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Learning Data Set Influence on Identification Accuracy of Gas Turbine Neural Network Model

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Abstract. There are many gas turbine engine identification researches via dynamic neural network models. It should minimize errors between model and real object during identification process. Questions about training data set processing of neural networks are usually missed. This article presents a study about influence of data set type on gas turbine neural network model accuracy. The identification object is thermodynamic model of micro gas turbine engine. The thermodynamic model input signal is the fuel consumption and output signal is the engine rotor rotation frequency. Four types input signals was used for creating training and testing data sets of dynamic neural network models – step, fast, slow and mixed. Four dynamic neural networks were created based on these types of training data sets. Each neural network was tested via four types test data sets. In the result 16 transition processes from four neural networks and four test data sets from analogous solving results of thermodynamic model were compared. The errors comparison was made between all neural network errors in each test data set. In the comparison result it was shown error value ranges of each test data set. It is shown that error values ranges is small therefore the influence of data set types on identification accuracy is low.

1. Introduction

Increased attention to the accuracy and reliability of gas turbine engine (GTE) control systemshas heightened the need for investigations into the use of neural networks to identify the dynamic model of the engine [1-5]. Therefore, of particular interest and complexity is the problem of development the techniquefor tuning a dynamic neural network (DNN) GTE model.

Artificial neural network (NN) model is a mathematic abstraction of biological neuron. NN consists of weights matrix and activation functions. The aim of NN learning is calculating such weights coefficients to get neural network output equal target output.DNN is a special class of neural network to be depending not only from input vector but from time too. This characteristic allows simulating any nonlinear dynamic processes such as GTE process. There are different types of DNN but for regression task the greatest interest is the next networks: recurrent neural network with feedback connection from output layer (Jordan network) or from hidden layer (Elman network) to input layer.

There is a vast literature on GTE modeling using neural networks [6-12]. Generally, these paperspay particular attention only to the problem of the practical application of GTE neural networks models. For example, Tayarani-Bathaie et al.[6] developed DNN identification of GTE specifically for detecting engine defects.Fast et al. [7] predicted industrial turbine operation at steady state modes using feedforward neural network. Wolff et al. [8] applied artificial neural networks for misfiring detection in an annular pulsed detonation combustor.Sisworahardjo et al. [9] drew a comparison between conventional PI-regulator and a regulator based on neural network which controlled a micro-gas turbine power plant. Although considerable research has been devoted to apply the neural network models to identify the operation modes of GTE, rather less attention has been paid to the problems of DNN GTE model creating.The neural network parameter selection such as a neural network type, a number of hidden neurons, a number of neurons in the input and output layers and their activation function is carried out without any justification.

A training sample is one of the crucial parameters used for developing neural networks.The reference [7] the training sample is represented by time histories of power plant main parameters obtained from field experimentwhich was conducted under different external conditions and loads. The same approach for neural network training is demonstrated byNikpey et al. [10]. The DNN employed by Asgari et al. [11]identifies the starting process of GTE. The data used for DNN training was also collected from the real engine operating process under the change of ambient conditions. The literature shows thatthe data used for GTE neural network identification is obtained from full-scale study.However, these data can be obtained only from the engine which has already been constructed. Moreover, for knowing all of engine parameters (temperature, pressure) in different places you should have a lot of sensors in the engine and you should use special test bench for contact each of them during engine fire test.These factors lead to low financial efficiency of the GTE identification process. Even more, the other disadvantage of GTE identification based on experimental data related to the impossibility of such procedure at the stage of a new engine designing. Therefore, more promising is the development of the GTE identification technique based on the neural network with the use of engine thermodynamic mathematical model. This technique was demonstrated by Asgari et al. [12].The neural network model was created using 13 different training functions. However, the problem of training functions substantiation was not considered.

In this paper, thenew investigation of the training functions type influence into the GTE neural network model accuracy is presented.

2. Methods

The identification accuracyof the gas turbine engine dynamic characteristics depending on the training sample was estimated using the following sequence. Firstly, several types of functions were selected. Each types of the function used as training and as tested function. Then, a neural network model based on each training function was designed. Then, each of models was tested by means of all types of test functions.

The fuel consumption was used as the input signal of the model, and the GTE rotor speed was used as an output signal.Four types of training and test functions were used, as follows: a step function (type 1), a ramp function with "fast" and "slow" signal change (type 2 and 3 respectively) and a combination of previous three function (type 4).

