Fuel Consumption Modeling of a Turbocharged Gasoline Engine Based on a Partially Shared Neural Network

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1. INTRODUCTION

As the main source of power for passenger vehicles, gasoline engines have played a pivotal role worldwide for a long time. With the increasingly stringent fuel consumption regulations, more and more technologies of the gasoline engine are being studied to improve the fuel economy performance, such as high-compression-ratio technology, fuel injection technology, EGR technology, variable valve technology (VVT), supercharging technology, etc. Among them, the combination of DVVT and high-compression-ratio technology enables the engine to work in the Miller cycle or Atkinson cycle, greatly improving the fuel economy of the gasoline engine, which has become one of the current mainstream technical solutions and realized mature industrial application. At the same time, many scholars have conducted research on this technical solution, and analyzed the effect of Miller cycle combined with high compression ratio on gasoline engine combustion and thermal efficiency improvement. Compared to the original production engine with CR 9.3, the fuel economy is improved at low load by 7.4% after the application of CR12.0 and EIVC. The authors have studied the Miller cycle of turbocharged gasoline engines before. A bench test and simulation studies have been conducted, and the results show that after the Miller cycle application, the fuel economy of the engine at different loads has been significantly improved (the thermal efficiency is increased by 2.8, 2.5, and 2.6% at low, medium, and high loads, respectively), and the effects of DVVT technology before and after the intervention of exhaust gas turbocharging are quite different.

With the continuous application of new gasoline engine technologies, the scope of engine control is also increased. To enable the engine to exert its optimal fuel economy and emission characteristics, calibration of the variable parameters of the engine management system (EMS) at the universal working conditions is key to the design and optimization of the engines. As the traditional engine has few control parameters, after the design parameters of the engine are determined and the prototype is manufactured, the calibration engineer performs a full factor sweep of the control parameters for each engine speed and load to be calibrated through a bench test. After storing the best control parameter sets in the EMS, which minimizes the fuel consumption with qualified emission performance, the calibration is completed. This calibration method is easy to implement, but has many shortcomings: Firstly, it is obvious that the calibration time (reflected in the sweep interval of each control parameter) is negatively related to the accuracy of the
result, and as the engine control freedom increases, the calibration time grows exponentially, which greatly consumes manpower and material resources; in addition, the geometric parameters of the engine are often unable to be optimized through experimental calibration. Instead, it relies more on the prior experience design of the engine design engineer, which greatly limits the potential of the engine calibration and optimization procedure.

In recent years, due to the rapid development of artificial intelligence, intelligent algorithms represented by machine learning have been widely used in the field of engine modeling and calibration. The engine response for various parameters is acquired through bench tests. With the help of the artificial neural network (ANN), support vector machine (SVM), etc., a multi-input model of the engine performance is established to realize further calibration and optimization, which has been more and more successfully applied. This method directly establishes the engine performance model through a limited test sample, which greatly reduces the time and money cost for the calibration test compared with the traditional method. However, the sample size obtained by only relying on the bench test is often not particularly large. Among the studies, no more than 130 sample data sets with 4 or more parameters is acquired by experiment, which causes instability from the $R^2$ value of 0.75 to 0.97 during the prediction on performance. Therefore, when there is a considerable number of control parameters, the sampling of each parameter will be sparse and discrete, which deteriorates the prediction accuracy and generalization of the engine performance model to a certain extent.

With the development of CFD simulation of the engines, one-dimensional and three-dimensional simulation models are being increasingly used in the research of fuel economy and emission analysis. Among them, the one-dimensional engine gray box model established by GT-Power as a representative shows excellent simulation accuracy under a fixed working condition and provides convenience for engine performance research and prediction. In terms of engine modeling and calibration, there has been some frontier progress in that the experimental result of the bench test is used to establish one-dimensional models of engines under multiple fixed working conditions. Subsequently, a multiparameter data set under fixed working conditions of the engine is sampled through the design of experiment (DOE) method. Combined with basic machine learning algorithms or improved algorithms, a performance prediction ensuring full coverage over the whole working condition region of the engine over multiple parameters is achieved. This modeling method contains a large size of samples. In the literature, the size of the sample data set with 6 parameters reaches 2500 to train the model, contributing to an accurate and steady prediction on engine performance. Moreover, except for the engine working conditions, the input parameters that need to be considered in the model can be continuously and completely sampled through the DOE method in the one-dimensional simulation model. Therefore, the established model is of good robustness, high accuracy, and excellent generalization. In addition, the one-dimensional simulation model integrates a variety of physical models in the calculation, so it can predict the impact of the design parameters of an engine, such as the geometric compression ratio, on engine performance, which greatly reduces the difficulty of engine calibration and optimization.

