AI-based Low Computational Power Actuator/Sensor Fault Detection Applied on a MAGLEV Suspension

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***Abstract*— A low computational power method is proposed for detecting actuators/sensors faults. Typical model-based fault detection units for multiple sensor faults, require a bank of observers (these can be either conventional observers of artificial intelligence based). The proposed control scheme uses an artificial intelligence approach for the development of the fault detection unit abbreviated as 'iFD'. In contrast with the bank-of-estimators approach, the proposed iFD unit employs a single estimator for multiple sensor fault detection. The efficacy of the scheme is illustrated on an Electromagnetic Suspension system example with a number of sensor fault scenaria.**

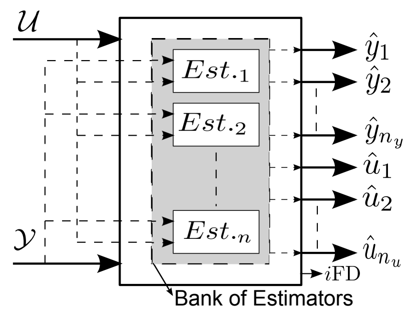

Fig. 1. Actuator/sensor fault detection with typical bank of estimators (dotted lines) and the proposed iFD (straight line).

I. INTRODUCTION

Modern industrial systems require careful design as performance and reliability standards are demanding while cost is an important constraint. A trade-off between economical design in one hand and system performance and reliabilities in the other exists, in which engineers have to take into consideration in order to obtain the most appropriate solution. In addition, reliability issues is an important area to consider during design, as it is vital in many applications in terms of system safety, e.g. public transportation systems. Failure of such systems, referred to as safety-critical systems, is not an option hence the scientific community developed methods of fault tolerance.

Fault **T**olerant **C**ontrol (FTC) Systems aim to reduce cost while maintain high reliability. Some small but expensive systems (eg. Unmanned Aerial Vehicles [1]) have limited computational resources which makes it difficult to achieve fault tolerance as they require respectable computational power. This paper deals with two vital and vulnerable components of such control systems, the actuators and sensors. In the case that one or more of such devices fail during operation the system can go unstable therefore immediate remedial actions have to be taken right after the fault occurs in order to maintain stability (even if the performance have to degrade), this being a distinct characteristic of FTC system behaviour.

FTC systems classification falls in two categories, i.e. **P**assive **F**ault **T**olerant **C**ontrol (PFTC) and **A**ctive **F**ault **T**olerant **C**ontrol (AFTC) [2]. In the former case a prior knowledge of the fault is required in order to design a controller insensitive to faults that are taken into consideration, while in the latter case proposed in this paper, a **F**ault **D**etection and **I**solation (FDI) mechanism is required combined with a variable structure controller. When one or more actuator/sensor faults occur, the FDI unit detects, isolates and instructs the controller to reconfigure itself. Reconfigurable FTC control gained a lot of intention over the past years due to the necessity to design reliable control systems with lower cost [3]. The FDI mechanism first receives data both from the sensor and the actuator and based on that information is able to distinguish which is(are) the faulty one(s), and then it isolates and reconfigures the controller in order to maintain performance using the remaining healthy actuator/sensors. Some other approaches are using information from the remaining healthy sensors in order to reconstruct the lost signal from the impaired sensor(s), see [4]. Such methods include the use of a bank of **N**eural **N**etworks (NNs) or **K**alman **E**stimators (KE) [5], [6] with both proving useful when aiming to avoid sensor redundancy. In contrast to the KEs approach, NNs have increased **F**alse **A**larm **R**ates (FAR) due to the fact that they are able to estimate the faults, however, they are still used because they can be designed without having precise knowledge of the model of the system under test, see [7], [8], [9], [10].

In any case, if there are many actuators/sensors, a bank of estimators needs to be designed in order to detect multiple faults. This is depicted in Fig. 1 with dotted lines. Hence, 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 **A**rtificial **I**ntelligence (AI), specifically a neural network, is presented reducing the complexity and computational power of a bank-based FD i.e., the bank of the estimators is replaced with one

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estimator which is able to perform similar to the bank-based FD but with lower computational cost. The presented work is an extension of the work presented in [11].

