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Journal of Tertiary and Industrial Sciences *Vol. 6, No. 2, 2026*
ISSN 2709-3409 (Online)

CONTENTS

AGRICULTURE

MECHANICAL ENGINEERING

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ISSN 2709-3409 (Online)

Classification of Troubleshooting in a Mechanical System for Fault Detection and Diagnosis with the aid of a Neural Network

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Abstract

The internal combustion engine (ICE) is widely used in applications such as automobiles, motorcycles and ships. After its long-term use faults occur that degrade its performance or cause it to malfunction. Therefore, ICE fault detection and diagnosis (FDD) research is important for preventing serious economic loss and even human injuries caused by undetected faults. The development of an ICE FDD for the prediction of faults is described in this work. The setup uses sensors to measure the ICE variables and LSTM techniques implemented in a computer program. The common ICE faults which are the common rail injection fault, the fuel consumption and the coolant temperature faults are carefully studied. The objective of the FDD is to determine if there is any of the above-mentioned faults in the Hyundai Santa fe 2008 model car. Several FDD algorithms are proposed, one category of which is based on data processing techniques such as the LSTM Recurrent Neural Network is implemented to arrive at our results. This category of FDD algorithms includes the LSTM-based FDD algorithm. The LSTM-based FDD algorithm introduces a new FDD index based on LSTM and statistics recorded from the car. According to the included experimental results, all of these algorithms are capable of detecting and locating these faults with 99.999% accuracy.

Key words: Classification; troubleshooting; mechanical system; Fault Detection and Diagnosis; neural network.

1. Introduction

Thermal engines have a large area of use especially in the means of transportation (such as automobiles, aircraft, ships, and motorcycles). These engines after a very long functioning period usually result to low or poor performance and troubleshooting when the working conditions are not met up. This may lead to a break down and could intend affect the output. Hence the research of the classification of troubleshooting for fault diagnosis and detection in a mechanical system such as a thermal engine for normal working conditions is important in order to increase efficiency. According to Gertler (1998) [1]; fault detection and diagnosis systems aim to accomplish the following three tasks: 1) Fault detection: the indication that something is going wrong in the monitored system, 2) Fault isolation: the determination of the exact location of the fault, 3) Fault identification: the determination of the magnitude of the fault (Yifei Feng, 2016 [2]). This research work is focused on the Process History –Based, and it is a quantitative study based on the Neural Network approach. This is applied to a

Hyondai Santa fe 2008 model of a car engine.

Classification and diagnosis of faults is carried out in the thermal engine. The reason behind this classification is to help troubleshooters to easily identify the fault that leads to the engine malfunction. These faults are the most observed by field mechanics. The identification of these particular faults in some given systems part of the thermal engine may put the engine to its normal functioning mode and thereby assure proper running of the vehicle. After isolation and detection of the faults in a given thermal engine, some observations are made and then immediate analysis are being carried out to know the main cause of the fault. The detection and analysis of faults is done by using the neural network.

In order to better get more insights in this work and to improve on our results, we considered many scientific and engineering approaches. Some of these approaches or models have been applied in different domain of research and satisfactory results observed and taken into consideration. Some of the models used are; the fault classification model especially the Knowledge base technique (Maintenance Table), and the Neural Network Hybrid technique, mainly the Wavelet and ANN Technique - LSTM (Long –Short Term Memory), for fault detection and diagnosis which is the main model used here for the classification and diagnosis of the fault prediction in the engine. Neural networks are nonlinear, multivariable models built from a set of input/output data. They can be used as event detectors, detecting events and trends. They can also be used as diagnostic models in model-based reasoning, or used directly as classifiers for recognizing fault signatures.

Today, the classification of trouble shooting is of prime importance in a mechanical system such as in the ICE and at times in a more complex industrial system which is of prime necessity. These systems in the case of industries or a vehicle are constantly working in order to increase production or making life easier, more comfortable and more reliable till these systems fail. The failure in the system is due to the occurrence of a fault. Fault is defined by Isermann and Balle (1997) [3] as: fault is an unexpected deviation of at least one characteristic property or parameter of the system from the usual or standard condition. Generally, fault in some complex terms are events that happen rarely at unexpected moments of time (Erdal, 2005) [4].

Irrespective of the maintenance procedure and safety rules put in place, it may be very difficult to predict and prevent fault in a mechanical system. Faults may lead to Economic and Human losses by incidents in any mechanical system. Several examples are; The Mbanga-Pongo plane crash (Douala, Cameroon) of 5 May 2007, with 114 killed (source: Cameroon Tribune, 6 May 2009 [5]) and the Eseka train incidence of October 21st 2016 with the official number of casualties of 70 killed, with 152 injured (source: Cameroon Tribune, 24 May 2017 at 12:27 pm [6]), and the several car incidents on the highway roads in Cameroon.

2. *Materials and methods*

2.1 Materials selection

The materials used in this work are: Hyundai Santa fe 2008 vehicle model, Toshiba 4 GB DDR2 RAM, 250 GB HDD and MATLAB software containing simulation tools such as ANFIS and SIMULINK. The figures 6(a), (b) and figure 7 in the appendix 4 shows the set-up materials.

Table 2.1: Characteristics of Hyundai Santa fe vehicle

№	Engine parameters	Readings
1	Vehicle mass	1789 kg
2	Fuel tank capacity	75 L
3	Number of cylinders	4
4	№ of valves per cylinder	4
5	Piston stroke	2188mm
6	Designed power	155hp /4000 tr/min
7	Engine couple	343 Nm / 1800 tr/min
8	Active power	9 hp
9	Maximum speed	180 km/h
10	Acceleration 100km/h	11.3 seconds
11	Transmission	Forward
12	Box	Mechanical

2.2. Data collection

OBD (On Board diagnostics) is a standard which allows accessing the status of sensors of a vehicle via a port referred to as the OBD port. Few of those sensors can be stated as speed, engine rpm, coolant temperature, fuel consumption, common rail injection pressure, Malintha, 2012 [7].

