Fuzzy Neural Network Learning for Practical Intelligent Powertrain Exhaust Gas Temperature Prediction

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Abstract: The exhaust gas temperature plays a leading role in the thermal efficiency of the automotive powertrain system. It also determines the performance of catalytic converters for removing toxic gases. When the exhaust temperature is excessively high, it will give rise to extra heat energy loss in the exhaust systems. Meanwhile overheating leads to engine component damage, engine knock, fuel pre-ignition and emission after-treatment system failure. The inherent formation mechanism of exhaust temperature is highly complicated, which depends on multiple factors in the combustion process as well as heat and mass transfer. The maximum combustion efficiency itself requires the stoichiometric mixture (air to fuel ratio equal to 14.7). Two parameters with dominant impact on exhaust gas temperature are engine speed and engine load. Some typical delays occur in engine operations as well due to fuel atomization, air and fuel mixing, vaporization, heat transfer, and so on. It is essential to operate at the optimal exhaust temperature to maximize the performance to cost ratio and to avoid severe damage. Ambiguity and uncertainty are inevitable, which gives rise to high complexity in modeling and prediction of the exhaust gas temperature. The goal of this research instead is to design a feasible and applicable simple exhaust gas temperature model for potential optimal engine design. The intelligent hybrid fuzzy neural network learning is proposed to model the exhaust gas temperature in the powertrain system with high nonlinearity, high complexity and high uncertainty. The fuzzy system is introduced to deal with the uncertainty and ambiguity through fuzzy sets, covering fuzzification, inference engine and defuzzification subsystems. Hybridization is made when artificial neural networks involve in together with the fuzzy system. In this case, training, learning, predication and validation of the hybrid fuzzy neural network powertrain exhaust gas temperature model can be implemented. This simple model can be accomplished with ease, which can also be extended to the exhaust gas temperature model prediction across arbitrary types of automotive engines.

Key-Words: Fuzzy System, Artificial Neural Networks, Machine Learning, Automotive Powertrain, Exhaust Temperature, Engine Load, Engine Speed

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1 Introduction

The exhaust gas temperature takes on a crucial role in engine overall performance optimization, such as the automotive engine combustion efficiency, heat energy converting efficiency, exhaust emission reduction, catalytic device converting efficiency, engine overheating prevention, safety operation of sensors and actuators, as well as the stability issue of powertrain control systems. It acts as one of the key parameters of engine performance management. For instance, its impact on the exhaust gas after-treatment system has been well documented decades ago, in which the optimal exhaust gas temperature range has been indicated [1].

There are numerous factors which will affect the exhaust gas temperature, such as engine speed, engine load, combustion efficiency, air/fuel ratio, operating modes (idling, light load, heavy load), intake air temperature, coolant temperature, valve timing, heat transfer (in-cylinder, exhaust manifold, and tailpipe), and so on. On the other hand, it is impractical to construct an accurate and precise mathematical model of the exhaust gas temperature, which could potentially take all these factors into account. Usually exhaust gas temperature modeling focuses on certain aspects of physical phenomena, such as the combustion mechanisms, heat transfer principles or exhaust gas flow dynamics. It gives rise to various mathematical models, ranging from simple zero-dimensional models, one-dimensional models based on computational fluid dynamics, up to the complex multi-dimensional models with the presence of high computational complexity [2-3]. Instead of conventional exhaust gas temperature modeling, various artificial intelligence approaches have been successfully applied to some other topics of automotive engine modeling, control and optimization issues (e.g. nonlinear idle speed control systems) as well as many diversified engineering practices (e.g. biomedical sample characterization). By virtual of artificial intelligence, it is potentially feasible to build some accurate prediction models for the exhaust gas temperature with the least effort.

From a comprehensive overview on automotive ISC (Idle Speed Control) systems with high nonlinearity and complexity, it is concluded that nearly all engineering practices of classical control, modern control and intelligent control theories can be successfully implemented on ISC modeling and control, even against severe vehicle NVH (Noise, Vibration, and Harshness) conditions and with diverse types of delays. Meanwhile these techniques can be easily extended to other complex electrical, mechanical, aeronautical, automotive, robotic and biomedical systems. For example, artificial neural networks are proposed to train the engine idle speed fuzzy controller. As a result, a hybrid fuzzy-neural control system has been set up. Under various types of torque disturbances, excellent performance on controller actions and system responses has been observed. The fuzzy logic and neural networks model has been implemented on other automotive control systems recently. To decrease levels of vehicle exhaust emissions and fuel consumptions, optimal gear shifting control schemes are proposed and comparisons are made. It is shown that both types of intelligent control approaches can work properly. It is noticed that the artificial neural network model works best on the cases of single objective optimization, while the fuzzy logic control provides the best overall performance of multi-objective optimization, by trading off between the engine fuel consumption and exhaust gas emission reduction [4-6].

