The gas emissions temperature in relation of CO, HC, NO and smoke

Charalampos Arapatsakos, Dimitrios Christoforidis

Abstract: - Clean air is an important factor in the quality of life. Therefore, air pollution is something that we cannot really ignore, as it affects negatively the environment and consequently the sustainability of our lifestyle and production methods. Air pollution is evident from the moment we step out of our house and greeted with black colored smog that hit us directly. This smog is not due to climate but rather due to each and every one of us. This work examines the correlation of exhaust gases temperature and rounds/min with gas emissions (CO, HC, NO, smoke) in a four-stroke diesel engine, using Multillayer Perceptrons (MLP) Networks. The Multilayer Perceptrons Network relates with high precision the temperature of exhaust gases and rounds/min of the engine, with gas emissions. The importance of this work is that when measuring the exhaust gases temperature and the rounds/min of engine forecast with very high precision their gas emissions. The comparison of results became using measurements from the real function of engine.

Key-Words: - Gas emissions, Multillayer perceptrons (MLP) networks

I. INTRODUCTION

Air pollution includes all contaminants found in the atmosphere. These dangerous substances can be either in the form of gases or particles. The main sources of air pollution are the industries, agriculture and traffic as well as energy generation. Some of these substances are not directly damaging to air quality but will form harmful air pollutants by reactions with other substances that are present in air. Because it is located in the atmosphere, air pollution is able to travel easily. As a result it is a global problem that it needs to be considered globally. The sources of air pollution are both natural and human based. Humans have been producing increasing amounts of pollution as time has progressed and they now account for the majority of pollutants released into the air. Some examples of human sources are traffic, agriculture or industries. Natural sources are being dust storms, volcanic eruptions and emissions from plants. Also the weather plays an important role in the formation and disappearance of air pollution. This is mainly influenced by wind and temperatures. Some areas and mainly cities with large number of automobiles or those that use great quantities of coal often suffer more severely from problems of air pollution. Furthermore the internal combustion engines that burn fossil fuels such as gasoline and petroleum. These fuels are used because they release significant amounts of energy when they are being burned[1].

The pollutants that are being produced from internal combustion engines include carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NOx) and smoke.

Carbon Monoxide is produced from the exhaust of motor vehicle, the burning of materials such as coal, oil and wood and releases from industrial processes and waste incineration. Carbon Monoxide can be harmful for humans because it reacts with hemoglobin and forms carboxyhemoglobin that reduces the oxygen-carrying capacity of the blood [1,2]. Furthermore, carbon monoxide can be converted to carbon dioxide (CO_2) when it reacts with hydroxyl radical (OH) [2]. Carbon dioxide contributes to long-term environmental damage because it has effect on global warming of the atmosphere (greenhouse effect) [3,45]. Heat from the flow of exhaust gases is transported in to the environment.

′′Constructal′′ method can be applied to the flows of heat in the atmosphere and also to determine the optimal distribution and sizes of discrete heat sources in a vertical open channel cooled by natural convection[4].

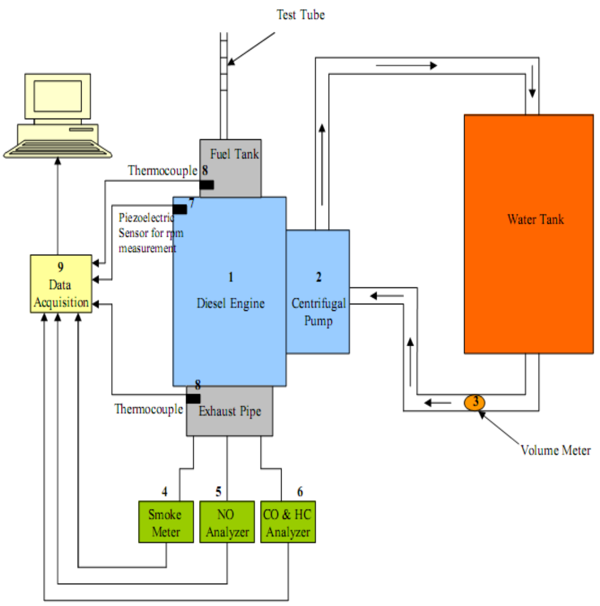
Hydrocarbons are released to the environment as a result of fuel combustion processes. The largest fuel sources are the natural gas and petrol. Hydrocarbons can enter the environment both as evaporative emissions from vehicle fuel systems, or in exhaust emissions. They are also a component of the smoke from wood fires. Some hydrocarbons such as benzene and 1,3-butadiene are toxic and can cause cancer to humans [2]. Reactive hydrocarbons can contribute to ozone production [5]. The oxides of nitrogen can cause human respiratory tract irritation and can contribute to photochemical smog. When nitrogen oxides combine with water produce acids which means that can contribute to acid rain formation [6,7]. The health effect of particulate matter depends on the size of the particulate. Very small particulates are not filtered at the nose and can travel into the lungs causing tissue damage [8,9,10,11,12].

