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ON SENSOR FDI BY FUNCTIONAL AND PHYSICAL REDUNDANCY APPLIED TO DP SYSTEMS

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Abstract

The research work is focused on sensors fault detection and isolation (FDI), exploiting the synergy of functional and physical redundancy. Functional and physical redundancy is applied under a novel methodological approach to isolate individual sensor faults. The contribution uses a heuristic algorithm which combines a rule based strategy associated to a process parameter identification procedure to be applied on instrumentation FDI tasks. Implementation procedure is carried out on a dynamic positioning system (DP) equipped with supervision facilities, which efficiently manage databases, rule based systems and appropriate identification algorithms on a simulation basis.

Keywords: Dynamic Positioning Systems, Fault detection, Fault isolation, Expert systems, Functional redundancy, Physical redundancy, and Rule based system.

INTRODUCTION

Most of the supervisors design methods are based on the plant models. Additionally, the implementation of intelligent control technology based on soft computing methodologies such as expert systems and artificial intelligent techniques can notably enhance the supervision and advanced control capabilities of many industrial processes such as process engineering industries and many other complex chemical engineering processes (Lippmann, R. P., 1987). A necessary requirement to succes-

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sfully be applied, such state of the art techniques needs to operate with highest-quality data, which means a considerable effort on applying sensors faults isolation and/or faults tolerant strategies. The typical faults encountered in industrial applications are commonly classified into some of the following typical groups: Process parameter changes, Disturbance parameter changes, Actuator malfunctions, and Sensor malfunctions.

The sequence of subtasks to be carried out to ensure correct process operation is at the heart of process supervision, usually referred to as process monitoring tasks, including, fault detection, fault identification, fault diagnosis, and fault removing by process intervention, process recovery or process reconfiguration. Process monitoring is based on data acquisition and data processing procedures. An introduction on this topic can be found at (Ferreiro García R., 2007).

Among data driven methods, Partial Least Squares (PLS) are data decomposition methods for maximizing covariance between predictor block and predicted block for each component (Wise B. M. and Gallagher N. B., 1996) (MacGregor J. F., 1994) (Piovoso M. J. and Kosanovich K. A., 1992) (Piovoso M. J. and Kosanovich K. A., 1994).

Regarding analytical methods, they use residuals as features which are commonly referred to as analytical redundancy methods. The residuals are the result of consistency checks between plant observations and their math-model. The residuals will be sufficiently large values in the presence of faults and small or negligible in the presence of disturbances, noise and/or modeling errors (Frank P. M., 1993), (Gertler. J. J. 1998) (Hodouin D. and Makni, 1996). Three main methods are commonly used to generate residuals: Parameter estimation, Observers and Parity relations.

In the case of parameter estimation, the residuals are the difference between the nominal model parameters and the estimated model parameters. Deviations in the model parameters are an indicator used as the basis for detecting and isolating faults (Isserman R., 1998) (Mehra R. K. and Peschon J., 1971).

In the observer-based methods, system output is reconstructed from measurements or a subset of measurements with the aid of observers. The differences between actual measured output and estimated output are the residuals (Frank P. M., 1990) (Clark R.N. et all., 1975).

The parity relations strategy checks the consistency of the mathematical equation of the system with real time measurements. The parity relations are subjected to a linear dynamic transformation as the transformed residuals are used in detection and isolation tasks (Gertler, J. J., 1995) (Mironovski L. A., 1979) (Mironovski L. A., 1980). The aforementioned analytical approach that has been commented on requires error-free mathematical models in order to be effective.

Knowledge-based methods, extensively applied in process monitoring tasks, include: Causal analysis, Expert systems and Pattern recognition (Doyle R. J. et all., 1993).

These techniques are based on qualitative models, which can be obtained via one of the following ways:

— Causal modeling of the systems (Lee G. et all., 1999) (Mo K. J. et all., 1998) (Mo K. J. et all. 1997).

