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Wavelet Neural Networks for Predicting Engine Emissions

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Abstract

In this work, a wavelet neural network (WNN) model of internal combustion engine emissions is presented. We collect data of a 1.6L spark ignition gasoline engine. The engine was coupled to a hydraulic dynamometer to control the engine speed in real time. Setting four parameters specifies the set point, so the engine speed, the injection time, the injected fuel mass flow and the angle of the admission throttle valve are the input variables to the engine model. The output parameters that were measured at the exhaust tile pipe are hydrocarbons (HC), carbon monoxide (CO) and nitrogen oxides (NOx). Performances of the different predictor models were evaluated using standard statistical evaluation criteria. The results showed that the use of wavelets neural networks can describe the emission behavior of the studied gasoline engine. High correlation values $R^2$ of 0.9714, 0.9626 and 0.9929 were observed between the measured and predicted HC, CO and NOx exhaust emissions respectively.

Keywords: Engine calibration, Neural Networks, Wavelets, Exhaust emissions

1. Introduction

Vehicles release tons of greenhouse gases into the atmosphere each year, in the form of nitrogen oxides (NOx) and carbon monoxide (CO), and additionally hydrocarbons (HC) and particulate matter (PM) contributing to global warming. Requirements have been imposed by governments that set specific limits to the amount of pollutants that can be released into the environment, as the new European driving cycle (NEDC) which is a driving cycle designed to assess the emission levels of car engines. In order to reduce exhaust emissions of an internal combustion engine (ICE) it is necessary to recalibrate the look-up tables stored in the electronic control unit (ECU) for a driving cycle. A manual calibration at the engine test bench is a very demanding task of time and resources, so it is best to have a computer model of the engine and carry out the calibration offline in the PC and then upload the new values of the operating parameters to the ECU. Some models have been developed to explain the phenomena inside of an internal combustion engine [1-3].
however, several are in the form of black-box models [4-8]. Recently, wavelet neural network modeling has been widely used in various topics of engineering due to their good ability for modeling nonlinear phenomena [9,10]. In particular, the structure of Wavelet Neural Networks (WNNs) enables them to model complex nonlinear multiple problems, which makes them an appropriate method for pollutant modeling. In this work, WNN modeling was used to predict CO, NOx and HC exhaust emissions in a gasoline engine through of the engine operating parameters values. Performances of the different predictor models were evaluated using standard statistical evaluation criteria.

2. Experimental setup

Carbon monoxide, nitrogen oxides and hydrocarbons exhaust emissions were measured in static mode in the engine, for different values of operating parameters as engine angular speed in revolutions per minute \( n_{\text{eng}} \) in rpm), injection time in milliseconds \( t_{\text{inj}} \) in ms), the injected fuel mass flow \( m_{\text{fuel}} \) in lb/hr), and the angle of the admission throttle valve \( \alpha_{\text{th}} \) in \%. In Table 1 are shown the characteristics of the studied internal combustion engine.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>Z16SE 2005</td>
</tr>
<tr>
<td>Maximum power</td>
<td>100 Hp to 5600 rpm</td>
</tr>
<tr>
<td>Displacement</td>
<td>1597 cc.</td>
</tr>
<tr>
<td>Race</td>
<td>81.5 mm</td>
</tr>
<tr>
<td>Compression ratio</td>
<td>9.4:1</td>
</tr>
<tr>
<td>Injection type</td>
<td>Sequential</td>
</tr>
<tr>
<td>Maximum torque</td>
<td>138 Nm to 3200 rpm</td>
</tr>
</tbody>
</table>

The taken values of operating parameters are described in Table 2. It were evaluated in the experimental setup, 4 angles of the admission throttle valve for 15 engine speed values, is that, a total of 60 operating points for collect the values of NOx, CO and HC emissions.

