Sensor Fault Detection with Low Computational Cost: A Proposed Neural Network-based Control Scheme

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Abstract

The paper describes a low computational power method for detecting sensor faults. A typical fault detection unit for multiple sensor fault detection with model-based approaches, requires a bank of estimators. The estimators can be either observer or artificial intelligence based. The proposed control scheme uses an artificial intelligence approach for the development of the fault detection unit abbreviated as 'i-FD'. In contrast with the bank-estimators approach the proposed i-FD unit is using only one estimator for multiple sensor fault detection. The efficacy of the scheme is tested on an Electro-Magnetic Suspension (EMS) system and compared with a bank of Kalman estimators in simulation environment.

1. Introduction

Modern control systems require careful and economic design with maximum performance and reliabilities. Such design is a trade-off between the economic and control and reliability properties i.e. use the most economic way where control performance and reliability are both achieved at the desirable level. Such systems are classified as safety-critical systems where the faults must be accommodated before the impaired system becomes unstable. Therefore the Fault Tolerant Control (FTC) concept is used to accommodate possible faults [1] eg. sensor faults. Particularly, the information fed into the controller using sensors is vital for the stable and reliable operation of a control system, therefore fault tolerance for sensor failure(s) must be considered.

FTC systems are classified into to types, **P**assive **F**ault **T**olerant **C**ontrol (PFTC) and **A**ctive **F**ault **T**olerant **C**ontrol (AFTC) [12] in the first case a prior knowledge of the fault is required in order to design a controller which will be insensitive to the faults while in the latter case (used in this paper) a **F**ault **D**etection and **I**solation (FDI) mechanism is required in combination with a variable structure controller. When one or more sensor faults occur, the FDI unit detects, isolates and instructs for controller reconfiguration. Reconfigurable FTC control has gain a lot of intention the last years because of the necessity to design reliable control systems with lower cost [7, 17].

Even though in any control system, both actuator and sensor failures can occur, this work deals only with sensor fault detection and accommodation via controller reconfiguration (i.e. via AFTC). The FDI mechanism read both sensor and actuator information and based on that is able to distinguish which is(are) the faulty one(s). After that it isolates and reconfigures the controller in order to maintain the performance using the remaining healthy sensors. Other methods are using the information from the remaining healthy sensors in order to reconstruct the lost signal from the faulty sensor i.e. Samy(2011) [16]. These include the use of a bank of **N**eural **N**etworks (NNs) or **K**alman **E**stimators (KE) [11, 15]. Both prove to be useful when aimed to avoid sensor redundancy.

In any case, if there are many sensors, a bank of those is needed to be designed in order to detect multiple faults. For example, if an n number of sensors are used, then the number of faults that could happen is $2^n - 1$ (assuming that not all sensors can fail). Therefore if fault tolerance is to be considered, the control design becomes more complex and requires additional computational power. The contribution of this work lies on the fact that a low computational cost FDI mechanism based on neural networks is presented reducing the complexity and computational power of a bank-based FD unit.

NNs have been extensively used in many engineering fields including control systems [6] as well as for fault detection in FTC systems [13, 14] and particularly in Sensor FDI and Accommodation (SFDIA) (see Samy (2011) and references therein [16]).

The novelty of this paper focuses on the development of a NN based FDI unit (i-FD) which is able to detect multiple sensor faults with low complexity computational power.

The rest of the paper is organized as follows: Section 2

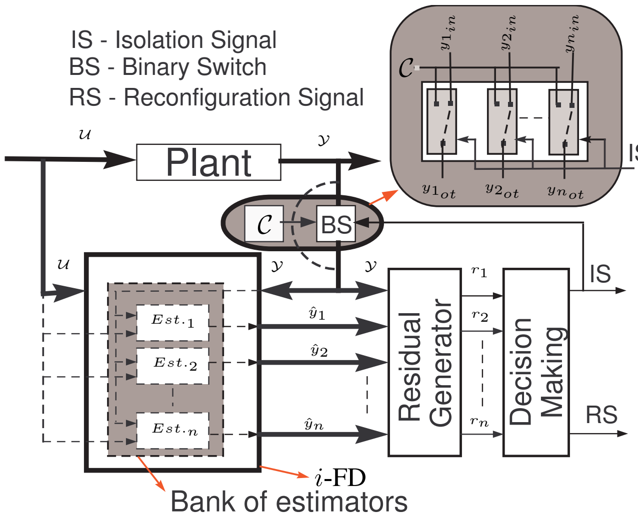

Figure 1. A general diagram of SFDI with the proposed i-FD (bolted lines) and a bank of estimators (dotted lines).

