Feature Selection Combined with Neural Network for Diesel Engine Diagnosis

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Abstract: The Feature selection is an essential step for data classification used in fault detection and diagnosis process. In this work, a new approach is proposed which combines a feature selection algorithm and neural network tool for leaks detection task in diesel engine air path. The Chi^2 is used as feature selection algorithm and the neural network based on Levenberg-Marquardt is used in system behaviour modelling. The obtained neural network is used for leaks detection. The model is learned and validated using data generated by xMOD. This tool is used again for test. The effectiveness of proposed approach is illustrated in simulation when the system operates on a low speed/load and the considered leak affecting the air path is very small.

1 INTRODUCTION

In order to reduce air pollution caused by automotive engine, several legislations are introduced. The first legislation is proposed by the California Air Resources Board in 1970; it has been continuously updated and it became very strict. Since 1993, marked by the introduction of the Kyoto Protocol, the European anti-pollution standards are becoming more stringent where the authorized emissions of a diesel vehicle are decreased from (NOx = nil, CO =2720, HC+NOx=970, PM=140) in Euro1 standard to (NOx = 80, CO =500, HC+NOx=170, PM=5) in Euro6 standard. Typically, each fault that increases the emission level must be detected and isolated. The leaks in the intake canal are among the most difficult faults to manage.

The ability of neural networks to approximate a nonlinear function propels it to become one of the best tools for fault detection and isolation. By exploring these artificial intelligence techniques, another class of fault detection and isolation algorithms is appeared. In (Isermann, 1984), Isermann discussed the superior features of the neural networks in fault classification and recognition. Sorsa and Costin (Sorsa and Costin, 1993) show the capabilities of supervised neural networks as Multilayers Perceptron (MLP) and Radial Basis Function (RBF) to perform a good and effective fault detection and isolation tasks. Another work using MLP network is presented in (Capriglione et al., 2003). The RBF was used in on-board fault diagnosis for the air path of spark ignition engine (Sangha et al., 2006). The leakage problem of gasoline-engine is treated in (Chen, 2011) where the neural network based on the steepest-descent method combined with a back propagation algorithm is developed to train three detection systems.

Because of an increased complexity of the today engines which are characterized by an important number of sensors, the reduction of the acquired data becomes essential. Feature selection is one of important step before beginning a data classification task, especially when this task is dedicated to fault detection and isolation (FDI). It refers to the problem of selecting the input features that are most predictive for given outcome. The feature selection problems are found in all supervised and unsupervised machine learning which include classification, regression, time-series, prediction and clustering. The feature selection tasks try to achieve three main purposes: reduce the cost of extracting features, improve the classification accuracy and the reliability of the estimated performances.

There are many works that used the feature selection algorithm for fault detection and diagnosis. In reference (Christina and Tshlizidzi, 2006), a new approach for intrusion detection and diagnosis is

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proposed. In (Sugumaran et al., 2007), the authors use the decision tree to identify the best features in classification task, they use a proximal support vector machine characterized by its capability to classify efficiently the faults in Roller Bearning system.

In this paper, new methodology dealing with small leaks detection problem in diesel air path is developed. To achieve this goal, a new scheme based on neural network technique is proposed. The nominal mode (without leak) and leakage mode corresponding to several diameters of leak were trained using a Levenberg-Marquardt algorithm. Before using the acquired data, a feature selection task is proposed in order to reduce the complexity of the problem. The main challenge of the proposed approach is the use of a selected sensors leading to a reduced cost. The data of two considered modes are generated using xMOD platform which will be described later.

The paper is organized in this way. First, the considered problem is presented in section 2. Section 3 describes the proposed approach in details where a brief description of neural networks used, which based on steepest-descent and Gauss-Newton method, is given and main detection scheme is illustrated. After a brief description of xMOD tool used in engine data collecting, the section 4 gives some obtained results using our approach. Then, these results are discussed and commented in order to illustrate the effectiveness of leakage detection.

