Chapter 21
A Predictive Model of Artificial Neural Network for Fuel Consumption in Engine Control System

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Abstract This paper presents analyses and test results of engine management system's operational architecture with an artificial neural network (ANN). The research involved several steps of investigation: theory, a stand test of the engine, training of ANN with test data, generated from the proposed engine control system to predict the future values of fuel consumption before calculating the engine speed. In our paper, we study a small size 1.5 L gasoline engine without direct fuel injection (injection in intake manifold). The purpose of this study is to simplify engine and vehicle integration processes, decrease exhaust gas volume, decrease fuel consumption by optimizing cam timing and spark timing, and improve engine mechatronic functioning. The method followed in this work is applicable to small/medium size gasoline/diesel engines. The results show that the developed model achieved good accuracy on predicting the future demand of fuel consumption for engine control unit (ECU). It yields with the error rate of 1.12e-6 measured as Mean Square Error (MSE) on unseen samples.

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21.1   Introduction

ANN have received much attention in recent years due to the number of functions which can be applied to engines such as modelling, controller design, on-board testing and diagnostics. ANN is an information processing paradigm that is inspired by biological nervous systems, functions, and mathematical and physical methods of information processing. The latter is composed of many simple processing units working in parallel to each other which are connected insome way and depend on the status of the dynamic response of the external input information computer system. It is a simple simulation of the brain with specific smart features and rapid processing abilities to perform [1].

Neural networks generally contains three layers: input layer, hidden and output layer. Each of them consists of nodes or neurons. Moreover, ANN can solve classification problems and function approximation. Applications of ANN model start operate correctly if the design of data satisfies all the dynamics of the system. Furthermore, structures and combinations of networks considerably affect the performance level of system. This article will describe data acquiring procedures, construction of the experiments and neural network description. Collection of data needs to be done precisely and the size of data is another important factors of ANN. The data needs to be determined if transient behavior or steady-state operations provide sufficient features for training and validation. The more features the training data covers, the better the network is trained for the generalization of engine behavior. Designing of experiments has a significant impact on the model performance and especially for engine systems [2].

21.2   Research Background

Neural networks, and fuzzy systems can be significant in the usage of advanced control strategies. The authors of [3] used IC (Internal combustion) engines with highly nonlinear characteristics containing variable time constant terms and delays.

The capability of smart systems performances, for instance neural networks and fuzzy methods: if we relate these nonlinear properties, ANN becomes excellent tool in the modeling of engines [4]. The authors of [5] discuss a technique where static neural networks (SNN), time delayed neural networks (TDNN) and dynamic neural networks are used for modeling an spark-ignition (SI) engine.

Similarly, in our investigation, computational intelligence is used at 2 stages of our work. At first, the management of ECU is directed by creating an application of fuzzyneural network (FNN). Afterwards, once the developed model of ECU passes the hot test procedure, we created another model of ANN for prediction. The objective for designing this model was, to predict the future demand of fuel consumption in engine by taking previous time interval and speed (rotation per minute) as an input.

21.3   Experimental Setup

The experimental setup of our work consists of three steps. In the first step we develop a model for engine control system of vehicle motor. The controlling and management unit is based on neuro-fuzzy system. Afterwards, the hot test procedure is implemented to test the developed ECU which is the second step in our procedure. The next step is to construct a predictive model, which is capable to estimate the unknown values of fuel consumption for future time intervals. The steps are further discussed in details.

21.3.1   Engine Control System

Neural networks can only come into play if the problem is expressed by a sufficient amount of observed examples. These observations are used to train the black box (as element of ECU). In this case no prior knowledge about the problem needs to be given. In our case to develop engine management (controlling) algorithm, we use the attributes of FNNs. The learning procedure is constrained to ensure the semantic properties of the underlying fuzzy system. A neuro-fuzzy system approximates n-dimensional unknown functions which and partly represented by training examples. A neuro-fuzzy system is represented as a special three-layered feedforward neural network as shown in Fig. 21.1.

