Optimal Control of Diesel Engines: Methods and Applications

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***Abstract*—In the last two decades, engine and exhaust gas modeling have become more and more vital to the engines' producers and especially with the employment of new equipments installed on Diesel engines such as the common rail system, the variable geometry turbocharger and the exhaust gas recirculation, which require the control of five to ten actuators, thus making the optimal control scheme very difficult and sometimes impossible to find. In this paper, we describe two successful methods to model the engine and the exhaust gas; the first one is a classical physical approach based on the mean value modeling and the second one is a revolutionary method based on the neural networks. The simulation results are in good agreement with the experimental data measured on test bench. These models are then used in an upper-level dynamic optimization process that aims to find the optimal control scheme over a dynamic trajectory. We end this paper by a comparison between the two models showing its advantages and limitations.**

***Keywords*—Diesel Engines, Optimal Control, Mean Value Modeling and Neural Networks.**

I. INTRODUCTION

DIESEL engines are typically equipped with high pressure common rail system, variable geometry turbocharger and exhaust gas recirculation [1], [2] that are set to increase engine's efficiency while keeping the regulated gas emissions below their fixed limits (European standards). These devices increase the control parameters of the engine from the two conventional variables (the load and the fuel flow rate) to five to ten parameters that interact with each other, thus making the optimal control scheme of the engine very complex to find and sometimes unreachable by the traditionally used methods. These methods are time consuming and are all based on experiments that involve two phases, the first one is done on a static test bed and is used to construct the static cartographies of the engine while the second phase is done on a dynamic test bed and is used to properly adjust the values of the memorized cartographies to take into account the dynamic behavior and performance of the engine. Consequently, the need of a reliable optimization process becomes a necessity that has occupied the engines' producers for the last two decades. Such a process requires the build up of consistent engine and exhaust gas models to replace the expensive experiments and to predict the engine's response when varying the engine's control parameters. In this paper, we describe two different techniques that can be used to model the engine's performance and the exhaust emissions:

1 - A physical mean value model [3]-[5] based on the ideal gas state equation, the mass and energy conservation principles, the fundamental principle of the dynamic and semi-empirical equations that describe the states differential equations of the different blocks that constitute the engine.

2 - A black box model based on neural networks, [6]-[10].

These models are then used in a dynamic optimization process based on algorithms that are properly chosen to meet the selected models. For the first model, we choose the quasi-Newton algorithm which is a deterministic algorithm based on the gradient information and for the second one, we choose the genetic algorithm [11]-[13] which is a stochastic algorithm that is commonly used in the highly nonlinear optimization problem and that is based on the survival of the fittest theory.

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 are the results of an iteratively optimization process of the control parameters done on a static test bench.

Afterward, the primary values obtained from the basic cartographies are adjusted "on line" by using the control techniques [14]-[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

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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.

A. *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 into 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 (Fig. 1). 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…

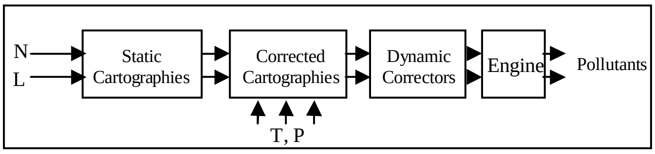


Figure 1: Open loop control.

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 [9]:

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

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.

B. *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 (fig. 2). 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…).

C. *Methodology*

Diesel engines can be modeled by two different approaches: The models of knowledge (quasi-statics, draining-replenishment, semi mixed, bond graph), and the models of representation (transfer functions, temporal series, neural networks). In this paper, we will present two different models representing the two approaches.

In the first category, we choose the semi-mixed mean value model which is the simplest analytic model that can be treated in an optimization process. The engine is divided to several blocks where the gas states can be described by their differential equations; these equations are deduced from the physical laws governing their movement and transformations and by expressing their characteristic variables in semi-empirical equations identified from static experimental data.

In the second category, we choose the neural networks. These networks have the capacity to approximate any continuous nonlinear function with an arbitrary fixed precision by simply learning from examples. In addition, we can select the variables to be modeled without the need of describing the intermediate states of the gas in the different blocks of the engine.

Then these models are used in a dynamic optimization process that aims to find the optimal engine control parameters over a specified dynamic trajectory such as the New European Driving Cycle (NEDC) where we have interest in finding the optimal control scheme in order to respect the European emissions standards.

