NEURAL NETWORK ADAPTIVE SEMI-EMPIRICAL MODELS FOR AIRCRAFT CONTROLLED MOTION

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Abstract

A simulation and system identification problem is discussed for aircraft as nonlinear controlled dynamical system. The main goal is to demonstrate capabilities for semi-empirical models combining theoretical domain-specific knowledge with training tools of artificial neural network field as applied to the aircraft motion simulation problem. The obtained results confirm efficiency of the proposed simulation approach.

1 Introduction

A behavior of aerospace vehicle is characterized by possible unpredictable changes during its operation. This feature should be taken into account in the course of vehicle models development, otherwise usage of resulting model in vehicle onboard systems can lead to emergency conditions. One of possible ways to solve this problem is generation of models with adaptability feature.

Such adaptive models can be obtained using the semi-empirical modeling approach [1], which allows us to combine theoretical knowledge about the concerned system with empirical model refinement methods. The theoretical knowledge is represented in this case by differential equations describing operation of the system. Model refinement procedures are based on learning techniques for artificial neural networks. The results of computational experiments for a simple problem presented in [1] confirm high efficiency of semi-empirical modeling approach in contrast to traditional empirical ("black box") models such as NARX.

A simulation and system identification approach is discussed in the paper for nonlinear controlled dynamical systems under multiple and diverse uncertainties including knowledge imperfection concerning simulated plant and its environment exposure. The uncertainty can be caused by the plant failures and damages as well. The main goal of the paper is an advance on semi-empirical dynamical models combining theoretical knowledge for the plant with training tools of artificial neural network field. Simulation is carried out to confirm efficiency of the proposed approach.

Traditional artificial neural network based models (ANN-models) are pure empirical ones (black box models) they are based only on experimental data describing a behavior of the simulated dynamic system [2]. Modular dynamic networks proposed in the paper take into account both experimental data and theoretical knowledge. These networks can be classified as semi-empirical models (gray box models) [1, 3, 4].

Development process for semi-empirical adaptive ANN-model in the form of modular dynamic network consists of the following stages:

1. development of continuous-time theoretical model for the considered dynamic system as well as acquisition of experimental data about behavior of the system;

2. accuracy evaluation for the theoretical model of the dynamic system using the collected data;

3. conversion of the original continuous-time model into a discrete-time model [5];

4. generation of ANN-representation for the discrete-time model [6, 7];

5. training of the ANN-model [8, 9, 10];

6. structural adjustment of the ANN-model to fit modeling accuracy requirements.

2 Semi-empirical ANN-model for a simple dynamic system

We consider a controlled continuous-time dynamic system as a simulated plant. The theoretical model of the system is a set of ordinary differential equations (ODE). The original continuous-time model is conversed into discrete-time models using Euler and Adams difference schemes.

Semi-empirical ANN-model generation process can be demonstrated using the simple dynamic system as an example [3]:

$$\begin{aligned} \dot{x}_1(t) &= -(x_1(t)+2x_2(t))^2+u(t) \\ \dot{x}_2(t) &= 8.322109\sin(x_1(t))+1.135x_2(t). \end{aligned} \tag{1}$$

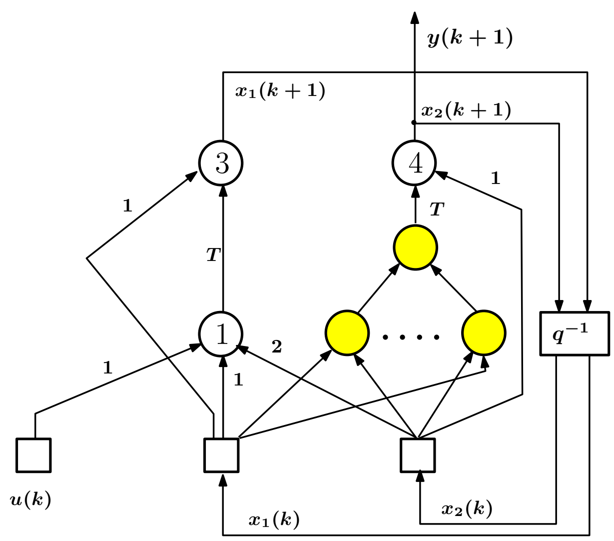

Fig. 1 Structural organization of semi-empirical ANN-model for dynamic system given by Eq. 1 according to the Euler difference scheme

