IFAC Publications
www.elsevier.com/locate/ifac

DEVELOPMENT AND APPLICATION OF METHODS FOR ACTUATOR DIAGNOSIS IN INDUSTRIAL CONTROL SYSTEMS (DAMADICS): A BENCHMARK STUDY

Michal Syfert*, Ron Patton+, Michal Bartyś, and Joseba Quevedo++**

**Warsaw University of Technology, {msyfert@mchtr.pw.edu.pl}*
+The University of Hull, {r.j.patton@hull.ac.uk}
***Warsaw University of Technology, {bartys@mchtr.pw.edu.pl}*
++Universitat Politècnica de Catalunya, {joseba@esaii.upc.es}

Abstract: This paper provides the description and presentation of a new actuator benchmark for fault diagnosis studies developed in the framework of the EC-funded Research Training Network *DAMADICS*. The paper also introduces 3 special sessions of papers providing an evaluation of methods and results focussed on the benchmark problem. The benchmark is FDI method independent and based on an in-depth study of the phenomena that can lead to likely faults in valve actuator systems. The study uses a detailed consideration of the physics and electro-mechanical properties of the valve together with typical engineering requirements of a valve operating under challenging industrial conditions. The benchmark study is available on the internet at *http://diag.mchtr.pw.edu.pl/damadics/* and provides a set of performance indices for evaluating the results. *Copyright © 2003 IFAC*

Keywords: Industrial actuators, fault detection and isolation (FDI), benchmark study, intelligent components and instruments

1 INTRODUCTION

The purpose of this benchmark study is to compare and contrast a wide range of fault detection and isolation (FDI) methods within a strongly oriented focus on application to industrial actuator examples in a sugar factory. This paper provides an overview of the benchmark problem to which partners have referred in preparing papers for three sessions in the IFAC Symposium *SAFEPROCESS 2003*.

The likelihood that actuator systems (e.g. control valves, servomotors, positioners) will malfunction is significant when these components are installed in harsh environments (e.g. with high temperature, humidity, pollution, chemical solvents, aggressive media etc.). The determination of the development of small (incipient – hard to detect) faults before they become serious clearly has an important influence on the predicted lifetime of an industrial actuator. Valve faults causing process disturbance and shut-down are of major economic concern and can sometimes be an issue of safety and environmental pollution. In any case, when actuators do not function correctly the final product quality is influenced. The monitoring of the development of incipient faults is therefore an issue not only for predicting maintenance schedules but also for monitoring the performance of the process concerned.

Forecasts show that the spectrum of diagnostic functions of intelligent actuators will expand as a consequence of these requirements. On-line diagnosis of actuator (and indeed sensor) components can be achieved either via a remote or supervisory diagnostic system or autonomously. A very good example of this activity has arisen from the SEVA research programme of Oxford University (Yang & Clarke, 1997; Henry, 2000).

The related research topic of FDI has, over two decades demonstrated great activity at least amongst the academic community (Patton, Frank & Clarke, 1989, 2000; Gertler, 1998); Chen & Patton, 1999; Simani, Fantuzzi & Patton, 2002). FDI methods are based on various forms of modelling (both quantitative and qualitative) but can also include data-driven modelling or soft computing using neural networks, fuzzy logic (or a combination of these, the so-called neuro-fuzzy paradigm) (Calado *et al*, 2001).

The ideas and concepts are hard to put into application without intermediate steps involving full partnership between universities and industry and making use of in-plant application.

Indeed a wide investigation and appraisal of the suitability of fault diagnosis and condition monitoring methods is important, although full plant evaluation studies will not be possible on many types of processes. However, an opportunity of progress with some process systems can provide insight into the general value of these methods towards a general drive for the integration of cost efficient intelligent instruments within modern processes.

A recent special issue (Tombs, 2002) shows strong evidence of industrial involvement in the development and application of self-validating instruments. Applications of FDI and advanced condition monitoring methods are still lagging behind the development of the intelligent instruments. This paper describes the development of an opportunity with a sugar factory, Cukrownia Lublin SA, Poland. The collaboration between the sugar factory staff and 8 partners of the EC-funded contract: *Development and Application of Methods for Actuator Diagnosis in Industrial Control Systems* or *DAMADICS* has led to the development of this engineering benchmark study into the technology requirements and methods that can be used for FDI. The sugar factory process being monitored concentrates on 5-stage sugar evaporation process and power station boiler involving chosen three control valve actuators operating at different conditions and environments. The research focuses on the development, and integration of model-based, statistical and soft computing diagnosis methods using different levels of benchmark study and comparison. The aim of the longer-term research is to provide further technology transfer into the development of intelligent actuation systems (e.g. "smart positioners", etc) within the framework of activity described by Tombs (2002).

Under the *DAMADICS* contract a scheme of real system fault injection has been developed in which three sugar factor actuators have been modified to facilitate the introduction of mechanically and electronically induced "faults". The faults are emulated under carefully monitored conditions, keeping the process operation within acceptable quality limits. Actuator data are made available to all of the partners using the internet so that diagnostic benchmark tests can be carried out; a realistic programme of benchmarking has been set up, providing a rich facility for research training in the *DAMADICS* network.

The *DAMADICS* study is based on several levels of (a) data generation and collection, (b) benchmarking study, (c) modelling and (d) pure research. The benchmark study takes on two forms based on: (i) modelling and (ii) real data recording and in-process fault emulation. This paper outlines how the results of these two benchmark studies are being integrated into the research program. The second paper (Bartyś & de la Heras, 2003) defines the actuator simulation. The following are the six main domains of research in the *DAMADICS* research study from which the papers in the three sessions are developed:

Development of analytical methods and techniques. This research involves both structure determination (for example of parity equations or observer residuals) (Frisk *et al*, 2003) as well as a number of investigations into the use of state estimation observer approaches to give robust detection and isolation of faults in the presence of modelling errors and uncertainty. The robust observer approaches use either active or passive methods according to a definition by Chen and Patton (1999). The passive methods (Stancu *et al.*, 2003) are based on the interval observer that has also been compared in this study (Puig *et al.*, 2003) against the automata and quantised modelling approaches of Lunze *et al.* (2003). The active approaches (Uppal *et al.*, 2003; Witczak *et al.*, 2003) use soft computing methods to realise robust designs. Uppal *et al.* (2003) use a novel neuro-fuzzy network technique for designing multiple-model observers. Witczak *et al.* (2003) use a genetic algorithm approach to identify state-space models with suitable structure for robust fault detection. Several other contributions have been made which are referred to in the session papers.

Development of model-free diagnosis methods. Some of the *DAMADICS* studies have driven in the direction of methods that do not require system of process models (in this case no models of the actuator are required). This is appropriate, as the benchmark study itself makes no provision of an analytical model. Studies of this kind include spectral estimation (Previdi *et al.*, 2003) and pattern recognition methods (Marciniak *et al.*, 2003). Other methods that can be classed as "model-free" belong to the field of soft computing. A review of these methods under the framework of the *DAMADICS* contract has already been given (Calado *et al.*, 2001). The second of our proposed benchmark sessions contains papers focussed on neural networks and neuro-fuzzy methods.

