Estimation of Particulate Loading in Diesel Particulate Filter Using Neural Network*

Abdul Rahman BOHARI** and Naoki MIZUNO**

A diesel particulate filter system is very effective for reducing the amount of particulate matter in the exhaust emission of diesel engines. This system catches particulate matter in its filter and therefore, with time, the filter will be fully loaded such that it cannot be used. The filter must then be regenerated by burning the accumulated particulate matter. To effectively control the filter regeneration, an accurate and reliable estimation of particulate accumulation is required. However, due to unknown factors in filter dynamics and operating conditions, it is not easy to estimate particulate accumulation analytically. A map of particulate accumulation, can actually be constructed by conventional methods, nevertheless it requires such a large amount of data that it is very difficult to apply. To overcome this problem, it is proposed, in this work, to employ a feedforward neural network which is widely known for its capability to model nonlinear systems. The experimental results show that particulate accumulation can be estimated with the desired precision for a wide range of operating conditions. This subsequently makes regeneration control flexible enough that the system can easily be used.

**Key Words:** Diesel Particulate Filter, Filter Dynamics, Nonlinear System, Estimation, Neural Network, A Learning Algorithm, Modeling

1. Introduction

The diesel particulate filter (DPF) system is a set of devices in which a ceramic filter is used to catch and eliminate particulate matter in the exhaust emission of diesel engines\(^1\). It is widely recognized that this system can reduce the amount of particulate matter in the exhaust emission effectively. With time, however, the filter of the system will be fully loaded such that it cannot be used. The filter must then be regenerated under the parked condition. During this regeneration phase, the filter is heated, then the accumulated particulate matter is gradually burned. In this case, the maximum permissible volume of particulate matter in the filter must be limited, since excessive particulate accumulation in the filter drastically increases the burning temperature during the regeneration phase. A high burning temperature subsequently damages the filter due to thermal shock. Hence it is desirable to employ a practical technique for estimating particulate accumulation, in which the temperature can be kept within the range of safe regeneration. So far, some researches\(^2,\(3\) have been conducted to deal with this problem. However, obtaining an effective and reliable estimation method with the desired precision under all operating conditions (including steady-state and transient driving conditions) is still an unsolved problem.

In this study, a neural network, which can adaptively estimate a function from data without specifying mathematically how outputs depend on inputs, is employed to compensate the characteristics of the DPF system\(^4\) under all operating conditions. The neural network\(^5,\(6\) used is a 3-layered feedforward neural network (FFNN) with a faster and more accurate version of the backpropagation (BP) algorithm, i.e., a hybrid algorithm. To enhance the performance of the conventional hybrid algorithm, momentum terms were added as they can reduce oscillation and hasten the learning process. The structure of the neural network used in this work was determined by trial and error.

The experimental results show that the
particulate accumulation can be estimated for a wide range of operating conditions, including the transient driving condition. This subsequently makes the system flexible and easy to use.

This paper consists of 5 sections. An outline of the DPF system is explained in the following section and the neural network modeling and its learning algorithm are presented in section 3. The configuration of the experiment and evaluation are in section 4, and finally the conclusions are summarized in section 5.

2. Outline of DPF System

The configuration of the system for estimating particulate loading is shown in Fig. 1, where the DPF is installed in the exhaust pipe. Actually, the weight of accumulated particulate matter can be measured for experimental purposes by dismantling the filter. However, for an on-road system, a reliable method should be employed for on-line estimation of the accumulated particulate, based on back pressure and engine speed such that the filter can be regenerated effectively. For implementation of this system, the data of engine speed and back pressure were obtained using some sensors and employed as inputs to the neural network. The back pressure used here is the difference between the pressures at the inlet and outlet of the muffler. Hence the measurement of back pressure required two pressure sensors. Measured weights of particulate accumulation are used as teacher signals to train the neural network.

3. Neural Network Modeling and Its Learning Algorithm

A neural network (NN) is a massively parallel interconnected system which has the ability to learn and adapt to a given environment by self-adjustment of its internal conditions. It consists of nonlinear elements, which are called neurons, and the NN processes information by connecting these neurons with synaptic weights. A NN which has an excellent ability to approximate nonlinear functions and model nonlinear systems using experimental data, is employed in this work to enhance the performance of the DPF system.