Insufficient accuracy of a model based on the theoretical domain-specific knowledge about the simulated system is caused usually by some factors which are significant for the system but they are not included into the model. Experimental data about behavior of the system allow to refine the model by means of its tuning or training, in ANN terms. If the training process does not lead to a model with required accuracy level then it means that structural modifications of the model are needed. These modifications are based on some hypothesis about possible causes of simulation failures.

Suppose that we know exactly only the first equation in Eq. 1. We will write initially the second equation in some simplified form to simulate our imprecise knowledge about considered dynamic system:

$$\dot{x}_2(t) = 8.32x_1(t). \tag{2}$$

Behavior analysis for the modified system (system Eq. 1 with Eq. 2 instead of the second line in it) using ODE numerical integration shows unacceptable results. The MSE values are 0.13947 and 0.07143 for Euler and Adams difference schemes respectively. These results are much more than 0.01 specified as the target MSE value.

Obviously this failure is caused by the kind of equation Eq. 2. The possible reasons are:

- inaccurate value of numerical parameter in Eq. 2;
- inadequacy of linear dependence on x_1 in Eq. 2;
- absence of dependence on x_2 in Eq. 2.

Semi-empirical form of the ANN-model allows us to include required changes using some subnet as the module implementing a needed nonlinearity.

Simulation results for the semi-empirical model related to the Eq. 1 system with all necessary modifications in it are presented in Table 1. Some abbreviations are used in this table: ODE — results for the system Eq. 1 with Eq. 2 instead of the second line in it; ANN-1, ANN-2, ANN-3 — results for the initial model after first, second and third modification stages; Opt — results for the best version of the NARX model related to Eq. 1 system.

As we can see from the column marked "ANN-1" in Table 1 tuning of the numerical parameter value as the first step of the modification process for the model does not enhance significantly the accuracy of the simulation results. Let's try to implement the second modification stage. We need to replace linear relationship Eq. 2 in the second line of Eq. 1 system by a nonlinear one depending on x_1. This modification is carried out using some nonlinear MLP-type ANN module embedded in the original ANN-model instead of the single neuron corresponding to the linear relationship described by Eq. 2. Simulation results presented in Table 1 were obtained for the one-hidden-layer MLP module. There are 10 sigmoidal neurons in the hidden layer, this value was stated by means of computing experiments.

The column marked "ANN-2" in Table 1 shows us that the second modification stage is not successful as well as the first one. It seems that we lack dependency on second variable x_2, hence we add connection from the corresponding input to MLP's hidden layer. As we can see from the column marked "ANN-3" in Table 1 the third modification stage allows us to obtain acceptable simulation accuracy level for the Eq. 1 system.

Simulation results for the NARX-type empirical model are presented in the column marked "Opt" of Table 1. The best simulation accuracy was obtained for the NARX network with 3 sigmoidal neurons in one hidden layer and 5 feedback delays. The data from Table 1 show clearly the superiority of semi-empirical models over the empirical one. We see that even for models based on the Euler difference scheme MSE value is 0.01394 against 0.02821 for the NARX case. The accuracy level is higher for the Adams difference scheme and it equals 0.01219.

