Neural Network–Based Modeling and Optimization for Effective Vehicle Emission Testing and Engine Calibration

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In automotive manufacturing, vehicle emission testing and engine calibration are the key to achieving emission standards with satisfactory fuel economy. Because of the complexity of physical and chemical phenomena occurring during engine combustion and catalytic conversion and the lack of real-time measurements of key process and performance parameters, engine calibration and emission testing are still experiment-assisted trial-and-error practices, which are always expensive and inefficient. In this article, a neural network (NN)–based modeling approach is introduced to characterize engine and catalytic converter operations. A model-based optimization method is also introduced to identify optimal engine calibration parameters so that emission reduction and fuel efficiency improvement can be achieved simultaneously. This development facilitates a comprehensive performance analysis of engine and catalytic converters with much less effort required for experiments.

Keywords Emission reduction; Engine calibration; Neural networks; Optimization; Process modeling

Introduction

Automotive emission of hydrocarbons (HC), carbon monoxide (CO), and nitrogen oxides (NOₓ) has been blamed as one of the main reasons for urban air pollution (Gerard and Lave, 2005). In 1981, for the first time, automobiles were required to meet the amended Clean Air Act standards for exhaust emissions, which were 0.25 grams/mile HC, 0.4 grams/mile NOₓ, and 3.4 grams/mile CO. The technologies employed were three-way catalysts (TWC) and on-board computer control systems with oxygen sensors (Kaneki et al., 1978; Falk and Mooney, 1980; Adomaitis and Heck, 1988; Heywood, 1988; Yamada et al., 1992; Wang et al., 1993; Lenz and Schroeder, 1996; Brandt et al., 2000). Over the past decade, stringent standards have been set to progressively bring down the permissible emission level, and the industry has responded very positively by developing various new emission control technologies (U.S. EPA, 1994).

In automotive manufacturing, engine calibration and emission testing are key to ensuring compliance with emission standards and maintaining satisfactory fuel economy. However, engine combustion and catalytic conversion are quite complicated;
various process and performance parameters exist and they interact so strongly that
the intrinsic correlation has not been fully understood. Consequently, the character-
ization of emissions, catalyst efficiency, and fuel economy is often imprecise and not
comprehensive, and calibration and testing are still very expensive and inefficient
(Stabell and Hayes, 1996).

Engine calibration and emission testing can be significantly improved by using
advanced process modeling, control, and optimization techniques. In recent years,
modeling of steady-state or dynamic behavior of nonlinear systems using artificial
neural network (ANN) or more simply called neural network (NN) techniques has
received considerable attention in many fields of engineering. The neural network
technique is a nonlinear statistical data modeling tool that is, in principle, capable
of identifying a mapping function from the independent input variables to the depen-
dent output variables of a process with arbitrary precision (Dayhoff, 1992; Huang
et al., 1994; Browne, 1997). In this article, an NN-based engine-catalytic converter
modeling method is introduced to characterize precisely and quickly engine oper-
ation and catalytic conversion. Furthermore, an NN model–based nonlinear optimi-
ization method is introduced for optimizing engine calibration to achieve minimum
emissions and best possible fuel efficiency.

Modeling of Engine and Catalytic Converter

Development of a satisfactory NN-based engine-catalytic converter model is critical
for achieving effective model-based emission control. In model development, experi-
ments need to be designed properly to ensure the availability of reliable data.

Emission Control System

Emissions from a spark-ignited engine using unleaded gasoline can be controlled by
using a three-way catalytic converter in the exhaust system. The catalytic converter
should efficiently convert HC, CO, and NOx to CO2, H2O, and N2 when the engine is
operated at an appropriate air mass to fuel mass ratio (or the air-fuel ratio). It is
shown that precise control of the ratio around stoichiometry is essential for efficient
emission abatement (Woestman and Logothetis, 1995). The control system has an
exhaust gas oxygen sensor (see Figure 1). The goal voltage is set to control the
air-fuel ratio, and the kicks is a signal added on the controller to generate an air-fuel
ratio oscillation. The exhaust gases through the exhaust pipe are measured by the
oxygen sensor; they pass through the catalyst where they are converted and then exit
the tailpipe. The oxygen sensor generates a voltage that will be compared with the
gal voltage to indicate whether the air and fuel mixture is rich (excess fuel) or lean
(excess air). The tail gas and the exhaust gas are sent to an analyzer for chemical
concentration analysis, from which the fuel efficiency (denoted as $E_{FE}$) and the cata-
lyst efficiencies for HC, CO, and NOx (denoted as $E_{HC}$, $E_{CO}$, and $E_{NOx}$, respectively) can
be calculated.

