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Abstract: In the context of motorcycle, we can assist to an increasing interest toward semi-active suspension control systems able to improve both the comfort and the passenger's safety in both racing and original equipment manufacturer applications. Such systems implement suitable strategies based on the measure of several quantities, among which the relative velocity of the wheels respect to the vehicle body with the aim of regulating in real-time the damping forces. The actual effectiveness of such strategy strongly depends on the reliability and accuracy of the data measured by the sensors involved in the control loop. Due to their simplicity and good performance in terms of linearity, the most used sensors for suspension displacement measurements are based on linear potentiometers but such kind of sensors suffer of wear and tear and aging higher than the other sensors involved in the control loop strategy. As a consequence, the fault detection of such sensor is strongly recommended to avoid wrong and in some cases dangerous suspension behaviors.
To this aim, in this paper a Fault Detection scheme for the rear suspension stroke sensor is designed and verified. The residual generation is based on the use of a Nonlinear Auto-Regressive with eXogenous inputs (NARX) network which is able to effectively take into account for the system nonlinearity. Experimental results have proven the good promptness and reliability of the scheme in detecting different kind of faults as "un-calibration faults" (e.g. due to slight variations of the input/output sensor curve), "hold-faults" (e.g. due to the breaking of the potentiometer cursor), "open circuit" and "short circuit" (e.g. due to electrical interruptions and short circuits, respectively).
In addition, to verify the feasibility of a real-time implementation on actual processing units employed in such context, the scheme has been successfully implemented on a microcontroller STM32 based on the general-purpose ARM-M4 architecture. The validation tests and analysis have shown that the proposed Instrument Fault Detection scheme could be successfully developed on these kind of architectures by assuring a real-time operating.

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LETTER TO THE GUEST EDITOR AND REVIEWERS

Dear Guest Editor and Reviewers,

Thank you for the opportunity to submit this paper for the special issue of the Measurement journal.

We have completely revised the paper and we have significantly extended it beyond the scope of the paper appeared in the conference proceedings. The kind comments of colleagues who revised the paper for 15th IMEKO TC10 Workshop on Technical Diagnostics have been also taken into account in this extended version.

Beyond changing the title to "NARX ANN-BASED INSTRUMENT FAULT DETECTION IN MOTORCYCLE" in order to catch the wider scope of this new paper, we have extended the paper as follows:

- references have been updated and the IMEKO TC-10 paper is now referenced in the text (ref. 20);
- the abstract and introduction has been completely rewritten;
- section II has been updated and a new figure (figure 2) has been added to better explain the system under test;
- section III has been updated and new figures (figure 3, figure 4, figure 6 and figure 8) have been added to better explain the proposed IFD scheme and choices made for the selection of the design parameters. In particular:
  - figure 4 compares the performance of the NARX networks for different number of neurons;
  - figure 6 shows the benefits of the moving average-based residual calculation;
  - figure 8 explains the fault detection rules
- a new section (sect. 4) and new tables (Table IV-XV) are added to analyse in detail the test results;
- a new section (sect. 5) and a new table (Table XVI) are added for describing the feasibility analysis for on-board implementation;
- conclusions (sect. 6) are accordingly modified;
- all the text was revised looking for improving its clearness and readability.

Sincerely,

Domenico Capriglione

NARX ANN-BASED INSTRUMENT FAULT DETECTION IN MOTORCYCLE

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Abstract: - In the context of motorcycle, we can assist to an increasing interest toward semi-active suspension control systems able to improve both the comfort and the passenger's safety in both racing and original equipment manufacturer applications. Such systems implement suitable strategies based on the measure of several quantities, among which the relative velocity of the wheels respect to the vehicle body with the aim of regulating in real-time the damping forces. The actual effectiveness of such strategy strongly depends on the reliability and accuracy of the data measured by the sensors involved in the control loop. Due to their simplicity and good performance in terms of linearity, the most used sensors for suspension displacement measurements are based on linear potentiometers but such kind of sensors suffer of wear and tear and aging higher than the other sensors involved in the control loop strategy. As a consequence, the fault detection of such sensor is strongly recommended to avoid wrong and in some cases dangerous suspension behaviors.
To this aim, in this paper a Fault Detection scheme for the rear suspension stroke sensor is designed and verified. The residual generation is based on the use of a Nonlinear Auto-Regressive with eXogenous inputs (NARX) network which is able to effectively take into account for the system nonlinearity. Experimental results have proven the good promptness and reliability of the scheme in detecting different kind of faults as "un-calibration faults" (e.g. due to slight variations of the input/output sensor curve), "hold-faults" (e.g. due to the breaking of the potentiometer cursor), "open circuit" and "short circuit" (e.g. due to electrical interruptions and short circuits, respectively).
In addition, to verify the feasibility of a real-time implementation on actual processing units employed in such context, the scheme has been successfully implemented on a microcontroller STM32 based on the general-purpose ARM-M4 architecture. The validation tests and analysis have shown that the proposed Instrument Fault Detection scheme could be successfully developed on these kind of architectures by assuring a real-time operating.