The research work on modeling and prediction of the exhaust gas temperature is relatively limited. Temperature modeling based on the Wiebe equation has been developed to identify key parameters of the zero-dimensional combustion model. It is however not suitable for the real time applications. Thus the control-oriented temperature model is proposed which can still exploit its temperature analytical solution. Integration of the control-oriented model and dynamic model has been made whose testing results are validated under diverse transient state conditions. Machine learning has been introduced as well to predict the exhaust gas temperature in some preliminary studies. The simple linear model of the exhaust gas temperature in terms of dominant engine speed and engine load with delays has been established. Markov Chain Monte Carlo is applied for optimal parameter identification. The posterior density of Monte Carlo integration is substituted by the stationary probability instead for numerical integration on a basis of the discrete-time Markov chain. The model prediction outcomes and testing data have shown close matches [7-8].

In fact the feasibility of artificial intelligence based modeling, optimization and control practices has been well documented and validated across numerous disciplines of science and engineering already. It is the common knowledge that fuzzy models can well describe imprecise data and vague information with uncertainty via mathematical fuzzy sets. The linguistic fuzzy modeling focuses more on interpretability (e.g. Mamdani model). The precise fuzzy modeling focuses more on accuracy (e.g. Takagi-Sugeno model). Neural networks instead help for engineering problem solving and pattern recognition by mimicking the work of biological neurons for machine learning and deep learning. The fuzzy neural networks incorporate the human reasoning interpretation of fuzzy systems via fuzzy sets and some specified If-Then fuzzy rules for learning and prediction. It is also feasible for fuzzy logic to be applied on the intricate stochastic optimal control system design [9-11].

In some early studies of other engineering topics, the fuzzy system has been applied to noise filtering for Raman spectrum for the potential to enhance remote robotic surgery in real time. As a result, fuzzy logic filter is adopted to eliminate the rapidly varying unpredictable noises. Both the singleton fuzzifiers and Gaussian fuzzifiers are testified to enhance the quality of biomedical sample spectrum identification. More recently a similar fuzzy neural network model has also been applied to differentiate Raman spectra of human blood samples between healthy people and patients, where the principal component analysis is used for dimensionality reduction so as to reduce the number of neurons in the input layer. The hidden layer serves as the fuzzy inference engine by generating fuzzy rules. Then the output layer is applied for defuzzification. The model prediction results outperform those through backpropagation neural networks. It indicates the feasibility to apply fuzzy neural network learning on spectroscopic diagnosis techniques. Essentially the diverse approaches of artificial intelligence can be comprehensively implemented together for problem solving on biomedical sample characterization via Raman spectroscopy, including fuzzy logic, genetic algorithms, artificial neural networks and principal component analysis. The systematic approach can be easily expanded to other challenging engineering areas [12-13]. In this research, without loss of generality, the hybrid fuzzy neural network model is presented for accurate prediction of the exhaust gas temperature of the lean burn spark ignition engine under frequent operating mode switching and time varying conditions under different scales of air/fuel ratios. The convincing temperature model prediction outcomes have been reached on a basis of the hybrid Fuzzy Neural Network model prediction.