Today the measurements of exhaust gases become with gas analyzers which are adapted in the extraction of exhaust gases. The question that arises is if exists correlation between the temperature of gas emissions and the rounds/min of engine with the gas emissions. This correlation was developed with the help of Artificial Neural Networks. The artificial intelligence has been applied successfully in various fields, bringing a new approach for solving complex problems. The main representatives of artificial intelligence are Neural networks with an open field of research in the international bibliography and with many successful applications too. In order to deal with the problem, by taking into a great degree its natural dimension, it has been given a significant advantage in neural networks over conventional methodologies, which are mainly based on purely mathematical approach to the problem. Neural network is a series of weighted non linear functions, selected a-priory and it is characterized by the process of learning, aiming to identify best price vector weights in order to approximate a function with unknown analytical form.

II. INSTRUMENTATION

For the tests used four-stroke air cooled diesel engine, with one cylinder, named Ruggerini type RD-80, volume 377cc with one cylinder and max power 8.2hp/3000rpm. The engine was connected with a centrifugal water pump.

The engine was function on in accidental rounds with different real load conditions, using as fuel mixture of diesel-60% palm oil. During the experiments, it has been measurement, the %,CO the HC(ppm), the NO(ppm), the % smoke, the gas emissions temperature and the rounds of engine. The measurement of rounds/min of the engine was made by a portable tachometer (Digital photo/contact tachometer) named LTLutron DT-2236. Smoke was measured by a specifically measurement device named SMOKE MODULE EXHAUST GAS ANALYZER MOD 9010/M, which has been connected to a PC unit. The CO and HC emissions have been measured by HORIBA Analyzer MEXA-324 GE. The NO emissions were measured by a Single gas analyzer SGA92-NO. The experimental layout appears in the following picture:



Picture1. Experimental layout

2.1 Artificial Neural Networks

Humans over the years were trying to understand the way that human brain is thinking. And as the Neurology discovers that brain consists of a huge number of biological neurons (figure 1) this was a great step for analyzing the way that brain "functions".

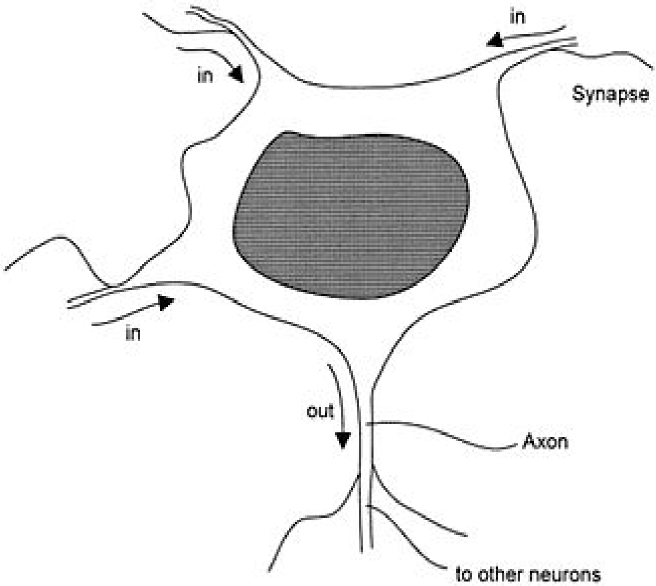


Figure 1. A structure of a typical biological neuron.

So in recent years with the invention of the computational machines trying to resemble the brain, they discover Artificial Neural Networks. And as Haykin says, (Neural Networks A Comprehensive Foundation)[12]: "A neural network is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available for use." We can also say in a more sophisticated definition that: Artificial Neural Networks (ANNs) are highly distributed parallel parameterized interconnections of adaptive nonlinear processing elements (PEs) (also called neurons or cells). In computer implement, the PE is a simple sum of products followed by nonlinearity (McCulloch-Pitts neuron)[13]. An artificial neural network is a collection of such interconnected PEs (figure 2). The connection strengths, also called the network weights, can be adapted such that the network's output matches a desired response[14,15,16].

