GPMAS – AN INTEGRATED ENVIRONMENT FOR THE SETUP OF MODEL BASED FAULT DETECTION TOOLS

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Abstract: This paper describes the capabilities of black box models of detecting incipient faults on complex systems; an example with a centrifugal gas compression system is reported. The algorithms proposed are able, on the one side, to detect even incipient faults, while on the other to prevent the raise of false alarms by a combined use of filtered data and a model validity check. The algorithms proposed are not case dependent since they can easily be configured following a training procedure and, moreover, can be applied to a variety of cases such as automotive, Metals industry, Oil & Gas industry, etc. (Deckers, *et al.,* 2003).

Keywords: industrial diagnostics, fault detection and identification, compression systems.

1. INTRODUCTION

In the last few years the number of sensors installed on a single plant has started to grow rapidly, due to the reduction of their installation costs, and has reached such a high number that plant operators might find difficulties in controlling and monitoring all of them, with the risk of missing or misinterpreting important symptoms and the causes of alarms and warnings.

This applies particularly when incipient faults cause signals' patterns to change very slowly, or when only comparing and correlating different signals at the same time can detect faults. Moreover, even if the operator detects an abnormal behaviour, he/she might find it very complex to recognize and locate its cause, thus to decide in time the proper corrective actions.

The use of models can definitely support the operator in these tasks, thanks to their capability of reproducing the normal behaviour of one or more output signals, as a function of a pre-defined set of input signals. By comparing the simulated output of a model with the measured ones the detection of faults is possible at their onset and evolution, well before they fully develop.

Generally speaking these models can be divided into two categories (Bittanti, 2002):

a. Transparent box (TB) models;

b. Black box (BB) models

A TB model is obtained using the description of the system parts, by the laws (physical, chemical, etc.) ruling them.

BB models are used when the user is not interested, or it is not possible to obtain a "physics based" model, and the main aim is to reach a synthetic description of the system, subsystems or components, which could describe the dynamics of some measurable signals in the system with a certain accuracy. In this case a physical background of the process or component to be modelled is not mandatory for creating the model, yet it would guide the model creation process. These models are created following the concepts of the system identification theory, i.e. by training certain general algorithms (e.g. State Space, Neural Networks, etc.) on a subset of measured input and output signals and validating and testing the parameters obtained with a different subset. An advantage of BB models over TB ones lies in their computing efficiency and formal simplification, so that both can be useful at different stages of the project/process lifetime. Of course hybrid approaches can be used, to describe subsystems whose physics and real parameters are fairly well known together with others whose are not.

For the application described in this paper a TB model of a compression system (*COMPSYS*™) (Brighenti, 1995; Brighenti, *et al.,* 1999; Brighenti and Boatto, 2000) has been used to generate a realistic set of signals that could eventually be measured in a real system to be monitored (both in normal operating and in faulty conditions). These signals are referred to in the following as "pseudo-measured" data, in order to highlight that they have been produced by simulations using a TB model. Signals for training and testing BB models have then been extracted from these histories. Finally the BB models have been used for virtually monitoring the signals generated by the TB model and detecting the simulated faulty conditions.

Usually both the *training* and *testing* signals shall be acquired using the Plant Data Acquisition System (PDAS) during the commissioning phase, but the use of a TB model (if available) would allow a lot of time and effort to be saved, since:

a. a lot of experience can be gained on the system itself, without interfering with the productive cycle, at least during the first development stage;

b. experiments on the real plant can be limited and studied off-line in order to produce robust results.

In the following a detailed description of the models' creation and fault detection procedure applied to a gas centrifugal compressor system is described, with an example based on a *state space* type BB model.

2. GPMAS - FDI SYSTEM CONFIGURATION

The configuration of the Fault Detection Identification system (briefly FDI) has been performed using the General Purpose Mathematical Application Server (*GPMAS*™), a software product or service allowing the following phases:

a. Signals acquisition: collection of a set of signals suitable for training the model, and different test sets, for testing the fault detection capabilities of the algorithms (section 2.1);

b. Model Identification: identification of a State Space Model for simulating one or more output (section 2.2);

c. Fault Detection Algorithms Configuration (sections 2.3 to 2.6).