2 Exhaust Gas Temperature Model

Theoretically the conservation law of energy should be typically applied to compute the exhaust gas temperature of automotive powertrain systems. A set of differential equations is needed to describe the physical principles of the in-cylinder combustion process as well as the heat and mass transfer processes. In fact, engine exhaust gas temperature depends on numerous parameters such as engine speed, engine load, ambient temperature, coolant temperature, and air/fuel ratio. Engine speed is measured as the revolution per minute (RPM) of the crankshaft while engine load is measured as the manifold absolute pressure (MAP). In fact virtually it is impossible to build an accurate analytical exhaust temperature model applicable to all types of automotive engines. Numerical solutions are more feasible than the “universal” model instead to determine the exhaust temperature profile across diverse operating conditions with uncertainty and nonlinearity. At the same time, any simple exhaust temperature model must be represented by a causal system, which only depends on present and past engine speed and engine load inputs. When engine speed increases, the intake air flow rate increases. Extra fuel is injected to combustion chamber, which elevates the combustion temperature, so does the exhaust gas temperature. Similarly when the intake manifold absolute pressure (MAP) increases, the intake air to the cylinder becomes dense. Complete combustion induces extra heat generation, which also increases the exhaust gas temperature. Due to numerous latent types of physical delays and chemical delays in engine combustion systems and heat and mass transfer propagation processes, the normalized engine exhaust gas absolute temperature (T_{Exh}) can be simply modelled as the nonlinear function of the normalized engine speed (n) and normalized engine load (p) with delays, as shown in (1), where T refers to the sampling time of the discrete time system and k refers to the index of the discrete time. The first order, second order, and higher order backward difference terms (∇, ∇^2, ...) should be taken into account for the causal engine temperature control systems.

$$\begin{aligned} T_{Exh}[k] &= f(n[k], n[k-1], n[k-2] \\ &,\cdots, p[k], p[k-1], p[k-2], \cdots) \\ &= g(n[k], \nabla n[k]/T, \nabla^2 n[k]/T^2, \\ &,\cdots, p[k], \nabla p[k]/T, \nabla^2 p[k]/T^2, \cdots) \end{aligned} \tag{1}$$

3 Fuzzy Takagi-Sugeno (T-S) Model

To model a powertrain sub-system with uncertainty and ambiguity, a Takagi-Sugeno (T-S) fuzzy model can be selected to depict complex highly nonlinear powertrain systems via a set of linear sub-models. T-S fuzzy models can further simplify complex systems with fewer rules and higher accuracy than other fuzzy models. The time-varying fuzzy membership functions are parts of the T-S fuzzy model in order to describe both the input data and output data qualitatively. In this case, the T-S fuzzy model is suitable for characterization of the exhaust gas temperature that lacks of the certainty, as shown in (2). For matter of simplicity, it can be rewritten as (3), which acts as a linear combination of the engine parameter set $\{x_1, x_2, \ldots, x_6\}$ and the corresponding fuzzy membership functions $\{\mu_1, \mu_2, \ldots, \mu_6\}$.

$$\begin{aligned} T_{Exh}[k] &\approx \mu_1 n[k] + \mu_2 \nabla n[k] + \mu_3 \nabla^2 n[k] \\ &+ \mu_4 p[k] + \mu_5 \nabla p[k] + \mu_6 \nabla^2 p[k] \end{aligned} \tag{2}$$

$$\begin{aligned} T_{Exh}[k] &\approx \mu_1 x_1[k] + \mu_2 x_2[k] + \mu_3 x_3[k] \\ &+ \mu_4 x_4[k] + \mu_5 x_5[k] + \mu_6 x_6[k] \end{aligned} \tag{3}$$

The fuzz membership function defines a degree of membership of an input variable to a fuzzy set between 0 and 1, where “0” refers to non-membership and “1” refers to full-membership. Partially true or false is represented by certain degree within 0 and 1. It provides the flexibility to manifest the arbitrary condition of vagueness and uncertainties, so as to deal with the inaccuracy and imprecision. The fuzzy model is accompanied by the fuzzy rules expressed as the if-then statements showing fuzzy relationship between inputs and outputs. The output fuzzy set is a set of membership degrees for each output value. The T-S fuzzy model actually has the advantage of a small number of fuzzy rules. Each fuzzy rule R^i is straightforwardly formulated as (4):

If x_1 is S_1^i, x_2 is S_2^i, …, x_m is S_m^i;
Then $y_i = c_0^i + c_1^i x_1 + \ldots + c_m^i x_m$. (4)

where S_j^i is the fuzzy set, c_j^i [j=1, 2, …, m] is the parameter set, y_i [i=1, 2, …, n] acts as the crisp output. 3 steps of fuzzification, inference engine and defuzzification are implemented to convert crisp inputs to fuzzy sets, to formulate control actions, and to convert fuzzy sets obtained by the inference engine back to the crisp value.

The Gaussian fuzzifier has been proposed to define the fuzzy membership μ_j^i,

$$\mu_j^i = e^{\frac{-(x_j - z_j^i)^2}{w_j^i}} \quad i=1,2,\ldots,n;\ j=1,2,\ldots,m \tag{5}$$

where z_j^i and w_j^i are the center and width of the Gaussian fuzzifier; n is the number of fuzzy subsets; m is the number of input parameters. Parameter initializations of $[z_j^i, w_j^i]$ are randomly generated and then Gaussian fuzzifier is constructed.