The first layer corresponds to the input variables—acquired data from sensors. The second layer symbolizes the fuzzy rules—processes in the engine control unit.

Fig. 21.1 The architecture of a neuro-fuzzy system: the use of neural networks in an engine management system
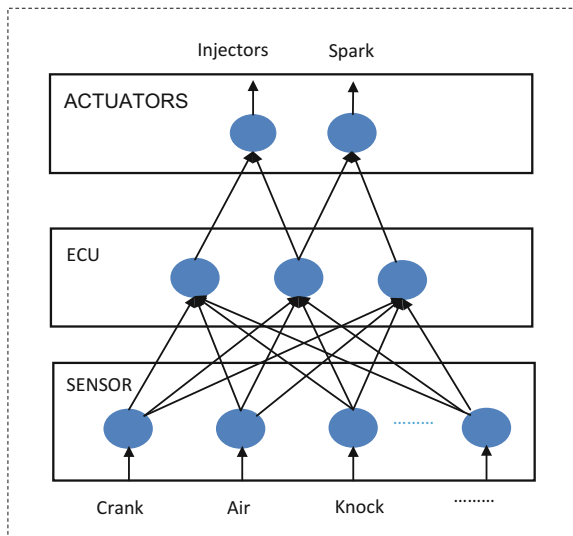
The third layer represents the output variables—output signals from the control unit to actuators. The fuzzy sets are converted as (fuzzy) connection weights.

21.3.2 Engine Hot Test Process

The hot test process consists of two main offline tests which includes production and durability hot tests. A production hot test (idle running engine) was used for the engine start verification prior to shipment to avoid costly final assembly plant warranty issues. These stations are often used as a confidence test for the quality process, and also act as a low cost electrical test. Often operator subjective, an noise vibration harshness (NVH) test looking for odd engine noise may also be used in this test, as well as for fuel and oil leakage. On the other hand, a durability hot test which (puts a well-controlled load on the engine during running) is used in large diesel markets, where horsepower verification and fuel consumption, emission and calibration can only be done while running the engine.

In our case, the engine hot test process included the checking of the main engine parameters and engine performance data acquisition. The engine was rigged up on a trolley outside the test container as shown in Fig. 21.2. Subsequently, the trolley was connected automatically through the connection plate to the test stand. After manual release by the worker, the trolley is automatically pulled to the test position and fixed.

On the test stand and on the trolley, connection plates with quick fit connectors, guarantee a fast docking. If the engine is properly connected to the test stand, the test stand program will start the test cycle. During the hot test the following parameters test the performance of power: torque with either oil, water or fuel leakages under warm conditions. The next step is to record engine control module

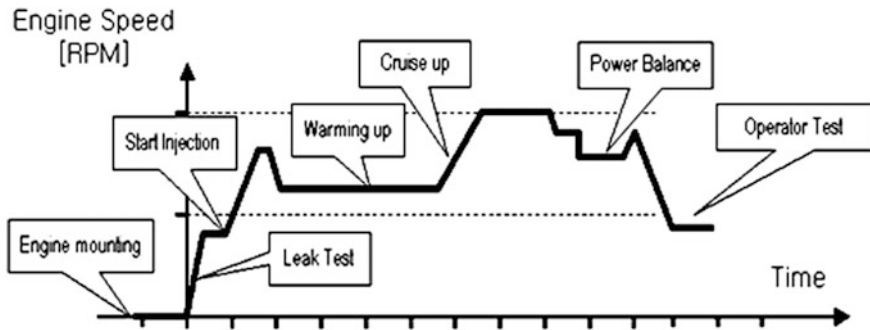**Fig. 21.2** Engines hot test machine (container type)

Fig. 21.3 Hot test sequences

(ECM) trouble codes, noise, electrical and mechanical functions, fuel consumption and emission. The test consist of different sequences and steps illustrated in Fig. 21.3.

After the automatic test run, the observed results were transferred to the test field server via an ethernet interface. The outcomes were reported in an Excel file. The measured results of other test runs were saved simultaneously on the server. The last observations run was saved and automatically opened in the post-processing of personal computer (PC) [6].