Data was collected from a user owning vehicle. This large set of data was collected from a Hyundai Santa fe 2008 model vehicle. Once our MATLAB was installed in the laptop, it was used for data collection, processing, and analysis for faults prediction in the various systems considered in this our study.

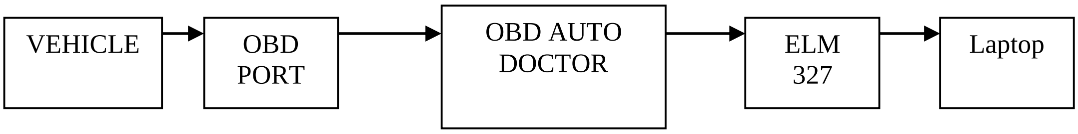


Figure 2.1: Data acquisition procedure

2.3. Modeling procedure of ANFIS

The simplest learning rule of ANFIS is “back-propagation” which computes error signals recursively from the output layer (Layer 5) backward to the input nodes (Layer 1). This learning rule is exactly the same as the back-propagation learning rule used in the common feed-forward neural networks. Although this method can be applied to identify the parameters in an ANFIS network, the method is generally slow and likely to become trapped in local minima. Different learning techniques, such as a hybrid-learning algorithm or genetic algorithm, can be adopted to solve this training problem. Better performance of ANFIS models has been shown by adopting a rapid hybrid learning method, which integrates the gradient descent method and the least-squares method to optimize parameters. Thus, in this paper, the hybrid learning method is used for constructing the proposed models.

2.3.1. Application of recurrent neural network

Step 1: Gradient descent

The gradient descent can be calculated as below:

$$J(W,b) = 1/2\sum |h^{(L)}(W,b,xi) - yi|^2 \qquad (2.2)$$

From the Gradient descent to find the optimum values of W, b

$$W^{(i)} \leftarrow W^{(i)} = \alpha \partial J(W,b)/\partial W^{(i)} \qquad (2.3)$$

Step 2: Forward- backward Propagation

Forward-backward propagation to calculate the gradient $\partial J(W,b)/\partial W^{(i)}$, Backward propagation for $l = L-1,\ldots,2$,

$$\delta^{(l)} = ((W^{(l)})^T \delta^{(l+1)}) \odot g'(W^{(l-1)}h^{(l-1)} + b^{(l-1)}) \qquad (2.5)$$

$$\partial J(W,b)/\partial W^{(l)} = \delta^{(l+1)} \cdot (h^{(l)})^T \qquad (2.6)$$

Step 3: Optimization

For optimization, we have:

$$\mathrm{Min}\,(W,b) = \tfrac{1}{2}(h^{(L)}(W,b,x) - y)^2 \qquad (2.7)$$

Equation (2.7) is never convex unless $h^{(L)}(W,b,x)$ is linear in (w,b).

Step 4: Borel measurable mapping

From Cybenko, 1989 theorem, the set of functions of the form:

$$\sum w_j^{(2)} \sigma((w^{(1)})^T x + b_j), \qquad (2.10)$$

Where $w^{(1)} \in R$, and $w_j^{(2)}$, $b_j \in R$, and dense in the space of continuous functions in the range $x \in [-1, 1]^n$

For any Borel measurable mapping $\rightarrow$ $G: R \quad R$, define,

$$\sum{}^{r}(G) = \{f: R \rightarrow R \mid f(x) = {}^{q}\sum_{i=1} \beta_i G(A_j(x)), \qquad (2.13)$$
$$x \in R^r, \beta_i \in R, A_j \in A^T, q \in N\}$$

step 5: Robust training

Fitting the neural network parameters to the pairs $(x_i + \varepsilon_i, y_i)$ to minimize

$$J(W,b) = \max_{(|\varepsilon| \leq c)} \sum 1/2\, |h^{(L)}(W,b,x_i + \varepsilon_i) - y_i|^2, \qquad (2.14)$$

Step 6: Time series prediction

Consider the time series given by T data samples, $(x_1, y_1), (x_2, y_2) \dots (x_t, y_t), \dots (x_T, y_T)$. Suppose that $h_t = f(x_t, h_{t-1})$ and $y_t = g(h_t)$, for some measurable functions; $f: R^{m+n} \rightarrow R^n$ and $g: R^n \rightarrow R^p$; Approximate of f and g with Neural Network (NN). Approximating f and g with the Recurrent Neural Network (RNN), we have the given functions

$$h_{t+1} = \sigma_h (Wxhx_t + U_h h_{t-1} + b_j) \text{ and } y_t = \sigma_y (Whyh_t + b_y). \quad (2.16)$$

step 7: Back-Propagation Through Time (BPTT)

Forward-backward propagation over layers and time. Unfolding over time gives a chain of T hidden layers. Important constraint: The weights Wxh, U_h, b_h, Wh_y,b_y are identical for each layer. Forward pass $h_1,\dots,h_T$. Consider each parameter as if it was different for each layer:

$$h_{t+1} = \sigma_h(W^{(t)} x_h x_t + U^{(t)} h\, h_{t-1} + b^{(t)} h) \text{ and } y_t = \sigma_y(W^{(t)} h_y h_t + b^{(t)}{}_y). \quad (2.18)$$

step 8: Long Short-Term Memory (LSTM)

However, there is a problem of exploding/vanishing gradient in RNN. Suppose that $\sigma_h = \sigma_y = id$ (or ReLU) in

$h_{t+1} = \sigma_h (W_x h\, x_t + U_h h_{t-1} + b_h)$ and $y_t = \sigma_y (Wh_y h_t + b_y)$. Then we see that:

$$h_t = U^{t-1}{}_h h_1 + \cdots. \quad (2.19)$$

One solution is to introduce Long Short-Term Memory (LSTM). Some applications of the LSTM can be listed as follows: Handwriting recognition, speech recognition, handwriting generation, machine translation, image capturing, text parsing, and prediction of engine faults (this is applicable to the method in this work).