The learning algorithm used for NN training in this work is a hybrid algorithm\(^{(6)(7)}\). This algorithm is employed in this work since it is faster and more accurate than conventional backpropagation. The hybrid algorithm uses an adaptive algorithm\(^{(8)}\) instead of BP to tune the weights between the hidden layer and the output layer of the networks, and conventional BP to adjust the weights between the input layer and the hidden layer.

The architecture of the FFNN, as shown in Fig. 2, consists of one input layer, one hidden layer and one output layer. The activity of a neuron in the hidden layer is determined by a set of input signals \(x_k\), \(k=1, 2, \cdots, i\), and synaptic weights \(w_{ki}\), \(l=1, 2, \cdots, j\). \(i\) is the number of input neurons and \(j\) is the number of hidden neurons. The output of hidden neurons \(h_l\) is described by

\[
h_l = f\left(\sum_{k=1}^{i} x_k w_{ki} + w_0\right).
\]  

In the same way, we can derive the equation for the output of neurons in the output layer.

\[
y_{on} = f\left(\sum_{l=1}^{j} h_l v_{lm} + v_0\right)
\]  

Fig. 1 Experimental system for estimation of particulate loading in DPF

Fig. 2 Internal structure of 3-layered feedforward NN
\[ f(s) = \frac{1}{1 + e^{-as}}, \quad a > 0 \quad (3) \]

where
\[ m = 1, 2, \ldots, n, \]
\[ n : \text{number of the output neurons}, \]
\[ w_b \text{ and } v_b : \text{thresholds}, \]
\[ y_{\text{op}} : \text{output of the output neurons}, \]
\[ p : \text{number of patterns}, \]
\[ f(s) : \text{a sigmoid function as shown in Eq. (3)}, \]
\[ a : \text{a sigmoid function parameter}. \]

Here, the adjustment of synaptic weights is considered so as to minimize the discrepancy between the output of neurons in the output layer and given teacher signals. Let us consider an error signal which is taken from the discrepancy between the signal produced by inverse sigmoid transformation of the teacher signal and the signal from the output layer before transformation by the sigmoid function. This error signal is defined as
\[ e_{\text{opp}} = f^{-1}(y_{\text{Dmp}}) - s_{\text{op}}, \quad (4) \]
\[ f^{-1}(y) = -\frac{1}{a \log(1/(y-1)),} \quad (5) \]

where
\[ f^{-1}(y) : \text{inverse sigmoid function}, \]
\[ e_{\text{opp}} : \text{modified error signal}, \]
\[ y_{\text{Dmp}} : \text{desired signal (teacher signal)}. \]

The output signal of the output layer, taken before transformation by the sigmoid function, is
\[ s_{\text{op}} = \sum_{i=1}^{m} v_{i} h_{i} \]
\[ = V_{a} H_{p}, \quad (6) \]

where
\[ V_{a} = [v_{1}, v_{2}, \ldots, v_{m}]^T, \]
\[ H_{p} = [h_{1}, h_{2}, \ldots, h_{p}]^T. \]

The adaptation of \( v_{i} \) is done by minimizing
\[ E_{\text{sm}} = \frac{1}{2} \sum_{i} (e_{\text{sm}})^2 \text{ in terms of } v_{i} \text{ such that its optimal value can be found:} \]
\[ \frac{\partial E_{\text{sm}}}{\partial v_{i}} = \sum_{p} H_{p} H_{p}^T V_{a} - \sum_{p} H_{p} f^{-1}(y_{\text{Dmp}}) = 0. \quad (7) \]

Hence the optimal value of \( V_{a} \) can be written as follows.
\[ V_{a} = (\sum_{p} H_{p} H_{p}^T)^{-1} \sum_{p} H_{p} f^{-1}(y_{\text{Dmp}}) \quad (8) \]

By employing an adaptive algorithm which is based on recursive least-squares estimation\(^\text{10}\), the adjustment of \( V_{a} \) can be expressed by
\[ \Delta V_{a} = \frac{I_{a} - \Gamma_{p-1} H_{p}}{1 + H_{p}^T I_{p-1} H_{p}} e_{\text{opp}}, \quad (9) \]
where the gain matrix \( I_{a} \) is updated as
\[ I_{a} = \frac{1}{\lambda_{a}} \left[ I_{a} - \lambda_{a} \frac{\Gamma_{p-1} H_{p}}{1 + H_{p}^T I_{p-1} H_{p}} \right], \quad (10) \]
\[ \text{where} \]
\[ 0 < \lambda_{a} < 1, \quad 0 < \lambda_{a} < 2 : \text{the forgetting factors} \]
\[ I_{a} = \gamma I; \quad \gamma > 0 : \text{initial value of matrix} \]
\[ I : \text{unity matrix}. \]