21.3.3 Prediction for Fuel Consumption

The engine hot test machine generates 2 types of output data: graphical—curves of separate engine characteristics and numerical data. The numerical data are used for ANN training process with detail breakdown which gives outputs from 24 engine parameters recorded frequently after every 0.47 s.

As much information we get from the training process as "smarter" our controlling system performs. In engine control unit system, amount of fuel being used is very crucial. Fuel consumption is the weight flow rate of fuel required to produce a unit of power or thrust. That is the reason to know in advance the consumption of fuel. Fuel consumption in the designed engine management control system is predicted one time step earlier with ANN model.

The two attributes speed and time are taken from the dataset generated by ECU, to train the ANN model for prediction of fuel consumption. The data is scaled in the range of [0, 1] for the artificial neural network to learn the underlying nonlinear structure and dependencies present in the dataset. Further to this, in contemplation to predict accurate fuel consumption values over step ahead, as it is discussed earlier that the choice of ANN used here is nonlinear autoregressive exogenous
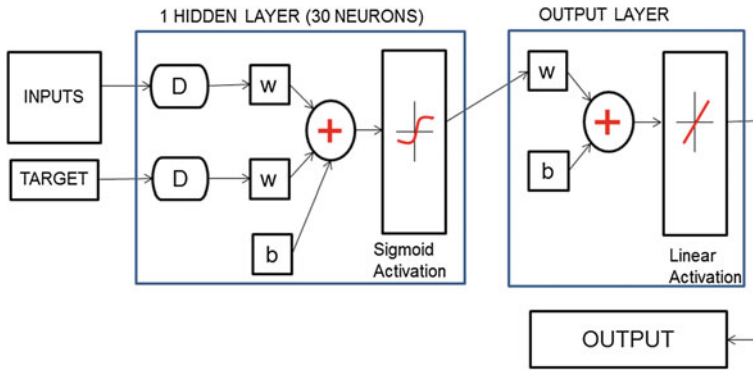
Fig. 21.4 Architecture of model NARX ANN

model (NARX), which is a recurrent neural network. The expression of that model is given in Eq. (21.1).

$$y(t) = f(u(t - nu), \ldots, u(t - 1), u(t), y(t - ny) \ldots, y(t - 1)) + \in \qquad (21.1)$$

which identifies that in order to predict the future values of y, the past values of same parameters and the current and the past values of external variable u are far most crucial. It is the realization in literature that the recurrent neural networks with sufficient number of hidden neurons having nonlinear activation function behaves in the manner of nonlinear autoregressive moving average (ARMA) method for time series forecasting [7, 8]. Inputs to our adopted model comprises of time (sec) and engine speed (rpm).

Output of model is a future value of fuel consumption. Figure 21.4 depicts the architecture is based on input layer, 1 hidden layer containing 30 hidden nonlinear neurons with sigmoid activation function, and 1 output layer containing one linear neuron. The selection of hidden neurons is based on Monte-Carlo simulation [9, 10].

21.4 Results and Discussion

The NARX model is trained on 40,000 samples of data set. In order to avoid the over fitting of model on data and to improve generalization, the dataset is divided in 70% for training, 15% for validation check and 15% for testing the model performance. The rest of dataset samples are kept aside to evaluate the efficiency of network on unseen data. The performance of the network is measured by Mean Square Error (MSE) as given in Eq. (21.2).

$$MSE = \frac{1}{N} \sum_{i=1}^{N} [y(t) - \hat{y}(t)]^2 \tag{21.2}$$

where $\hat{y}$ is a vector of n predictions, and y is the vector of observed values corresponding to the inputs to the function which generated the predictions. Practices of model can be observed from Fig. 21.5a and b which shows the measures related with the training set of model.

The model is trained using Levenberg-Marquardt training Algorithm, training stops as the error is not reduced further on validation set by choosing the early stopping criteria. However the model completes 333 epochs of iteration to minimize the error on predictions. The overall network performance measure is 3.5603e-05 MSE.