The proposed FD mechanism, abbreviated as iFD, is tested on a safety-critical system, the MAGLEV **E**lectro-**M**agnetic **S**uspension (EMS) system that is inherently unstable with non-trivial control requirements and non-linear characteristics [12].

The rest of this paper is organized as follows: Section II describes the working principle of the iFD and the key points relating to train it, Section III outlines the NN algorithm that is used, while Section IV the basics on modelling issues and how this is combined with iFD. Analysis of simulation results and conclusions are presented in Sections V and VI, respectively.

II. THE PROPOSED i-FAULT DETECTION SCHEME

The FD unit is used to detect actuator/sensor faults and instruct for controller reconfiguration. The proposed FD scheme is based on NN and the principle of operation is illustrated in Fig 3. Any typical industrial system has a set of inputs (control signals) and a set of outputs (measurement signals). In practice, the inputs are driven by a set of actuators, $\mathcal{U}$, and the outputs (measurement signals) are given by a set of sensors, $\mathcal{Y}$. The design engineer uses $\mathcal{U}$ and $\mathcal{Y}$ to design a controller with which a desired closed-loop performance is achieved (controller is not depicted on the particular diagram). In that sense the control and measurement signals refer to actuators and sensors respectively. When the actuator or the sensor is impaired, those signals are distorted leading to performance degradation or even instability of the closed-loop. The sets of actuators and sensors are defined as $\mathcal{U} = [u_1, u_2, \dots u_{n_u}]$ and $\mathcal{Y} = [y_1, y_2, \dots u_{n_y}]$. Where u_i, y_i and n_u and n_y are the i^{th} actuator and sensor, and the total number of actuators and sensors, respectively. Since faults may occur in any of the aforementioned parts, the mechanism employed to detect the faults is comprised of a NN-based estimator, a **R**esidual **G**enerator (RG) and a **D**ecision **M**echanism (DM).

The estimator is trained (this is the key point of the proposed method which is explained later in this section) in order to estimate the $\mathcal{U}$ and $\mathcal{Y}$. The input to the estimator is obtained from the so called **B**inary **S**witches (BS). The BS have three inputs; one represents the real measured values of the $\mathcal{U}$ and $\mathcal{Y}$ and the other comes from the functions $\mathcal{C}_{u_i}$ and $\mathcal{C}_{y_i}$ defined as $\mathcal{C}_{u_i} = [c_{u_1}, c_{u_2} \dots c_{u_{n_u}}]$ and $\mathcal{C}_{y_i} = [c_{y_1}, c_{y_2} \dots c_{y_{n_y}}]$. $\mathcal{C}_{u_i}$ and $\mathcal{C}_{y_i}$ are two arrays that contains predefined functions that are used during the training and operation of the iFD. Since these values are application dependent there is no systematic way to calculate them, therefore the designer has to figure them out from experience. The third input (IS_{u_i,y_i}) is a binary input which controls switching between the inputs eg. from u_1 to c_{u_1}. A typical example is given in Fig. 2. The output y_{BS_i} of the BS is given by:

$$y_{BS_i} = \begin{cases} y_i, if IS=1 \\ c_{y_i}, if IS=0 \end{cases} \tag{1}$$

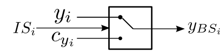


Fig. 2. Diagram of a binary switch (BS_i).

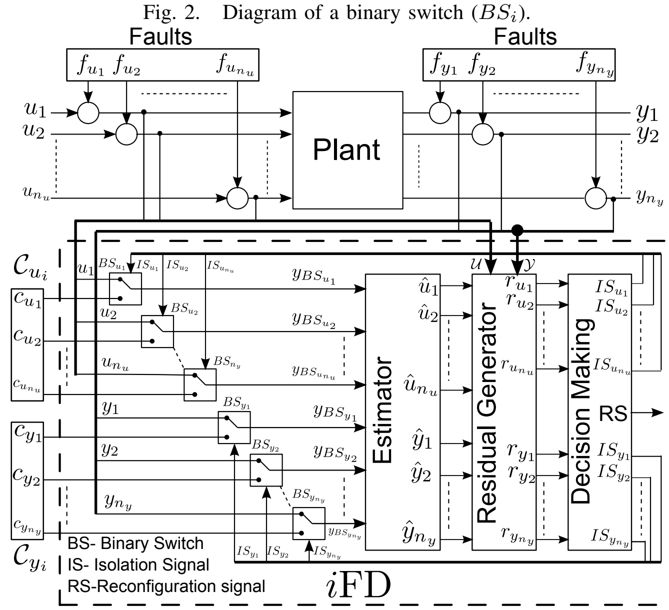


Fig. 3. The block diagram of the proposed AI-based iFD unit.

