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Use of Supervised Learning in a MagLev SISO System for Fault Detection

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Abstract: This paper proposes a model based on supervised learning for fault detection and diagnosis of a SISO magnetic levitator (MagLev) system. The approach combines multilayer feedforward networks, signal filters, and a NARX model for preprocessing to detect actuator, sensor, and plant faults. Faults such as bias, noise, and equilibrium change located in the sensor, actuator, and plant are combined as a benchmark to be detected in real-time to evaluate this proposal. Therefore, the whole system considers one input signal, one transfer function, two types of filters, one NARX neural network, and six feedforward neural networks, where each output is associated with a specific type of fault. The proposed model manages to estimate the faults presented with an accuracy higher than 95%.

Keywords: Supervised Learning, Fault Detection, SISO Systems, Magnetic Levitator.

1. INTRODUCTION

In industrial processes, faults could generate big interruptions in the production lines. These interruptions or stops could affect efficiency and productivity, and increase the operative costs. Diagnosing faults implies identifying their origin, which depending on their complexity and experience could take some minutes or a couple of hours [1]. Once detected, repair time will depend on the availability of spare parts and tools, as well as the severity of the problem. The implementation of predictive maintenance and automated systems can drastically reduce these times, minimizing losses and improving operational continuity [2].

Magnetic levitator (MagLev) models are gaining popularity since the end of the 20th century [3]. Their principal applications include magnetically suspended trains, electrodynamic suspension and future applications such as flying cars and space rockets [4].

In the 21st century, fault detection models related to machine learning, neural networks and supervised learning are gaining popularity. Ince et al. propose in [5] a supervised learning-based model that use 1-D convolutional neural networks to estimate mechanical bearing related faults in a motor. This model also includes filtering methods to avoid power system frequencies in the motor performance.

Suryawan et al. propose in [6] the use of B-Splines and linearized residual values to detect, isolate, and recover faults in a magnetic levitator system. The authors uses the control signal u and the output sensor signal z as residual generator input. The detection system considers two stages, first a residual generator model to find residuals values and the fault detection and isolation unit, which uses B-Splines and linear regression to estimate the faults.

Yetendje, Seron, Dona, and Martinez propose in [3] a fault-tolerant system applied to the controller in a Quanser magnetic levitator (MagLev). The faults evaluated are position sensor and actuator noise fault, and bias. Also, the speed sensor has the same faults. Although the research is not focused on fault detection, just tolerance and control. It helps to determine what kind of faults are commonly applied in magnetic systems.

This paper proposes a supervised learning-based model that can detect and classify different types of faults in a magnetic levitator model and controller proposed by Nayak in [7]. The faults to evaluate are the sensor, actuator, and some external faults that affect the plant directly. To evaluate the accuracy of the neural networks some simulations are developed.

This paper is organized as follows. Section 2, the magentic levitator, the fault estimation approach and fault case scenarios are introduced. The model is evaluated and validated by simulation in section 3, and the final section presents the conclusions.

2. METHODOLOGY

2.1. System Overview

We use a linearized MagLev model proposed by Nayak in [7], representing a classic SISO configuration with the control signal $u(t)$ as input and the sensor-driven levitation height $y(t)$ as output. Eq. 1 shows the system transfer function, where $K_i = \frac{2g}{i_0}$ and $K_x = -\frac{2g}{y_0}$ represent a relationship between the acceleration of gravity g with the level and the current equilibrium point y_0 and i_0.

$$G(s) = \frac{-K_i}{s^2 + K_x}. \tag{1}$$

Using the following values 9.81 m/s^2, 0.8A and 0.009m for g, i_0 and y_0 respectively, Nayak proposes the PID controller $PID(s) = 1050 + \frac{20600}{s} + 13.4$ to maintain system stability.

2.2. Fault Case Scenarios

Faults induced in the MagLev model are grouped into three main categories. The first one groups all the faults that could affect the actuator, such as a change in i_0, noise applied, or a burned actuator. These faults are bias (ABF), noise (ANF), and burned (ASF). The second group refers to all the faults that could affect the sensor such as bias

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(SBF), and noise (NBF). Finally, the third group includes two particular faults that may affect the model due to internal problems in the plant or external factors. These are gravity fault (PGF) and equilibrium fault (PEF). These faults are induced into simulation signals to test fault detection model accuracy.

2.3. Fault Detection Model Architecture

The supervised learning model proposed in this research is based on a series of artificial neural networks (ANN) that includes pattern recognition networks, NARX-NN and some filters to smooth the input and output signals of each neural network. This proposal includes three fault detection models. Fig.1 shows that FDM use $u(t)$ and $y(t)$ as input, and give a binary value as output for each measured fault.

