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ON-LINE ACTUATOR DIAGNOSIS BASED ON NEURAL MODELS AND FUZZY REASONING: THE DAMADICS BENCHMARK STUDY

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Abstract: This paper described on-line diagnostic system for the final control elements. The system makes possible early fault detection and isolation. The neural models of actuator components, information system theory with faults-symptoms relation and fuzzy logic are applied. The paper presents results of laboratory and industrial tests. The laboratory tests were done with application of Simulink actuator model. For industrial tests real devices working in technological installation in sugar factory where investigated. *Copyright © 2003 IFAC*

Keywords: diagnostic system, actuator, fault detection, fault isolation, neural networks, fuzzy logic, diagnostic matrix.

1. INTRODUCTION

Final control elements are applied for acting on energy or mass flows. Because the actuators are installed mainly in the harsh environment (high temperature, humidity, pollution, aggressive media) they frequently become damaged. The failures or malfunction are causing long-term process disturbs, which may influence the final product quality. Moreover, actuators faults sometimes forces the installation shut down. To reduce economical losses caused by faults of final control elements it is necessary to apply the on-line diagnostics of actuators.

2. ALGORITHM DESCRIPTION

The overall actuator diagram that is considered in this paper is shown on Fig. 1. More detailed actuator description can be found in (Kościelny and Bartyś, 2002).

The on-line fault detection and isolation system performs diagnostic tests based on process variables. The process variables are obtained from SCADA or DCS system. For the diagnostic purposes, in real industrial applications, the following process variables are commonly accessible:

- CV – positioner set-point signal,
- Z – servo motor rod displacement,
- P1 – pressure on valve inlet,
- P2 – pressure on valve outlet,
- F – media volume flow rate.

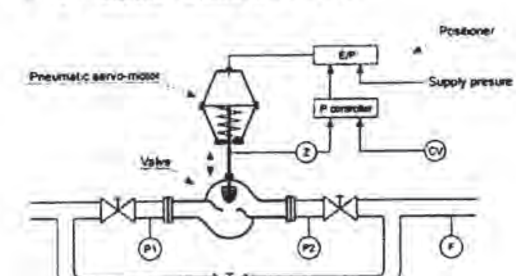

Fig. 1. Actuator diagram.

Table 1 Actuator faults

Fault	Description
f_1	Valve clogging
f_2	Valve plug or valve seat sedimentation
f_3	Valve plug or valve seat erosion
f_4	Increased 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
f_8	Twisted servo-motor's piston rod
f_9	Servo-motor's housing or terminals tightness
f_{10}	Servo-motor's diaphragm perforation
f_{11}	Servo-motor's spring fault
f_{12}	Electro-pneumatic transducer fault
f_{13}	Rod displacement sensor fault
f_{14}	Pressure sensor fault
f_{15}	Positioner feedback fault
f_{16}	Positioner supply pressure drop
f_{17}	Unexpected pressure change across the valve
f_{18}	Fully or partly opened bypass valves
f_{19}	Flow rate sensor fault

The set of 19 faults has been defined (Kościelny and Bartyś, 2002) for actuator shown in Fig. 1.

Available process variables are used to calculate redundant process variables. The redundant variables are calculated basing on neural models of actuator components. The following models can be used to fault diagnostic purposes:

- servomotor rod displacement model,

$$\hat{Z} = f(CV), \tag{1}$$

- control valve model,

$$\hat{F} = f(Z, P_1, P_2), \tag{2}$$

- actuator model,

$$\hat{F} = f(CV, P_1, P_2) \tag{3}$$

In industrial applications of the actuator the relation between valve plug position and the pressures before and after the valve is evident. It is caused by the technological constraints and the influence of other part of the process. In such a case, two supplementary models can be applied:

- the simplified model of the control valve,

$$\hat{F} = f(Z), \tag{4}$$

- the simplified model of actuator,

$$\hat{F} = f(CV), \tag{5}$$

Basing on calculated models outputs the residuals are calculated as a difference between process variable and corresponding simulated variables. Finally, the following residuals are generated:

$$r_1 = Z - \hat{Z}(CV), \tag{6}$$

$$r_2 = F - \hat{F}(Z, P_1, P_2), \tag{7}$$

$$r_3 = F - \hat{F}(CV, P_1, P_2), \tag{8}$$

and simplified residuals:

$$r_4 = F - \hat{F}(Z), \tag{9}$$

$$r_5 = F - \hat{F}(CV), \tag{10}$$

On Fig. 2 the example of rod displacement modelling (model 1) have been presented.