Development of neural and fuzzy approaches.

Neural networks provide an excellent framework for modelling and are especially suitable for handling non-linear systems, as no explicit mathematical model of the system is needed. On-line training makes it possible to change the FDI system easily when changes are made in the physical process, the control system or parameters. Neural networks have the ability to make intelligent decisions in cases of noisy or corrupted data. It is important to realise that neural networks do not require an explicit mathematical model of the system being modelled/monitored. They can also operate simultaneously on qualitative and quantitative data and they are readily applicable to multivariable systems. In this benchmark study 6 papers (Rzepiejewski *et al.* ; Patan *et al.* ; Mrugalski *et al.* ; Uppal *et al.* ; Papadimitropoulos *et al.* ; Calado *et al.*, 2003) have focused on neural networks or neuro-fuzzy approaches to the benchmark problem.

Development of qualitative, bond-graph and statistical approaches.

The research focuses on the development of diagnostic methods that use qualitative information about the actuators to be diagnosed rather than analytical models. The novel methods including bond-graph techniques, structural analysis techniques and qualitative models, which represent continuous-variable systems in a discrete-event mode are being investigated. Dynamic models with parameters set with their values bounded in intervals are applied. Once the interval model has been produced it can be used in fault detection using several strategies: in simulation, in prediction or in observation. In this benchmark study 4 papers (Previdi *et al.* ; Lunze *et al.* ; Stancu *et al.* ; Frisk *et al.*, 2003) have focused on fault detection using spectral estimation approach, timed automata application and structural analysis of faulty behaviour models to the benchmark problem.

2 NECESSITY FOR ADVANCED DIAGNOSIS (INDUSTRIAL EXAMPLES)

2.1 System Description.

If we focus attention on the technological apparatus shown on Fig. 1, this is a typical evaporator known from many installations around the world. The thin sugar beet juice is fed into the evaporator passing through the series of pre-heaters. The local PI control loop controls the juice level in evaporator throttling juice inflow by acting on control valve (shown in the circle).

The set-point of juice level value in the evaporator is equal to 500mm and should be controlled within the limits of a few percent. The alarms are set when the juice level is lower then 250mm or higher then 750mm. Both situations are dangerous for the process and process operators. In the case of too low juice level in the evaporator, the danger of exploding the boiler due to its overheating occurs.

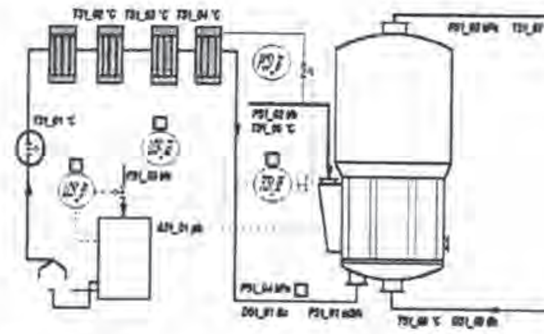


Fig. 1. 1st stage of multi-section evaporisation station at the Lublin Sugar Factory.

When the juice level is too high, the sugar particles are thrown out into the vapours leaving the evaporator, thus polluting further parts of the installation. This leads to process shut down and the necessity of running special cleaning procedures what is time and energy expensive. The flow rates are of the order of $360m^3/h$. From knowledge of the juice volume in the evaporator one can easily deduce that a dangerous situation could be detected by alarm analysis within 30s, giving a further 30s for operator intervention. Shortening the analysis time may be the crucial point in this case. This is principally the task of advanced on-line fault diagnosis based rather on signal processing than on alarm analysis. The application of new diagnostic algorithms in smart final control elements may bring significant increase to overall system safety, reliability and economy whilst also providing a powerful tool for local performance monitoring.

The following subsections provide descriptions of the different examples included in the benchmark study.

2.2 External fault in evaporator (caused by human factor)

When analysing standard statistical factors or distributions one can recognise some faulty states. However, *a'posteriori* knowledge may only be helpful when analysing or reconstructing the history of the events. The experience gained may also be useful when developing new projects or involving new process safety insurance procedures. If we look at the histogram of juice level in the first evaporator taken from the data acquired along one day of operation (Fig. 2) some valuable conclusions may be drawn out. The juice level histogram seems to be distributed narrowly around the mean value of 47%. In this case, the process value standard deviation may be treated as a factor for evaluating process control quality. However, this was conducted on a day when the positioner controlling the juice inflow to the evaporator was replaced by its intelligent counterpart. During the replacement, the manual operation mode of automatic control system was switched on. The only juice control possibility was throttling the flow using the hand driven valve V_3 shown in Fig. 8 (by closure of valves V_1 and V_2).

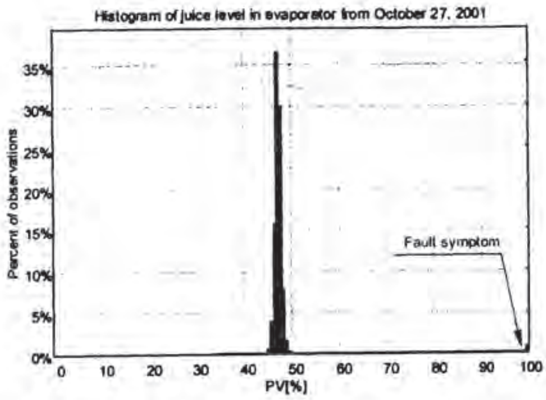


Fig. 2. Histogram of juice level in evaporator, 1 day time window and 1 s sampling interval.

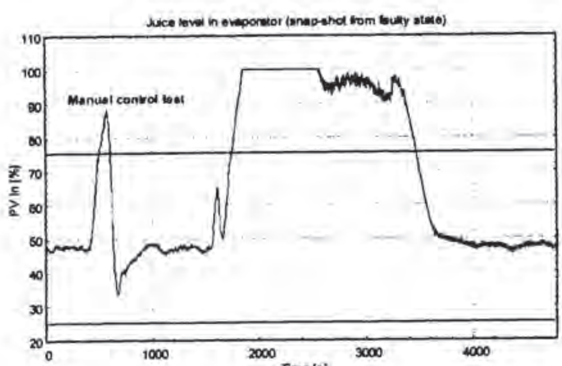


Fig. 3. Evaporator juice level time series for faulty state; time window 1h 36'.

