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ABSTRACT

Modern diesel engines are equipped with an increasing number of actuators set to improve human comfort and fuel consumptions while respecting the restricted emissions regulations. In spite of the great progress made in the electronic and data-processing domains, the physical-based emissions models remain time consuming and too complicated to be used in a dynamic calibrating process. Therefore, until these days, the calibration of the engine's cartographies is done manually by experimental experts on dynamic test bed, but the results are not often the best compromise in the consumption-emissions formula due to the increasing number of actuators and to the nonlinear and complex relations between the different variables involved in the combustion process. Recently, neural networks are successfully used to model dynamic multiple inputs - multiple outputs processes by learning from examples and without any additional or detailed information about the process itself.

In this paper, we fully describe the construction and applications of a nine inputs dynamic emissions' model based on neural networks. The simulations' results are in good agreement with real engine data measured on test bed. The emissions' model is conceived to be used in an upper-level dynamic optimization process based on genetic algorithm. Our goal is to present, while using the minimum number of experimental tests, a fast and practical optimization procedure capable of finding the optimal calibration values of the seven engine's actuators over the New European Driving Cycle (NEDC). The results are very promising.

Keywords: Neural Network, Calibration, Dynamic, Emissions' models, Optimization and Genetic Algorithm.

I INTRODUCTION

Internal combustion engines installed on vehicles are subjected to a series of laws which limits their harmful effects on the environment and human health. These laws are expressed in the form of fixed upper limits of the legislated pollutants that the vehicle must respect when it is tested over a normalized driving cycle (the New European Driving Cycle NEDC, figure 1). Table 1 recapitulates the European emission standards of the Diesel vehicle since Euro I (1992) until the limits proposed in Euro V (2008).

Euro		Date	CO	NOx	HC+NOx	PM
I		1992	2.72	-	0.97	0.14
II	DI[1]	1996	1	-	0.7	0.08
	IDI[2]	1996	1	-	0.9	0.1
III		2000	0.64	0.5	0.56	0.05
IV		2005	0.5	0.25	0.3	0.025
V		2008	0.5	0.2	0.25	0.005
1 → Diesel Direct Injection				2 → Diesel Indirect Injection		

Table 1: European Emission Standards for the Diesel vehicle in g/Km.

Facing these restricted regulations, the manufacturers of Diesel engines propose two main operational categories for the optimal management of the pollution's reduction: the control of the engine and the post-treatment.

In the first category, the control schemes vary according to the instruments that the engine can be equipped with: the variable geometry turbocharger [1], the turbo-compressor with a waste-gate, the recirculation of exhaust gas (EGR), the common rail injection system [2, 3], the electric compressor [4], the Bi-turbo with variable geometry and waste-gate, the Continuously Variable Transmission (CVT)…

In the second category, we can find the following instruments that are used to treat the gases emissions after they passed the exhaust manifold: the NOx absorbers [5], the Pt-based catalyst [6], the SOx traps, the particulate filters, the Selective Catalyst Reduction (SCR)…

In the last two decades, the modeling of the emitted pollutants of the Diesel engines has more and more gained the interests of the engines' producers and mechanical engineers, they needed a reliable and fast modeling tool to replace the expensive and time consuming processes based on experiment and to overcome the difficulties of finding the optimal control parameters with the increasing number of the actuators used in the control scheme. But, in spite of the important evolutions done in the data-processing and electronic fields and the great capacity and precision of the sensors installed on the engines, and until now, they did not succeed to construct dynamic, robust and practical pollutants' models that are utilizable in a dynamic optimization process. The existing emissions models with satisfying results are based on decomposing the combustion chamber into three-dimensional grids and applying to each infinitesimal volume the laws of conservation of mass and energy [7, 8, 9]. Also, these models can be better adapted to a specific engine's applications by adjusting the values of the parameters of the law of combustion and heat transfer, this is done experimentally by comparing the models' results to the data measured on a static test bench. However, these models remain not suitable for the engine optimization problem since they consume too much time. Recently, neural networks have found their way to engine' applications [10, 11] and have been successfully used to model the emission of their pollutants [12, 13].

In this paper, we are interested in minimizing the pollutants production of the Diesel engine by acting at the problem's source and by finding the optimal control scheme for the different engine's actuators in order to obtain a better combustion in the cylinders and to assist the engine's producers in their challenge against the future emissions regulations. Consequently, our objective is to seek the minimum of the cumulated mass production of the noxious pollutants over the New European Driving Cycle NEDC (Figure 1).

The paper is divided to nine sections as follows: In section I, we introduce the current problem and we explain the purpose of this paper. In section II, we briefly present the existing control schemes applied to Diesel engines. In section III, we present a new methodology to find the optimal values of the control variables. In section IV, we describe the experimental test cell used for data acquisition and the engine's general characteristics and control parameters. In section V, we design and build the dynamic models of the pollutants CO_2, NO_x and Opacity based on neural networks, the models' results are in good agreement with experimental data. This models are then used in an upper-level optimization procedure based on genetic algorithm as explained in section VI, the optimization results are in good agreement with the optimal values of the control variables obtained by experiment. We end this paper by our conclusion and remarks in section VII followed by our acknowledgments and a list of the articles and papers that the readers can be referred to.

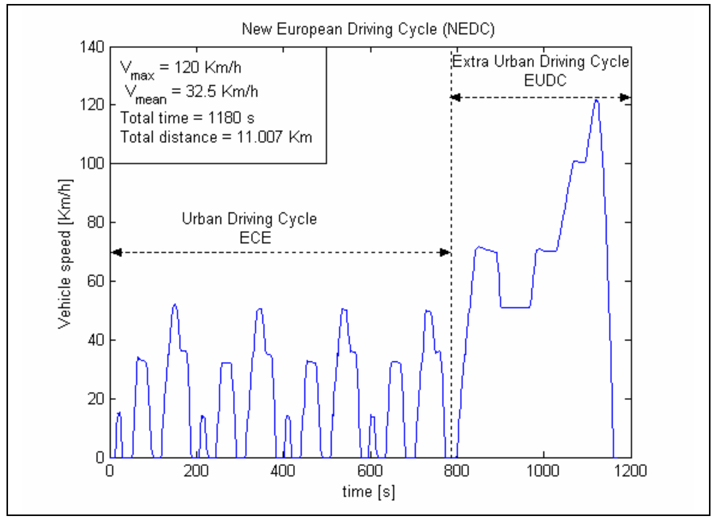


Figure 1: Vehicle speed over the New European Driving Cycle (NEDC)

II PROBLEMATIC AND CONTROL SCHEMES

At the present time, the control diagrams applied to vehicles are mainly based on interpolations of the values of two-dimensional cartographies that are stored in the engine control unit (ECU) and that are function of the crankshaft angular speed and the engine load (or sometimes crankshaft angular velocity and fuel flow rate). These cartographies which are called basic cartographies (figure 2) are the results of an iteratively optimization process of the control parameters done on a static engine test bench.