Experimental Design

An automotive emission test cell is a complex system that consists of a group of test
benches, a dynamometer, and other facilities and instruments (see Figure 2). In test-
ing, the exhaust emissions are collected by a sampling system for chemical analysis,
and the engine parameters (i.e., the engine speed and the engine load) are recorded by the interrogator box (IBOX). A host computer is responsible for data collection, calculation, and test synchronization. The experiments in this work are designed to obtain data on fuel efficiency and catalyst efficiencies under various combinations of engine speeds and loads. The conventional emission test cycles consisting of cold-start, transient, and/or hot-start phases are not applied.

Experimental data are needed for developing an NN-based engine-catalytic converter model (see Figure 1). Each set of data consists of four model inputs (i.e., engine speed, engine load, goal voltage, and kicks) and four model outputs (i.e., fuel efficiency and catalyst efficiencies for HC, CO, and NOx). The engine speed is given in revolutions per minute (RPM), and the engine load is represented by the absolute pressure of air in the intake manifold, or manifold absolute pressure (MAP). Catalyst efficiency can indicate emission reduction efficiency, and fuel efficiency is calculated based on the content of CO₂ in the exhaust gases.

Figure 1. Emission control system and information sources for modeling of an engine-catalytic converter.

Figure 2. Experimental setup for emission testing and engine calibration (Gullitti, 1999).
For each model input variable, an appropriate operating range is selected based on the understanding of the process. As shown in Figure 3, the engine speed and the engine load can be divided into a number of subregions called cells. In this work, 24 cells are defined, where cells 1 to 4 represent the engine deceleration regions that are experimentally not feasible for emission testing. Among the 20 feasible cells (cells 5 to 24), only 12 cells (i.e., cells 5, 6, 9–15, 18, 19, and 22, which are outlined by a thick line in the figure) are reachable under practical experimental conditions. Experiments need to be designed properly to unveil engine combustion and catalytic conversion dynamics in all reachable cells. In each reachable cell, a number for the values of the goal voltage and the kicks should be selected (in this study, the levels of goal voltage and the kicks are 5 and 3, respectively). Factorial design for each cell is utilized to ensure the coverage of the operating ranges of the goal voltage and the kicks, which results in a requirement of 15 (i.e., $5^2 \times 3$) experiments for each cell. A complete set of the experimental points can be expressed as:

$$N = N_c \times L_g \times L_k$$

where $N_c$ is the number of reachable cells and $L_g$ and $L_k$ are, respectively, the levels of the goal voltage and the kicks in each cell. In this case, the total number of experiments is 180 (i.e., $12 \times 5 \times 3$).

The designed experimental points (marked as black dots) are shown in Figure 3. Note that different values of the goal voltage and the kicks need to be considered for each selected pair of engine speed and engine load. This means that one dot in the figure may represent several experimental points. Restricted by the experimental facility, the selected speed-load pairs may not be uniformly distributed in each cell, but the data obtained from such experiments are adequate for model development because of the inherent learning and adaptive capability of neural networks.

**Model Development**

The engine-catalytic converter model is a three-layer feed-forward NN (see Figure 1), which can be developed by following the steps below.

![Figure 3. Engine speed-load operational regions and experiment placement in the reachable testing cells for model development.](image-url)
**Step 1.** Select $N_t$ sets of training data from $N$ sets of experimental data. The experimental design and data acquisition approaches are presented in the previous section. In this case, a total of 160 sets of training data are selected.

**Step 2.** Specify the NN structures to be constructed. Since a three-layer NN is selected, and the number of input nodes and output nodes is fixed, the structural difference between the constructed models is only the number of nodes in the hidden layer.