Similar analysis was carried out for two more versions of the Eq. 1 system with appropriate simulation results presented in Table 2 and Table 3. The first version uses an equation with harmonic members in it

$$\dot{x}_2(t) = 8.322109 sin(x_1(t)) + 0.7\cos(1.33\pi x_2(t)) \tag{3}$$

instead of the second relationship in Eq. 1. The second version of the Eq. 1 encloses slightly more complex mixture of harmonics as compared to Eq. 3:

$$\dot{x}_2(t) = 8.322109 sin(x_1(t)) + 0.7\cos(1.33\pi x_2(t))^2 \tag{4}$$

A structure of semi-empirical ANN-model corresponding to Eq. 1 is presented on Fig. 1 for the Euler difference scheme case. The semi-empirical model structure based on the Adams difference scheme looks similarly. The model is structurally adjusted by means of appropriate selection of the yellow-marked model subsystem which corresponds to multilayer perceptron (MLP) with one hidden layer. The training set for the MLP is obtained by numerical integration of Eq. 1 original mathematical model using random signal as an input. This model is trained in the Matlab Neural Network Toolbox using Levenberg-Marquardt optimization algorithm. The Jacobian matrix needed to run this algorithm is calculated by means of RTRL (Real-Time Recurrent Learning) technique [9, 10].

As it was mentioned already, accuracy characteristics are compared for traditional empirical NARX (Nonlinear AutoRegression with eXogeneous inputs) type model and the proposed semi-empirical model with the structure shown on Fig. 1. Obtained results confirm efficiency of the proposed simulation approach in comparison with traditional ANN-based empirical approach. For example, value of the mean square error (MSE) for a typical simulation run is 0.01394 for the semi-empirical ANN-model based on the Euler difference scheme and 0.02821 for the NARX model. Replacement of the Euler scheme by the Adams difference scheme [5] leads to a slight enhancement of the semi-empirical ANN-model accuracy. The MSE value is 0.01219 for this case. The difference between MSE for semi-empirical an empirical models increases with complexity growth of a simulated system. Simulation data contained in Table 1, Table 2 and Table 3 demonstrate this tendency for Eq. 1 system and its versions.

Table 1 Simulation error for the system described by Eq. 1

	ODE	ANN-1	ANN-2	ANN-3	Opt
Euler	0.13947	0.13593	0.12604	0.01394	–
Adams	0.07143	0.07104	0.03883	0.01219	–
NARX	–	–	–	–	0.02821

Table 2 Simulation error for the case with second equation Eq. 3

	ODE	ANN-1	ANN-2	ANN-3	Opt
Euler	0.15684	0.15224	0.14079	0.01400	–
Adams	0.07931	0.07858	0.05312	0.01185	–
NARX	–	–	–	–	0.03418

Table 3 Simulation error for the case with second equation Eq. 4

	ODE	ANN-1	ANN-2	ANN-3	Opt
Euler	0.18052	0.16880	0.15379	0.01272	–
Adams	0.15394	0.14970	0.13111	0.01266	–
NARX	–	–	–	–	0.08403

3 Semi-empirical simulation of short-period longitudinal aircraft motion

The short-period longitudinal aircraft motion simulation problem is discussed in the paper as the second example to demonstrate capabilities of the semi-empirical simulation approach. This kind of motion is described traditionally by means of a system of ordinary differential equations (ODE) which can be written for example in the form [11]:

$$\begin{aligned} \dot{\alpha} &= q - \frac{\bar{q}S}{mV} C_L(\alpha, q, \varphi) + \frac{g}{V}, \\ \dot{q} &= \frac{\bar{q}Sc}{J_y} C_m(\alpha, q, \varphi), \\ T^2\ddot{\varphi} &= -2T\zeta\dot{\varphi} - \varphi + \varphi_{act}, \end{aligned} \tag{5}$$

where α is angle of attack, deg; q is pitch angular velocity, deg/sec; φ is deflection angle of elevator, deg; C_L is lift coefficient; C_m is pitching moment coefficient; m is mass of aircraft, kg; V is airspeed, m/sec; $\bar{q} = \rho V^2/2$ is airplane dynamic pressure; ρ is mass air density, kg/m^3; g is acceleration of gravity, m/sec^2; S is wing area of aircraft, m^2; c is mean aerodynamic chord, m; J_y is pitching moment inertia, kg $\cdot$ m^2. Dimensionless coefficients C_L and C_m are nonlinear functions of angle of attack; T, ζ are time constant and relative damping factor for elevator actuator; φ_{act} is command signal value for the elevator actuator limited by $\pm 25°$. Variables α, q, φ and $\dot{\varphi}$ are aircraft states, variable φ_{act} is aircraft control.

