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ANN-based IFD in Motorcycle Rear Suspension

Domenico Capriglione, Marco Carratù, Paolo Sommella, Antonio Pietrosanto

Dept. of Industrial Engineering
University of Salerno
Via Giovanni Paolo II, 132 Fisciano (SA)
ITALY

***Abstract* – Semi-active suspension control needs to measure the relative velocity of the wheels respect to the vehicle body to regulate the damping forces. Linear potentiometers are the most used sensors in racing for linearity and simplicity, but they suffer of wear and tear and aging higher than the other sensors involved in the control loop. As a consequence, to save the efficiency and the effectiveness of the suspension control strategy, an Instrument Fault Detection (IFD) system able to detect the faults occurring on such a sensor should be adopted. . In this framework, the paper proposes a IFD scheme based on the analytical redundancy existing among the quantity measured by the rear suspension sensor and the other quantities involved in a typical suspension control loop. In other words, the fault detection is made by comparing the actual sensor output with the expected one provided by a "soft" sensor. In particular, the soft sensor has been implemented by suitably designing and tuning a Nonlinear Auto-Regressive with eXogenous inputs (*NARX*) network which is able to take into account for the system nonlinearity. Experimental results have proven the good promptness and reliability of the scheme in detecting also "small faults" (e.g. due to slight variations of the input/output sensor curve).**

I. INTRODUCTION

Today's vehicles are increasingly adopting sensors and electronic instrumentation to assure the passenger safety and enhance the driving experience. As an example, the suspension is one of the most critical subsystem which directly influences the comfort and the vehicle handling: it ensures the contact between tires and road, and at the same time isolates the vehicle frame from the road roughness. As a solution, semi-active suspensions and suitable strategies are being developed to real-time control [1] the corresponding 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).

Driven by the primary goals of cost-saving and safety, the smart sensing [2] has become an interesting research topic through the development of new solutions such as Soft sensors: the process of estimating any system or process variable by adopting mathematical models, replacing some physical devices and using data acquired from some other available sensors. They represent a good solution successfully applied to solve various problems such as the back-up of measurement systems [3], the what-if analysis, the prediction for real-time plant control and sensor validation [4].

As an example, the soft sensor for the rear suspension stroke may be useful for multipurpose. First of all, the inferential model intended to reduce the measuring hardware requirements (rear stroke sensor, pair of accelerometer and so on) may result into a significant source of budget saving and increasing system reliability (about the series system, the fault probability is strongly influenced by the amount of the devices operating in the harsh environment). As a second application, the soft sensor may be adopted to the real-time estimation of the system variable to limit the time delay introduced by the corresponding hardware devices of measurement and/or actuation. More in details, during riding at low-medium vehicle speed, the control unit devoted to the real-time prediction of the suspension dynamics could also compensate for the time response of the semi-active shock absorber (such as the Magneto-Rheological damper [5]). Probably the main application of the soft sensor is the Sensor Validation (the particular kind of fault detection, in which the system to be monitored is a sensor or a set of

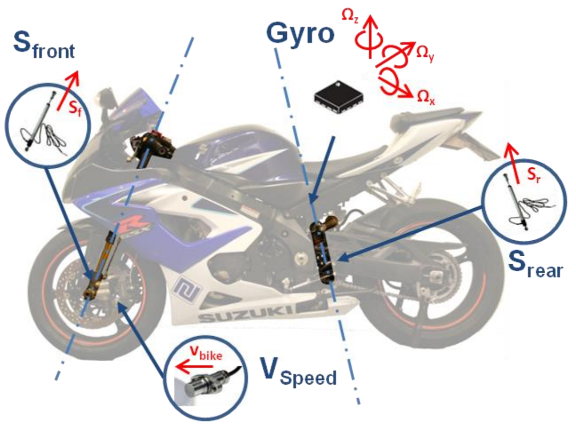

Fig. 1. The system under test

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

sensors) following the (physical/analytical) redundancy-based approach typically exploited in the automotive safety. In such framework, the soft stroke sensor may be paralleled with the actual stroke sensor, and faults can be detected by monitoring the residual resulting from the outputs of actual and soft sensors. Once a fault is detected and isolated for the actual sensor, the soft sensor may be adopted as a back-up device till the actual sensor is not replaced during the servicing.

Starting from previous work [6-7] focused on Artificial Intelligence techniques for the Sensor Validation, the present paper describes the development of an Instrument Fault Detection and Isolation (IFD) scheme to be applied to the motorcycle suspension system, which is based on the analytical redundancy and adoption of the graphical tools for the characterization of Neural Networks [8].

