basic Solution

We consider here complex systems (with several hundreds channels), no *a priori* known models and "sufficiently rich" data. As such systems are often used to monitor industrial plants, we look for a solution able to detect reliably even small anomalies in real time. Such a combination - fast but accurate – is usually impossible for many real plants. In order to fulfill both requirements we propose a multilayer fault diagnosis system, with each layer being tuned to satisfy either speed or precision demands.

Fig. 1 shows schematically such a system with several FDI levels. The first (fast) fault detection block is designed to be simple and fast, to run continuously, to analyze all available data from the data stream and to minimize the number of missed detections, even if the over-detection rate increases. The second (precise) fault

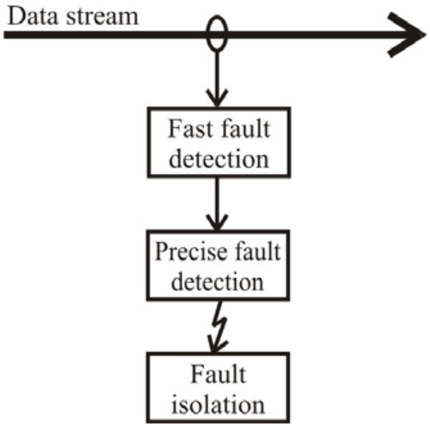

Fig.1. Scheme of a multilayer fault diagnosis system.

detection block is triggered by fault detection(s) from the first FD block, and is designed to "filter" as much as possible the cases of overdetection from the first block and then to focus on the measurement channels likely to contain a measurement or process fault. The fault detections which are still present after the second FD step trigger the fault isolation block, which produces the FDI statement.

The fault isolation step relies first on the use of the original models, which, however, may not contain the adequate "orthogonal" information required to separate channels. For this reason, an iterative "Model on Demand" (MoD) procedure has been used, which uses the original full data set not to determine the existence of a failure but to locate it.

3 Algorithmic structure

Fig. 2 shows the basic steps necessary to complete FDI in a complex measurement system. The process shown is very general, and can be applied to any test facility. The procedure includes four basic steps: data acquisition, data preprocessing, modeling and fault diagnosis.

3.1. Automatic Data Preprocessing

The preprocessing step is designed to extract information from data and includes steps like removing trends and drifts, outliers and other disturbances, dealing with missing portions of data (reconstruction of data), prefiltering of data and data segments selection. This phase is critical for the later performance: a simple prefiltering of data influences directly the fault diagnosis statement (see *e.g.* in [8]). Preprocessing can include as well other functions like down-sampling, time-delay estimations and detection of redundant channels. This can have a twofold advantage; it can be used to reduce the search space, but can also be used for fault detection.
Data segments selection seems to be of particular importance for the structural identification of models. The selection can be done according to different criteria, but the determination of steady-state segments has been

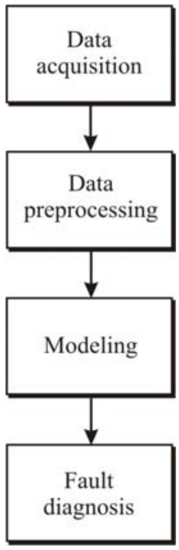

Fig.2. Automatic data plausibility check (fault diagnosis procedure). Basically, the complete fault diagnosis procedure consists of four basic steps: data acquisition, data preprocessing, modeling and fault diagnosis.

found to be quite useful if a two step modeling procedure (first static then dynamic maps) is used.

At the end of the data preprocessing step, the original data set is divided into three subsets containing stationary data clusters, transient data clusters and data without information. The data without information are usually omitted from the following steps.

3.2. Automatic Modeling

A systematic overview of modeling methods used for fault detection is given *e.g.* in [2].

Theoretically, a model of the target channel y_i can be made using all other channels considered in the diagnostic system, or formally:

$$\hat{y}_i = f(\tilde{y}_1, \tilde{y}_2, ..., \tilde{y}_{i-1}, \tilde{y}_{i+1}, ...\tilde{y}_n, \tilde{u}_1, ..., \tilde{u}_m) \qquad (1)$$

However, since this approach would lead to complex models, in practice the case is that only several of other channels considered by the diagnostic system are actually used for modeling of the target channel. The selection of the model structure (or the structural identification) plays the key role in automatic modeling and data plausibility check.