2 PROBLEM STATEMENT

For several years, the anti-pollution standards are dramatically increased and the constraints in automotive industry become very complex. The main objective of these standards is to reduce the emissions level of cars. In the case of diesel engines, there are several pollutants: carbon monoxide, unburned hydrocarbons, nitrogen oxides (NOx) and diesel particulates mater. Usually, the emissions level proportionally increases with the appearance of faults in diesel engines, more precisely in diesel air path. These faults can be due to sensor failures, actuator failures or system degradation. In this paper, the last failures class is considered. More precisely, the leakage detection in diesel air path is studied. This failure can cause multiple non-desired system behaviour. In addition to the high emissions level, this failure causes multiple non-desired effects such as:

- Operating points changing of the air path subsystems,
- Incomplete combustion in cylinders,
- Appearance of smoke and the reduction of performances.

Often, this type of failure can be confused with the two other types of faults, i.e. sensors or actuators; consequently, it is very important to distinguish this fault from others.

Additionally to the main objective of this paper, the feature selection problem is considered. We all know that today’s vehicles are characterized by an increased complexity justified by the important number of embedded sensors which grow significantly. Consequently, the uses of selected subset of sensors data which are correlate the considered problem is widely desired in such applications.

In this work, our main objective is to detect air leaks in diesel air path regardless of their diameters. Before performing leaks detection, we make a feature selection in order to reduce the data complexity.

It is important to specify that, for this application, small leaks are hidden and are very difficult to detect because of phenomenon of non-solicitation system.

3 PROPOSED APPROACH

Nowadays, the neural network is an essential tool used in many research activities for industrial complex systems. An advantage of using neural network to detect faults of systems is that it can get the knowledge denoted by data. Over and above remembering ability of learned information, a neural network has both, ability to generalize an obtained model and apply the associative property into the available memory. The error tolerance, characterizing the neural network, effectively treats the errors of the model. Additionally, it can perform a nonlinear mapping and also learn dynamic behaviors in order to generalize the obtained models.

Generally, the collected data for detection process are noisy, but, the error tolerance ability of neural network makes the detection scheme be able to differentiate the pattern from noise. So, the last property is a huge advantage in fault detection and isolation problem. Additionally, the similar patterns are separated using a generalization property characterizing a neural network.

The leak detection in intake system is very difficult to achieve especially when the operating point corresponds to low load-torque couple. In these conditions, the compressor in air path is not solicited by the driver, allowing to a similar pressure between the intake system and atmospheric one. This constraint needs an improved detection system. The proposed system must, increase the accuracy of model, enhance the performances of vehicle and grantee the management of small leaks. In this paper, the Levenberg-Marquardt (LM) algorithm (Levenberg, 1944) is proposed to realize the detection tasks. The LM algorithm is used to train the air path diesel dynamics. Ones the dynamics are modelled, the leak is detected by comparing the new measurements with model established using neural network. The proposed approach contains two blocks which are the training block and the decision block. This approach is shown in this diagram.

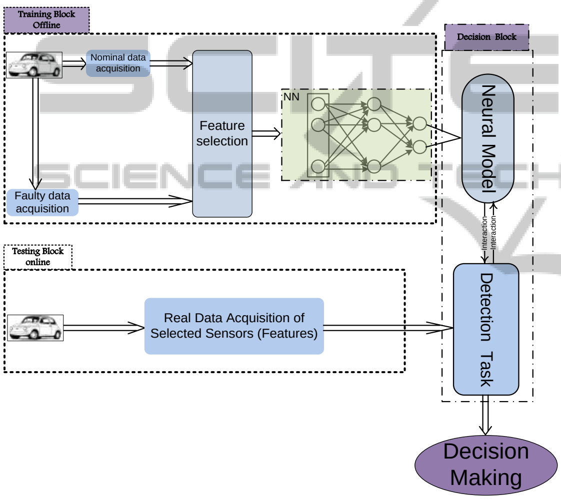

Figure 1: Detection scheme.