In a fault free state the residual values vary around zero. Variations are caused by measurement and modelling errors. It is difficult, theoretically or even practically, to define the threshold value of residual, which indicates fault occurrence. Therefore, the fuzzy logic for residual evaluation has been applied. For each residual, three linguistic values of fuzzy variable has been defined: "N^-", "P" and "N^+" one. The example of membership functions for diagnostic signal S_l has been shown on Fig 3. The parameters of each trapezoid membership function have been defined by the expert for each residual separately.

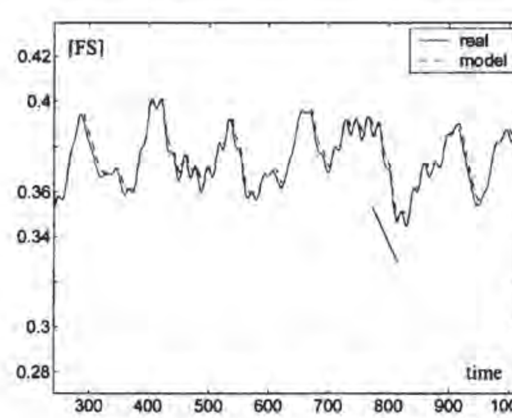

Fig. 2. Modeling results of servo motor rod displacement.

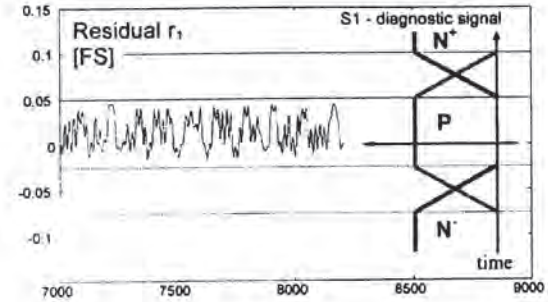

Fig. 3. Fuzzy residual evaluation.

If the difference between measuring process variables and model outputs is close to zero then the value of membership function of "*P*" is the biggest. It means that the fault is not present in the system or this residual is not sensitive for this fault. In other case, if the fault occurs, which changes residual's value, then value of membership function of negative symptoms is the biggest.

The fault isolation is based on a diagnostic matrix shown in Table 2. This matrix describe dependencies between diagnostic signals (evaluated residual values) and faults. The "*P*" values of diagnostic signals are omitted in the table. In fact, the columns in the table represents elementary blocks, i.e. the set of unisolable faults. The table includes column E_0 with all positive diagnostic signal values that corresponds to the fault free state of actuator.

Basing on proposed models the fault f_{11}, servo-motor spring fault, can not be detected. It is necessary to use additional pressure sensor installed in a chamber of pneumatic servomotor.

In the isolation algorithms the elementary blocks certainty factors are calculated using PROD operator, as multiplication of membership function values of this diagnostic signal values that are defined in diagnostic relation, which is as follows:

$$\mu_R = \mu_{S_1} \cdot \mu_{S_2} \cdot \mu_{S3} \cdot \mu_{S_4} \cdot \mu_{S_5}\,, \tag{11}$$

The configuration of the system to work with specific actuator requires:

- identification of neural network model parameters,
- defining parameters of diagnostic signals membership functions.

3. CONFIGURATION OF V-DIAG SYSTEM

Described in Section 2 methodology was implement and tested in V-DIAG which is a special, dedicated for actuator diagnosis version of DIAG system.

