

Real Time Prediction of Particle Sizing at the Exhaust of a Diesel Engine by Using a Neural Network Model

Ferdinando Taglialatela and Mario Lavorgna
STMicronics

Silvana Di Iorio, Ezio Mancaruso, and Bianca Maria Vaglieco
Istituto Motori CNR

ABSTRACT

In order to meet the increasingly strict emission regulations, several solutions for NO_x and PM emissions reduction have been studied. Exhaust gas recirculation (EGR) technology has become one of the more used methods to accomplish the NO_x emissions reduction. However, actual control strategies do not consider, in the definition of optimal EGR, its effect on particle size and density. These latter have a great importance both for the optimal functioning of after-treatment systems, but also for the adverse effects that small particles have on human health. Epidemiological studies, in fact, highlighted that the toxicity of particulate particles increases as the particle size decreases.

The aim of this paper is to present a Neural Network model able to provide real time information about the characteristics of exhaust particles emitted by a Diesel engine. In particular, the model acts as a *virtual sensor* able to estimate the concentration of particles with a specific aerodynamic diameter on the basis of some engine parameters such as engine speed, engine load and EGR ratio.

CITATION: Taglialatela, F., Lavorgna, M., Di Iorio, S., Mancaruso, E. et al., "Real Time Prediction of Particle Sizing at the Exhaust of a Diesel Engine by Using a Neural Network Model," *SAE Int. J. Engines* 10(4):2017, doi:10.4271/2017-24-0051.

INTRODUCTION

In recent years, there has been increasing concern on the depletion of fossil fuels and on pollutant emissions, such as NO_x and particulate matter (PM), as well as CO₂ emissions, one of the greenhouse gases. Diesel engines are widely spread in Europe because of the higher thermal efficiency, reducing fuel consumption and slowing down global warming. However, they are the main source of NO_x and PM in the urban area. Due to their adverse effect on the environment and human health, stringent emissions standards has been introduced. Epidemiological studies [1, 2, 3] highlighted that small particles can have a negative effect on human health. In particular, the toxicity increases as the particle size decreases. Fine particles have considerably enhanced toxicity per unit mass as compared to coarse particles. Furthermore, smaller particles have a higher probability to be inhaled and deposited in the respiratory tract and in the alveolar region by diffusion causing respiratory diseases, inflammation, and damage to the lungs [4]. For this reason, according to EURO 6 rules, a restriction on number of particle emissions was introduced as well [5].

To comply with the more stringent requirements of environmental regulations, several solutions for NO_x and PM emissions reduction have been studied. Exhaust gas recirculation (EGR) technology has become one of the more used methods to accomplish the NO_x emissions reduction [6]. The EGR acts reducing the in-cylinder temperature and the available oxygen in the cylinder, but for this reason, the PM increases [7, 8, 9, 10, 11, 12, 13]. In facts, particles

are formed in the cylinder in the locally rich regions. The mass, size, number, and particle composition are strongly affected by the combustion process [14, 15, 16, 17]. Moreover, a strong correlation between EGR ratio and particle number and size [18, 19, 20] has been observed.

Based on the instantaneous value of some engine parameters, such as angular speed and load, engine control maps provide an optimal value of EGR ratio considering a trade-off between NO_x and smoke emissions. However, the actual control strategies do not take into account the effect of EGR ratio on particle size and number, which is regulated as well as mass. Moreover, deposition of particles on the wall of the EGR cooler and on the EGR valve can occur, thus modifying the real EGR ratio with respect to the nominal one. This can lead to a decrease of the NO_x reduction efficiency and a further worsening of the PM emissions [21, 22, 23, 24, 25].

In order to have a more efficient control of PM emissions, also in terms of particle size and number, real time information about the characteristics of the emitted particulate should be available. In this sense, use of a *virtual sensor* based on Artificial Neural Networks (ANNs) could be a possible methodology. ANNs are data-processing systems inspired by biological neural system and are widely used in the areas of science and engineering where the conventional modeling methods fail because the non-linear and chemical processes. The ANNs possess, in fact, the ability to 'learn' what

happens in the process without actually modeling the physical and chemical laws that govern the system [26]. The prediction by a well-trained ANNs is normally much faster than the conventional simulation programs or mathematical models [27] and can be used to predict the performance and exhaust emissions [28, 29, 30, 31, 32], as well as the specific fuel consumption and fuel air equivalence ratio of a Diesel engine [33].

In the present work, a neural network model that provides real time information on the characteristic of exhaust particles from a Diesel engine has been proposed. The model is able to estimate the effect of EGR on particle number and size. In particular, it is composed by an array of neural network sub-models having as output the concentration of particles with a specific aerodynamic diameter. The paper also describes a possible closed-loop control system that employs the proposed neural model to real time manage the particle sizing at the exhaust of a Diesel engine.