The terms of "fast" and "slow" signal change is related to the ratio of signal acceleration and acceleration of the GTE rotor.The acceleration of fast signal is twice as much as the average acceleration of the rotor during the process of switching from idle mode to full throttle and back. The acceleration of slow signal is twice smaller than the average acceleration of the rotor during the injectivityprocess.Thus, the average value of the acceleration of the rotor is used as some reference value for selecting the acceleration of the sampling signal.A step signal was selected as thelimiting case to simulate a sudden change in the signal, which usually occurs when identifying the signal from the speed sensor in the presence of a noise component of the measurement.Combined or random signal includes all of these three signal types.Thus, four variants of the neural dynamic GTE model were developed, which were tested on four sets of test signals.

The simulation used a network with the following structure: one input neuron (fuel consumption), one hidden layer neuron and one output neuron (engine rotor speed).

3. Results and discussion

3.1. GTE rotor mean acceleration estimation

To determine the mean value of the acceleration of the rotor, a step fuel consumption signal is set from the value of the small gas to the maximum mode (Figure 1).

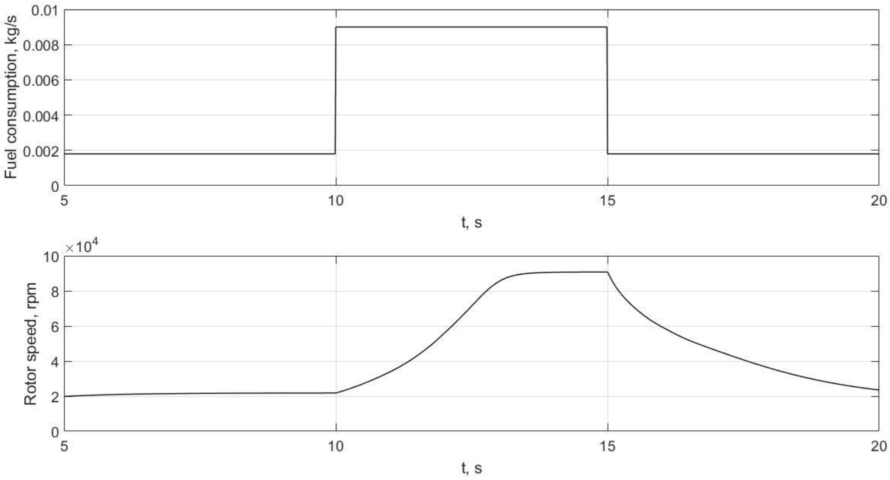

Figure 1. Step signal of fuel consumption (top) and rotor speed transition process (bottom)

The module of engine rotor acceleration is different for acceleration (transition stage from the minimum frequency to the maximum) and deceleration (transition stage from the maximum frequency to the minimum). Therefore different values of acceleration should be used. The average acceleration of the rotor during the transition stage from the minimum to the maximum mode is 18,000 rpm per s.The average deceleration during engine braking under similar conditions is 6,960 rpm per s.To simplify the work with the neural network, the mean acceleration values were normalized to the GTE speed at the maximum mode of 90,600 rpm (Figure 1).Then, the average reduced acceleration was 0.20 s^{-1}, and 0.08 s^{-1} during engine acceleration and braking respectively. Thus, the reduced signal acceleration at the input was obtained. The assumption that the acceleration of the signal at the output has the same value was made. Then, for the case of a rapid change in the signal during the engine speedup, the acceleration was 0.40 s^{-1}, and during the braking the acceleration was 0.16 s^{-1}.In the case of a slow signal change, the value of the reduced acceleration was0.10 s^{-1} and 0.04 s^{-1} during the engine speedup and braking, respectively.Figures 2-5 show four cases of input signals, including both the training sample and the test sample.

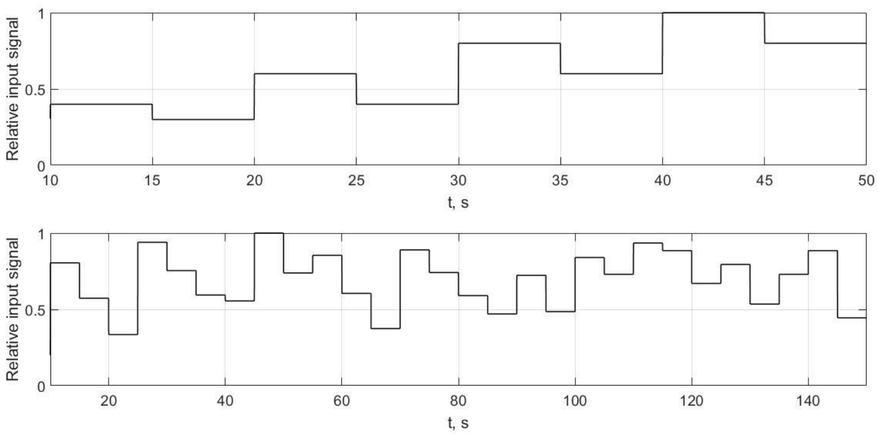

Figure 2. Step relative input signal for learning process (top) and test process (bottom)