**Step 3.** Train the NNs one by one using the regularization-based Levenberg-Marquardt algorithm. The objective function for the training can be expressed as:

$$\text{Min } J_p = \omega \cdot E_{\text{tot}} + (1 - \omega) \cdot R$$

where $\omega \in [0, 1]$ is a parameter used for adjusting the preference between the error term ($E_{\text{tot}}$) and the regularization term ($R$). Variable $E_{\text{tot}}$ is the arithmetic mean of summed squares of the model errors, which is expressed as:

$$E_{\text{tot}} = \frac{1}{N_t} \sum_{i=1}^{N_t} (\hat{y}_i - y_i)^2$$

where $\hat{y}_i$ and $y_i$ are, respectively, the model prediction and the experimental data. In this work, they are either fuel efficiencies or catalyst efficiencies. A regularization learning method is adopted here to improve the generalization ability of the NNs (Buntine and Weigend, 1991; Mackay, 1992; Williams, 1995). The regularization term, $R$, is introduced to penalize the large weights in the model, which is expressed as:

$$R = \frac{1}{m} \sum_{j=1}^{m} w_j^2$$

where $w_j$ is the $j$-th weight and $m$ is the total number of weights in the model. Adding this regularization term to the objective function for NN training will result in smaller weights and biases in the NN. This will force the network response to be smoother and less likely to overfit.

**Step 4.** Select an NN that gives the minimum value of $J_p$ (see Equation (2)).

**Step 5.** Output the selected NN model with its parameters.

Figure 4 shows an example where 10 NNs are evaluated, and the one with three hidden nodes shows the best performance, with a trade-off between model generalization and prediction error minimization. Note that $\omega$ is set to 0.5 for the training of all the NNs.

**Model Validation**

The selected model is validated using 18 sets of experimental data. The experimental points (denoted as triangles in Figure 5) are uniformly distributed in 12 reachable cells. For each experimental point, the goal voltage and the kicks are randomly selected from five and three specified levels, respectively. The validation results shown in Figure 6 indicate that the model predictions match the experimental data very well, except for the prediction of NOx efficiency. Since NOx efficiency changes greatly under
different operating conditions (see Figure 6(c)), more experimental data obtained over a complete operating range will be helpful for model performance improvement. However, taking experimental costs and time minimization into account, the current model, which correctly predicts the trend of NOx efficiency testing data, is considered sufficient for system analysis and engine calibration optimization.

**Model-Based System Analysis and Optimization**

The validated model is used to conduct system performance analysis. Model-based optimization is also conducted to optimize engine calibration.

![Figure 4](image)

**Figure 4.** Performance analysis of the NN models using different numbers of hidden nodes ($\omega = 0.5$).

![Figure 5](image)

**Figure 5.** Engine speed-load operational regions and experiment placement in the reachable testing cells for model validation.
Cell-Based System Analysis

The developed model is suitable for predicting catalyst efficiency and fuel efficiency when information on engine speed, engine load, goal voltage, and kicks is available. Figure 7 shows some results plotted in 3-D, each of which is for a specific cell with a representative load-speed pair given. Each plot shows the change of catalyst efficiency or fuel efficiency along the goal voltage and the kicks for the specific load-speed pair. These results reveal that if the engine speed, the engine load, and the goal voltage are kept constant, a change of the kicks has a negligible influence on the emission and the fuel efficiency. On the other hand, if the engine speed, the engine load, and the kicks remain constant, a change of the goal voltage has various effects on each of the three catalyst efficiencies and the fuel efficiency. Figure 8 shows an example when the kicks has a value of 0.3 in cell 5. In this cell, the engine speed ranges from 0 to 1,728 RPM, and the load range is from 26 to 40 MAP.