Key-Words: - artificial neural networks, real-time, software sensor, instrument fault detection, stroke sensor

I. INTRODUCTION

Today we can assist to a continuous increasing of the use of sensors and electronic devices inside automobiles and motorcycles [1], [2]. They are widely employed for assuring high level of safety with passive and active systems, comfort, engine efficiency, compliance with even more severe emission limits established by international regulations for containing the environmental pollution [3]. The correct working of the involved subsystems strongly depends on the reliability and accuracy of the outputs of the sensors in the involved control loops, therefore, it becomes fundamental to implement suitable Instrument Fault Detection (IFD) schemes able to on-line identify the faults that could occur on the sensors. By this way, ad-hoc recovery strategies can be in real-time triggered to manage (or accommodate in some cases) an occurred fault [4].
Focusing the attention on the motorcycle context, great efforts are made for improving the passenger's safety in both racing and original equipment manufacturer applications [5]-[7]. Indeed, the vehicle handling, as well as passenger safety and comfort strongly depend on the suspension system, this one guarantees contact among vehicle tires and road, and at the same time it isolates vehicle body from the roughness of the road. This problem is even more evident for motorcycles, because they are much sensitive than other vehicles to the load variations and shocks caused by the road asperities. A semi-active or active-suspension system looks like being a solution for such goals, if a suitable control strategy is available to adjust the damping force versus vehicle dynamics and riding style [8], [9]. In particular, the real-time control of the damping coefficient as function of the suspension stroke, the pitch rate and/or other measurements about the vehicle dynamics from a set of sensors (typically including accelerometers, stroke sensors, gyroscope and magnetic encoders) is today successfully developed [10]. Among these sensors, the one used to measure the vertical extensions and vertical compressions of the rear suspension plays a fundamental role in the control strategy. Due to their simplicity, low costs and good performance in terms of linearity, the most used sensors are linear

potentiometers. Nevertheless, they could be unreliable in the long run (mainly for their mechanical wear and tear and aging higher than the other sensors involved in the control loop strategy), thus pushing toward the employment of soft sensors and suitable data fusion techniques for overcoming such reliability troubles [11]-[15].

As a consequence, the fault detection of such sensor is strongly recommended to avoid wrong, and in some cases, dangerous motorcycle behaviors [16]-[19]. To this aim, due to the correlations existing among the quantities measured by the sensors involved in the control loop, an analytical redundancy-based IFD scheme has been proposed and preliminary tested in [20]. Following the recent trends in IFD [21]-[26], and on the basis of the experience in the field, artificial neural networks are adopted to generate the residuals for the rear suspension fault detection.

In particular, the proposed solution employs a Nonlinear Auto-Regressive with eXogenous inputs (*NARX*) network because its attractive feature in effectively take into account for the nonlinearities of the system under test [20], [26], [27]. The preliminary results proved very promising features in terms of both diagnostic performance and promptness against some kind of "un-calibration faults" (e.g. due to slight variations of the input/output sensor curve).

In this paper the use of the proposed scheme has been extended to the diagnosis of further kind of faults that could occur in the practice as "hold-faults" (e.g. due to the breaking of the potentiometer cursor), "open circuit" and "short circuit" (e.g. due to electrical interruptions and short circuits, respectively). A deeper characterization of the IFD scheme has allowed to better identify the influence of tuning parameters on the diagnostic performance of the scheme and on both system promptness and sensitivity.

Finally, to verify the feasibility of a deployment on processing units typical of the motorcycle context, the IFD scheme has been implemented on a microcontroller STM32 based on the general-purpose ARM-M4 architecture. The validation tests and analysis have shown that the proposed IFD scheme can be successfully developed on these kind of architectures by assuring the real-time operating.

Thus, the paper is organized as follows: the system under test is detailed in Section 2, whereas in Section 3 and 4 respectively the main IFD issues are discussed and the outcomes from the performance characterization are analyzed. Section 5 describes the feasibility analysis for the real-time implementation on the ARM-based architecture, and finally, main conclusions are drawn in Section 6.

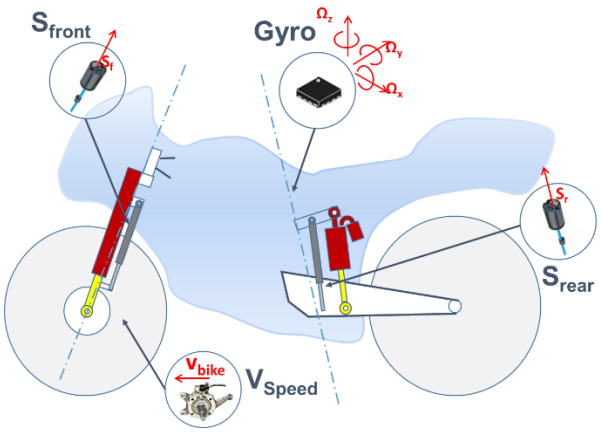

Figure 1. The system under test

II. THE SYSTEM UNDER TEST

The IFD scheme has been developed for motorcycle SUZUKI GSX-1000 model (schemed in Fig. 1), suitably equipped with the sensors included in Table I.

The behavior of the motorcycle may be firstly modeled by a rigid system, where the rear suspension stroke, although greatly dependent from the road profile, also takes into account the heavy movement of the front suspension and the pitch of the vehicle frame. Such a model highlights a strong correlation among the vertical dynamics quantities for two-wheeled vehicles. It allows to design an IFD scheme based on the analytical redundancy existing among the front and the rear suspension positions (S_{front} and S_{rear}, respectively) as well as the motorcycle pitch and the vehicle speed (*Gyro* and V_{bike}, respectively) [11].