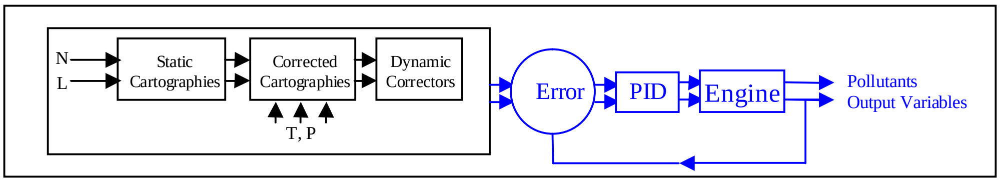


Figure 2: Closed loop control

Our proposed methodology is divided into five steps (fig. 3):

1. Experimental data acquisition. This phase depends

upon the chosen modeling process. If we are heading to build up a physical model, we need static experimental data representing the whole functioning area of the engine with detailed information about the states of the gas in the different engine blocks. If we are heading to build up a neural model, we need dynamic experimental data measured over the dynamic courses where we are concerned in finding the optimal control scheme.

2. Engine and exhaust gas modeling. We have the choice between two models, physical or neural models.
3. Model validation. The models simulations are compared to experimental data taken over dynamic trajectories.
4. Dynamic optimization process. Our objective is to search for the optimal control scheme over a specified dynamic trajectory.
5. Optimization results and validation.

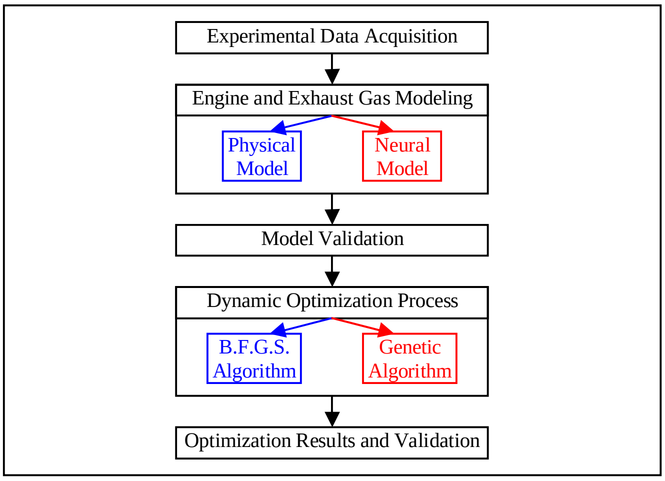


Figure 3: proposed methodology.

III. OPTIMIZATION PROCESS USING THE PHYSICAL MODEL

A. Engine and exhaust gas modeling

We used in this section a 9.8 l. Diesel engine equipped with a variable geometry turbocharger. The engine is divided to four blocks described by their differential equations:

$$\frac{dX}{dt} = f\left(\overset{\circ}{X},\overset{\circ}{U},R,t\right) \quad (2)$$

$$Y = f\left(X,U,R,t\right) \quad (3)$$

Where X is the gas states vector (intake and exhaust pressure, crankshaft and turbo-compressor angular speed), U is the actuators vector (fuel flow rate, position of the variable geometry vanes of the turbine, start of fuel injection), R is the resistant torque, t is the time, f is a nonlinear function deduced from the physical laws (the mass and energy conservation and the fundamental law of dynamic) and from the semi-empirical equations (engine effective efficiency, compressor and turbine isentropic efficiency…) and Y is the output vector representing the exhaust gas emissions (opacity, nitrogen oxide…).

The parameters of the semi-empirical equations are identified using static experimental data representing the functioning area of the engine measured on a test bed equipped with a brake controlled by the current of Foucault. As examples we can quote the engine effective efficiency and the corrected air mass flow rate of the turbine expressed by:

$$\eta_e = \lambda \cdot \left(\begin{array}{l} c_1 + c_2 \cdot \lambda + c_3 \cdot \lambda^2 + c_4 \cdot \lambda \cdot w \\ + c_5 \cdot \lambda^2 \cdot w + c_6 \cdot \lambda \cdot w^2 + c_7 \cdot \lambda^2 \cdot w^2 \end{array} \right) \quad (4)$$

$$\dot{m}_{t,corr} = \frac{\dot{m}_t \cdot \sqrt{T_e}}{P_e \cdot 10^{-3}} = \left\{ \begin{array}{l} \frac{\sqrt{T_{ech}}}{P_{ech}} \cdot \left[2 \cdot \pi_t \cdot (1-\pi_t)\right]^{0.5} \cdot (h_1 \cdot GV + h_2) \\ \cdot \left[h_3 \cdot \left(\frac{1}{\pi_t} - 1 \right) + h_4 \right] \end{array} \right\} \quad (5)$$