describes the proposed i-FD approach, Section 3 gives a short description of the NN used for the i-FD training followed by the EMS model description and the implementation with the i-FD in Section 4. Section 5 gives the analysis of the results and the paper concludes in Section 6.

2 The Proposed i-Fault Detection scheme

A typical multiple sensor fault detection mechanism requires a bank of estimators. Typically such FD mechanism is depicted in Fig. 1 with dotted lines (note that BS and C are used only for the i-FD). Assuming a plant with a set of actuators, $\mathcal{U}$ and a set of sensors, $\mathcal{Y}$ the sensor FD can be done using a bank of estimators that read the actual measurements from actuators and sensors and generates the estimated signal, $\hat{y}_i$ for each sensor. Both the actual and estimated signals are fed into the residual generation unit where one residual is generated from each sensor measurement. Each residual indicates whether the actual measurement coming from a particular sensor is faulty or not. Since this FD method is model-based, the model of the plant should be well known otherwise the rate of false alarms could be high reducing the reliability of the FD mechanism. A moving average filter is used for each sensor for the residual generation, shown in (1).

$$r_i = \sum_{i-(N-1)}^{i} \frac{(y_i - \hat{y}_i)^2}{N} \tag{1}$$

where y_i is the actual measurement and $\hat{y}_i$ is the estimated one. N is the number of past residual samples

As it was mentioned, the estimator can be observer or artificial intelligent-based where a bank of dedicated observers [8] or NNs [16] can be used for signal estimation.

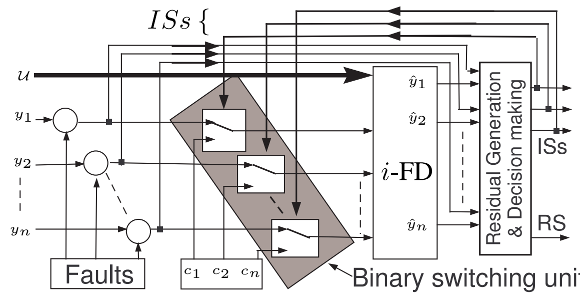

Figure 2. The detailed diagram of the i-FD.

However, these techniques use more computational resources with increased applicability complexity than the method proposed in this paper. Both estimators require some form of off-line preparation. In the case of the observer-based technique the observer has to be tuned in order to minimize the error between the actual and estimated measurements while in the NN case the estimator must be trained. The proposed i-FD mechanism uses a NN-based approach where one estimator is trained for all the sensor fault scenarios and produces the estimated sensor signals accordingly. The training method is explained latter in Section 3. As it can be clearly seen in Fig. 1 the proposed i-FD diagram depicted with bolted lines can easily replace the bank of estimators with only a slight modification, or in particular by adding the Binary Switches (BS) that control the input at the i-FD and a set of functions $\mathcal{C}$. Both the $\mathcal{U}$ and $\mathcal{Y}$ are fed into the i-FD and the estimated measurements are fed into the residual generator producing one residual for each measurement. If there is one or more faulty measurements the decision unit will detect this and produce two signals: (i) the **R**econfiguration **S**ignal (RS) which instructs for changing controller that is a priori tuned to work with the remaining healthy sensors, (ii) a vector of binary type Isolation Signals (ISs) which will remove the faulty sensors from the loop and simultaneously connect the corresponding predefined functions c_i at the input of the i-FD using the BS. A typical decision making for a IS is given in (2).

$$y_{i_{ot}} = \begin{cases} y_{in} & if \ IS=1 \\ c & if \ IS=0 \end{cases} \tag{2}$$

The detailed diagram of the proposed i-FD is shown in Fig. 2. The set of actuators $\mathcal{U}$ and sensors $y_1, y_2 \ldots y_n$ with a number of n sensors is fed into the i-FD unit along with the actual measurements set. The estimated measurements are compared with the actual ones and the residuals are given to the decision mechanism. When one or more sensor failures occur the decision mechanism will give the RS and the IS to the switching unit for isolating the faulty signals and give new inputs i.e. c_i functions to the i-FD estimator.