To design and validate the IFD scheme on real data, a measurement campaign involving the system under test was performed. As for sensor output in fault-free conditions, the motorcycle riding refers to a test lap (8 km approximated length) which includes various profiles (cobblestone stretch, urban and extra-urban road,

Table I Main sensors for measuring the vertical dynamics of the test motorcycle

Sensor Type	***Model***	***Manufacturer***	***Symbol***	***Mounting notes***
Linear Displacement Sensor	SLS130	Penny & Giles	S_{front}	fixed to the fork and measuring the front suspension stroke
			S_{rear}	mounted between the frame and rear wheel and measuring the rear suspension stroke
Magnetic Encoder	970-011	Dorman	V_{bike}	fixed to the front wheel and measuring the motorcycle (longitudinal) speed
Gyroscope	L3GD20	ST Microelectronics	*Gyro*	fixed to the frame and measuring the motorcycle pitch and roll velocities

concentrated obstacles) in order to introduce different excitation modes of the suspension system. As a result, a data logging about 6 hours was achieved by completing more than 40 test laps (mean lap time equal to 500 seconds) with reference to the following signals: fork stroke, pitch rate, vehicle speed and the rear shock stroke. As for data logging, a suitable data acquisition system was designed for sampling and storing the data collected by the sensors. Data recording was carried out at the sampling frequency of 1 kHz with a 12 bit-ADC. A normalization process was carried out on data acquired to constraint the input data in the range [0÷1]. In particular, the samples were normalized according to the following formula (1) and the values of Table II:

$$Q(i) = \frac{q(i) - \max(q)}{\max(q) - \min(q)} \qquad \text{Eq. (1)}$$

where, i is the i-th sample, q is the considered quantity, Q is the corresponding normalized value, *max(q)* the maximum value of q and *min(q)* the minimum value of q.

A preliminary experimental campaign has been performed to verify the typical behaviour of the rear suspension position measured by the stroke sensor when the motorcycle overpasses multiple bumps at different speed values in the range 55-90 km/h. As shown in figure 2, the settling time of the corresponding transients are about 150-200 ms. Consequently, a re-sampling frequency equal to 100 Hz, allows to well tracking the time evolution of the rear suspension and matching the dynamics of the motorcycle suspensions without a significant loss of information. Moreover, thanks to the reduced number of samples (if compared with higher frequencies) it makes the implementation of electronic control units to be easier both in terms of memory and execution time requirements for real-time signal processing. In the following a 100 Hz-sampling frequency is considered.

As far as faulty conditions is concerned, it was impracticable to produce real faults on the rear suspension sensor during motorcycle operation; therefore a suitable set of possible faults was simulated on the basis of data acquired in fault-free conditions. In particular, short circuit, open circuit, hold and un-calibration faults were

Table II. Values adopted for the quantities normalization

Quantity (q)	min	max
Front stroke [mm]	0	150
Rear stroke [mm]	0	150
Pitch rate [°/s]	-80	+80
Speed [m/s]	0	180

simulated by the following ways:

- short circuit, by setting the sensor output value to zero;
- open circuit, by setting the sensor value to full scale;
- hold, by setting the sensor output equal to the last fault-free value;
- un-calibration, by multiplying the fault-free value by 1.1 for simulating a gain error of 10 %;

and, finally, adding noise with normal distribution to short circuit, open circuit and hold output signals in order to simulate the ADC quantization.

III. THE PROPOSED IFD SCHEME

The proposed scheme for detecting the faults interesting the rear stroke sensor is depicted in Fig. 3, which highlights three main blocks:

- a soft sensor developed by adopting artificial intelligence techniques and able to predict the suspension position output from the rear stroke sensor;
- a residual generator devoted to compute the difference between the hard and the soft sensor output and able to highlight the symptom of the faults;
- a decision maker block which implements the rules needed to correctly detect different types of faults.

A. The soft sensor

The soft sensor for prediction of the rear suspension position has been developed by adopting a *Nonlinear Auto-Regressive with eXogenous inputs* (*NARX*) *Neural Network*, which takes into account the front suspension position, the pitch rate of the motorcycle body and the longitudinal speed of the vehicle. These quantities are strictly correlated to the rear suspension behavior as highlighted by the half car model proposed to predict the

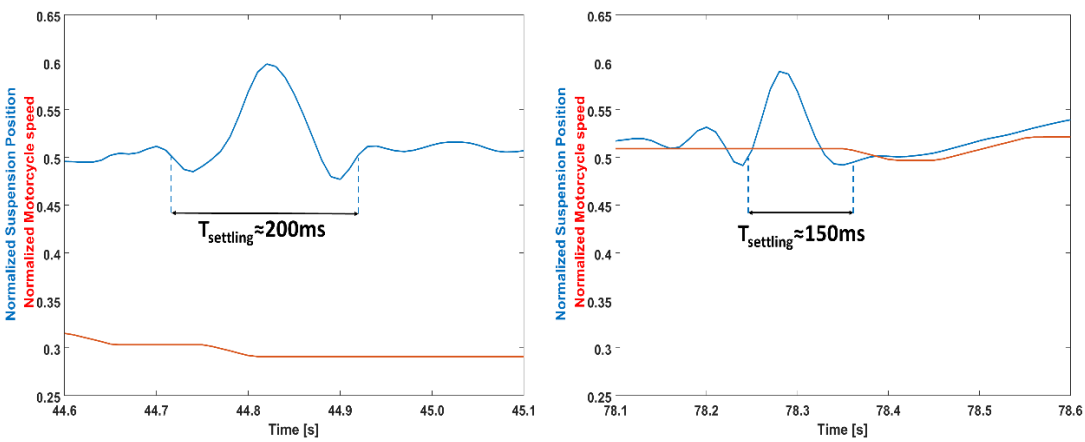

Figure 2 Time evolution of the suspension position for motorcycle negotiating bumps at different speed values.

