Optimal Control of a Variable Geometry Turbocharged Diesel Engine Using Neural Networks: Applications on the ETC Test Cycle

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Abstract—Modern diesel engines are typically equipped with variable geometry turbo-compressor, exhaust gas recirculation (EGR) system, common rail injection system, and post-treatment devices in order to increase their power while respecting the emissions standards. Consequently, the control of diesel engines has become a difficult task involving five to ten control variables that interact with each other and that are highly nonlinear. Actually, the control schemes of the engines are all based on static lookup tables identified on test-benches; the values of the control variables are interpolated using these tables and then, they are corrected, online, by using the control techniques in order to obtain better engine’s response under dynamic conditions. In this paper, we are interested in developing a mathematical optimization process that search for the optimal control schemes of the diesel engines under static and dynamic conditions. First, we suggest modeling a turbocharged diesel engine and its opacity using the mean value model which requires limited experiments; the model’s simulations are in excellent agreement with the experimental data. Then the created model is integrated in a dynamic optimization process based on the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. The optimization results show the reduction of the opacity while enhancing the engine’s effective power. Finally, we proposed a practical control technique based on the neural networks in order to apply these control schemes online to the engine. The neural controller is integrated into the engine’s simulations and is used to control the engine in real time on the European transient cycle (ETC). The results confirm the validity of the neural controller.

Index Terms—Diesel engines, dynamic optimization process, mean value model, optimal control and neural networks.

I. INTRODUCTION

DIESEL engines are typically equipped with control and post-treatment devices [1]–[5] that are set to increase engines’ power and human comfort while reducing engines’ harmful emissions. These devices increase the number of the control variables from the two conventional variables (fuel flow rate and crankshaft angular speed) to five to ten variables thus making the search for the optimal control schemes highly complex and time consuming. Actually, the control of the engine is based on two dimensional static lookup tables with inputs the crankshaft angular speed and the fuel flow rate, these tables, called basic lookup tables, cover the whole functioning area of the engine and are identified from steady state experiments using experimental optimization process. The primary values of the control variables are computed using these maps. Then these values are adjusted online using corrected lookup tables that take into consideration the changes in the engine’s environment and the evolution of the engine’s states variables detected in real time using different sensors. Finally, in order to meet the emissions standards and to increase the efficiency of the engine and enhance its response under dynamic charge, the corrected values are modified using the control techniques [6]–[8]. These methods are characterized by control parameters that are tuned experimentally on a dynamic test-bench. Therefore, the control of the engine is clearly very difficult and time consuming; it requires steady state and dynamic experiments and highly depends upon the judgment of the experimental staff where we cannot eliminate the possibility for human errors especially with the rising number of the control variables. Consequently, the need of a reliable optimization tool has become a necessity that occupied the engines’ producers for the last two decades. Such a process requires the buildup of consistent engine and emissions models to replace the expensive experiments and to predict the engine’s response when varying the control variables.

In this paper, we presented the principal control algorithms of the engine and we discussed the different strategies commonly used to control the air management system. Then, we proposed a new methodology to control the engine. First, we used the mean value model to describe the engine’s states variables and exhaust emissions [9]–[12]; the model is 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 relations between different states variables of the engine. We adopted this modeling technique because it is precise and simple enough to be used in a mathematical optimization process, and it requires limited experimental data to identify the model’s parameters. Then the engine’s model is integrated in a dynamic optimization process based on the BFGS algorithm [13]. Our objective is to find the optimal values of the engine’s control variables over dynamic courses in order to create dynamic lookup tables that can be directly applied to the corresponding actuators. This optimization
process cannot be used directly in vehicles by a control processor because it is time consuming, so, first, we used it offline to create a large database, and then the database can be exploited to create a controller based on the neural networks that can be integrated in the engine control unit (ECU) which manages in real time the different control variables. The neural network is a powerful tool that can be used to approximate any functions by simply learning from examples [14]–[19]. It is accurate and not limited with the number of inputs and its response is almost instantly which makes it an excellent controller [19].

II. PROBLEM STATEMENT AND CONTROL SCHEMES

In this section, we introduce the control algorithms and strategies commonly used, without largely developing the theory of the control systems. Afterward, we present the different steps of our proposed methodology which can be used to control the engine and to replace and outperform the existing control algorithms.

A. Open-Loop Control

The open-loop control mainly depends on controlling the engine’s actuators under steady-state conditions. Beside basic lookup tables, corrective tables 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 (see Fig. 1). Among these variables which are measured in real time by sensors mounted on the vehicle, we can quote, as examples; the temperature of the cooling water, the temperature of the ambient air, the atmospheric pressure, etc. Thus, for a given fuel flow rate and crankshaft angular speed, the primary values of the basic lookup tables are multiplied by a factor (correction) function of the cooling water temperature, the fuel flow rate, and the velocity, then by another one, function of the ambient air temperature, the fuel flow rate, and the velocity, and so on.

Afterward, a predictive dynamic corrector is generally used to compensate the dynamic behavior of the engine and enhance its performance. For example, a predictive correction can take the following form [20]:

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

where \( y_2(t) \) is the corrected value of the control variable varying with time, \( y_{10} \) and \( y_{20} \) are respectively its initial and final value given by the static lookup tables, \( T_Y \) is a time constant describing the response time of the engine and \( T_Y \) is a parameter identified and tuned using dynamic experimental data.