— Expert knowledge (Kramer M. A and Palowitch J.B.L., 1987) (Li X, and Yao X, 2005) (Kramer M. A. and Finch F. E., 1988) (Bakshi B.R. and Stephanopoulos G., 1994).

— A detailed model describing the system (Nekovie, R. and Sun, Y., 1995), (Demuth, H. and Beale, M. 1998).

— Fault-symptom based cases. (Isserman R 1993) (Yong-Guang Ma, Liang-Yu Ma and Jin Ma, 2005).

Among the outlined supervision methods, none of them is qualified to carry out the overall safely supervision task on the vast amount of different processes and variety of instruments. As consequence of such drawbacks, the proposed research work is focused on a problem-solving strategy which combines into a heuristic search path driven on the basis of a flow chart, a rule base processor with an appropriate identification method. The proposed strategy supposes a novel, general and effective alternative on FDI sensors diagnosis. Thus, the work is centered on the task of detection and isolation sensor faults using a model based approach which deals with a model parameter identification technique associated to a rule based scheduler oriented to FDI tasks mainly applied in process supervision, including decision-making procedures according to well-known rule-based techniques. To carry out proposed tasks, the identification algorithm based on the collection of real-time data for transient state operation conditions is presented using the facilities of (DeltaV™. V.8.4. 2007).

The work is organized by describing the strategies to synthesize FDI rule bases on the basis of an analytical function approximation model based approach. Finally an illustrative example of sensors FDI is presented. Validation is based on the results achieved from an application on the pilot plant.

FAULT DETECTION AND ISOLATION STRATEGY

Being FDI a crucial part of an asset management task, as shown in (Chow M., 2000) (Kusiak A. and Shah S., 2006) (Li. T., 1989), the principles of predictive maintenance apply to all machines, processes and industrial applications, where expert systems play relevant and important role. However, the knowledge storage required for the implementation of an expert system is significant, particularly for systems that require decisions to be based upon the knowledge base. In fact, as stated in (Kusiak A. and Shah S., 2006), expert systems cannot respond creatively under unexpected scenarios or circumstances and no deterministic answer to determine when the input values go outside a predefined range is available but rather random.

Nevertheless, Rule Based Systems (RBS) may be used to solve difficult problems that typically require significant human expert intervention. By emulating the expertise and the decision-making ability of a human it is possible to reduce the effort and cost of making the knowledge of multiple experts available continuously, simultaneously, and permanently; thereby increasing reliability and performance.

In this work it is described how the inherent advantages of RBSs can be embedded into a scalable process control system. It also presents a prototype of a highly interactive and user friendly environment that simplifies and speeds the configuration of an expert system and makes it easy and intuitive for the typical plant engineer to incrementally apply his process knowledge.

Such a tool can be used to monitor and process and to address abnormal condition management by continuously evaluating real-time and historical data, watching for events and abnormal conditions, providing reliable diagnosis and advice, and taking corrective actions when necessary in order to support the plant operators to manage their monitoring operations. The core technology and functionality is implemented using DeltaV inference engine.

Analytic modeling is the modeling technique chosen to handle process changes detection tasks in this work. The main reason is that analytical modeling represents the process dynamics as function of available and accessible measured variables and parameters. Consequently it can be updated without via on-line parameter identification.

Sensor Faults Characteristics

A sensor fault can be defined as a deviation from its normal readings. Excluding complete failure, sensor faults are classified into four types (Abdelghani M. and Friswell M.I., 2007) (Qin S.J. and Li W.H., 1999): bias, drift, precision degradation, and multiplication fault. The reading of a fully functioning sensor at time t is $x^*(t)$. Sensor malfunction could cause the reading to deviate from the actual value. For bias fault, $x(t)$ is the sensor reading and can be expressed as

$$x(t) = x^*(t) + b \tag{1}$$

where b is constant and could be positive or negative. For the drift fault,

$$x(t) = x^*(t) + a \cdot (t - t_f) \tag{2}$$

where a is a constant, t_f is the time stamp when the drift begins. Over time the drift fault becomes larger.