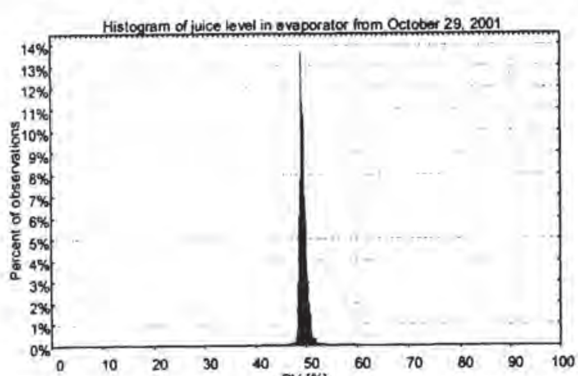


Fig. 4. Histogram of juice level in evaporator; time window - 1 day, sampling time 1 s.

The positioner replacement operation took approximately 20 minutes. During this relatively short period the evaporator juice level exceeds the allowed level for about 2 minutes. This was a typical faulty state caused by poor process control in manual mode. The small rectangle in the right lower part of the histogram on Fig. 2 reflects this event. The chemical analysis of vapours detected some portion of dispersed sugar. The process value histogram two days later (Fig. 4) differs significantly from that shown in Fig. 2 but in this case the process limits were not exceeded.

2.3 Actuator fault

An interesting example of the convolution of sensor, and actuator faults involves the water level control loop in a power station boiler. During standard operation, the control valve plug displacement signal X follows the actuator set-point signal CV (see Fig. 5). As a consequence of a break in the boiler water level signal (not shown in Fig.5) the controller of water level control loop suddenly forces the control value CV to try to compensate the (supposed) unexpected water level drop. The valve was fully opened and locked into the uppermost position.

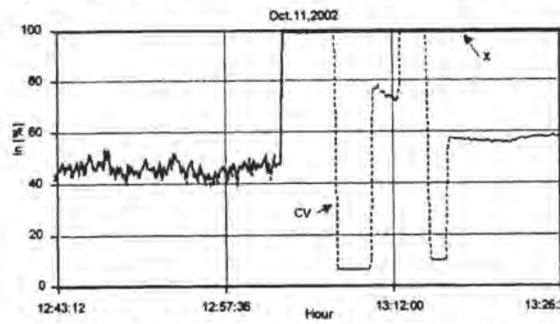


Fig. 5. Example of actuator fault (valve plug blockage) caused by temporary fault in water level sensor.

After recovery of the water level signal, the controller attempts to close the valve. The actuator valve plug does not follow the CV signal due to mechanical blockage of the valve. Hand driven cut-off valves were used to recover control of the process.

The water level drop velocity in boiler was not realistic from the physical point of view except of blast what was not a case. The fault might be easily detected and isolated when applying elementary diagnostics. The process safety and economic advantages of actuator diagnostics are here evidential.

2.4 Sensor fault in evaporator

The unstable juice control system behaviour is captured on. The instability of the control system however is not caused by improper controller design. This phenomenon is rather caused by instability of juice level sensor (see Fig. 6).

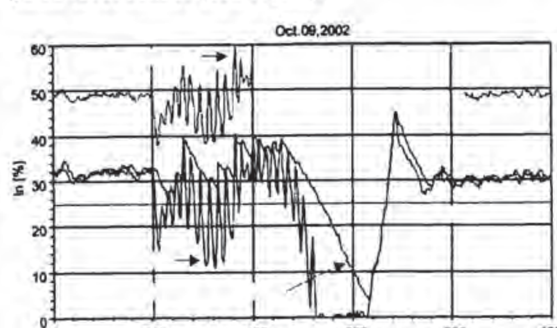


Fig. 6. Example of juice level control. System instability caused by a sensor fault.

The registered file show that juice level measurements are involving serious controller output oscillations. Due to unstable control system operation the juice level drops down below low alarm level thus making process highly unsafe. Due to unstable control system operation the juice level drops down below the lower alarm threshold. The effect of the process operator fighting to recover the system stability can be clearly seen. The low-pass characteristic of the actuator is clearly seen. The damping action on juice flow fluctuations is also very important. By applying heuristic knowledge, the operator suppresses only juice level measurement instabilities. This is achieved by temporarily setting the juice level set-point to a suitably high enough level. However, this action disturbs the process, lowers the process quality and does not reject the real reason or cause of the faulty process behaviour.

This simple example shows the scale of diagnostic complexity especially when the modelling and heuristic knowledge about the process being diagnosed is insufficient.

2.5 Introduction of artificial external faults

Some classes of FDI algorithms need to be designed or trained using faulty states from the process. Although this requirement is difficult to achieve in practice it may be realised in a suitable way by running artificial fault generation procedures. However, it is clear these procedures can cause unacceptable disturbance to the process, lowering the quality of the end product, compromising economic factors and decreasing process safety. The scenarios of artificial fault generation procedures were also developed for the *DAMADICS* task requirements. It was possible to run these procedures as a special exception. For example Fig. 7 shows the result of the bypass pipe valve V_3 being partly open (corresponding to an external leakage fault). The system responds to this fault by throttling the flow in the main pipe. This event is easily recognised when observing the CV value. Thus, one can state that this correlation may be useful when detecting and localisation of external leakage.

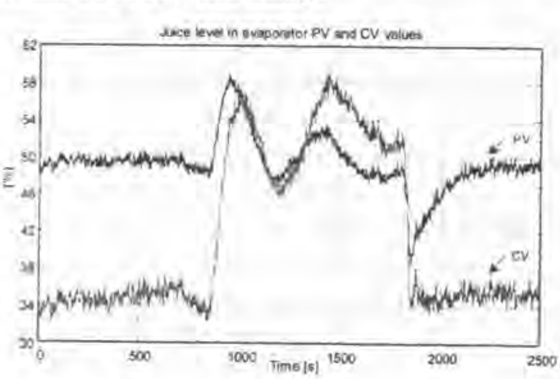


Fig. 7. Fault-induced CV changes (external loop controller compensates by-pass valve leakage).

3. THE SET OF ACTUATOR FAULTS

The actuator benchmark study is based on the electro-pneumatic actuator system (Fig.8.). The system consists of smart positioner, control valve and diaphragm-spring pneumatic servomotor assembly.

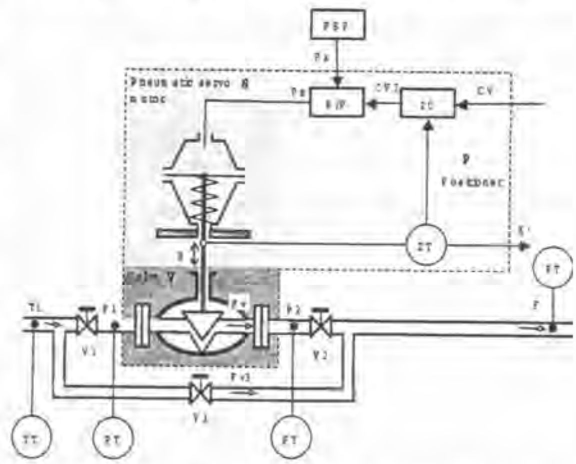


Fig. 8: Scheme of smart positioner, control valve and diaphragm-spring pneumatic servomotor assembly.

