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State Estimation of Aftertreatment System Using Modeling Method Based on Machine Learning (First Report)

- Proposal of NOx Storage Reduction Catalyst Model and Evaluation of Estimation Accuracy Using Actual Engine Data -

Takato Ikedo [1)] Hideto Inagaki [1)] Matsuei Ueda [1)] Sayaka Nojiri [1)]

1) TOYOTA CENTRAL R&D LABS., INC.
41-1 Yokomichi, Nagakute, Aichi, 480-1192, Japan (E-mail: e1615@mosk.tytlabs.co.jp)

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To deal with increasingly severe exhaust gas and fuel efficiency restrictions for diesel engines, it is necessary to improve the purification performance of NOx storage reduction catalysts (NSR catalysts). If the estimated state variable of an NSR catalyst, i.e., the NOx storage amount, is too large compared to the true value, extra fuel is consumed due to the increased frequency of rich spike control. In contrast, if the estimated value is too small compared to the true value, emissions increase due to continuous deterioration of the NOx storage performance. Therefore, to fully utilize the performance of an NSR catalyst, the NOx storage amount must be estimated precisely. This report proposes a model that estimates the NOx storage amount with high accuracy.

The NOx storage amount is given by Eq. (1) from the NOx purification reaction process of an NSR catalyst and the mass conservation of NOx in the inspection area shown in Fig. 1. Discretizing Eq. (1) by forward difference yields Eq. (2).

$$\frac{\mathrm{d}}{\mathrm{dt}} NO_{x,st} = NO_{x,in} - NO_{x,rdct} - NO_{x,out} \tag{1}$$

$$NO_{x,\ st}[k+1] = NO_{x,\ st}[k] + \Delta t (NO_{x,in}[k] - NO_{x,\ rdct}[k] - NO_{x,out}[k]) \tag{2}$$

where, $NO_{x,st}$: NOx storage amount, $NO_{x,in}$: NOx flowing into the NSR catalyst, $NO_{x,rdct}$: NOx storage amount reduced by rich spike control, $NO_{x,out}$: NOx flowing out from the NSR catalyst, k: discrete time, Δt: sampling time interval.

The proposed model shown in Fig. 2 combines neural networks and a physical model. From the data at the inlet of the NSR catalyst and the estimated value of the NOx storage amount at time k, the NOx storage amount at time $k+1$ is estimated based on Eq. (2). The components of the proposed model are 1 and 2 below.

1. NOx storage rate model (neural network)
   This model estimates the NOx storage rate in Eq. (3) and calculates the difference between $NO_{x,in}$ and $NO_{x,out}$ $(= NO_{x,in}[k] - NO_{x,out}[k])$.

$$R_{NOx,conv}[k] = (NO_{x,in}[k] - NO_{x,out}[k]) / NO_{x,in}[k] \tag{3}$$

2. NOx reduction rate model (neural network)
   This model estimates the ratio of stored NOx reduced by the rich spike control to the NOx storage amount $(= NO_{x,rdct}[k]/NO_{x,st}[k])$, and calculates the amount of NOx reduced by the rich spike control.

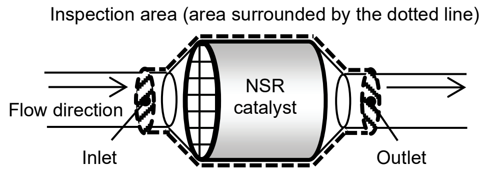

Fig.1 Inspection area

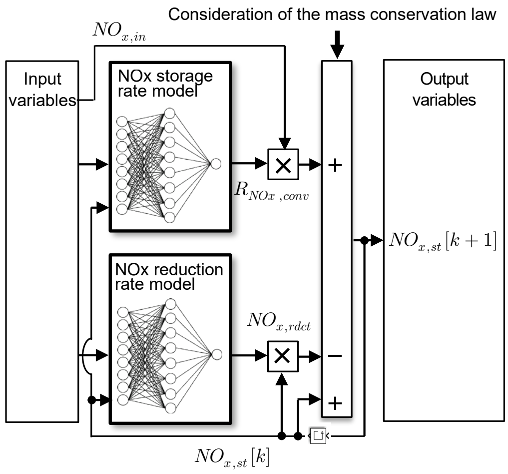

Fig.2 State estimation model for NSR catalyst

Fig. 3 compares the results estimated using the proposed model with actual engine test data. When the estimation accuracy was evaluated against the test data, it was found that the NOx storage amount could be estimated with an accuracy containing a maximum absolute error of less than 44.8mg (4.3% of the correct value) in all sections. Compared with a model that does not consider the mass conservation law, i.e., a model composed only of a neural network, the maximum absolute error and mean absolute error of the NOx storage amount are both reduced by at least 80% by the proposed model. As a result, this confirms the effectiveness of calculating the NOx storage amount based on the mass conservation law by combining neural networks and a physical model.

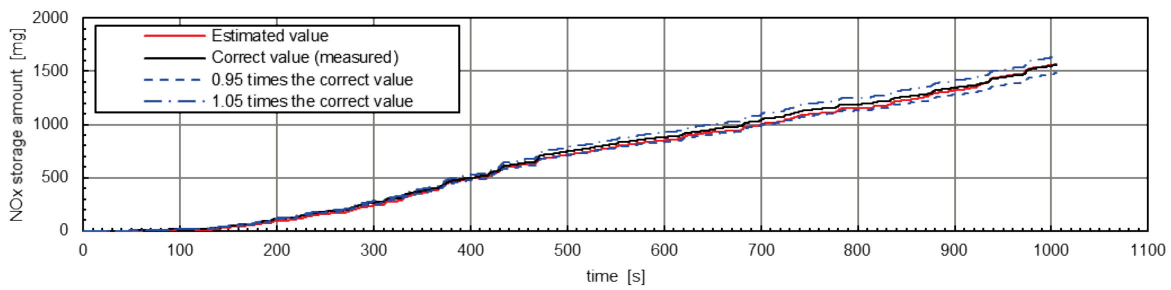

Fig.3 Comparison of estimated results using the proposed model with actual engine test data