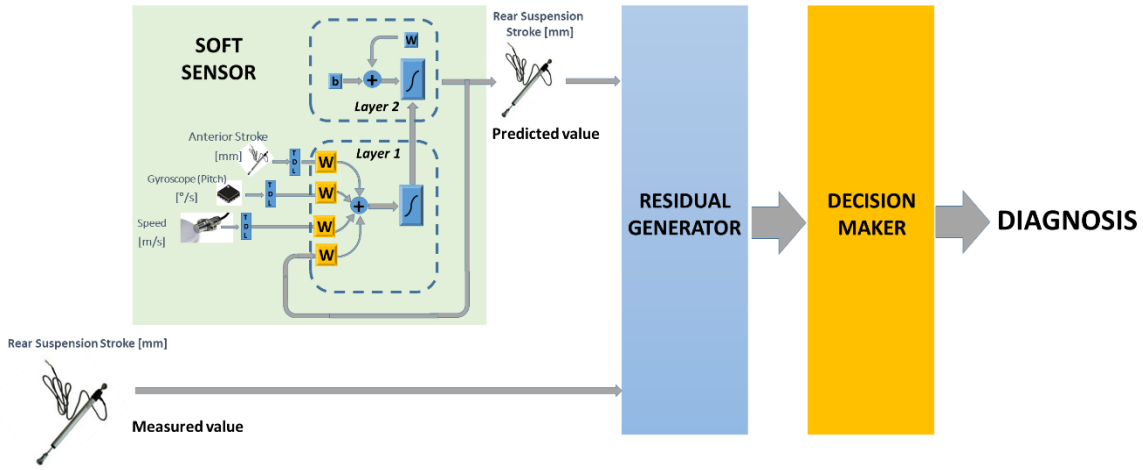

Figure 3. Structure of the NARX Network for predicting the rear stroke

steady state conditions for the in-plane motorcycle dynamics. However, the simplified model does not allow the steering and the linkage nonlinear effects to be correctly estimated in terms of the corresponding varying wheelbase and transfer load. Following the trend in the literature about the prediction of non-linear dynamic systems, the choice of the NARX neural networks seem to be the most promising solution thanks to the good capability of noise filtering typically exhibited [26], [27].

Different NARX Networks have been analyzed by adopting the Matlab Neural Toolbox and varying the following parameters:

- N, number of neurons in the (unique) hidden layer in the range [5÷20];
- d_{in} the tapped delay of the input signals in the range [50÷200] ms according to the previous consideration about the motorcycle dynamics;
- d_{out} the tapped delay of the output signal in the range [50÷200] ms.

The Fig. 4 reports the performance of the different NARX networks in terms of Regression Error Characteristic Curves (REC) [28], when d_{in} and d_{out} are equal to 100ms.

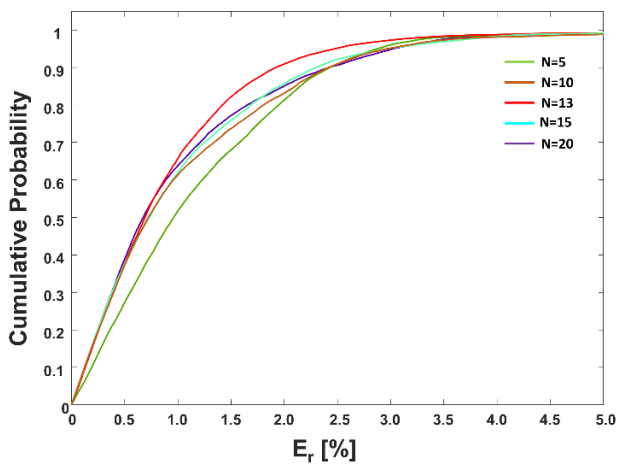

Figure 4 Comparison of NARX networks as the neurons (N) is varying

It shows that N=13 neurons in the hidden layer guaranties the best prediction.

To reduce the dependency from particular learning (training and test) set adopted, the *K-fold cross validation technique* has been adopted to verify the network general performance. In particular, let $E_{R\_J\%}$ be the mean percentage error evaluated on the *J-th* fold (containing N_J-fold test samples), with J=1,…,K. The global performance index, $E_{R\_MEAN\%}$, is given by:

$$E_{R\_MEAN\%} = \frac{1}{K}\sum_{J=1}^{K} E_{R\_J\%} \qquad \text{Eq. (2)}$$

In our analysis, we have:

- the learning (training + test) set is constituted by 200,000 experimental samples acquired in different working conditions of the system under test;
- K = 10 (i.e. 10 different learning sets have been realized, thus the circular permutation of the learning set is made by considering a sliding window length equal to 10% of the starting learning set);
- N_J = 100,000 (i.e. for each training session, the learning set was divided in two subsets, training and test sets, each one constituted by 100,000 samples).