Figures 7(a) and 8(a) show that the catalyst efficiency for HC changes only slightly along with the goal voltage. This is because the efficiency is always at a very high level (>90%) after the catalyst converter functions. However, the catalyst

Figure 6. Comparison of catalyst efficiencies and fuel efficiency between model prediction and experimental data.
efficiency for CO decreases when the goal voltage increases (see Figures 7(b) and 8(b)), which means decreasing goal voltage contributes to CO emission reduction. In Figures 7(c) and 8(c), the catalyst efficiency for NO\textsubscript{x} increases along with the goal voltage, which indicates that increasing goal voltage contributes to NO\textsubscript{x} emission reduction.
reduction. Figures 7(d) and 8(d) reveal that the influence of the goal voltage on the fuel efficiency can be safely neglected. Note that the model predictions in those unreachable cells (i.e., cells 7, 8, 16, 17, 20, 21, 23, and 24) that are not shown in Figures (7) and (8) could contain noticeable errors, because no experimental data were available for model development.

**Engine Calibration Optimization**

A typical engine calibration optimization problem can be stated as follows: given specific engine speed and engine load, determine a set of optimal calibration parameters (e.g., goal voltage and kicks) so that the emission can be minimized and the fuel efficiency can be maximized, while all constraints are satisfied.

**Optimization Formulation**

The optimization target is to maximize the catalyst efficiency and the fuel efficiency, i.e.,

$$\text{Max } J = \alpha (\beta_1 \cdot E_{HC} + \beta_2 \cdot E_{CO} + (1 - \beta_1 - \beta_2) \cdot E_{NOx}) + (1 - \alpha) \cdot E_{FE}$$  \hspace{1cm} (5)

where $E_{HC}$, $E_{CO}$, and $E_{NOx}$ are, respectively, the catalyst efficiencies for HC, CO, and NOx; $E_{FE}$ is the fuel efficiency; parameter $\alpha \in [0, 1]$ is for balancing the environmental and economic objectives; and parameters $\beta_1$ and $\beta_2 \in [0, 1]$ are for adjusting the weight preference among the pollutants in exhaust gases.
The optimization is subject to a set of constraints, which include the engine-catalytic converter model, the acceptable ranges for calibration parameters, the emission levels for HC, CO, and NOx, and the limit on fuel efficiency.

**Solution Derivation**

Optimal solutions can be derived readily. It is shown that the variations of the goal voltage and the kicks have a negligible influence on the fuel efficiency, but the catalyst efficiencies may change greatly along with the goal voltage. Thus, assigning a greater weight to the catalyst efficiencies can lead to a better solution. In this case, weight $a$ is set to 0.95. Concerning pollution reduction, decreasing the level of NOx is the most important. Thus, a weight of 0.70 is assigned to minimize NOx. Between HC and CO, CO emission may need more attention and thus weight $\beta_1$ is set as 0.1 and $\beta_2$ as 0.2.

**Individual Cell-Based Optimization.** The optimal settings of the goal voltage and the kicks for each cell can be quickly determined by solving the optimization model, given the speed and the load in a selected cell. In this case, for example, the speed and the load in cell 5 are set to 1,378 RPM and 34 MAP, respectively.

The optimization results for a total of 20 cells are depicted in Figure 9, each of which is marked by ◆ (where the calibration data for the cell were available in modeling and thus the results are reliable) or ◊ (where the calibration data for the cell were not available in modeling and the model prediction is based on model extrapolation, and thus the optimization results may contain noticeable errors). The speed and the load used in the optimization for each cell are indicated. For instance, for cell 15, the representative speed and load are 2,848 RPM and 60 MAP, respectively.

By comparing with the industrial settings of the goal voltage (2.6667 V) and the kicks (0.3) for all the cells of a particular model vehicle, the optimization shows that the goal voltage should be in the range from 2.69 to 2.98 V, while the kicks should be between 0.2988 and 0.312; these are cell dependent. With the cell-dependent optimal settings, the fuel efficiency, the catalyst efficiencies, and the objective function value in each reachable cell are shown in Table I, where the results obtained using the original settings (i.e., industrial settings) are also included in the table for comparison. It shows that after optimization, the objective function value in each individual cell increased, which indicates a better overall system performance in terms of emission reduction and fuel efficiency improvement. The effects of the weights can be seen from the averaged results. The original average NOx catalyst efficiency is 85.7%. After optimization, it increased to 91.8%. It is understandable that the efficiencies for HC and CO are reduced. To demonstrate clearly the effects of optimization, Figure 10 shows how each catalyst efficiency and fuel efficiency are changed along with the goal voltage in the reachable cell 15. Note that the use of the optimal goal voltage (i.e., 2.79) increases the catalyst efficiency for NOx but brings down the HC and CO efficiencies. It can be anticipated that, if the weight for NOx in Equation (5) is greater than the current value (i.e., 0.7), the derived optimal goal voltage will be greater than 2.79, and the NOx efficiency will be increased further, but the HC and CO efficiencies will be decreased further.