X\Y	0.00	20.00	40.00	60.00
750.00	230	230	230	230
900.00	250	250	250	250
1000.00	264	265	273	284
1200.00	279	284	308	329
1400.00	293	308	339	367

Figure 2: Two-dimensional cartography of the Rail Pressure with entries the crankshaft angular speed and the torque.

Afterward, the primary values obtained from the basic cartographies are adjusted "on line" by using the control techniques [14, 15, 16] before being applied to the corresponding actuators. The modified values take into consideration the changes in the surrounding environment and the evolution of the states of the engine, and ensure a better adaptation of the engine to the dynamic applications of the vehicle. In the next sub-sections we will present the simplified structure of the algorithms commonly used in the engine's control without largely developing the theory of the control systems.

II. 1 OPEN LOOP CONTROL

It mainly depends on determining the various control parameters of the engine's actuators under the steady operating conditions.

Beside basic cartographies, corrective cartographies are integrated into the ECU to take in consideration the evolutions of certain variables describing the states of the engine and the surrounding environment and to adjust the primary values according to these changes (Figure 3). Among these variables which are measured in real time by sensors installed on the vehicle, we can quote, as examples, the temperature of the cooling water, the temperature of the ambient air, the atmospheric pressure… Thus, for a given load and crankshaft angular velocity, the primary values of the basic cartographies are multiplied by a factor (correction) function of the cooling water temperature, the load and the velocity, then by another one, function of the ambient air temperature, the load and the velocity, and so on…

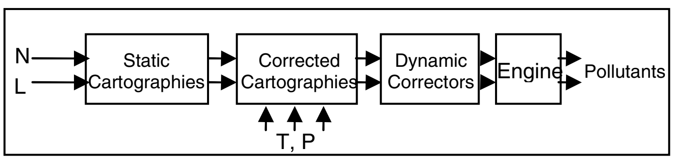


Figure 3: Open loop control.

Afterward, a predictive dynamic corrector is generally used to compensate the dynamic behavior of the engine and enhance its functioning performance. For example, a predictive correction can take the following form [13]:

$$y_2(t) = y_{10} + (y_{20} - y_{10}) \cdot \left[1 - \left(1 - \frac{T_V}{T_1} \right) \cdot e^{-\frac{t}{T_1}} \right]$$

Where $y_2(t)$ is the corrected value varying with time, y_{10} and y_{20} are the static initial and final value given by the cartographies, T_1 is a time constant describing the response time of the engine and T_V is a parameter identified by experiment on a dynamic test bed.

II. 2 CLOSED LOOP CONTROL

The main objective of this type of control is to act continuously on the different engine's actuators in order to force an output variable to follow a predetermined set point. It is used to guarantee the independence of the engine behavior with respect to its operating conditions or external disturbances (figure 4). We can quote as examples of the variables concerned by this control, the air to fuel ratio, the engine idle speed, the start of combustion... The control processes are in general described by their transfer functions which are equal to the ratio of the Laplace transforms between the variable to be controlled and the concerned entries. The transfer functions are characterized by their zeros and poles which are respectively the roots of the numerator and the denominator. Their positions in the complex plan determine the system stability and its dynamic response and performance (examples: control PID, self-adapting control…).

III SUGGESTED METHODOLOGY

Our objective consists in proposing a new methodology that is capable, with the minimum number of experimental tests, to find the optimal values of the engine control parameters that minimize the weighted sum of the cumulated emitted mass of the different pollutants when the vehicle is tested over the New European Driving Cycle (NEDC).

This approach requires the development of the mass flow rate models of the different pollutants in order to predict their instantaneous emissions response when varying the engine control parameters. As explained in the introduction, this is a critic and difficult task that we successfully solved by using the neural networks magic box.

Also, seen the dependence between the different engine variables and the movement of the crankshaft, we suggested the use of the neural networks to build up a model describing this recurrent relation. The creation of this model is an essential task in the optimization process in order to assure the following of the vehicle speed to the target speed fixed by the normalized cycle.

Finally, we propose to use the genetic algorithm as an optimization tool to find the optimal control parameters of the engine over the normalized cycle.

III. 1 THE DIFFERENT PHASES OF THE METHODOLOGY

The proposed procedure is divided into seven steps that can be grouped in two main phases (figure 5):

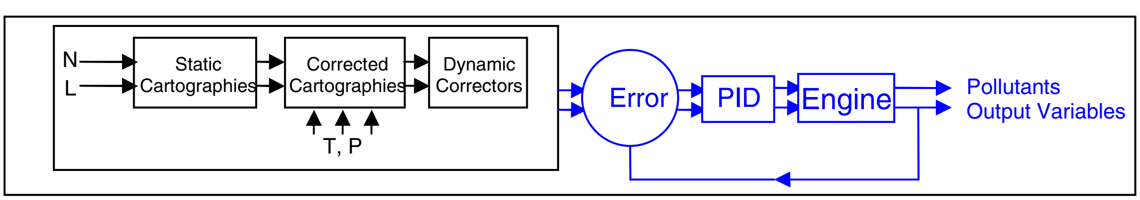


Figure 4: Closed loop control

Phase 1: Development of pollutants model:

1. Data acquisition on a chassis dynamometer of the engine variables and pollutants over the cycle NEDC.
2. Dynamic modeling of the pollutants by recurrent neural networks
3. Models validation:
    a. Study of the sensitivity of the models to the variations of the control parameters and validation of the models in predicting the emissions on new experimental data not used for training the networks. If the results are satisfying, go to step 4, if not, go to step 3.b.
    b. Repeat the experimental test on the chassis dynamometer over the cycle NEDC (same vehicle speed) with different values of the control parameters of the Diesel engine (Changing cartographies) and go to step 2.

Phase 2: Optimization of the control parameters:

4. Dynamic modeling of the crankshaft angular speed by neural network using the same experimental data base used to create the pollutants' neural models.
5. Finding the best values of the engine control parameters by dynamic minimization of the pollutants' production using the genetic algorithm.
6. Curves smoothing of the obtained results.
7. Validation of the optimization results.

In this paper, we used the experimental data of five different set of control parameters of the cycle NEDC to train the neural models.