As to phase 'c', it is constituted by two different sub-phases: the creation of a function for evaluating the reliability of the State Space Model (section 2.3) and the definition of the parameters needed to perform the fault detection (section 2.4).

During phases 'b' and 'c', a certain number of case dependent parameters (e.g. residuals' standard deviations, Butterworth filter parameters, prediction horizon, etc.) must be defined by the user. These parameters are used to *configure* one or more tests, referred to as *detection test (DT)* in the following, before using them with real signals (section 2.6).

2.1. Signals acquisition

In order to create a BB model, historical data should be obtained from a Database or the PDAS, pre-processed (e.g. filtered, outliers replaced, data synchronized, etc.) and made available to the Systems Identification Engineer (SIE) or the Diagnostic Engineer (DE).

According to the nature of the process to be monitored, the data acquisition issue, can reveal some limiting aspects (Bittanti, 2002) like the constraint to record real signals only during the normal operating conditions (no external disturbance can be injected into the system). In other cases small disturbances can be injected into the system but only by small changes of some quantities (valve opening, gas density modification, etc.). In these cases the experiments through which the necessary *training* data are acquired can be planned, to obtain data, which make the identified model more robust.

The signals acquisition described in this paper is based on a TB model used to simulate the measured data coming from the PDAS; therefore the above limitations do not apply and it has been possible to obtain sufficient *training* and *testing* sets. In particular the *testing* data was created injecting a variety of faults (e.g. a valve leakage) into different points of the system (sections 3.1 and 3.3).

2.2. Process Model Identification

Once the SIE (or DE) has data available, he/she should perform the following steps to identify a model suitable for fault diagnosis:

a. Selection of the BB model family;

b. Selection of the model's input and output;

c. Definition of the model complexity.

The choice of the model family (e.g. State Space, Neural Networks, Signal Based, etc.) is driven by some physical considerations (e.g. whether the relationships between input and output are linear or non-linear, etc.) and also by the available computational time (e.g. a Neural Network approach is usually more demanding than a State Space one). In this work a State Space Model has been chosen, namely a system ruled by equation (1), for a discrete time model, where A,B,C,D,K are the so-called State Space Matrices, *u(t)* is the input vector, *y(t)* is the output vector, *x(t)* is the states vector and *e(t)* is a "white noise signal", with a specific variance.

$$\begin{cases} x(t+1) = Ax(t) + Bu(t) + Ke(t) \\ y(t) = Cx(t) + Du(t) + e(t) \end{cases} \tag{1}$$

Since during the selection of the model input and output, a huge amount of measured signals might be available the choice of the important ones might be quite complex. Therefore knowledge of the process to be monitored is essential and the support of a Process Engineer (PE) may be necessary.

As to the definition of the model structure complexity, it is unlikely that sufficient a-priori information concerning the model order that best describes the system is available, so that different models with different complexity should usually be evaluated. Then, according to some "quality criteria" (e.g. white noise pattern of the residuals), the most suitable one shall be chosen.

2.3. Reliable Domain of the Model: model validity

The BB model has been identified using a set of samples of the input/output relationship (the *training* set). Therefore the estimation of the output will be reliable (Muñoz and Sanz-Bobi, 1998) inside the region of the input space $U \subset \Re^n$, where n is the number of inputs, represented by the input samples of the training set. This region of the input space will be called the *reliable domain* of the model.

Using the input samples, the *probability density function* (PDF) of the inputs has been evaluated. Let $p_u[k]$ be the estimated PDF of the input vector $u[k]$. High values of $p_u[k]$ indicate a good representation of $u[k]$ in the training set, and, hence, a good characterization of the simulated output $y[k]$, under normal operating conditions. Vice versa, low values of $p_u[k]$ would indicate a poor representation of the input vector $u[k]$ in the training set, hence, a low level of reliability of the simulated output $y[k]$.

