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Elaboration of Simulation Complex for Realization of Adaptive Neural Flight Control System to be used on Commercial Aircraft in Compliance with EASA-FAA Standards

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Abstract

In this paper, the typical scheme of the adaptive neuron technology of automatic control systems (ACS) of aircraft, which is adhered to by all the main developers of control systems, is considered. The theoretical justification of the current tendencies of reducing the volume of flight tests by increasing the volume of mathematical modelling and bench testing has been given.

Keywords: Automatic flight control system (ACS), mathematical modelling, simulation, visualization.

INTRODUCTION

For controlled dynamical systems, ordinary differential equations are most widely used as a modelling tool. These models, in combination with the corresponding numerical methods, are widely used in solving problems of synthesis and analysis of controlled motion of aircraft (AC) of various classes.

Methods for the formation and use of a model of the traditional type have been developed in sufficient detail to date and are successfully used to solve a wide range of problems. However, in relation to modern and promising complex technical systems, a number of problems arise, the solution to which cannot be provided by traditional methods. These problems are caused by the presence of various and numerous uncertainties in the properties of the corresponding system and in the conditions of its functioning, which can be countered only if the system under consideration has the properties of adaptability, that is, the means of operatively adjusting the control algorithm of the system and its model to the changing current situation. In addition, the requirements for the accuracy of models imposed on the basis of the specifics of the applied problem being solved, in a number of cases exceed the capabilities of traditional methods.

As the experience shows, the most adequate modelling apparatus for the current situation is methods and tools based on the concept of an artificial neural network. This approach can be regarded as an alternative to traditional methods of modelling dynamic systems, providing, among others, the possibility of obtaining adaptive models. At the same time, neural network models of dynamic systems in their traditional design, which are most often used for modelling controlled dynamic systems, are purely empirical ("black box" models), i.e. they are based solely on experimental data on the behaviour of the object. However, in problems of the level of complexity that is typical for aviation technology, it is very often that for such empirical models it is not possible to achieve the required level of accuracy, which provides, for example, the solution of problems of aircraft motion control. In addition, due to the peculiarities of the structural organization of such models, they do not allow solving the problem of identifying the characteristics of a dynamic system (for example, the aerodynamic characteristics of an aircraft), which is a serious drawback of this class of models.

One of the most important reasons for the low efficiency of traditional neural network models in problems associated with complex technical systems is that a purely empirical model ("black box") is being formed, which should cover all the nuances of the behaviour of a dynamic system. To do this, it is necessary to build neural network models of a sufficiently high dimension (i.e., with a large number of adjustable parameters in it). At the same time, it is known from modelling experience that the larger the dimension of the neural network model, the more training data is needed to set it up. As a result, given the amount of experimental data that can actually be obtained for complex technical systems, it is not possible to train such models and provide a given level of their accuracy.

To overcome this kind of difficulties, typical for traditional models of both types – in the form of differential equations and in the form of neural network models – it is proposed to use a Hierarchical-correlation method. It is based on neural network modelling, with the use of special software mathematical modules using adaptive control, and successfully tested at the beer stand of the Antonov State Enterprise.

1. HIERARCHICAL-CORRELATION METHOD FOR BUILDING AN ADAPTIVE NEURAL NETWORK

This method belongs to the category of synergistic networks. The network starts with only input and output neurons. During training, neurons are selected from the candidate pool and added tothe hidden layer. Hierarchical-correlation network and adaptive neural network (HCNANN) have a number of advantages over multilayer perceptron networks:

1. Since they are self-organising and grow a hidden layer during training, there is no need to worry about deciding how many layers and neurons to use in the network.
2. The training time is very fast - often two orders of magnitude faster than a network of perceptrons. This makes HCNANN suitable for large training sets.
3. Typically, feed-forward ANNs are small, often having less than a dozen neurons in the hidden layer. At the same time, probabilistic neural networks require a hidden layer of neurons for each training case.
4. HCNANN training is quite reliable, and good results can usually be obtained with little or no parameter adjustment.
5. HCNANN is less likely to fall into the trap of local minima than multilayer reception networks.

The disadvantages of this approach include the following:

1. They have an extraordinary potential for overfitting training data. This results in excellent accuracy for training data, but poor accuracy for new, unseen data.
2. It is possible that such networks may be less accurate than probabilistic and general regression neural networks on small and medium-sized tasks (less than a couple of thousand training series). This requires further research in this area. However, hierarchical correlation scales up to solvinglarge problems much better than probabilistic or general regression networks.

The architecture of the HCNANN consists of a structure in which hidden neurons are added to the network one by one and do not change after they are added. The hierarchy means that the output of all neurons already in the network is fed into the new neurons. When new neurons are added to thehidden layer, the learning algorithm tries to maximise the correlation between the output of the new neuron and the residual error of the network, which should be minimised.

HCNANN has three layers: input, hidden and output.