2.4. Design of the NN system model

2.4.1. Data Mining Technique

Following the definition of Mitchell (1997) [8], machine learning techniques are defined as an intelligent algorithm that has the ability to learn from historical data. The task of machine learning can be divided into clustering, classification, and prediction.

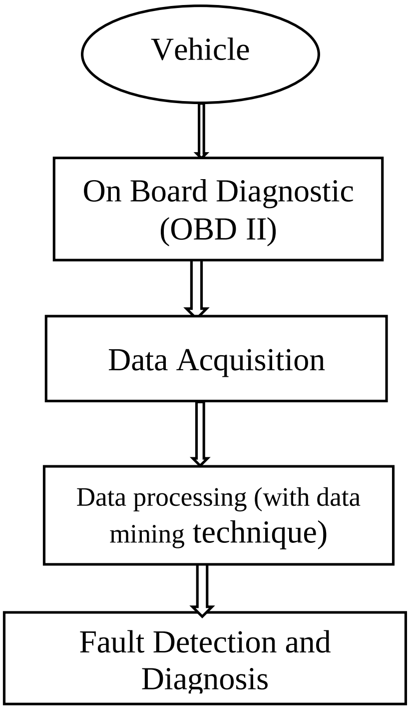


Figure 2.2: Machine learning algorithm for fault Detection and Diagnosis (Omid, 2017)

Table 2.3: Data Mining parameters

Faults	Predicted parameters	Input network variables
Common rail injection fault	Rail injection pressure	1. The internal pressure values in the common rail injection, 2. the air pressure in the admission valve, and 3. the engine power.
Abnormal increase in consumption fault	Fuel consumption	1. The internal values of fuel consumption 2. the engine torque, 3. the air pressure in the intake valve, 4. the error of the EGR, 5. The accelerometer data.
Engine cooling circuit fault	Coolant temperature	1. The internal temperature of the coolant, 2. the flow rate of the intake air, 3. the car speed, 4. the pressure of air in the intake valve, and 5. The state of the engine.

In this our work, we are going to use the prediction data mining technique since the LSTM model is based on a time series prediction.

- *Data preparation*

```
load('dataset')
load('driversPatterns.mat')
Timestep=MyData.TimeStep;
EngineLoad=MyData.EngineLoad;
CoolantTemp=MyData.CoolantTemp;
MAP=MyData.MAP;
RPM=MyData.RPM;
Speed=MyData.Speed;
IntakeAirTemp=MyData.IntakeAirTemp;
MAF=MyData.MAF;
Pressure=MyData.FuelRailPressure;
CommandEGR=MyData.CommandEGR;
EgrError = MyData.EgrError;
FuelConsumption=MyData.FuelConsumption;
Power=MyData.Power;
Torque=MyData.Torque;
BoostPressure=MyData.BoostPressure;
```

2.4.2. LSTM model construction

The most effective solution so far for FDD classification is the Long Short Term Memory (LSTM) architecture, Hochreiter and Scmidhuber (1997) [9]. The LSTM architecture consists of a set of recurrently connected subnets, known as memory blocks. These blocks can be thought of as a differentiable version of the memory chips in a digital computer. The LSTM network is a type of RNN (Recurrent Neural Network) capable of a long term dependency of data in a chronological series. The main components of the LSTM network are: an input layer and the LSTM layer. The input layer permits to introduce time series data into the network. For the LSTM layer, it permits to learn the dependency for a long time range. The figure 2.5 below presents an internal LSTM architecture layer. With D the time series of length S in the input to predict an output h. The D time series are contained in an input vector X.