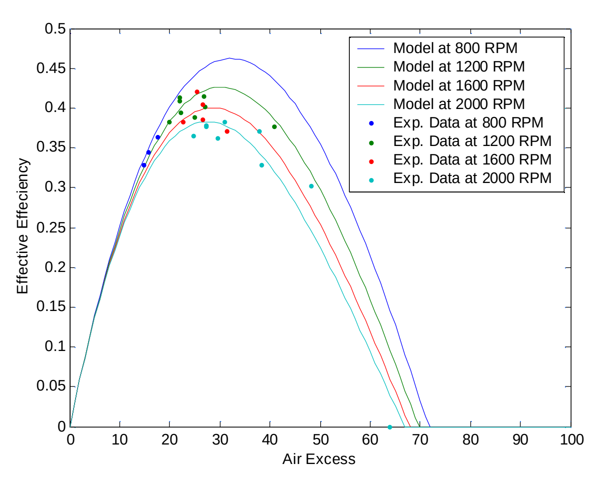


Figure 4: Comparison between the effective efficiency's calculated using (4) and the experimental data measured on test bench for different values of the air excess ratio at different engine angular speed.

Where λ is the air excess ratio, w is the engine angular speed, c_i are constants identified from experimental data, η_e is the engine effective efficiency, and $\dot{m}_t$ is the turbine mass flow rate, $\pi_t = P_{ech}/P_e$ is the relaxation ratio, GV is the vanes position, P_e, P_{ech} and T_e, T_{ech} are respectively the pressure and temperature at the entrance and the exit of the turbine, h_i are constants identified from experimental data and $\dot{m}_{t,corr}$ is the corrected mass flow rate of the turbine. Figures 4 and 5 show a comparison between the experimental data and the equation results calculated using (4) and (5).

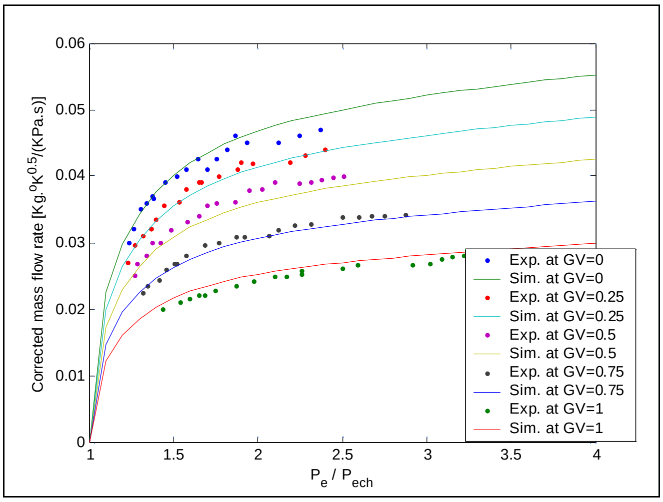


Figure 5: comparison between the corrected air mass flow rate of the turbine calculated using (5) and the experimental data given by the turbo-compressor constructor for different openings of GV versus the relaxation ratio.

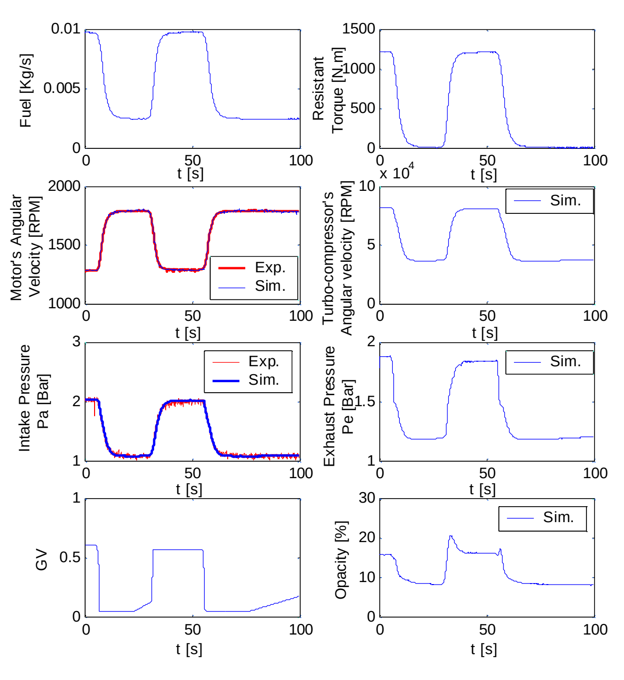


Figure 6: Comparison between the simulation results of the engine complete model and the experimental data.

