18th IMEKO TC10 Conference
"Measurement for Diagnostics, Optimisation and Control to Support Sustainability and Resilience"
Warsaw, Poland, September 26–27, 2022

An LSTM based soft sensor for rear motorcycle suspension

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Abstract **– The increasing development of neural networks for classification and prediction of temporal sequences has opened the way for a new development of mathematical models for soft sensor design. In particular, Long Short-Term Memory (LSTM) networks have greatly improved execution time and reduced error in both single-step and multi-step prediction. In this context, it is therefore possible to improve on the current concept of Instrument Fault Detection and Isolation (IFDI), reducing costs and footprint by not using physical redundancies of sensitive elements but by employing virtual sensors themselves. Therefore, the work aims to develop a soft sensor for rear suspension stroke using an LSTM network. This new approach was trained on over 50000 samples acquired in a real-world environment, and the results were compared with ground truth on a total of over 100000 samples. The results of the analysis showed excellent potential of the method and wide room for improvement in future developments.**

Keywords – Soft Sensor, Deep Neural Network, LSTM, IFDI, Industry Innovation and Infrastructure, SDG 9.

I. INTRODUCTION

The automotive field is undergoing major changes due to the increasingly pervasive spread of technology and its integration into the mechanical elements that make up motor vehicles and motorcycles. The process has been facilitated by the disruptive development of intelligent and interconnected wireless sensor networks in the Internet of Things[1]-[4]. The increase in computational power accompanied by the reduction in size, due to the ever-increasing miniaturization of hardware elements, has made it possible to implement not only systems capable of providing real-time vehicle status diagnostics, but also to monitor and act on vehicle processes characterized by extremely faster dynamics. Examples include powertrain management in hybrid engines characterized by algorithms capable of choosing the right strategy for utilizing the thermal and electrical part of the powertrain based on numerous factors measured in real time, such as state of charge, temperature and power demand [7]-[11].

Another example is the management systems of fully electric vehicles, which need to measure numerous parameters in real time, such as battery cell working area for maintaining the Safe Operating Area, operating voltage of individual cells, state-of-charge balancing, charging through regenerative braking, and others in order to comply without delay with requests made by the driver.

The development of measurement systems has also opened the door to active and intelligent management of vehicle setups, operated according to the type of strategy desired and adapted to road and operational conditions. This makes it possible, among other things, to improve safety on board when the vehicle is in risky conditions, such as on ice or slippery road surfaces, but also to be able to always obtain the best set-up to maximize the vehicle's potential in sports driving [12].

These applications therefore require a sensor network that is always operational and free from errors and malfunctions, as incorrect data can completely invalidate the strategies adopted by the vehicle's ECU, affecting performance or even causing damage to the vehicle.

Extensive use of physical and analytical redundancy has been made to overcome these problems. Physical redundancy in particular aims to increase the number of sensing elements per individual measurand in order to recognize and isolate a possible failure (IFDI) while ensuring system uptime through the backup sensor [13].

Although the solution is the one that gives the highest guarantee of fault isolation, it has cost and space as major limitations: in fact, it is not always possible to add more sensing elements to the systems, due to scarce space available because of an already very demanding mechanical design. The economic aspect is also very important, since, according to the logic of physical redundancy, each measurand would have to be associated with two or more sensors, levitating the final design costs considerably.

Analytical redundancy, on the other hand, does not present the problems outlined above. This in fact is based on the use of mathematical models instead of physical sensors. Mathematical models take as input some physical quantities that have causal relationships with the phenomenon to be measured and estimate the value of the same. This concept is called soft sensing or virtual sensing [14]-[15]. In this context, it is possible to apply soft