Table 2 Diagnostic matrix for three-value residual evaluation

S/E	E_0	E_1	E_2	E_3	E_4	E_5	E_6
s_1		N^+,N^-			-N	N^-	
s_2			N^-	N^+	N^+,N^-		
s_3		N^+,N^-	N^-	N^+	N^+,N^-	N^+	
s_4			N^-	N^+	N^+,N^-		N^+,N^-
s_5		N^+,N^-	N^-	N^+	N^+,N^-	N^+	N^+,N^-
f	fault free	f_1 f_4 f_8 f_{12} f_{15}	f_2 f_5 f_{13} f_{19}	f_3 f_6 f_{13} f_{18}	f_7	f_9 f_{10} f_{16}	f_{17}

The system was preliminary tested in the laboratory with use of Simulink actuator model that was elaborated in the framework of DAMADICS project, see (Bartyś, 2001). Then, the industrial test based on real devices working in technological installation where carried out.

The overall diagram of the V-Diag system is shown on Fig. 4. In both cases of laboratory and industrial test the configuration of the system was the same except of data source:

- during laboratory test the system uses in real-time mode the process data that where recorded during simulation,
- during industrial test the data are collected in real-time, on-line mode via OPC connection with Industrial IT system that was installed in sugar factory for data acquisition and archivisation.

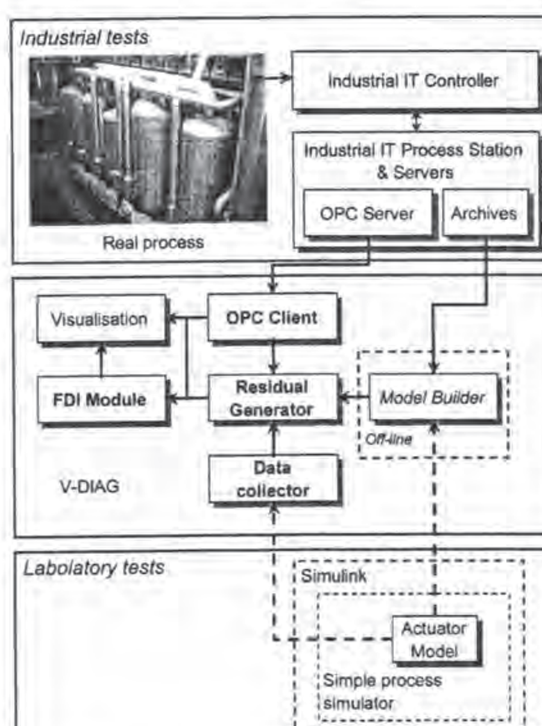

Fig. 4. Block diagram of V-Diag system configuration.

The main parts of the V-Diag system are:

- data acquisition modules,
- residual generator responsible for calculating model outputs and residuals,
- FDI module that implement residual evaluation and fault isolation,
- visualisation module
- model builder used in off-line mode for building neural network models.

All results of the tests presented in further sections where achieved with used of and from V-Diag system.

4. LABORATORY TESTS

Research and development of diagnostic algorithm in industrial practice is difficult because we cannot introduce some faults, such as valve plug or valve seat erosion. Moreover we cannot disturb technological process by simulating faults. To overcome this problem, in the framework of DAMADICS project, the Simulink model of an actuator was development. This model is able to simulate all considered faults. The detailed description of the model can be found in (Bartyś, 2001). Basing on this model it is possible to carry out complete tests of proposed algorithm.

The artificial process variables, simulating fault-free actuator work in technological installation, where generated with use of Simulink models. Those data were used to create neural models of actuator components.

The parameters of membership functions were defined basing on analysis of residual changes in a fault free state. It is shown on the Fig. 6. Non zero value of residuals is caused by measurement noises generated by Simulink model and modelling errors.
Below, the example of fault detection and isolation is presented. The fault *f2*, valve plug or valve seat sedimentation, was simulated. The incipient fault scenario was chosen. The fault was introduced at t_{from}=13:08 and it achieved 0.3 of maximum value at t_{to}=13:23s.