The complete engine model is then validated using dynamic experimental data as shown in fig. 6. The opacity is chosen as a pollution criterion to be minimized and is expressed by:

$$\boxed{Opacity = m_1 \cdot w^{m_2} \cdot \dot{m}_a^{m_3 \cdot w + m_4} \cdot \dot{m}_f^{m_5 \cdot w + m_6} \qquad (6)}$$

Where $\dot{m}_a$ is the air mass flow rate entering the cylinders, $\dot{m}_f$ is the fuel mass flow rate and m_i are constants identified from experimental data.

B. *Optimization process*

In vehicles, the depollution is classically done in two steps: - at the source, at the motor's level itself by using different equipments (TGV, EGR, …) and control schemes (ECU), and – at the exhaust of the gases, after the combustion process, by using the different systems of post-treatment (SCR, Catalytic pot, ….). Here we are only interesting in resolving the pollution problem at the motor level.

Our goal is to minimize the complete pollutants production without deteriorating the engine performance over a dynamic course in order to replace the existing static cartographies with dynamic ones. Consequently, the problem is to find, for a given resistant torque and engine angular speed course, the optimal values of the actuators that fulfill our objectives. The problem is highly nonlinear, the analytic approach is unrealistic and we must pass to the descritized form of the equations. Therefore the problem can be defined as follow:

Minimize the objective function:

$$\boxed{f = -\frac{1}{\mathrm{P}_{\max}} \sum_i \mathrm{P}_i + \frac{1}{Opacity_{\max}} \sum_i Opacity_i \qquad (6)}$$

Under the equalities constraints:

$$\left\langle \begin{array}{l} (2) \Rightarrow \dfrac{X_{i+1} - X_i}{\Delta t} = f\left(\overset{\circ}{X}_i, \overset{\circ}{U}_i, R_i, t_i\right) \\ w_i = w_{ref} \\ R_i = R_{ref} \end{array} \right. \qquad (7)$$

And under the inequalities constraints representing the permissible range of variation of the different variables:

$$\left\langle \begin{array}{l} \underset{\circ}{X}_{\min} \le \underset{\circ}{X}_i \le \underset{\circ}{X}_{\max} \\ U_{\min} \le U_i \le U_{\max} \end{array} \right. \qquad (8)$$

The subscript max represents the maximum value that the variable can reach in order to have a comparable scale between the different variables and P is the effective power produced at the crankshaft. The subscript ref represents the reference values fixed by the dynamic trajectory. We chose the opacity as a pollution criterion because of the simplicity of the model and the priority to present the optimization methodology but the method is universal and it can involve other criteria such as the nitrogen oxide, the carbon monoxide and the unburned hydrocarbons.

To solve this difficult problem, we used the Broyden-Fletcher-Goldfarb-Shanno (B.F.G.S.) algorithm which is a sequential algorithm based on the gradient that can be calculated using (6)-(8). The results are reported in fig. 7 and 8. The gain in opacity reduction is very promising.

IV. OPTIMIZATION PROCESS USING THE NEURAL MODEL

A. *Engine and exhaust gas modeling*

We used in this section a 1400Kg passenger car equipped with a four cylinders diesel engine, a variable geometry turbocharger (TGV), a system of exhaust gas recirculation (EGR), a common rail injection system and a catalyst for the reduction of CO and HC. We are only interested in modeling the exhaust gas emissions that figures in the objective function and the crankshaft angular speed to assure the following of the reference speed set by the dynamic trajectory.

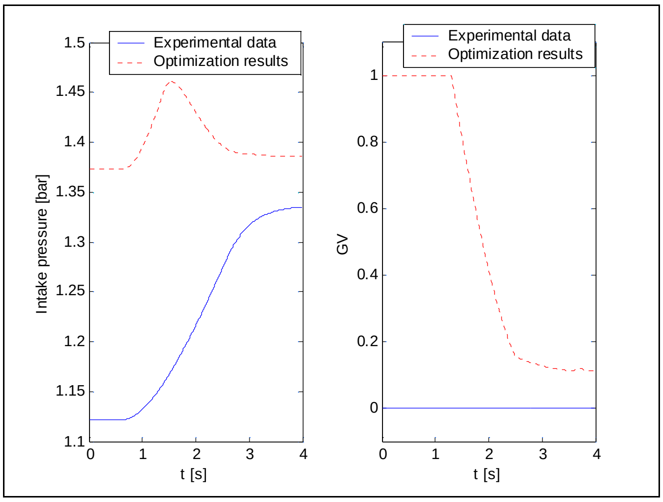


Figure 7: Comparison between the intake pressure and the position of the variable geometry vanes of the turbine obtained by the optimization procedure and the experimental data.