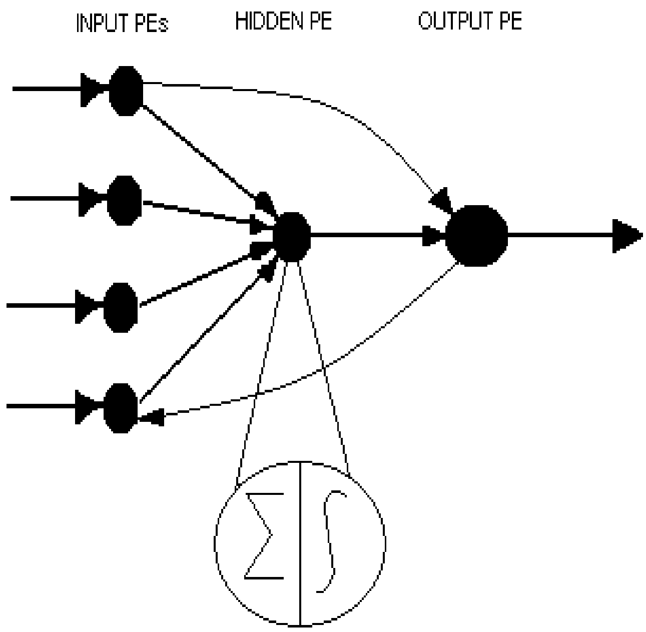


Figure 2. Artificial Neural Networks

$$x_i = \sigma\left(\Sigma\, w_{ij}\, x_j\right)$$

$\mathbf{x_j}$ are the inputs to j unit j, $\mathbf{x_i}$ is the output of unit i, $\mathbf{w_{ij}}$ are the weights that connect unit j to unit i, where $\boldsymbol{\sigma}$ is a nonlinearity.

Distributed computation has the following advantages:

- reliability,
- fault tolerance,
- high throughput (division of computation tasks)
- cooperative computing,

but generates problems of locality of information, and the choice of interconnection topology. Adaptation is the ability to change a system's parameters according to some rule (normally, minimization of an error function). Adaptation enables the system to search for optimal performance, but adaptive systems have trouble responding in a repeatable manner to absolute quantities. Nonlinearity is a blessing in dynamic range control for unconstrained variables and produces more powerful computation schemes (when compared to linear processing) such as feature separation. However, it complicates theoretical analysis tremendously. These features of distributed processing, adaptation and nonlinearity are the hallmark of biological information processing systems. ANNs are therefore working with the same basic principles as biological brains, but probably the analogy should stop here[16]. We are still at a very rudimentary stage of mimicking biological brains, due to the rigidity of the ANN topologies, restriction of PE dynamics and timid use of time (time delays) as a computational resource. A more detailed view of one of the PEs is shown in the figure 3:

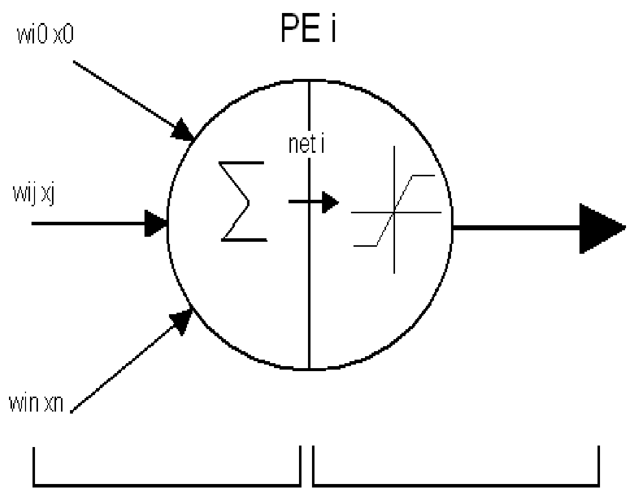


Figure 3. The McCulloch-Pitts processing element

Two basic blocks can be identified: a linear map, the weighted sum of activations from other units (implemented as a sum of products) which produces the local variable net_i given by

$$\mathbf{net_i = \sum_j w_{ij}\, x_j}$$

and an instantaneous nonlinear map that transforms net_i to the output variable xi, the activation of i-th PE, given by

$$\mathbf{x_i = \sigma(net_i)}$$

Here w_{ij} are the weights feeding the i-th PE, x_j is the activation of the j-th PE, and the summation runs over all the PEs that feed the i-th PE.
In general, the form of the nonlinearity is a smooth, monotonically increasing and saturating function. Smooth nonlinearities are required when error back propagation learning is used.