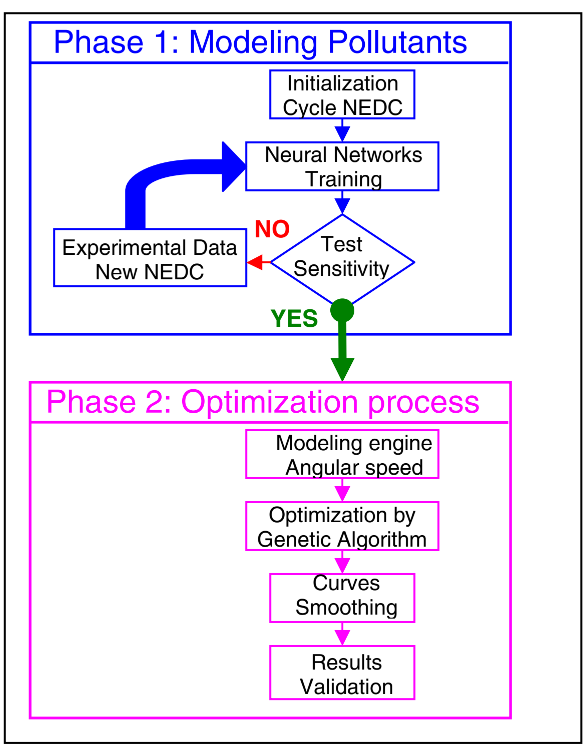


Figure 5: Suggested methodology

III. 2 ADVANTAGES OF THE NEURAL NETWORKS

We propose to model the pollutants emitted by the engine by using the artificial neural networks. The idea is to use the experimental data measured on the chassis dynamometer over the cycle NEDC to train the neural networks which have a great capacity to learn the complex nonlinear relations between the different engine variables and their effects on the pollutants emissions.

Since a score of years, these networks have drawn the attention of many scientists in different fields because of their capacity to solve nonlinear complex problems by simply learning from examples. Between the various neural architectures found in the literature, the multi-layer perceptrons are the most popular networks that are used for modeling the systems response and behavior.

Among the numerous existing models which can be used to describe a nonlinear physical dependence, the three layers perceptrons with one hidden layer possess the following interesting characteristics: They are black box models with great capacity for universal, flexible and parsimonious functions approximation.

Several works [17, 18] show that these networks are universal approximation models, and that they are capable of approximating any continuous nonlinear function with an arbitrary fixed precision, while they require the identification of a smaller number of parameters than the other models like the polynomial models, the trigonometrical series, the Splines or the series of orthogonal functions, in this way, they are parsimonious.

In addition, these networks constitute a very flexible tool for regression: The rising complexity and nonlinearity of the system to be modeled can be easily expressed in the network by simply increasing the number of neurons in the hidden layer, without changing the total form of the model.

III. 3 ADVANTAGES OF THE GENETIC ALGORITHMS

The genetic algorithms try to imitate the natural evolution process of the populations (survival of the fittest) according to the Darwinian model in a given environment. They use a vocabulary similar to that of the natural genetics. Therefore, a population is made of a number of individuals; each one is represented by a chromosome which contains the hereditary genes of the individual. For an optimization problem, an individual represents a point in the states space, a potential solution. Moreover, each individual is characterized by the value of the function to be optimized, his adaptation, which is called the fitness function.

We start by generating an initial population with individuals randomly chosen from the state space. Then the genetic algorithms apply the following three rules to the individuals of the current population to create the ones of the next generation (figure 6):

- The selection rule which is used to randomly select the parents to be reproduced to form the children (individuals) of the next generation. The individuals with better fitness function have a higher probability to be selected. The most popular selection rules are the Roulette rule and the Tournament rule.
- The crossover rule which describes how two individuals are combined to form new ones. The most popular crossover rules are the Scattered rule and the Heuristic rule.
- The mutation rule which describes how the genes of an individual are manipulated to form a new mutated one. The most popular mutation rule is the Gaussian rule.

The principles of selection, crossover and mutation are inspired from the natural processes that carry the same name. However, the natural processes to which they refer are much more complex. The purpose of the selection is to choose the best elements of the population (the more adapted), the crossover and the mutation ensure the exploration of new regions in the states space.

Initialisation: Random population
↓
Evaluating initial Fitness functions
↓
Repeat → Selection
↓
Crossover
↓
Mutation
↓
New population
↓
Evaluating Fitness functions
↓
Until → Stopping Criteria

Figure 6: Genetic Algorithm diagram

Recently, the genetic algorithm has constituted an interesting optimization tool for different engines' applications [19, 20, 21] because of their attractive capacity to search a large area of the states space, with the minimum of information (the fitness value), and their ability to find the global minimum even in the case of highly non linear functions where the domain surface is full of local minimums and where the traditional optimization algorithms may get stuck.

IV DATA ACQUISITION

IV. 1 CHASSIS DYNAMOMETER TEST CELL

Installed in an air-conditioned and isolated cell, it includes (figure 7):

- The rollers that receive the driving wheels of the vehicle. The rollers' resistance to motion is adjusted to simulate the friction losses and the aerodynamic drag that the vehicle is submitted to on the real road, also an inertial mass is added to the rollers to simulate the vehicle's inertia. Finally a fan, running at constant speed and facing the vehicle, is set to cool the motor's different blocks and the cooling water.
- The driving monitor placed under the eyes of the driver where he follows the different phases of the cycle in the form of a graphic speed with respect to time. The vehicle speed is represented in real time by a luminous point that the driver tries continuously to coincide with the graph with an interval of tolerance of ± 2 km/h (figure 8).
- The sampling system of the exhaust gases:
    a. After the silencer, the exhaust gases are directed through tubes to a tunnel where they are diluted with fresh air by the constant flow sampling technique, known as Constant Volume Sampling (CVS), then a part is sent towards the instantaneous measuring devices and the other part is conducted towards the bags where the gases are accumulated until the end of the cycle, when they will be analyzed in order to deduce the average masses of the various pollutants emitted during the test in g/Km.
    b. The emitted particles are differently measured in comparison with the other pollutants. The diluted gases pass through three filters which represent three different phases of the cycle: the first ECE, the three ECE which follow and the EUDC (figure 1). The emitted mass is the difference between the mass of the filter before and after each phase.
    c. The regulated gases are the carbon monoxide (CO), the unburned hydrocarbons (HC), the nitrogen oxide (NOx), and the particulate matters (PM).
    d. The instantaneous pollutants emission measured in real time are: the carbon monoxide CO, the hydrocarbons HC, the carbon dioxide CO2, the nitrogen oxide NOx and the Opacity. The sampling frequency is 1 Hz.