The proposed approach is designed to operate on on-line mode, thus, a classical process of real data acquisition is adopted in this work. It is important to remember that in this application we only use sensors selected by feature selection algorithm and summarize the intake behaviour of diesel air path. The data acquired in this step are sent to the decision block in order to detect the leaks affecting vehicle.

3.1 Training Block

3.1.1 Feature Selection

In this work, a most popular feature selection is chosen; it is Chi2 algorithm (Alexandrov et al., 2001). Chi2 is simple and general algorithm which achieves feature ranking using a discretization process. This algorithm is combined with neural network classifier to select the feature that we must keep.

The Chi2 algorithm is based on the X^2 which runs on two stages in this manner:

- **Stage1:**

1) Set the *sigLevel* to 0.5 for all features;
2) Sort each feature according to its values;
3) Compute the X^2 value for every pair of adjacent intervals;

$$X^2 = \sum_{i=1}^{2} \sum_{j=1}^{k} \frac{(A_{ij} - E_{ij})^2}{E_{ij}} \quad (1)$$

Where:
k: number of class;
A_{ij}: number of samples in the ith interval and jth class;
R_i: number of samples in the ith interval;
G_j: number of samples in the jth class;
N: total number of samples;

$$E_{ij} = R_i * C_j / N \quad (2)$$

4) Merge the pair of adjacent interval with the lowest X^2 value until the X^2 value of each pair of adjacent intervals exceeds *sigLevel*;

This process is repeated by decreasing *sigLevel* until inconsistency rate δ is exceeded in the discretized data.

- **Stage2:**

5) Start with the *sigLevel0* corresponding to the last value of *sigLevel* determined in the first stage;
6) Associate *sigLevel(i)* with each features and run merging;
7) Consistency test:
If inconsistency $<\delta$ merge intervals and decrease *sigLevel(i);*
Else if inconsistency $>\delta$ eliminate the ith features for the next step.

Firstly, the WEKA (Witten et al., 2005) data mining tool is used to perform Chi2 ranking. The features are sorted according to their rank. Secondly the most important features are selected using the neural network classifier which will be described later. More precisely, the features will be eliminated iteratively from least important to most important and the weight of the eliminated feature is evaluated according to the obtained classification Mean Squared Error (MSE).

3.1.2 Training

Pattern classification using neural network aims to determinate the class boundaries by the classifier. The training phase of neural network achieves this

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goal. In this paper, a gradient-based training algorithm is used. This category of algorithms is most commonly used by researchers. One of these algorithms is Hessian-based algorithms; they can significantly reduce the convergence time. The Levenberg-Marquardt algorithm belongs to Hessian-based techniques; it makes use the advantages of Hessian-based algorithm in the optimization of nonlinear least squares.

The Levenberg-Marquardt algorithm is a well-known optimization technique. It locates the minimum of a function which is expressed by the sum of squares of nonlinear functions. This algorithm, widely used in several disciplines, is a combination of Steepest-Descent with Gauss-Newton method. According to the current position compared with the correct one, these techniques act by intermittently; if the current position is far then the correct one the steepest-Descent is applied, by against, if it's neighboring the current solution, the Gauss-Newton takes over. The Steepest-Descent technique used in LM algorithm is slow, but it guarantees the convergence property. When the current position becomes near to correct one the LM algorithm switches to Gauss-Newton method which converges rapidly.

For the neural network training the objective function is the error of the type:

$$MSE = \frac{1}{2}\sum_{k=1}^{p}\sum_{i=1}^{n_0}(y_{kl} - a_{kl})^2 \tag{3}$$

Where y_{kl} are real data of diesel engines, a_{kl} are a network output, p is the total number of samples and n_0 represents the total number of nodes in the output layer.

