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Application of neural network technology and high-performance computing for identification and real-time hardware-in-the-loop simulation of gas turbine engines

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Abstract

The engineering method for the recurrent neural network construction and identification of a mathematical model of gas turbine engines on a real data is proposed, describing the learning algorithm and the network structure. The complete process of modeling and experimental investigation – from designing of a gas turbines model in form of neural networks to its testing and debugging on the test-bed – are presented. The method was approved on a hardware-in-the-loop test-bed with a FADEC closed loop control for the start-up, ground and flight modes.

Keywords: gas turbine engine, FADEC, neural network, identification, nonlinear dynamics, hardware-in-the-loop simulation, high-performance computing

1. Introduction

During operation of an aircraft, the engines gradually use their resources that leads to performance degradation. In the process of analysis and synthesis of automatic control systems, there is a need to adjust and adapt the existing gas turbine engine model for a specific engine for its effective performance. To solve this problem, it is necessary to have the adaptive models, which are identified by real characteristics and operation conditions of the control object.

In recent decades the intelligent technology based on neural network are widely used in investigation and development of the complex control systems for the gas turbine engines (GTE). There are different directions of research using neural networks (NN) in this field: identification, detection of engines' operation modes, trend analysis, classification, state prediction, etc. [1-3]. In foreign literary sources and doctoral theses [4-6] the modern

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methodologies of modeling and control of gas turbine engines using artificial intelligence and machine learning are described. The PhD theses [4] explores the application of static and dynamic neural networks – modelling of steady-state and transient behaviors of gas turbines with the use of Matlab computing environment. The book [5] provides new approaches and novel solutions to modeling, simulation, and control of gas turbines using artificial neural networks, including methods of "white-box" and "black-box" identification. The paper [6] investigates the possibility of application of artificial neural networks to perform the fluid flow calculations through both damaged and undamaged turbine blading. A hardware-in-the-loop (HIL) simulation is already used in modelling and testing of automatic control systems by joint use of a real control system (such as FADEC) with a mathematical model of a GTE and its subsystems, for example, a gas generator, oil, fuel and other subsystems. However, the problem of adequacy and applicability of the GTE mathematical models (usually represented as piecewise-linear dynamic models) in HIL test-beds is still important [7].

The research objective is the effectiveness increase of complex HIL simulation and testing of a FADEC by using nonlinear dynamic mathematical models of gas turbines and its systems in the form of recurrent neural networks as a part of the HIL test-bed. The paper describes the complete process of modeling and experimental investigation – from designing of a GTE mathematical model in form of neural networks to its testing and debugging on the test-bed. The paper proposes the engineering method for construction the recurrent neural network and identification of a mathematical model of GTE on a flight data, describing the learning algorithm, the network structure and the hidden layer size.

2. Method of neural network identification

The mathematical representation of the nonlinear dynamic model of a two-shaft gas turbine engine can be represented as a system of differential equations as:

$$\begin{cases} \Delta\dot{n}_{\mathrm{LP}t} = a_{11}\cdot\Delta n_{\mathrm{LP}t\text{-}1} + a_{12}\cdot\Delta n_{\mathrm{HP}t\text{-}1} + a_{13}\cdot\Delta T_{\mathrm{LPT}t-1} + a_{14}\cdot\Delta\pi_{\mathrm{C}t-1} + \ldots + b_{11}\cdot\Delta G_{\mathrm{f}\,t}; \\ \ldots \\ \Delta\dot{T}_{\mathrm{LPT}t} = a_{31}\cdot\Delta n_{\mathrm{LP}t\text{-}1} + a_{32}\cdot\Delta n_{\mathrm{HP}t\text{-}1} + a_{33}\cdot\Delta T_{\mathrm{LPT}t-1} + a_{34}\cdot\Delta\pi_{\mathrm{C}t-1} + \ldots + b_{31}\cdot\Delta G_{\mathrm{f}\,t}; \\ \ldots \\ \Delta\dot{\pi}_{\mathrm{C}t} = a_{51}\cdot\Delta n_{\mathrm{LP}t\text{-}1} + a_{52}\cdot\Delta n_{\mathrm{HP}t\text{-}1} + a_{53}\cdot\Delta T_{\mathrm{LPT}t-1} + a_{54}\cdot\Delta\pi_{\mathrm{C}t-1} + \ldots + b_{51}\cdot\Delta G_{\mathrm{f}\,t}. \end{cases}$$

Where a_{ij} and b_{ij} are the coefficients for each operation mode, the control signal G_f are the fuel consumption, the state variables in the previous step are: $n_{\mathrm{LP}\,t\text{-}1}$ and $n_{\mathrm{HP}\,t\text{-}1}$ – low- and high-pressure compressor rotor speeds, $T_{\mathrm{LPT}\,t\text{-}1}$ – the gas turbine outlet temperature, $\pi_{\mathrm{C}\,t\text{-}1}$ – the compressor pressure ratio.

The use the recurrent multilayer perceptron (NARX - nonlinear autoregressive neural network with external input) is proposed for designing such nonlinear dynamic model. NARX network is a dynamic neural network that characterized by a delay of input and output signals, combined in the network input vector (Fig. 1). The mathematical model in the form of NN with a feedback allows taking into account non-linear dynamic characteristics of an engine and ensures the structural-parametric adequacy of an analytical GTE model.

The input vector x is given by $x(t) = [1, x(t), x(t-1), ..., x(t-D_1), y(t-D_2), y(t-(D_2+1)), ..., y(t-1)]^T$, where D_1 – number of input delays, D_2 - number of output delays. Depending on the GTE model and the operation modes (start-up, ground or flight), the vector x is formed according to the parameters, specified in the requirements specification, such as altitude, speed, fuel consumption, operation mode, discrete parameters of a starter, etc. The output vector of the network is as follows: $y(t+1) = f(x(t), x(t-1), \ldots, x(t-D_1), y(t-1), y(t-2), \ldots, y(t-D_2))$, then a recurrent network characterized by a set of numbers (D_1, D_2, [K_1, K_2, ..., K_n]), where K_n – number of neurons in a n-hidden layer. The values of D_1 and D_2 selected as 1..2.

Two neural networks are trained for the start-up mode and for the ground and flight modes, which are combined into one NN model during implementation in the HIL test-bed. One NN model simulates the whole set of GTE parameters. For the training of such networks the Bayesian regularization based on back propagation error algorithm is used, which modifies the values of the weighting factors and offsets in accordance with the algorithm of Levenberg-Markarth.