From a practical point of view, every automatic modeling procedure must be seen as an approximation with two targets: represent correctly the actually known values and extrapolate as correctly as possible the future values. Such an aim can be reached by three steps:

1) Information sorting
   As the first step, for each sub-model of the system (for each target channel), information sorting is performed, in order to identify the most relevant measurement channels for that sub-model. Only a number of the most relevant measurement channels are retained to form the model input structure.

2) Parallelizing
   A model of the process is considered to be a collection of sub-models. Each sub-model is considered as a model with one output and, at first, an unknown number of inputs. The models are built automatically, and different modeling methods are applied. As a result of the parallelizing step, several models with different structure of a single measurement channel can be made. Note that the parallelizing step allows forming of analytical redundancy, an important feature for fault diagnosis.
3) Evaluation
   A decision subsystem is used to select models from the pool of models, which have appropriate characteristics to be used in the fault diagnosis process.

3.3. Quantitative Measure of Model Quality

In the case of models with learning properties, the evaluation of the model quality is performed continuously.

The selection of the models is based on several criteria. Three of them can be taken as important ones for the purpose discussed in this paper:

- training data requirements;
- model (computational) structure;
- model accuracy.

There exist several different ways to quantitatively measure the quality of the modeling process [10]-[14]. A standard approach includes discussion of the model bias and variance [10]. Bias error is the reflection of the fact that the observed system is not within the chosen model structure, while the variance error is a consequence of the noise corruption of observed data. The total model error is therefore given as:

$$Err(\hat{y}_i) = E\left[(y_i - \hat{y}_i)^2\right] = \sigma_\varepsilon^2 + Bias^2(\hat{y}_i) + Var(\hat{y}_i), \quad (2)$$

where bias and variance errors are given as:

$$\begin{aligned} Bias(\hat{y}_i) &= E[\hat{y}_i] - y_i \\ Var(\hat{y}_i) &= E[\hat{y}_i - E[y_i]]^2 \end{aligned} \quad (3)$$

In equations (2) and (3), $E[\cdot]$ represents the expected value, while $\sigma_\varepsilon^2 = Var(\varepsilon)$ denotes the variance of the irreducible modeling error ε, $y_i = f(X_i) + \varepsilon$.

Based on the total model error, the quality of the resulting model can be measured by a mean-square error criterion, where the bias contribution and the variance contribution can be split [7]:

$$J(\hat{y}_i) = J_B(\hat{y}_i) + J_V(\hat{y}_i) \quad (4)$$

A critical place in the present system identification theory is taken by the so-called bias/variance tradeoff. In [10] the authors suggest that the bias error drops with increasing model order, since the generality of the model structure is increased. In [7] the author suggests reducing the bias by employing larger and more flexible model structures, requiring more parameters, but having the increase of the variance, since it typically increases with the number of estimated parameters. The bias / variance tradeoff can be formalized as a minimization of (4) with respect to the model structures. A slightly different approach was taken in [12], where the quality of the model is estimated using Variance Accounted For (*VAF*) function, defined as:

$$Q = VAF(y, \hat{y}) = \max\left(1 - \frac{S_N(y - \hat{y})}{S_N(y)}, 0\right) \quad (5)$$

where S_N denotes variance function. Note that using VAF it is possible to obtain a statistical judgment of a model quality (only the model output is used), not considering the actual model structure.

The estimation of model quality is not a simple problem. The difficulties can appear when there is significant difference between training and test data sets. A portion or the complete test data set can belong to a process operational range which is poorly covered by the training data set. Thus, the model quality calculated on the basis of the training data is not representative and can not be used in the process of automatic data plausibility analysis. In those cases a possible solution can be extended or weighted model quality:

$$Q_{Wi} = W \cdot Q_i \quad (6)$$

The model quality can have double function: as a criterion for automatic selection of the appropriate modeling method, then to set achievable bounds of fault detection (and respectively of fault isolation), and can also be used to automatically set fault detection thresholds. In this paper the model quality is used as a measure of the model suitability of data based models which are to be used for prediction of the modeled process, as well as to automatically set thresholds for fault detection:

$$thres(y_i) = n \cdot Var(|\hat{y}_i - y_i|) = f(Q_i) \quad (7)$$

where n is a multiplicative factor, in most cases between 2 and 3, and *Var* denotes the variance function.