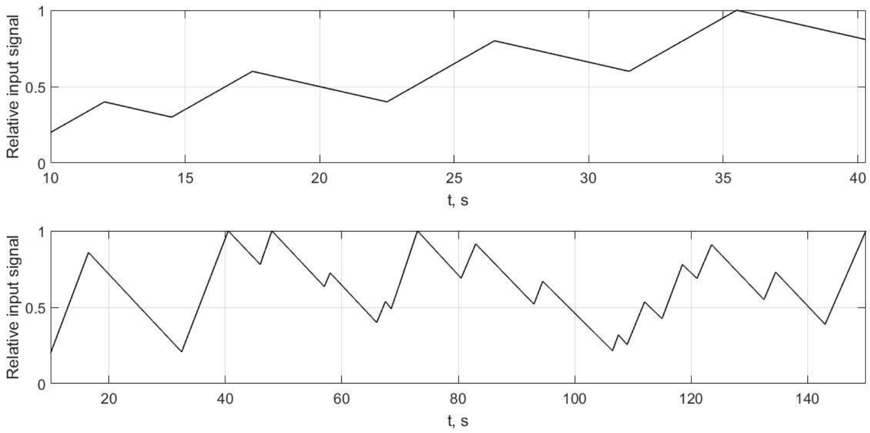

Figure 3. Slow relative input signal for learning process (top) and test process (bottom)

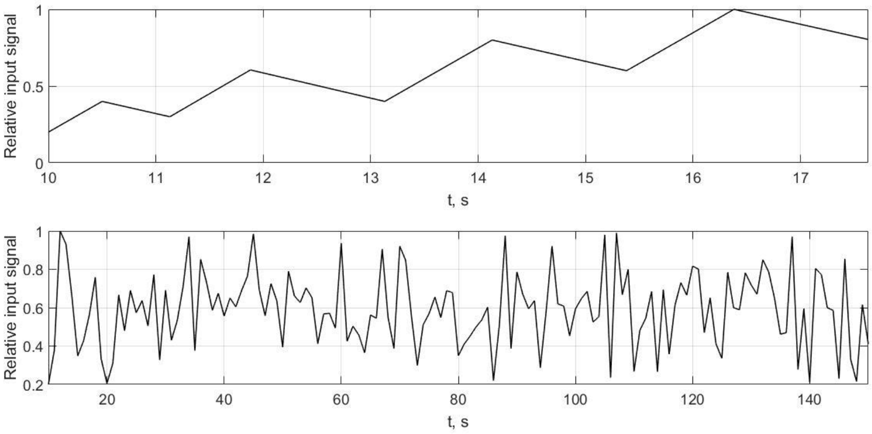

Figure 4. Fast relative input signal for learning process (top) and test process (bottom)

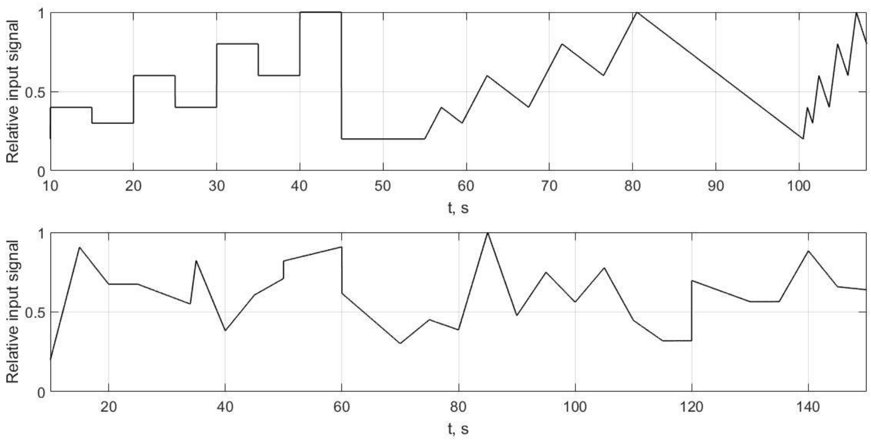

Figure 5. Random relative input signal for learning process (top) and test process (bottom)

3.2. Model testing and comparison of the results

As an example, Figure 6 depicts the comparison of GTE rotor speeds obtained fromthe neural network model which was tested on random relative input signal (type 4).