For the precision degradation fault,

$$x(t) = x^{*}(t) + \varepsilon \tag{3}$$

where ε is a random variable following the normal distribution $N(0,\sigma^2)$. The value of ε usually has a larger variation than the white noise.

For the multiplication fault,

$$x(t) = c \cdot x^{*}(t) \tag{4}$$

where c is a constant. In a generic case, the sensors fault scenario could be due to a combination of the four types of faults. For this reason, the main goal is simply to isolate the faulty sensor in order to apply a decision making strategy and a problem solving procedure.

Proposed FDI Algorithm

In this work FDI tasks is associated with two aspects of redundancy combined among them as required:

— Functional redundancy
— Physical redundancy

Functional redundancy deals with two or more functions describing the same process, while physical redundancy is referred to several hardware devices applied to measuring the same variable. Since analytical models in general don't represent effectively the behavior of nonlinear processes, it is justified the use of back propagation neural networks (BPNN) based functional approximation techniques in nonlinear process modeling, not used in this work.

Functional Redundancy on the FDI Procedure

Let's consider a *free fault* (FF) process defined by means of an analytical function approximation procedure (Deckert J.C. et all., 1977). With regard to functional redundancy, to describe at least two functions of the same variable (manipulated variable) first principles are to be applied. Consequently, a manipulated variable can be described as an active function *MVa*, while a process inverse model provide a reactive function *MVr* as response to the excitation constituted by the manipulated variable.

The complete open loop process can be described by means of model based functions as shown in (5),

$$
\begin{aligned}
&MVa = f(X_1, X_2, \ldots X_N) \\
&MVa' = f(X_1', X_2', \ldots X_N') \\
&MVr = f(Z_1, Z_2, \ldots Z_M) \\
&MVr' = f(Z_1', Z_2', \ldots Z_M')
\end{aligned}
\tag{5}
$$

where *MVa'* and *MVr'* are respectively physically redundant functions of *MVa* and *MVr*.

where

X_1, X_2,..X_N, are inputs from hardware devices to the function *MVa*,

X_1', X_2',..X_N' are the physical redundant inputs to *MVa'*,

Z_1, Z_2,..Z_M are inputs from hardware devices to the function *MVr*, and

Z_1', Z_2',..Z_M' are the physical redundant inputs from hardware devices to the function *MVr'*.

In figure 1 it is depicted the functional redundancy concept implemented on the basis of functional approximation architectures as defined by (5)

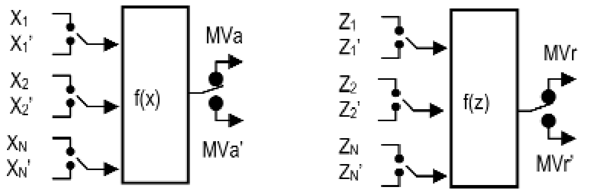

Fig. 1. Functional redundancy implemented under model based functions.

Furthermore, sub-index *N* is the number of instruments assigned to the active function, and sub-index *M* is the number of devices assigned to the reactive function. Described model based functions are experimentally obtained by means of an on-line parameter identification procedure.

Under normal and FF conditions the following functional relations are fulfilled:

First principles

$$MVa = MVr \tag{6}$$

Physical Redundancy

$$
\begin{aligned}
&MVa = MVa' \\
&MVr = MVr'
\end{aligned}
\tag{7}
$$

With such premises the basis for the proposed strategy is stated.

FDI Procedure

Considering equations (5) (6) and (7), a FDI scheduler is developed and represented by means of a close loop sequence of tasks, implemented by means of the flow-chart depicted with figure 2.

According this flow-chart, starting procedure requires a safety operating condition. Once system operation is verified as nominal free-fault or safe condition, then the diagnostic task begins. Human operator intervention is necessary since system reconfiguration doesn't solve the problem of repairing or substitution faulty sensors. Furthermore, if at least one of the sensor fails, in order to keep the required redundancy, this problem must be solved before to continue towards the next flow-chart step. In safety-critical systems, under severe situations a double redundancy may be applied. In such a case system reconfiguration consists in discard the faulty sensor thus avoiding human intervention, but assuming the disadvantage of hardware cost increment.

