

Neural Network Semi-empirical Modeling of the Longitudinal Motion for Maneuverable Aircraft and Identification of Its Aerodynamic Characteristics

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Abstract. A modelling and simulation problem is considered for longitudinal motion of a maneuverable aircraft that is viewed as a nonlinear controlled dynamical system under multiple and diverse uncertainties. This problem is solved by utilizing semi-empirical neural network based approach that combines theoretical domain-specific knowledge with training tools of artificial neural network field. Semi-empirical approach allows for a substantial accuracy improvement over traditional purely empirical models such as the Nonlinear AutoRegressive neural network with eXogenous inputs (NARX). It also provides solution to system identification problem for aerodynamic characteristics of an aircraft, such as the coefficients of aerodynamic axial and normal forces, as well as the pitch moment coefficient. Representative training data set is obtained using an automatic procedure which synthesizes control actions that provide a sufficiently dense coverage of the region of change in the values of variables describing the simulated system. Neural network model learning efficiency is further improved by the use of special weighting scheme for individual training samples. Obtained simulation results confirm the efficiency of proposed simulation approach.

Keywords: Nonlinear dynamical system · Semi-empirical model · Neural network · System identification

1 Introduction

When designing an aircraft, one of the most important problems is identifying of its aerodynamic characteristics. An approach was proposed in [1–3] to solve this problem using semi-empirical artificial neural network (ANN) models of nonlinear controlled dynamical systems. These semi-empirical models are based on the grey-box model concept introduced in [4, 5].

This approach differs significantly from the traditionally accepted method for solving problems of this class, which are based on the use of the linearized model of the aircraft disturbed motion. The conventional approach uses the

representation of the dependences for the aerodynamic forces and moments in the form of their Taylor series expansion, leaving in it, as a rule, only members not higher than the first order.

Accordingly, the solution of the identification problem with the conventional approach is reduced to reconstructing from the experimental data the dependences describing the coefficients of the Taylor expansion, in which the derivatives of the dimensionless coefficients of the aerodynamic forces and moments with respect to the various parameters of the motion of the aircraft ($C_{L\alpha}$, $C_{y\beta}$, $C_{m\alpha}$, C_{m_q} etc.) are determining.

In contrast, the semi-empirical approach performs the reconstruction of the relations for the force coefficients C_D , C_L , C_y and moments C_l , C_n , C_m as some whole non-linear dependences on the corresponding arguments, without their series expansion and linearization, i.e. the functions themselves, represented in the ANN-form, are evaluated, and not the coefficients of their expansion in the series. Each of these dependences is implemented as a separate ANN-module, built into a semi-empirical ANN-model. Derivatives $C_{L\alpha}$, $C_{y\beta}$, $C_{m\alpha}$, C_{m_q} and others can be found, if necessary, using the results obtained during formation of the ANN-modules for the coefficients of forces and moments within the semi-empirical ANN-model.

A mathematical model of the longitudinal motion of a maneuverable aircraft is derived, which is used as a basis in the formation of the corresponding semi-empirical ANN-model, as well as for the generation of a training set. An algorithm for this generation is proposed, which provides a fairly uniform coverage of the possible values of state variables and controls for the maneuverable aircraft by training examples. Next, a semi-empirical ANN-model of the longitudinal controlled motion of the aircraft is formed, including the ANN-modules realizing the functional dependences for the coefficients C_D , C_L and C_m . The identification problem for these coefficients is solved when learning the obtained ANN-model. The corresponding simulation results characterizing the accuracy of the obtained ANN-model as a whole are given as well as the accuracy of the solution of the identification problem for aerodynamic coefficients.

2 Mathematical Model of Longitudinal Motion for Maneuverable Aircraft

To solve the problem, it is required to form a source mathematical model of the longitudinal motion of an aircraft. This model is represented by a system of nonlinear ordinary differential equations (ODE), traditional for aircraft flight dynamics [6].

The model consists of 9 equations of the first order for aircraft state variables, including 4 equations for variables V_T , γ , R and h , describing trajectory aircraft motion; 2 equations for the variables Θ and q , describing angular aircraft motion; 1 equation for the variable \bar{T} for aircraft engine power level response; 2 equations for variables δ_e and $\dot{\delta}_e$ describing the actuator dynamics for the aircraft elevator. Here V_T is aircraft total velocity, m/s; γ is flight path angle, deg; R is range of

flight, m ; h is altitude, m ; Θ is pitch angle, deg ; q is body-axis pitch rate, deg/s ; \bar{T} is actual power level of the aircraft engine; δ_e is elevator deflection, deg ; $\dot{\delta}_e$ is rate of elevator deflection, deg/s . The right-hand sides of the equations of motion contain the relations for aerodynamic forces, axial C_X and normal C_Z , and also for the aerodynamic pitch moment C_m . These relations are non-linear functions of the appropriate arguments, namely, the angle of attack α and also V_T , δ_e and q . Command signal of the elevator actuator $\delta_{e_{act}}$ and engine throttle setting δ_{th} were used as control signals.