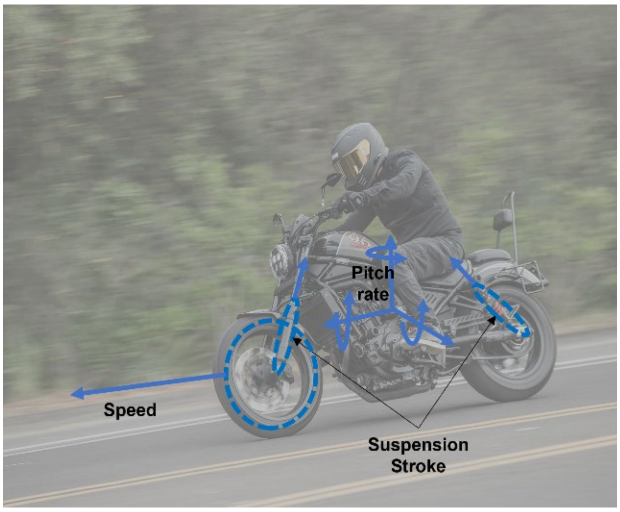

Fig. 1 System under test

sensing techniques to IFDI: in particular, it is possible to associate each sensor physically installed in the equipment to be monitored with the output of a soft sensor, so that there are two signals. In the event of a malfunction of the physical sensor, it will therefore be possible to isolate the fault thanks to the comparison with the output provided by the soft sensor.

The complexity in developing a soft sensor concerns mathematical modelling: in fact, it is not always possible to develop a model that relates, uniquely, the inputs to the desired output. Recently, the development of new machine learning and deep learning techniques has made it possible to greatly improve the development of soft sensors even without direct knowledge of the mathematical model, for example, through the use of NARX networks (nonlinear autoregressive network with exogenous inputs) [15] and other algorithms for data forecasting [17].

As for new deep learning techniques, Long Short-Term Memory (LSTM) networks have found great application in the area of classification and prediction of temporal sequences, which makes them particularly suitable for use as an algorithmic basis for soft sensor development [18],[19].

Therefore, this work will deal with the development of a soft sensor using a novel neural network architecture based on LSTM cells. The suspension system of a motor vehicle will be examined for the application case. The next section will describe the system under consideration, and Section III will describe the development of the LSTM network. Finally, Section IV will present the results.

Table I. Normalization values

Measured quantity	Min	Max
Front stroke [mm]	0	150
Rear stroke [mm]	0	150
Pitch rate [°/s]	-80	+80
Speed [m/s]	0	56

Table II. Proposed Neural Network Architecture

Layer	Type	Shape
1	Input	(Batch, 100, 3)
2	LSTM	(Batch, 32)
3	Dense (Output)	(Batch, 1)

II. SYSTEM DESCRIPTION

The system under consideration concerns the suspension dynamics of a motorcycle. The set goal was to develop the virtual version of the linear displacement sensor for monitoring the rear suspension stroke. Thus, the main influencing factors on the rear suspension stroke were examined, which were found to be: the front suspension stroke, pitch rate and speed.

In this way, it would be possible to compare the residual nominal operating values of the rear suspension stroke, calculated by the neural network, with those obtained from the sensor, in order to assume a fault state of the sensor itself, and thus to isolate it.

Therefore, the sensors chosen were Linear Displacement Sensors, for measuring front and rear suspension stroke, a magnetic encoder mounted on the front wheel for measuring motorcycle speed, and a gyroscope for measuring motorcycle pitch (figure 1).

Data collection took place on a stretch of road of about 10 km in order to obtain data as close to reality as possible. The data were subsampled at 100 Hz, a frequency consistent with the dynamics of the phenomena under investigation.
Eventually, three batches of data consisting of 50000 samples each have been obtained

The data have then been normalized according to the values given in Table I and with the specific equation (1) as a requirement of the LSTM network optimizer.

$$Q(i) = \frac{q(i) - \max(q)}{\max(q) - \min(q)} \tag{1}$$

III. SOFT SENSOR DESIGN

As mentioned in the introduction, it was decided to employ a recurrent neural network, specifically a network composed of LSTM cells, for the development of the soft sensor. The LSTM is an improvement of fully connected neural networks and has better performance, especially for medium to long sequences [20].

Therefore, the designed neural network has been equipped with 3 inputs, one per time sequence of input to the soft sensing system. The inputs data have been:

- Front suspension stroke;
- Pitch rate;
- Speed.

The central layer, the core of the network, has been

Table III. Training Hyperparameters

Hyperparameter	Value
Learning rate	0.001
Batch Size	128
Warm up samples	100
Epochs	60

equipped with 32 LSTM units. This number resulted from a series of experimental tests, as there is no unambiguous methodology for defining the optimal number of LSTM units. The number of LSTM and hidden layer units was specifically chosen as a tradeoff between required computational power and prediction error [21]. The number of neurons in the output layer has been one, with no activation function, since the task of the network is not to classify a time sequence but to predict the value of the output from the inputs provided. The output of the neural network has been the Rear Suspension Stroke data.