B. Closed-Loop Control

The main objective of the closed-loop control is to continuously manage the engine’s actuators in order to force an output variable to follow a predetermined set point. It is used to ensure the independence of the engine’s behavior with respect to its operating conditions or external disturbances (see Fig. 2). We can quote as examples of the variables concerned by this control algorithm; the air to fuel ratio, the engine idle speed, the start of combustion, etc. The control processes are in general described by their transfer functions which are characterized by their zeros and poles. Their positions in the complex plane determine the system stability and its dynamic response and performance (examples: proportional-integral-derivative (PID) control, self-adapting control, etc).

C. Control Strategies

In this subsection, we will discuss the principal strategies under studies or actually used to control the air management system in the Diesel engine.

In [20], Watson and Banisoleiman proposed to control the boost pressure by regulating the turbocharger angular speed. Based upon a boost pressure target reference, the compression ratio is computed, then using the compressor chart and a desired compressor air flow, the required turbocharger angular speed can be set. This control scheme is not suitable for real time engine applications because of the strong dispersion (±10%) of the variable geometry turbocharger (VGT) and the need to equip the vehicles with tachometers in order to continuously measure the turbocharger speed.

Another strategy consists in modeling the boost pressure based upon the position of the vanes of the turbine’s variable geometry in order to use it in a boost pressure control scheme. Buratti [21] used first-order models to describe the relation between the boost pressure and the VGT actuator, the crankshaft angular speed and the fuel flow rate, under steady and transient conditions. Afterwards he used a gain-scheduled PID controller to set the position values of the turbine’s vanes.

In [22], the model of the air management system includes different engine’s state variables: the intake and exhaust pressure and the air and gas flow across the compressor, the engine and the turbine. Then a fuzzy control technique is used to control the turbocharger actuator; it consists in defining a significant number of classes of inputs (the errors and the derivative of the errors). An optimization algorithm is used to generate the membership functions in order to obtain the same behavior of a PID controller. By exploring this technique the feasibility of a fuzzy controller was checked and a better dynamic behavior was obtained.

Fig. 1. Open-loop control.

Fig. 2. Closed-loop control.
Another strategy consists in controlling the air’s partial pressure in the intake manifold. Kolmanovsky and Stotsky [23] used a throttle valve to control the air flow into the intake manifold based on EGR flow rate that is estimated using a dynamic observer and an estimation of the partial air fraction in the exhaust gas products.

The linear quadratic regulator (LQR) theory proposes to minimize a certain quadratic criterion (the pollution) to obtain the optimal controller. The linear quadratic Gaussian (LQG) control which is an extension of the LQR control, takes into consideration the uncertainties related to the models by associating to the LQR a Kalman filter. This control technique can also be exploited in the automotive field [7], [24]. The use of various control techniques is necessary (in particular, the techniques anti-windup) because of the limitation of the operating ranges of the actuators. This theory necessitates the division of the problem to several subproblems, each one described by a linear model. In a highly nonlinear system such as the diesel engine, the number of the sub-models becomes very important especially with the increasing number of the control actuators.

The control strategy developed in [1] consists in using two control schemes of the air management system: one to control the air flow rate and another one to control the boost pressure. The required compressor power is calculated based on the target references of the fresh air flow and the boost pressure. Then based on the power requested and the pressure in the intake manifold, the nonlinear controller determines the required turbine’s flow rate and thus its vanes’ position. By using this control technique, the target references of the air flow rate and boost pressure are precisely and quickly followed under steady and transient conditions. However, the identification of the engine’s model parameters is time consuming and the nonlinear controller remains complex. Studies are currently in progress [25], [26] in order to improve the online identification of the engine and turbocharger dynamic behavior.

Finally, Clarke [27] exploited the generalized predictive control (GPC). The control structure includes a cost function to be minimized and an identification function to determine the exact operating conditions and to adjust the engine’s model parameters. In general, the GPC control gives excellent results in term of precision and shortening the time required to reach the target value. However this technique requires the exploitation of an accurate predictive model under steady and transient conditions. This can be done by using the robust predictive control [28]. An improvement of the control structure is proposed in [29] and realized in [30] by associating the predictive control to the flatness property. This technique increases the precision of the system under transient operating conditions [31].

D. Proposed Methodology

Diesel engines can be modeled by two different approaches: the models of knowledge (quasi-static, draining-replenishment, semi mixed, bond graph) and the models of representation (transfer functions, temporal series, neural networks). In this paper, we choose the quasi-static mean value model which is the simplest analytic model that can be used in an optimization process. The engine is divided to several blocks where the gas state variables 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 steady-state experimental data. Once the parameters of the engine’s model identified and the model validated using dynamic experimental data, it is integrated in a dynamic optimization process that searches for the optimal values of the control variables over dynamic courses. The courses are chosen arbitrary to cover the whole functioning area of the engine. Then the created database is used to train a neural network which can predict online the optimal values of the control variables, thus, the memorized lookup tables previously described are replaced with the values of the weights and bias of the neural network.

Consequently, the proposed methodology can be divided into seven steps (see Fig. 3):

1) experimental data acquisition;
2) engine and exhaust gas modeling;
3) model validation: the model’s simulations are compared to dynamic experimental data;
4) dynamic optimization process: concept and validation;
5) creation of a large database of the optimal control variables using the dynamic optimization process;
6) creation of the neural network;
7) validation of the neural control;
8) integration of the neural controller in real time engine simulations. Comparison between the ECU’s classic controller and the neural controller on the ETC test cycle.