The RG, reads the estimated actuators/sensors signals and compares these with the real ones. Several different methods exist in the literature for the residual generation, with the choice in this paper being the moving average filter, defined as follows:

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

where r_i is the residual, y_i and $\hat{y}_i$ are the real and estimated signals (for the actuators the y is replaced by u) and N is the total number of the past samples. The particular filter is useful because is able to accommodate the noise coming from the sensors reducing the FAR. The decision mechanism, decides whether one or more devices are faulty. The engineer has to define thresholds for each residual, while the DM will decide whether a device is faulty or not. Threshold selection is a non-trivial task to perform because on one hand affects the sensitivity of the DM to fault detection and on the other hand, it affects the FAR. Taking into account the property of the AI nature of the iFD which is able to estimate the faults, the threshold selection needs to be done very carefully. This is a field that gains a lot of attention but is beyond the scope of this paper. Another signal at the output of the DM is the **R**econfiguration **S**ignal (RS) which is basically the corresponding identifier for the controller reconfiguration.

In conclusion, the proposed iFD works as follows:

- At first, assuming a normal situation, the actuator and sensors signals are accurately estimated and then are fed into the residual generator. Subsequently, the generator calculates the residual (this corresponds to a very small value at normal operation) for each actuator/sensor and feeds it to the DM. Lastly, the DM will produce the IS and RS signals (the IS signals in a healthy situation are all 1).

TABLE I

STRUCTURE OF THE DATA USED FOR THE iFD TRAINING.

Sensor Set Status	Measured					Estimated		
	y_1 i	y_2 $(z_t - z)$	y_3 $\dot{z}$	y_4 $\ddot{z}$	u_c u_c	$\hat{y}_1$ $\hat{i}$	$\hat{y}_3$ $\hat{\dot{z}}$	$\hat{y}_4$ $\hat{\ddot{z}}$
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_k^1	$D^2_{y_2^k}$	$D^2_{y_3^k}$	$D^2_{y_4^k}$	$D^2_{u^k_{y_2,y_3,y_4}}$	c_k^1	$D^2_{\hat{y}_3^k}$	$D^2_{\hat{y}_4^k}$
Faulty	c_1^1	$D^3_{y_2^1}$	c_1^3	$D^3_{y_4^1}$	$D^3_{u^1_{y_2,y_4}}$	c_1^1	c_1^3	$D^3_{\hat{y}_4^1}$
y_1, y_3	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	c_k^1	$D^3_{y_2^k}$	c_k^3	$D^3_{y_4^k}$	$D^3_{u^k_{y_2,y_4}}$	c_k^1	c_k^3	$D^3_{\hat{y}_4^k}$
Faulty	c_1^1	$D^4_{y_2^1}$	c_1^3	c_1^4	$D^4_{u^1_{y_2}}$	c_1^1	c_1^3	c_1^4
y_1, y_3, y_4	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	c_k^1	$D^4_{y_2^k}$	c_k^3	c_k^4	$D^4_{u^k_{y_2}}$	c_k^1	c_k^3	c_k^4

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

- As a consequence of one or more actuators/sensors failure, the corresponding residuals will start increasing. In this case the DM will detect the change by comparing the residuals with the thresholds. Next, the ISs will change in order to instruct the corresponding BS to modify the output to c_i, while the RS will take the necessary value and pass it to the controller for the reconfiguration to take place. In this stage the BSs will also isolate the signals of the faulty devices from the estimator so that the latter ”sees” some ”known” data based on its trained knowledge.
- Lastly, the controller will reconfigure itself and the stability and performance will be maintained.

A. The iFD unit training: obtaining the learning set

The key point here is the method by which the estimator of the iFD mechanism is been trained. In order to train the iFD unit, data sets have to be taken using the various sub-sets of the selected sensor set, $\mathcal{Y}_o$. The collected data sets are then packed together in the format shown on Table I. The measurements from each sensor set, form the overall 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. Following this manner the iFD learns to respond to sensor faults in such a way that the iFD unit itself continually check for faults of the full sensor set and its sub-sets.