IV. 2 VEHICLE AND ENGINE DESCRIPTION

The vehicle used for the tests is a 1400Kg ITW passenger car equipped with a four cylinders diesel engine, a variable geometry turbocharger (TGV), a system of exhaust gas recirculation (EGR), a Delphi Multec DCR 1600bar Common Rail injection system and a catalyst for the reduction of CO and HC. The vehicle is not equipped with particulate filter and its control and equipments were set to respect the Euro III emissions standards.

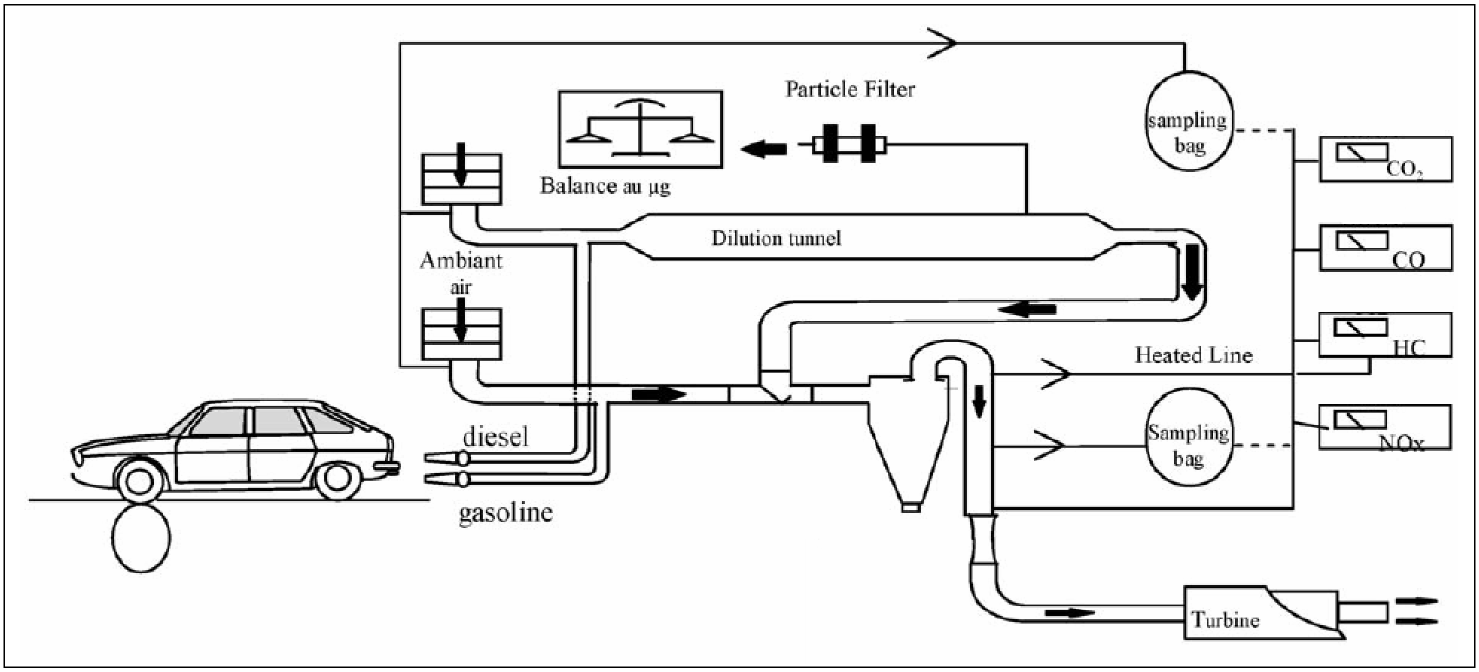


Figure 7: Emissions measurement on chassis dynamometer test bench

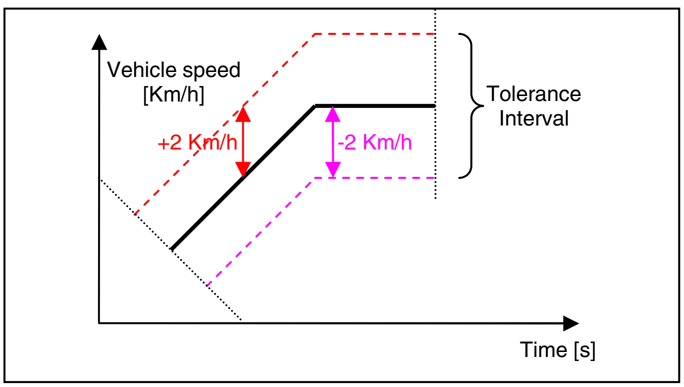


Figure 8: Interval of tolerance between real time vehicle speed and target curve.

IV. 3 CONTROL PARAMETERS

The functioning and dynamic behavior of the engine is mainly defined by the values of seven completely independent parameters that are controlled by the ECU, these variables are:

- The fresh air flow rate entering the combustion chamber.
- The engine boost pressure at the intake manifold.
- The start of the Main injection.
- The quantity of the Pilot fuel injection. The fuel injection into cylinders is split into two injections: Pilot and Main. The Pilot fuel injection is prior to the Main injection and is much smaller in quantity.
- The separation time between Pilot and Main fuel injection.
- The total quantity of fuel injection.
- The rail pressure.

The figures 9 and 10 represent the experimental measurements of the following variables taken at **DELPHI** Technical Centre in Blois - France over a complete cycle NEDC:

- Engine variables: the fresh air flow rate, the total fuel flow rate, the crankshaft angular speed, the gear ratio and the vehicle speed.
- Pollution: HC, CO, CO2, NOx and Opacity.

The engine's variables are recorded directly on a portable computer connected to the ECU of the vehicle. These values are measured by the sensors already installed on the vehicle and that are used by the ECU to control the engine.