III. EXPERIMENTAL DATA ACQUISITION

The test-bench used for data acquisition involves a six-cylinders turbocharged Diesel engine, a brake controlled by the current of Foucault, a Bosch smoke detector, and various sensors to measure the gas’ state variables in the different blocks of the engine. Engine’s characteristics are reported in Table I.

IV. ENGINE AND OPACITY MODELING

The engine (see Fig. 4) can be divided to four blocks (the intake manifold, the exhaust manifold, the engine and the variable geometry turbo-compressor), each one described by differential equations governing the dynamic or the gas state changes in the
A. Intake Manifold

Neglecting the heat losses through the manifold walls and considering the air as an ideal gas with constant specific heats, the differential equation of the intake pressure is computed using the principle of the energy conservation and the ideal gas’ state equation:

\[ \dot{p}_a = \frac{\gamma_a \cdot R}{V_a} \cdot (\dot{m}_{ai} \cdot T_{HE} - \dot{m}_{ai} \cdot T_a) \]  \hspace{1cm} (2)

where \( p_a \), \( V_a \), and \( T_a \) are, respectively, the pressure, the volume, and the temperature of the air in the intake manifold, \( R \) is the mass constant of the ideal gas, \( \gamma_a \) is the ratio of the heat capacities at constant volume and pressure, \( \dot{m}_{ai} \) is the compressor air mass flow rate, \( \dot{m}_{ai} \) is the air mass flow rate entering the engine, and \( T_{HE} \) is the temperature of the air exiting the cooling water heat exchanger.

\( \dot{m}_{ai} \) is given by

\[ \dot{m}_{ai} = \eta_r \cdot \dot{m}_{ai,th}. \]  \hspace{1cm} (3)

\( \dot{m}_{ai,th} \) is the theoretical air mass flow rate capable of filling the cylinders volume at the pressure and temperature conditions of the intake manifold

\[ \dot{m}_{ai,th} = \frac{N_{cy1} \cdot V_{cy1} \cdot \omega \cdot p_a}{4 \cdot \pi \cdot R \cdot T_a} \]  \hspace{1cm} (4)

\( N_{cy1} \) is the total number of cylinders, \( V_{cy1} \) is the displacement of one cylinder, \( \omega \) is the engine angular speed, and \( \eta_r \) is the volumetric efficiency expressed by the semi-empirical equation

\[ \eta_r = \alpha_0 + \alpha_1 \omega + \alpha_2 \omega^2 \]  \hspace{1cm} (5)

where \( \alpha_0 \) are constants identified from experimental data. The hot air exiting the compressor is cooled by a water cooled heat exchanger before entering the intake manifold, the temperature \( T_{HE} \) is computed using the following equation:

\[ T_{HE} = (1 - \eta_{ech}) \cdot T_c + \eta_{ech} \cdot T_{water}. \]  \hspace{1cm} (6)

\( T_c \) is the temperature of the air at the compressor’s exit, \( T_{water} \) is the temperature of the cooling water supposed constant, and \( \eta_{ech} \) is the efficiency of the heat exchanger also supposed constant. The temperature \( T_c \) is computed using the isentropic efficiency of the compressor

\[ T_c = T_0 \left( 1 + \left( \frac{p_a}{p_0} \right)^{\gamma - 1/\gamma_a} - 1 \right) \frac{1}{\eta_c}. \]  \hspace{1cm} (7)
\(p_0\) and \(T_0\) are, respectively, the atmospheric pressure and temperature, and \(\eta_c\) is the isentropic efficiency of the compressor.

The air mass change in the intake manifold is computed using the mass conservation principle

\[
\dot{m}_a = \dot{m}_c - \dot{m}_{ai}.
\]  

The temperature of the air in the intake manifold is deduced from the ideal gas' state equation

\[
T_a = \frac{p_a \cdot V}{m_a \cdot R}.
\]  

B. Exhaust Manifold

Neglecting the heat losses through the manifold walls and considering the exhaust gas as an ideal gas with constant specific heats, the differential equation of the exhaust pressure is computed using the principle of the energy conservation and the ideal gas state equation

\[
\dot{p}_e = \frac{\gamma_e \cdot R}{V_e} \cdot (\dot{m}_t \cdot T_e - \dot{m}_{e0} \cdot T_x).
\]  

\(p_e\), \(V_e\), and \(T_e\) are, respectively, the pressure, the volume, and the temperature of the air in the intake manifold, \(\gamma_e\) is the ratio of the heat capacities at constant volume and pressure and \(\dot{m}_t\) is the turbine mass flow rate. \(\dot{m}_{e0}\) and \(T_x\) are, respectively, the gas' mass flow rate and temperature exiting the engine. \(\dot{m}_{e0}\) is computed using the following equation:

\[
\dot{m}_{e0} = \dot{m}_f + \dot{m}_{ai}.
\]  

\(T_e\) is expressed by the following semi-empirical equation:

\[
T_e = T_a + \frac{b_1 + b_2 \cdot \lambda + b_3 \cdot \lambda^2}{1.2 + \frac{b_4}{\omega} + b_5},
\]  

\(\dot{m}_f\) is the fuel mass flow rate, \(\lambda\) is the air to fuel ratio, and \(b_k\) are constants identified from experimental data. Fig. 5 shows that the equation's results using (12) are in good agreement with the experimental data.