**All-Cell-Based Optimization.** One of the most attractive features of the modeling and optimization methods developed in this work is that it allows developing a relationship between the goal voltage (or the kicks) and any pair of the speed-load that is applicable for all cells. This can give rise to a whole-range smooth control.
of emission and fuel efficiency when a vehicle runs at any engine speed and any engine load, as long as they are in the permissible ranges. Note that to achieve smooth control for an unsmooth trip (i.e., off-highway travel with a frequent change of speed), the response time of the emission control system should be short enough that the control system can respond promptly to the change of the set points for the goal voltage and the kicks. In the example shown in Figure 9, connecting the optimization results by dashed lines gives two nonlinear relationships:

\[
V = 7.08 \times 10^{-4} S + 5.76 \times 10^{-3} L - 7.15 \times 10^{-6} S \cdot L - 2.15 \times 10^{-7} S^2
+ 2.31 \times 10^{-5} L^2 + 1.05 \times 10^{-9} S^2 \cdot L + 2.53 \times 10^{-8} S \cdot L^2
+ 2.27 \times 10^{-11} S^3 - 3.51 \times 10^{-7} L^3 + 2.08
\]  

(6)

**Figure 9.** Cell-based optimization results (\(x = 0.95, \beta_1 = 0.1, \beta_2 = 0.2\)): (a) the optimal goal voltage and (b) the optimal kicks.
Table I. Comparison between optimal and original results

<table>
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<tr>
<th>Cell no.</th>
<th>HC efficiency (%)</th>
<th>CO efficiency (%)</th>
<th>NO\textsubscript{x} efficiency (%)</th>
<th>Fuel efficiency (%)</th>
<th>Objective value</th>
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<td>Original</td>
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\[ J = 0.95 \times (0.1 \times E_{HC} + 0.2 \times E_{CO} + 0.7 \times E_{NO_x}) + 0.05 \times E_{FE}. \] The original goal voltage is 2.6667 V and the original kicks is 0.3.
\[ V = 3.90 \times 10^{-5} S + 4.45 \times 10^{-4} L + 2.58 \]  
\[ K = 1.57 \times 10^{-6} S + 1.79 \times 10^{-5} L + 0.30 \]

**Concluding Remarks**

Engine emission testing is an extremely important task in automotive manufacturing. In this work, a neural network (NN)-based engine-catalytic converter modeling approach and an engine calibration optimization procedure are introduced to facilitate engine emission testing. The developments help advance the current
trial-and-error practice, as they are proven to be a systematic, comprehensive analysis approach. The optimization method ensures identification of superior solutions for emission reduction and fuel efficiency improvement through adjustment of engine calibration parameters.

The developed modeling and optimization methodology is generally applicable for emission testing and engine calibration of any type of model vehicle, regardless of new types of catalysts in the converter. The methodology can also be used to enable vehicles to operate over a greater range of operating conditions necessitated through the use of alternative fuels (e.g., ethanol). As long as sufficient and reliable experimental data that cover the complete operating conditions (i.e., a range of the air-fuel ratio or a range of goal voltage and kicks values) are available, the modeling and engine calibration optimization methodologies can be readily used for solution identification. Also, the introduced methods can be implemented in the on-board

Figure 11. Cell-based optimization results ($a = 0.7, \beta_1 = 0.33, \beta_2 = 0.33$): (a) the optimal goal voltage and (b) the optimal kicks.
computer chip of vehicles. This will allow a continuous, smooth adjustment of key engine parameters for minimizing emission and maximizing fuel efficiency.

Acknowledgments

This work is in part supported by the Institute of Manufacturing Research of Wayne State University. Technical assistance from Daimler-Chrysler Company is gratefully acknowledged.

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