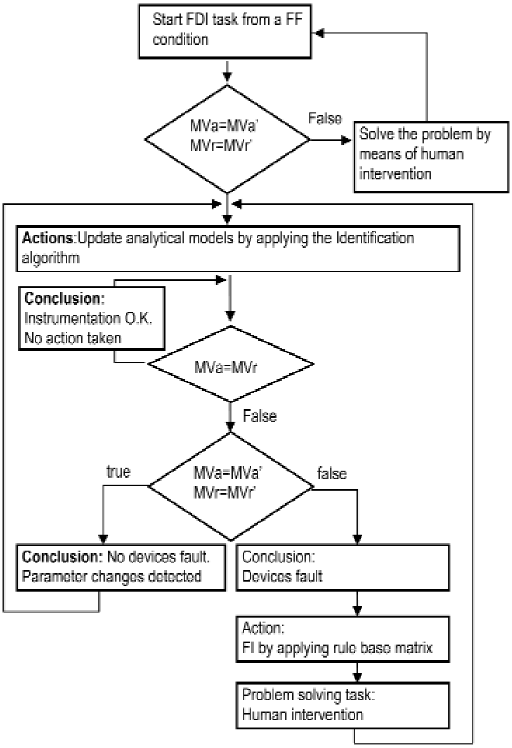

Fig. 2. Flow-chart of the FDI scheduler.

The Identification procedure

Although in many recent research works reasonably efforts on neural networks based fault detection techniques are being used, such in, in order to gets an analytical function describing the manipulated variable *MVa*, as function of its device outputs and model parameters, as well as an analytical function *MVr* describing the process inverse model as function of the process variables and parameters, an on-line identification method is then proposed and applied. The identification procedure of both models *MVa* and *MVr* is carried out simultaneously.

Experimental identification of process dynamics has been an active area of research in several areas of engineering. A Variety of techniques has been proposed. In this work it will be applied a conventional one widely used in process engineering. General nonlinear estimation uses linear estimation iteratively applied to linear approximations of the model until coefficients converge. On the other hand the Extended Kalman Filter (EKF) is probably the most widely used estimation algorithm for nonlinear systems. However, more than three decades of experience in the estimation community has shown that is difficult to implement, difficult to tune, and only reliable for systems that are almost linear on the time scale of the updates. To overcome these drawbacks and limitations, the selected parameter estimation method is based on the time-domain fitting of step test data.

The most direct way of obtaining a linear dynamic model of a process is to find its parameters that fit the experimentally obtained step response data. It is based on applying a disturbance and record the output variable *x(t)* and its successive derivatives as a function of time. With achieved data it is possible to estimate a set of model parameters proceeding by means of the linear least squares algorithm. In order to be prepared to apply the estimation procedure let's review the method by starting from a linear model such that

$$y = X\text{è} + e \tag{8}$$

where y is an N by 1 vector, X is N by K matrix, where K is the number of model variables, è is a K by 1 vector of unknown coefficients, and e is an N by 1 vector of errors.

The vector of parameter estimates is straightforward achieved from least squares algorithm according

$$\hat{\text{è}} = \left(X^T X\right)^{-1} X^T y \tag{9}$$

where its covariance matrix is then

$$V\left[\hat{\text{è}}\right] = s^2 \left(X^T X\right)^{-1} \tag{10}$$

with s^2 the estimated mean squared model error.

Rule Base Matrix

A rule base matrix is developed in order to deterministically decide the faulty group. The faulty device will be isolated by applying the properties inherent to physical redundancy. The rule base matrix is composed by an *m*.x.*n* order, where $m = n$, which means a square matrix. The corresponding entries of rows and columns are matched by means of an *If Then* rule of the form:

IF group (a) is equal to group (r) THEN Conclusion (True or False)

	MVa	MVr	MVa’	MVr’
MVa		0		
MVr	0		0	0
MVa’		0		
MVr’		0		

Table I. Full single redundancy rule matrix.