The notation used in Fig. 8 is:

S	- pneumatic servo-motor
V	- control valve,
V1,V2,V3	- cut-off valves
P	- positioner
ZC	- positioner internal P type controller
E/P	- electro-pneumatic transducer
ZT	- rod position transmitter
PT	- pressure transmitter
TT	- temperature transmitter
FT	- flow rate transmitter
X	- valve plug displacement
X'	- valve plug displacement measurement
F	- flow rate
P1, P2	- pressures on valve: inlet and outlet
T1	- medium temperature
CV	- process control value
PSP	- positioner supply pressure
Ps	- E/P transducer output pressure
Pz	- positioner air supply pressure
CVI	- internal current acting on E/P unit

The positioner is a control element commonly used in the industrial practice. More detailed information about the actuator can be found in Bartyś & de la Heras (2003).

Realistic assumptions have been taken into account that for diagnostic purposes the following signal values are available (see Fig. 8): CV - process control value (positioner set-point signal), CVI - control current of electro-pneumatic transducer, Ps – electro-pneumatic transducer output pressure, X – valve plug displacement, F - media volume flow rate. In the actuator, faults could appear in: control valve, servomotor, electro-pneumatic transducer, diaphragm stem travel transducer, pressure transmitter or microprocessor control unit. The auto-diagnostic functions of the microprocessor control unit allow for detection of its internal faults.

Let us assume that the set of possible primary faults of the assembly: control valve, pneumatic linear servomotor, positioner is known (Koj, 1998; Koscielny & Bartyś, 2000).

The total of 19 faults $\{f_1 .. f_{19}\}$ are distinguished. The faults are falling into four following groups:

- Control valve faults:
  - f_1 - Valve clogging,
  - f_2 - Valve or valve seat sedimentation,
  - f_3 - Valve or valve seat erosion,
  - f_4 - Increase of valve or bushing friction,
  - f_5 - External leakage (leaky bushing, covers, terminals),
  - f_6 - Internal leakage (valve tightness),
  - f_7 - Medium evaporation or critical flow.
- Servomotor faults:
  - f_8 - Twisted servo-motor stem,
  - f_9 - Servomotor housing or terminal tightness,
  - f_{10} - Servomotor's diaphragm perforation,
  - f_{11} - servomotor's spring fault.
- Positioner faults:
  - f_{12} - Electro-pneumatic transducer fault,
  - f_{13} - Stem displacement sensor fault,
  - f_{14} - Pressure sensor fault,
  - f_{15} - Positioner spring fault.
- General faults/external faults:
  - f_{16} - Positioner supply pressure drop,
  - f_{17} - Unexpected pressure change across valve
  - f_{18} - Fully or partly opened bypass valves,
  - f_{19} - Flow rate sensor fault.

The set of above defined actuator faults is of special meaning for actuator benchmark (see next Section). All benchmark tests assume the same, common for all participants, fault set. The main aim of actuator benchmark being defined in the *DAMADICS* contract project is the evaluation of industrial applicability of FDI methods under assumption of pour or unavailable analytical description of the process and actuator itself.

4 THE BENCHMARK PROBLEM

A number of powerful methods have been developed for early detection and isolation of actuator faults (Blanke & Patton, 1995; Patton, Frank & Clarke, 2000). In pre-application phases the methods should be appropriately evaluated to certify industrial applicability. There is a lack (Mediavilla, *et al.*, 1997) of well defined benchmarks suited for performing this task especially when considering the wide-spread use of industrial actuators of the form described in Section 3. The well known "three tank system" (Patton, *et al.*, 2000) benchmark extensively used for FDI methods evaluation seems to be inadequate when considering industrial implementation. The currently defined benchmark appears to be a good development of the ship engine governor actuator benchmark delivered at *SAFEPROCESS 1994* by Blanke and Patton and co-workers (see Blanke & Patton, 1995 and complete special issue on this subject).

A well defined benchmark that can ensure comparable results for different FDI methods must provide at least the following specifications:

- Use of a common process,
- Use of common data sets,
- Standardise fault scenarios,
- Standardise reporting of results.

Additionally, all the above specifications must be formulated taking into account the possibility to check the industrial applicability of proposed FDI solutions.

In this section the concept and definition of an industrial actuator benchmark is proposed. When developing the benchmark some important and substantial assumptions were made. The benchmark must:

- be FDI method independent,
- be focussed on the industrial actuator introduced in Section 3
- use both a Simulink model of the actuator as well as real process data,
- not contain any analytical description of the actuator,
- not describe the analytical model of the controlled system.

Those assumptions seems to be realistic taking into account industrial implementation requirements.

The benchmark structure consists of three well defined main parts (or steps) (Syfert, *et al.*, 2002) allowing evaluation, testing detectability and isolability features and appraising the applicability of FDI methods. The purpose of the benchmark steps is as follows:

- step I for evaluation of FDI methods,
- step II for testing features of FDI methods,
- step III for approving applicability of FDI methods.

First two steps of the benchmark are based on the actuator Simulink model (Bartyś, 2001; Bartyś and Syfert, 2002; Bartyś and de la Heras, 2003), third step is based on process data. FDI algorithms may be tested using any subset of given steps, however *linear* passing from benchmark Step I to benchmark Step III is strongly recommended. The benchmark structure reflects the way of passing from laboratory tests to industrial implementation.

Common process and data sets. The actuator Simulink model suited for Steps I and II was tuned and validated using data originating from real industrial process. The model is used for generating the data from normal and abnormal (faulty) states, thus allowing learning or tuning FDI algorithms. A special, user-friendly Simulink library (Bartyś and Syfert, 2002) was developed to perform benchmark Steps I and II and this is described in the Section "Simulink Library"

The real process data comes from three actuators installed in the Lublin Sugar Factory: actuators in the inlet and outlet of the evaporation station and one controlling water inflow to the steam boiler system. These data where collected for fault-free states as well as for some faulty states.

In both cases, when artificial or real process data are used, the set of 5 available measurements is considered (see Section 3): output signals from the external controller CV, values of medium pressure on the valve inlet P1 and outlet P2, stem displacement X, medium flow F and medium temperature T1. It is assumed that all measurements (except the CV values that come from the control unit) include disturbances.

All FDI methods should only use the specified process variables. However, the additional tests can be carried out with extended set of measurements that additionally includes: air supply pressure P_z', electro-pneumatic transducer current CVI' and servomotor chamber pressure P_s'.
The results of such tests, if provided, should be added as comments to standard tests specified in benchmark steps definitions.

Standard fault scenarios. Due to unlimited number of possible fault scenarios some limitations concerning the set of considered faults and failure modes where done. Additionally, it was assumed that only single faults scenarios are considered and simulated.