Up to now, most of the engine performance models have been trained indiscriminately using working condition parameters, design parameters, and control parameters as model inputs during the establishment process to directly obtain the training results. However, compared with using continuous samples of various design parameters and control parameters output by the one-dimensional simulation model through the DOE method, the working condition parameters are often relatively sparse and discrete. Therefore, during the model establishment process, the performance prediction over working condition parameters may appear overfitting. In addition, most studies only use the verification data set or test data set extracted from the original sample data set as the basis for model accuracy judgment after the engine performance model is established, and the working condition input range of these test samples is exactly a proper subset of that in the training set. As a result, it is difficult to prove the predictive accuracy of the model outside the original data set of working conditions. Taking the research results from the literature as an example, this research established a one-dimensional engine model with external characteristics from 1000 to 4500 r/min with an interval of 500 r/min, which is quite discrete in terms of the working condition parameter. Based on the DOE method and the neural network, an engine performance prediction model that includes multiple inputs over design and control parameters has been established, showing extremely high prediction accuracy. It can be found that the working condition input in the whole test data set only contains the data from 1000 to 4500 r/min with an interval of 500 r/min. Therefore, the prediction accuracy of the model outside these discrete working conditions is still worthy of scrutiny and difficult to verify (1750, 2700, or 3300 r/min for instance). Therefore, after the engine performance model is established, it is necessary to carry out the bench test again and use a sufficiently convincing test data set (experimental values) to verify the performance of the model.

This paper innovatively proposes a partially shared neural network to improve the engine fuel consumption model based on discrete load samples. The whole data set is obtained by the combination of an engine bench test, numerical simulation, and DOE. A skeleton layer is shared in the model with a nonshared layer for each working condition according to the characteristics of the DOE sample. Meanwhile, a targeted secondary training method of the nonshared layer is put forward. This novel structure with its training method has not been explored in this field yet. Moreover, considerable samples with different compression ratios, loads, and other control parameters at 3000 r/min are acquired through the bench test as the test data set to judge the performance of the model, which is very rare in the existing similar literature. In the fine-tune stage of the model, different training conditions of the shared layer and different sampling methods for the load parameters are compared to explore the optimal structure of the partially shared neural network; a test data set with full load coverage of the engine at compression ratios of 11.5, 12.5, and 15 is obtained through the engine bench test. The test results of this model are compared with those of the traditional neural network model, showing the improvement over fuel consumption prediction through the novel model under the continuous load test samples. The second section introduces in detail the engine calibration test equipment and methods, the establishment and calibration of the GT-Power one-dimensional simulation model, and the design process of the data set based on the DOE method. The third section introduces the basic concept of a neural network and describes the problem of the discreteness of the samples on...
the parameters of the working condition in the process of establishing the engine fuel consumption model; the partially shared neural network is proposed as a solution, including model optimization based on a different sampling and shared layer training conditions method. The fourth section analyzes the partially shared neural network structure and the training process; the performance of the optimal model is compared with the traditional neural network. Finally, the fifth section presents the conclusions.

2. MODELS AND METHODS

In this section, the test of the turbocharged gasoline engine, the establishment and calibration of the one-dimensional engine simulation model, and the establishment of the DOE-based data set are completed. Firstly, the engine test equipment and procedure are introduced. Subsequently, a one-dimensional simulation model of the engine is established by GT-Power software and calibrated based on the experimental data. Finally, the establishment of the DOE-based data set is introduced to prepare for the follow-up neural network fuel consumption model.