3.4. Achievable limits of fault detection

The key point for the definition of achievable bounds of fault diagnosis is the question of the faults propagation through (large) measurement systems and also through modeling systems.

Using standard approach for analysis of the faults propagations through measurement systems given in [16], as well as the model quality estimation (5) and the results from [8], it is possible to derive the following condition for a minimum process fault in the observed measurement channel y_i which can be detected:

$$|\xi_i| \geq \sqrt{1 - Q_i} + \sqrt{\sum_{\substack{j=1 \\ j \neq i}}^{n} \left(\frac{\partial f}{\partial y_j} \cdot |\zeta_j|\right)^2 + \sum_{k=1}^{m} \left(\frac{\partial f}{\partial u_k} \cdot |\zeta_k|\right)^2} + |\zeta_i| \quad (8)$$

where are:

ξ_i – minimum process fault of the target variable (*i*-th measurement channel) possible to detect, $\xi_i \in [0,1]$;

Q_i - model quality of the model of the target variable (*i*-th measurement channel), calculated as *VAF*, $Q_i \in [0,1]$;

ζ - sensor accuracies (given by producers) in form of maximum error of current measurement; meaning of indexes: *i* - target variable; *j* - system outputs; *k* - system inputs (actuators), $\zeta \in [0,1]$.

The equation (8) can be used to set model dependant thresholds for fault diagnosis (in particular, for fault detection). Since information about sensors accuracies ζ are normally available, and if a minimum process fault to be detected is defined, it is possible to bound the necessary model quality:

$$|\xi_i| \geq f(|\zeta|, Q_i) \;\Rightarrow\; Q_{i\,\min} \geq g(|\zeta|, |\xi_i|) \qquad (9)$$

This information can be used in selection (discrimination) of available models for fault diagnosis (in particular for fault detection).

3.5. Algorithm of iterative multilayer fault diagnosis

The main idea of the Model-on-Demand (MoD) process for fault diagnosis is sharpening of the FDI statement through reduction of the problem order on one side, and through iterative increase of model suitability (in terms of model quality and model orthogonality) to describe the modeled process on another.

Fig. 3 schematically illustrates this idea, presenting how the complexity of a fault diagnosis problem is expected to change during the fault diagnosis process. The first step includes preprocessing and information sorting, and it usually results in identification of redundant measurement channels and measurement channels which does not carry any information useful for the fault diagnosis process. Those channels can be omitted, what immediately results in reduction of the problem complexity. Even simple modeling procedure, like using redundant measurement channels or simple expert models, can produce models with enough quality to be used in fault diagnosis. After the first fault diagnosis a (simple) fault diagnosis statement is obtained. The results of the first fault diagnosis statement allow some additional measurement channels to be omitted, reducing further the complexity of the problem. The sophisticated modeling (the fourth step) is generally of higher complexity than the simple modeling, but it will never overrun the complexity level set after the first fault diagnosis. The second fault diagnosis can produce the final fault diagnosis statement, but if necessary the process can be continued until a satisfying fault diagnosis output is reached.

In each modeling step the MoD procedure can be applied, as shown schematically in Fig.4.

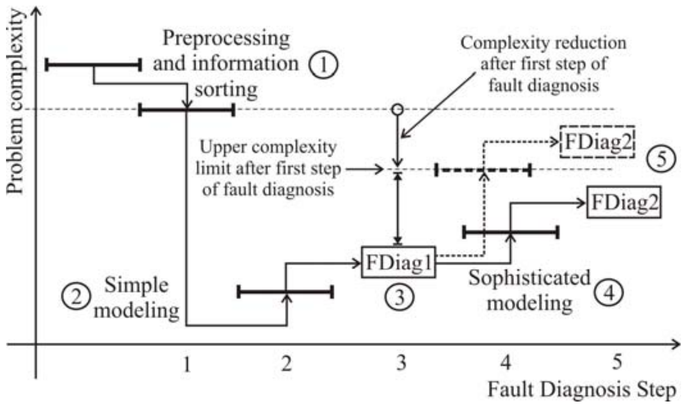

Fig.3. Complexity of a fault diagnosis problem versus steps in fault diagnosis.