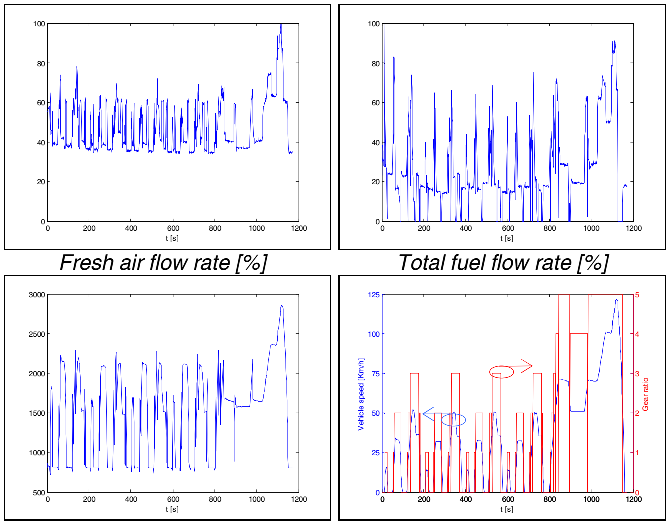
V MODELING POLLUTANTS BY NEURAL NETWORKS

In this paper, we are only interested in modeling the following pollutants CO2, NOx and Opacity because the vehicle is already equipped with a catalyst for reducing the HC and CO and the measured data was taken after that the emitted gases have been treated in the catalyst.

The entries of the neural models are necessarily those variables that have some influence at the pollutants emission, so we chose as inputs, the seven control variables described in section IV.3, the crankshaft angular velocity, the coolant temperature and the pollutant, at different instants. The result is a recurrent model that can be described by the following equation:

$$Pol(t) = f\begin{pmatrix} X(t), X(t-1)\ldots, X(t-k), \\ Pol(t-1),\ldots, Pol(t-l) \end{pmatrix}$$

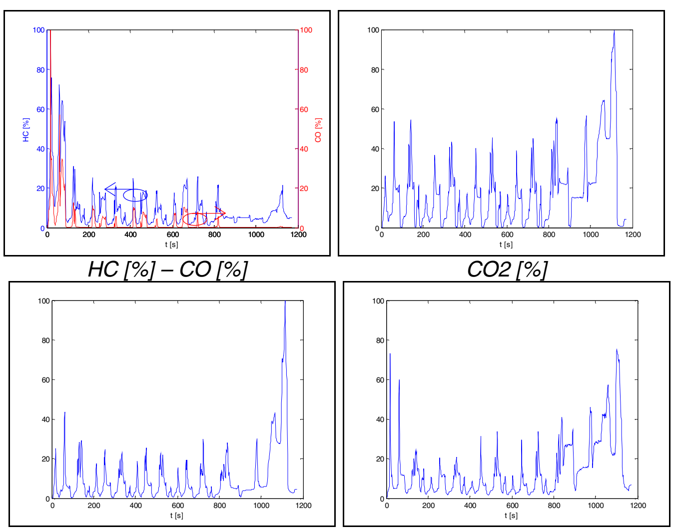
Where t represents the present time, X is a vector containing the nine variables of the engine as described previously and Pol is the pollutant to be modeled, k and l are integers representing the delay and response time of the instantaneous measuring devices.



Fresh air flow rate [%] *Total fuel flow rate [%]*

Crankshaft angular speed [rpm] *Vehicle speed [Km/h] - gear ratio*

Figure 9: Examples of engine variables



HC [%] – CO [%] *CO2 [%]*

NOx [%] *Opacity [%]*

Figure 10: Measured pollutants

The neural networks chosen to model the pollutants have three layers (figure 11): an input layer, one hidden layer containing ten neurons and an output layer. The transfer functions at the hidden layer are sigmoid functions and those at the output layer are linear functions. We also selected the feed-forward back-propagation algorithm to train the networks; this algorithm uses a sequential method based on the gradient, such as the quasi-Newton algorithm, to adjust the weights and bias of the neurons in a way to minimize a performance function selected as a criterion to reflect the capacity of the model to predict the true outputs. Given its attractive generalization property and its capacity to obtain stable model, the performance function chosen as a criterion to train our networks has the following form:

$$f = \frac{\gamma}{N} \cdot \sum_{i=1}^{N} e_i^2 + \frac{1-\gamma}{N} \cdot \sum_{i=1}^{N} w_i^2$$

Where e is the error between the output of the network and the training data, w is the weights and bias of the neurons, N is the number of couples (Inputs-Output) used in the training data and γ is a real number between zero and one.

The value of γ equal to one leads to a minimal error between network outputs and training data, but the model will not be robust. We continue to decrease this factor until obtaining a model that is sensitive to the variations of the various entries and that is capable of predicting, with a desired precision, the pollutant's emission of the engine when it is faced with new data that is not used in the learning phase.

The figures 12, 13 and 14 show a comparison between the output of the trained models of CO2, NOx and Opacity, and experimental data measured over the complete cycle. The results of the models are in good agreement with experiment.

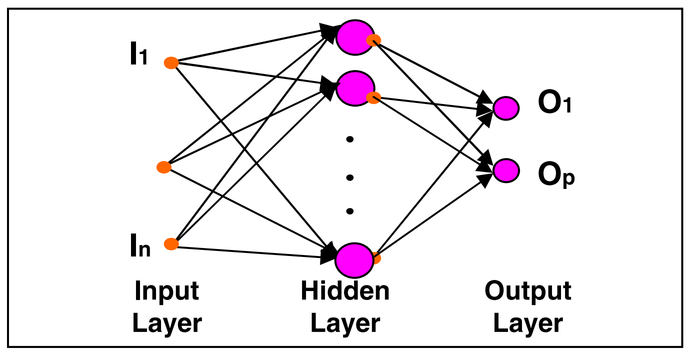


Figure 11: Neural network architecture.

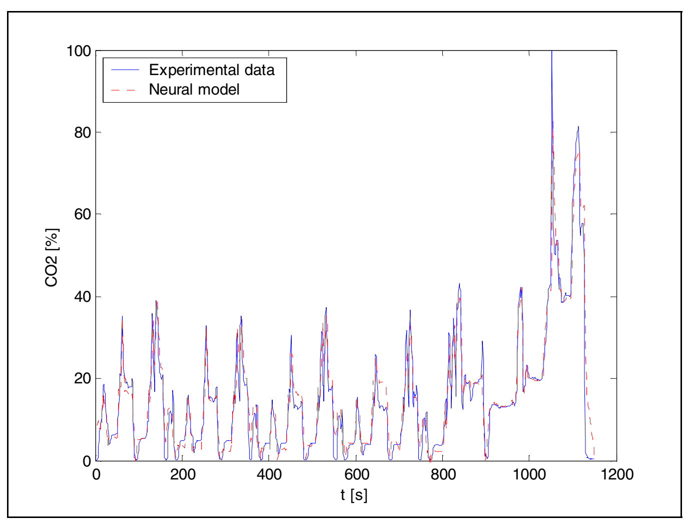


Figure 12: Comparison between neural model of CO2 and experimental data over a complete cycle NEDC.