2.1. Experimental Methodology. 2.1.1. Equipment. The target engine is a gasoline engine equipped with a 350-bar high-pressure fuel injection system, a double VVT system, and a turbocharger (Figure 1). The specifications are shown in Table 1.

![Figure 1. Layout of the engine bench test.](image)

Table 1. Specifications of the Research Engine

| Parameter                          | Value                  |
|------------------------------------|------------------------|
| Displacement                       | 1.5 L                  |
| Stroke                             | 86.6 mm                |
| Bore                               | 74 mm                  |
| Number of cylinders                | 4                      |
| Rated power                        | 124 kW                 |
| Rated speed                        | 6000 rpm               |
| Maximum torque                     | 250 N·m                |
| Speed at maximum torque            | 1700−4300 rpm          |
| Brake specific fuel consumption    | 240 g/kWh              |
| Compression ratio                  | 11.5:1                 |

During the data collection, data such as power, torque, and brake specific fuel consumption (BSFC) during the test are collected by the dynamometer and engine test bench; the control parameters such as VVT and ignition timing during the engine operation are communicated and adjusted by ETAS-INCA (v7.2, ETAS GmbH, Stuttgart, Germany); the Kistler combustion analyzer (Kistler Group, Winterthur, Switzerland) analyzes the data collected from the cylinder pressure sensor, and then calculates the combustion performance parameters such as CA10, CA50, and CA90 during the engine operation. To purify possible gaseous and particulate emissions, a three-way catalyst converter (TWC) and gasoline particulate filter (GPF) are equipped. The main equipment of the test bench and measurement errors are shown in Table 2.

2.1.2. Procedure. The baseline engine is a turbocharged gasoline engine with DVVT. The maximum lift of the intake valve is 7 mm and the maximum lift of the exhaust valve is 7.5 mm. The duration of the intake valve is 130°CA, and the duration of the exhaust valve is 150°CA. Taking TDC at the end of the compression stroke as the reference point, the variable

![Table 2. Equipment of the Test Bench](image)
range of the engine’s intake valve opening (IVO) is 326.5–371.5 °CA, and the variable range of the exhaust valve closing (EVC) is 319–384 °CA.

There are two main purposes of this test: (1) providing test data for the subsequent calibration procedure of the one-dimensional engine model; (2) providing test data for model accuracy verification for the final fuel consumption model. Therefore, for the first purpose, different loads at 3000 r/min of the baseline engine as the test conditions are chosen. The baseline engine is operated under the test conditions. After keeping the combustion stable for 2 min, the data is recorded.

For the second purpose, the test still chooses different loads at 3000 r/min of the engine as the test conditions. However, as the geometric compression ratio, intake and exhaust VVT, and ignition timing have a great influence on the fuel economy of the engine.
engine, the geometrical parameters and operating variables change in a wide range. Specifically, in addition to the baseline engine compression ratio (11.5), the compression ratios of 12.5 and 15 are replaced on the engine for testing; at each geometric compression ratio, the IVO, EVC, and ignition timing were subjected to a wide range of changes randomly as control parameter sets without knocking. After each control parameter set is adjusted, the data will be recorded after the engine is stable for 2 min.

2.2. Simulation Methodology. 2.2.1. 1D CFD Models. The one-dimensional simulation model is established in GT-Power software. The model includes the combustion chamber, intake and exhaust ducts, and exhaust turbocharger modules. The simulation is based on the calibration data of the baseline engine in the bench test, and the models of different loads at 3000 r/min are established. Among them, the models for low loads use PID control to automatically adjust the throttle opening angle to the required load, while the models at medium and high loads use PID control to automatically adjust the electric waste gate (EWG) opening angle to the required load with the throttle kept in the full open state, which can well reproduce the load control strategy of the baseline engine in the bench test. The heat transfer model uses the Woschni model. The completed one-dimensional simulation model is shown in Figure 2.