In this work, the used neural network contains five layers. The first layer is the input layer which receives the data corresponding to the selected sensors which are used in this application. The three following layers are the hidden ones which represent the network core. The last one is the output layer which generates two signals corresponding to the detection task ("without leak" or "with leak").

The steps required in neural network using L-M algorithm in batch-mode training are the following:

- Compute the corresponding network outputs and evaluate the mean square error for all inputs as in equation (1);
- Calculate the Jacobian matrix *j(x)*, where x represents the weights and biases of the network;
- Solve the equation which adapts weights in order to obtain Δx, The update of the weighted vector Δx is computed as follows:

$$\Delta x = [J^T(x)J(x) + \mu I]^{-1}J^T(x)R \tag{4}$$

Where μ is the training parameter and R is a vector of size pn_0 computed as follows:

$$R = \begin{pmatrix} y_{11} - a_{11} \\ y_{12} - a_{12} \\ \dots \\ y_{21} - a_{21} \\ y_{22} - a_{22} \\ \dots \\ y_{pn_0} - a_{pn_0} \end{pmatrix} \tag{5}$$

$J^T(x)J(x)$ is referred to as the Hessian matrix.

- Recalculate the error using $x + \Delta x$. If there is the reduction of the error calculated in step 1, the training parameter μ is reduced by μ^-, keep $x = x + \Delta x$ and return to the step 1. If there is not reduction, increase μ by μ^+ and go back to step 3. μ^+ and μ^- are fixed by the user;
- The algorithm is stopped in two cases; when the gradient is less than the predefined value, or when the error is reduced to some error objective.

Generally, the training step in neural network is very complex and it needs important computing resources, especially in on-line case. In this work, the training problem is realized in off-line mode, then, the obtained neural model is used to detect leakage in on-line mode. The adopted neural network returns both the nominal behaviour corresponding to the system without leakage and the faulty system behaviour (occurrence of leakage).

3.2 Decision Block

The decision block is the most essential components of the proposed scheme where the leaks in the intake of air path are detected using the neural model developed in the training step. Direct interactions are established between the detection block and the neural network model in order to estimate the actual state of the system. The decision block works on "detection mode" to distinguish between "No Leakage" and "Leakage" modes.

4 APPLICATION

Critical operating mode system is considered to illustrate the effectiveness of the proposed approach. This mode concerns the case of low "load/engine speed" couple, where the leak detection problem is not systematically realized. In this application the data acquisition is realized using xMOD tool software.

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4.1 xMOD Tool Software

xMOD is a software platform that was developed at “IFP Energies Nouvelles” combining both environmental of heterogeneous models integration and a virtual experimentation laboratory. These heterogeneous models are generated by different simulation tools, like Matlab/Simulink, AMESim, Dymola, SimulationX, GT Power … etc. An optimal combination of these latter enables collecting the advantages of each modeling and simulation tool, and the user can freely select these tools.

In this work, xMOD is used to simulate the diesel engine functioning, especially, the air path behaviour. The simulation model produced by IFP “Energies Nouvelles” is used on which a leak model has been added. The diameter of the leak can freely be adjusted. The results of simulation can be recovered and stored on text files.

4.2 Mse Evolution: Selected Feature Vs. All Features

Before presenting the results with selected features, a comparison of MSE evaluation of a both all and selected features is presented in table I.

In order to illustrate the advantage of feature selection, the MSE values are jointly showed with theirs training run times. In this table, we can firstly observe that MSE values corresponding to the use of all features are greater than MSE values when the selected features are used. Secondly, we observe that the run time corresponding to the use of all features is always higher than when the selected features are used. For example, when the torque value is set to 40Nm, all MSE values of the all features case are greater than those corresponding to selected features case. The same conclusion can be made for the remained three cases except some values. The detection task results are presented for the selected features case.

4.3 Detection Task Results

The main property of the proposed approach is the detection ability. In this situation, the neural network trains two classes which are “No Leakage mode” and “Leakage mode”. The training set consists of 10000 samples without leak and 10000 samples with leak. We choose three values of leak, 0.1mm, 0.4mm and 0.9mm.