3. The Neural Network Algorithm

A dynamic nonlinear input-output NN model with tapped delay lines at the input was used for time-series

prediction. The neural network's main work is to perform similarly as a bank of KE in the feedback loop and to predict future values based on past values of one or more time series. More specifically, to predict $y(t)$ series based on n past values of $x(t)$ series such that $y(t) = f(x(t-1), ..., x(t-n))$. It is obvious that the NN structure in this application significantly simplifies the feedback scheme in terms of filter resources and reduces the computational complexity plus it makes the feedback loop less error prone.
The NN has 5 inputs (u and $i, (z_t - z), \dot{z}, \ddot{z}$) and 3 outputs ($\hat{i}, \hat{\dot{z}}, \hat{\ddot{z}}$). Its internal architecture is realised as a hidden layer (with one delay and 20 hidden neurons) and an output layer with sigmoid and linear functions respectively. A fast convergence method for training moderate sized feed-forward neural networks is the Levenberg-Marquardt backpropagation [5] (also see Ch. 11 and 12 of [4]) algorithm which was used as the training method for the NN in order to fit the inputs and targets. The training data that were later used to train the NN, were collected in an online model working state with the $\mathcal{H}_\infty$ **L**oop-**S**haping **D**esigned **P**rocedure (LSDP) controllers in the feedback loop, and by successively in equal time windows ($T = 6.6s$) failing sensor set combinations with $1kHz$ sampling time. The resulting training sets are: 52808×5 for the inputs and 52808×3 for the outputs. The stopping criteria used is the **M**ean **S**quare **E**rror (MSE$\leq 10^{-5}$) or the maximum number of epochs set at 1000. The structure of the training data is explained next.

3.1 The i-FD unit training: obtaining the learning set

The key point here is the method the i-FD mechanism is trained. In order to train the i-FD unit, data have to be taken using the various sub-sets of the selected sensor set, $\mathcal{Y}_o$. The collected data are then packed together in the format shown in Table 1. The measurements from each sensor set, form the data set $\mathcal{D}$ that is listed for each sensor set. In places where the sensor(s) is(are) assumed to be faulty, a known input c_i, is given by the user. Such that the i-FD learns to respond to sensor faults in a way that the same i-FD unit continually check for faults of the full sensor set and its sub-sets.

4. The EMS system - A test case

4.1 The EMS model

The single-stage, one degree-of-freedom model of the EMS system represents the quarter of a typical MAGLEV vehicle. The EMS is a non-linear, inherently unstable, critical-safety system with non-trivial control requirements. A few details are given about the EMS model in this section, however, a rigorous analysis is reported in Michail(2009) [9].
The state space equations expressing the linearised model are given as:

$$\dot{x} = Ax + B_{u_c}u_c + B_{\dot{z}_t}\dot{z}_t \qquad y = Cx \tag{3}$$

The state vector is $x = [i \quad \dot{z} \quad (z_t - z)]^T$, where i is the current, $\dot{z}$ the vertical velocity and $(z_t - z)$ the airgap to be controlled (with z_t being the rail's position and z the electromagnet's position), $\dot{z}_t$ is the velocity of the track input and u_c is the control (voltage) input. The matrices A,B_{u_c},$B_{\dot{z}_t}$ and C are given in (4)-(6). C is the output matrix that gives the measurements used as $y = [i, (z_t - z), \dot{z}, \ddot{z}]$.