2.2.2. Calibration. Due to the requirement of multiple adjustment on the geometric parameters and control parameters in the process of analysis and optimization, a predictive demand of the model is considered in this paper. Instead of the SIWiebe model commonly used to analyze the fuel economy performance of the engine, the SITurb model, which is a more accurate quasi-three-dimensional model, is adopted to conduct the research on the performance of the engine. The model can consider factors such as the geometry of the cylinder, ignition timing, air

Figure 3. Comparison of the cylinder pressure between simulation and experiment under different loads at 3000 r/min. (a) 2 bar, (b) 6 bar, (c) 10 bar, and (d) 14 bar.
movement, and fuel properties. Compared with the commonly used SI Wiebe combustion model, it can more accurately predict the geometric compression ratio, VVT operation, air–fuel ratio, and ignition timing versus the influence of the combustion heat release rate in the cylinder. As a result, the trend of fuel consumption at the target working condition of the engine can be well obtained after the geometric parameters and control parameters change.39

By adjusting the parameters of the combustion model, the simulation results of the one-dimensional engine model obtained are consistent with the calibration data from the bench test. Figure 3 shows a part of the comparison between the cylinder pressure output by the simulation model and the tested cylinder pressure under different loads at 3000 r/min. Figure 4 shows the maximum relative error over the in-cylinder pressure between test and simulation, and the comparison between the BSFC output by the simulation model and the tested BSFC under different loads at 3000 r/min.

As shown in Figures 3 and 4, it can be found that the error between the simulated BSFC and the test value under different loads at 3000 r/min is within 1%, representing the accuracy of the steady-state output parameter of the model. The maximum relative error over the in-cylinder pressure between test and simulation under different loads shows a trend of valley. The maximum values appear at the peak of the in-cylinder pressure. The small absolute value at low load and the unpredictable intense combustion at high load cause a relatively large error. All in all, the maximum errors at all loads are below 14%, which is acceptable in transient-state output requirements.

Besides, the total trend of the simulated in-cylinder pressure in Figure 3 is close to the test value, indicating that the simulation of combustion phases such as CA10, CA50, and CA90 is satisfactory. Therefore, the output results of the simulation model are in good agreement with the calibration test results. The model can be used as an analysis basis to predict the fuel economy of the baseline engine at the above-mentioned working conditions after changing the geometric parameters and control parameters.

2.2.3. DOE Setup. To ensure the accuracy of the fuel consumption model based on the neural network, enough data is required to train the network. Based on the simulation model established above, the simulation conditions are designed through the DOE method. This paper intends to explore the influence of load, intake and exhaust VVT, ignition timing, and geometric compression ratio on the fuel economy performance. The characteristics at different loads have been achieved by setting different combustion model parameters in each simulation model (currently still discretized). Since the intake and exhaust VVT, ignition timing, and geometric compression ratio contain a large range of changes, in order to take the full coverage of the variable range of each parameter into account in

![Figure 4. Comparison between simulation and experiment under different loads at 3000 r/min.](image1)

(a) The result of Latin hypercube sampling at 3000 r/min and 2 bar (The ignition timing is not displayed)  
(b) The result of Latin hypercube sampling at 3000 r/min and 2 bar (The geometric compression ratio is not displayed)

![Figure 5. A schematic diagram of the results by Latin hypercube sampling. (a) Result of Latin hypercube sampling at 3000 r/min and 2 bar. (The ignition timing is not displayed.) (b) Result of Latin hypercube sampling at 3000 r/min and 2 bar. (The geometric compression ratio is not displayed).](image2)
the sampling process with high efficiency, this paper adopts the Latin hypercube sampling method. The simulation model of each load at 3000 r/min is designed with 400 sampling points. Taking the model at 3000 r/min and 10 bar as an example, Figure 5 is a schematic diagram of the results by Latin hypercube sampling.

3. NEURAL NETWORK MODEL

3.1. Basic Conception. The neural network is a black box model with powerful self-learning, fault-tolerant, adaptive, and nonlinear mapping functions. This section will give a basic introduction to the concept of neural networks and establish a traditional neural network with 2 hidden layers to predict fuel consumption based on the data obtained from the DOE results as a benchmark model for comparison.