1) Case1: Leak = 0.1mm:

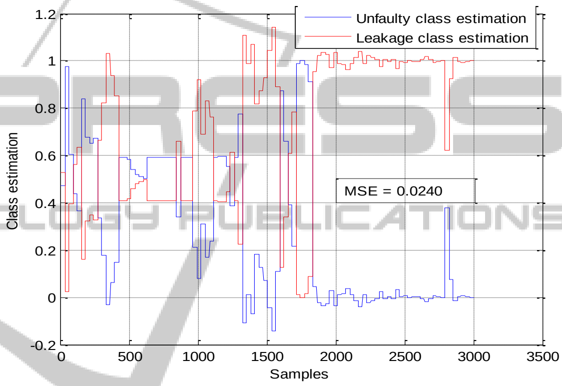

Figure 2: Engine_speed = 1000 rpm & torque =110 Nm.

Table 1: MSE evolution with torque variation.

Torque	40Nm (MSE/Run Time)		110Nm (MSE/Run Time)		130Nm (MSE/ Run Time)		150Nm (MSE/Run Time)	
Leaks	All Features	Selected Features	All Features	Selected Features	All Features	Selected Features	All Features	Selected Features
0.1mm	0.208/14’59”	0.0221/10’35”	0.168/12’40”	0.0166/10’41”	0.167/14’50”	0.0109/8’40”	0.00547/15’06”	0.00799/8’59”
0.2mm	0.0449/16’29”	0.0189/8’49”	0.00790/12:44	0.0147/8’55”	0.00988/13’10”	0.0163/8’45”	0.00083/15’47”	0.000812/10’15”
0.3mm	0.0270/18’44”	0.0114/9’19”	0.00608/12’52”	0.00871/9’44”	0.00298/16’23”	0.00266/8’45”	0.00430/14’17”	0.00165/10’03”
0.4mm	0.0205/15’24”	0.0204/9’25”	0.00239/14’39”	0.00413/10’15”	0.00219/13’55”	0.00401/10’53”	0.00273/13’23”	0.00419/11’38”
0.5mm	0.0186/18’41”	0.0127/8’34”	0.00458/14’02”	0.00369/7’57”	0.00156/12’22”	0.00222/10’23”	0.00208/13’44”	0.00428/11’25”
0.6mm	0.0121/15’50”	0.00807/9’30”	0.00447/14’17”	0.00315/9’52”	0.00351/14’12”	0.00104/9’34”	0.00656/15’00”	0.00221/11’04”
0.7mm	0.0180/15’57”	0.00404/9’43”	0.00669/16’11”	0.00234/9’07”	0.00100/8’02”	0.00102/8’40”	0.00601/14’33”	0.000873/10’01”
0.8mm	0.00867/17’26”	0.00727/8’21”	0.00584/13’42”	0.00198/9’54”	0.00099/7’18”	0.00101/9’56”	0.000897/13’35”	0.00193/9’52”
0.9mm	0.00618/14’30”	0.00910/8’56”	0.00451/13’32”	0.00415/9’33”	0.00211/13’28”	0.00131/8’58”	0.00270/13’36”	0.00087/11’29”
1.0mm	0.00989/13’11”	0.00638/9’14”	0.00217/15’01”	0.00111/9’43”	0.00102/13’10”	0.00099/5’09”	0.00392/13’15”	0.000896/8’41”

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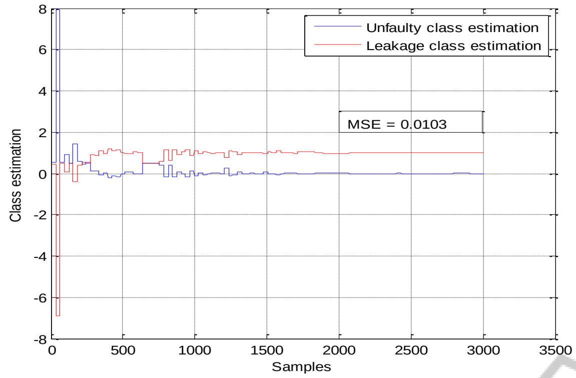

Figure 3: Engine_speed = 1000 rpm & torque =130 Nm.