Table III. Performance of the Narx Networks for different K-Learning sets

Learning set #	$E_{R\_J\%}$
1	1.9
2	3.1
3	2.2
4	1.8
5	2.0
6	1.7
7	2.2
8	3.8
9	2.1
10	3.6

The results of such analysis are shown in Table III where the values of $E_{R\_J\%}$ are reported for the K-test sets.
As you can see, the global performance of the network is quite independent on the learning (training + test) set selected. Moreover, we achieve that $E_{R\_MEAN\%}$ = 2.45 % and $E_{R\_J\%}$ is always less than 4 %, which are very good targets for such kind of application where the measurement uncertainties approach few %.

B. The residual generator

The second block of the proposed IFD scheme compares the prediction of the soft sensor based on NARX neural network with the output of the rear stroke sensor.
As previously reported, the instantaneous prediction of the soft sensor is satisfying for most of the experimental dataset (see Fig. 5.a). However, some conditions remain, where the percentage difference between the ground-truth and the predicted position are significant (see the highest peaks in Fig. 5.b).
Thus, a strategy based on moving average is employed for computing a more accurate residual. As an example, Fig. 6.a reports the comparison between the output of the soft and hard stroke sensors, with reference to a poor local prediction of the rear suspension position (percentage error greater than 40%).
Fig. 6.b shows the residual $E_{mean,L}$ computed by the proposed block according to:

$$E_{mean,L}(i) = \frac{1}{L_S}\sum_{k=0}^{L_S-1}\left|\frac{y_p(i-k)-y_m(i-k)}{y_m(i-k)}\right| \qquad \text{Eq. (3)}$$

where y_p and y_m are the predicted and measured stroke, L_s is the number of samples included in the moving window length L.

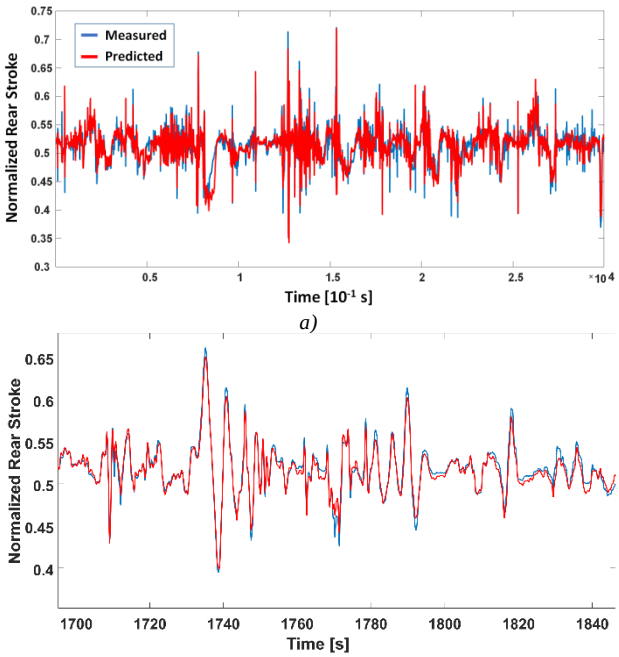

Figure 5. Prediction of the rear suspension stroke by the NARX Network for Test set #5: a) results about experimental dataset; b) magnification of a).

As expected, greater values for L allow limiting the height of the local peaks introduced in the residual signal by the poor prediction. On the other hand, exceeding in the moving average leads to obtain a not accurate prediction of the error when long observation periods are considered. Indeed, the local accuracy of the NARX Network with