For all benchmark tests of Steps I-III the set of 19 actuator faults was assumed and considered (see Section 3). The detailed description can be found in (Bartyś and Syfert, 2002).

In each benchmark step only the predefined fault scenarios are considered. Each *fault scenario* consists of: *fault selection, failure mode* and *fault direction*. The *failure mode* is described by *fault strength* and *fault strength time development*. For the benchmark purpose the three standard values of *fault strength* where defined. These are referred to as: *small-long, medium & big-short* (see Fig.10) and correspond to 0.25, 0.5 and 0.75 normalised values. Two *fault strength time developments* are considered: abrupt and incipient (see Fig. 10).

The *fault direction* is used in the case when the fault can influence the system in two different ways, e.g., the sensor fault can increase or decrease the value of the measurement. Most of the faults considered have only one direction.

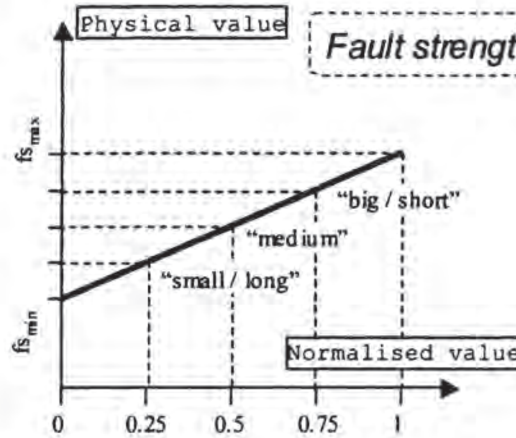


Fig. 9. Definition of fault strength

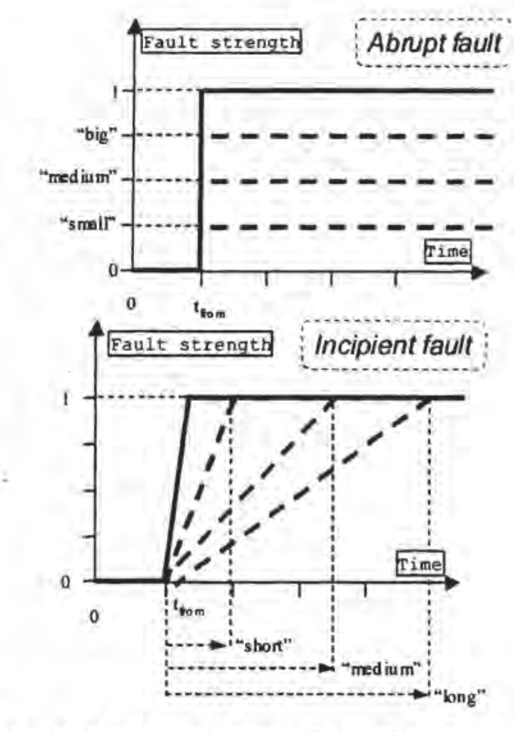
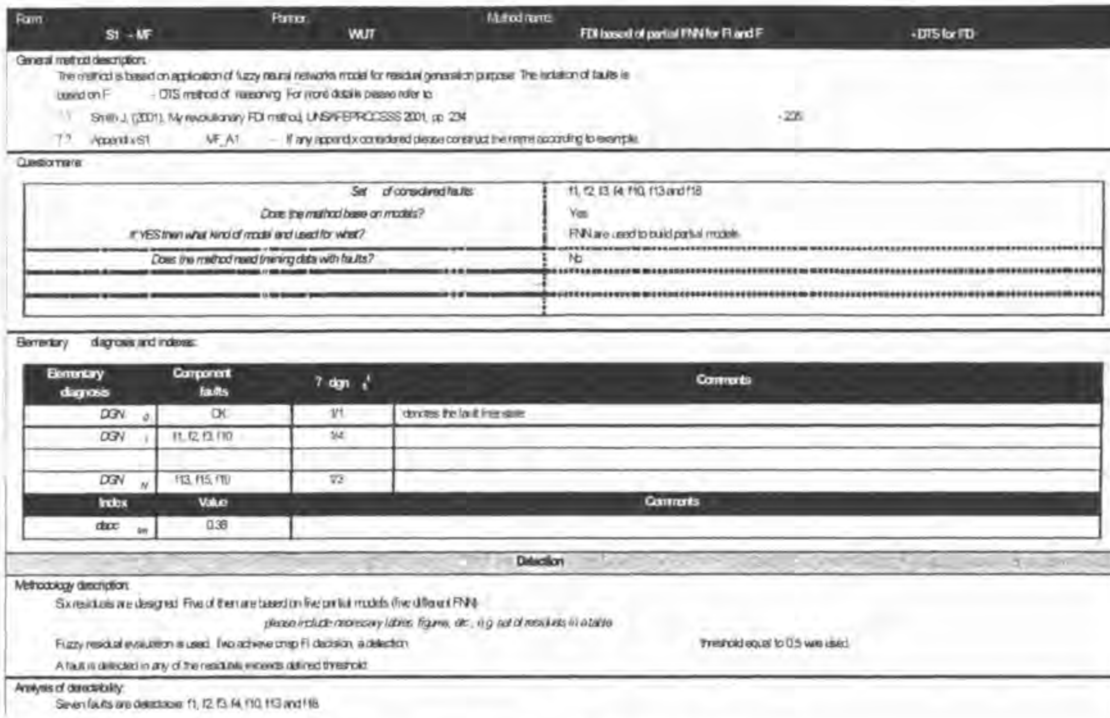


Fig. 10. Definition of abrupt and incipient faults.

Standardise results reports. Finally, to assume comparability of the results of different actuator FDI methods, a standardised way of reporting is proposed. For each Step, the set of reports that should be completed by the benchmark participants is designed. Fig. 11 shows an example of a standard report form.

Step I
The first step is suited for preliminary evaluation of FDI. It is based on the data generated by data generator and actuator simulator. In this Step the actuator is considered as a stand-alone unit.(Fig. 12).



Form: S1 - MF	Partner: WUT	Method name: FDI based of partial FNN for FI and F - DTS for FD

General method description:
The method is based on application of fuzzy neural networks model for residual generation purpose. The isolation of faults is based on F - DTS method of reasoning. For more details please refer to:
1.1 Smith J. (2001). My revolutionary FDI method, UNSAFEPROCSSS 2001, pp. 234 - 235
1.2 Appendix S1 MF_A1 – If any appendix considered please construct the name according to example.