The training procedure of the iFD unit synopsises to the following steps:

- Collect the input-output data from the closed-loop system using *each* sensor set.
- Decide which function to use for each actuator/sensor(i.e. decide the $\mathcal{C}_{u_i}, \mathcal{C}_{y_i}$).
- Merge the data with the functions as shown on Table I.
- Train the iFD using one of the available NN algorithms.

Note that for the MAGLEV suspension the particular table has to be formed twice, namely one for its deterministic and one for its stochastic response.

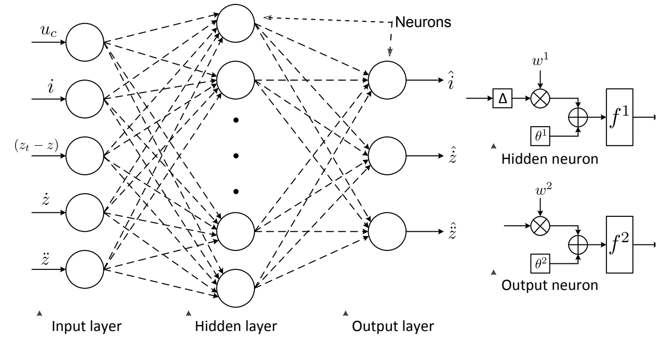


Fig. 4. The Neural network architecture for the iFD.

III. THE NEURAL NETWORK ALGORITHM

A dynamic nonlinear input-output time delay NN (TDNN) model 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 EMS system has one input and five outputs that are fed into the NN (the input voltage u and the outputs: current i, airgap $(z_t - z)$, vertical velocity $\dot{z}$ and vertical acceleration $\ddot{z}$). The NN is trained in order to estimate i, $\dot{z}$ and $\ddot{z}$ symbolised as $\hat{i}$, $\hat{\dot{z}}$ and $\hat{\ddot{z}}$. The NNs architecture is similar to a feedforward structure with the addition of delays in the hidden layer. 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 (see Fig.). A fast convergence method for training moderate sized feed-forward neural networks is the Levenberg-Marquardt backpropagation [13] (also see Ch. 11 and 12 of [14]) algorithm which was used as the training method for the NN in order to fit the inputs and targets. The training data were collected in an online model working state using sub-sets of the full sensor set (with appropriately tuned controllers in the feedback loop) in equal time windows ($T = 6.6s$) with $1kHz$ sampling time. The control design method used is the well-known $\mathcal{H}_\infty$ **L**oop-**S**haping **D**esigned **P**rocedure (LSDP). The resulting dimensions of the training sets are: 52808×5 for the inputs and 52808×3 for the outputs (2 sets of data are merged, one for the deterministic and one for the stochastic response of the suspension). The stopping criteria set to a **M**ean **S**quare **E**rror (MSE$\leq 10^{-5}$) or a maximum number of epochs=10^3. The structure of the training data is explained next.

IV. THE CASE STUDIED: EMS SYSTEM

A. Modelling the EMS

The single-stage, one degree-of-freedom model of the EMS system represents a quarter of a typical MAGLEV vehicle. The EMS is a non-linear, inherently unstable, safety-critical system with non-trivial control requirements. Due to space constraints only the basic information given about the EMS modelling. Nevertheless, the interested reader can refer to Michail(2009) [15] for the rigorous analysis.

The state space equations expressing the linearised model as extracted from the non-linear counterpart using the small variations around the operating point approach are given by:

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

A is the state matrix with the state vector given as $x = [i \quad \dot{z} \quad (z_t - z)]^T$, 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. B_{u_c} is the input matrix, $B_{\dot{z}_t}$ is the disturbance matrix and C is the output matrix with the measurements given as: $i, (z_t - z), \dot{z}, \ddot{z}$ ($\ddot{z}$ is the vertical acceleration). Matrices A,B_{u_c},$B_{\dot{z}_t}$ and C are given as

$$A = \begin{bmatrix} -4.762 & -634.9 & 0 \\ 1.962 & 0 & -1308 \\ 0 & -1 & 0 \end{bmatrix} \tag{4}$$

$$B_{u_c} = \begin{bmatrix} 0.4762 & 0 & 0 \end{bmatrix}^T, B_{\dot{z}_t} = \begin{bmatrix} 634.9 & 0 & 1 \end{bmatrix}^T \tag{5}$$

$$C = \begin{bmatrix} 1 & 0 & 0 \\ 0.1 & 0 & -66.67 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1.962 & 0 & -1308 \end{bmatrix} \tag{6}$$

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 [16]. 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 specifically: Number of turns $N_c = 2000$, coil's resistance $R_c = 10\Omega$, coil's inductance $L_c = 0.1H$ and the pole face area $A_p = 0.01m^2$.