To enhance the performance of the conventional hybrid algorithm, momentum terms were added to Eq. (9). Thus the adjustment of synaptic weights between hidden and output layers can be expressed as
\[ \Delta v_{\text{op}}(t) = \frac{I_{p} - \Gamma_{p-1} H_{p}}{1 + H_{p}^T I_{p-1} H_{p}} e_{\text{op}} + \alpha_{1} \Delta v_{\text{op}}(t-1), \quad (11) \]

where
\[ t : \text{number of iterations}. \]

The adaptation of synaptic weights between input and hidden layers by BP, is shown as
\[ \Delta w_{a}(t) = -\eta \frac{\partial E_{\text{sm}}}{\partial w_{a}(t)} + \alpha_{2} \Delta w_{a}(t-1), \]
\[ = -\eta e_{\text{opp}} f(s_{\text{op}})(1-f(s_{\text{op}})) v_{\text{in}} f(u_{i})(1-f(u_{i})) x_{a} + \alpha_{2} \Delta w_{a}(t-1), \quad (12) \]

where
\[ \eta : \text{learning rate}, \]
\[ e_{\text{opp}} : \text{discrepancy between the expected output and network output}, \]
\[ \alpha_{1}, \alpha_{2} : \text{momentum rates}. \]

The estimated error for all patterns is defined as
\[ E_{e} = \frac{1}{2} \sum_{p} (e_{\text{opp}})^2. \quad (13) \]

4. Construction of Neural Network Modeling and Its Evaluation

4.1 Measurement of experimental data and its preprocessing

Using sensors, the data of engine speed and back pressures were measured in the range of 0~50 s\(^{-1}\) and 0~2\times10\(^{5}\) Pa respectively. All of these data were transformed into 0~2 v. Then the signals were converted into 10-bit digital data with a sampling period of 100 ms. Finally the data were processed as a usable data file for NN training. The NN training was performed using 64-bit floating arithmetic. The forklift used for the measurement had manual transmission with double speed in both forward and reverse, and a maximum loading capacity of 2.5 ton. The weight of the load used in the experiment was 1.75 ton. The specifications of the forklift engine and the DPF are listed in Tables 1 and 2.

Experimental data were measured during test operation under all operating conditions, which included loading, unloading, and driving with and without a load on the forklift. One data file consists of data taken in two cycles where 1 cycle requires around 2

<table>
<thead>
<tr>
<th>Item</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engine Displacement</td>
<td>3.0\times10^{-3}(m^3)</td>
</tr>
<tr>
<td>Configuration</td>
<td>D 1, 4 cylinders</td>
</tr>
<tr>
<td>Aspiration</td>
<td>Naturally aspirated</td>
</tr>
</tbody>
</table>

Table 1 Engine specifications


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minutes and 40 seconds. Teaching signals used in NN training were taken from the measurement of the weight of particulate accumulation. The increase of particulate loading for one cycle of operation could be neglected since it was so small. Here, the temperature of the DPF at the time of weight measurement was set above 200°C so that there was no influence of the moisture. Under these conditions, 13 data files were taken using DPF No. 1 and DPF No. 2, as listed in Table 3.

### 4.2 Neural network design and its off-line training

To model the DPF system, NN training was conducted by employing 13 data files, where each data file consisted of 3,000 datum each for back pressure and engine speed. These back pressure and engine speed data were employed as inputs to the NN, and measured particulate loading was used as teacher signals. To equalize the effect of input signals in the modeling and to enable mapping by the sigmoid function, input signals and teacher signals were normalized as follows: back pressure (Pa)/0.52 × 10^6 (Pa), engine speed (s⁻¹)/50 (s⁻¹), and (particulate loading (g/l) + 2 (g/l))/14 (g/l). Therefore estimated particulate loading (g/l) = (output signals of NN × 14 (g/l)) − 2 (g/l). Parameters of the neural network used were determined by the heuristic approach, as listed in Table 4.

Initial values of synaptic weights were randomly set in the range of −1.0 to 1.0. The adjustment of the synaptic weights is shown in the flowchart in Fig. 3. A training completing 13 data files was considered to be one set of training. Under these specifications, NN was trained off-line with the configuration indicated in Fig. 4.