$$A = \begin{bmatrix} -\frac{R_c}{L_c + \frac{K_b N_c A_p}{G_o}} & -\frac{K_b N_c A_p I_o}{G_o^2\left(L_c + \frac{K_b N_c A_p}{G_o}\right)} & 0 \\ -2K_f\frac{I_o}{M_s G_o^2} & 0 & 2K_f\frac{I_o^2}{M_s G_o^3} \\ 0 & -1 & 0 \end{bmatrix} \tag{4}$$

$$B_{u_c} = \begin{bmatrix} \frac{1}{L_c + \frac{K_b N_c A_p}{G_o}} & 0 & 0 \end{bmatrix}^T \tag{5}$$

$$B_{\dot{z}_t} = \begin{bmatrix} \frac{K_b N_c A_p I_o}{G_o^2\left(L_c + \frac{K_b N_c A_p}{G_o}\right)} & 0 & 1 \end{bmatrix}^T$$

$$C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ -2K_f\frac{I_o}{M_s G_o^2} & 0 & 2K_f\frac{I_o^2}{M_s G_o^3} \end{bmatrix} \tag{6}$$

The basic variables that give the non-linear characteristics of the EMS are namely: the force F, the flux density B, the airgap G and the coil's current I [3]. The values of these for a quarter car vehicle with $M_s = 1000kg$ are given as $F_o = 9810N, G_o = 15mm, B_o = 1T, I_o = 10A$ with an operating voltage of $V_o = 100V$. The parameters of the electromagnet are: Number of turns $N_c = 2000$, Coil's Resistance $R_c = 10\Omega$, Coil's Inductance $L_c = 0.1H$ and a pole face area $A_p = 0.01m^2$.
At the input $\dot{z}_t$, there are two types of disturbances in the vertical direction, one is the gradients onto the track and the other comes from the track irregularities and unevenness of the track during the installation. In this paper, only the former type of disturbance is considered. A deterministic input with a gradient of 5% at a vehicle speed of $15m/s$, an acceleration of $0.5m/s^2$ and a jerk of $1m/s^3$ is used as illustrated in Fig. 3 [9]. The control design requirements of an EMS system depend on the type and speed of the train [2]. Typically, the EMS should be able to follow the gradient onto the rail (deterministic input). The control performance requirements of the EMS with deterministic input are listed on Table 2.

Table 2. Control constraints of the EMS.

EMS limitations	Value
Maximum airgap deviation,$(z_t - z)_p$	$\leq 7.5mm$
Control effort,u_{c_p}	$\leq 300V$
Settling time, t_s	$\leq 3s$
Airgap Steady state error,$(z_t - z)_{e_{ss}}$	$= 0$

Table 1. Structure of the data used for the i-FD training.

Sensor Set Status	Measured					Estimated		
	y_1 i	y_2 $(z_t - z)$	y_3 $\dot{z}$	y_4 $\ddot{z}$	u u	$\hat{y}_1$ $\hat{i}$	$\hat{y}_3$ $\hat{\dot{z}}$	$\hat{y}_4$ $\hat{\ddot{z}}$
Healthy	$D^1_{y_1^1}$	$D^1_{y_2^1}$	$D^1_{y_3^1}$	$D^1_{y_4^1}$	$D^1_{u^1_{y_1,y_2,y_3,y_4}}$	$D^1_{\hat{y}_1^1}$	$D^1_{\hat{y}_3^1}$	$D^1_{\hat{y}_4^1}$
Set	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	$D^1_{y_1^k}$	$D^1_{y_2^k}$	$D^1_{y_3^k}$	$D^1_{y_4^k}$	$D^1_{u^k_{y_1,y_2,y_3,y_4}}$	$D^1_{\hat{y}_1^k}$	$D^1_{\hat{y}_3^k}$	$D^1_{\hat{y}_4^k}$
Faulty	c^1_1	$D^2_{y_2^1}$	$D^2_{y_3^1}$	$D^2_{y_4^1}$	$D^2_{u^1_{y_2,y_3,y_4}}$	c^1_1	$D^2_{\hat{y}_3^1}$	$D^2_{\hat{y}_4^1}$
y_1	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	c^1_k	$D^2_{y_2^k}$	$D^2_{y_3^k}$	$D^2_{y_4^k}$	$D^2_{u^k_{y_2,y_3,y_4}}$	c^1_k	$D^2_{\hat{y}_3^k}$	$D^2_{\hat{y}_4^k}$
Faulty	c^1_1	$D^3_{y_2^1}$	c^3_1	$D^3_{y_4^1}$	$D^3_{u^1_{y_2,y_4}}$	c^1_1	c^3_1	$D^3_{\hat{y}_4^1}$
y_1, y_3	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	c^1_k	$D^3_{y_2^k}$	c^3_k	$D^3_{y_4^k}$	$D^3_{u^k_{y_2,y_4}}$	c^1_k	c^3_k	$D^3_{\hat{y}_4^k}$
Faulty	c^1_1	$D^4_{y_2^1}$	c^3_1	c^4_1	$D^4_{u^1_{y_2}}$	c^1_1	c^3_1	c^4_1
y_1, y_3, y_4	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	c^1_k	$D^4_{y_2^k}$	c^3_k	c^4_k	$D^4_{u^k_{y_2}}$	c^1_k	c^3_k	c^4_k