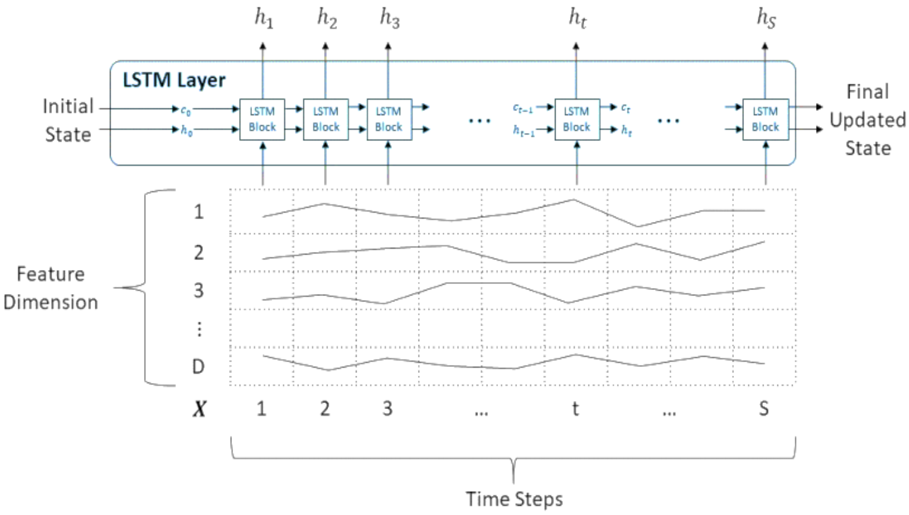


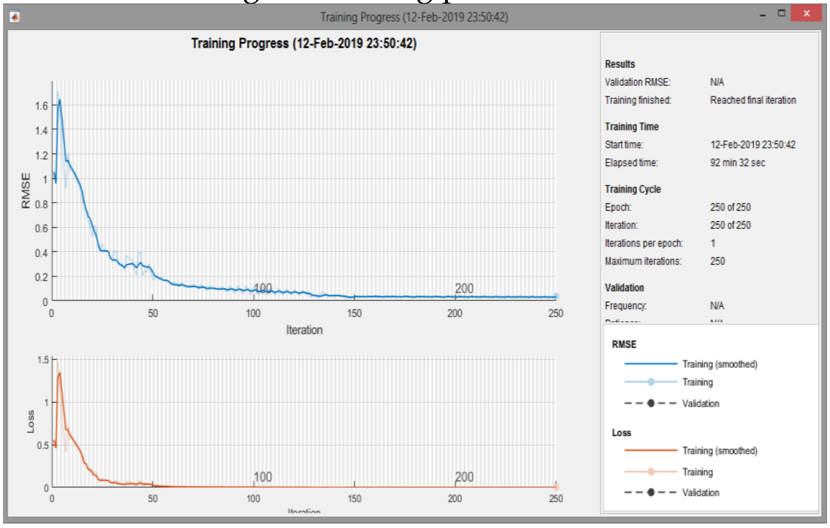
Figure 2.5: Internal Architecture of the LSTM layer [Source: Mathworks]

3. *Results and Discussion*

3.1. Training curves for the Neural Network

3.1.1. The Root Mean Square Error and the number of iterations

The curve below represents the RMSE (Root Mean Square Error) and the number of iterations carried out during the training process.



Training Progress (12-Feb-2019 23:50:42)

Results
Validation RMSE: N/A
Training finished: Reached final iteration

Training Time
Start time: 12-Feb-2019 23:50:42
Elapsed time: 92 min 32 sec

Training Cycle
Epoch: 250 of 250
Iteration: 250 of 250
Iterations per epoch: 1
Maximum iterations: 250

Validation
Frequency: N/A

Figure 3.1: Error curve for Neural Network training

The figure 3.1 above helped us to determine the MAPE (Mean Absolute Percentage Error) in each of the parameters for fault prediction. The MAPE was calculated using equation 2.23 above.

3.2. Results for Common rail injection fault

3.2.1. Correlation between the predicted output and the real output by LSTM

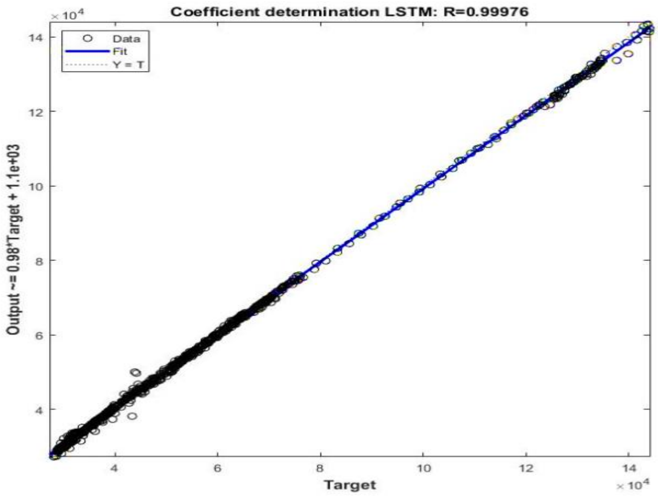


Figure 3.2: Correlation between the predicted output and the real output by LSTM

The LSTM network was implemented using a LSTM layer containing 300 LSTM cells. The optimisation function used was the ADAM algorithm. On the test data, the model produced a MAPE (Error Percentage) of 0.082828%, given a prediction of 99,917172%. With a determination coefficient R = 0.99976. R> 0.7 which interprets a strong relation between the predicted output and the real output. The regression gradient obtained with the LSTM model between the predicted output and the real output is shown in the figure 3.2 above.

3.2.2. The LSTM prediction curve and the Error distribution curve

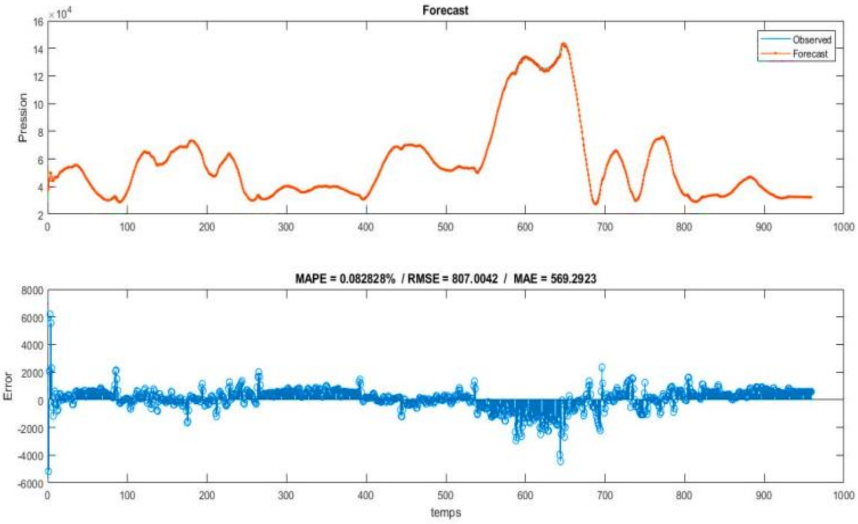


Figure 3.3: The LSTM prediction curve and the Error distribution curve

Figure 3.3 above represents the Real curve (in blue) and the predicted curve (in red) with the LSTM model, and also the Error distribution curve.

