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Deep Neural Network Modeling of Diesel Engine for Application of Model Predictive Control

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We have proposed a fast derivation method of MPC with deep learning (DNN) model in our previous studies. This method converts the control problem of MPC into a mixed integer linear programming problem, and achieves both precise control and reduction of calculation load by using a high-precise model. The transformation of a model predictive control problem with a DNN model into a mixed integer linear programming problem requires an equivalent transformation of the activation function of the DNN model with propositional logic and inequality conditions. In this paper, we report a comparative study of modeling methods suitable for conversion based on prediction accuracy and structure of activation function. The DNN model was constructed by using various linear and piecewise linear functions as the activation function, and the modeling method in which the suitability of equivalent transformation and model accuracy were compatible was investigated. Table1 shows the verification results of MAP model and MAF model. The MAP model and MAF model can be constructed with high accuracy by using (c)ReLU, (d)ClippedReLU, (e)Satlins, (f)LeakyReLU, and (g)Tribas. In the equivalent change of the activation function, if the piecewise linear number of the activation function is large, the number of 0 -1 variables used in the conversion also increases. Therefore, the condition to be considered increases and affects the calculation load. Column 5 of Table1 shows the piecewise linear number, and column 6 of Table1 shows the number of 0 -1 variables. From the table, it can be seen that ReLU and LeakyReLU are activation functions suitable for equivalent transformation. In addition, since ReLU which makes the negative value to be 0 has the characteristic which makes the learning parameter comparatively sparse in the modeling, further speedup of the calculation is possible. Therefore, we adopt DNN using ReLU as the activation function, which is suitable for the equivalent transformation and can reproduce the object with high accuracy. Fig. 1 shows the results of WHTC mode evaluation using DNN model with ReLU as activation function. The result shows that the actual value follows the target value well.

In the future, further reduction of the calculation load will be attempted by examining reduction of the model. We will also evaluate the proposed MPC with DNN model on the actual engine.

Table1 Results of cross validation using MAP and MAF model

Activation Function		(a)Tanh ※ref	(b)Hard lims	(c)ReLU	(d)Clipped ReLU		(e)Satlins	(f)Leaky ReLU		(g)Tribas
Setting		-	-	-	Lim		-	Scale		-
					1	10		0.1	0.5	
Cross validation average	MAP	0.986	0.362	0.985	0.984	0.985	0.985	0.986	0.986	0.985
	MAF	0.989	0.194	0.988	0.984	0.988	0.988	0.987	0.988	0.980
Num of Piecewise Linear		-	2	2	3	3	3	2	2	4
Num of Binaries		-	1	1	2	2	2	1	1	3

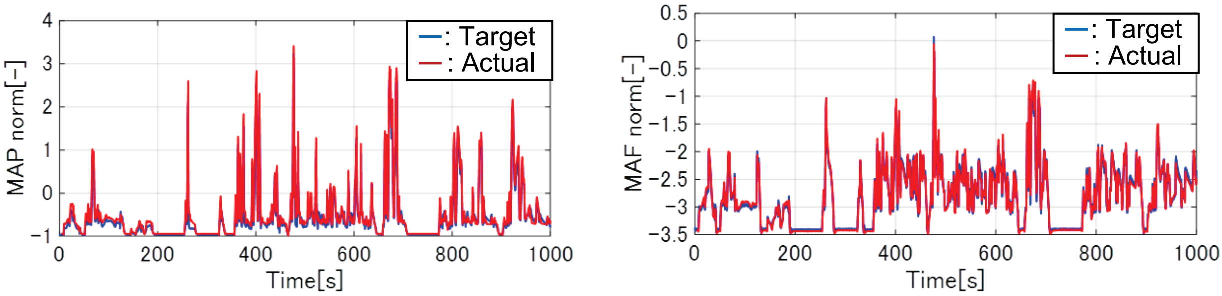

Fig.1 Results of WHTC (Activation Function : ReLU)

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