A traditional neural network with 2 hidden layers is shown in Figure 6. It includes five input neurons, one output neuron, and two hidden layers with N neurons. In the hidden layer, each neuron contains the corresponding weight (\(w\)) and bias (\(b\)). Except for each neuron in the input layer that receives input directly from the outside, the rest of the neurons receive the input of the previous layer and perform calculations to generate output. Taking the first neuron of hidden layer 1 as an example, the output calculation is shown in formula 1

\[
a_1^1 = f \left( \sum_{i=1}^{s} w_{i1}^1 x_i + b_1^1 \right)
\]

(1)

In formula 1, \(a_1^1\) represents the output value of the first neuron of hidden layer 1, where superscript 1 represents the first hidden layer and subscript 1 represents the first neuron; \(x\) represents the input value, \(w_{i1}^1\) represents the weight of the first neuron connected to the input value of hidden layer 1, \(b_1^1\) represents the bias of the first neuron of hidden layer 1, and \(f\) represents the activation function.

As a multilayer perceptron model, the BP neural network adopts the back propagation (BP) algorithm proposed by Rumelhart, which successfully solved the linear inseparability problem of single-layer perceptron. The BP algorithm has also become one of the most widely used neural network learning algorithms. In this paper, when modeling the fuel consumption model, the BP algorithm is selected to train the neural network.

3.2. A Partially Shared Structure. The previous section showed the establishment of the traditional neural network fuel consumption model with 2 hidden layers. This method uses the engine working condition parameters, geometric parameters, and control parameters as the input of the neural network, and the BSFC is trained as the neural network output based on the experimental data or simulation data, which has been studied in many research works and has yielded good results. However, in terms of all of the inputs, due to the DOE method, the geometric parameters and control parameters of the engine are relatively continuous, but the working conditions parameters are very sparse and discrete. Therefore, if the difference of the characteristics among the input parameters is not well distinguished, a simple training procedure will limit the prediction accuracy of the model.

This section will propose a partially shared neural network structure to distinguish the characteristics of the load and other parameters. The diagram is shown in Figure 7.

The training of the model will be divided into two stages. The first stage is consistent with the traditional neural network training procedure. The difference is that in the first stage of training, instead of directly dividing the data set obtained by the DOE method into the training set and the validation set, the whole data set is considered as the training set. This is because the purpose of training at this stage is to train a shared layer that can extract all of the parameter features except for the load, so a data set with better continuity is required.

After the first stage of training is completed, a traditional neural network with 2 hidden layers is established. The first hidden layer with its corresponding weights is maintained as the shared layer. Then, for the 9 loads corresponding to the simulation model in this paper, 8 nonshared layers are allocated to predict the BSFC within each load interval, whose number of hidden neurons is the same as the shared layer and the initial weights are random. For example, Network 1 including Layer 1 performs fuel consumption prediction in the load range from 2 to 4 bar; Network 2 including Layer 2 performs fuel consumption prediction in the load range from 4 to 6 bar.

In the second stage of training, each of the same shared layers is connected to a specific layer and uses a special training method to accurately predict the fuel consumption in the specific load.
The training method of the second stage is as follows: Taking the prediction of Network 4 in the load range from 8 to 10 bar as an example, first connect Layer 4 to the shared layer to form a new neural network with 2 hidden layers. It should be noted that the weights of the shared layer have been trained in the first stage of training. To ensure the accuracy of the shared layer in fitting other continuous parameters except for the load, the weights of the shared layer will only be subjected to fine-tuning or even frozen operations during the training in the second stage. In terms of Layer 4, the regular learning rate is set for training; while a targeted training to the fuel consumption characteristics within a specific load interval is needed, two types of sampling method will be proposed when setting the data set in the second stage (shown in Figure 8):

1. Randomly select about 250 data sets corresponding to the upper and lower bounds of the load within a specific load interval (Figure 8a).
2. Taking the center of the load interval as the reference and use the Gaussian distribution for random sampling.

The formula for calculating the number of samples extracted from each load is given by:

$$y = \frac{A}{\sqrt{2\pi}\sigma} e^{-\left[\frac{\text{BMEP}_{\text{target}} - (3 + 2n)^2}{2\sigma^2}\right]}$$

In the formula, BMEP_{target} represents the load to be sampled; n represents the currently trained nth subnetwork; and σ represents the variance, which is taken as 3 in this paper; A is the coefficient for adjusting the total number of samples, which is taken as 1000 in this paper.
The complete training flow chart of a partially shared neural network is shown in Figure 9.