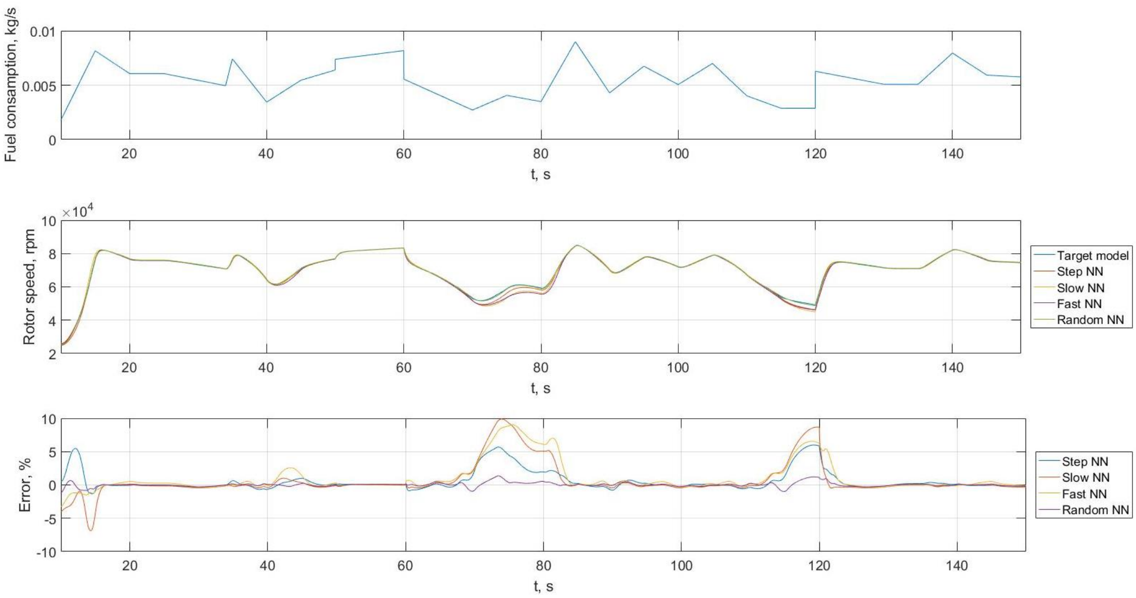

Figure 6. Results of testing different NN models on random signal.
Transition process (top) and identification errors (bottom)

A strong stratification of characteristics around the 80th and 120th seconds was due to the insufficient number of training data at low rotational speed.This stratification is true for all model types and has a local character regardless of NN model type (with the exception of the Random NN because it has more learning examples). In addition, this has little effect on the models average error magnitude over the entire operation time. The results of deviations for all neural network models are given in Table 1.

Table 1. Errors of NN models on different test data sets in %.

Test \Learn	Step NN model	Slow NN model	Fast NN model	Random NN model
Step test data set	0.7421	1.8770	0.8845	0.6414
Slow test data set	0.9451	0.4758	0.7944	0.6414
Fast test data set	1.7780	1.3810	0.7193	0.3035
Random test data set	0.8146	1.1980	1.2280	0.2047

3.3. Analysis

According to Table 1, for each of the test samples and the neural network models corresponding to them, it can be seen that the minimum error value corresponds to cases when the neural network model was tested on a sample of the same character as used for its training.

For the model trained on a type 1 sample, the error range was 1.036% for the type 2 it was 1.401% for the type 3 it was 0.5087 and for the type 4 it was 0.4367. The lowest value of the error was shown by a model trained on data of a type 4 (random type).The model, trained at slowly changing fuel consumption, showed the greatest value of the error. However, the difference in accuracy is negligible.

As can be seen, there is no fundamental difference between models trained on different types of input functions.Hence, when creating a neural network model, the researcher can choose the test method and those samples that will be most convenient for the modeling process.

The research was limited to the gas turbine scope, however, considering the universality of the structure and learning of the neural network models, it can be concluded that this study will show similar results on the other objects.

4. Conclusion

The results of the training function type influence to the accuracy of the dynamic neural network GTE model are obtained. It was found that the accuracy of the developed models is virtually independent of the sample on which the neural network was trained. The results are approximately the same for both a stepped input signal and a smoothly varying one.The average model error did not exceed 1.9%.In general, the increase in accuracy can be achieved by using the full spectrum of changes in all the parameters of interest in training samples, but often this is unnecessary and, as shown in this study, is not required to obtain sufficiently accurate models.

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