<table>
<thead>
<tr>
<th>( n_{\text{eng}} ) (rpm)</th>
<th>1500</th>
<th>1750</th>
<th>2000</th>
<th>2250</th>
<th>2500</th>
<th>2750</th>
<th>2900</th>
<th>3000</th>
<th>3100</th>
<th>3200</th>
<th>3300</th>
<th>3400</th>
<th>3500</th>
<th>3750</th>
<th>4000</th>
</tr>
</thead>
</table>

The gas analyzer type FGA4000XDS was used to measure exhaust emissions, the injected fuel mass flow \( m_{\text{fuel}} \) was measured by the software of the Super Flow SF-902 hydraulic dynamometer, which is used to provide load to the engine. The time of the open state of an injector \( t_{\text{inj}} \) was measured by a Tektronix oscilloscope. Figure 1 shows the engine test-bench used in this work, it consists of a dynamometer connected with the crankshaft of the engine to control the load torque in real time. Some sample data of combustion engine for an operating point are shown in Table 3.

3. Wavelet neural network models for engine emissions

A particular artificial neural network (ANN) is defined using three fundamental components: transfer function, network architecture, and learning law, these components have to be define for develop a suitable
Table 3. Measurement results of the parameters for an operating point of the gasoline engine

<table>
<thead>
<tr>
<th>$n_{\text{eng}}$</th>
<th>$t_{\text{inj}}$</th>
<th>$m_{\text{fuel}}$</th>
<th>CO</th>
<th>HC</th>
<th>NOx</th>
</tr>
</thead>
<tbody>
<tr>
<td>2500 rpm</td>
<td>(ms)</td>
<td>(lb/hr)</td>
<td>(%)</td>
<td>(ppm)</td>
<td>(ppm)</td>
</tr>
<tr>
<td>$\alpha_{\text{th}} = 25%$</td>
<td>9.1</td>
<td>18</td>
<td>0.58</td>
<td>553</td>
<td>471</td>
</tr>
<tr>
<td>$\alpha_{\text{th}} = 50%$</td>
<td>11.6</td>
<td>21</td>
<td>0.6</td>
<td>568</td>
<td>507</td>
</tr>
<tr>
<td>$\alpha_{\text{th}} = 75%$</td>
<td>11.9</td>
<td>21</td>
<td>0.56</td>
<td>567</td>
<td>523</td>
</tr>
<tr>
<td>$\alpha_{\text{th}} = 100%$</td>
<td>13</td>
<td>22.8</td>
<td>2.55</td>
<td>683</td>
<td>308</td>
</tr>
</tbody>
</table>

Fig. 1. Experimental setup of internal combustion engine

model [11]. In a wavelet neural network, a wavelet function (WF) is incorporated in the architecture of ANN. Wavelets are defined in the following form:

$$\Phi_j(x) = |a_j|^{-\frac{1}{2}} \phi \left( \frac{x - b_j}{a_j} \right)$$

with $a_j \neq 0$, where $\Phi_j(x)$ represents the family of wavelets obtained from the single $\phi(x)$ function by dilations and translations, where $a_j = \{a_{i,j}, a_{2,j}, ..., a_{m,j}\}$ and $b_j = \{b_{1,j}, b_{2,j}, ..., b_{m,j}\}$ are the dilation and the translation parameters respectively, $x = \{x_1, x_2, ..., x_m\}$ are the input variables, $j = 1, ..., n$, where $n$ is the number of output variables and $\phi(x)$ is called a mother wavelet. Wavelet networks include wavelet functions in the neurons of the hidden layer of the network. The output of WNN is calculated as:

$$y = \sum_{j=1}^{k} w_j \Phi_j(x) = \sum_{j=1}^{k} w_j |a_j|^{-\frac{1}{2}} \phi \left( \frac{x - b_j}{a_j} \right)$$

where $\Phi(x)$ is the WF of the $j$th unit of the hidden layer, $w_j$ are weight coefficients between the input and the hidden layers, $a_i$ and $b_j$ are the parameters of WF as described above. WNN can approximate complex functions, have good generalization ability, and can be easily trained than other networks, such as multilayer perceptrons and radial-based networks [9,10]. The dilation and the translation parameters of the wavelet were initialized randomly. In this work, the Morlet wavelet is used in the hidden layers.