The model structure for the MoD step is derived from both the results of the preprocessing and variable selection steps and from the results of the previous fault diagnosis step. In the modeling process the models are selected on the basis of a quantitative criterion, like for example model quality. In the previous section we suggested that the minimal required model quality can be established for each single fault diagnosis problem. To reach that lower limit, several methods can be used:

- by influencing the structure of the model. (in most of the cases increasing the number of channels involved in models, or by selection of the basic mathematical functions in some grey-box models);
- by proper choice of static or dynamic, linear or nonlinear models;
- by increasing the measurement sample rate (in some of the cases).

The MoD process for each modeled variable is stopped when the required minimum model quality is reached or when there is no further significant increase in the model quality. The increase of variance of prediction can be used as auxiliary stopping criteria. The prediction is based on the model derived from the training data, but calculated using the test data. If the increase of the variance of the prediction is significant, the MoD process should be stopped.

The next step requires setting thresholds for FD and FI, having in mind the characteristics of the measurement system as well as the characteristics of the improved models. Results obtained after all levels of fault diagnosis form the final fault diagnosis statement.

4 Experimental results

The experimental data set originated from an engine test bench, describing the operation of a commercial BMW 320D car engine on a complex test bench. This work was performed inside a European project (AMPA). Due to the usual measurement methodology, only the

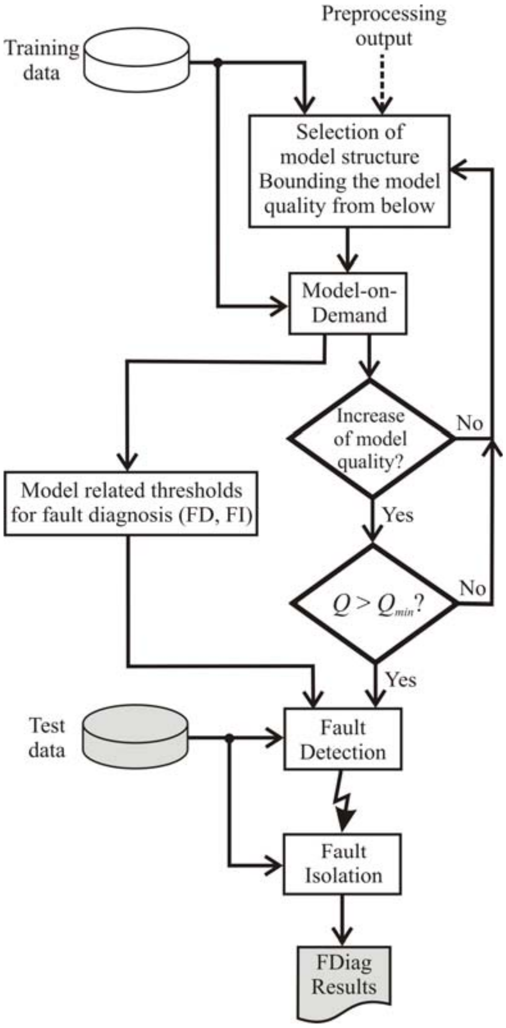

Fig.4. The process of modeling which utilizes the Model-on-Demand, a sophisticated modeling with pre-defined parameters.

stationary points are measured, and then the recorded dynamic data were averaged, producing one value per each measurement channel and each stationary point. In order to test the fault diagnosis, a total of 9 different artificial faults were introduced in the test data set, affecting the total of 10 measurement channels. The artificial faults were chosen in such a way to reflect the real faults.

Fig. 5 shows the results of the first level of fault diagnosis process (fault detection and isolation), which includes simple modeling and weighted fault isolation [3], [5]. In the first level of fault diagnosis, 7 of 9 artificial faults (affecting 8 measurement channels) were detected and (at least partially) isolated. (The isolated measurement points are shown in black.) The isolation in the measurement channel No.8 was essentially wrong, since that channel did not contain any known artificial fault. Two faults were not detected:

- temperature T_A was approx. 30% higher than normal (measurement channel No.20, measurements 15-28, simulates a sensor calibration error);