The gas mass change in the exhaust manifold is computed using the mass conservation principle

\[
\dot{m}_e = \dot{m}_{ai} + \dot{m}_f - \dot{m}_t.
\]  

The temperature of the gas in the exhaust manifold is deduced from the ideal gas state equation

\[
T_e = \frac{\dot{p}_e \cdot V_e}{m_e \cdot R}.
\]  

C. Engine

Applying the principle of energy conservation to the crankshaft gives

\[
\frac{d}{dt} \left( \frac{1}{2} \cdot J(\theta) \cdot \omega^2 \right) = P_e - P_r,
\]  

\(J(\theta)\) is the moment of inertia of the engine, it is a periodic function of the crankshaft angle due to the repeated motion of the pistons and connecting rods, but for simplicity, in this paper, the inertia is considered as a constant. \(P_e\) is the effective power produced by the combustion process

\[
P_e = \eta_c \cdot \dot{m}_f \cdot H_f.
\]  

\(H_f\) is the fuel heating value and \(\eta_c\) is the effective efficiency of the engine expressed by the semi-empirical equation

\[
\eta_c = \lambda \cdot \left( c_1 + c_2 \cdot \lambda + c_3 \cdot \lambda^2 + c_4 \cdot \lambda \cdot \omega + c_5 \cdot \lambda^2 \cdot \omega + c_6 \cdot \lambda \cdot \omega^2 + c_7 \cdot \lambda^2 \cdot \omega^2 \right).
\]  

where \(c_i\) are constants identified from experimental data. \(P_r\) is the friction power

\[
P_r = C_r \cdot \omega.
\]  

\(C_r\) is the friction torque controlled by the brake. Fig. 6 presents a comparison between the effective efficiency computed using (17) and the experimental data. The equation’s results are in good agreement with the experiments.
D. Variable Geometry Turbo-Compressor

The variable geometry turbo-compressor can be divided into three parts: the compressor, the variable geometry turbine and the mechanical coupling.

1) Compressor: The air mass flow rate at the exit of the compressor is expressed by the following semi-empirical equation:

\[ \dot{m}_c = \Phi \cdot \frac{P_0}{rT_0} \cdot \frac{\pi}{4} D_c^2 \cdot U_c. \]  
(19)

\( D_c \) is the diameter of the compressor’s wheels and \( U_c \) is the velocity of the air at the extremity of the compressor’s blades, it is proportional to the turbo-compressor’s angular speed \( N_{tc} \) and is expressed by

\[ U_c = \frac{\pi}{60} \cdot D_c \cdot N_{tc}. \]  
(20)

\( \Phi \) is a correction factor expressed by

\[ \Phi = \frac{k_3 \cdot \Psi - k_1}{k_2 + \Psi}, \]  
(21)

\[ k_3 = k_{c1} + k_{c2} \cdot M. \]  
(22)

where \( k_{ij} \) are constants identified from experimental data. \( M \) is the Mach number; it is the ratio of the blade’s velocity \( U_c \) to the velocity of the sound at the entry of the compressor

\[ M = \frac{U_c}{\sqrt{\gamma a \cdot r \cdot T_0}}. \]  
(23)

The parameter \( \Psi \) in (21) is given by the equation

\[ \Psi = \frac{C_p T_0 \left( \left( \pi_c \right)^{\gamma a} - 1 \right)}{0.5 \bar{c}^2}. \]  
(24)

\( C_p \) is the heat capacity of the air at constant pressure and \( \pi_c \) is the compression ratio of the compressor

\[ \pi_c = \frac{P_a}{P_0}. \]  
(25)

The power consumed by the compressor is expressed by

\[ P_c = \dot{m}_c C_p T_0 \left( \left( \pi_c \right)^{\frac{\gamma a}{\gamma a - 1}} - 1 \right) \frac{1}{\eta_c}. \]  
(26)

\( \eta_c \) is the compressor isentropic efficiency expressed by

\[ \eta_c = d_0 + d_1 \Phi + d_2 \Phi^2 \]  
(27)

where \( d_i \) are calculated using the following equation:

\[ d_i = d_{i1} + d_{i2} \cdot M + d_{i3} \cdot M^2. \]  
(28)

\( d_{ij} \) are constants identified from the experimental maps of the compressor.

Figs. 7 and 8 show, respectively, the air mass flow rate and the isentropic efficiency of the compressor simulated using (19) and (27); the equations’ results are in good agreement with the experimental data.