3.2.3. Interval view (Zoom) of Common rail injection pressure

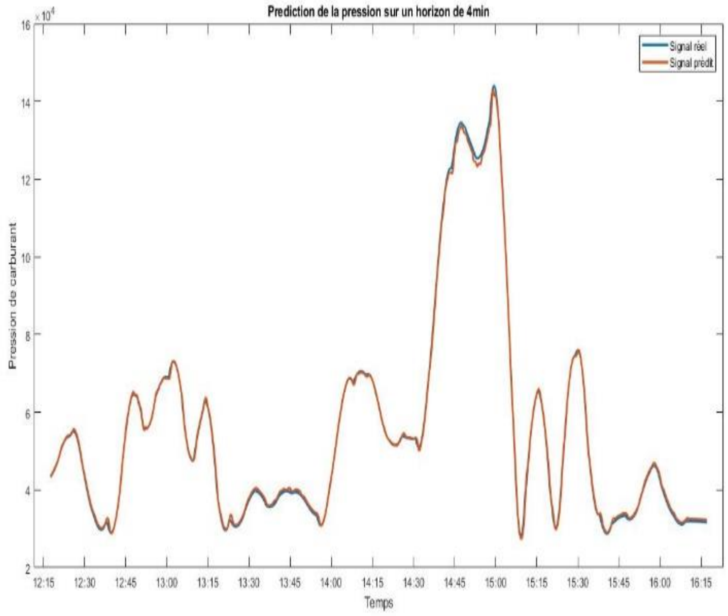


Figure 3.4(a): Zoom 1 of Common rail injection pressure for 4 minutes

The figure 3.4(a) above, presents a very high common rail injection pressure within the time range of 14 :30 – 15 :08 (representing the gap of the 3rd minutes); which equally represents the common rail injection pressure above 14.

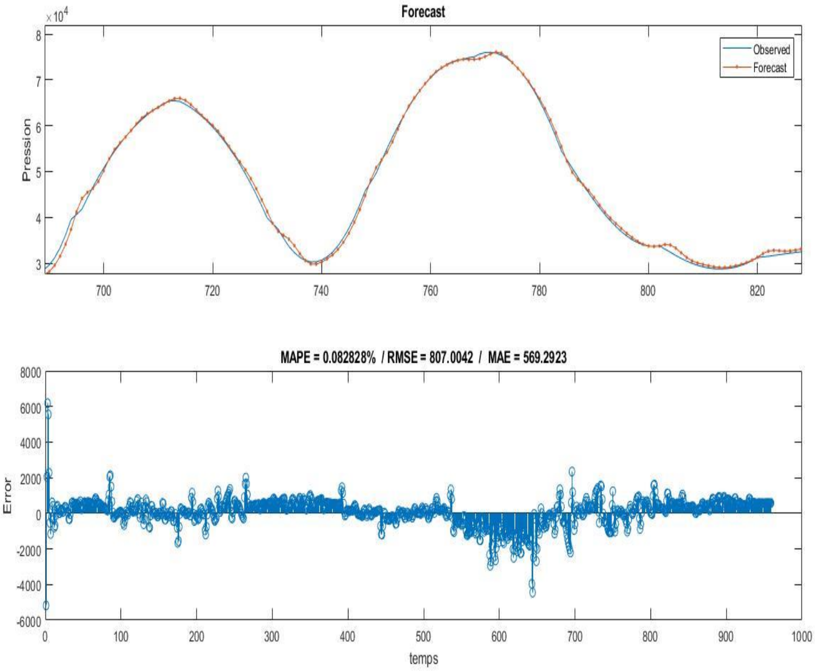


Figure 3.4(b): Zoom 2 of Common rail injection pressure from 700 – 820 seconds

The LSTM model prediction presented in figure 3.4(b) above represents the Real curve (in blue) and the predicted curve (in red) with the LSTM model, and also the Error distribution curve with MAPE = 0.082828%, RMSE = 807.0042, and MAE = 569.2923.

3.3. Results for the fuel consumption fault

3.3.1. Correlation between the real output and the predicted output by the LSTM model of the fault « abnormal increase in fuel consumption»

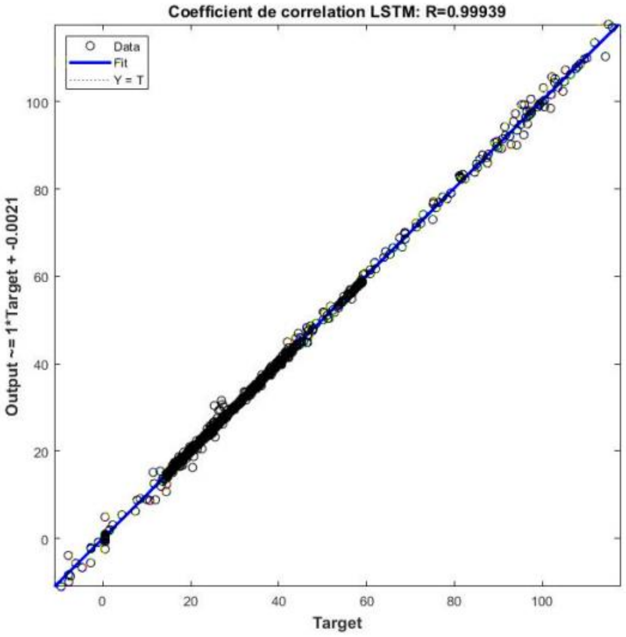


Figure 3.5: Correlation between the real output and the predicted output by the LSTM model of the fault « abnormal increase in fuel consumption»

From the figure 3.5 above, the LSTM network was implemented using a LSTM layer containing 36 LSTM cells, with a Learning gap of 0.005. The optimisation function used was the ADAM (Adaptative Moment Estimation) algorithm, and the convergence was obtained for 300 epochs (iterations). On the test data, the model produced a MAPE (error percentage) of 0.12396%, given a prediction of 99,87604%. With a determination coefficient R = 0.99939. R> 0.7 which interprets a strong relation between the predicted output and the real output. The regression gradient obtained with the LSTM model between the predicted output and the real output is shown in the figure 3.5 above.