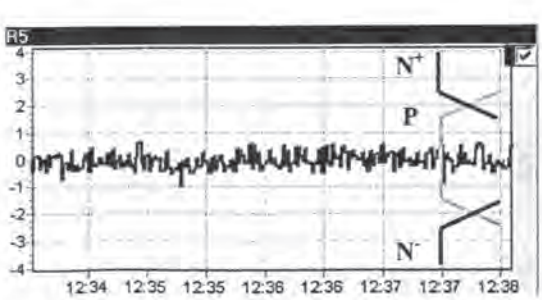

Fig. 5. Fuzzy residual r_5 evaluation

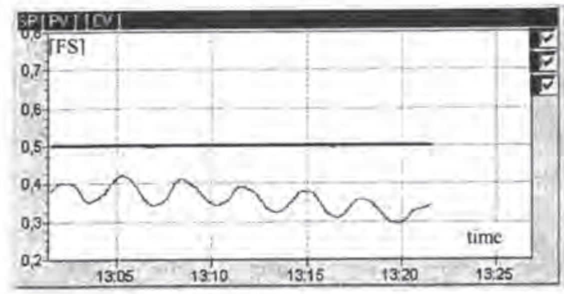

Fig. 6. Technological process variables.

Such a fault is very difficult to be detected by the process operator because it is a parametric fault with a relatively small strength.

Process variables that are concerned the device with fault's increase are shown on Fig 6. Simulated sedimentation is based on decreasing effective flow surface between valve seat and plug. To keep the flow on the desired level, the controller increases the valve opening degree.

Additionally, in real process where the working point is changing much more and when the fault can develop in much longer period of time, e.g., few weeks, than the detection and isolation would be even more difficult.

The Fig.7 shows the comparison of time series of real flow throw the valve with sedimentation and the modelled one for a fault free model. Increasing fault causes growing difference between these signals.

The fault caused the change of four residuals. The following symptoms appeared: S_2="N^-", S_3="N^-", S_4="N^-" and S_5="N^-".

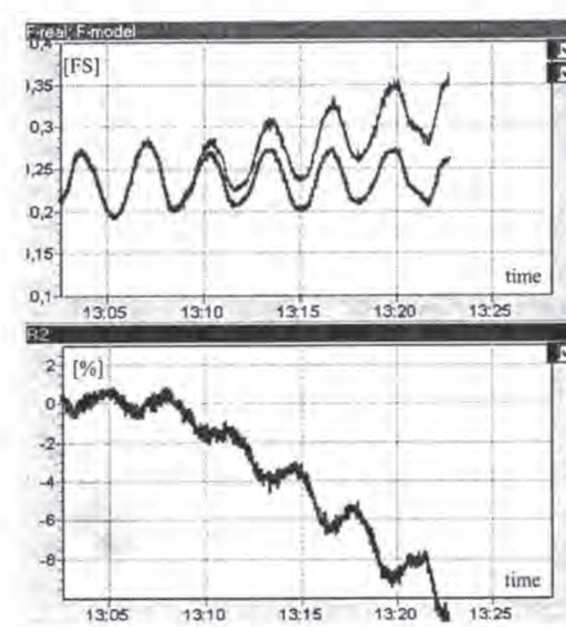

Fig. 7. Modeled, real flow values and residual signal in the case of incipient f_2 simulation.

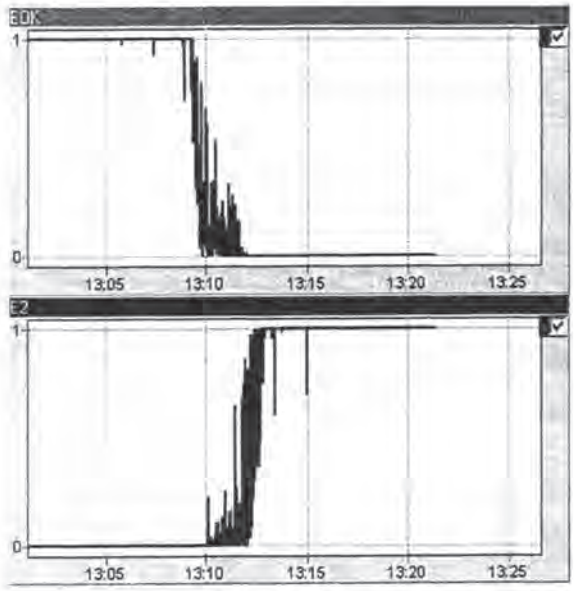

Fig. 8. The degree of certainty of fault free E_0 elementary group and elementary group E_2 that includes simulated fault f_2.