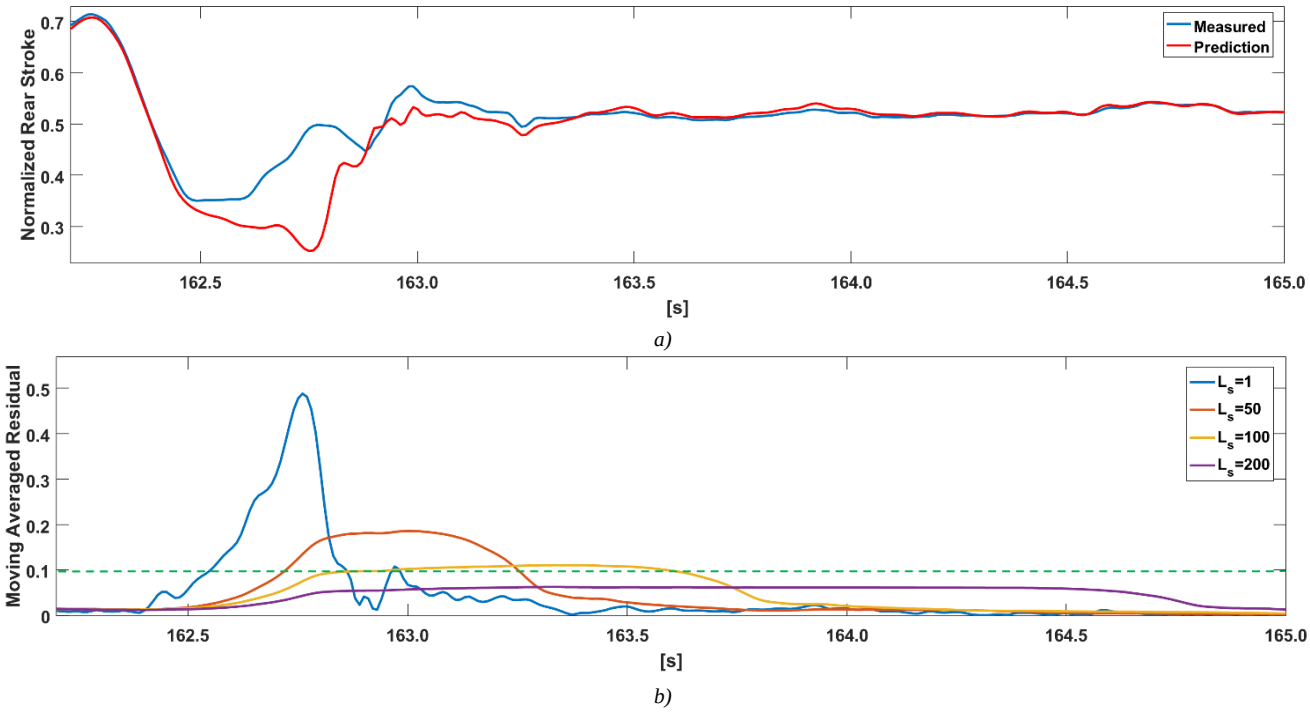

Figure 6. a) Measured and predicted normalized rear stroke; b) Moving averaged residual versus L_S

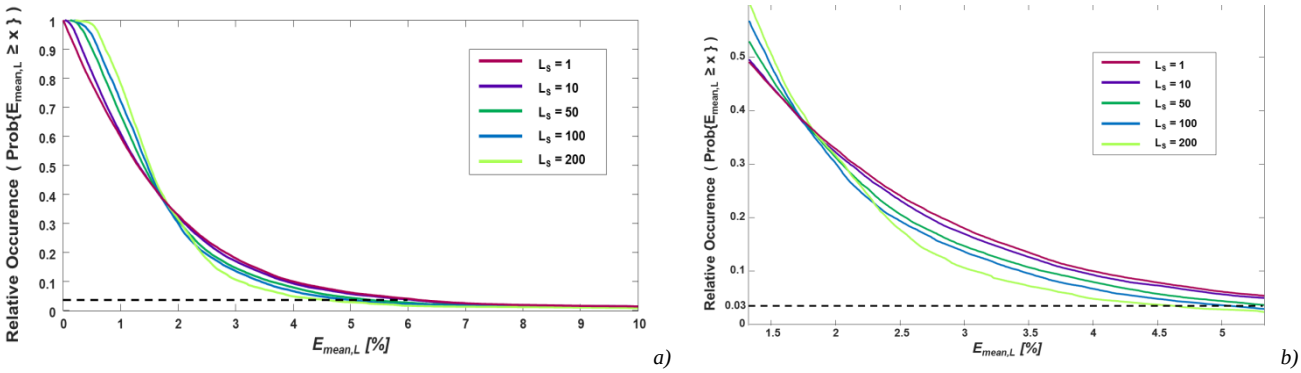

Figure 7. a) SOE curves for NN as function of the window length L; b) Magnification of a).

reference to the experimental dataset may be revealed by the graphical tool proposed in [29]. The *Sliding Occurrence Error* (*SOE*) curve plots the mean relative deviation $E_{mean,L}$ on the x-axis and the corresponding relative occurrences in the moving window of the regression error on the y-axis.

Thus, the SOE curve may be interpreted as the survivor function of the error tolerance.

As depicted in Fig. 7, about the worst predicted cases by the NARX Network (ten percent of the experimental dataset), the minimum value for the relative deviation $E_{mean,L}$ is less than 5%, when L equal to 500 ms is considered. Thus, a compromise value for L should be selected according to the methodology described in the following.

C. The fault detection rules

The proposed IFD scheme for the rear stroke sensor aims to reveal firstly the small faults, also known as "un-calibration faults", mainly due to the device wear and tear and aging, or to other influence factors as the variation of the sensor power supply and which results as changing of the input/output curve of the sensor.

Such a kind of fault generally appears as slight amplitude deviation from the expected behavior and could be detected through the plausibility checks typically implemented in automotive ECUs only after hours or days from the occurrence, when the performance degradation implies unacceptable risk levels. Moreover, the proposed scheme is devoted to also detect the open, short-circuit and hold faults.

According to the proposed strategy schemed in Fig. 8, a fault is detected when the residual computed by the corresponding block exceeds a fixed threshold $T_{\%}$ longer than an integer multiple K of the sliding window L.

IV. TEST RESULTS

Focus has been devoted to analyze the optimal value for the window length L and the integer n when the most accurate NARX model and the level of the un-calibration $T_{\%}$ are fixed.

For each class of interest (un-calibration faults not lower than $T_{\%}$=10%, as well as the open, short-circuit and hold faults), the instrument fault detection scheme has been verified against N_{faults}=1000 faults randomly introduced in the (measured) rear stroke samples of dataset, by considering the following performance indexes:

- the percentage $FA_{\%}$ of false alarms, when threshold is exceeded for predicted samples corresponding to faulty-free sensor output;
- the percentage $MD_{\%}$ of missed detections, when either threshold is not exceeded for predicted samples corresponding to faulty sensor output or threshold is exceeded after a maximum delay $t_{d,max}$ with respect to the fault insertion time;
- the percentage $CD_{\%}$ of correct fault detections, when threshold is exceeded for predicted samples corresponding to unhealthy sensor output by the maximum observation time $t_{d,max}$.

The test results are summarized in Tables IV-XV for L and n varying in the ranges [10÷200] ms and [1÷5] respectively, when t_{max} = 120 s is considered.