3.3.2. *Fuel Consumption prediction with LSTM model and the presentation of the error distribution curve*

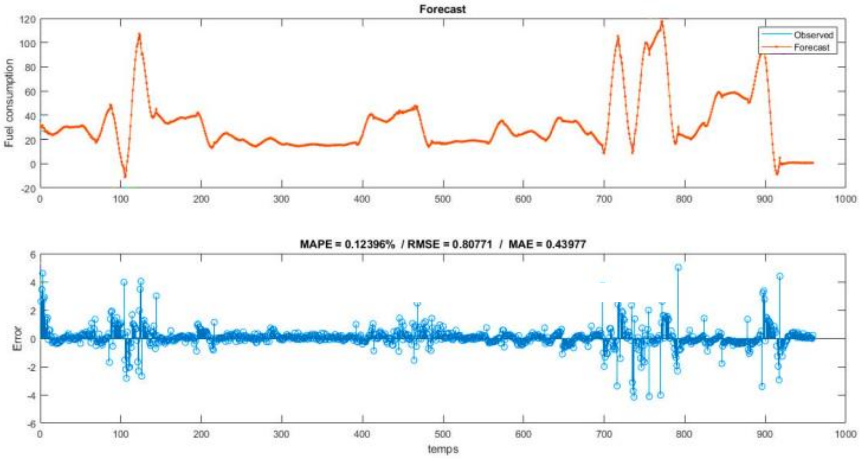


Figure 3.6: Fuel Consumption prediction with LSTM model and the presentation of the error distribution curve obtained.

Figure 3.6 above represents the predicted curve by the LSTM model and also the error distribution curve. We noticed a very similar error distribution with that obtained with the NARX network.

3.3.3. *Interval view (Zoom) of fuel consumption*

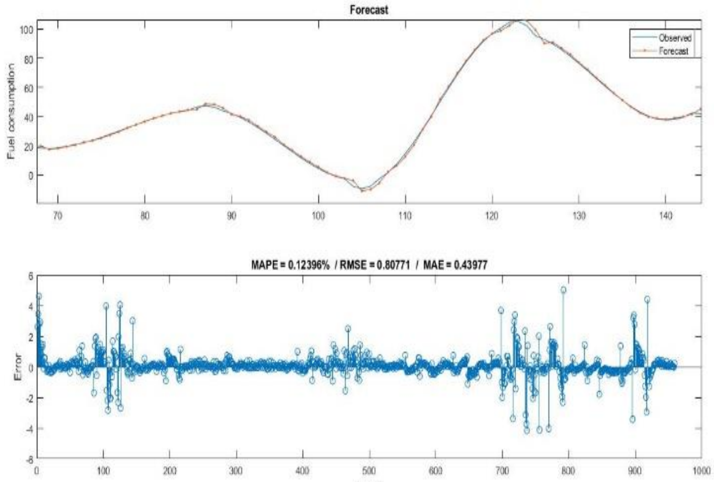


Figure 3.7(b): Zoom 2 of the fuel consumption from 70 – 140 seconds

The maximum fuel consumption with the time range of 110- 130 seconds; with approximately at the time t = 124 seconds recording the maximum fuel consumption of more than 100. The abnormal increase in fuel consumption fault may be due to high engine torque or high air pressure in the intake valve. The LSTM model prediction presents an error of the fault as MAPE =0.12395%, RMSE =0.80771, MAE =0.43977.

3.4. Results of the abnormal heating fault

3.4.1. Correlation between the real output and the predicted output of the LSTM model of the fault « abnormal fuel heating

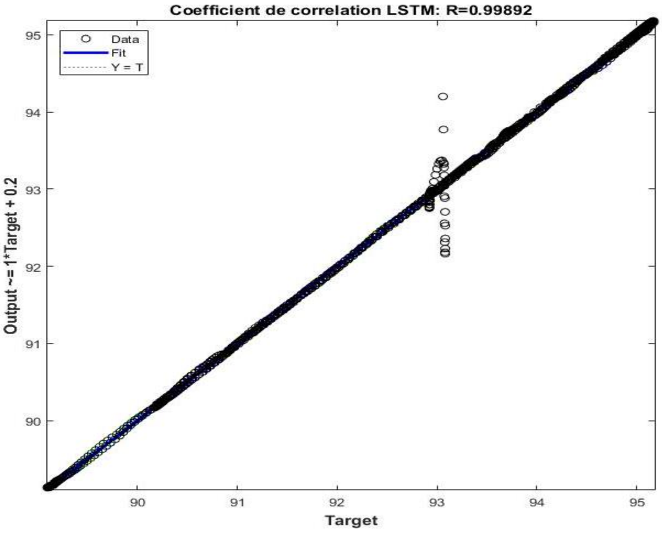


Figure 3.8: Correlation between the real output and the predicted output of the LSTM model of the fault « abnormal fuel heating »

The LSTM network was implemented by using a LSTM layer containing 50 LSTM cells, with a learning gap of 0.005, and an adaptation factor of the learning gap of 0.2. The optimisation function used is the ADAM algorithm, the convergence was obtained for 200 epochs (iterations). For the test data, this model produces a MAPE (error percentage) of 0.2153%, given a precision of 99,7847%. And a determination coefficient R= 0.99892. R > 0.7 which gives a strong relation between the predicted output and the real output. The regression straight line between the predicted output and the real output obtained by LSTM model is represented in figure 3.8 above.