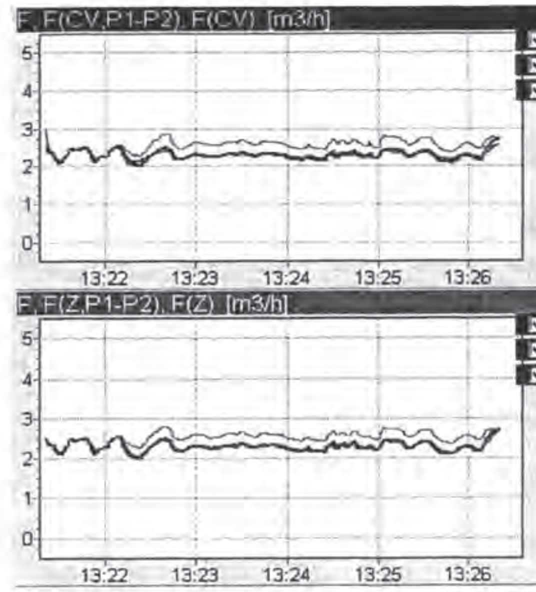

Fig. 9. Comparing measured process variables to variables received from models in laboratory tests

Based on values of diagnostic signals the isolation algorithm has specified elementary group E_2 in which there is fault f_2. Fig. 8 shows detection of fault and the coefficient of diagnosis accuracy.

During the laboratory researches the system was tested also on the laboratory installation. This installation consists of industrial actuators and measuring devices. The industrial system DCS – DeltaV – is used to control the installation. The process variables are sampled every second. Actuators are overseen by the V-Diag diagnosis system. V-Diag system gets process variables through the OPC server from control system.

It was possible to prepare all five neural models for actuators in this installation. Models simulate properly the work of these devices in all operating range. Modeling deviation is lower than 5% of the range.

There is presented the example of modeling on the Fig. 9. Charts show comparing measured process variables to variables received from models.
The fault f17 - unexpected pressure change across the valve – was simulated. The fault was introduced at t_{from}=13:22. Value of measured process variables and value of variables received from models (2) and (3) are the same – that is because one of models input is difference between before and behind the valve. Values received from simplified model (4) and (5) are different than measured variables value.

5. INDUSTRIAL TESTS

Utilisation of Simulink model or laboratory stand during laboratory tests allows to generate and use complete data sets for neural networks learning. It is easy to achieve data sets that cover the whole range of work. Very precise and complete models could be identified in a relatively simple way. In the case of industrial tests the process of collecting learning data is much more complicated. Usually, there is only a possibility to use historical data from archives. The possibility to carry out special tests and to record data is also very limited or even impossible.

Archive data usually did not cover the hole range of possible changes. Before using this data, one must be sure that they were collected when the actuator was completely efficient, i.e., there were no faults.

Considering the above mentioned facts, learning of model (2) and (3) basing on real process data can be difficult. The main reason of this is an existence of a cross-correlation between the inputs of these models. It is a very common situation for real actuator applications. In such a case, it is very important to find and prepare such a learning data in which the medium pressure on the actuator inlet and outlet is changing not only due to the degree of valve opening, e.g., decrease of pump efficiency, throttling on the inlet or outlet, etc. If such a situation can not be observed in learning data then the models (4) and (5) can be applied instead of (2) and (3).

During the industrial researches the system was tested in Lublin Sugar Factory. Three devices worked in technological installation were overseen. V-Diag system gets process variables through the OPC server from control system – Industrial IT. The process variables are sampled every second.

It was possible to prepare neural models (1), (4) and (5) for these actuators. Modeling deviation is lower than 5% of the range.
It was impossible to prepare models (2) and (3) because cross-correlation between valve plug and pressure before/behind valve was too strong.