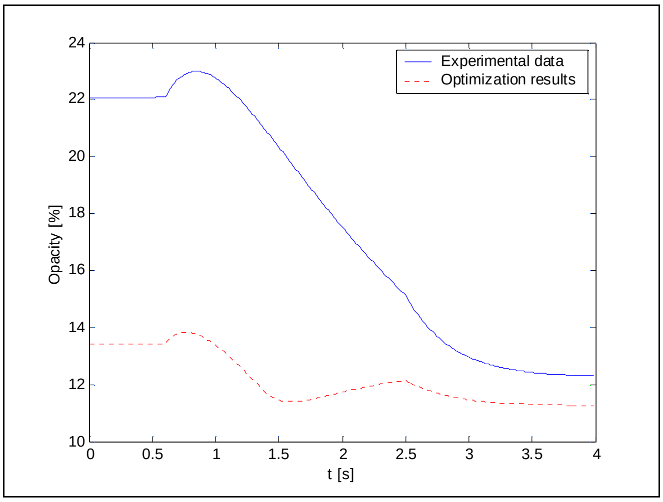


Figure 8: The gain in opacity reduction when using the optimal values of the actuators.

The neural networks chosen to model the pollutants and the crankshaft angular speed have three layers: an input layer, one hidden layer and an output layer. The transfer functions at the hidden layer are sigmoid functions and those at the output layer are linear functions. These networks are black box models with great capacity for universal functions approximation. We selected the feed-forward back-propagation algorithm to train the networks. The output variables can represent the whole functioning area of the engine or a specified zone depending on the experimental data used in the training process. The acquisition of the experimental data is done on a chassis dynamometer over the New European Driving Cycle which is our zone of interest. The output variables are presented in their descritized form and can be described by the following recurrent equations:

$$Pol_i = Net\begin{pmatrix} U_i, U_{i-1}..., U_{i-k}, w_i, w_{i-1},..., w_{i-k}, \\ R_i, G_i, Pol_{i-1},..., Pol_{i-l} \end{pmatrix} \qquad (9)$$

$$w_i = Net\begin{pmatrix} U_i, U_{i-1}..., U_{i-k}, \\ R_i, G_i, w_{i-1},..., w_{i-k} \end{pmatrix} \qquad (10)$$

Where Pol is the pollutants (opacity, oxide nitrogen, carbon dioxide), w is the crankshaft angular speed, U is the seven control parameters (fresh air flow rate, intake pressure, start of Main fuel injection, Pilot fuel flow rate, separation time between Main and Pilot fuel injection, total fuel flow rate and rail pressure), R is the resistant torque, G is the gearbox ratio, k and l are integers representing the recurrent order of the input and output variables and Net is the nonlinear function approximated by the neural networks.

The model results are in good agreement with the experimental data. As an example, fig. 9 shows a comparison between the neural model of CO2 and the experimental data.

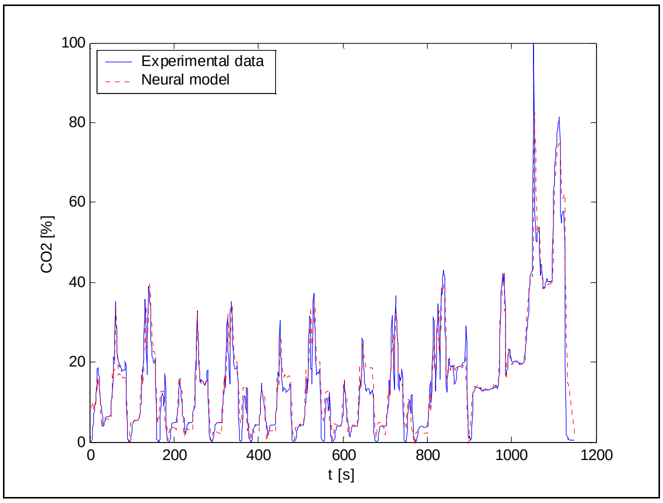


Figure 9: Comparison between the neural model of CO2 and the experimental data over a dynamic course.