Another validation parameter R is used, involves analyzing the goodness of fit of the regression. Monitoring whether the regression residuals are random, and checking whether the model's predictive performance deteriorates substantially when applied to data that were not used in model estimation. The graph of the regression is illustrated in Fig. 21.6. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. On the other hand, if R is close to zero, then there is no linear relationship between outputs and targets. Figure 21.7 depicts the behavior of actual fuel consumption and predicted fuel consumption with time. The deviation of predicted samples from the actual ones can be properly seen in Fig. 21.8a and b.

Figure 21.8b shows 20 samples prediction of fuel consumption using one step ahead prediction, the average difference between the actual and the predicted samples is around 1.1242e-06, which is nearly accurate. This model helps to know
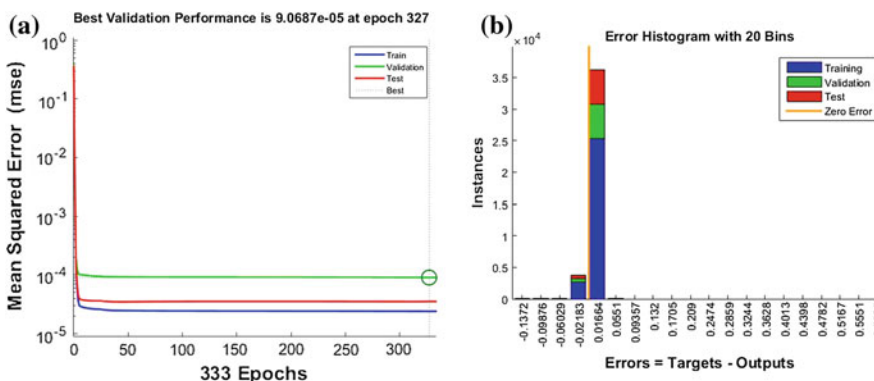

Fig. 21.5 a Performance of model on training, validation and test sets b error histogram of training, validation and testing
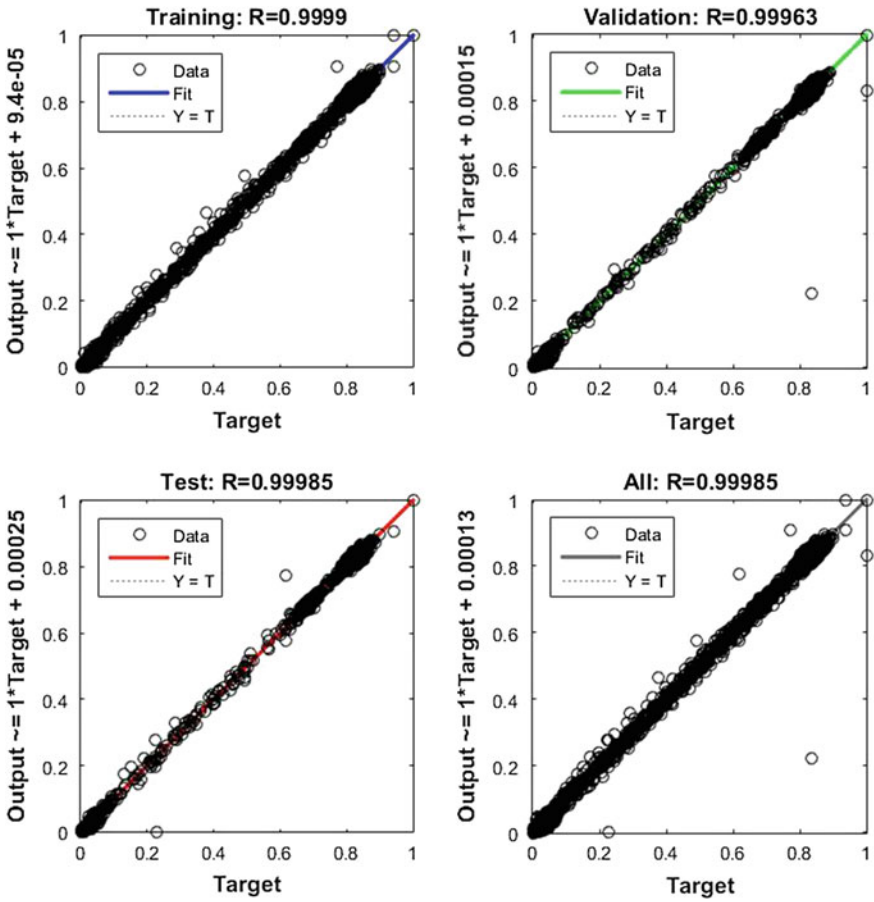
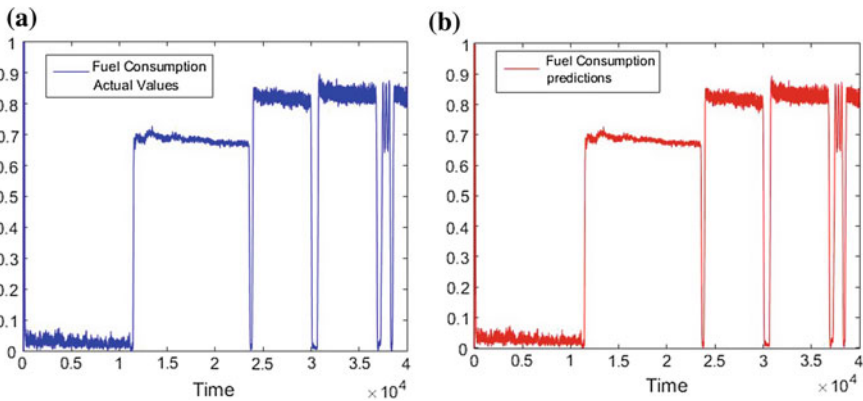**Fig. 21.6** Regression plots of training, validation, test and all in one