4. RESULTS AND DISCUSSION

Firstly, in order to obtain the best network performance, the relationship between the number of neurons, epochs, and the fitting accuracy of the traditional neural network needs to be studied. The learning performance of the traditional neural network is shown in Figures 10 and 11. Among them, the learning rate between the layers is consistent and all of them are 0.015.

Figures 10 and 11, respectively, show the performance of prediction accuracy versus the number of neurons in the hidden layers, and the epochs of the neural network on the training data set and the validation data set. It can be found from Figure 10 that when the number of hidden-layer neurons is less than 20, even if the epochs continue to increase, the performance of the network still cannot be improved. This is because the characteristics of the influence of the geometric and control parameters on fuel consumption cannot be well presented by a simple neural network; when the number of hidden-layer neurons is increased to about 20–30, the network performance is improved, but it still shows instability; as the number of hidden-layer neurons continues to increase, as the network keeps iterating, the $R^2$ is maintained above 0.95, which means that the network performance becomes excellent and stable.

It can be seen from Figure 11 that the trends of the traditional neural network performance on the validation set and the training set are very similar, and the prediction accuracy is high enough, which means that when the epoch reaches about 10 000 times, the network shows an excellent prediction performance without overfitting. As the epoch further increases, the
performance of the network on the validation set may decrease; that is, the overfitting occurs.

Through the analysis above, in the follow-up research, this paper determines the traditional neural network structure to be 5-50-50-1 (that is, the number of hidden-layer neurons is set to 50). Moreover, the epoch is set to 10,000 times as the skeleton model of a partially shared neural network. The performance of the traditional neural network is also applied for benchmarking. The results show that the $R^2$ of the traditional neural network on the training set is 0.989, and the $R^2$ on the validation set is 0.982.

The ultimate purpose of the engine fuel consumption model is to predict the fuel economy performance of the actual engine under the change of the input parameters. Therefore, a quantity of 115 data sets as the test data set at 3000 r/min has been designed in this paper through the bench test, which includes 62 measuring points with a compression ratio of 11.5, 24 measuring points with a compression ratio of 12.5, and 29 measuring points with a compression ratio of 15. The load, IVO, EVC, and ignition timing of each measuring point are in random and different from each other. Figure 12 shows the performance of the trained traditional neural network on the test set, and Figure 13 shows the error distribution of the traditional neural network when it makes predictions on the test set.

It can be found from Figure 12 that the $R^2$ of the trained traditional neural network on the test set is 0.918. Combined with Figure 13, it can be found that the fuel economy prediction of the traditional neural network can be achieved overall, but there are two shortcomings: 1. Compared with medium and high loads, the prediction accuracy at low loads is poorer. 2. Since the load in the training set is discrete (taking this paper as an example, the training set selected in this paper is distributed in 2, 4, 6, 8 bar, etc.), when the load in the test set deviates from the training load by a large amount, the prediction error is increased significantly (reflected in the prediction results of 3, 5, and 9 bar in this example).

The reason for the first shortcoming may be that compared with medium and high loads, the fuel consumption at low loads (especially near 5 bar) has a more significant changing rate relative to the load. Moreover, when the turbocharged gasoline engine studied in this paper is running at the working condition from 5 to 6 bar, as the pressurization begins to intervene gradually, the control of the engine becomes more complicated. The reason for the second shortcoming is that in the training process of the traditional neural network, the discrete working condition parameter and the continuous geometric and control parameters are undifferentiated considered as the model input. The problems caused by ignoring the difference between the discrete parameters and the continuous parameters are inevitable.

The following part will focus on the second shortcoming and improve the fuel consumption model through the partially shared neural network. The prediction results are analyzed and compared with the traditional neural network model.