The resulting "gray box" neural network based model includes two "black box" modules that correspond to lift and pitching moment coefficients and represent a nonlinear function of the angle of attack and some other flight parameters. These neural network based modules are subject of refinement process accomplished through learning procedures, with values of observable state space variables used as a training dataset.

It is needed to determine relationships for C_L and C_m coefficients using available experimental data to make this model more concrete. Such kind of problem represents well-known system identification problem for aircraft. The identification problem is solved to achieve required simulation accuracy for aircraft motion.

The structure of semi-empirical ANN-model corresponding to Eq. 5 is presented on Fig. 2. The adjusted subnets of the model in this case correspond to the C_L and C_m relationships represented as MLP with one hidden layer.

The training dataset should be representative

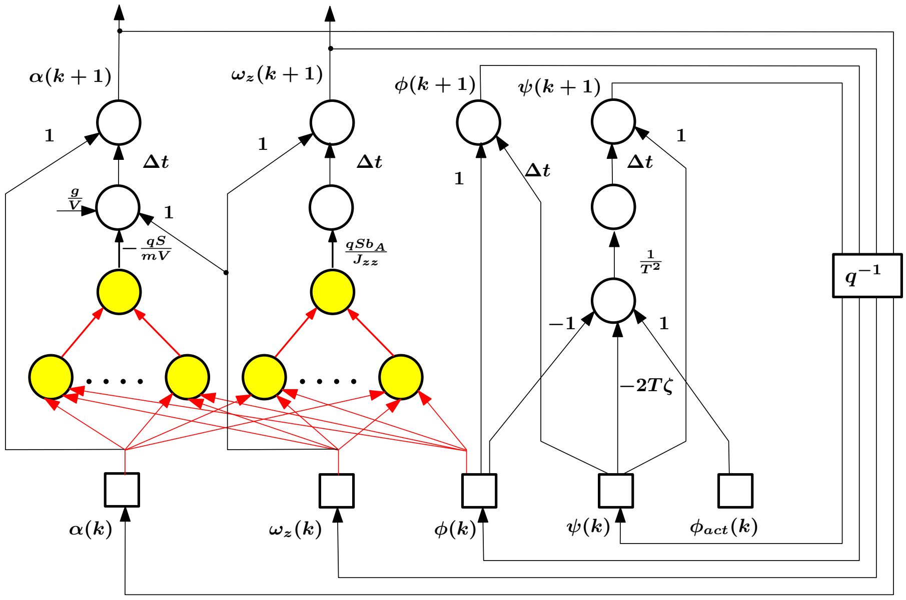

Fig. 2 Structural organization of semi-empirical ANN-model for dynamic system Eq. 4 according to the Euler difference scheme