2.2 Network Topology

In this paper we are trying to find a "function approximation" Neural Network to connect the input data with the desired output data. A "very good" topology of the ANNs that is used for this purpose is called Multilayer Perceptrons (MLP). Multillayer Perceptrons (MLP) Networks invented from the need of "producing" a much larger class of discriminate functions (to approximate any continuous function to an arbitrary accuracy). Multilayer neural networks employ adaptive basis functions with parameters (weights) that may be estimated from the training data. It's a feed forward-supervised network. The MLP networks constituted from 1 Input Layer, 1 Output Layer and 1 or more Hidden Layers (figure 4):

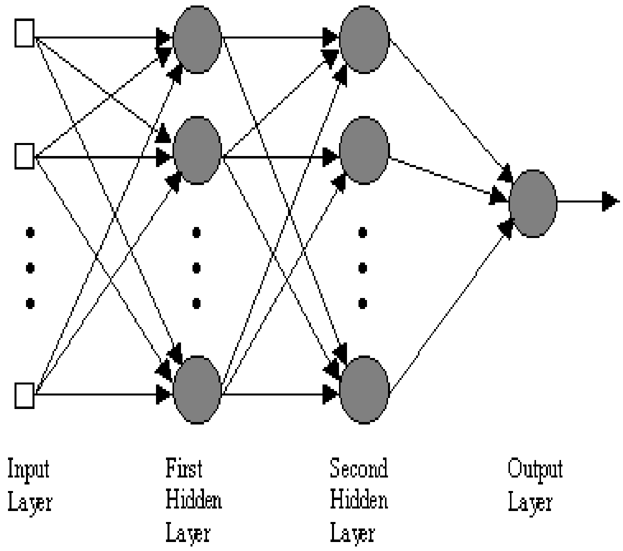


Figure 4. A graphical representation of a MLP

2.2.1Bulding the ANNS

In our case we build a network with one input layer, two hidden layers, and one output layer. The Input Layer has two neurons (as our input values) which are the Exhaust's Temperature and the rpm of the engine. The first hidden layer has thirty five neurons (also called processing elements PEs), the second hidden layer has twelve neurons and the Output Layer has four neurons which are the four Emissions of the Engine such as smoke(%), CO(%), HC(ppm), NO(ppm).We trained the Network with the backpropagation algorithm using the gradient descent method, with transfer function the Hyperbolic Tangent in the 2 hidden layers and the output layer also, and the Momentum learning rule. For comparing the desired output with network output, we used the L_2 Criterion which implements the quadratic cost function. This is by far the most applied cost function in adaptive systems. The error reported to the supervised learning procedure is simply the squared Euclidean distance between the network's output and the desired response.

2.3 Train And Testing The ANNS

We first randomized the data to avoid the overtraining of the network. Then we normalized the input data and we trained the network with data. In the training procedure we train the network trying to minimize the MSE training using 5000 epochs. Finally we test the network comparing the desired and the actual output.

2.3.1 Performance Measures

The Performance Measures provides six values that can be used to measure the performance of the network for a particular data set. These values are:

a) *MSE - Mean Squared Error*

The formula for the Mean Squared Error (MSE) is:

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}(d_{ij}-y_{ij})^2}{N\ P}$$

where P = number of output processing elements
N = number of exemplars in the data set
y_{ij} = network output for exemplar i at processing element j
d_{ij} = desired output for exemplar i at processing element j

b) NMSE - Normalized Mean Squared Error

The Normalized Mean Squared Error (NMSE) is defined by the following formula:

$$NMSE = \frac{P\ N\ MSE}{\sum_{j=0}^{P}\frac{N\sum_{i=0}^{N}d_{ij}^{\,2}-(\sum_{i=0}^{N}d_{ij})^2}{N}}$$

where P = number of output processing elements
N = number of exemplars in the data set
MSE = mean squared error
d_{ij} = desired output for exemplar i at processing element j

c) MAE - Mean absolute error

The mean absolute error is a quantity used to measure how close the output of the ANN are to the eventual outcomes. The mean absolute error (MAE) is given by