The experimental data, used both for training and validation of the neural network model, were collected on a Common Rail 1.9 l, 16 v Diesel engine. Particle number size distribution was measured in the range 7 nm-10 μm .

EXPERIMENTAL SETUP

Engine

A four-stroke FIAT 1910 JTD diesel engine, with four in-line cylinders 16 valves, a displacement of 1.9 l and a compression ratio of 17.5:1, was used.

This engine was equipped with a Common Rail injection system, which allowed two injections (Pilot - Main) for each cycle (Unijet), the Engine Control Unit (ECU) had a PC interface for the control of all parameters. More details about the engine are reported in [Table 1](#).

Table 1. Engine specifications.

Engine	1910 JTD
Engine Design	4 Cylinders, in-line
Bore/Stroke/Displacement	82 mm / 90.4 mm / 1910 cm ³
Max Torque	286 Nm / 2500 rpm
Max Power	88 kW / 4000 rpm
Compression Ratio	17.5 : 1
Max Speed	4500 rpm
Injection System	Common Rail Unijet™ (Bosch)
Max Injection Pressure	1350 bar

The in-cylinder pressure signal was measured for every engine cycle with a piezoelectric pressure transducer. A high precision Crank Angle Encoder was used for angle-based measurements. Flywheel generated trigger and crank angle degree marker pulses were produced at 0.05 crank angle degree (CAD) resolution. 150 cycles of pressure data were recorded on 0.1° crank angle resolved basis for each operating condition using AVL Indimodul system. Integrated combustion parameters (e.g. heat release, IMEP) were calculated by integrating the in-cylinder pressure data [17].

The experiments were performed using Italian commercial diesel fuel with sulphur content less than 250 ppm.

The engine was provided with an Exhaust Gas Recirculation (EGR) system. The basic element of the EGR circuit is an electro-valve controlled by the electronic control unit. The electro-valve receives an electrical signal (duty-cycle) and orders a pressure reduction to the mechanical valve (EGR valve) placed between the outlet and the inlet pipes. When the depression is applied, the EGR valve allows the addition of part of exhaust gases to the airflow. The whole process is controlled by the electronic control unit by means of characteristic diagrams saved in its memory. The actual EGR percentage, according to the conventional definition [35], can be obtained measuring the aspired air ($\dot{m}$) with and without EGR and using the following equation:

$$EGR\% = 1 - \frac{\dot{m}_{airwEGR}}{\dot{m}_{airw/oEGR}} \cdot \frac{P_{w/oEGR}}{P_{wEGR}} \cdot \frac{T_{wEGR}}{T_{w/oEGR}} \quad (1)$$

in order to get the exact EGR percentage values; corrections of pressure and temperature are necessary. The presence of exhaust gases in the inlet manifold does not imply the same reduction of the aspired fresh air. This is due to the contribution of exhaust gases thermal energy, it leads to an increase of the aspired fluid temperature and therefore to its expansion.

Gas and Particle Exhaust Instruments

Steady-state measurements of CO, CO₂, O₂, HC and NOx were made in the raw exhaust by a commercial analyzer: DiGas4000 by AVL. CO, CO₂ and HC were measured by Non-Dispersive Infrared Detectors (NDIR); NOx and O₂ were detected by means of electrochemical sensor. An opacimeter was used to measure particulate mass concentration as a function of time. Opacimeter is a partial-flow system that measures the visible light attenuation (550 nm) from the exhaust gases. The instrument has a 1 second resolution. It was possible to convert the opacity percentage in particulate mass concentration on the basis of the following empirical correlation, which is reported in [36]:

$$c = k \cdot \ln(100/(100 - (T_0 - T))) \quad (2)$$

where c is mass concentration [g/m³], K is a calibration factor [g/m³], T is the opacity [%] and T_0 [%] is the opacity at zero concentration.

Aerosol size distributions at the Common Rail Diesel engine exhaust were evaluated by means of ELPI, which is an electrical impactor working at low pressure. It is able to measure real time particles aerodynamic diameters in the range 7 nm-10 μm [37].

In ELPI, the sample first passes through a unipolar positive polarity charger where the particles are electrically charged by ions produced in a corona discharge. After the charger, the particles pass in a low-pressure impactor where they are classified according to their aerodynamic diameter. The stages of the impactor are electrically insulated and each stage is individually connected to an electrometer

current amplifier. The charged particles collected in a specific impactor stage produce an electrical current, which is recorded by the respective electrometer channel.