In this work the PDF function is normalized using its maximum value (thus the region with the highest PDF will have a value equal to 1) and the validity of each input sample, thus the instantaneous *model validity (MV)*, is computed using this normalized function. If the input vector falls outside the input space of the training set (even with only one component), a PDF equal to zero is assigned to this sample. The MV calculation can optionally feature a current predictor (CP) of the process under diagnosis. The use of a model with a CP allows tuning the dynamics of the model error, to obtain a faster convergence and to limit the initial numerical transients of the model, occurring when its initial state is unknown. Alternatively, when the signals history is long enough, a settling time (ST) criterion can be used to downscale the MV during a worse estimate duration of the numerical transient (Brighenti, *et al.,* 2004).

2.4. Diagnosis of faulty conditions

In order to detect faulty conditions of the process, the model's *residuals* (i.e. the differences between the measured and simulated outputs) must be analysed, and, in particular, the following characteristics should be checked:

a. Thresholds trespassing;

b. Residual derivative analysis.

According to the system identification theory (Bittanti, 2002), the model's residuals should reveal a "white noise pattern", i.e. have a mean equal to zero and a normal distribution. Normal distribution implies that 99.73% of the measurements (model errors) should fall within the $\pm 3\sigma$ interval during normal operating conditions, where equations (2) and (3) show the signals' standard deviation and the signals' mean, with N number of samples.

$$\sigma = \left(\frac{1}{N-1} \sum_{i=1}^{N} \left(x_i - \bar{x} \right) \right)^{\frac{1}{2}} \tag{2}$$

$$\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i \tag{3}$$

First of all, the output residuals of the training set are used for evaluating the standard deviations, in order to define the $\pm 3\sigma$ interval. These upper and lower thresholds will be used during the fault DT to check the value of the residuals. Low pass filtering of the signals is convenient even during the on-line operation, to avoid false alarms.

The analysis of the residual derivative, allows an advance warning of future alarms, unlike the $\pm 3\sigma$ thresholds criterion that would only detect faults already occurred. The derivative of each filtered residual signals is calculated and compared with a pre-defined value, which can be customized on a case-to-case basis, using the following equation:

$$f'_{\max}(\varepsilon) = \frac{3\sigma}{PH} \tag{4}$$

where PH (prediction horizon) is the time interval for which the trend should be checked (see Fig. I).

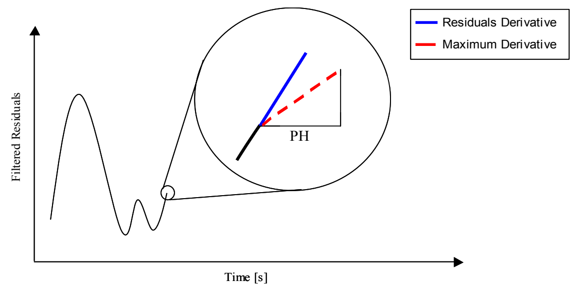


Fig. I. Residuals trend analysis.

The maximum absolute value allowed of the derivative, $f'_{\max}(\varepsilon)$, is the value that would lead the corresponding residual signal to trespass its $\pm 3\sigma$ within the PH. The signal of the residuals derivative is normalized using $f'_{\max}(\varepsilon)$, in order to combine the two pieces of information in a standardised three-dimensional fuzzy logic function (Fig. II), which defines the system behaviour referred to in the following as *decision validity* (DV).

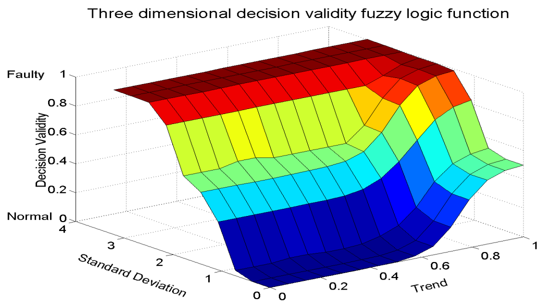


Fig. II. Three dimensional DV fuzzy logic function.