By taking into account that the sum of the proposed indexes is equal to 100% for each combination of the L and n parameter, a satisfying performance may be obtained for all the fault types:

- very low values for the $FA_{\%}$, and $MD_{\%}$ indexes (not greater than 1.0% and 2.0% respectively) are achieved

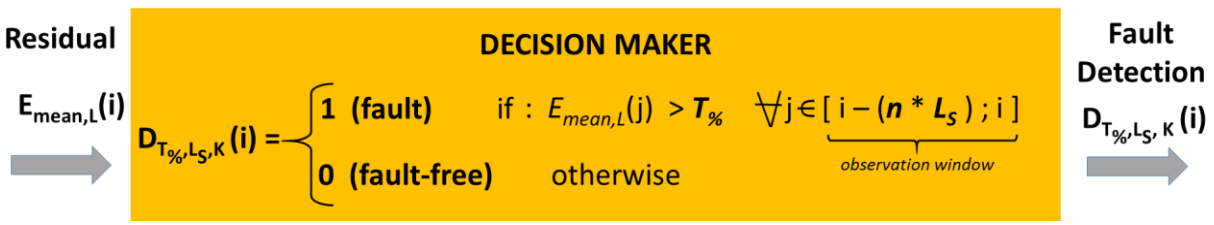

Figure 8. The proposed detection rules

Table IV Detection of uncalibration faults: False Alarm percentage

n \ L[ms]	10	20	50	100	150	200
1	97.7	97.6	54.0	0.2	0.0	0.0
2	97.6	0.6	0.7	0.0	0.0	0.0
3	97.6	0.4	0.0	0.0	0.0	0.0
4	0.5	0.4	0.0	0.0	0.0	0.0
5	0.3	0.0	0.0	0.0	0.0	0.0

Table V Detection of Open Circuit faults: False Alarm percentage

n \ L[ms]	10	20	50	100	150	200
1	99.0	98.9	53.1	0.5	0.0	0.0
2	99.0	0.9	0.6	0.1	0.0	0.0
3	99.0	0.9	0.6	0.1	0.0	0.0
4	1.1	0.9	0.2	0.1	0.0	0.0
5	1.1	0.9	0.2	0.1	0.0	0.0

Table VI Detection of Short Circuit faults: False Alarm percentage

n \ L[ms]	10	20	50	100	150	200
1	98.6	98.6	53.9	0.4	0.0	0.0
2	98.6	0.7	0.7	0.2	0.0	0.0
3	98.6	0.7	0.7	0.2	0.0	0.0
4	0.9	0.7	0.7	0.2	0.0	0.0
5	0.9	0.7	0.7	0.2	0.0	0.0

Table VII Detection of Hold faults: False Alarm percentage

n \ L[ms]	10	20	50	100	150	200
1	98.2	97.9	51.3	0.0	0.0	0.0
2	98.0	0.2	0.0	0.0	0.0	0.0
3	98.0	0.2	0.0	0.0	0.0	0.0
4	0.2	0.2	0.0	0.0	0.0	0.0
5	0.1	0.2	0.0	0.0	0.0	0.0

Table VIII Detection of uncalibration faults: Correct Detection percentage

n \ L[ms]	10	20	50	100	150	200
1	2.3	2.4	46.0	99.7	99.1	99.1
2	2.4	99.3	98.9	98.1	89.7	97.2
3	2.4	98.8	98.2	50.6	0.0	0.0
4	99.4	98.7	98.1	0.0	0.0	0.0
5	99.2	98.6	0.0	0.0	0.0	0.0

Table IX Detection of Open Circuit faults: Correct Detection percentage

n \ L[ms]	10	20	50	100	150	200
1	1.0	1.1	46.9	99.4	99.5	99.2
2	1.0	99.0	99.2	99.1	98.8	98.7
3	1.0	98.9	99.2	98.7	98.5	97.9
4	98.8	98.9	99.0	98.6	97.9	96.9
5	98.8	98.8	98.9	98.4	97.0	96.5

Table X Detection of Short Circuit faults: Correct Detection percentage

n \ L[ms]	10	20	50	100	150	200
1	1.4	1.4	46.1	99.6	99.7	99.5
2	1.4	99.3	99.2	99.3	99.2	98.6
3	1.4	99.3	99.2	99.0	98.6	98.6
4	99.1	99.2	98.8	98.4	98.6	98.2
5	99.1	99.1	98.7	98.4	98.4	98.0

Table XI Detection of Hold faults: Correct Detection percentage

n \ L[ms]	10	20	50	100	150	200
1	1.8	2.1	48.7	92.2	88.2	84.4
2	2.0	99.4	90.8	76.6	67.0	42.1
3	2.0	97.8	86.6	65.2	28.6	13.7
4	99.2	96.8	74.9	38.1	12.5	7.9
5	98.1	89.4	58.1	22.1	7.6	7.1

Table XII Detection of uncalibration faults: Missed Detection percentage

n \ L[ms]	10	20	50	100	150	200
1	0.0	0.0	0.0	0.1	0.9	0.9
2	0.0	0.1	0.4	1.9	10.3	2.8
3	0.0	0.8	1.8	49.4	100.0	100.0
4	0.1	0.9	1.9	100.0	100.0	100.0
5	0.5	1.4	100.0	100.0	100.0	100.0