B. Optimization process

The problem is defined as in section III.B. We added to the pollution criteria the nitrogen oxide and we substitute the maximization of the effective power by the minimization of the carbon dioxide which has the same effect. Consequently, the objective function becomes:

$$f = \left\{ \begin{array}{l} \dfrac{1}{Opacity_{\max}} \sum_i Opacity_i + \dfrac{1}{NOx_{\max}} \sum_i NOx_i \\ + \dfrac{1}{CO2_{\max}} \sum_i CO2_i \end{array} \right\} \qquad (11)$$

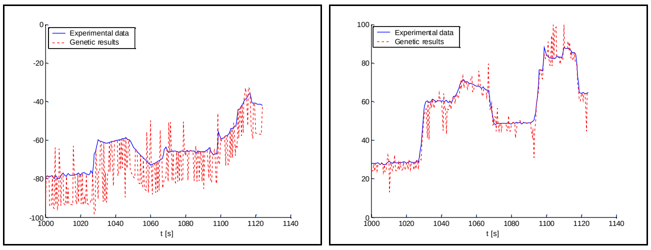
Under the equalities constraints:

$$\left\langle \begin{array}{l} (10) \Rightarrow Net\begin{pmatrix} U_i, U_{i-1}..., U_{i-k}, \\ R_i, G_i, w_{i-1},..., w_{i-k} \end{pmatrix} = w_{ref} \\ R_i = R_{ref} \\ G_i = G_{ref} \end{array} \right\rangle \qquad (12)$$

And the inequalities constraints:

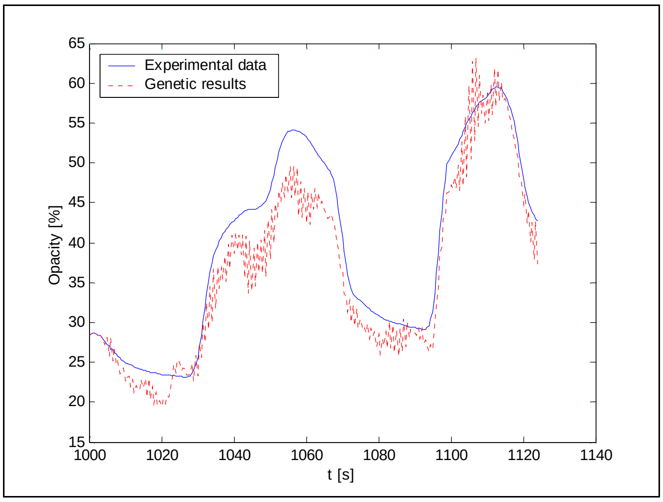
$$U_{\min} \leq U_i \leq U_{\max} \quad (13)$$

To solve this problem, we used the genetic algorithm which is a stochastic algorithm with great ability to find the global minimum even in the case of highly nonlinear functions as in our case where the domain surface is full of local minimums and where the traditional optimization algorithms may get stuck In addition, seeing the large number of the control parameters to be found, the genetic algorithm requires considerably less computation time than the B.F.G.S. algorithm which necessitates the calculation of the gradient and the approximation of the Hessian. An example of the optimization results is shown in fig. 10. The gain in opacity reduction is promising.



Start of Main fuel injection [%]

Total fuel injection [%]



Opacity [%]

Figure10: Comparison between the optimization results and the experimental data.

V. DISCUSSION

The suggested methodology has proven to find the optimal control parameters over a dynamic course, thus the static and corrected cartographies and the control techniques as reported in fig. 1 and 2 can now be substituted by dynamic cartographies applied directly to the actuators. This methodology requires by far less experiments than the existing optimization process which is done manually by experts on a test bench.

The neural networks have the advantage of modeling the exhaust gas emissions with unlimited number of control parameters while the physical approach requires previous knowledge about their behavior to the variation of these parameters which become a very difficult task when we are faced to a large number of parameters that interact with each other.

Also, the neural networks have the advantage of modeling the exhaust gas in a specified zone while the physical approach necessitates their modeling in the whole functioning area of the engine.

While the physical approach requires the modeling of the different engine blocks, the neural networks are capable of modeling directly the variables of interest without additional information about the states of the gas in the different engine blocks.

Finally, while the pollutants' production in the engine is not fully understood, the existing physical models lack for precision. This is the main advantage of the neural networks which have proven to approximate any nonlinear function with the desired precision.

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