k is the total number of all samples in the training data set

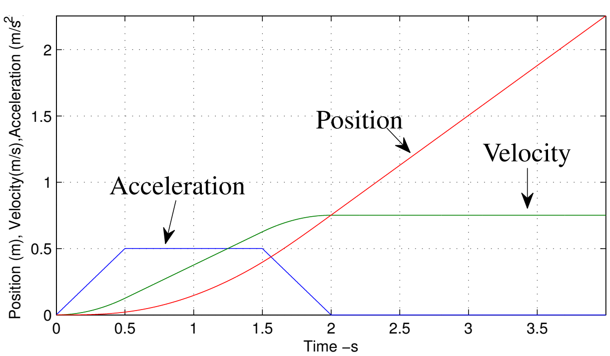

Figure 3. Disturbance Input to the EMS.

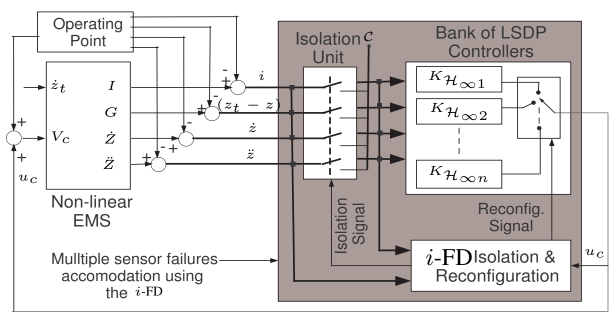

Figure 4. The proposed i-FD for the EMS system.

4.2 The i-FD applied on the EMS system

This i-FD mechanism is successfully combined with the FTC system of the suspension as illustrated in Fig. 4. A bank of $\mathcal{H}_\infty$ LSDP designed controllers is used to accommodate sensor faults. The EMS system has a total of 5 measurements from where 4 are used for control i.e. $\mathcal{Y}_o = \{i, (z_t - z), \dot{z}, \ddot{z}\}$. There are different sensor fault combinations that could occur, totally $2^4 - 1 = 15$. However, due to the control method used is the LSDP, which requires the airgap as a standard measurement, the total sensor fault combinations that could happen reduces to $2^3 - 1 = 7$. Therefore, 7 $\mathcal{H}_\infty$ loop-shaping design controllers are used to cover the sensor faults. When one or more sensors fail, the fault is detected, isolated and a new controller is introduced in the loop which is tuned a priori. For the demonstration of the proposed FD the results from [10] are used.