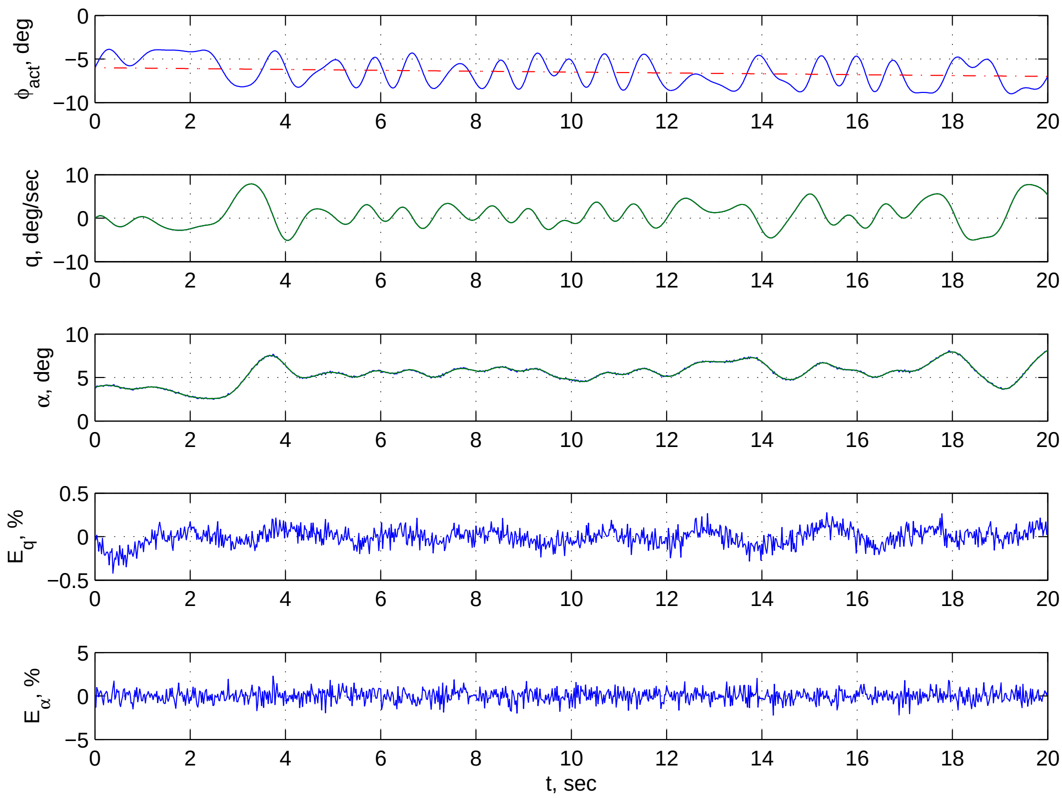

Fig. 3 Simulation results for semi-empirical model of aircraft short-period longitudinal motion: plant output, model output and flight maneuver are marked with green, blue and red color respectively

to obtain the model with needed accuracy level. An analysis was carried out to reveal an influence of control signals disturbing a motion of the vehicle on the training set representativity. Sequences of typical control signals such as step, pulse, doublet and random signal were compared to a multisine signal constructed by means of special procedure. Aforementioned comparison was conducted under various flight maneuvers, including steady state straight line horizontal flights ("point mode") and flights with angle of attack linear increasing ("monotonous mode").

The training set $\{\alpha_i, q_i, \varphi_i, \dot{\varphi}_i\}$, $i = 1, \ldots, N$ for this identification problem was obtained by numerical integration of Eq. 5 mathematical model using polyharmonic signal as an input [13]. An ANN-based semi-empirical model corresponded to Eq. 5 were derived according to the [6] with C_L and C_m represented as multilayer perceptrons (MLP) with one hidden layer. This model is trained in the Matlab Neural Network Toolbox using Levenberg-Marquardt optimization algorithm. The Jacobian matrix needed to run this algorithm is calculated by means of RTRL (Real-Time Recurrent Learning) technique [9, 10]. As a result, relationships for aerodynamic coefficients C_L and C_m are obtained according to the available experimental data. These relationships used in the semi-empirical model ensure high simulation accuracy.

Simulation results for one of numerous runs concerning to the short-period longitudinal aircraft motion problem are demonstrated in Table 4 and on Fig. 3. These results were obtained with regard to F-16 fighter aircraft using the data published in [12].

Accuracy characteristics are compared for traditional empirical NARX (Nonlinear AutoRegression with eXogeneous inputs) type models and proposed semi-empirical model. The obtained results confirm efficiency of the proposed simulation approach in comparison with traditional ANN-based empirical approach. For example, values of the mean square error (MSE) for a typical simulation run (polyharmonic test signal, monotonous mode) are $\mathrm{MSE}_\alpha = 0.0491$ grad, $\mathrm{MSE}_q = 0.1169$ grad/sec for the semi-empirical model and $\mathrm{MSE}_\alpha = 1.3293$ grad, $\mathrm{MSE}_q = 2.7445$ grad/sec for the NARX model.