By this method a faulty alarm (DV) is raised the closer and/or the faster the absolute value of any filtered residuals approaches the respective $\pm 3\sigma$ thresholds. The DV is increased when both value and trend are close to their maxima, as shown in Fig. II.

2.5. Anomalous patterns definition rules (symptoms)

The output of a DT is a *symptom*, which can be defined as "a judgement on the plant/system behaviour". It is built up using the two quantities: DV, a judgement on the system operating condition (0 normal – 1 faulty) and MV, a judgement on the reliability of the identified model (0 not valid – 1 fully valid).

Other algorithms, configurable by the *GPMAS™*, would make it possible to identify the most likely cause of the detected symptoms. They were developed in the ongoing European project, MAGIC[1], whose aim is the development of an agent based diagnostic system running on a distributed computer architecture (Albert, *et al,* 2003, Köppen-Seliger, *et al* 2003, Ploix *et al* 2003).

2.6. Detection test software service activation

A DT can be performed using a model based function code only once all the necessary parameters have been defined (namely the DT has been configured) during the *training* session.

During the operational phase, if the test is called for the first time, the MV is treated using both the PDF and the CP or ST. Otherwise, if the DT is called more than once, two scenarios can take place:

a. The time histories of the two calls overlap one another, at least for one sample: in this case information concerning the previous states of the system can be obtained from preceding DT, and, since the initial state is known, the CP or ST correction of the MV can be avoided;

b. The time histories of the two calls do not overlap one another: in this case information concerning the previous states of the system are not available and the CP or ST correction of the MV must be used.

Both approaches are foreseen in the diagnostic tools developed in the above-mentioned MAGIC project.

3. FDI OPERATIONAL PHASE: APPLICATION TO A NATURAL GAS COMPRESSION SYSTEM

3.1. Plant Description.

The practical example taken for this work refers to a typical large compression facility, e.g. for pipeline transport, part of which is shown in the process scheme of Fig. III. Such a complex plant includes several controllers to maintain the plant safety and the process and machines efficiency as high as possible, the latter being associated to several MW power.

Simulations, based on TB models, are frequently used during the design phase of these systems to verify the capability of valves and controllers to prevent unwanted dangerous situations.

COMPSYS™ is a proprietary compression systems simulation environment and library, based on MATLAB®-SIMULINK®, implementing a TB modelling approach, which was qualified through various services performed on behalf of important compressors manufacturers and engineering companies (Brighenti, 1995; Brighenti, *et al.,* 1999; Brighenti and Boatto, 2000). This simulator is able to describe: real gas thermodynamics, 3D dynamic compressor maps, non linear gas dynamics, dynamics of heat exchangers, separation of gas components fractions below the dew point, drivers shaft dynamics and the various system controllers (Brighenti, *et al.,* 2004).

3.2. Possible fault example (ASV leakage).

One possible fault, which could arise in a compression system like the one shown in Fig. III, is the offset of a stage antisurge valve (ASV) actuator, yielding valve leakage. This causes recirculation of gas from the discharge to the suction side of the compressors, reduction of flow and loss of power and efficiency. The effect differs if the leaking valve takes gas from upstream or downstream the compressor stage discharge after-cooler. This is a significant, though not the sole, possible example of application of FDI techniques to these complex systems, which is used in this work as a test case.

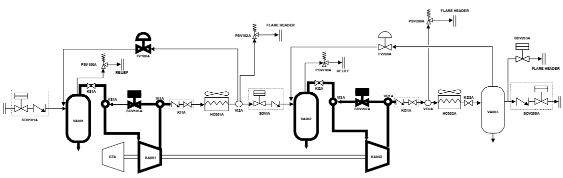


Fig. III. Simplified PFD of a typical gas compression train for a large pipeline booster station.

3.3. Signals generated.

The "pseudo-measured" signals for the BB model *training* have been generated as summarised in Table 1. Instead, those for *testing* (1STCBLEAK and 2NDCBLEAK, respectively for the 1st and 2nd stage) have been generated as summarised in Table 2.