Questionnaire:

Set of considered faults:	f1, f2, f3, f4, f10, f13 and f18
Does the method base on models?	Yes
If YES then what kind of model and used for what?	FNN are used to build partial models
Does the method need training data with faults?	No

Elementary diagnosis and indexes:

Elementary diagnosis	Component faults	? dgn	Comments
DGN 0	OK	1/1	denotes the fault free state
DGN 1	f1, f2, f3, f10	1/4	
DGN N	f13, f15, f10	1/2	
Index	**Value**	**Comments**	
dacc	0.38		

Detection

Methodology description:
Six residuals are designed. Five of them are based on five partial models (five different FNN).
please include necessary tables, figures, etc., e.g. set of residuals in a table
Fuzzy residual evaluation is used. Two achieve crisp FI decision, a detection threshold equal to 0.5 was used.
A fault is detected in any of the residuals exceeds defined threshold.

Analysis of detectability:
Seven faults are detectable: f1, f2, f3, f4, f10, f13 and f18

Fig. 11: An example of a standard report form.

All inputs of the actuator model are driven independently.

The benchmark participants use two kinds of data:

- Learning data generated using the actuator model. Each benchmark participant can create his own data sets by feeding the model with any data he likes. These data are then used for tuning the FDI algorithms. The records from fault-free states as well as from faulty ones can be obtained.
- Testing data set generated by specially prepared data generator.

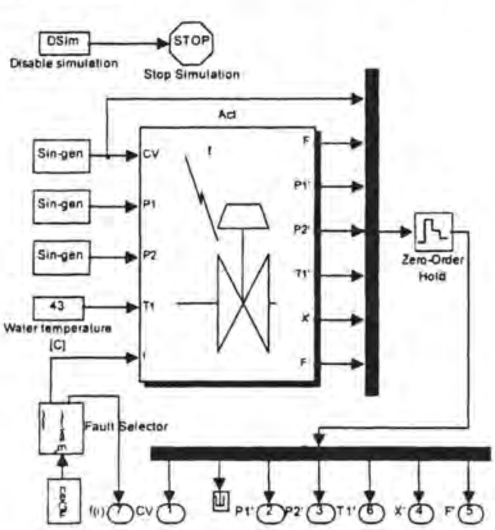


Fig. 12. Data generator internal structure in Step I: Actuator considered as stand-alone unit.

A total of 44 fault scenarios have been chosen for the investigation. For all scenarios two time zones were fixed:

- First time zone. This is a *set-up zone* used to avoid taking into account false FDI decisions that can occur at the beginning, e.g., some FDI methods need to be tuned properly before starting. This zone is limited by the time t_{on} (see Fig. 13)
- The second zone is a *benchmark zone*. All results (figures, performance indices, etc.) are referred to this zone. This zone is limited by the time horizon:

$$t_{hor} = t_{from} + t_{fd} + t_{ov} \tag{1}$$

where t_{ov} is a preset period from the moment where the fault strength reaches maximum value.

Time horizon t_{hor} defines moment of finishing FDI tests. All performance indices are calculated up to t_{hor} moment. The time parameters of each fault scenario are well defined in the benchmark. For detailed specification of defined fault scenarios see Syfert, *et al.* (2001).

Each benchmark participant has to demonstrate the FDI results for all considered fault scenarios.

Two different kinds of reports must be filled in:

- reports presenting features of applied FDI methods, and
- reports of carried out tests for each foreseen scenario.

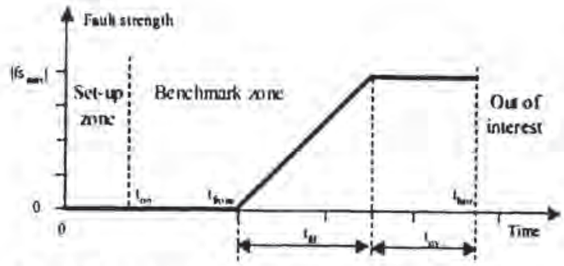


Fig. 13. Definition of time parameters of a benchmark Step I.

Due to the performance indices introduced in the section "Performance Indices" and a common presentation format the collected results can be treated as a basic description and comparison of applied FDI techniques. No additional comments should be necessary.

Step II

During Step II the evaluation of detectability and isolability of FDI methods is carried out.

Step II is also based on the data generated by data generator. However, in Step II the actuator is considered as a part of a process. The same set of process variables is available but because of simple process modelling some of the inputs are correlated (see Fig.12). This is a realistic situation that brings the benchmark study closer to the industrial application.

For the purpose of Step II four fault scenarios are anticipated, one allocated to each fault group. These fault scenarios are kept hidden from the benchmark participants and are proposed by the benchmark supervisor. Based on the chosen scenarios, data files are generated by the benchmark supervisor using an additional data generator block. The corresponding data files have been disseminated to the benchmark participants using internet communication facilities.

In this case, only the benchmark set-up zones are defined. The fault scenario time parameters are hidden for benchmark participants until the FDI results are collected by the benchmark supervisor.

Each benchmark participant must carry out FDI tests under all fault scenarios using the delivered data files. For each scenario the performance indices must be calculated. The results of each participant are described in a separate report similar to Step I.

When the FDI results are collected, the fault scenarios are published. The benchmark supervisor in co-operation with all partners makes common evaluation of achieved results.

Step III

Step III of the benchmark is suited for approving applicability of FDI methods.

This Step is very similar to Step II and is based on the real process data from three chosen actuators installed in the Lublin Sugar Factory. Step III is the closest to industrial application. The benchmark participants use two kinds of data:

- Learning data collected in fault free states during normal operation. This data are used for tuning FDI algorithms.
- Testing data set with hidden faults. Only this data are used to generate FDI results that are investigated and then described in reports.

For generating of data files from faulty states the five artificial fault scenarios were chosen and simulated in Lublin Sugar Factory. These fault scenarios are unknown for all benchmark participants. They are published after collecting FDI reports from all the participants.

The same as in Step II, each participant has to carry out FDI tests and prepares reports. The benchmark supervisor in co-operation with all partners makes common evaluation of achieved results

4.1. Performance indices

For evaluating and ranking the FDI methods, a set of 18 performance indices has been defined. One can distinguish three groups of indices, describing detection, isolation and general features of diagnosis as illustrated in Table 1. The indices describe the basic features of diagnostic decisions (isolation and detection) produced by FDI algorithms. Their definitions are very general and method independent (Syfert, *et al.*, 2002). For example, Fig. 14 illustrates how the detection time, the fault detection sensitivity factor, and the true and false detection rates are calculated based on the detection decision produced by the FDI procedures.