2) Variable Geometry Turbine: The gas mass flow rate at the entrance of the turbine \( \dot{m}_t \) is deduced from the empirical equation of the turbine’s corrected flow rate

\[ \begin{align*}
\frac{\dot{m}_t \sqrt{T_I}}{P_{ech}} &= \frac{\sqrt{T_{ech}}}{P_{ech}} \cdot \left[ \left( \frac{2 \cdot \pi_t \cdot (1 - \pi_t))^{0.5} \cdot AA \right) \right] \\
AA &= \left( h_1 \cdot GV + h_2 \right) \cdot \left[ h_3 \cdot \left( \frac{1}{\pi_t} - 1 \right) + h_4 \right].
\end{align*} \]  
(29)

\( P_{ech} \) and \( T_{ech} \) are the pressure and temperature at the turbine’s exit and \( \pi_t \) is the turbine relaxation ratio

\[ \pi_t = \frac{P_0}{P_c}. \]  
(30)
are given by the following equations:

\[ \text{moment of inertia} = I \]

\[ \text{heat capacity} = C \]

\[ \text{particulate matter (PM)} = \text{PM} \]

By setting to zero, the power produced by the turbine is expressed by

\[ P_t = \eta_t C_{pe} T_e \left( 1 - (\pi_t)^{\gamma - 1/\gamma} \right) \eta_k. \]  \( (31) \)

\( \eta_t \) is the isentropic efficiency of the turbine modeled by

\[ \eta_t = k_1 + k_2 \left( \frac{U}{C} \right) + k_3 \left( \frac{U}{C} \right)^2 + k_4 \left( \frac{U}{C} \right)^3. \]  \( (32) \)

\( k_i \) and \( U/C \) are given by the following equations:

\[ k_i = (k_{i1} + k_{i2} \cdot \eta_{i1} + k_{i3} \cdot \eta_{i2}^2 + k_{i4} \cdot \eta_{i3} \cdot GV + k_{i5} \cdot GV^2) \]

\[ + k_{i6} \cdot \eta_{i4} \cdot GV) \]

\[ U = \frac{\pi N_{te} D_t}{60 \sqrt{2 C_{pe} T_e \left( 1 - (\pi_t)^{\gamma - 1/\gamma} \right)}}. \]  \( (34) \)

\( D_t \) is the diameter of the turbine wheels, and \( C_{pe} \) is the heat capacity of air at constant pressure, at the temperature \( T_e \).

Figs. 9–11 show a comparison between the equations’ simulations of the turbine’s flow rate and isentropic efficiency using (29) and (32) and the experimental data for different positions of the variable geometry \( GV \). The models’ results are in good agreement with the experimental data provided by the turbine-compressors’ producer.

3) Mechanical Coupling: The fundamental principle of the dynamics applied to the shaft of the turbo-compressor gives

\[ I_{tc} \omega_{tc} \frac{d\omega_{tc}}{dt} = (\eta_m P_t - P_c). \]  \( (35) \)

where \( I_{tc} \) and \( \eta_m \) are, respectively, the moment of inertia and the mechanical efficiency of the turbo-compressor.

E. Pollution

The pollutants that characterize the Diesel engines are mainly the nitrogen oxides (NOx) and the particulate matter (PM).

In this paper, we are interested in presenting the optimization process and its advantages without complicating the pollution’s models, that is why we choose the opacity as a pollution criterion which is expressed by the following semi-empirical equation:

\[ \text{Opacity} = m_1 \cdot \omega^{m_2} \cdot \eta_{i1}^{m_3} \cdot \omega^{m_4} \cdot \eta_{i2}^{m_5} \cdot \omega^{m_6}. \]  \( (36) \)

\( m_i \) are constants identified from the experimental data.

F. Engine’s Complete Model

The different engine’s state variables are computed by solving simultaneously (2)–(36) at an instant \( t \). The complete engine’s model is characterized by six principal state’s variables.
(\(P_a\), \(m_a\), \(P_e\), \(m_e\), \(\omega\), and \(\omega_e\)), two inputs \((\dot{m}_f\) and \(C_r\)), one control variable \((GV)\), and the following six differential equations representing the dynamic processes in the different engine’s blocks:

\[
\begin{align*}
(2) & \quad \frac{d(P_a)}{dt} = \frac{\pi \rho \Omega}{\pi_a} \left( \dot{m}_e \cdot T_{HE} - \dot{m}_{ai} \cdot T_a \right) \\
(8) & \quad \frac{d(m_a)}{dt} = \dot{m}_e - \dot{m}_{ai} \\
(10) & \quad \frac{d(P_e)}{dt} = \frac{\pi \rho \Omega}{\pi_e} \left( \dot{m}_e \cdot T_e - \dot{m}_{e0} \cdot T_e \right) \\
(13) & \quad \frac{d(m_e)}{dt} = \dot{m}_{ai} + \dot{m}_f - \dot{m}_k \\
(15) & \quad J \cdot \dot{\omega} = \eta_e \cdot \dot{m}_f \cdot H_f - C_r \cdot \omega \\
(35) & \quad I_{e\omega} \cdot \dot{\omega} = (\eta_m P_t - P_e)
\end{align*}
\]

V. MODEL VALIDATION

Figs. 12 and 13 show a comparison between the experimental data measured on the test-bench and the simulations of the engine’s complete model using (2)–(36); the experiments are characterized by simultaneous changes in the engine inputs and control variable: the fuel flow rate, the friction torque and the position of the turbine’s variable geometry. The model’s results are in excellent agreement with the experimental data.

VI. DYNAMIC OPTIMIZATION PROCESS

A. Problem Statement

When conceiving a new engine, engines’ producers and mechanical engineers have always to confront and properly solve the contradictory problem of producing maximum power (or minimum fuel consumption) and respecting the pollution’s constraints (European norms). In vehicles, emissions reduction is classically done in the following two steps:

1) at the engine level by using different equipments (VGT, EGR, etc.) and control schemes;
2) at the exhaust of the gases, by using post-treatment devices (SCR, Catalytic pot, etc.).