Two types of disturbances exist in the vertical direction at the input $\dot{z}_t$, the first one is caused by the gradients onto the track and the other one originates from the track irregularities and unevenness of the track during the installation. *Stochastic Inputs:* The stochastic inputs are random variations of the rail position as the vehicle moves along the track. Considering the vertical direction, the velocity variations $(\dot{z}_t)$ can be approximated by a double-sided power spectrum density (PSD) and the corresponding autocorrelation function assuming a vehicle velocity, V_v of $15m/s$ and track roughness, $A_r = 1 \times 10^{-7}$ [15]. *Deterministic Input:* The main deterministic input to the suspension in the vertical direction is due to the transition onto a gradient of the rail. In this work, the deterministic input is a rail gradient of 5% at a vehicle speed of $15m/s$, an acceleration of $0.5m/s^2$ and a jerk of $1m/s^3$ as shown in Fig. 5 [15].

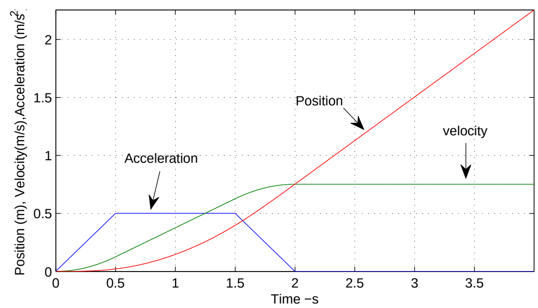


Fig. 5. Deterministic disturbance input to the EMS.

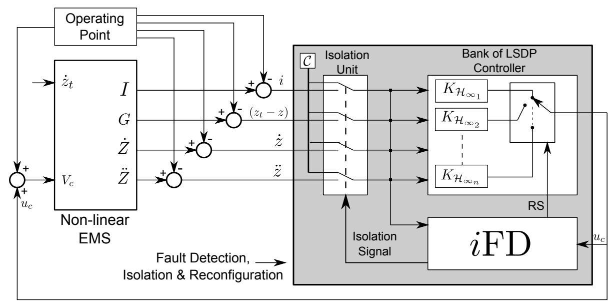


Fig. 6. The proposed iFD applied to the MAGLEV EMS system.

The control design requirements of an EMS system depend upon the type and speed of the train [17]. Typically, the EMS should be able to follow the gradient onto the rail (deterministic input) while at the same time reject the inputs from the random variations of the rail. The control performance requirements of the EMS with deterministic and stochastic inputs are listed on Table II.

TABLE II
CONTROL CONSTRAINTS FOR THE ELECTRO-MAGNETIC SUSPENSION.

	Control requirements	Value
Stochastic track profile	RMS acceleration,$\ddot{z}_{rms}$	$\leq 0.5ms^{-2}$
	RMS airgap variation,$(z_t - z)_{rms}$	$\leq 5mm$
	RMS control effort,$u_{c_{rms}}$	$\leq 300V$
Deterministic track profile	Maximum airgap deviation,$(z_t - z)_p$	$\leq 7.5mm$
	Maximum control effort,u_{c_p}	$\leq 300V$
	Settling time, t_s	$\leq 3s$
	Airgap steady state error,$e_{(z_t - z)_{ss}}$	$= 0$

B. The iFD applied on the EMS system

This iFD is combined with the FTC system of the suspension as illustrated in Fig. 6. A bank of $\mathcal{H}_\infty$ LSDP designed controllers is used for the accommodation of sensor faults. The EMS system has a total of 5 sensors 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, since the LSDP method 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 designed 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 as explained in Section II. For the demonstration of the iFD the results from [18] are used.