Table 1 Performance Indices

Detection / Isolation Indices	
Detection / Isolation Time	t_{dt}, t_{it}
Detection / Isolation Recovery Time	t_{drt}, t_{irt}
Detection / Isolation Moment	t_{dm}, t_{im}
Detection Recovery Moment	t_{drm}, t_{irm}
False Detection / Isolation Rate	r_{fd}, r_{fi}
True Detection / Isolation Rate	r_{td}, r_{ti}
Mismatch Isolation Rate	r_{mi}
Fault Detection / Isolation Sensitivity Factor	Fs_d, fs_i
General Diagnosis Indices	
Theoretical Diagnosis Accuracy	$Dacc^j_t$
Theoretical Mean Diagnosis Accuracy	$Dacc_{tm}$

Diagnosis Accuracy	*Dacc*

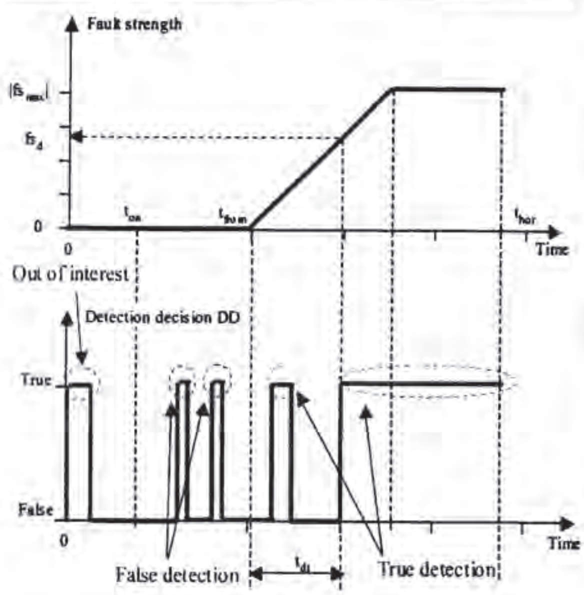


Fig. 14. Example how to calculate performance Indices t_{dt}, fs_d, r_{fd} and r_{td}.

As a consequence of the very general form of definitions of the indices definitions are a variety of possible situations that can occur in reality some problems in definition interpretations can arise. To ensure common way of calculating PI the performance indices calculator was developed. This is a part of the Simulink library used to carry out the benchmark steps.

4.2. Simulink library

A powerful Matlab-Simulink "DABlib" library was created to support benchmark steps. In fact, every benchmark participant must use it.

The core of the library is the actuator model. This is a model based on physical principles and engineering knowledge of the industry actuator. This model was tuned and validated using data originating from real industry process. The core of actuator model in hidden for the users and is only used by other library components. More detailed description can be found in (Bartyś, 2001; Bartyś & de la Heras, 2003). All library blocks are divided into three groups: actuator blocks, data generators and utility blocks. Each group will be shortly characterised in following sections.

Actuator blocks

The user can use two actuator blocks. The first is a basic actuator block 'Act' with only five, basic process variables available. This block is used in the benchmark Step I for generating learning data sets. The second one, 'ExtAct' is an extended version of the first one. It has all (8) process variables available. It can be used only for advanced tests.

All analogue inputs and outputs of actuator block are disturbed by random white noise simulating measurement noise and electromagnetic susceptibility of physical sensors. However, the noise can be switched off on special user request.

Data generator blocks.

This group includes two blocks used for automatic generation of repeatable pattern data sets for benchmark Step I and II purposes.

The first block, 'DGen', is used for generating data sets according to 44 fault scenarios defined in the benchmark Step I. This block uses the basic actuator block 'Act' as a stand-alone unit. The 'Act' inputs are driven by predefined low-frequency sine waves.

As distinct from the first generator, the second block 'CorDGen' must be driven by a fault strength signal that defines the fault and how it is simulated. This block is used by the benchmark supervisor for generating data files with hidden faults for the purpose of benchmark Step II. This block uses the basic actuator 'Act' block as a part of small process. So, the 'Act' inputs are correlated in a similar manner to those of the real processes.

Utility blocks

This is a group of additional blocks that can be used by the benchmark participants. The most important block in this group is the performance indices calculator 'PICalc'. This facilitates a simple and effective on-line calculation of performance indices based on diagnostic decisions produced by FDI algorithms.

Examples

For a better understanding of the "DABLib" library components and the idea of benchmark the set of example Simulink models are delivered together with the library. Illustrated examples shows how to use the various blocks in different benchmark steps. A simple example application of the library blocks to other example is shown for tutorial purposes.

6. CONCLUSIONS

The EC funded research network study *DAMADICS* has provided the opportunity to integrate together the expertise of 8 university partners and a sugar factory with broad experience in modelling, fault diagnosis, process control, computational intelligence and mechatronics. The application study of fault diagnosis of actuators in a sugar factory at Lublin has enabled some interesting and realistic industry-focused research to be carried out. The usual scenario is that work of this nature is carried out by control system suppliers at high cost; the commercial and cost implications normally rule out the development and application of novel university-based methods. Some of the ideas, concepts and results of this work are presented in this paper but the work is on-going and both results and plant data are generally available

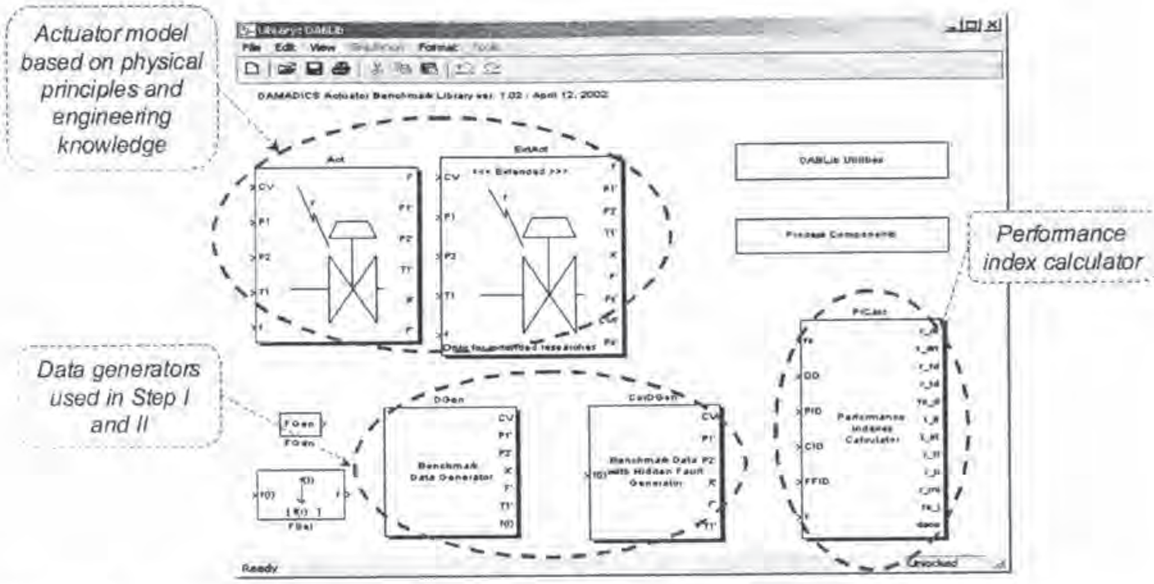


Fig. 15. The components of DAMADICS actuator benchmark library.

for research and development. This facility will continue to provide an important facility for the evaluation of control systems and process monitoring concepts, including fault-tolerant control and supervision

The benchmark is strongly oriented towards industrial application. It may be used either in the FDI development phase or for industrial pre-implementation tests. Besides its primary functions, the benchmark may also be used for tuning FDI algorithms, be used as a learning data generator for neural model based FDI or applied for fault detection sensitivity analysis. The benchmark has the advantage of the independence of the FDI methods tested.