For each subset, the fuzzy multiplicative operator is applied to compute the fuzzy membership μ^i, where

$$\mu^i = \mu_j^1(x_1) * \mu_j^2(x_2) * \ldots * \mu_j^m(x_m),\ i=1,2,\ldots,n \tag{6}$$

The fuzzy output can be calculated via (7), where (3) turns out to be its special case on applications of exhaust gas temperature prediction. Initialization of the parameter set c_j^i [j=1, 2, …, m] is also randomly generated with constraints.

$$y_i = \frac{\Sigma_{i=1}^n \mu^i [c_0^{\ i} + c_1^{\ i} x_1 + \ldots + c_m^{\ i} x_m]}{\Sigma_{i=1}^n \mu^i} \tag{7}$$

3 T-S Fuzzy Neural Network Training and Learning

The fuzzy neural network system is the hybrid machine learning model based on combination of artificial neural networks and fuzzy logic. In terms of the underlying T-S fuzzy model, the fuzzy neural networks employ the adaptive data-driven learning scheme to train the fuzzy neural network system. It is necessary to retain the semantics of the T-S fuzzy system via constraints across the entire learning procedures. The fuzzy neural networks could be formulated as three-layer neural networks. The first layer is the input layer covering all input variables. The second layer is the hidden layer encompassing the fuzzy rules. The third layer is the output layer producing the output variables. The adaptive self-learning algorithm is applied in the fuzzy neural networks to update the parameters and to make adjustment on synaptic weights with respect to the gradient vector. It consists of error computation, weighting vector correction and parameter update. The squared error loss function to be minimized is computed as (8).

$$e = (y_d - y_o)^2 / 2 \tag{8}$$

where e is the loss function, y_o is the actual output from the measurement, y_d is the desired output from the hybrid fuzzy neural network model. The parameters are subject to modification following a set of learning rules in (9-10). The back propagation scheme has been applied using the typical gradient descent method.

$$c_j^{\ i}(K) = c_j^{\ i}(K-1) - \rho \frac{\partial e}{\partial c_j^{\ i}} \tag{9}$$

$$\frac{\partial e}{\partial c_j^{\ i}} = \frac{(y_d - y_o)\mu^i}{\sum_{i=1}^{n} \mu^i x_j} \tag{10}$$

where c_j^i is the parameter set of the linear fuzzy model to be updated, μ^i is the multiplicative fuzzy membership, x_j is the input fuzzy set, ρ is the learning rate of the parameter set c_j^i. The parameters in fuzzy membership functions are subject to update as well, as shown in (11) and (12), where θ is the learning rate of $[z_j^i, w_j^i]$ in the Gaussian fuzzifier.

$$z_j^{\ i}(K) = z_j^{\ i}(K-1) - \theta \frac{\partial e}{\partial z_j^{\ i}} \tag{11}$$

$$w_j^{\ i}(K) = w_j^{\ i}(K-1) - \theta \frac{\partial e}{\partial w_j^{\ i}} \tag{12}$$

The higher the learning rate, the faster the learning process. The lower the learning rate, the smoother and more stable the learning process. A tradeoff is potentially needed in general. The total number of iterations must also be defined beforehand. Via fuzzy neural network training, the network keeps adjusting its fuzzy membership functions iteratively using a backpropagation learning algorithm, in order to reduce the squared error loss function and enhance the network accuracy. Via fuzzy neural network learning, the goal is to reach the best parameter set so as to minimize the loss function and optimize the system performance. Eventually the resulting best set of parameters for fuzzy neural networks will be chosen for exhaust gas temperature model testing, predication and validation.

4 Numerical Simulations and Testing

Based on the simplified exhaust gas temperature model via fuzzy neural network training, numerical simulations will be conducted in this session. The number of neurons (N_I) in the input layer is set to 6 as being discussed in context and the number of neurons (N_O) in the output layer is equal to 1 corresponding to single output of the exhaust gas temperature. The number of neurons (N_H) in the hidden layer must be determined ahead to avoid over-fitting. An empirical formula should be used to determine the range of N_H instead. The objective is to restrict the number of nonzero free parameters within a limited degree of freedom with respect to the data set. The degree of freedom of the data is the product between the number of samples (N_S) and the dimension of each sample as shown in (13), where λ is the scaling factor between 2 and 10.

$$N_S = \lambda * (N_I + N_O) * N_H \tag{13}$$

Now for instance, when the scaling factor λ is 3 and the number of samples is 300, then the number of neurons in the hidden layer is about 15. Thus the hidden layer with 15 neurons will be applied in the numerical simulations.