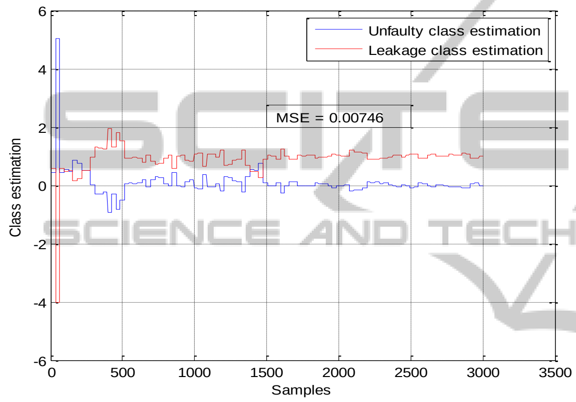

Figure 4: Engine_speed = 1000 rpm & torque =150 Nm.

1) Case2: Leak = 0.4mm:

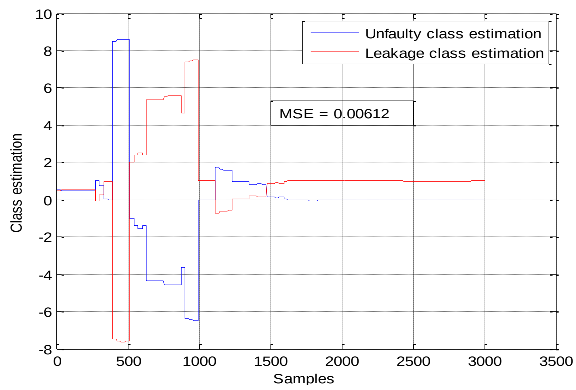

Figure 5: Engine_speed = 1000 rpm & torque =110 Nm.

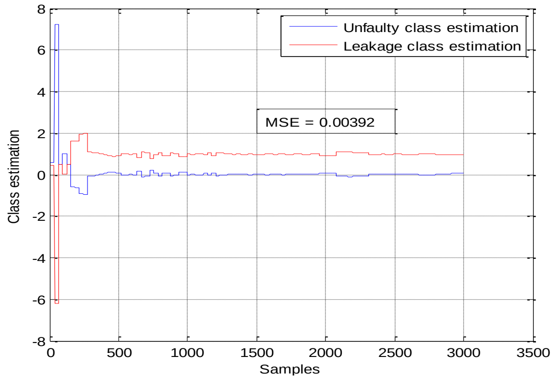

Figure 6: Engine_speed = 1000 rpm & torque =130 Nm.

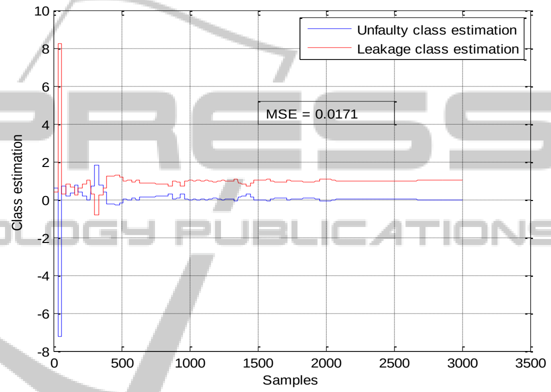

Figure 7: Engine_speed = 1000 rpm & torque =150 Nm.