In this paper, we are only interesting in resolving the pollution’s problem at the engine level, by searching for the optimal control variables that minimize a desired cost function expressing the producers need. Consequently, the problem can now be defined; it consists in the following multi-criteria function:

\[
\begin{align*}
\{ & \text{Maximize } \text{"Power" } \\
& \text{Minimize } \text{"Pollutants". } \}
\end{align*}
\]

Considering that the passenger car engine usually runs under dynamic charges, an optimization process that search for the optimal control variables under steady state conditions would be inefficient, that is why we propose a dynamic optimization process that search for these variables over dynamic courses where the engine’s inputs are allowed to change. We should also note that the proposed optimization process can be easily adapted to search for the engine’s optimal control scheme under steady conditions by simply using constant inputs. The multi-criteria objective function described in (38) can now be expressed by a single non-dimensional mathematical equation defined over a time interval \([0, T]\)

\[
f = -\int \frac{P}{P_{\text{max}}} \cdot dt + \sum_i \left\{ \int \frac{\text{Poll}_i}{\text{Poll}_{i,\text{max}}} \cdot dt \right\}.
\]
\( P \) is the engine effective power, Poll is a type of pollutant, and the indication max is the maximum value that a variable can reach. The integral represents the sum of the pollutants and power over the dynamic course. In this paper, we will only use the opacity as an indication of the pollution seen the simplicity of the model and the priority given to the presentation of the method, but we should note that the optimization process is universal and it can involve as many pollution’s criteria as we want.

\[
(39) \rightarrow f = - \int \frac{P}{F_{\text{max}}} \cdot dt + \int \frac{Op}{O_{\text{Pmax}}} \cdot dt.
\]

\( (40) \)

\[ \text{(41)} \]

**B. Problem Formulation**

Every optimal control problem is defined by specifying the inputs, the optimization variables to be identified, the objective function to be minimized, the equality constraints describing the relations between the different optimization variables and inputs, and the inequality constraints representing the lower and upper limits of each variable. In our case, the inputs are the fuel flow rate \( \dot{m}_f(t) \) and the friction torque \( C_f(t) \), the optimization variables are: \( p_a(t), m_a(t), p_c(t), m_c(t), \omega(t), \omega_c(t), \) and \( GV(t) \). The objective function is computed using (16), (36), and (40)

\[
f = - \frac{H_f}{F_{\text{max}}} \cdot \int \eta_c \cdot \dot{m}_f \cdot dt + \frac{m_1}{O_{\text{Pmax}}} \cdot \int \omega_{m2} \cdot \dot{m}_a m_{\omega+4} \cdot \dot{m}_f m_{\omega+5} \cdot dt.
\]

The equality constraints are the differential equations representing the dynamic behavior of the engine (37).

The inequality constraints describe the physical and mechanical limits that the air to fuel ratio, the intake pressure, the exhaust pressure, the crankshaft angular speed, and the turbo-compressor angular speed must respect

\[
\begin{align*}
15 \leq \lambda & \leq 80 \\
9.5 \cdot 10^4 \leq p_i & \leq 30 \cdot 10^4 \text{ [Pa]} \\
9.5 \cdot 10^4 \leq p_e & \leq 30 \cdot 10^4 \text{ [Pa]} \\
83 \leq \omega & \leq 280 \text{ [rad/s]} \\
2 \cdot 10^3 \leq \omega_c & \leq 13 \cdot 10^3 \text{ [rad/s]}.
\end{align*}
\]

\( (42) \)

\( \lambda \) is computed using (3)–(5)

\[
\lambda = \frac{\dot{m}_{ai}}{\dot{m}_f} = \frac{\left( \theta_0 + \theta_1 \omega + \theta_2 \omega^2 \right) \cdot N_{cy1} \cdot V_{cy1} \cdot \omega \cdot p_a}{4 \cdot \pi \cdot \dot{m}_f}.
\]

\( (43) \)

\[ \text{C. Problem Discretization} \]

The problem previously described is highly nonlinear and it is a functional optimization, then no closed-form solution can be obtained. Therefore, the problem must be reformulated in its discretized form. The time interval is discretized to \( N \) points \( t_i \) using a time step \( h \). The integrals in (41) become simple sums of the integrated functions at different instant \( t_i \)

\[
f = \left\{ \begin{aligned}
- \frac{H_f}{F_{\text{max}}} \cdot \sum_{i=1}^{N} \left( \eta_c \cdot \dot{m}_f \right)_{(i)} \\
+ \frac{m_1}{O_{\text{Pmax}}} \cdot \sum_{i=1}^{N} \left( \omega_{m2} \cdot \dot{m}_a m_{\omega+4} \cdot \dot{m}_f m_{\omega+5} \right)_{(i)}
\end{aligned} \right\}.
\]

\( (44) \)