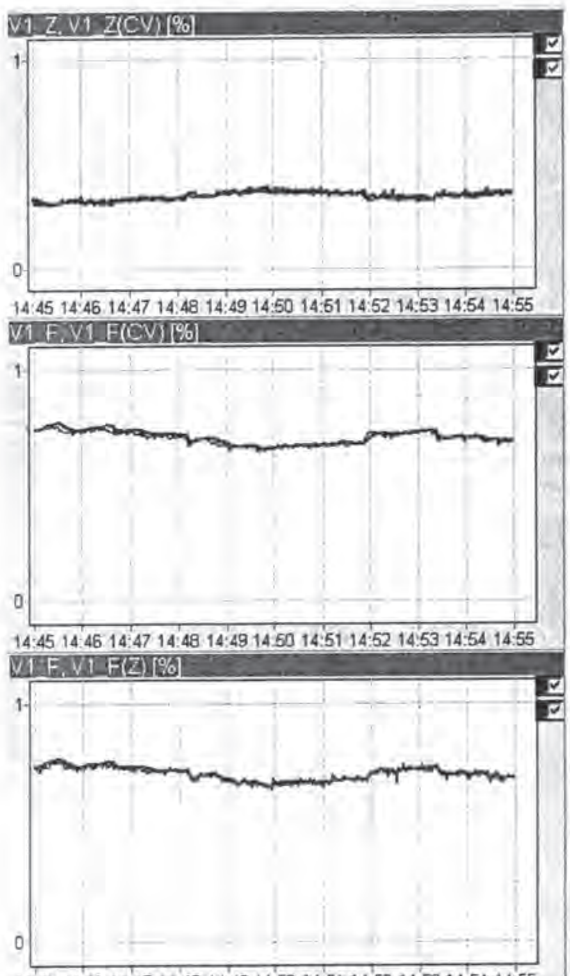

Fig. 10. Comparing measured process variables to variables received from models in industrial tests.

6. END REMARKS

The main features that testify and enable industrial applicability of presented algorithm are as follows:

- neural network models can be achieved basing on real process data coming from fault free states
- the models of faulty components do not have to be identified
- in case of many processes it is impossible to prepare models (2) and (3)
- system V-Diag is based on only accessible values of process variables, and operation of algorithm does not influence in the technological process
- the given system may operate with different types and manufacturers of the actuators
- for this diagnosis system, additional sensor or equipments in actuator are not required
- the algorithm can detect the faults, which weren't stipulated by the developer
- the algorithm is very simple

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REFERENCES

Bartyś M. (2001) How to build a benchmark problem for FDI evaluation. In proc. of: *Vacation School on Neuro-Fuzzy Methods for Modelling and Fault Diagnosis, II Vacation School of the EC FP5 Research Training Network DAMADICS,* Technical University of Lisbon, Portugal, pp.36.

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

Bartyś M., Syfert M. (2001) Using Damadics Actuator Benchmark Library (DABLib). In manuscript on: *http://diag.mchtr.pw.edu.pl/damadics/.*

Kościelny J. M., Bartyś M. (1997) Smart Positioner with Fuzzy Based Fault Diagnosis. In proc. of: *IFAC Symposium SAFEPROCESS '97*, Kingston Upon Hull, UK, pp. 603-608.

Kościelny J.M, Bartyś M. (2001) Fuzzy logic application for actuator diagnosis. *AI-MECH,* Gliwice, Poland.

Kościelny J.M., Bartyś M. (2002) Application of Information Theory for Actuators Diagnosis. In proc. of: *IV IFAC Symposium SAFEPROCESS '00*, Budapest, Hungary, **Vol.2**, pp.949-1054.

Isermann R., Raab U. (1993) Intelligent Actuators - Ways to Autonomous Actuating Systems. *Automatica*, **29, (5)**

Syfert M., Bartyś M., Quevedo J. (2001) Benchmark definition. In manuscript on: http://diag.mchtr.pw.edu.pl/damadics/.

Rzepiejewski P., Jegorov S., Mikalauskas A. (2002) Neural network and fuzzy logic application for on-line actuator diagnosis. AI-MECH, Gliwice, Poland, pp. 349-352.