1) Case3: Leak = 0.9mm:

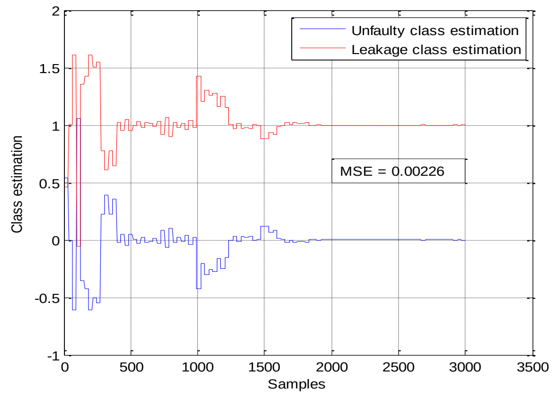

Figure 8: Engine_speed = 1000 rpm & torque =110 Nm.

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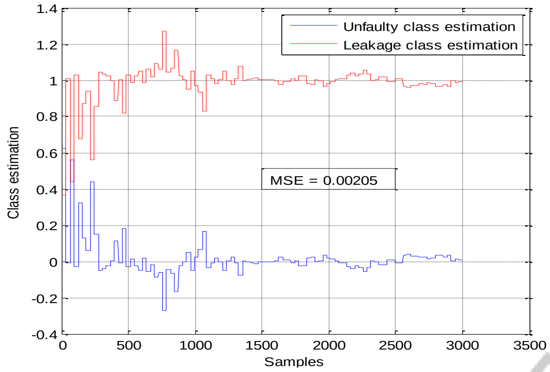

Figure 9: Engine_speed = 1000 rpm & torque =130 Nm.

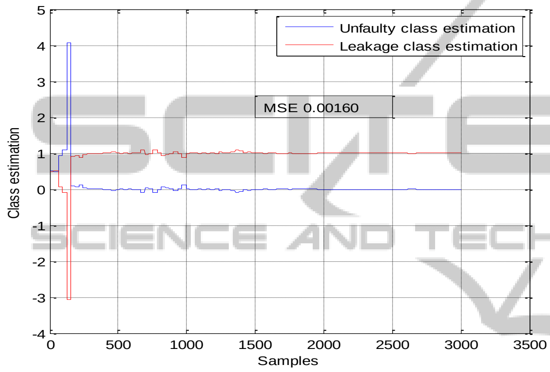

Figure 10: Engine_speed = 1000 rpm & torque =150 Nm.

Interpretation

The exposed figures (Fig.2 to Fig.10) show the effectiveness of the proposed approach where we can see that the leak is detected for all considered diameters. Mean Squared Error (MSE) values give information about the accuracy of the used neural network. From the obtained results we can first remark that the MSE values increase when the torque values decrease. For example, in the first case (Fig.2 to Fig.4) when the leak diameter is set to 0.1mm, the MSE value decreases from 0.0240 (2.4%) to 0.00746 (0.7%) when the torque increases from 110Nm to 150Nm. this observation can be explained by the fact that air path system (compressor) works in reduced operating. On other words, in the low speed, the mechanical compressor of the air path is not solicited. The same remark is applied in both cases 2 and 3.

Naturally, the leak is easily detected when it’s important, but, it becomes strongly difficult to detect it in very small case. The obtained results show that proposed approach can effectively address the problem and the leak is detected in all cases even when it is equal to 0.1mm (almost negligible leakage).

5 CONCLUSIONS

A leak detection approach for diesel air path has been developed. The proposed approach contains two blocks: training block and decision block. The first one is realized off-line and combines feature selection algorithm with neural network which based on the Levenberg-Marquardt optimization. The L-M function was chosen for its accuracy and adaptation; it combines two different techniques according to the current position of the solution compared to the best one. The second block uses the neural model obtained in training phase in order to detect leaks that appear in air path system. The detection capability is evaluated using the MSE index.

The proposed approach effectively achieves the leak detection process, especially in the case of small leaks in critical operating points (low Torque/speed couple).

In a future work, this approach will be extended in the case of leak characterisation in Diesel engine air path. The final objective in this work is to implement obtained algorithms in a real diesel engine.

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