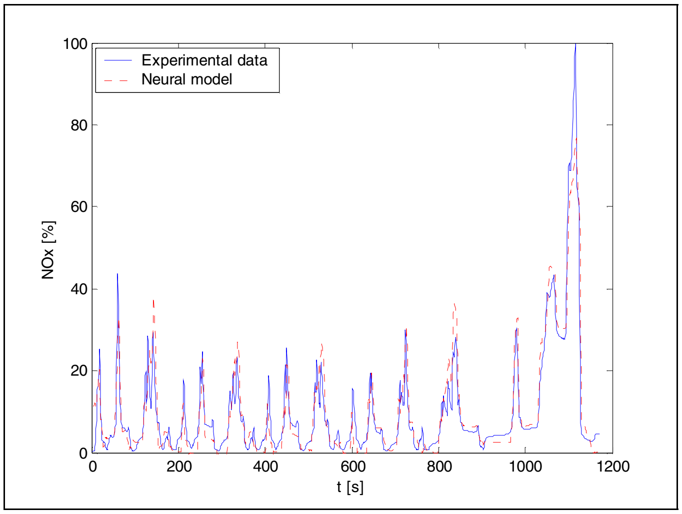


Figure 13: Comparison between neural model of NOx and experimental data over a complete cycle NEDC.

VI OPTIMIZATION BY ALGORITHM GENETIC

An engine is conceived to produce the maximum of power while respecting the constraints of pollution. Given that the engine is judged by the quantities of its regulated pollutants emitted over a normalized cycle and while reasoning only at the source level, a multicriterion function called "Objective" can be defined over the NEDC cycle as follows:

<< Maximum Power >>

<< Minimum Cumulated Regulated Pollutants >>

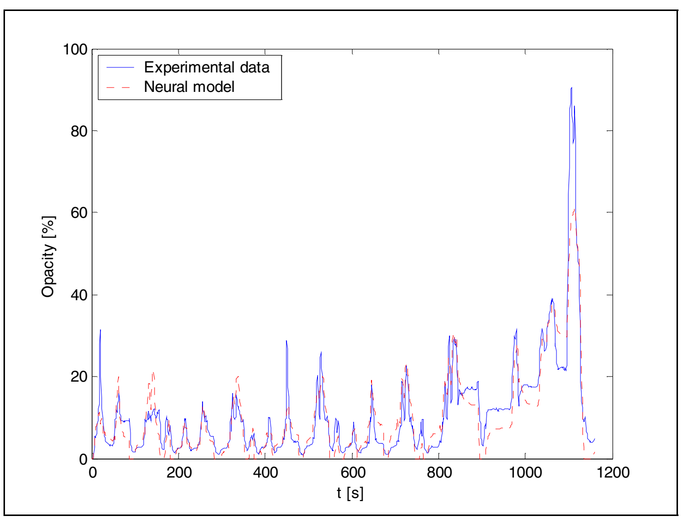


Figure 14: Comparison between neural model of Opacity and experimental data over a complete cycle NEDC.

VI. 1 PROBLEM FORMULATION

Since the chassis dynamometer test cell is not equipped with an instantaneous particles measuring device, we will use the opacity criterion instead which has the same behavior of the particles emission with respect to the different changes of the engine's variables. Also we will exclude in the function "objective" the emission of the HC and CO because the vehicle is equipped with a catalyst for their reduction. Finally we have interests in replacing the term "Maximum Power" by an equivalent term which is "the minimum of the emission of CO2", given that the committees of the standardized emissions are heading for regulating the emission of the dioxide of carbon in the future legislations, so we can combine the two terms of the function "Objective" into one equation:

$$f = \sum_{i=1}^{3} \left\{ \int_0^t \frac{Pol_i(t)}{Pol_{i,\max}} \cdot dt \right\}$$

Where Pol represents the pollutants: CO2, NOx and Opacity, and max is the maximum value that the pollutant can reach, this constant value is used to have a comparable scale for the different pollutants. The integral represents the cumulated emission of the pollutants on the dynamic course of the NEDC.

This function is subjected to the following equality constraints representing the fact that the vehicle speed must follow the target curve defined by the cycle:

$$N_{crankshaft}(t) = N_{target}(t)$$

And under the following inequality constraints which are imposed by physical and mechanical restrictions describing the lower and upper range of the different actuators and variables of the engine:

$$P_{\min} \le P(t) \le P_{\max}$$

Reformulating the problem into its discretized form, the integrals in the function "Objective" becomes a simple sum of the values of the pollutants emitted at different instants t_i of the cycle. We fixed the step of discretization to 0.5 seconds which is the same step used for modeling the crankshaft angular speed as it will be explained in the next sub-section. Let N be the number of the discretized points taken over the entire cycle, thus the problem will have the following form:

$$f = \sum_{i=1}^{N} \frac{(CO2)_i}{CO2_{\max}} + \sum_{i=1}^{N} \frac{(NOx)_i}{NOx_{\max}} + \sum_{i=1}^{N} \frac{(Opacity)_i}{Opacity_{\max}}$$

Under the equality constraints:

$$(N_{crankshaft})_i = (N_{target})_i, i = 1 \ldots N$$

And the inequality constraints:

$$P_{\min} \le (P)_i \le P_{\max}, i = 1 \ldots N$$

VI. 2 CRANKSHAFT MODEL

The neural network model of the crankshaft angular speed has the same characteristics of the networks used for modeling the pollutants, but with different entries. The variables used as inputs to the network are: the seven control variables as described in section IV.3, the coolant temperature, the load applied to the engine, the gearbox ratio, the reduction ratio between the crankshaft rotation speed and the wheel rotation speed and the crankshaft angular speed at different instants. After many tests and simulations with different time steps, we fixed the discretization step to 0.5 s; we found that this step is suitable to describe the engine's dynamic because of the slow dynamic nature of the NEDC cycle. The figure 15 shows a comparison between experimental data taken over the cycle NEDC and the model's outputs, the model's results are in good agreement with experiment.