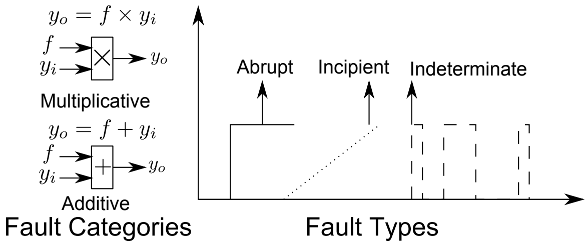
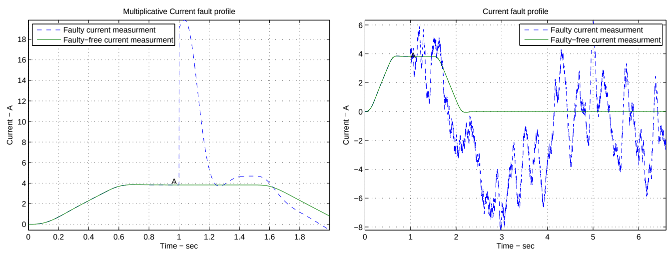


Fig. 7. Sensor fault categories and types.



(a) Abrupt/multiplicative profile (b) Abrupt/additive profile

Fig. 8. Current sensor fault profiles

C. Sensor Fault Scenaria

When a sensor fails, its output can be unpredictable. The sensor faults are separated into additive and multiplicative categories. Three types of faults belong to each category: (i) abrupt or step-type fault, (ii) incipient or soft fault and (iii) indeterminate fault (see Fig. 7).

The faults considered here are additive and multiplicative faults, both abrupt type. 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/multiplicative and abrupt/additive sensor fault profiles for the current (i) sensor are illustrated in Fig. 8. Both faults occur at $1s$ (see point A on the figures). Figure 8(a) depicts the current sensor that is suddenly damaged at $1s$ and its output becomes 5 times larger than the normal. In Fig. 8(b) the impaired sensor gives the normal current value superimposed with a simulation low frequency random signal.

V. SIMULATION AND DATA ANALYSIS

In order to show the effectiveness of the proposed iFD unit a summary and the main points are provided in this section. The following scenario is selected for the seek of the detailed explanation on the iFD working principle:

- Three sensors are impaired with a time difference as follows: accelerometer at $0.5s$, velocity at $1.5s$ and current at $2s$),
- the deterministic disturbance to the suspension is used and
- an abrupt/multiplicative type of fault is injected for each sensor at each time instant mentioned above (eg. see Fig. 8(a)).

The airgap sensor output in the case of such a fault profile is depicted in Fig.9. The figure illustrates the airgap with fault-free case (i.e. healthy sensor set) and under the fault scenario mentioned. The acceleration sensor is impaired

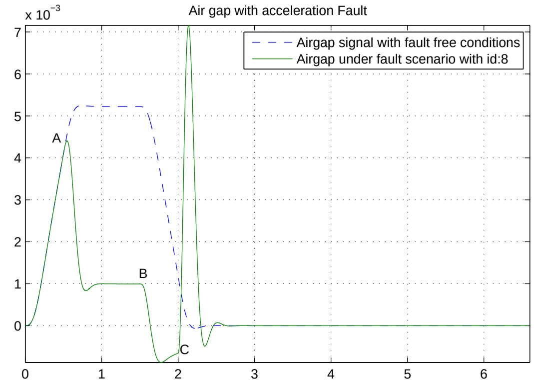


Fig. 9. Airgap sensor signal with fault-free and with the fault scenario, id:8 of Table III.

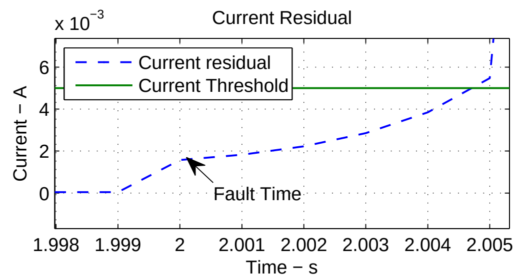


Fig. 10. Current sensor residual when fault occurs at $2s$.

at $0.5s$ (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 IV. As a result of this fault, the velocity sensor fails (point B) together with the current sensor at (point C). All three subsequent faults are successfully detected and accommodated.