Table XIII Detection of Open Circuit faults: Missed Detection percentage

n \ L[ms]	10	20	50	100	150	200
1	0.0	0.0	0.0	0.1	0.5	0.8
2	0.0	0.1	0.2	0.8	1.2	1.3
3	0.0	0.2	0.2	1.2	1.5	2.1
4	0.1	0.2	0.8	1.3	2.1	3.1
5	0.1	0.3	0.9	1.5	3.0	3.5

Table XIV Detection of Short Circuit faults: Missed Detection percentage

n \ L[ms]	10	20	50	100	150	200
1	0.0	0.0	0.0	0.0	0.3	0.5
2	0.0	0.0	0.1	0.5	0.8	1.4
3	0.0	0.0	0.1	0.8	1.4	1.4
4	0.0	0.1	0.5	1.4	1.4	1.8
5	0.0	0.2	0.6	1.4	1.6	2.0

Table XV Detection of Hold faults: Missed Detection percentage

n \ L[ms]	10	20	50	100	150	200
1	0.0	0.0	0.0	7.8	11.8	15.6
2	0.0	0.4	9.2	23.4	33.0	57.9
3	0.0	2.0	13.4	34.8	71.4	86.3
4	0.6	3.0	25.1	61.9	87.5	92.1
5	1.8	10.4	41.9	77.9	92.4	92.9

when the proposed fault detection scheme is adopted by considering the moving observation window L_{obs} ($n*L_S$ consecutive samples) in the range [40÷200] ms (see the blue regions highlighted in the corresponding Tables IV-VII and XII-XIV);

- the adoption of shorter sliding windows for residual generation (L < 50 ms) typically leads to poor performance in terms of $FA_{\%}$ (see the values in the top-left corner of the Tables IV-VII) because of the prediction limits exhibited by the NARX model about

the signal tracking for 10% of the Test set samples (as previously observed in Fig. 7.b);

- a larger sliding window (L > 150 ms) leads to poor performance in terms of $MD_{\%}$ (see the values in the bottom-right corner of the Tables IV-VII) because the threshold exceeding is not completely satisfied for all the output samples within the observation time window (as depicted in the corresponding examples of Fig. 6.b);
- the open and short faults represent the easiest conditions to be detected (as shown by the large blue areas highlighted in the corresponding Tables IX-X) because of the significant residual achieved in correspondence of the fault insertion due to the extreme values for the measured signal;
- reasonably satisfying values of $CD_{\%}$ and $MD_{\%}$ may be achieved for the hold faults through shorter observation windows (see the small blue area highlighted in the corresponding Tables XI and XV). Indeed, the measured suspension stroke is near the balance position for the greatest part of the dataset. Thus, further research could be addressed to include other detection rules based on the analysis of the derivative signal for the measured rear suspension stroke.

Moreover, a very good promptness of the decision maker has been achieved: for all types of the faults, the corrected detection are obtained after a mean time delay $t_{d,mean}$ lower than (L_{obs} + 2 seconds).

V. FEASIBILITY ANALYSIS FOR ON-BOARD IMPLEMENTATION

In order to verify the compatibility of the IFD proposed scheme with the on-board hardware features typical of motorcycle context, it was simulated on a STM32 microcontroller based on the general-purpose architecture ARM Cortex-M4 core with DSP and FPU. The software has been implemented in C language by using the Keil µVision environment. In Table XVI the main characteristics of the microcontroller used are reported.

The resources needed for the implementation of the IFD software were investigated by evaluating both memory usage and running times required. In particular, we have obtained:

- Flash RAM used: 7 kB;
- SRAM used: 42 kB;
- Execution time: 328 µs @ 168 MHz;
- Execution time: 518 µs @ 96 MHz;
- Execution time: 1910 µs @ 22 MHz.

These results prove the real feasibility for an on-board application and real-time processing also for the lowest clock value (as previous said the sampling time is 10 ms).

VI. CONCLUSION

The paper has described the design and the development of a scheme for the fault detection of the rear suspension stroke sensor in motorcycle, which is typically based on linear potentiometer principia. The IFD scheme is thought for identifying the most common faults that could occur on this kind of sensor, namely open circuit, short circuit, hold and un-calibration faults.

The residual generation for the fault diagnosis is based on the use of a NARX Neural Network, which has been trained and validated by means of actual data acquired on the field. The NARX Neural Network revealed as very reliable tool in estimating the sensor output expected value. The deep analysis performed in terms of REC and SOE curves has proved that the prediction error can be limited to 10%, which allows to identify also very small un-calibration faults in few seconds, thus enabling the capability of quickly triggering recovery or predictive maintenance procedures with the aims of improving the driver safety and holding high the real effectiveness of the suspension systems. The K-fold cross validation technique, employed for verifying the performance of both NARX Neural Network and of the IFD scheme, has proved the independence of the obtained results on the learning (training and test) set adopted.

To verify the possibility of implementing the IFD scheme on control units typically employed in the motorcycle context, it was entirely developed on a STM32 microcontroller. Experimented memory usage and running times were strongly compliant with the existing constraints: memory required is less than 25 % of the one available, and in all clock configurations considered the execution times were always less than the sampling time (10 ms). These results prove that the proposed IFD scheme could be successfully developed on these kind of architectures by assuring the real-time processing.

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Table XVI. Main microcontroller features

Parameter	Value
Clock	168 MHz/96 MHz/22MHz
SRAM	192 kB
Flash RAM	1MB
Multiplier	32*32 bit
DMIPS	210

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