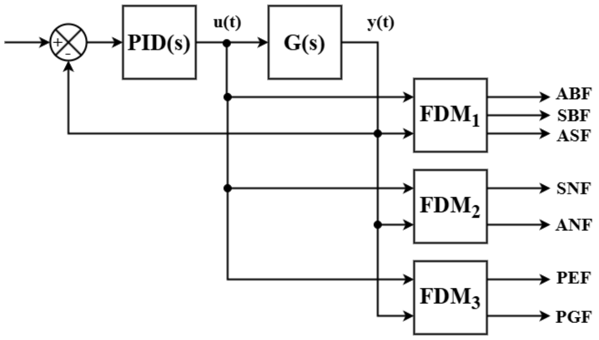

Fig. 1 Fault detection model block diagram

FDM_1 aims to estimate faults related to bias or offset and burned actuator. Fig. 2 shows that the model uses a two-layer feed forward neural network with 20 neurons in each layer, a Savitzky-Golay filter for signal preprocessing, and threshold filtering for signal postprocessing.

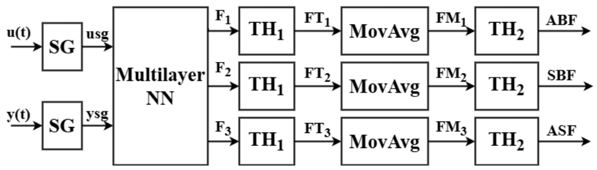

Fig. 2 Fault detection model 1

FDM_2 aims to detect noise-related faults. Fig. 3 shows that this model includes a multilayer NN with 25 and 23 neurons for ANF detection, and a single-layer NN of 30 neurons with a previous Gaussian filtering preprocessing for SNF. Both detection systems includes also a dynamic thresholding.

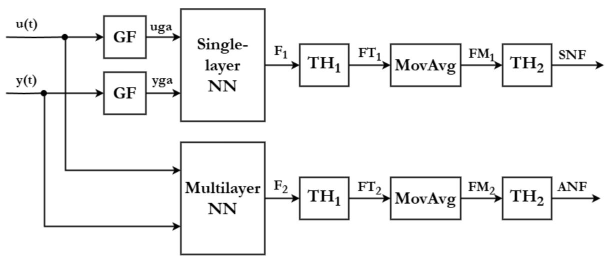

Fig. 3 Fault detection model 2

Unlike previous models, FDM_3 tries to estimate faults that are located in the plant (PEF) or related to environmental factors (PGF). This types of faults needs a second validation to get higher accuracy, therefore, Fig. 4 shows that the model includes NARX-NN for signal estimation and error $e(t)$ calculation. This and the previous inputs feed a multilayer feedforward for PGF and PEF. As well as the previous models, after the NN, the signal pass for a filtering process to get a more accurate value.

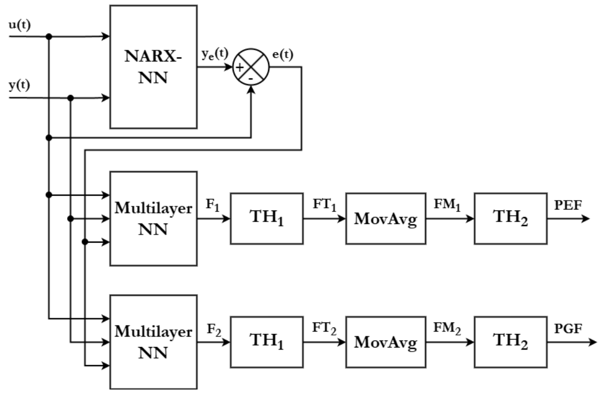

Fig. 4 Fault detection model 3

Each FDM uses filters such as moving averages to reduce false positives and produce binary outputs. Also, Savitzky-Golay filter is used for smoothing without distorting signal trends which is good for bias fault detection, Gaussian filters are used for noise attenuation, and NARX models are suitable for temporal dependencies in plant-related faults.

3. SIMULATION RESULTS

Two simulations were performed to evaluate the accuracy of the proposed model. The first simulation consists of induced faults in the system in certain intervals of time. On the other hand, second simulations includes induced faults at the same time.

3.1. Individual fault detection

This simulation consists of evaluating the three fault detection models by injecting faults one at a time across 800s. Table 1 shows the interval of time when faults interrupt the system. Both input signals $u, y(t)$ are shown in the first two graphics of Fig. 5.