4 Semi-empirical simulation of spatial aircraft motion

Similar results are obtained also for a more complicated short-period spatial (three-dimensional) aircraft motion problem. There are three input variables in this problem instead of one variable in the problem mentioned above: ailerons, rudder and elevator deflection angles. Accordingly, five relationships (for lift and side force coefficients, pitching moment, rolling moment and yawing moment coefficients) instead of two ones are needed to be restored basing on available experimental data.

Simulation results for one of numerous runs are demonstrated on Fig. 4 and Fig. 5, where α is angle of attack, deg; q is pitch angular velocity, deg/sec; φ is deflection angle of elevator, deg; φ_{act} is command signal value for the elevator actuator, β is sideslip angle, deg; r is yaw angular velocity, deg/sec; δ is deflection angle of rudder, deg; δ_{act} is command signal value for the rudder actuator; p is roll angular velocity, deg/sec. These results, similar the longitudinal motion case discussed above, were obtained with regard to F-16 fighter aircraft basing on the data published in [12].

Values of the mean square error (MSE) for a typical simulation run (random test signal, point mode) are $\mathrm{MSE}_\alpha = 0.0171$ grad, $\mathrm{MSE}_q = 0.0399$ grad/sec, $\mathrm{MSE}_\beta = 0.0080$ grad, $\mathrm{MSE}_r = 0.0193$ grad/sec, $\mathrm{MSE}_p = 0.0972$ grad/sec.

5 Conclusions

The obtained results demonstrate clearly that the ANN-based approach to complex nonlinear dynamic systems modelling is very effective from the standpoint of simulation accuracy, especially if we combine ANN training techniques with some knowledge about simulated object. This approach can be implemented for systems operating under various uncertainty conditions using adaptation mechanisms based on the ANN training tools.

Table 4 Simulation errors for various test sets (semi-empirical model)

	Point mode		Monotonous mode	
	MSE_α	MSE_q	MSE_α	MSE_q
Doublet	0.0202	0.0417	8.6723	34.943
Random	0.0041	0.0071	0.0772	0.2382
Polyharmonic	0.0029	0.0076	0.0491	0.1169