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i|.$$

As the name suggests, the mean absolute error is an average of the absolute errors $e_i = f_i - y_i$, where f_i are the output units of the network and y_i the desired response.

d) Min ABS Error

The minimum Absolute Error is given by the next function:

$$\mathbf{min\ ei\ =\ min\ |\ fi - yi\ |}$$

where f_i are the output units of the network and y_i the desired response.

e) Max ABS Error

The maximum Absolute Error is given by the next function:

$$\mathbf{max\ ei\ =\ max\ |\ fi - yi\ |}$$

where f_i are the output units of the network and y_i the desired response.

f) Correlation Coefficient (r)

The size of the mean square error (MSE) can be used to determine how well the network output fits the desired output, but it doesn't necessarily reflect whether the two sets of data move in the same direction. For instance, by simply scaling the network output, we can change the MSE without changing the directionality of the data. The correlation coefficient (*r*) solves this problem. By definition, the correlation coefficient between a network output *x* and a desired output *d* is:

$$r = \frac{\frac{\sum_i (x_i - \bar{x})(d_i - \bar{d})}{N}}{\sqrt{\frac{\sum_i (d_i - \bar{d})^2}{N}}\sqrt{\frac{\sum_i (x_i - \bar{x})^2}{N}}}$$

The correlation coefficient is confined to the range [-1,1]. When *r* =1 there is a perfect positive linear correlation between *x* and *d*, that is, they co vary, which means that they vary by the same amount. When *r*=-1, there is a perfectly linear negative correlation between *x* and *d*, that is, they vary in opposite ways (when *x* increases, *d* decreases by the same amount). When *r* =0 there is no correlation between *x* and *d*, i.e. the variables are called uncorrelated. Intermediate values describe partial correlations. For example a correlation coefficient of 0.88 means that the fit of the model to the data is reasonably good.

III APPLICATION

The parameters are dependent on the neural model, but all require a function (e.g. Hyperbolic Tangent-tanh) to specify the behavior of the PEs. Each one of these functions applies a static map to the data it receives. The map can be linear or nonlinear, or it can normalize the input to the PE. In addition, each layer has an associated learning rule and learning parameters.

Learning from the data is the essence of neurocomputing. Every PE that has an adaptive parameter must change it according to some prespecified procedure. Backpropagation is by far the most common form of learning. Here it is sufficient to say that the weights are changed based on their previous value and a correction term. The learning rule is the means by which the correction term is specified. Once the particular rule is selected, the user must still specify how much correction should be applied to the weights, referred to as the learning rate. If the learning rate is too small, then learning takes a long time. On the other hand, if it is set too high, then the adaptation diverges and the weights are unusable. One of the parameters of Newral Networks is the learning rule and a common method is the momentum component. In searching with the momentum component there are two parameters to be selected: the step size and the momentum. We can modify these two parameters when learning is unstable or very slow.

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This form of optimization requires that the network be trained multiple times in order to find the settings that produce the lowest error. The Maximum Epochs field specifies how many iterations (over the training set) will be done if no other criterion kicks in. The Error which has to minimize is the mean squared error (MSE) of the training set.

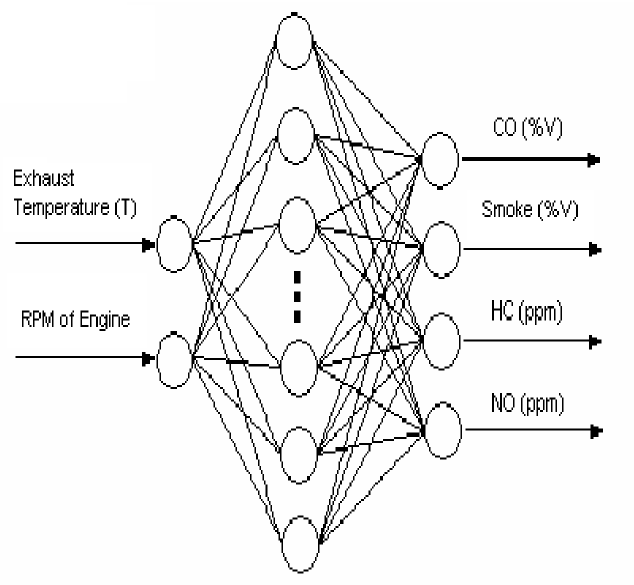

Figure 5. The specific Neural Network that we are examine

The parameters for the specific Neural Network that we are examine the experiment results are:

Structure of Neural Network: Multilayer Perceptron
Input Processing Elements = 2
Hiden Layers = 1
Output Processing Elements = 4

<u>*Input Processing parameters:*</u>

Processing Elements (PE) the following 2:
1) Exhaust temperature and
2) RPM of engine

<u>*Hiden layer parameters:*</u>

Processing Elements (PE): 9
Learning rule: Momentum (= 0,70) with Step size (= 1,00)
Transfer function: Tanh (Hyperbolic Tangent)

<u>*Output processing parameters*</u>

Processing Elements (PE) the following 4:

1) CO (% vol)
2) NO (ppm)
3) HC (ppm)
4) Smoke (%)

Also,
Learning rule: Momentum (= 0,70) with Step size (= 1,00)
Transfer function: Sigmoid

And finally Maximum Epochs = 3000

The other option of MSE termination is to base the stop criteria on the cross validation set (from the Cross Validation panel) instead of the training set. As mentioned earlier, this tends to be a good indicator of the level of generalization that the network has achieved. Increase is the default function when using the cross validation set for MSE termination. This stops the network when the MSE of the cross validation set begins to increase. This is an indication that the network has begun to overtrain. Overtraining is when the network simply memorizes the training set and is unable to generalize the problem. The other two stopping functions described above can be applied to the cross validation set as well as the training set.

IV. EXPERIMENTAL RESULTS

The results refer to CO, HC, NO and smoke emissions in correlation to the gas emissions temperature and the rounds/min of the engine. On the figures below appears that desired output (real data) and actual network output using 3000 epochs.