Table 1 First sequence of faults

Start (s)	End (s)	Name
100	150	Actuator Noise Fault (ANF)
300	350	Plant Gravity Fault (PGF)
350	400	Actuator Bias Fault (ABF)
450	500	Sensor Noise Fault (SNF)
550	600	Plant Equilibrium Fault (PEF)
650	700	Sensor Bias Fault (SBF)
750	800	Burned Actuator Fault (ASF)

The third, fourth and fifth graphic of Fig. 5 shows the simulation for FDM_1, sixth and seventh are the results of FDM_2 and finally, eighth and ninth graphics are

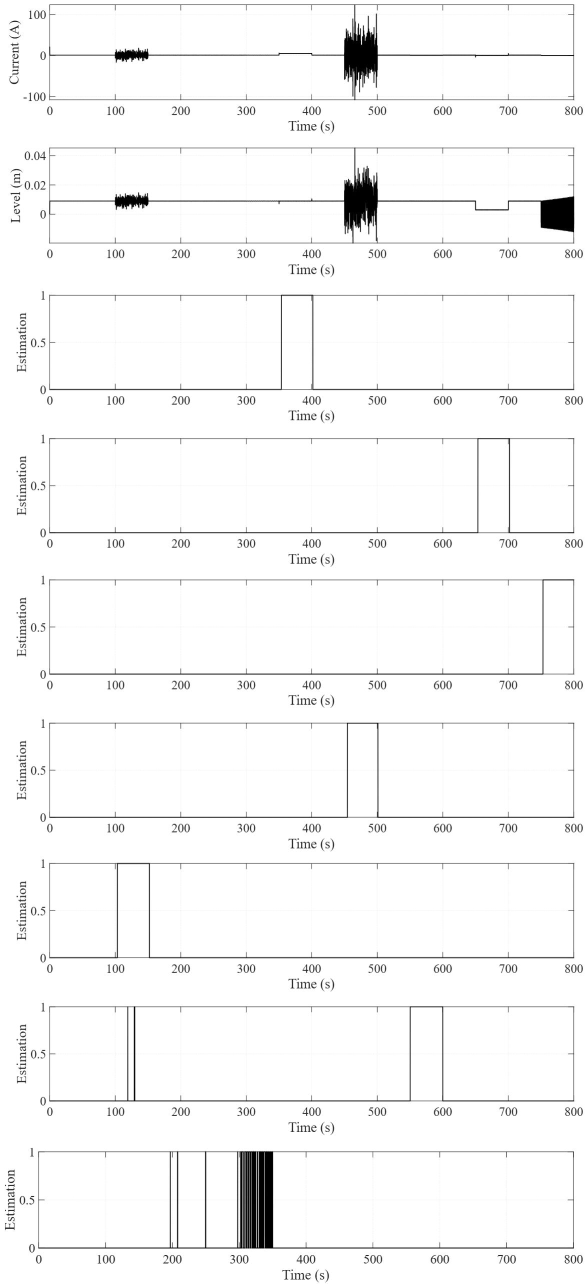

Fig. 5 Level and control signal with induced faults and $FDM_{1,2,3}$ outputs

Model	Fault	Accuracy
FDM_1	ABF	99.36%
	SBF	99.31%
	ASF	99.63%
FDM_2	SNF	99.33%
	ANF	99.34%
FDM_3	PEF	99.95%
	PGF	96.85%

Table 2 Accuracy values of single fault detection

the results for FDM_3. The accuracy values in Table 2 shows that most of the accuracy values in the fault detection models surpass 95%. These values need to be as high as possible to avoid false information and prevent unnecessary stops.

3.2. Multiple faults detection

The second simulation follows the same guidelines as the previous one, injecting faults and observing the behavior of $FMD_{1,2,3}$. Table 3 and Fig.6 shows that there are some faults that happen at the same time in some intervals. As the previous results, the following three graphics correspond to the results for FDM_1, the following two for FDM_2, and the last two for FDM_3.

Table 3 Second Sequence of Faults

Start (s)	End (s)	Fault ID
450	500	SNF
400	450	SBF
150	200	ANF
100	250	ABF
650	800	ASF
300	350	PGF
550	600	PEF

The accuracy values in Table 4 show that the three fault detection models maintained robustness, with slight accuracy drops and minor detection delays due to filtering. As in the previous simulation, PEF and PGF are affected by complex signal patterns in both inputs, again making PGF the fault estimation model with the lowest accuracy. Despite being the lowest, PGF detection accuracy remains high and relevant for recovery models.