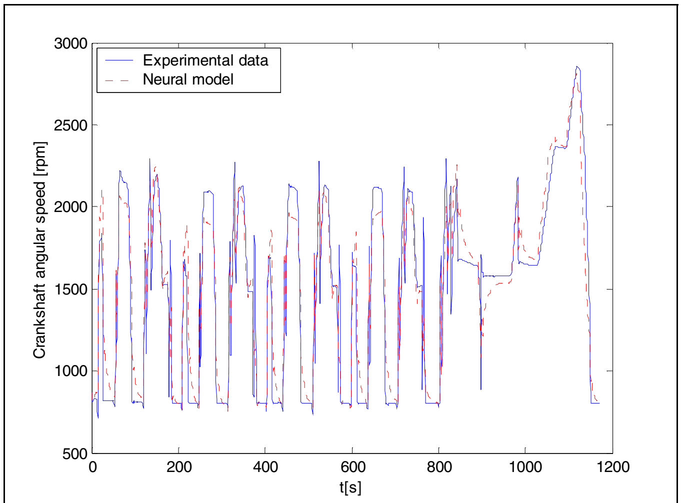


Figure 15: Comparison between neural model of crankshaft angular velocity and experimental data over a complete cycle NEDC.

VI. 3 OPTIMIZATION APPLICATIONS AND RESULTS

The variables to be identified by the optimization process are the seven control parameters described in section IV.3. The time interval of the cycle is 1180 s and the discretization step is 0.5 s. Consequently, the number of variables to be identified is 1180 × 2 = 2360, the number of equality constraints is 2360 and the number of inequality constraints is 33040. Obviously, the solution of this problem exceeds the machine capacity. Fortunately, we don't have to apply the optimization procedure to all the points of the cycle at the same time; it is sufficient to take a shorter path on the cycle limited by two stabilized vehicle speeds at the beginning and the end of the course and that for the following reasons:

Let (c) be an intermediate instant of time between the start (a) and the end (b) of the cycle, the function "objective" becomes:

$$\sum_i \int_a^b \frac{Pol_i}{Pol_{i,\max}} \cdot dt = \sum_i \left\{ \int_a^c \frac{Pol_i}{Pol_{i,\max}} \cdot dt + \int_c^b \frac{Pol_i}{Pol_{i,\max}} \cdot dt \right\} = \sum_i \int_a^c \frac{Pol_i}{Pol_{i,\max}} \cdot dt + \sum_i \int_c^b \frac{Pol_i}{Pol_{i,\max}} \cdot dt$$

If we choose the point at the instant (c) of the cycle that corresponds to a steady state period, then the values of the velocity and pollutants before and after this moment will be independent since the engine and emissions were stabilized and we can write:

$$\rightarrow MIN\left\{ \sum_i \int_a^b \frac{Pol_i}{Pol_{i,\max}} \cdot dt \right\} = \left[\begin{array}{l} MIN\left\{ \sum_i \int_a^c \frac{Pol_i}{Pol_{i,\max}} \cdot dt \right\} \\ + MIN\left\{ \sum_i \int_c^b \frac{Pol_i}{Pol_{i,\max}} \cdot dt \right\} \end{array} \right]$$

Therefore, to find the minimum of the cumulated emission of the pollutants over the complete cycle is equivalent to seek the minimum of the cumulated emission on different parts of the cycle confined between two steady vehicle speeds.

We applied the optimization process to the part of the cycle encircled in dotted line in the figure 16. The figure 17 and 18 show the comparison between the optimization results obtained by experiment on dynamic test bench and the ones obtained by genetic algorithm with an initial population randomly chosen. The optimization results found numerically are in good agreement with experiment.

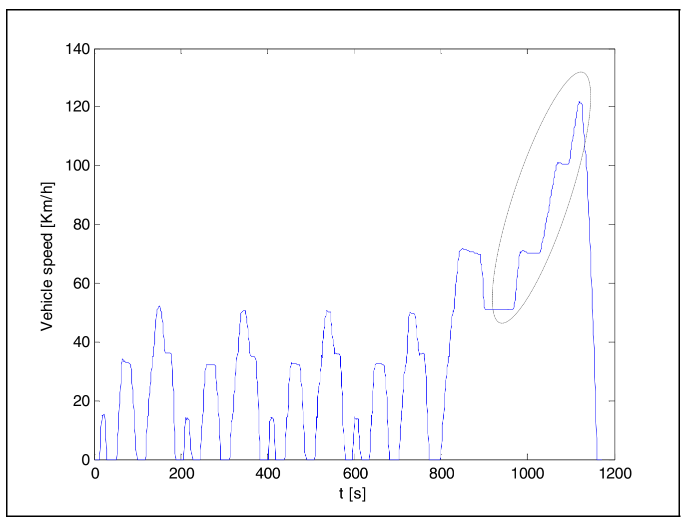
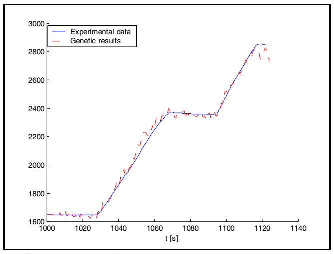


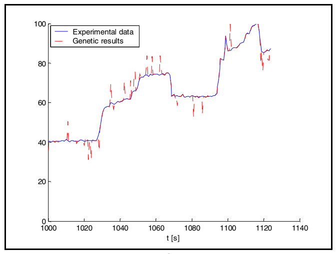
Figure 16: Vehicle speed over the NEDC; Application of the optimization process to the part encircled in dotted line.

VII CONCLUSION

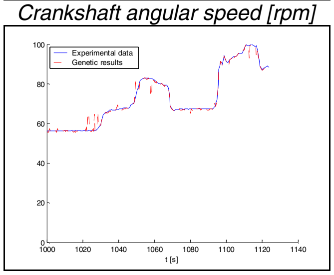
The proposed optimal control methodology, based on modeling by neural networks and optimization by genetic algorithm, made it possible to trace the dynamic optimal cartographies of the Diesel engine on a predefined course, in particular the New European Driving Cycle.