### 4.3 Training results and evaluation

The NN was first trained for thousands of iterations to determine minimum error and it was obtained at 975 iterations. After that the NN was trained for 975 iterations (75 training sets) where the average error, as can be seen in Fig. 5, decreased to 0.0037. The error function used to evaluate the training is defined as

\[ E_n = \frac{1}{2} \sum (e_{\text{esp}})^2. \]  

The trained NN is shown in Fig. 6. By employing this trained network, a nonlinear map of the estimation system of particulate loading is obtained, as shown in Fig. 7. All values of variables in this figure were normalized as described in section 4.2.

The on-line estimation results of particulate accumulation in the range of 0~9.32 g/l are listed in Table 5. The estimated particulate loading shown in
Table 5 Estimated results

<table>
<thead>
<tr>
<th>Loading</th>
<th>Real Particulate</th>
<th>Estimated Particulate Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean Value</td>
<td>Max. Value</td>
</tr>
<tr>
<td>9.32 g/l (DPF No. 2)</td>
<td>8.42g/l(-0.90g/l)</td>
<td>8.65g/l</td>
</tr>
<tr>
<td>8.28 g/l (DPF No. 2)</td>
<td>8.09g/l(-0.19g/l)</td>
<td>8.21g/l</td>
</tr>
<tr>
<td>7.16g/l (DPF No. 2)</td>
<td>7.09g/l(-0.07g/l)</td>
<td>7.24g/l</td>
</tr>
<tr>
<td>5.96g/l (DPF No. 2)</td>
<td>6.06g/l(+0.10g/l)</td>
<td>6.25g/l</td>
</tr>
<tr>
<td>4.48g/l (DPF No. 2)</td>
<td>3.71g/l(-0.77g/l)</td>
<td>4.12g/l</td>
</tr>
<tr>
<td>0.00g/l (DPF No. 2)</td>
<td>-0.04g/l(-0.04g/l)</td>
<td>0.75g/l</td>
</tr>
<tr>
<td>9.16 g/l (DPF No. 1)</td>
<td>8.54g/l(+0.02g/l)</td>
<td>8.70g/l</td>
</tr>
<tr>
<td>7.88 g/l (DPF No. 1)</td>
<td>8.11g/l(-0.23g/l)</td>
<td>8.26g/l</td>
</tr>
<tr>
<td>6.88g/l (DPF No. 1)</td>
<td>7.26g/l(+0.38g/l)</td>
<td>7.46g/l</td>
</tr>
<tr>
<td>4.68g/l (DPF No. 1)</td>
<td>5.37g/l(+0.05g/l)</td>
<td>5.68g/l</td>
</tr>
<tr>
<td>3.92g/l (DPF No. 1)</td>
<td>5.14g/l(+1.22g/l)</td>
<td>5.35g/l</td>
</tr>
<tr>
<td>3.32g/l (DPF No. 1)</td>
<td>3.25g/l(+0.07g/l)</td>
<td>3.57g/l</td>
</tr>
<tr>
<td>0.00g/l (DPF No. 1)</td>
<td>-0.07g/l(-0.07g/l)</td>
<td>0.79g/l</td>
</tr>
</tbody>
</table>

the middle shows the ideal condition under which the estimated values exactly match the real values; this is very difficult to achieve due to unknown factors in filter dynamics and operating conditions. However, as it is clearly shown in Fig. 8, the on-line estimated particulate loading satisfies the required precision (±2 g/l from real particulate loading) where moving average errors of the estimation are in the range of −0.90～+1.22 g/l.

5. Conclusions and Future Work

In this work, the particulate loading estimation problem of the DPF system, which is strongly nonlinear and very difficult to model analytically, could be well modeled by employing a NN. The obtained model was used to estimate on-line the particulate loading in the range of 0～9.32 g/l where all of the estimation
Fig. 9  Input signals (upper two figures) and estimated results

were in the range of the desired practical precision. The estimation was conducted under all operating conditions (including steady-state and transient driving conditions) using only two input variables, i.e., back pressure and engine speed. This means that the estimation is satisfactory and has the desired precision even under the transient driving condition.

The neural network structure used in this work was determined by trial and error. It is desirable to employ an algorithm which can determine automatically the optimum structure for each given problem.

Acknowledgments

The authors would like to thank Mr. H. Taniguchi, who belongs to Toyoda Automatic Loom Works Ltd., Mr. T. Okazaki, and Dr. T. Yamada of our laboratory for their useful suggestions.

References