The normalized engine speed (n), its first order backward difference term and its second order backward difference term (∇n, $\nabla^2 n$), as well as the normalized engine load (p), its first order backward difference term and its second order backward difference terms (∇p, $\nabla^2 p$) are used as the input variables to the Gaussian fuzzifier. T-S fuzzy neural network model is applied for training and learning. The output variable will be the normalized exhaust gas temperature (T_{Exh}). 300 existing data samples will be collected for fuzzy neural network training with the parameter sets. Another 300 data samples will be applied for fuzzy neural network learning for the updated parameter sets to substitute the existing parameter sets. The simulation results after the fuzzy neural network training are shown in Fig. 1 and Fig. 2.

In Fig.1, the desired and actual normalized exhaust gas temperature (T_{Exh}) as well as the estimation error are shown. In Fig.2, the corresponding input sample data of engine speed and engine load are shown. The fuzzy neural network training results at this stage are reasonable but not optimal indeed.

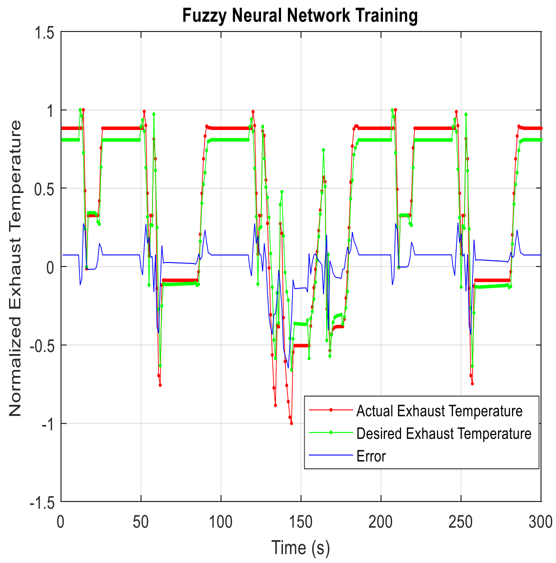

Fig. 1 Fuzzy Neural Network Training
(Output: Normalized Exhaust Temperature)

In Fig. 3, the desired and actual exhaust gas absolute temperature (K) as well as the estimation error are shown, together with the corresponding engine speed and engine load. Via intelligent learning, the fuzzy neural network training provides better match between desired and actual results of exhaust gas absolute temperature. Then the updated parameter set will be used as the reference for fuzzy neural network based exhaust temperature prediction. After minimizing the loss function, it provides the optimal solution based on the defined loss function.

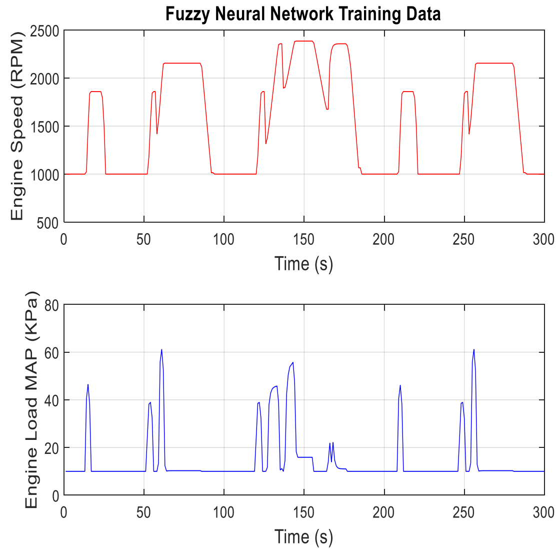

Fig. 2 Fuzzy Neural Network Training (Inputs)
(Top: Engine Speed; Bottom: Engine Load)