Every element of the rule base matrix is the conclusion of every processed rule that means a deterministic decision about the matched group of instruments by applying (6) and (7).

Table I shows the structure of a full single redundancy set of instruments associated by groups identifying the rule matrix entries. The shadowed cells are not applicable.

For instance, with regard to table I, if any device of the group of instruments *MVr* fails, then the result derived from the fact of matching this group against the remaining groups of the rule base matrix, is false (0). Otherwise, is true (1), according the decisions of the rules shown in rule matrix of table I. According to the given explanation, the decision of the rest of table cells is a logic one.

IMPLEMENTATION PROCEDURE ON DP PROPULSION SYSTEM

In order to show the supervision procedure under described methodology, a basic propulsion system equipped with a set of instruments for an autonomous vehicle dynamic positioning control system is to be described

This propulsion system is specifically selected in this work to test DP propulsion related instrumentation, being equipped with physical redundancy instrumentation for most of the relevant variables. The application is focused on the supervision of the instrumentation associated to the thrust forces caused by propulsion effectors. Such vehicle is equipped with a fully redundant positioning system designed to ensure that position monitoring can be carried out throughout all phases of ship operation and in the specified environmental condition.

The Propulsion Model

The analysed propulsion system correspond to a shunt DC motor driven by a full-bridge thyristor rectifier (SCR), which has separately supplied field winding and armature (rotor) winding. The armature current is transferred from the stationary terminals to the rotor by use of brushes connected to the rotating commutator.

In a shunt DC motor the induced armature voltage is proportional to the magnetic field and rotational speed. The magnetic field is a function of the field current, and because of saturation effects, they are in practice not proportional. However, if neglecting the saturation, the armature voltage is:

$$V_a = k \cdot \Phi(I_f) \cdot n \approx k \cdot K_\Phi \cdot I_f \cdot n = K_V \cdot I_f \cdot n, \tag{11}$$

where K_V is the induced voltage constant, I_f is the magnetization (field) current, n is the rotational speed, K_Φ and K are proportional constants, and Φ is the motor flux.

The developed torque Q is proportional to armature current and magnetic field, according

$$Q = k \cdot I_a \Phi(I_f) \approx k \cdot I_a \cdot K_\Phi \cdot I_f = K_{TM} \cdot I_a \cdot I_f \tag{12}$$

where K_{TM} is the torque constant and I_a is the armature current. Since the DC motor must be supplied from a DC source with limited voltage, field, and armature currents, the characteristic boundary of operations will be also limited. Using expressions (11) and (12) conveniently, the motor torque can be expressed as function of the current and voltage of the armature. Furthermore the developed power is straightforward achieved according

$$\begin{aligned} Q &= \frac{1}{n} \cdot \frac{K_{TN}}{K_V} \cdot I_a \cdot V_a \\ Power &= Q \cdot n \cdot \frac{K_V}{K_{TN}} \end{aligned} \tag{13}$$

The torque control block diagram of an electric propulsion system is shown in figure 3.

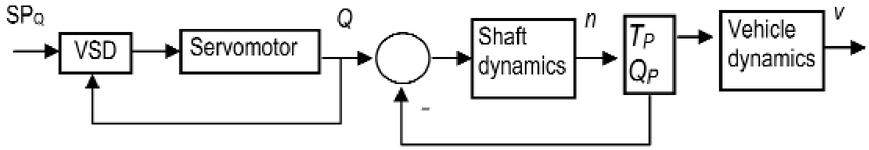

Fig. 3. Electric motor-propeller based propulsion scheme.

The torque Q is to be controlled by means of a variable torque/speed drive. The load is due to the propeller torque Q_P. The vehicle dynamics depends on propeller thrust T_P, hull resistances and external disturbances.