4.3 Sensor Fault Scenarios

When a sensor fails, its output can be unpredictable. The sensor faults can be added or multiplied with the sensor's output as depicted in Fig. 5. Therefore the fault categories are separated to additive and multiplicative faults with the former been considered in this paper. Further more, the types of faults can be separated into three types: (i) abrupt or step-type fault, (ii) incipient or soft fault and (iii) indeterminate fault as given in the same figure.
A number of sensor fault scenarios is given in this section. The faults considered are additive faults, both abrupt and incipient types. In total there are 4 sensors in the selected sensor set, but the assumption is that only 3 can fail, the current i, the vertical velocity $\dot{z}$ and the vertical acceleration $\ddot{z}$. Both the abrupt and incipient sensor fault profiles for the current (i) sensor are illustrated in Fig. 6. Both faults are additive and occur at 1s (at point A on the fig-

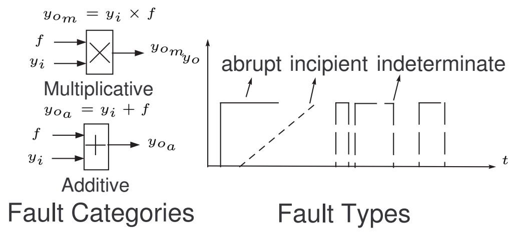

Figure 5. Sensor fault categories and types.

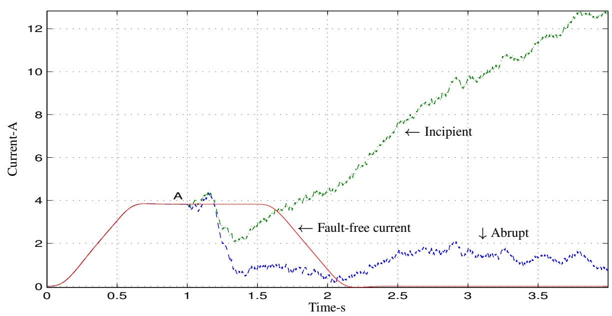

Figure 6. Current sensor fault and fault-free profiles.

ure).

Using these fault profiles for the other two sensors the total sensor fault scenarios used for the test of the proposed i-FD with the EMS system are listed on Table 3. There are 8 scenarios with either abrupt of incipient fault making a total of 15 test cases. For the sensor fault scenarios some assumptions hold:(i) when a sensor fails the damage is permanent i.e. no indeterminate faults are considered, (ii) when a series of sensor failure occurs the fault is either abrupt or incipient for each sensor and (iii) when a series of sensors fail there is a time difference of 1 sec.

5 Simulations and results analysis

Not all results from the simulations can be presented here, however a summary and the main points to show the effectiveness of the proposed i-FD unit are described. A detailed analysis for the situation where the current sensor is impaired at time of one second is considered. The sensor's output suddenly gives a low frequency signal with random characteristics as shown in Fig. 6. The airgap sensor output in the case of such a fault profile is depicted in Fig.7. The figure depicts the airgap with fault-free case (i.e. healthy sensor set) and with a current sensor fault. The fault starts at $1s$ (point A) and immediately afterwards a controller reconfiguration follows, where a new controller is introduced in the loop in order to maintain the stability and performance of the EMS. Both fault-free and fault conditions comply with the EMS requirements as described in Section 4. The sensor fault accommodation is done in three steps: (i) Sensor Fault Detection: When the fault occurs the residual of the current measurement r_i,

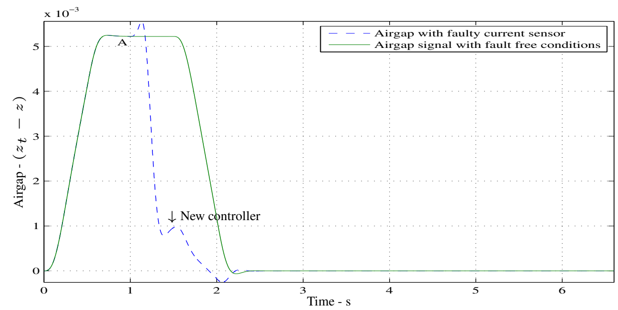

Figure 7. Airgap signal under current sensor fault.