An advantage of this benchmark over previous examples is that it uses real process data. The industrial actuator has also been instrumented to generate external faults whilst in real process operation. This represents a significant step forward in this field. The benchmark may be applied by engineers either when implementing new diagnostic schemes or for evaluating existing schemes. For researchers, the benchmark also permits the classification of those FDI algorithms that are based on unrealistic assumptions and constraints or are completely not applicable.

ACKNOWLEDGEMENTS

The authors acknowledge funding support under the EC RTN contract (RTN-1999-00392) DAMADICS. Thanks are expressed to the management and staff of the Lublin sugar factory, Cukrownia Lublin SA, Poland for their collaboration and provision of manpower and access to their sugar plant.

REFERENCES

Bartyś, M. (2001). Specification of Actuators Intended to Use for Benchmark Definition. In: *http://diag.mchtr.pw.edu.pl/damadics/*

Bartyś, M., and S. de las Heras (2003). Actuator Simulation of the *DAMADICS* Benchmark Actuator System. In: preprints of *5-th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes*, Washington, USA.

Bartyś, M. and M. Syfert (2002). Using Damadics Actuator Benchmark Library (DABLib). In manuscript on: *http://diag.mchtr.pw.edu.pl /damadics/*.

Blanke, M. and R.J. Patton (1995). Industrial actuator benchmark for fault detection and isolation. In: *Control Engineering Practice*, **3**, (12)

Calado, J.M.F., Korbicz J., Patan K., Patton R.J. and J.M.G. Sá da Costa (2001), Soft Computing Approaches to Fault Diagnosis for Dynamic Systems, In: *European Journal of Control*, Vol. 7, (2-3).

Chen, J., and R.J. Patton (1999). *Robust model-based fault diagnosis for dynamic systems*, Kluwer Academic Publishers.

Gertler, J. (1998). Fault detection and diagnosis in engineering systems, M. Dekker, New York.

Henry, M.P. (2000). Plant assessment management via intelligent sensors: digital, distributed and for free. In: *Computing & Control Engineering J*, **11**, (5), pp 211-213.

Koj, J. (1998). The Fault Sources of Pneumatic Servo- Motor-Control Valve Assembly. *III Polish National Conference on "Diagnostics of Industrial Processes"*, Jurata, Poland, pp. 415-419 (in Polish).

Koscielny, J. M. and M. Bartyś (2000). Application of Information Theory for Actuators Diagnosis. In: *4-th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes*, Budapest, Hungary, Vol. **2**, pp. 949-954.

Mediavilla, M., L.J. de Miguel and P. Vega (1997). Isolation of Multiplicative Faults in the Industrial Actuator Benchmark. *IFAC Symposium SAFEPROCESS '97*, Kingston Upon Hull, UK, pp. 855-860.

Patton, R.J., P.M. Frank and R.N. Clark (1989). Fault diagnosis in dynamic systems: theory and application, Prentice Hall, London.

Patton, R.J., P.M. Frank and R.N. Clark (2000). Issues in fault diagnosis for dynamic systems, Springer Verlag, London.

Simani, S., C. Fantuzzi and R.J. Patton (2002). Model-based Fault Diagnosis in Dynamic Systems using Identification Techniques, Springer Series: Advances in Industrial Control.

Syfert, M., M. Bartyś and J. Quevedo (2002). Benchmark definition. In manuscript on: *http://diag.mchtr.pw.edu.pl/damadics/*.

Tombs, M. (2002). Intelligent and self-validating sensors and actuators, Special Feature Editorial in: Computing & Control Engineering Journal, **13**, (5), 218-220

Yang, J. C., and D.W. Clarke (1999). The Self-Validating Actuator. *Control Engineering Practice*, **7**, pp. 249-260.

Previdi, F. and T. Parisini (2003). Model-free actuator fault detection using a spectral estimation approach: the case of the *DAMADICS* Benchmark Problem. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Marciniak A., C.D. Bokaniala, R. Louro, J. Sa da Costa and J. Korbicz (2003). Pattern recognition approach to fault diagnosis in the *DAMADICS* Benchmark flow control valve. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Rzepiejewski, P., M. Syfert and S. Jegorov (2003). On-line actuator diagnosis based on neural networks and fuzzy reasoning: The *DAMADICS* Benchmark Study. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Patan, K. and T. Parisini (2003). Dynamic Neural Networks for Actuator Fault Diagnosis: Application to the *DAMADICS* Benchmark Problem. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Mrugalski, M., E. Arinton and J. Korbicz (2003), Fault detection with dynamic GMDH neural networks: application to the *DAMADICS* Benchmark Problem. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Uppal, F.J., R.J. Patton and M. Witczak (2003). A hybrid neuro-fuzzy and de-coupling approach applied to the *DAMADICS* Benchmark Problem. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Papadimitropoulos, A., G.A. Rovithakis and T. Parisini (2003). Neural approximators for fault detection of actuators in the presence of friction: the Case of the *DAMADICS* Benchmark Problem. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Calado, J.M.F., R. Louro, M.J.C. Mendes, J. Sá da Costa and M. Kowal (2003). Fault isolation based on HSFNN applied to the *DAMADICS* Benchmark Problem. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Frisk, E., D. Dustegor, M. Chrysander and V. Cocquempot (2003). Improving isolability properties by structural analysis of faulty behavior models: application to the *DAMADICS* Benchmark Problem. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Stancu, A., V. Puig, J. Quevedo and R.J. Patton (2003). Passive robust fault detection using non-linear interval observers: Application to the *DAMADICS* Benchmark Problem, In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Witczak, M., R.J. Patton and J. Korbicz (2003). Fault detection with observers and genetic programming: Application to the *DAMADICS* Benchmark Problem. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Lunze, J. and P. Supavatanakul (2003). Application of timed automata to the diagnosis of the *DAMADICS* Benchmark Problem. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Puig, V., J.Quevedo, A. Stancu, J. Lunze, J. Neidig, P. Planchon and P. Supavatanakul (2003). Comparing interval models and quantised systems in fault detection of the *DAMADICS* Benchmark Problem. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.

Calado, J.M.F., F.P.N.F. Carreira, M.G.J.C.Mendes, J.M.G. Sá da Costa and M. Bartyś (2003). Fault detection approach based on fuzzy qualitative reasoning applied to the *DAMADICS* Benchmark Problem. In: preprints of *5-th IFAC Symposium SAFEPROCESS '2003*, Washington, USA.