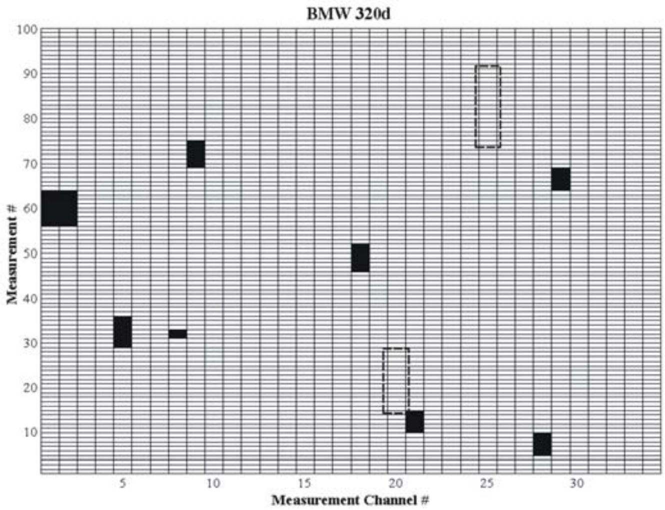

Fig.5. Fault isolation matrix for the BMW 320d data set after the first level of fault diagnosis (using simple modeling).

- temperature T_{IA} was approx. 20% lower than normal (measurement channel No.25, measurements 75-90, simulates a leakage of intake air).

The fact that two faults were not detected is an important aspect of such methods. The model buildup happens in real time together with the diagnosis, i.e. the information basis can be too small to detect early occurring errors. Furthermore, the measurements come in as they use to, and, as a consequence, the information and model build up is not homogenous. A further possible cause can be found in the fact that changes not present in the training data will not be detected. All this is not detrimental of the presented approach: perfect fault detection and zero overdetection in large and essentially unknown systems is clearly impossible, and this paper presents only results for single event - single channel faults - a clearly extreme situation, as usually faults affects several channels and last more than one sample.

After the first level of fault diagnosis the artificial fault in channel T_A was only partially detected and isolated. Fig. 6 shows the result of the variable selection for the channel T_A. It has been shown that 10 most influencing channels (inputs) contain almost the whole necessary information, but also the five most influencing channels will lead to a satisfactory model, which allows significantly better fault diagnosis results, after the second iteration step (MoD) has been performed. Similar situation was also with the channel T_{IA}, which was marked as "unchecked" after the first iteration step. Using a model with first six relevant channels as model inputs, it was possible to detect the artificial fault in channel T_{IA}.

Fig.7 shows the regions of the fault isolation matrix where two the previously discussed artificial faults are introduced. As it can be seen now, it was possible to detect and isolate the artificial faults in channels T_A and T_{IA}, improving the overall fault diagnosis statement.

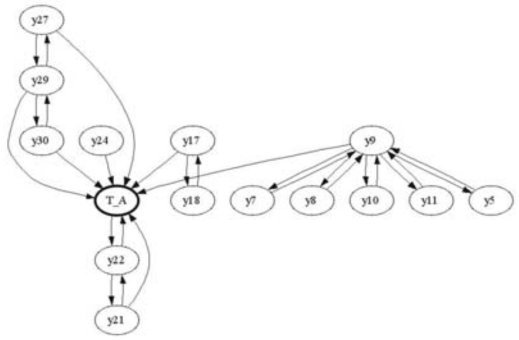

Fig.6. Result of variable selection for measurement channel T_A as the target channel. The relevance search was done using the stationary data clusters hypothesis.

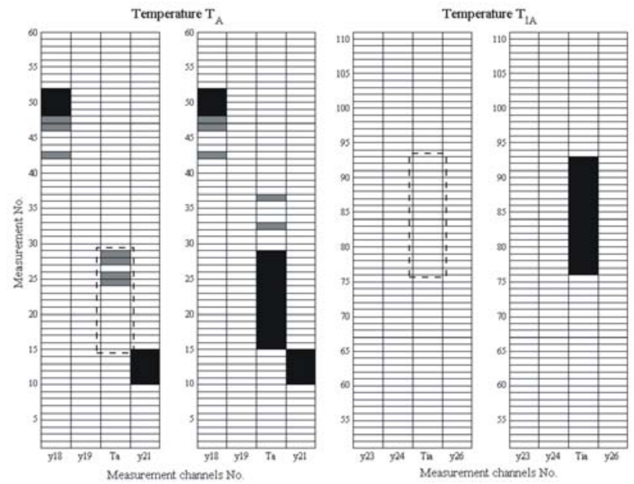

Fig.7. Parts of the fault isolation matrix for the measurement channels T_A and T_{IA} after the first level of fault diagnosis (always on left) and after the second level of fault diagnosis (always on right). The black colored boxes indicate likely fault isolations for a specific measurement channel and measurement, while grey colored boxes indicate less likely fault isolations.