3.4.2. Prediction of the coolant temperature by the LSTM model and the presentation of the obtained error distribution

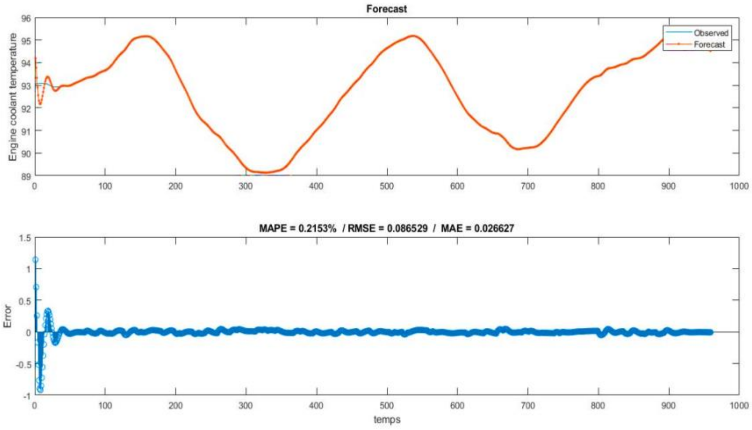


Figure 3.9: Prediction of the coolant temperature by the LSTM model and the presentation of the obtained error distribution.

The Figure 3.9 above represents the predicted curve by the LSTM model, and also the error distribution curve. We noticed a very important error distribution compared to that obtained with the NARX network.

3.4.3. Interval view (Zoom) of the coolant temperature

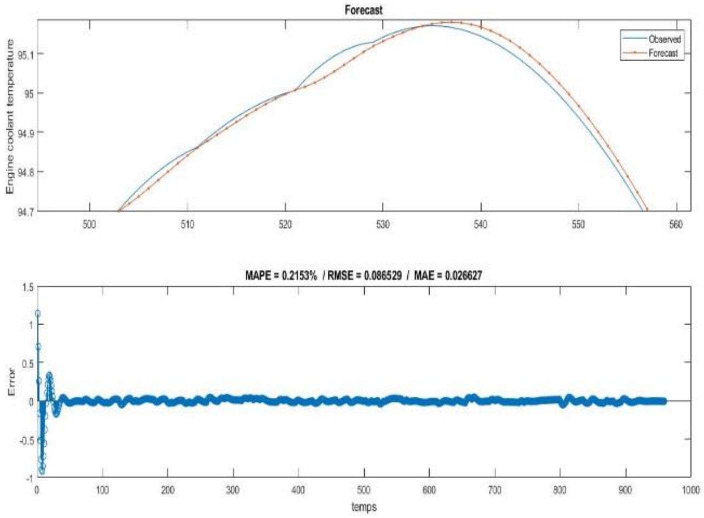


Figure 3.10(b): Zoom 1 of the coolant temperature peak value from 500 – 560 seconds

The zoom figure 3.10(b) shows increase in temperature of the coolant temperature in the graph engine coolant temperature vs time. The engine coolant temperature rises above 86.1 degree celcius within 530 -540 seconds. This temperature value (above 86.1 degreecelcius); which is above the normal engine functioning temperature clearly indicates the occurrence of a fault (the fault may be either: high flow rate of the intake air, high car speed, or high pressure of air in the intake valve). The LSTM prediction gives readings of (MAPE = 0.2153%, RMSE = 0.086529 and MAE = 0.26627).

3.5. The Fault Prediction in the real time

3.5.1. *End of the forecast of the model parameters*

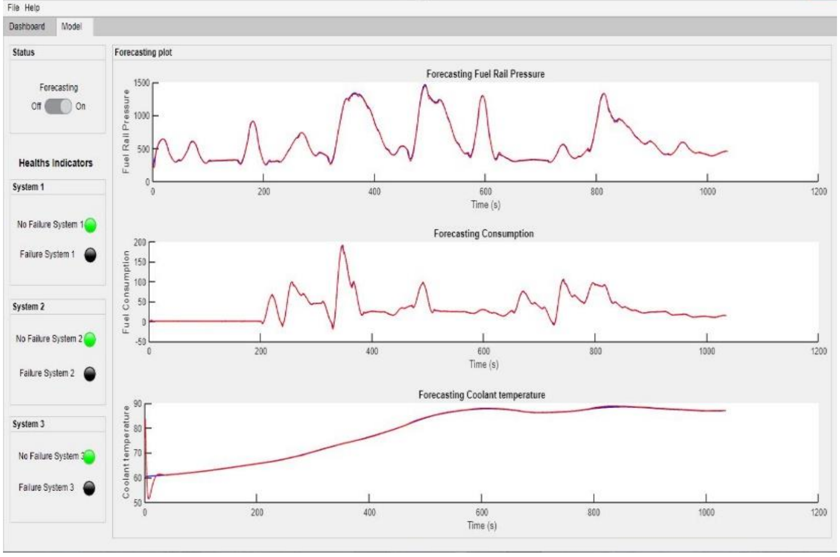


Figure 3.11: End of the forecast of the model parameters

The systems in fig.3.11 above is able to detect anomalies by calculating the probability of the prediction resulted by the fuel rail pressure, fuel consumption and the coolant temperature in the three systems presented above within the maximum data processing time. Once an anomaly is detected (failure system), it is noticed by the immediate indication of a red light on the button below the green light button. As indicated by figure 3.10 above, if the values in each system go above the threshold value (that is to say, the red line or the prediction) are identified as anomalous. The system may indicate that there is a predicted failure in that particular system. The threshold values range for the common rail injection pressure is 200 bars to 1800 bars, that of the fuel consumption is 1000L/100km and the threshold value for the coolant temperature is 100°C.

The LSTM executes the analytic scripts in a given time interval and performs the analytic regression to investigate the current status of the parameters in the system and to check whether there is an impending failure. It estimates the error percentages and the determination coefficients, which intends gives the calculated prediction percentages. The predicted results of the car or vehicle in study may serve for proper maintenance procedures and a better management of the car.