In Fig. 2 is shown the structure of the WNN used, in which the inputs are four operating parameters, engine speed, injection time, the injected fuel mass flow, and the angle of the admission throttle valve, and the output of the network is an exhaust emission.
3.1. Performance criteria

Sixty samples were collected for each input and output variable, this dataset was divided into training and testing datasets. Among the total datasets, 35 were chosen for training of the models, while the remaining 25 were used as validation data of the models. To secure a different result in each training and testing of the WNN, the training and test datasets was performed randomly. The input and output data $n_{\text{eng}}$, $\alpha_{\text{th}}$, $t_{\text{inj}}$, $m_{\text{fuel}}$, CO, HC, and NOx were scaled by factors of $1/1000$, $1/10$, $1/10$, $1/10$, 10, $1/10$ and $1/10$ respectively in order to avoid computational problems. For better adjustment of the WNN for a specific emission, one WNN was built for each emission. Once the different stages of the training process had been performed, it was important to estimate the WNN prediction qualities in order to determine a suitable architecture of models and validate these. For this, datasets that were not used for training networks were chosen. Unlike in [8] where the root mean square error (RMSE) was taken as a performance criterion, here models were assessed using different standard statistical performance evaluation criteria. The statistical measure considered were the mean absolute percentage error (MAPE) and the absolute fraction of variance ($R^2$). MAPE performance is calculated as:

$$\text{MAPE} = \frac{1}{25} \left[ \sum_{i=1}^{25} \left| \frac{y_{\text{measi}} - y_{\text{predi}}}{y_{\text{measi}}} \right| \right] \times 100$$

where $y_{\text{measi}}$ is measured value and $y_{\text{predi}}$ is predicted value by the neural model over all test dataset. Furthermore, the error arose during testing in each model can be expressed as absolute fraction of variance, which is given by:

$$R^2 = 1 - \left( \frac{\sum_{i=1}^{25}(y_{\text{measi}} - y_{\text{predi}})^2}{\sum_{i=1}^{25}(y_{\text{predi}})^2} \right)$$

The optimal values of the number of neurons of the hidden layer for each WNN model is obtained by trial and error method based on these performance criteria. Fig. 3 shows the mean absolute percentage error for the testing data when the number of hidden neurons is increasing for each neural network. Here, smaller values of MAPE are 13.36%, 14.80% and 6.95% for HC, CO and NOx WNNs models respectively, whereas that the behavior of $R^2$ varying the number of hidden neurons is shown in Fig 4. Accordingly, the WNNs architectures chosen for modeling HC, CO and NOx emissions are 4-15-1, 4-8-1, and 4-38-1 respectively. Finally, in Fig. 5 are shown the correlation between recorded and predicted exhaust emissions by using WNNs architectures with minimum MAPE and maximum $R^2$. In these figures it is visible that the obtained
values in each model are very close to the experimental data. The best values found of $R^2$ are 0.9714, 0.9626, and 0.9929 for testing datasets in the WNNs models in predicting HC, CO and NOx emissions respectively.

Fig. 3. MAPE behavior when is increasing the number of hidden neurons a) HC, b) CO, and c) NOx emissions
Fig. 4. $R^2$ behavior when increasing the number of hidden neurons a) HC, b) CO, and c) NOx emissions
Fig. 5. Correlation between predicted and measured a) HC, b) CO, and c) NOx emissions
4. Conclusions

With the aim of reducing the time of calibration of the engine parameters, in this paper, wavelet neural network (WNN) models for exhaust emissions of a spark-ignition gasoline engine are proposed. The modeled emissions of the studied engine are hydrocarbons (HC), carbon monoxide (CO) and nitrogen oxides (NOx). Performance of the WNNs has been evaluated by calculating mean absolute percentage error (MAPE) and absolute fraction of variance ($R^2$). WNNs with architectures 4-15-1, 4-8-1, and 4-38-1 were found to be capable to imitate the HC, CO and NOx emissions respectively for the studied gasoline engine. Comparison between WNNs in terms of $R^2$ showed that the developed models are capable to predict suitable results for HC, CO, and NOx emissions under static conditions of operation with $R^2$ of 0.9714, 0.9626, and 0.9929 respectively.

References