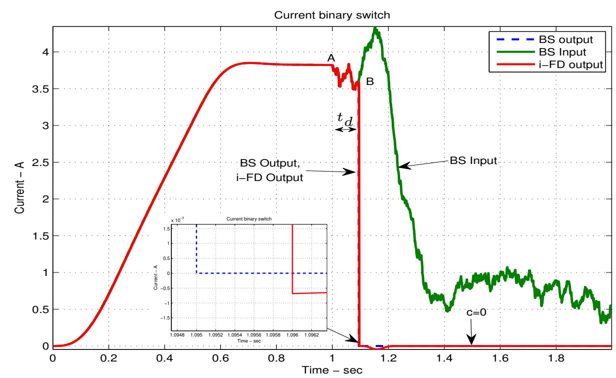

Figure 8. Input-output of the BS of the current sensor and the output of the i-FD.

starts increasing and as soon as it pass the threshold (see Fig. 9) the fault is detected. (ii) Fault Isolation: In this stage the faulty sensor is removed from the loop using a binary switch (BS) while a know function c_i is connected at the input of the i-FD. Figure 8 shows the signal at the input and output of the BS as well as the signal at the output of the i-FD are depicted. (iii) Controller reconfiguration: After the faulty sensor isolation a reconfiguration signal is generated and a new controller is introduced in the loop.

Taking a closer look in Fig. 8 after the fault occurs at point A, the i-FD detects the fault after $t_d = 0.095$ seconds (Point B), while in the next time step the i-FD reacts and drives its output at c value. In this way the residual is always large, which is why the proposed method is excluded from the indeterminate types of faults at the moment. This phenomenon can be observed on Fig. 9 where after the fault detection, the residual is abruptly increased.

As it was previously mentioned in Section 4.3, a number of fault scenarios have been investigated to test the i-FD, and the initial results have shown strong potential for future work. The results of 15 tests are tabulated on Table 3. It shows that the abrupt type of fault can be successfully accommodated with out leaving any false alarms while in the incipient case most of the faults where accommodated except in scenarios with id:4,7,8. The False Alarm (FA)

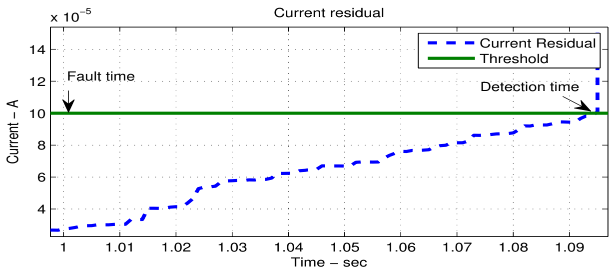

Figure 9. Current sensor residual at 1sec.

Table 3. Sensor fault scenarios for the EMS.

Scenario id	Faulty sensor(s)	Performance			
		Ab.	FA	In.	FA
1	No fault	✓	x	✓	x
2	i	✓	x	✓	x
3	$\dot{z}$	✓	x	✓	x
4	$\ddot{z}$	✓	x	✓	✓
5	$i \to \dot{z}$	✓	x	✓	x
6	$i \to \ddot{z}$	✓	x	✓	x
7	$\dot{z} \to \ddot{z}$	✓	x	✓	✓
8	$i \to \dot{z} \to \ddot{z}$	✓	x	✓	✓

Ab-Abrupt,In-Incipient,FA-False Alarm

means that a sensor looked impaired before it is actually damaged. In fact, this happens because it is harder to detect incipient faults as the NN nature of the i-FD allows it to follow the fault leaving a very small residual. Other than that, stability and performance were accommodated in all 15 scenarios.

Using the same sensor set, $y = \{i, (z_t - z), \dot{z}, \ddot{z}\}$ a simple comparison is to compare the time taken for a simulation taken to complete using the i-FD and a bank of 7 KE (one for each sub-set of y) using the same simulation parameters i.e. sampling time, solver type, operating parameters etc. The simulation shows that the i-FD is more that 10 times faster than the bank-estimator approach therefore at the Matlab simulation level the proposed fault detection method looks very fast and promising.

6 Conclusion

The paper presents a neural network-based method, the i-FD, for detecting sensor faults. A detailed analysis for the rationale is presented and a number of fault tests scenarios have been used to test the proposed method. The tests accounted for sensor fault scenarios with additive and abrupt or incipient type of faults, and have shown that this new approach has a strong potential for replacing a bank of estimators. In conclusion, the proposed method results in a simplified model-free FD, that requires significantly less computational power, its easier to train as there is only one estimator and is faster to implement since a minimum programming effort is required.

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