5 Conclusions

The automatic multilayer iterative approach to fault diagnosis in complex systems presented in this paper offer a good compromise between fast and precise fault diagnosis. The drawback of the proposed approach is the need to compute up to several hundreds of models, some of them being high dimensional, in the search phase, as it cannot be forecasted in advance which model will yield the necessary identification information. Some additional work on optimization will be necessary to reduce this effort.

References:

[1] D. Mowll, A. Raab, K. Binder, and J. Willand, "Issues arising from statistical engine testing", in: Statistics for Engine Optimization (S.P. Edwards, D.M. Grove and H.P. Wynn (Ed)), Professional Engineering Publishing, 2000, pp.37-48.

[2] P.J. Shayler, P.I. Dow, D.J. Hayden, and G. Horn, "Using Neural Networks in the Characterization and Manipulation of Engine Data", in: Statistics for Engine Optimization (S.P. Edwards, D.M. Grove, and H.P. Wynn, (Eds.)), Professional Engineering Publishing, 2000, pp.145-162.

[3] A. Schrempf, L. del Re, W. Groißböck, E. Lughofer, E. P. Klement and G. Frizberg, "Automatic engine modeling for failure detection," in Proc. 2001 ASME International Mechanical Engineering Congress and Exposition, New York, USA, 2001, vol.2, pp. 1–8.

[4] S. Jakubek, and T. Strasser, "Fault-Diagnosis using Neural Networks with Ellipsoidal Basis Functions", in Proceedings of the 20th American Control Conference, ACC 02, Anchorage, Alaska, USA, May 8-10, 2002, pp. 3846-3851.

[5] H. Efendic, A. Schrempf and L. del Re, "Data based fault isolation in complex measurement systems using models on demand," in Proc. 5th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, Washington DC, USA, 2003, pp. 1149–1154.

[6] R.B. Jørgensen, R.J. Patton and J. Chen, "An Eigenstructure Assignment Approach to FDI for the Industrial Actuator Benchmark Test", Control Engineering Practice, vol. 3, No.12, Elsevier Science Ltd., 1995, pp. 1751–1756.

[7] L. Ljung, System Identification, Prentice Hall Inc, New Jersey, 1999

[8] E. Lughofer, H. Efendic, L. del Re and E. P. Klement, "Filtering of Dynamic Measurements in Intelligent Sensors for Fault Detection based on Data-Driven Models, " in proc. 42nd IEEE Conference on Decision and Control, Hawaii, USA, December 9-12, 2003, pp. 463–468.

[9] H. Kantz and T. Schreiber, Nonlinear Time Series Analysis, Cambridge University Press, 1997.

[10] B. Ninness and G. Goodwin, "Estimation of model quality," Technical Report EE9437, Centre for Industrial Control Science and Department of Electrical and Computer Engineering, University of Newcastle, Australia, March 1995.

[11] P. Sreedharan and P. Haves, "Comparison of chiller models for use in model-based fault detection", presented at International Conference on Enhancing Building Operations, Austin TX, July 2001

[12] V. Verdult, M. Verhaegen, C. T. Chou and M. Lovera, "Efficient and systematic identification of MIMO bilinear state space models," in Proc. 37th IEEE Conference on Decision & Control, Tampa, Florida USA, 1998, pp. 1260–1265.

[13] R. Ouvrard, P. Coirault, T. Poinot and J.C. Trigeassou, "A new orthogonal basis functions for error quantification in system identification," in Proc. 12th IFAC Symposium on System Identification SYSID 2000, Santa Barbara, CA, USA, 2000, vol.1, pp. 187–192.

[14] J.C. Doyle and G. Stein, "Multivariable feedback design: concepts for a classical / modern synthesis," IEEE Trans. Automatic Control, vol. 26, pp. 4–16, 1981.

[15] I. Gertsbakh, Measurement Theory for Engineers. Springer - Verlag Berlin Heidelberg, 2003, pp. 87-94.

[16] M.W. Braun, D.E. Rivera, and A. Stenman, "A 'Model-on-Demand' identification methodology for nonlinear process systems", International Journal of Control, Vol.74, No.18, 2001, pp.1708