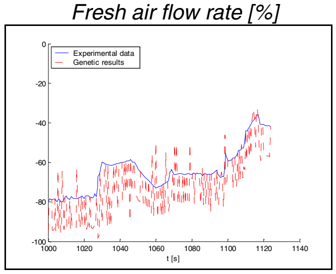
Crankshaft angular speed [rpm]



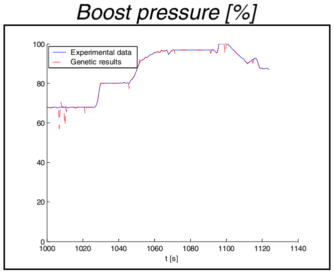
Fresh air flow rate [%]



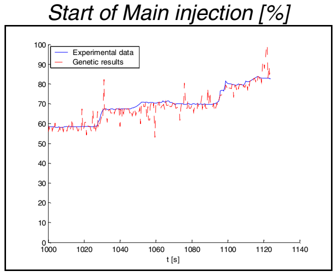
Boost pressure [%]



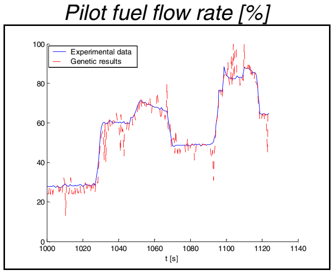
Start of Main injection [%]



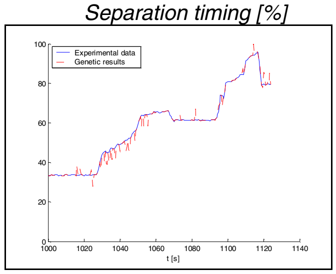
Pilot fuel flow rate [%]



Separation timing [%]



Total fuel flow rate [%]

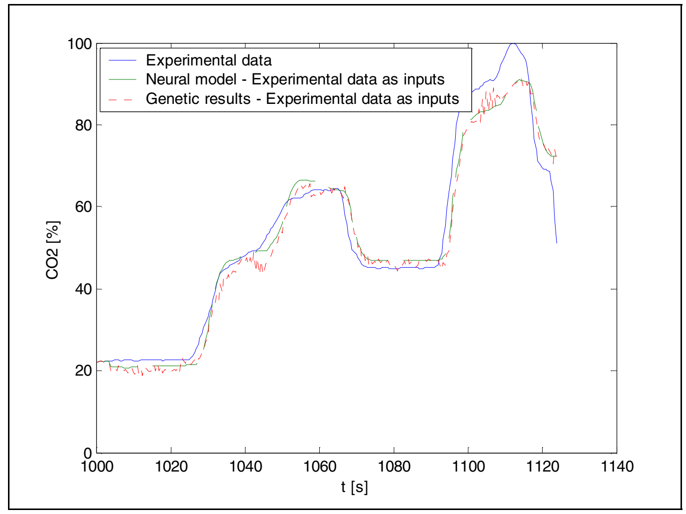


Rail pressure [%]

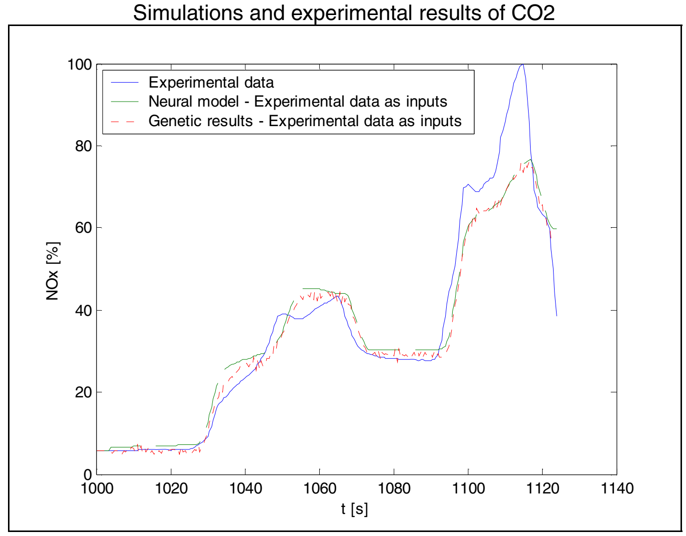
Figure 17: Comparison between the optimal engine's variables obtained by experiment and by the genetic algorithm.

Considering that the cycle NEDC is regarded as a tool for evaluating the engine's performance and legitimacy, it was important to be able to deduce the optimal controls of the Diesel engine over the cycle without being obliged to make many experimental tests or to model the pollutants' emission in the entire functioning range of the engine. Thus one of the advantages of this method is that it requires fewer tests then the other methods suggested in the literature.

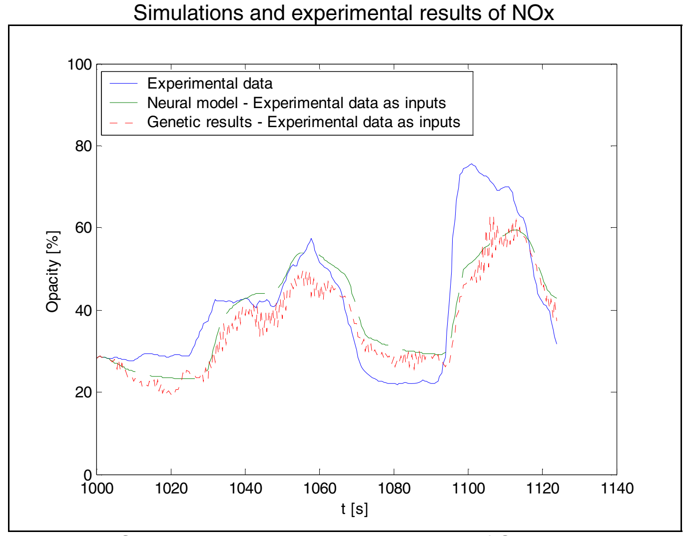
Moreover, the increasing severity of the emission regulations drives the engines' manufacturers to enlarge the number of actuators used to control the engine thus making more and more difficult the task of finding the optimal control scheme. In this article we proposed a universal and dynamic optimization procedure that is valid for an unlimited number of control variables to deduce the optimal control of the engine.



Simulations and experimental results of CO2



Simulations and experimental results of NOx



Simulations and experimental results of Opacity

Figure 18: Comparison between pollutants' emission obtained by experiment and by the genetic algorithm.

In addition, the proposed process can be easily enlarged to take into account the minimization of other criteria along with the regulated pollutants like engine's noise or non regulated emissions. For that, it is sufficient to model the criteria by neural network and include it in the function "Objective". Also we can choose to classify the minimization of the pollutants by priority order to reflect their importance, and that by simply multiplying each of the pollutants in the function “Objective” by a weight factor between zero and one.

Finally, we succeeded to model and predict the dynamic emissions of different pollutants by neural networks; the results are in good agreement with experimental data. Therefore the neural networks have proven to be a powerful modeling tool, especially in our case, where the pollutants’ production is not yet fully understood and the existing models are not reliable and appropriate for optimization problem. In addition, we should note that the precision of the neural models can be additionally improved by including new inputs into the networks like the position of the vanes of the variable geometry and the exhaust gas recirculation, the pressure and temperature at the exhaust manifold or the maximum pressure reached in the combustion chamber. Also the modeling of the crankshaft’s movement can be improved by using a mean value physical model based on the principles of the dynamics and semi-empirical relations; this will be the objectives of a future paper.

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