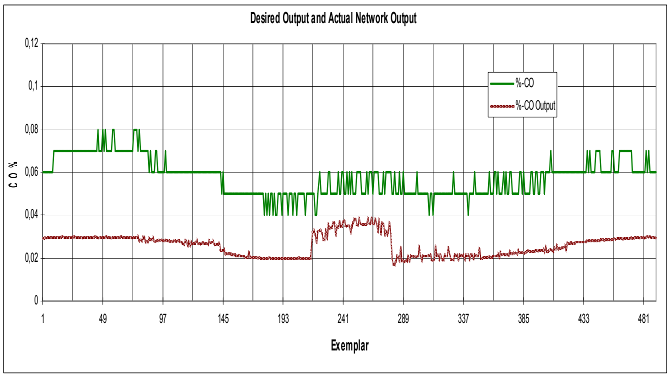

Figure 6. Desired output and actual network output about CO

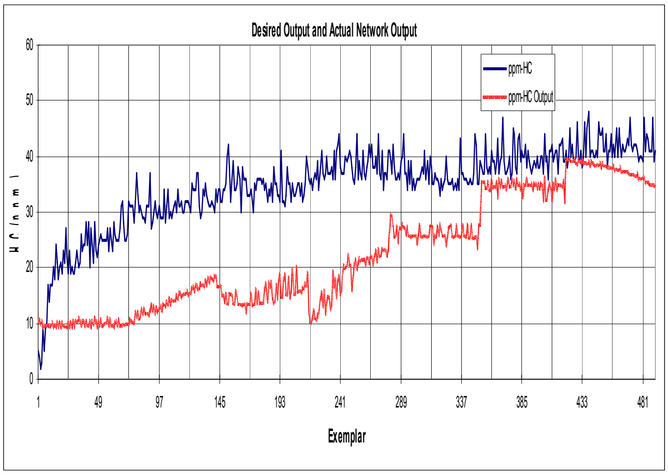

Figure 7. Desired output and actual network output about HC

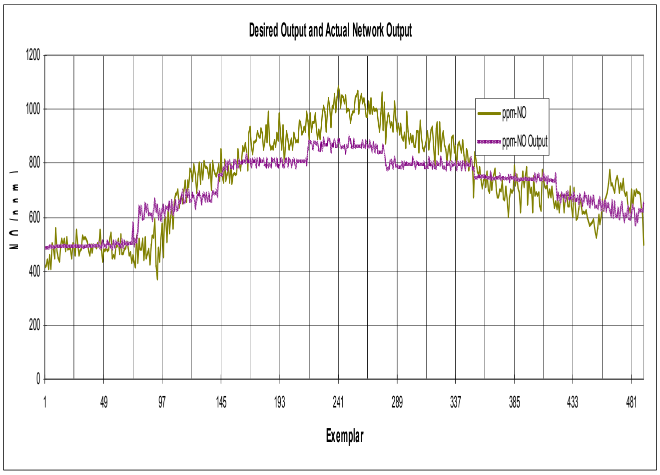

Figure 8. Desired output and actual network output about NO

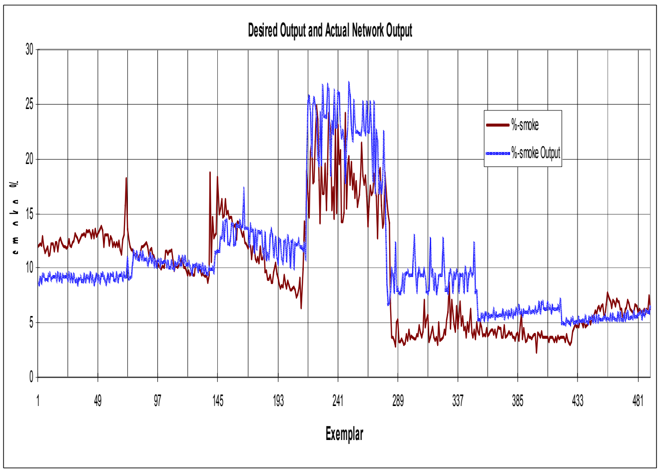

Figure 9. Desired output and actual network output about smoke

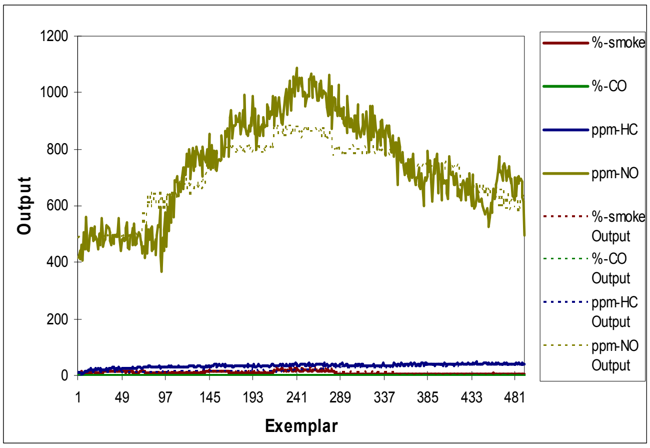

Figure 10. Desired Output and Actual Network Output

Performance	%smoke	%CO	HC(ppm)	NO(ppm)

MSE	13,01260664	0,001050481	206,6765938	8233,190076
NMSE	0,521675834	14,4480432	4,013314074	0,26500051
MAE	2,809884594	0,031569417	12,64467054	73,97683303
Min Abs Error	0,000687698	0,009089444	0,071440521	0,116112307
Max Abs Error	11,74717949	0,05201258	28,54904254	270,0913444
r	0,778163796	0,514317841	0,714606351	0,907016856

Table 1. The Performance Measures.

In the figures 6, 7, 8, 9 it is presented the desired output and actual network output about CO, HC, NO and smoke afterwards testing the real data of engine. Table 1 appears the performance measures provide six values where used to measure the performance of the network for a particular data set. Those values shown that the Multilayer Perceptrons Network that has been used it approached with high precision the reality. It should be noticed that tests have been also realised in the cases where the engine functioned with different fuels (mixtures of diesel –various vegetable oils) and with different temperatures fuel, the results with the use of Multilayer Perceptrons Network ware similar with negligible differences.

V. CONCLUSION

Multilayer perceptrons (MLPs) are layered feed forward networks typically trained with static back propagation. These networks have found their way into countless applications requiring static pattern classification. Their main advantages are that they are easy to use, and that they can approximate any input/output map. The key disadvantages are that they train slowly, and require lots of training data (typically three times more training samples than network weights).
Selecting Multilayer perceptrons (MLPs) Network must specify the parameters of each layer of processing elements (PEs). The uses of Multilayer Perceptrons Network relate with high precision the temperature of exhaust gases and the rounds/min of engine, with the gas emissions. The importance of this work is that when measuring the exhaust gases temperature and the rounds/min of engine forecast with very high precision their gas emissions[17,18].
Finally, it should be reported that those tests have been also realised in other engines giving similar results.

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