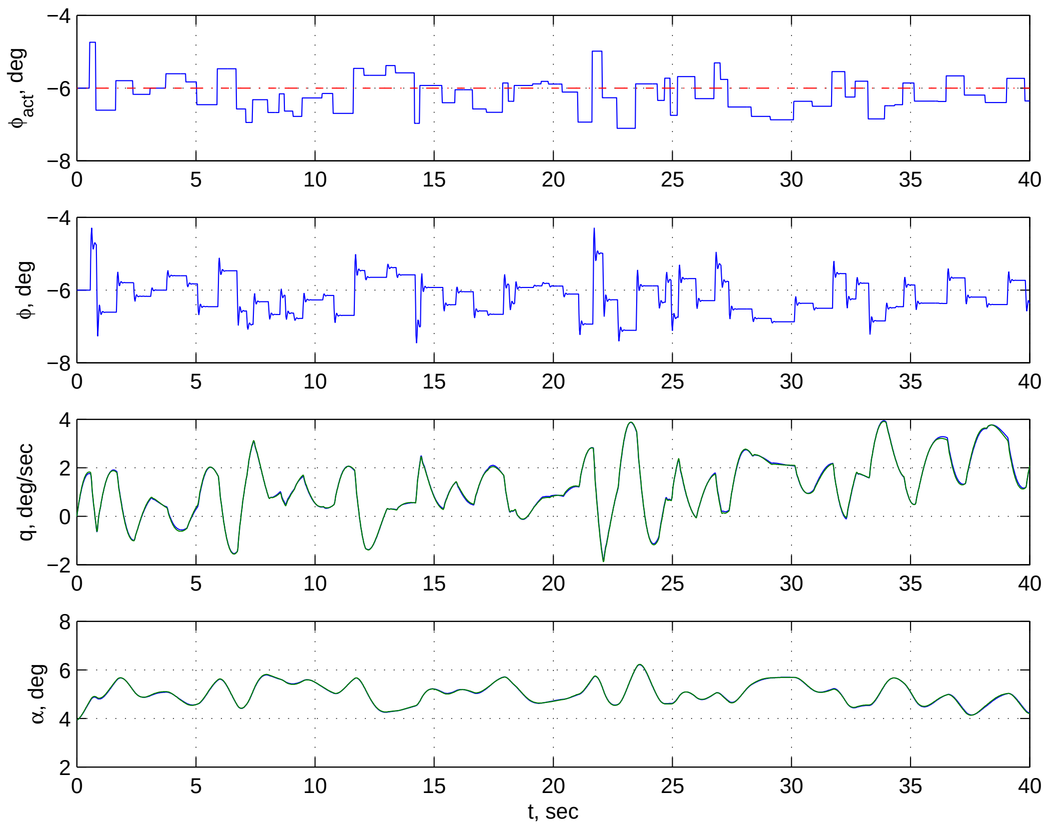

Fig. 4 Simulation results for semi-empirical model of aircraft short-period spatial motion: plant output, model output and flight maneuver are marked with green, blue and red color respectively

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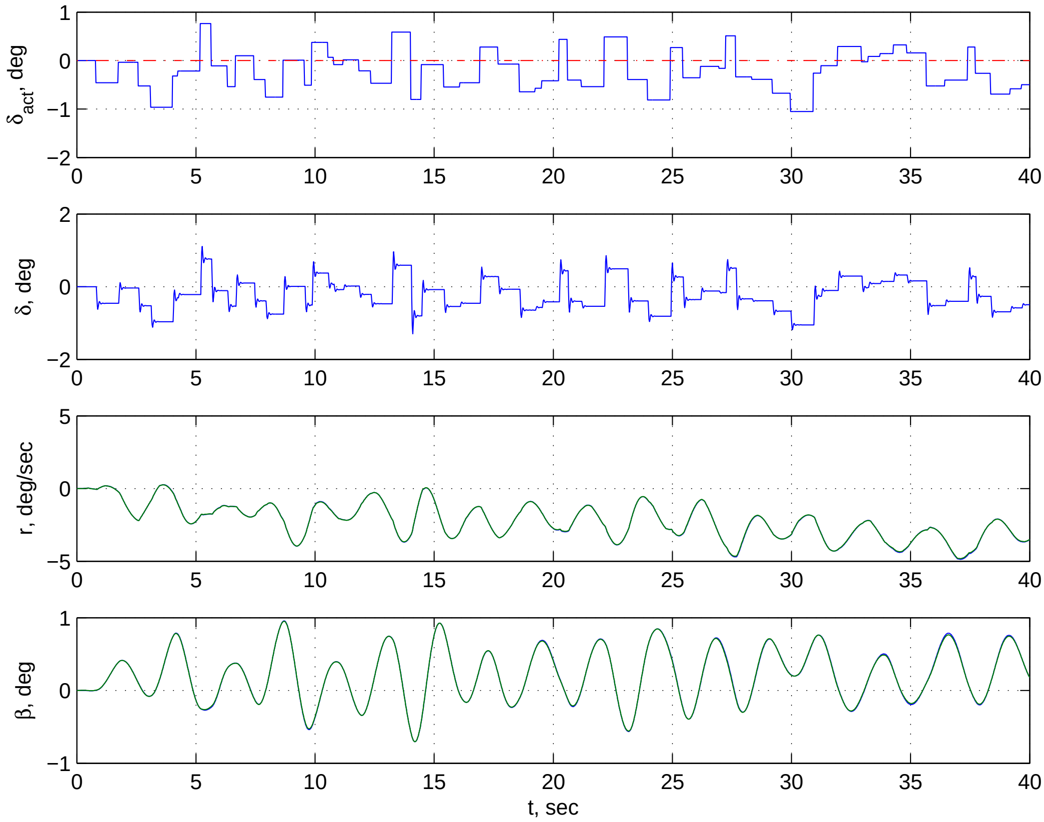

Fig. 5 Simulation results for semi-empirical model of aircraft short-period spatial motion: plant output, model output and flight maneuver are marked with green, blue and red color respectively

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