Propulsion system dynamics

It is assumed that the propeller shaft is driven by an electric motor, which generates a torque Q controlled by a variable speed drive (VSD) of the SCR type. The engine dynamics is split-up into two parts. The first part describes the relation between the developed torque (*PV*) and demanded torque (*SP*). The linear transfer function is modelled as a first order time constant according (R. Ferreiro, M. Casado, F.J. Velasco, 2005)

$$\frac{Q}{SP_Q} = \frac{K_Y}{T_c s + 1} \tag{14}$$

where K_Y is the gain constant and T_c is the time constant corresponding to the torque from motor and shaft inertia loads. The mentioned second part correspond to the shaft torque balance, being expressed as

$$Q = I_m \dot{n} + Q_f + Q_p \tag{15}$$

where I_m is the total moment of inertia of rotating parts, Q_p is the torque developed from the propeller and Q_f is the friction torque.

Propeller thrust dynamics

The propeller thrust and torque are modelled by the following relations

$$\begin{aligned} T_p &= K_T \rho D^4 |n| n \\ Q_p &= K_Q \rho D^5 |n| n \end{aligned} \tag{16}$$

where D is the propeller diameter and ρ is the mass density of water

Thrust coefficient

$$K_T = \frac{T_p}{0.5 \cdot \rho \cdot V_r^{\,2} \cdot A_0} \tag{17}$$

Torque coefficient

$$K_Q = \frac{Q_p}{0.5 \cdot \rho \cdot V_r^{\,2} \cdot A_0 \cdot D} \tag{18}$$

Where V_r is the relative speed of advance and A_0 is the propeller disc surface.

$$V_r^{\,2} = V_A^{\,2} + (0.7 \cdot R \cdot n)^2 \tag{19}$$

$$\beta = A\tan(V_A, 0.7 \cdot R \cdot n) \tag{20}$$

Where R is the propeller disc radius and V_A is the speed of advance (arriving water velocity to propeller)

Advance number

$$J = \frac{V_A}{n \cdot D} \tag{21}$$

By knowing experimentally the advance number of such particular hull-propeller vehicle, the speed of advance is calculated, and consequently, the relative speed of advance, the torque coefficient and the thrust coefficient which yields the propeller torque and propeller thrust necessary to establish the analytical redundancy.

Ship surge dynamics

The ship dynamics can be approached by the following non-linear differential equation

$$m\dot{v} = R(v) + (1 - t_T)T_p + T_{EXT} \tag{22}$$

where m is the total mass (ship mass plus added mass), $R(v)$ is the hydrodynamic resistance, $(1\text{-}t_T)$ is the thrust deduction factor, T_{EXT} is the total external forces and T_p is the thrust propulsion

After rearranging past equations, and neglecting the external forces, yields the final model for the shaft speed and vehicle speed as

$$Q = SP_Q \frac{K_Y}{T_c s + 1} \tag{23}$$

$$\dot{n} = \frac{1}{I_m}[Q - Q_f - Q_p] = \frac{1}{I_m}[Q - KF \cdot n - K_Q \cdot \rho \cdot D^5 \cdot n \cdot |n|] \tag{24}$$

$$\dot{v} = [-R(v) + (1 - t_T)T_p]/m = \frac{1}{m}[-R(v) + (1 - t_T) \cdot K_T \cdot \rho \cdot D^4 \cdot n|n|] \tag{25}$$

whose block diagram is achieved and shown in figure 4.

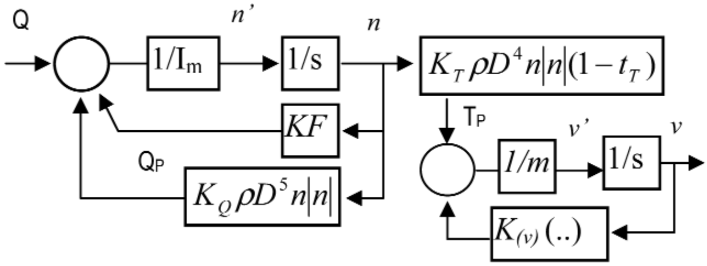

Fig. 4. Block diagram of propulsion system under state space phase variable model.