Input layer: a vector of values of predictor variables ($x_1 \ldots x_p$) is represented by the input layer. The input neurons do not perform any action on the values except to distribute them to the neurons in the hidden and output layers. In addition to the predictor variables, there is a constant inputof 1.0, called the offset, which is fed to each of the hidden and output neurons; the offset is multipliedby a weight and added to the sum that goes to the neuron.

Hidden layer: When it arrives at a neuron in the hidden layer, the value from each input neuronis multiplied by a weight, and the resulting weighted values are added together to create a combined value. The weighted sum is fed into a transfer function that outputs the value. The outputs from the hidden layer are distributed to the output layer.

Output layer: For regression tasks, there is only one neuron in the output layer. For classification tasks, there is a neuron for each category of the target variable. Each output neuron receives values from all input neurons (including biases) and all hidden layer neurons. Each value presented to the output neuron is multiplied by a weight, and the resulting weighted values are added together to create a combined value. The weighted sum is fed into a transfer function that outputs thevalue. The **y-values** are the outputs of the network. For regression tasks, the output neurons use a linear transfer function. For classification tasks, a sigmoid transfer function is used.

Learning algorithm HCNANN.

Initially, a cascade correlation neural network consists only of input and output layer neuronswithout hidden layer neurons. Each input is connected to each output neuron by a connection with anadjustable weight.

Each '**x**' represents a weight value between the input and output neuron. The values on the vertical line are added together after multiplying by their weights. Thus, each output neuron receives a weighted sum from all input neurons, including the offset. The output neuron sends this weighted input sum through its transfer function to produce the final result. Even a simple HCNANN without hidden neurons has significant predictive power. For a considerable number of problems, a cascade correlation network with fair input and output layers provides excellent predictions.

The input weights for the hidden neuron are shown as square boxes to indicate that they are fixed after the neuron is added. The weights of the output neurons, shown as "x", continue to adjust. Here is a diagram of a network with two hidden neurons. Note how the second neuron receives inputs from external inputs and existing hidden neurons.

Theoretical knowledge about the object of modelling, existing in the form of ordinary differential equations (these are, for example, traditional models of aircraft movement), is introduced in a special way into a neural network model of a combined type (semi-empirical neural network model). At the same time, a part of the neural network model is formed on the basis of the available theoretical knowledge and does not require further tuning (training). Only those elements that contain uncertainties, for example, the aerodynamic characteristics of an aircraft, are subject to adjustment and / or structural adjustment in the process of training a neural network model is formed.

To meet the requirements of the EASA FAA, the development of a simulation complex for the implementation of an adaptive neural flight control system can be performed in a Safety Critical Application Development Environment (SCADE).

The design technology for ACS has largely developed by now.

There are three major developments in design technology:

- development of software for modelling the dynamics of controlled movement of aircraft;
- software development (onboard programs);
- development of a bench complex for semi-natural modelling, which completes the development stage before flight tests.

The software allows for selecting and justifying the structure of the AFSC settings, analysing the stability of the system and proving the fulfilment of the requirements of the technical specification for the control system with a given probability.

The development of software ends with the synthesis of control algorithms based on a complete mathematical model of a closed control loop, including, among others, statistical modelling (Fig.1).