Fig. 21.7 **a** Actual fuel consumption samples scaled in [0.1] **b** outputs of step ahead prediction from model
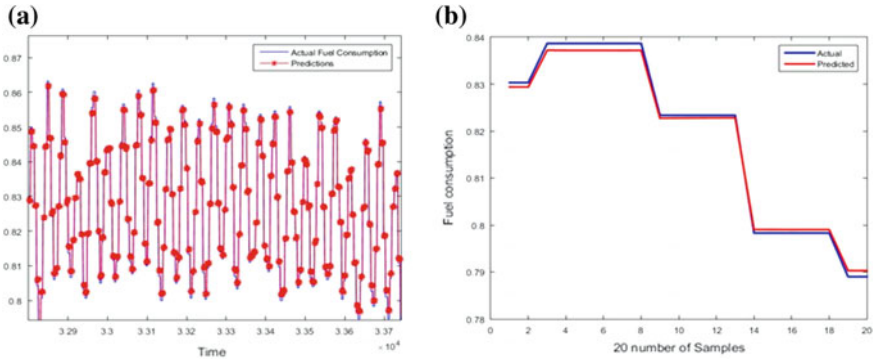
Fig. 21.8 a Actual and predicted values **b** 20 samples of actual and predicted FCs

in early time stamp what will be fuel consumption, even the speed is unavailable but focusing the rotation at previous time and the previous fuel consumptions one is able to infer the approximate fuel consumption for future.

21.5 Conclusion

In this paper we presented neural network approach to predict the fuel consumption of the engine based on NARX-models. The input to NARX is extracted from the resultant parameters of engine hot test. The hot test was conducted on ECU which is again based on neuro-fuzzy system. The ECU is further using ANN architecture which can manage engine controlling system precisely and outputs gave good results of learning and prediction. By predicting the fuel consumption earlier, we can manage more accurately air/fuel ratio, exhaust managing by exhaust gas recirculation (EGR) system and cam timing (if it is variable). As a result, it improves the main engine characteristic, effectiveness, fuel consumption, performance and pollutant volume.

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