Thus, the paper is organized as follows: the system under test is detailed in Section II with reference to a pilot motorcycle whereas, in Section III the main IFD issues are discussed and the outcomes from the preliminary experiments are analyzed. Finally, main conclusions are drawn in Section IV.

II. THE SYSTEM UNDER TEST

Following the data driven approach suggested in [9], the authors aimed to the soft sensing of the rear suspension stroke through a suitable exploitation of the analytical redundancy existing among the vertical dynamics signals for two-wheeled vehicles. Indeed, 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.

The mathematical model which allows the rear suspension stroke to be inferred from a set of influential variables during the motorcycle riding has been developed by considering the SUZUKI GSX-1000 model as test motorcycle (schemed in Fig. 1), suitably equipped with the sensors included in Table I.

To develop the IFD scheme, a measurement campaign based on real data acquired on the field was performed. In particular, the motorcycle riding refers to a test lap (8 km approximated length) which includes various profiles (cobblestone stretch, urban and extra-urban road, concentrated obstacles) in order to introduce different excitation modes [9-10] of the suspension system. As a result, a data logging about one hour was achieved by completing 12 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

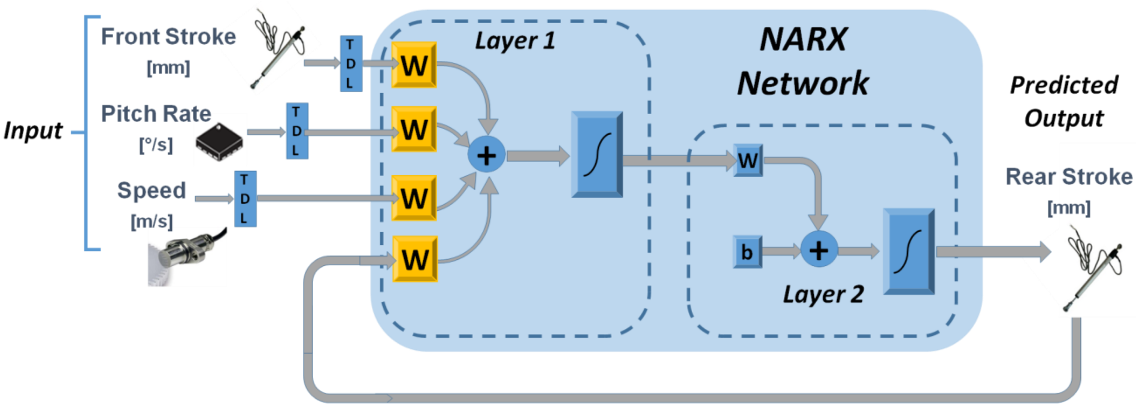

Fig. 2. Structure of the NARX Network for predicting the rear stroke

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	56

sampling frequency of 1 kHz, then a resampling at 100 Hz was performed to match the dynamics of the semi-active suspension and the loop frequency typically adopted by the control strategies.

III. IFD BASED ON SOFT STROKE SENSOR

A. The soft sensor

Since the main hypothesis of the *Half-Car Model* (i.e. a steady state condition for the motorcycle dynamics) does not allow the steering and the linkage nonlinear effects to be correctly estimated in terms of the corresponding varying wheel base and transfer load, the *Nonlinear Auto-Regressive with eXogenous inputs* (*NARX*) was adopted according to the structure reported in Fig. 2.

A preliminary normalization process was carried out 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.

The NARX Network [11] characterized by $N = 13$ neurons in the hidden layer, tapped delays $d_{in} = 100$ ms and $d_{out} = 100$ ms for input and output signals respectively, showed the best performance in terms of mean relative regression error $E_{R\_MEAN\%}$ estimated by considering the *K-fold cross validation technique* in order to reduce the dependency from particular learning (training and test) set adopted.

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. Then, 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 70000 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);
- $N_J = 35000$ (i.e. for each training session, the learning set was divided in two subsets, training and test sets, each one constituted by 35000 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 $E_{R\_MEAN\%} = 2.4$ % 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 %.