Implementation of the DP FDI Strategy

Given a DP propulsion plant corresponding to a marine vehicle described by means of analytical approximation procedures under *MVa*, *MVr*, and redundant groups of devices under *MVa' and MVr'*, by applying expression (5) on (13), (15) and (16) for the armature current, voltage and shaft speed it yields

$$\begin{aligned} MVa &= f(SP_Q, I_a, V_a) \\ MVa' &= f(SP_Q, I'_a, V'_a) \\ MVr &= f(Q_P, n) \\ MVr' &= f(Q_P, n') \end{aligned} \tag{26}$$

where (SP_Q, I_a,. V_a) are inputs to the function *MVa*, (I'_a, V'_a) are redundant inputs to *MVa'*, (n) is the input to the function *MVr*, and (n') is the redundant input to the function *MVr'*. With the model

Since the speed of advance V_A and consequently the advance factor J depend on the actual dynamic characteristics of the maneuver, estimation of thrust and torque coefficients according expressions (16-21) doesn't provide accurate results. Due to such ambiguity the actual measures of propeller thrust and motor current and/or power are available and measured. At zero vehicle speed, in keeping station conditions, a well experimental approach which relates the motor torque with propeller thrust is the used.

$$T_P = f_Q(Q) = f_n(n) \tag{27}$$

With the balance given by (27) expression (26) is being used on the FDI task. According (26), the corresponding rule base matrix is that of table V, in which a single full redundancy is being applied. Consequently, applying the FDI scheduler depicted by means of the flow-chart shown in figure 2, as part of the whole supervision system, yields the results (conclusions) of the on-line instrumentation supervision task. If there is full evidence of correct instrumentation operation, then the plant supervision task, which is beyond the scope of this research work, will be easier and deterministic. It must be also taken into account that if instrumentation operation is correct, then, standard plant FDI methods may be applied.

Simulation results

In order to verify a potential malfunction of the instrumentation (armature current, voltage and tachometer), the redundant current sensor is manually adjusted to be deviated from the actual value (shift) and consequently its behavior is the typical one of a faulty sensor affected by such fault. After starting up the FDI scheduler following the flow-chart shown in figure 2 with the rules described by (26), the FDI process begin.

	MVa	MVr	MVa'	MVr'
MVa		1	0	1
MVr	1		0	1
MVa'	0	0		0
MVr'	1	1	0	

Table II. Detection of the faulty group of instruments (Row and column of *MVa'=0*)

The rule base matrix which must be processed under the instrumentation structure is the one of table II according the flow-chart sequence. The results of processing the rule base are shown in table V, where the group of sensors denoted as *MVa'* is faulty.

As a fault has been detected, isolation of the faulty device is rather a straightforward action which consists in the comparison of every device of the faulty group with its redundant device. As consequence of the comparison between the readings on both groups of devices it yields $I_a \neq I_a'$. Since a fault has been detected and acknowledged, it is expected to solve the problem by re-adjusting the faulty current sensor. After acknowledging the human intervention, then the signal flow is returned to the origin to continue the on-line supervision task.

CONCLUSIONS

A systematic methodology to implement the supervision task of process instrumentation applied on the thruster equipment of a DP control system has been proposed and developed. The approach combines model based approximation implemented on the basis of parameter identification, with rule based strategies, both implemented with the facilities of an object oriented programming tool. This procedure solves an important task by deterministically deciding the health of the data acquisition system. The relevance of this fact is verified since the ambiguity on conventional system FDI tasks is avoided with the applied methodology. The problem associated with the most probable faults and decision making based on voting, as well as the most convenient number of redundant devices is solved by the procedure implemented by means of the developed supervision FDI scheduler.

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