The architecture of the proposed neural network is shown in Table II. One of the three batches of data, each consisting of 50000 samples, was used for network training, applying a training/validation split of 70%. Training of the neural network has been carried out using the mean squared error as the loss function. Moreover, the LSTM network has been trained and used in single step

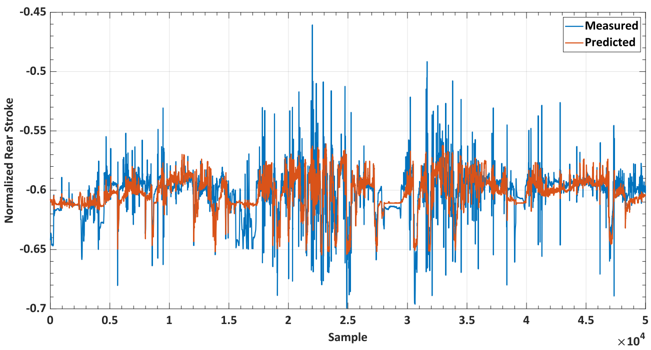

Fig. 2 Comparison of measured and predicted value for the first batch of data

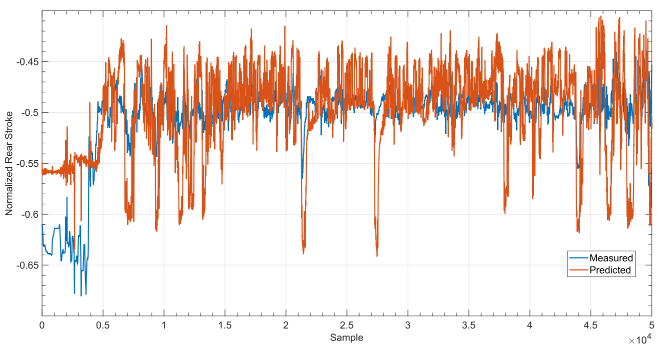

Fig. 3 Comparison of measured and predicted value for the second batch of data

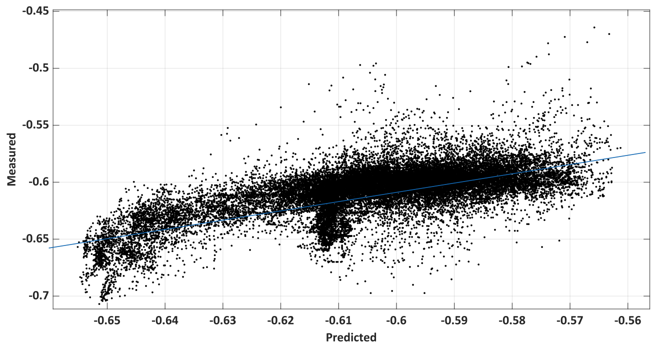

Fig. 4 Scatter plot of measured and predicted value for the first batch of data

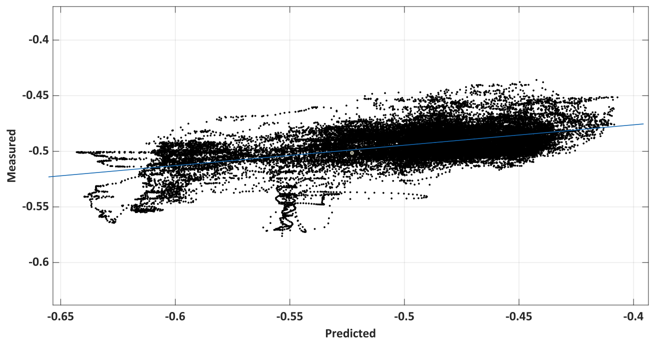

Fig. 5 Scatter plot of measured and predicted value for the second batch of data

mode, that is, the prediction was made and validated only for a future time step. This choice was motivated by the considerable variability of the measurands under consideration and the need not to know the values of rear suspension stroke too far into the future. The other hyperparameters used for training are shown in Table III.

IV. RESULTS AND DISCUSSIONS

For network testing, two data batches consisting of 50000 samples each were used, as explained in the previous section. These data are usable for testing because they are not extrapolated from either the train split or the validation split; therefore, there is no risk of altering the results with data similar to those seen by the network in training.

The best model used in training was thus employed for the inference of rear suspension stroke values, using as input the front suspension stroke, pitch and speed data belonging to these two batches.