The author will first apply the method (a) in Figure 8 and the method of freezing the shared layer described in Figure 9 to establish an example of a partially shared neural network and compare the prediction results on the test data with the traditional neural network. It should be noted that in the model fine-tune stage of the example model, the learning rate of the nonshared layer is set to 0.001, and the epoch is set to 8000. Figure 14 shows the comparison over error distribution of the...
traditional network and partially shared network for the test
data.

It can be found from Figure 14 that after the application of the
partially shared neural network with the training method of
upper- and lower-bound sampling and frozen, the error
distribution of the BSFC prediction results on the test set is
significantly improved at 3, 5, and 7 bar. Compared with the
prediction results of the traditional neural network, the relative
error of the prediction accuracy from the revised model at the
working condition of 3 bar is less than 2%, and it eliminates
the result of the traditional neural network prediction error greater
than 6% at the working condition of 5 bar. Therefore, it can be
shown that the improved fuel consumption model optimizes the
prediction accuracy of points that deviate from the discrete loads
in the process of training.

To find the optimal partially shared neural network, in the
following we will study the data-set sampling method and weight
update method in the second stage of the network training
process. The data-set sampling method in the second stage of
the network training process includes upper- and lower-bound
sampling and Gaussian distribution sampling. The basic
concepts have been mentioned above, while the weight update
method will adjust the shared layer learning rate (setting the
learning rate of the nonshared layer as 0.01 times that of the
shared layer) and the frozen method. In the training process of
all models, the basic learning rate and the epoch are consistent
with the example. Figure 15 shows the $R^2$ on the training set of
the submodels at each target load after training in different
methods. Figure 16 represents the relative error distribution of
the whole test data set for each model trained in different
methods. Table 3 shows the average relative errors and
variances.

It can be found from Figure 15 that compared to the upper-
and lower-bound sampling method, the Gaussian distribution
sampling takes the sampling continuity of the overall load
interval and the sampling density around the target load of the
model into account, so it shows better stability: the $R^2$ values of
the 8 submodels on the training set are above 0.98 when the
Gaussian distribution sampling is applied. On the other hand,
among the submodels applying upper- and lower-bound
sampling, Network 2, which is used to predict the load interval
from 4 to 6 bar, performs poorly; compared to the frozen
operation, the operation of reducing the learning rate of the
shared layer further improves the prediction accuracy of the
model on the training set.

As shown in Figure 16, when the fuel consumption models
make a prediction on the fuel consumption over test data, the
results are generally in a normal distribution trend. It can be
inferred from Table 3 that although the operation of decreasing
the learning rate of the shared layer further improves the
prediction accuracy of the model on the training set, compared
with the models applying the frozen operation, the variance of
the relative error of these two models on the prediction results
reaches 0.86 and 1.08% on the test data. The reason is probably
that after the first stage of the model training is completed, the

Figure 14. Comparison over error distribution between the traditional network and partially shared network (example) for test data (a) absolute error (b) relative error.

Figure 15. $R^2$ on the training set of the submodels at each target load after training in different methods.
The shared layer has learned the influence characteristics of the geometric and control parameters on the BSFC, and the operation of frozen can make a deeper learning nearby the target load while maintaining the learning results above. On the other hand, the operation of reducing the learning rate of the shared layer makes the model “forget” the learning results of the previous stage after the second stage of training is completed. Therefore, although the models with learning rate decreased perform better on the training set, the prediction performance on the test set is poorer; that is, a serious overfitting occurs. In addition, the average relative error of the prediction results on the test data set applying Gaussian distribution sampling combined with frozen and upper- and lower-bound sampling combined with frozen are both below 1% (0.87 and 0.49% relatively), and the former method has a smaller variance, which indicates a better stability. As a result, the model applying Gaussian distribution sampling combined with frozen is considered as the optimal partially shared neural network.

Figure 16 shows the comparison over the error and relative error distribution between the traditional network and the optimal partially shared network for the test data. Table 4 shows the proportion of the prediction results over the entire test data contained in each error segment.