3.6. Troubleshooting classification

From table 3.5 below, it is observed that the state of the engine can be classified following healths indicators readings. When the engine is functioning in a normal condition (good state), the readings in the common rail injection pressure is 1700 bars, the fuel consumption is at 860L/100km and the coolant temperature is at 90°C. Following the end prediction of the model parameters in figure 3.11 above, the healths indicators of the engine state indicates no failure in the system. This is seen by the indication of a green light button.

Still from table 3.5 below, it can be observed that the state of the engine may be classified following healths indicators readings. When the engine is functioning in an abnormal condition (bad state), the readings in the common rail injection pressure appears to be 1810 bars, the fuel consumption is at 1010L/100km and the coolant temperature is at 110°C. Following the end prediction of the model parameters in fig. 3.10 above, the healths indicators of the engine state indicates failure in the system. This may be seen by the indication of a red-light button. Thus, the classification of troubleshooting by the appearance in each of the studied systems is based on the indication of the healths indicators '*no failure system and failure system*' if the threshold value is attained.

Table 3.5: Troubleshooting classification in the vehicle

1	Common rail injection pressure fault		
Healths indicators	Engine state	Readings	Threshold value
	Mean	200 bar	1800 bar
	Good	1700 bar	
	Bad	1810 bar	
2	*Fuel consumption fault*		
Healths indicators	Mean	200 L/100km	1000L/ 100km
	Good	860 L/100km	
	Bad	1010 L/100km	
3	*Coolant temperature fault*		
Healths indicators	Mean	45°C	100°C
	Good	90°C	
	Bad	110°C	

3.7. Results validation

The results obtained using the LSTM model can be validated by comparing the calculated values of the MAPE, prediction % and the LSTM correlation coefficients R, in each of the faults studied from the standard values for the MAPE, prediction % and the LSTM correlation coefficients R. The table 3.6 below summarizes the obtained results.

Table 3.6: Results validation of classification of faults

1	Common rail injection pressure fault		
	Forecast coefficients	Test Result values	Standard values
	MAPE	0,082828%	100%
	R of LSTM	0,99976	1
	Prediction %	99,917172%	100%
2	Fuel consumption fault		
	MAPE	0,12396%	100%
	R of LSTM	0,99939	1
	Prediction %	99,87604%	100%
3	Coolant temperature fault		
	MAPE	0,21530%	100%
	R of LSTM	0,99892	1
	Prediction %	99.784%	100%

We can therefore conclude that the smaller the mean absolute percentage error of the predicted fault, the greater the correlation coefficient and it is more approximately closer to the standard value. Among the three faults studied above the common rail injection fault has a higher prediction percentage due to its low value of the estimated error. We can thus say with satisfactory results obtained; the LSTM model has a very performance for classifying faults in a mechanical system.

4. Conclusion and Recommendations

After obtaining the data from the OBD from the thermal engine, the LSTM model based on data processing techniques and artificial neural network techniques are proposed and verified.

A RNN network trained by the LSTM is shown to achieve 99.999% fault classification of the engine state accuracy when the features are used as its input.

The LSTM-trained RNN network is capable of approximately 100% accurately classifying the vehicle's working conditions with the determination coefficients, the MAPE, and Error distribution calculated.

This model may be implemented to other vehicles to ease maintenance procedures and to keep vehicles in a good state.

Contributions of the study to science

Our interest in this research work is to reduce the number of accidents due to faulty vehicles (reduce the occurrence of failure, which may contribute to road crashes) in an automobile vehicle and to build an optimized and more reliable system in the transport domain, on early fault detection. Deaths and injuries resulting from road traffic crashes remain a serious problem globally and current trends suggest that this will continue to be the case in the foreseeable future (WHO/Global Status on Road Safety, 2018). The performance to be enhanced from this research work shall be the maintenance efficiency and the reduction of risk in the transport systems. Considering the fact that this thesis is focused in giving quick maintenance report and actions in the case of any fault detection in a mechanical system, the prediction of fault in any given system of the vehicle on time may save time and generate more income into the industry or vehicle user.

Recommendations and suggestions

Based on the results and analysis presented in chapter 3, this study proposes the following recommendations for advancing the classification of troubleshooting in vehicle cooling, fuel consumption and rail pressure systems using OBD-II data. The recommendations are organized into domains: methodological, practical, data-related, and future research.

Methodological recommendation

- Shift from DTC- Based to Root-cause Based Classification.

The findings in chapter 3 demonstrate that classifying Diagnostic Trouble Codes (DTC) alone replicates the limitations of existing scan tools. To enhance diagnostic utility, subsequent studies should develop taxonomies that map OBD-II parameters to functional fault categories, such as thermostat-stuck-open, cooling-fan-circuit-fault, and ECT-sensor-failure. This approach aligns computational outputs with the causal reasoning employed by automotive technicians (Figure 3.9: Prediction of the coolant temperature by the LSTM model and the presentation of the obtained error distribution).

Recommendations for practical implementation

- Design for Pre-Diagnostic Trouble Code Prediction.

Results from chapter 3, section show that key thermal signatures (Figure 3.9: Prediction of the coolant temperature by the LSTM model and the presentation of the obtained error distribution). The development of prognostic classifiers capable of issuing Overheat Risk alerts prior to MIL illumination is recommended, as this capability has the potential to prevent secondary engine damage as quantified in section…

Recommendations for Future Research

- Evaluate Multimodal Sensor Fusion

The limitations noted in section 4(Results of coolant temperature) confirms that certain faults, especially Low Coolant Level and Radiator Internal Blockage, cannot be reliably classified from standard OBD-II parameters alone. Future research should quantify the diagnostic gain from fusing OBD-II with low-cost supplemental sensors, such as coolant level switches or differential temperature measurements across the radiator.

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