Table 1 Training Signals Description

Time	Plant Input
$0 \le t < 20\,\text{sec}$	normal operating condition with the plant's nominal mass flow rate
$t = 20\,\text{sec}$	+10% inlet mass flow rate step
$t = 120\,\text{sec}$	nominal mass flow rate
$t = 220\,\text{sec}$	-10% inlet mass flow rate step
$t \ge 320\,\text{sec}$	nominal mass flow rate

To give an idea of the sensitivity of the FDI features obtained, a 10% opening fault of the valve under

[1] MAGIC website: http://magic.uni-duisburg.de/

consideration yields only 1% of its maximum mass flow rate, likely to be undetected by the plant monitoring system. Valve proximity sensors are usually foreseen in real plants, yielding ON/OFF fault signals, with consequent null or overestimated level of alarm for the example considered.

Table 2 Testing Signals Description

Time	Plant Input
$0 \le t < 500\,\text{sec}$	Normal condition: the stage cold by-pass ASV valve is closed.
$t = 500\,\text{sec}$	Faulty condition: the stage cold by-pass ASV valve starts opening according to a linear trend.
$t = 1000\,\text{sec}$	Faulty condition: the same ASV stops opening after reaching 10% opening and starts closing according to a linear trend.
$t = 1100\,\text{sec}$	Normal condition: the stage cold by-pass ASV valve is back closed.

Table 3 Model monitoring the 1st stage mass flow rate (briefly M1STMFR)

Model characteristics	Description
Input	Driver Speed;
	1st stage suction temperature;
	1st stage suction pressure;
	1st stage discharge pressure
Output	1st stage mass flow rate;
Order	2

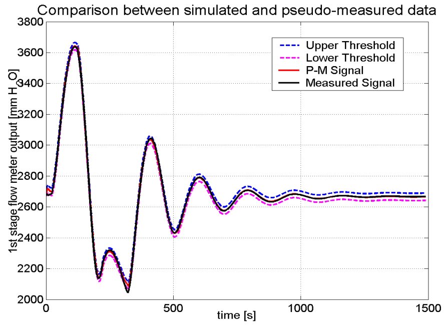
3.4. Identified model.

A BB MISO model was identified according to the procedure described in section 2.2. Its main characteristics are summarized in Table 3, while the results obtained using the training signals are shown in Fig. IV and Fig. V. The latter shows the effect of a low MV in the initial part of the training signal sample, due to the model numerical transient occurring because of the unknown initial state, which is considered, in this case by the ST criterion (section 2.6).

3.5. Running the FDT software.

The BB model identified was applied to the faulty conditions reported in section 3.3. In particular the BB model M1STMFR was used with “pseudo-measured” signals obtained in the faulty conditions for the same stage (1STCBLEAK). The relevant results are shown in Fig. VI-a and b.

These figures clearly show that a certain amount of time (100 s ca.) is needed by the BB model output to enter the interval of $\pm 3\sigma$, which is however smaller then the ST calculated in the identification phase.



(a)

Fig. IV. Comparison between the Pseudo-Measured (P-M) and the simulated output signals with the training set of BB model M1STMFR (flow rate measurement is expressed in mmH_2O).

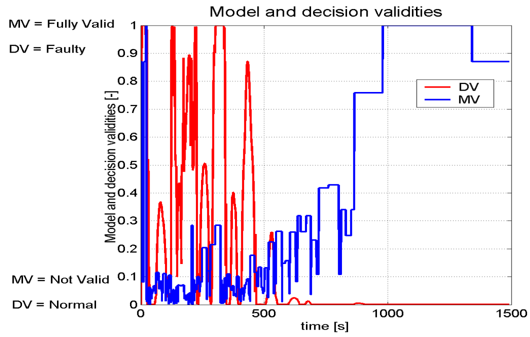
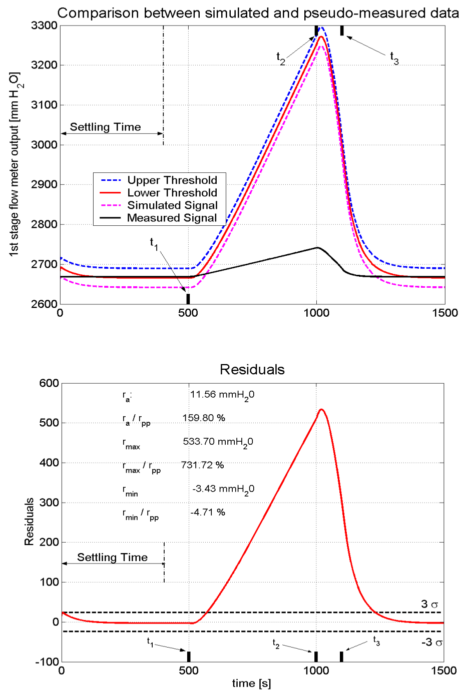