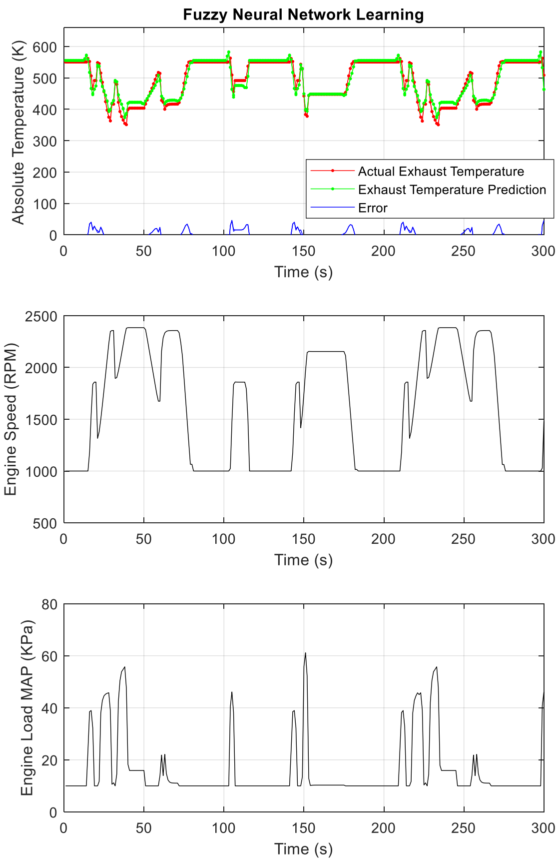

Fig. 3 Fuzzy Neural Network Learning
(Top: Engine Speed; Bottom: Engine Load)

Exhaust gas absolute temperature model predition is made next using hybrid T-S fuzzy neural network models. Additional 400 data sample points of engine speed and engine load data sets will be the testing inputs to the fuzzy neural networks after training and learning with optimal parameter sets obtained from fuzzy neural network learning. The prediction outcomes of the exhaust gas absolute temperature profile are directly compared with the experimental results. Best matches have been observed in Fig. 4, whose result is superior to both cases in Fig. 1 and Fig. 3. It shows the feasibility of the proposed and validated exhaust temperature fuzzy neural network modelling, optimization and control approach.

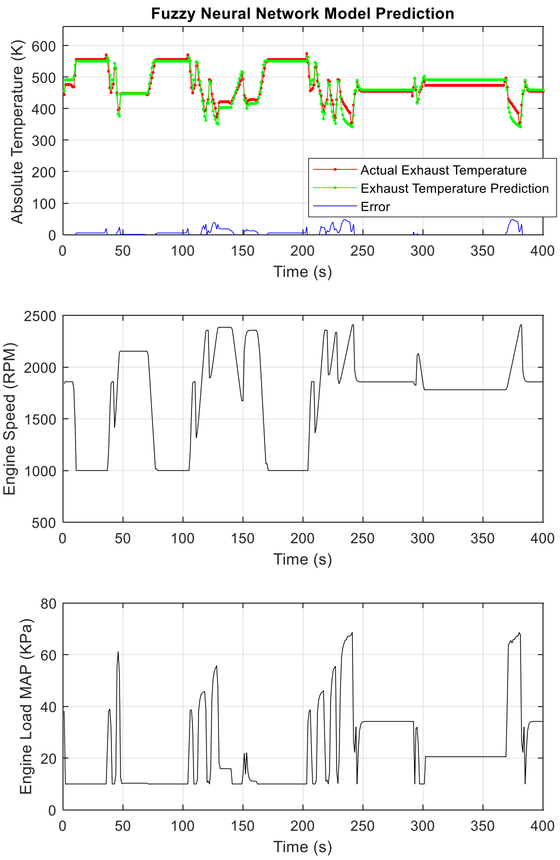

Fig. 4 Fuzzy Neural Network Testing and Prediction (Top: Engine Speed; Bottom: Engine Load)

5 Conclusion

The hybrid fuzzy neural network model has been well designed for complex exhaust gas temperature model prediction problems. The engine speed and engine load are two major parameters in nonlinear modeling, while exhaust gas temperature is directly dependent on engine speed and manifold absolute pressure. Both physical delays and chemical delays have been taken into account in the modeling process based on combustion systems as well as heat and mass transfer systems. Fuzzy logic has been applied for modeling the powertrain system uncertainty properly. The artificial neural networks are then implemented for training, learning and optimization. The nonlinear relationship between the exhaust gas temperature output and two inputs of engine speed and engine load has been well established using this approach. Based on numerical simulations, the hybrid machine learning model can be employed to emulate diverse complex nonlinear characteristics of the powertrain system and predict the exhaust gas temperature perfectly.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

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Conflict of Interest

The author has no conflict of interest to declare that is relevant to the content of this article.