As an example, Figure 3 compares the normalized values both measured and predicted ones for all samples

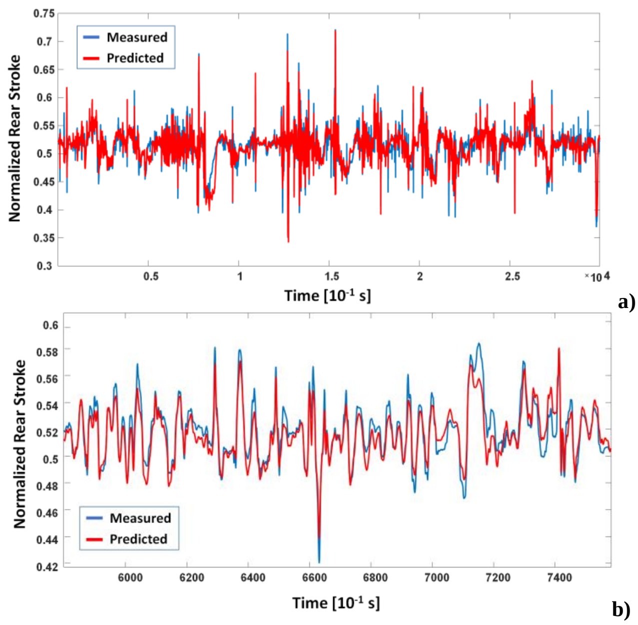

Figure 3. Prediction of the rear suspension stroke by the NARX Network for Test set #5: a) results about experimental dataset; b) magnification of a).

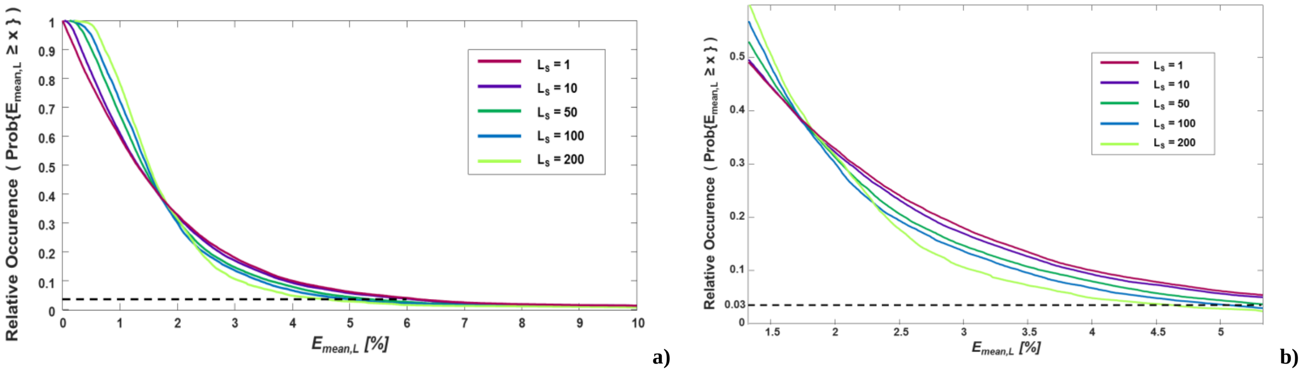

Figure 4. a) SOE curves for NN as function of the window length L; b) Magnification of a). (Test set #5 has been involved)

of the test set #5. It confirms the ability of the proposed Network in accurately predicting the expected values.

Furthermore, the satisfying local accuracy of the NARX Network is also revealed by the *Sliding Occurrence Error* (*SOE*) curve [8]. When a moving window including L_S successive output samples is considered, the 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. In details, at each output sample point, the mean relative deviation $E_{mean,L}$ is defined 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 window length L. Thus, the SOE curve may be interpreted as the survivor function of the error tolerance.

In details, 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.

B. The IFD scheme

The Soft Sensor S_{narx} represented by the NARX model has been adopted to implement an IFD scheme for the hard stroke sensor S_{rear}. In detail, the aim is to reveal 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 (to detect open or short-circuit temporary faults) only after hours or days from the occurrence, when the performance degradation implies unacceptable risk levels.

According to the proposed strategy, a fault is detected when the percentage (absolute) difference between the mean values for the measured output and the prediction exceeds a fixed threshold $T_{\%}$ longer than the sliding window L.

Focus has been devoted to determine the optimal value for the window length L about the most accurate NARX model and to develop effective IFD scheme. As shown in Fig. 4, by considering L = 1 s (corresponding to L_S = 100), the mean prediction error $E_{mean,L}$ is lower than 5% for over the 97% of the experimental dataset (Test set #5 has been involved).

The instrument fault detection scheme has been verified against (N_{faults}=1000) un-calibration faults (not lower than $T_{\%}$=10%) randomly introduced in the (measured) rear stroke samples of dataset, by considering different values for the sliding window L and adopting 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_{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_{max}.