The sensor fault accommodation is done in three steps. To assist in explaining the steps of the procedure, the current sensor fault will be interpreted: (i) Sensor Fault Detection, i.e. when the fault occurs the residual of the current measurement r_i, starts increasing and as soon as it pass the threshold (see Fig. 10) the fault is detected. (ii) Fault Isolation: At this stage the faulty sensor is removed from the loop using a BS while a 'known' function $c_i = 0$ is connected at the input of the iFD. Figure 11 clearly shows the signal at the input and output of the BS as well as the signal at the output of the iFD. (iii) Controller reconfiguration: After the faulty sensor isolation a reconfiguration signal is generated and a new controller is introduced in the loop.

Close investigation of Fig. 11 after the fault occurs at point A, shows that the iFD detects the fault after a few time steps, while in the next time step the iFD reacts and drives its output at $c_i = 0$. In this way the residual is always large, which is why the proposed method is excluded from the indeterminate types of faults at the present work. This phenomenon can be observed in Fig. 10 where after the fault detection, the residual is abruptly increased. In the same figure, the effects of the two previous faults, accelerometer and velocity, are shown at point B and C respectively.

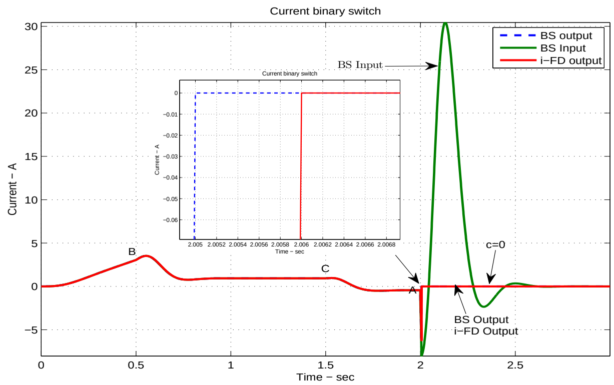


Fig. 11. Input-output of the BS of the current sensor and the output of the iFD.

As mentioned in Section IV-C, a number of fault scenaria have been investigated to test the iFD, and the initial results have shown strong potential for further research work. Table III tabulates the results of 32 tests. More specifically, it shows that the abrupt type of fault can be successfully accommodated without leaving any false alarms. The False Alarm (FA) means that a sensor that looked impaired before it is actually damaged. This cannot be expected with incipient type of faults due to the ability of the iFD to estimate the faults, leaving a small residual for the detection [11].

TABLE III

SENSOR FAULT SCENARIA FOR THE EMS.

		Performance with abrupt type of faults							
	Faulty	Mu.		FA		Ad.		FA	
id	sensor(s)	St.	Dt.	St.	Dt.	St.	Dt.	St.	Dt.
1	No fault	✓	✓	x	x	✓	✓	x	x
2	i	✓	✓	x	x	✓	✓	x	x
3	$\dot{z}$	✓	✓	x	x	✓	✓	x	x
4	$\ddot{z}$	✓	✓	x	x	✓	✓	x	x
5	$i \to \dot{z}$	✓	✓	x	x	✓	✓	x	x
6	$i \to \ddot{z}$	✓	✓	x	x	✓	✓	x	x
7	$\dot{z} \to \ddot{z}$	✓	✓	x	x	✓	✓	x	x
8	$\ddot{z} \to \dot{z} \to i$	✓	✓	x	x	✓	✓	x	x

Mult.-Multiplicative, Addi.-Additive, FA-False Alarm

Using the full sensor set, $y = \{i, (z_t - z), \dot{z}, \ddot{z}\}$ it is possible to compare the time taken for a simulation to complete using the iFD with the time taken using a bank of seven KE (one for each sub-set of y). In both cases the same simulation parameters are used i.e. sampling time, solver type, operating parameters, etc.

The simulation time requirement at a high level simulation (Matlab/Simulink) platform where performed, clearly shows that the iFD is more than 10 times faster than the bank-estimator approach, and proves that the proposed fault detection method is adequately fast and promising.

VI. CONCLUSIONS

The paper presents a neural network-based method, the iFD, for detecting actuator/sensor faults. A detailed analysis for the rationale is presented and a number of fault tests scenaria have been used to test the proposed method. The tests accounted for sensor fault scenaria with abrupt/multiplicative and abrupt/additive 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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