First, it was decided to compare the time sequences in their entirety by superimposing the results of the neural network inference and the values read from the corresponding sensor. The results of the comparison can be seen in Figure 2 and Figure 3.

Figure 4 and Figure 5 also show the results against the expected values in the form of scatter plot

Table IV. Average relative percent error

Data batch	ε_r
#1	1.66%
#2	6.38%

As can be seen from both measurements, the system is able to predict the average value of the rear suspension stroke very well, with the only exception of the first 5000 samples of batch two, which were acquired while the motorcycle was stationary, therefore have been excluded. The system has difficulties in following the signals when the dynamics become faster and with very intense gradients. This phenomenon does not represent a problem if the system is included in an instrument fault detection and isolation apparatus, since it is still possible to obtain, for each instant of time, a plausible value expected from the sensor under examination, thus being able to verify its actual functionality.

Two analyses were then carried out. The first was aimed at simply analyzing the error committed by the neural network throughout the entire batch of data, thus going on to calculate the average relative percent error (2) for each of the two batches of data.

$$\varepsilon_r = \frac{|y_p - y_m|}{y_m} \times 100 \qquad (2)$$

In equation (2), ε_r is the average relative percent error, y_m is the measured value and y_p is the value produced by the soft sensor.

The second analysis was aimed at checking the consistency and performance of the network over time In particular, an investigation has been made to determine whether the relative error results shown in Table IV were caused by persistent errors over time or by outliers. For this analysis, the results were analyzed with a sliding window, thus going to emulate the data flow in real time. With this data, Sliding Occurrence Error (SOE) has been calculated. This function allows estimating the probability distribution of the average relative error in the form of a survival function, as in (3).

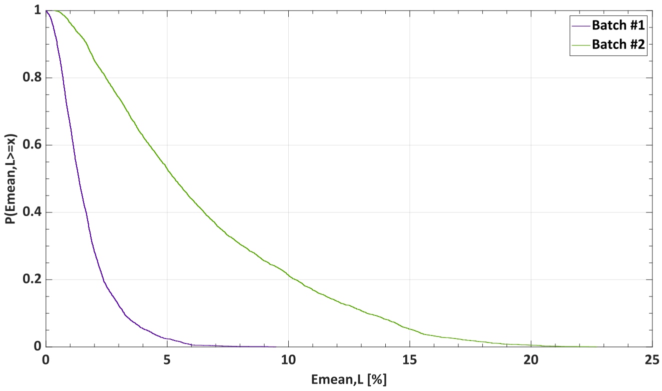

Fig. 6 SOE analysis for batch #1 and #2

$$S(t) = P(\{T > t\}) = \int_t^{\infty} f(u)du = 1 - F(t) \qquad (3)$$

Where T is a continuous random variable with cumulative distribution function F(t) on the interval [0, ∞)

Then, the average relative error was calculated using a sliding window on the dataset, according to equation (4). L_s specifies the width, in terms of the number of samples, of the sliding window, y_p the predicted value, and y_m the measured value.

$$E_{mean,L}(i) = \frac{1}{L_S}\sum_{k=0}^{L_S-1}\left|\frac{y_p(i-k) - y_m(i-k)}{y_m(i-k)}\right| \qquad (4)$$

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 prediction error on the y-axis.

The results of the first analysis are reported in Table IV, while the SOE curve for the two batch of data is visible in figure 6 and calculated with L_s equal to 60 and an overlap of the windows of 80.

As can be seen from the SOE analysis, the first batch of data reported better performance than the second batch of data. However, even in the worst case the occurrence of a relative error greater than 14% was no greater than 10% of the moving windows used for the analysis. These results are promising and in line with those obtained previously with NARX-type neural networks (nonlinear autoregressive exogenous model) [22].

V. CONCLUSIONS AND OUTLOOK

The work dealt with the development of a soft sensor for the rear suspension stroke of a motorcycle to explore the feasibility of an IFDI system based on software redundancy. In particular, the presented methodology can be exploited to detect and highlight abnormal values in sensors that may identify a potential malfunction of the same.

The soft sensor was developed using the deep neural network LSTM, predicting output from three inputs. The results showed a good ability of the network to estimate the mean value of the output, committing a larger error for the fast dynamics of the measurand.

Future goals will involve optimization of the network and comparison with soft sensing techniques present in the state of the art, such as those employing NARX networks.

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