The current value of each channel is proportional to the number of particles collected, and thus to the particle concentration in the specific size range. The current values are converted to an aerodynamic size distribution using particle size dependent relations describing the properties of the charger and the impactor stages. [8]

Upstream of ELPI, a two steps dilution device named Fine Particle Sampler (FPS) is placed. FPS allows to sample and control dilution ratio and temperature of exhaust gas.

Operating Conditions

The CR diesel engine worked at steady state in different operating conditions: engine angular speeds of 1000, 1500 and 2000 rpm engine were considered. The load was changed in the range 2-5 bar.

EGR percentage was varied in the range 0-56% for every condition, without changing the pilot and main fuel injection strategy. In this way, the air-fuel ratio decreased at increasing EGR due to the displacement of intake air.

PREDICTION AND CONTROL OF PARTICLE SIZING

Neural Network Model for Particle Sizing Prediction

The present work aims to develop a neural network model acting as a “supervisor” of PM emissions from a Diesel engine. In particular the model gives, for every engine operating condition, information about the characteristics of particulate emissions in terms of particle size distribution. Figure 1 shows the block diagram of the proposed model, called PSD (Particle Size Distribution) model.

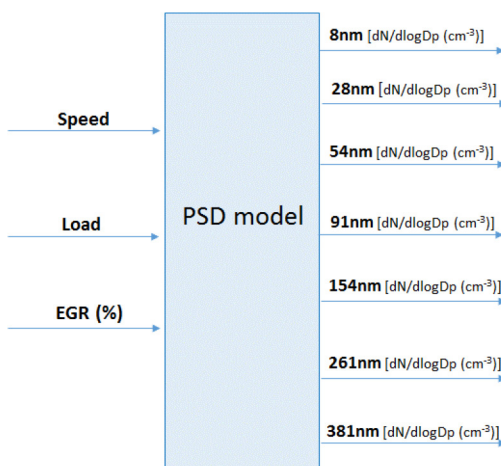


Figure 1. Particle Size Distribution (PSD) model for prediction of particulate emissions characteristics.

The neural network predictor has as output the concentrations of particulate particles with fixed aerodynamic diameters respectively of 8 nm, 28 nm, 54 nm, 91 nm, 154 nm, 261 nm e 381 nm, whereas the

inputs are the engine speed, the engine load and the actual EGR ratio. The proposed model has been conceived taking into account the paradigm of a learning machine trained and tested on experimental data. As learning machine model a feed-forward MLP (Multi-Layer Perceptron) neural network with one hidden layer has been chosen.

In order to improve the generalization capability of the neural network model, it has been considered an automated regularization procedure applied during the model training, known in literature as Bayesian regularization, see [38, 39]. Basically, the aim of a regularization procedure is to obtain a smoother network response through a modification in the objective function, adding a residual term consisting of the sum of squared weights of the network.

According to the Bayes' rule, the “best” model is defined as the model with the highest *a posteriori* probability of correctness; this means:

$$\min_{\theta} (-\log(P(D|H_{\theta})) - \log(P(H_{\theta}))), \quad (2)$$

where θ is the parameter of the model H_{θ} used to describe a system, whose observed event is indicated with D . In the equation (2), $P(D|H_{\theta})$ represents the probability of the event conditioned by the correctness of the model. In the context of a neural network model, the observed event of the system is:

$$D = \{(\bar{x}^i, \bar{y}_i) \mid i = 1, \dots, n\} \quad (3)$$

where $\bar{x}^i$ is the i -th input vector of the neural network model and $\bar{y}_i$ is the related i -th output vector used as data set for the model training. The neural network can be described as a non-linear map g_{θ} , which links the input-output data in function of the weights and biases (described by the vector θ) of the neurons in the hidden layer (see Eq (4)).

$$\bar{y}_i = g_{\theta}(\bar{x}^i) \quad (4)$$

In the Bayesian approach, a normal Gaussian data distribution is considered only if the model is correct. So, if θ is a correct parameter vector, the observed values y_i are normally distributed around $g_{\theta}(\bar{x}^i)$. After trivial calculations, it can be obtained that:

$$\begin{aligned} -\log(P(D | H_{\theta})) &= -\log \prod_{i=1}^n e^{-\frac{(\bar{y}_i - g_{\theta}(\bar{x}^i))^2}{2r^2}} = \\ &= \frac{1}{r^2} \sum_{i=1}^n \frac{1}{2} (\bar{y}_i - g_{\theta}(\bar{x}^i))^2 \end{aligned} \quad (5)$$

So, the function to be minimized during the training phase of the model is:

$$\min_{\theta} \left(\sum_{i=1}^n \frac{1}{2} (\bar{y}_i - g_{\theta}(\bar{x}^i))^2 - r^2 \log(P(\theta)) \right)$$