The concretization of this model of motion was carried out for the case of a maneuverable F-16 aircraft. The required data characterizing this aircraft, including the model of its engine, are taken from [7]. The computational experiments performed with this model were carried out in the altitude range from 1000 m to 9000 m and in the range of Mach numbers from 0.1 to 0.6.

3 Generation of a Representative Set of Training Data

When solving problems of the considered type, one of the most important tasks is the generation of a representative set of data that characterizes the behavior of the simulated dynamic system on a rather large range of values for the system state and control variables. This task is critically important for obtaining a authentic dynamic system model, but it has no simple solution. The required training data for the generated ANN-model can be obtained by means of specially organized test excitations for the simulated system.

The training set used in the experiments described in this article was formed using an automatic procedure proposed by the authors. This procedure synthesizes control actions that provide a sufficiently dense coverage of the region of change in the values of variables describing the simulated system. Then, the resulting set of control actions is applied to the simulation object and the obtained trajectories are used to generate the training set. The test set is formed in a similar way.

In addition to the representative training set, we use the weighting of individual examples from the training set to improve the learning efficiency for the ANN-model. It is based on the following considerations. If the arguments of the K examples from the training set are located in a small neighborhood, then this situation is analogous to giving weight K to some average example from this region. Thus, the irregular distribution of examples can lead to increased model accuracy in some areas due to its lowering in others. In order to avoid such a situation, after completing the procedure for synthesizing the training set, the elements of this set are weighed. For this purpose, set of vectors Λ is formed. Vectors $\lambda \in \Lambda$ consist of control variables and state variables of each selected trajectory $\langle u(t), x(t) \rangle \in Q$ at each moment of time $t \in [T_{min}, T_{max}]$, where $u(t)$ and $x(t)$ are control and state vector of simulated dynamical system. For each element $\lambda \in \Lambda$, we search for elements located in its ε -neighborhood. Then, the corresponding example from Q is assigned a weight inversely proportional to the number of neighbors found.

When implementing this algorithm on a computer, you should select an appropriate data structure for representing the set Λ and some auxiliary sets

associated with it. This structure should ensure the effective execution of operations for finding the nearest neighbor, searching for neighbors in a given neighborhood, and adding new elements in the generated training set. In this paper, as such a structure, we used a k -dimensional tree, namely, its implementation in the FLANN library [8].

This algorithm was successfully used to generate a training set for a semi-empirical ANN-model of the longitudinal motion for the F-16 maneuverable aircraft. The following range of variables was considered: $\delta_{e_{act}} \in [-25^0, 25^0]$, $\delta_e \in [-25^0, 25^0]$, $\delta_{th} \in [0, 1]$, $T \in [0, 100]\%$, $\gamma \in [-90^0, 90^0]$, $q \in [-100, 100]$ deg/s, $V_T \in [35, 180]$ m/s, $\alpha \in [-20^0, 90^0]$.

4 Semi-empirical Neural Network Model of Aircraft Longitudinal Motion

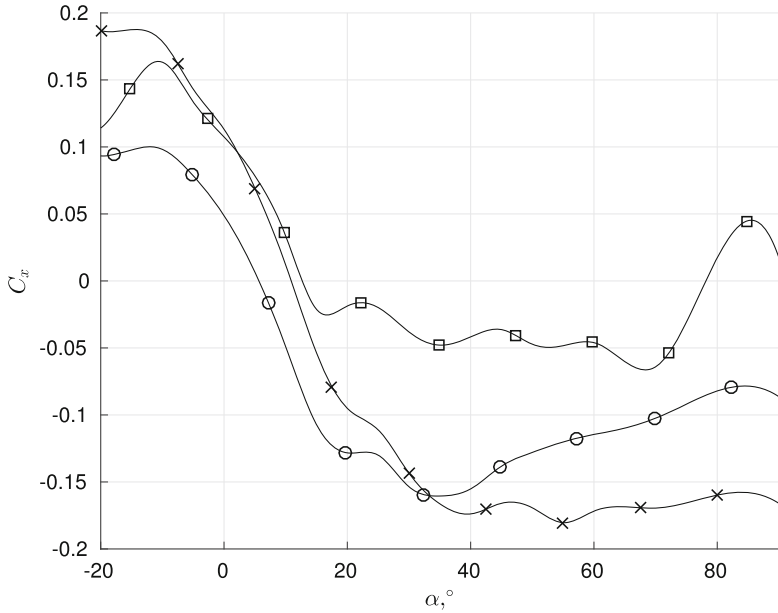
A general approach to the formation of semi-empirical ANN-models of controllable dynamical systems was presented in [1, 2]. For the problems of identification of aircraft aerodynamic characteristics these models are considered in [3], where using the mathematical model of complete aircraft angular motion were solved the problem of finding relationships for aerodynamic lateral and normal force coefficients C_Y and C_Z as well as for aerodynamic rolling, pitching and yawing moment coefficients C_l , C_m and C_n . In this section, we build a semi-empirical ANN-model of the aircraft longitudinal motion, based on the mathematical model mentioned above. This ANN-model allows us to find the relations for the coefficients C_X , C_Z and C_m , with respect to the vast range of possible values of the variables on which these relations depend.