Model	Fault	Accuracy
FDM_1	ABF	99.26%
	SBF	98.29%
	ASF	99.1%
FDM_2	SNF	99.24%
	ANF	99.26%
FDM_3	PEF	99.69%
	PGF	96.99%

Table 4 Accuracy values of multiple fault detection

Although the three fault detection models show high accuracy in simulation, the results should be interpreted with caution due to the idealized nature of the environment. The fault scenarios were artificially generated, and real-world factors such as sensor drift, disturbances, or noise were not considered. These may affect the robustness of the models. Experimental validation on physical MagLev systems and comparison with traditional techniques remain necessary to assess practical applicability.

3.3. Comparison with Conventional Methods

We evaluated the proposed Supervised Learning (SL) based model against two conventional approaches: a residual-based thresholding method and a B-Spline regression technique. All models were tested under the same simulated conditions (Simulation 1). Table 5 summarizes the detection accuracy for each method.

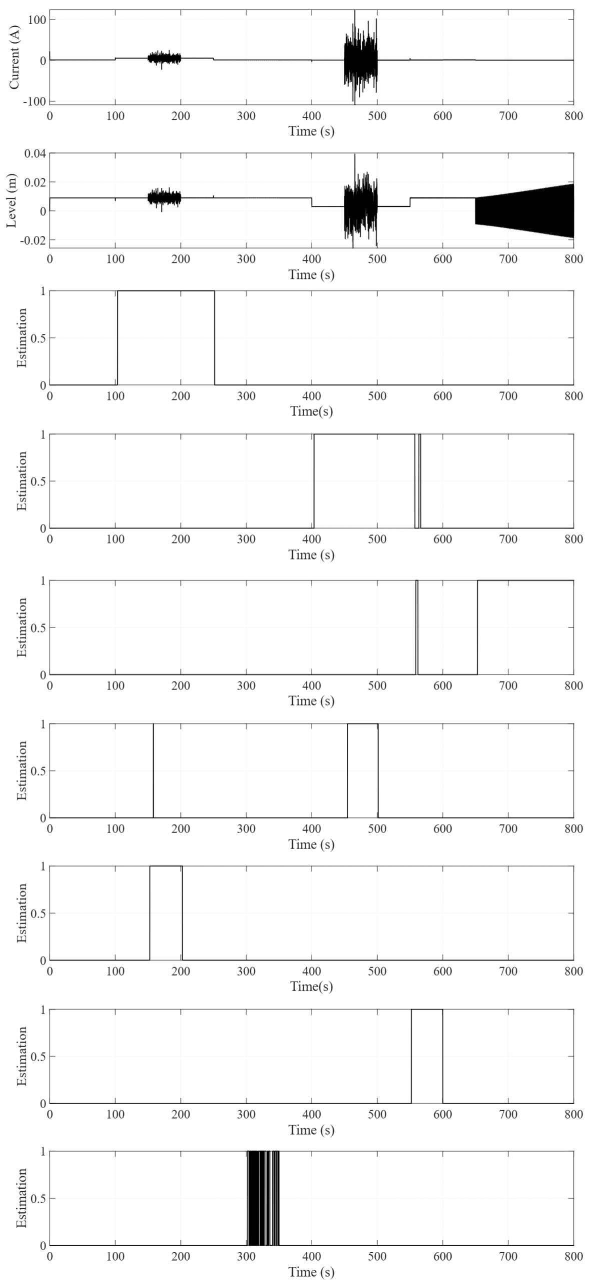

Fig. 6 Level and control signal with multiple induced faults at same time and $FDM_{1,2,3}$ outputs

Method	Accuracy (%)
Proposed SL Model	> 95.00
Residual Thresholding	81.22
B-Spline Regression	62.21

Table 5 Comparison of detection accuracy across methods

The supervised learning model outperforms traditional methods in detection accuracy and robustness, demonstrating its potential for more reliable fault detection in complex scenarios.

CONCLUSIONS

This paper presented a modular supervised learning approach for fault detection in a SISO magnetic levitation system. The proposed models effectively detect faults in actuators, sensors, and the plant using combinations of feedforward neural networks, filters, and a customized NARX architecture for each type of fault. Simulations showed strong performance with detection accuracy greater than 95%, including in multi-fault scenarios. However, since the models were tested in an idealized environment with artificially generated faults, their robustness under real-world conditions, such as sensor drift, external disturbances, or unexpected fault combinations remains uncertain. Future work will focus on experimental validation with physical MagLev systems and comparative studies against conventional fault detection techniques (e.g., residual and model-based methods), to better assess the practical applicability and scalability of the approach.

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