The dynamics of the system described in (37) are computed using the Taylor’s development truncated at first differential order

\[
\begin{align*}
p_a(i+1) - p_a(i) &= \frac{\dot{p}_m}{\dot{p}_a} \cdot \left( \dot{m}_{ai}(i) \cdot T_{HE}(i) - \dot{m}_{ai}(i) \cdot T_a(i) \right) = 0 \\
m_a(i+1) - m_a(i) &= \frac{\dot{m}_{ai}}{\dot{m}_a} \cdot \left( \dot{m}_{ai}(i) \cdot T_{HE}(i) - \dot{m}_{ai}(i) \cdot T_a(i) \right) = 0 \\
p_c(i+1) - p_c(i) &= \frac{\dot{p}_m}{\dot{p}_c} \cdot \left( \dot{m}_{ci}(i) \cdot T_{ci}(i) - \dot{m}_{ci}(i) \cdot T_a(i) \right) = 0 \\
m_c(i+1) - m_c(i) &= \frac{\dot{m}_{ci}}{\dot{m}_c} \cdot \left( \dot{m}_{ci}(i) \cdot T_{ci}(i) - \dot{m}_{ci}(i) \cdot T_a(i) \right) = 0 \\
\omega_c(i) \cdot \left( \dot{\omega}_c(i) - \omega_c(i) \right) &= - \frac{\dot{h}}{J_c} \cdot \left( \eta_{cm1} \cdot \dot{m}_f(i) \cdot H_f - C_{c1} \cdot \omega_c(i) \right) = 0 \\
\omega_{ct}(i) \cdot \left( \dot{\omega}_{ct}(i) - \omega_{ct}(i) \right) &= - \frac{\dot{h}}{J_{ct}} \cdot \left( \eta_{ml} \cdot P(i) - P_{ct}(i) \right) = 0
\end{align*}
\]

\( (45) \)

The inequality constraints described in (42) are expressed in its discretized form:

\[
\begin{align*}
15 \leq \lambda_i & \leq 80 \\
9.5 \cdot 10^4 \leq p_i & \leq 30 \cdot 10^4 \text{ [Pa]} \\
9.5 \cdot 10^4 \leq p_e & \leq 30 \cdot 10^4 \text{ [Pa]} \\
83 \leq \omega & \leq 280 \text{ [rad/s]} \\
2 \cdot 10^3 \leq \omega_c & \leq 13 \cdot 10^3 \text{ [rad/s]}.
\end{align*}
\]

\( (46) \)

\[ \text{VII. OPTIMIZATION ALGORITHM} \]

An optimization problem is usually defined using the following mathematical form:

\[
\begin{align*}
\text{Min} \{ f(X) \} \\
X &= (x_1, x_2, \ldots, x_n) \\
\text{Under Constraints} \\
h_i(X) &= 0 \quad i = 1, \ldots, m \\
g_i(X) \leq 0 \quad i = 1, \ldots, p
\end{align*}
\]

\( (47) \)

where \( f(X) \) is the objective function, \( h(X) \) the equality constraints, and \( g(X) \) the inequality constraints. The first step in resolving this problem is to reduce it to a problem without constraints by creating a global objective function \( \Phi(X, r) \) which regroups the original objective function and the equality and inequality constraints multiplied by a penalty number \( r \)

\[
\phi(X, r) = f(X) + r \cdot \sum_{i=1}^{m} \left[ h_i(X) \right]^2 + r \cdot \sum_{i=1}^{p} \left[ g_i(X) \right]^2
\]

\( (48) \)

\[ G_i(X) = \begin{cases} 
0 & \text{if } g_i(X) \geq 0 \\
g_i(X) & \text{else}
\end{cases} \]

\( (49) \)

\[ r = r_0^k \]

\( (50) \)

\( k \) is the number of iterations that tends toward the infinity, and \( r_0 = 3 \) is the initial penalty number. The optimization algorithm adopted in this paper is the BFGS algorithm that sums up as follows (see Fig. 14):

1. To start by an initial solution \( X^{(0)} \).
2. \( i = 0 \) and \( k = 1 \).
2) To compute $X_{i+1}^{(k)}$ using the following equation:

$$X_{i+1}^{(k)} = X_i^{(k)} - \alpha_i^{(k)} \cdot D_i^{(k)} \cdot \nabla \phi_i^{(k)}.$$  (51)

$\nabla \phi$ is the gradient computed by differentiating (48) with respect to $X$. $D$ is an approximation of the inverse of the Hessian matrix calculated using the Armijo–Goldstein approximation

$$\begin{align*}
D_i^{(k)} &= 
\begin{pmatrix}
\phi_i^{(k)} \cdot (X_i^{(k)} - \alpha_i^{(k)} \cdot D_i^{(k)} \cdot \nabla \phi_i^{(k)} - \nabla \phi_i^{(k)}) \\
\nabla \phi_i^{(k)} \cdot (X_i^{(k)} - \alpha_i^{(k)} \cdot D_i^{(k)} \cdot \nabla \phi_i^{(k)})
\end{pmatrix} \\
D_i^{(k)} &= I,
\end{align*}$$  (52)

$\alpha_i^{(k)}$ is the relaxation factor that must respect the Armijo–Goldstein condition:

$$\begin{align*}
\phi_i \left( X_i^{(k)} - \alpha_i^{(k)} \cdot D_i^{(k)} \cdot \nabla \phi_i^{(k)} + r_i^{(k)} \right) &
\leq S_i^{(k)} \\
S_i^{(k)} &= \phi_i^{(k)} - \beta \cdot \alpha_i^{(k)} \cdot \left( \nabla \phi_i^{(k)} \right)^T \cdot D_i^{(k)} \cdot \nabla \phi_i^{(k)} \\
&\quad (\beta \in [0, 1]).
\end{align*}$$  (53)

3) If $\|\nabla \phi_i^{(k)}\|$ $>$ Tolerance then: $i = i + 1$ and goto (b).