Experimental results are summarized in Table IV for L varying from 100 ms to 2 s, when t_{max} = 60 s is considered. A satisfying performance in terms of all the introduced

Table. IV Performance of the proposed IFD scheme based on soft sensor. (Test set #5 has been involved)

L [s]	$FA_{\%}$	$MD_{\%}$	$CD_{\%}$	$t_{d,mean}$ [s]
0.1	74.3	0.0	25.7	0.7
0.5	48.0	0.0	42.0	0.9
1.0	**0.4**	**3.6**	**96.0**	**19.9**
2.0	0.0	20.2	79.8	33.4

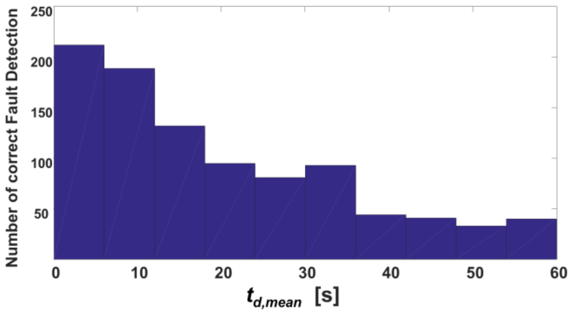

Figure 5. Histogram of observed fault detection times

indexes ($CD_{\%}$, $MD_{\%}$, $FA_{\%}$) is exhibited by the proposed fault detection scheme when the soft sensor is adopted by averaging the prediction every second (L_s = 100). Shorter sliding windows allow to achieve poor performance in terms of $FA_{\%}$ because of the prediction limits by the NARX model about the signal tracking for 10% of the Test set samples whereas, a larger sliding window leads to poor performance in terms of $MD_{\%}$ because the threshold exceeding is not completely satisfied for all the output samples within the observation time. Moreover, as shown from the mean delay time $t_{d,mean}$ for the correct fault detection, the sliding window length L equal to 1 second allows achieving a very prompt response of the IFD scheme (more than 50% faults detected by 20 seconds, see the corresponding histogram depicted in Fig. 5).

In order to verify the generality of the achieved performance indexes, a further analysis has been carried out by fixing the value of L to 1 second and by varying the learning set, once again considering the same 10 sets described in the previous section. Table V reports the related results. As you can see, for each figure of merit, the small values of the experimental standard deviations and the analysis of maximum and minimum values confirm the low dispersion of the performance indexes, thus proving the independence of the obtained results on the learning set adopted for the training and the test of the IDF system.

IV. CONCLUSION

An IFD scheme of the rear suspension stroke sensor of two-wheels vehicles has been developed according to a data driven approach by adopting a suitable NARX Neural Network. The proposed solution exhibits satisfying static and dynamical behaviors, represented respectively by the mean error and the sliding mean deviation in the output prediction. The accurate output prediction lead the authors to adopt the NARX model as a useful benchmark for the implementation of Instrument Fault Detection strategies for motorcycle rear stroke sensors. The adoption of Sliding Occurrence Error curves results together with a threshold identification (about the mean deviation and the sliding window length) allowed an effective detection scheme to be introduced. About the preliminary study based on numeric simulation, the residual generation (from the comparison between the measured and predicted sensor output) is able to detect the small faults which may typically affect the stroke sensors (due to both wear and tear and aging).

Table. V. Diagnostic Performance of the proposed IFD scheme based on soft sensor for different K-Learning sets.

Learning set #	***$FA_{\%}$***	***$MD_{\%}$***	***$CD_{\%}$***
1	1.9	0.0	98.1
2	1.6	0.0	98.4
3	2.8	0.0	97.2
4	0.7	0.0	99.3
5	0.4	0.0	99.6
6	0.4	0.0	99.6
7	0.4	0.0	99.6
8	0.2	0.0	99.8
9	1.5	0.0	98.5
10	0.4	0.0	99.6
Mean	**1.0**	**0.0**	**99.0**
Standard Deviation	**0.9**	**0.0**	**0.9**
Maximum	**2.8**	**0.0**	**99.8**
Minimum	**0.2**	**0.0**	**97.2**

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.

Finally, the very short times needed for detecting the faults enable the implementation of an IFD system for the rear suspension stroke sensor characterized by high promptness and reliability.

Further improvements will concern with the implementation of the proposed IFD system on a microcontroller-based platform for verifying its applicability on hardware architectures typical of the motorcycle context.

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