The training and test sets were formed according to the procedure described in the previous section, with a sampling step $\Delta t = 0.01$ s. The vector of state variables is partially observable $y(t) = [V_T(t), \alpha(t), q(t)]^T$, $\alpha = \Theta - \gamma$. The output of the system is affected by additive white noise with root mean square deviation (RMS) $\sigma_{V_T} = 0.01$ m/s, $\sigma_\alpha = 0.01$ deg, $\sigma_q = 0.005$ deg/s.

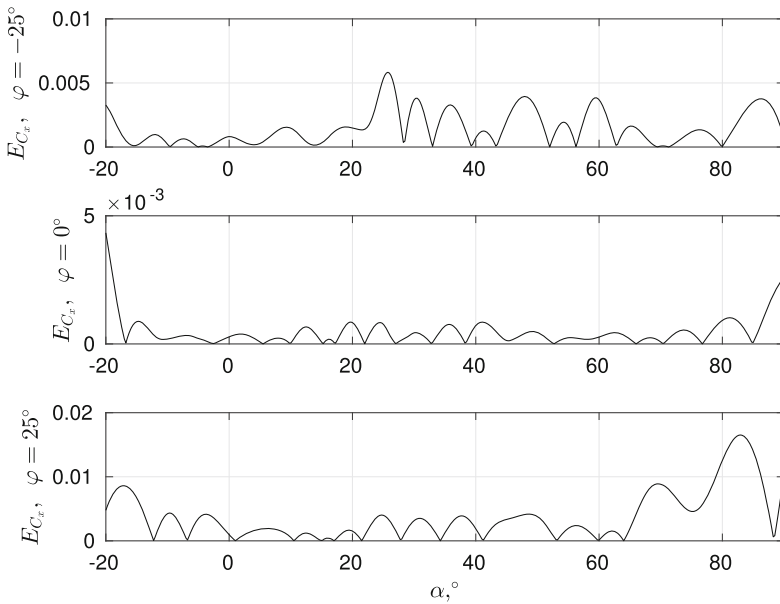
Training of semi-empirical ANN-models is a non-trivial task. The appropriate algorithms for solving it are considered in [3]. This training is carried out in the Matlab system for neural networks in the form of LDDN (Layered Digital Dynamic Networks) using the Levenberg-Marquardt optimization algorithm based on the root-mean-square error of the model [9]. The Jacobi matrix is calculated using the RTRL (Real-Time Recurrent Learning) algorithm [10].

ANN-modules for nonlinear functions C_X , C_Z and C_m are formed as sigmodal feed-forward networks. As inputs of each of the modules, the values of α , δ_e and q/V_T are taken. The ANN-modules for the C_X and C_Z functions have two hidden layers, the first of which includes 10 neurons and the second one contains 20. The ANN-module for the C_m function has three hidden layers, the first of which includes 10 neurons, the second one has 15 and the third has 20 neurons.

The simulation error on the test set for the obtained semi-empirical ANN-model of the longitudinal motion for the maneuverable aircraft is: $\text{RMS}_{V_T} = 0.00026$ m/s, $\text{RMS}_\alpha = 0.183$ deg, $\text{RMS}_q = 0.0071$ deg/s.



(a)



(b)

Fig. 1. Simulation results: **(a)** – coefficient $C_X(\alpha, \delta_e)$ for $\delta_e = -25^\circ$ (marker \square), $\delta_e = 0^\circ$ (marker \circ) and $\delta_e = -25^\circ$ (marker \times) according to [7]; **(b)** – approximation error E_{C_X} for fixed values of $q = 0$ deg/s and $V_T = 150$ m/s

The accuracy of the dependences representation for the aerodynamic coefficients can be seen from the example of the coefficient C_X as shown in Fig. 1. The upper part of this figure shows the actual values (according to the data from [7]) of the C_X depending on the angle of attack and the elevator deflection angle. The lower part of the figure shows the errors with which appropriate ANN-module reproduces the corresponding dependence. It can be seen that the accuracy achieved is very high. The results for the other two coefficients (C_Z and C_m) look similar.

5 Conclusions

The results presented above allow us to draw the following conclusions. As in the case described in [3] for the coefficients of aerodynamic forces C_L , C_y and moments C_l , C_n , C_m , methods of semi-empirical ANN-modeling provide the possibility to solve successfully the problem of longitudinal force coefficient identification if the characteristics of the engine are known. If data for these characteristics are not available, then the result of solving the identification problem will be the relationship for the total coefficient of axial force, whose arguments will include the δ_{th} control variable. Usually this is quite enough to simulate the motion of the aircraft.

The second important conclusion, which follows from the obtained results, is that the “computational power” of the semi-empirical ANN-model is quite sufficient to represent complex nonlinear functional dependencies defined on a broad range of their argument values, provided that there is a training set possessing the required level of representativeness.

The simulation results demonstrate the high accuracy of both the ANN-model of the obtained aircraft longitudinal motion and high representation accuracy for corresponding aerodynamic characteristics.

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