4) If $\|\nabla \phi_i^{(k)}\|$ $\leq$ Tolerance then: $X_i^{(k+1)} = X_i^{(k)}$

If $\|X_i^{(k+1)} - X_i^{(k)}\|$ $>\text{Tolerance}$ then: $k = k + 1, i = 0$

and goto (b)\{.

Else: End of search and $X_i^{(k+1)}$ is the optimal solution.

*Fig. 14. Optimization algorithm.*
VIII. OPTIMAL CONTROL DATABASE

The dynamic optimization process explained in Section VI cannot be directly integrated into the ECU and applied to real engine’s applications because of it is time consuming. It can be used to construct dynamic lookup tables that cover the entire functioning area of the engine and that replace the conventional control schemes as described in Section II-A and II-B but the huge memory size involved makes it unusable in passenger cars’ applications. Therefore another approach should be considered. We propose to use the neural networks as a control tool to predict “online” the optimal control variables to be applied to the engine. Neural networks are a powerful tool that can be used to approximate any multiple inputs—multiple outputs functions, it has the capacity to identify the nonlinear relations between the different inputs and to predict the correct output variables with a desired precision by simply learning from examples. Consequently the optimization process is used to build-up a large database that will be exploited to train the neural network; this database must cover the entire functioning area of the engine in order to improve the precision and the prediction capacity of the network. The courses \( \{ \hat{m}_f (t), C_r (t) \} \) are chosen randomly in a way to respect the inequality constraints as described in (42).

IX. NEURAL CONTROLLER

The neural network adopted in this paper is a three layers perception with one input layer, one hidden layer with 50 neurons, and one output layer. This type of neural networks is commonly used in function approximating problems. The transfer functions at the hidden and the output layer are sigmoid. We also selected the feed-forward back-propagation algorithm to train the network using the optimal control database; 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 which reflects the accuracy and prediction capacity of the neural network. Given its attractive generalization property and its capacity to obtain stable model, we used the following performance function to train the network:

\[
f = \frac{\mu}{Q} \sum_{i=1}^{N} e_i^2 + \frac{1-\mu}{Q} \sum_{i=1}^{N} w_i^2 \tag{54}
\]

where \( e \) is the error between the outputs of the network and the training data, \( w \) is the weights and bias of the neurons, \( Q \) is the number of couples (input–output) used in the training data and \( \mu \) is a real number between zero and one that must be properly tuned to obtain the desired precision. The value of \( \mu \) equal to one leads to a minimal error between the network’s outputs and the 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 inputs and that is capable of predicting, with a desired precision, the outputs when it is faced with new inputs that are not used in the training phase.

The inputs of the optimization problem are \( \{ \hat{m}_f, C_r \} \) and the exit variables are. The inputs of the neural network are the engine variables that can be measured online by sensors installed on the engine, the outputs of the network are the control variables which are in our case the position of the variable geometry turbine \( GV \). Also, the model should take into consideration the dynamic behavior of the engine to properly predict the optimal value of the \( GV \). Consequently, the neural model (see Fig. 17) becomes a recurrent model with inputs, shown in (55) at the bottom of the page. The output is \( \{ GV(t_i) \} \). We chose a time step suitable for real time engine’s applications and sensors’ response:

\[
t_i = t_{i-1} = 10 \cdot h = 0.1 \text{ s.} \tag{56}
\]

X. NEURAL CONTROL VALIDATION

Figs. 18 and 19 show a comparison between the neural network output and two examples chosen from the optimal control database; the first one is included in the training data and the second one is not, in order to show the capacity of the neural network to predict the optimal values of the control variable when it is faced with new inputs. The results are in good agreement.
with the optimal position of the turbine variable geometry calculated using the optimization process.

XI. INTEGRATION OF THE NEURAL CONTROLLER INTO THE ECU: APPLICATIONS ON THE ETC TEST CYCLE

In Europe, the ETC test cycle is used for emissions certification of heavy duty diesel engines. It involves three parts (Urban, Rural and Motorway Driving) where the friction torque and the crankshaft angular speed are fixed at different instants $t_i$. The duration of each part is equal to 600 s.

The neural controller created in Section VIII and validated in Section IX is now integrated into the engine’s complete model in order to control the engine in real time simulations on the ETC cycle. The simulations’ results generated by the neural controller are compared to the ones generated by the ECU using the static lookup tables identified by experiments.

Fig. 20 shows the simulations results of the neural controller integration into the engine complete model. Fig. 21 shows a comparison between the vanes positions of the turbine variable geometry (GV) generated using the neural controller and the ECU. In order to clearly observe the gain in opacity reduction obtained using the neural controller, we define the relative gain in opacity reduction as follows:

$$\text{Gain} = \frac{\text{Opacity}_{GV-ECU} - \text{Opacity}_{GV-Net}}{\text{Opacity}_{GV-ECU}} \times 100, \quad (57)$$

The results of the opacity reduction described in (57) are shown in Fig. 22 over the complete cycle. The results confirm the validity of the dynamic optimization process and the neural controller.
and the maximum relative gain in opacity reduction has reached 62% (see Fig. 22) which confirms the validity and importance of neural controller.


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