Table 3. Average Relative Errors and Variances for Each Model Trained in Different Methods on Test Data

| training method                                      | average relative error (%) | variance (%) |
|------------------------------------------------------|-----------------------------|--------------|
| upper- and lower-bound sampling + frozen              | 0.49                        | 0.57         |
| upper- and lower-bound sampling + learning rate decreased | 0.19                        | 0.86         |
| Gauss distribution sampling + frozen                  | 0.87                        | 0.44         |
| Gauss distribution sampling + learning rate decreased | 2.83                        | 1.08         |

Table 4. Proportion of the Prediction Results over the Entire Test Data Contained in Each Error Segment

| error segment (%) | proportion (traditional network) (%) | proportion (PS network) (%) |
|-------------------|--------------------------------------|-----------------------------|
| 0–1               | 33.1                                 | 33.9                        |
| 1–2               | 32.2                                 | 34.8                        |
| 2–3               | 15.7                                 | 18.3                        |
| 3–5               | 9.6                                  | 6.1                         |
| 5–8               | 4.3                                  | 5.2                         |
| 8–10              | 4.3                                  | 1.7                         |
| >10               | 0.9                                  | 0                           |

The points between the two dashed lines in Figure 17a represent the data whose prediction error is less than or equal to 5%. It can be found that the prediction results of the optimal partially shared neural network are more concentrated in the range where the error is less than or equal to 5%. As shown in Table 4, 87% of the fuel consumption results predicted by the traditional network fall within the 0–1% error range, whereas only 33.9% of the results predicted by the partially shared network fall within this range. This indicates a significant improvement in the predictive performance of the partially shared network.
optimal partially shared network on the test data set have an error of less than 3%, which is 6% higher than the result obtained by the traditional network. On the other hand, the partially shared network has also eliminated the data with an error of more than 10% and significantly reduced the proportion with an error of more than 5% by 2.6%. As a result, compared with the traditional network’s poor prediction accuracy on certain loads, the optimal partially shared network shows an excellent prediction robustness in the full load range.

As shown in Figure 17b, it can be found that the relative error distribution roughly conforms to the trend of the normal distribution. The average error of the optimal partially shared neural network prediction result is close to that of the traditional neural network, but the variance is decreased greatly from 0.91 to 0.44%, which achieved an improvement of over 50%. The result shows that the R² of the improved model is increased from 0.918 to 0.954 compared to the traditional model.

5. CONCLUSIONS

In this paper, based on the samples from an engine bench test, a high-precision turbocharged gasoline engine fuel consumption model is established through the partially shared neural network. The main achievements and conclusions are as follows:

1. The GT-Power one-dimensional model of the baseline engine was established and calibrated based on the engine bench test results of different loads at 3000 r/min; by means of Latin hypercube sampling, the targeted BSFC corresponding to different values of IVO, EVC, ignition timing, and geometric compression ratio under each discrete load are obtained and used as a driving data set.

2. The partially shared neural network trained by the method of learning rate decreased performs well on the training set, while it shows an unacceptable variance (0.86 and 1.08‰) on the test data due to the overfitting. The average relative error of the partially shared neural network applying Gaussian distribution sampling combined with the Frozen training method on the test data is below 1% with a variance of 0.44‰. The results show that the partially shared neural network applying Gaussian distribution sampling combined with the Frozen training method can achieve the optimal overall performance in fuel consumption prediction.

3. Compared with the traditional neural network, this model is designed to improve the discreteness of the training input load. The proportion with an error of less than 3% is improved by 6–87% on the fuel consumption results predicted by the optimal partially shared network on the test data set; meanwhile, all of the prediction errors are less than 10%. The R² is improved from 0.918 to 0.954 compared to the traditional model. This method improves the prediction accuracy of gasoline engine fuel consumption in the full load coverage and enhances the generalization performance and robustness of the model.

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Conceptualization, D.L. and Y.Z.; methodology, Y.Z. and L.F.; software, Y.Z.; validation, Y.Z. and L.F.; formal analysis, L.F.; investigation, D.L. and L.F.; resources, D.L.; data curation, Y.Z.; writing—original draft preparation, D.L. and Y.Z.; writing—review and editing, Y.Z. and L.F.; visualization, D.L. and Y.Z.; supervision, D.L.; project administration, D.L.; funding acquisition, L.F.

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NOTES

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