Fig. V. Symptom obtained on the *training* set of BB model M1STMFR.



(a)

(b)

Fig. VI. Comparison between Pseudo-Measured and BB simulated signals of a testing set of BB model M1STMFR used with faulty condition 1STCBLEAK - fault starts developing in t_1; fault stops developing in t_2; fault ends in t_3.

After the fault injection (time $t_1 = 500$ s) the BB model output amplifies the trend visible in the pseudo-measured signal; once the fault starts being reduced (time $t_2 = 1000$ s), the BB model output returns towards the pseudo-measured one, ending within the $\pm 3\sigma$ interval for normal condition.

Therefore, in a real situation, by a visual comparison between the BB model and the measured output, it would be possible to detect that a fault occurred or is occurring. In addition to this, the main aim of this work was to demonstrate that this check could be done automatically, which appears to have been fulfilled (Fig. VII).

Indeed the DT starts highlighting an abnormal operating condition 40 seconds after the fault started developing, when the valve opening is equal to 0.8% and the mass flow rate is 0.08% of its maximum, while it clearly raises an alarm after 70 s, when the valve opening is equal to 1.4% and the mass flow rate to 0.14%.

After 220 s the BB model starts loosing validity, since the fault is influencing the BB model's input, which then falls outside the training space.

Once the fault starts being reduced, then completely removed, the BB MV re-increases. After a certain amount of time, which is comparable to the time needed at the beginning to start providing stable results, it detects the fault removal, providing a DV equal to 0. Therefore, the Detected Fault Period (DFP) is 30% longer than the Actual Fault Period (AFP in Fig. VII).

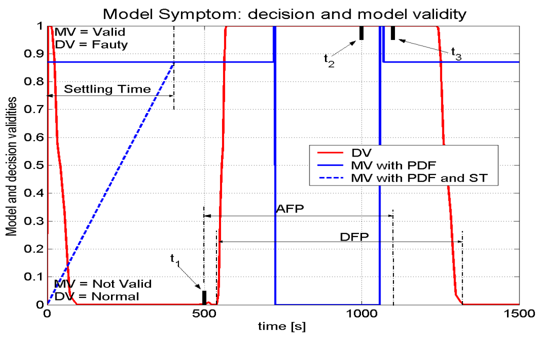


Fig. VII. Symptom obtained on the testing set of model M1STMFR used with faulty condition 1STCBLEAK - fault starts developing in t_1; fault stops developing in t_2; fault ends in t_3. AFP: Actual Fault Period. DFP: Detected Fault Period.

4. CONCLUSIONS

The work reported in this paper, aimed at demonstrating the feasibility of creating an automatic fault detection system based on "black box" modelling, showing the use of State Space models as an example.

The fault detection algorithms are based on the analysis of the differences between the outputs provided by an identified BB model and the measured ones, namely the model residuals, considering and verifying the MV under the running conditions.

The performances and reliability of the proposed approach have been improved coupling the fault detection algorithms with a MV estimator, based on the probability density function evaluation.

The DT has been tested on a real world problem simulated by a "transparent" model (*COMPSYS*™). The diagnosis of a centrifugal gas compression system has been reported, demonstrating its capabilities of detecting even incipient faults.

ACKNOWLEDGMENTS

The authors thank the European Commission for the financial support provided in the MAGIC project within the IST programme and the partners of this project, from which an important part of the background to this work was developed.

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