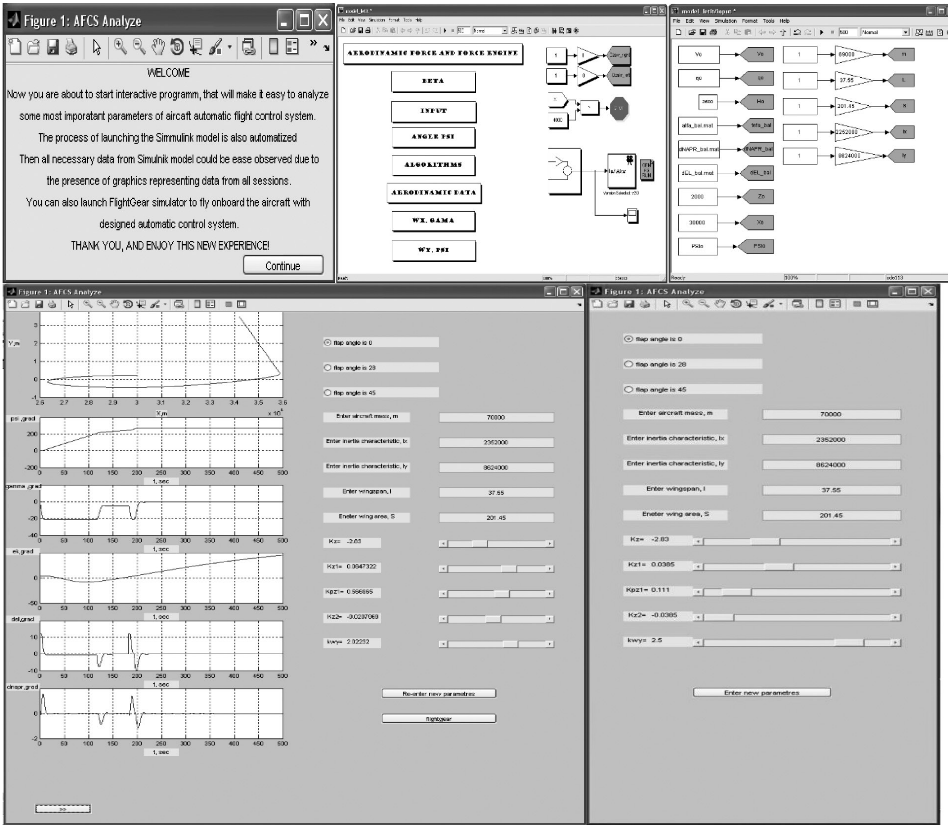


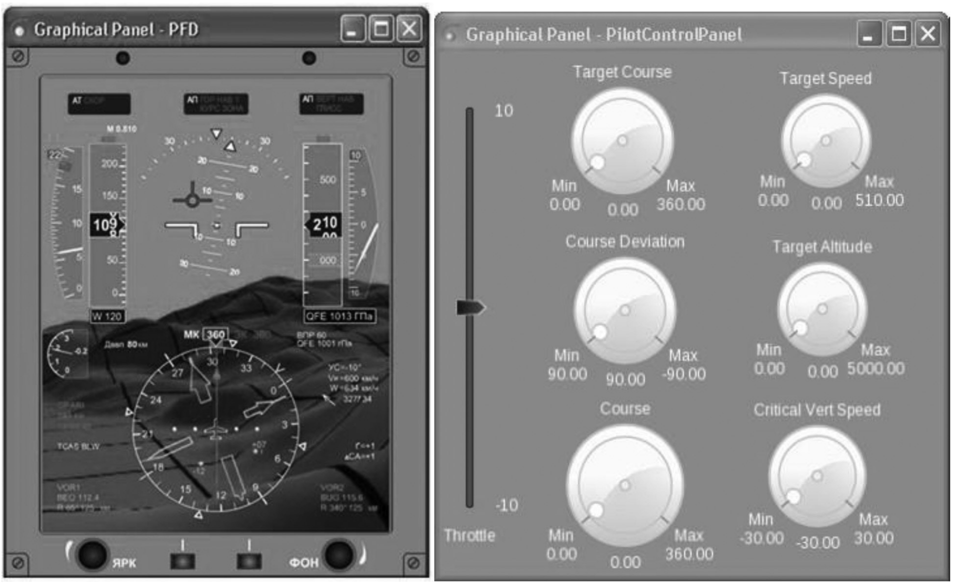
Fig.. 1. Development of the program for ACS development and analysing.

Software development refers to the development of onboard programs that implement synthesized algorithms. After the development of the stand complex, the development of a closed control loop should be done, which includes real computers, drives, and control panel. The developed stand complex is a symbiosis of hardware and software, which has versatility and allows quite simply reconfigure it for any aircraft with its aerodynamics, traction and inertial characteristics, control wiring, steering system and other features. When conducting mathematical modelling, blocks of deterministic and statistical modelling are provided.

The block of aerodynamic characteristics includes numerical data on the components of these characteristics, obtained from the aircraft designer, interpolation program in two, three variables, mass-director and combined trajectory control.

The outputs of the trajectory algorithms are signals that are transmitted to the control elements of the aircraft (elevator, ailerons, rudder, spoilers, stabilizer, etc.) or directly to the drives.

The mathematical model includes a block for graphical presentation of results and a block for statistical processing of simulation results (Fig. 2), which makes it possible to estimate thread the system for compliance with the requirements of technical specification.



a) b)

Fig. 2. a) Display of flight data processing results. Source: Author
b) Control panel for the virtual flight test bench display. Source: Author

Neural network simulations is the basis of Simulation complex for adaptive neural flight control system which will employ some software and mathematical modules that use adaptive control and have been successfully tested at the semi-natural stand of the Antonov company, as part of the work on the development of AN-158 and AN-178 aircraft. Neural adaptive control system with hierarchical-correlation neural grid (HCNG) is proposed, which refers to the direct-distribution artificial neural mesh with variable growing architecture. This hierarchical-correlation neural grid (NG) is formed as a multilayer grid of special hierarchical architecture. The specificity lies in the fact that it can be taught in a constructive way – when convergence to the neural grid is stopped, new neurons are gradually added. With further training, connections are added for added neurons. The HCNG formed in this way is an adequate task of managing a dynamic object. As a result, computational learning costs are significantly reduced. Such learning parameters as architecture, the size of the NG, or the parameters of the speed of learning are determined by the learning process itself.

Such an approach will allow to overcome the difficulties typical for traditional neural network models, such as the construction of a neural network model of a sufficiently high dimension (i.e., with a large number of adjustable parameters). At the same time, it is known from modelling experience that the larger dimension of the neural network model, the more training data is needed to set it up. As a result, given the amount of experimental data that can actually be obtained for complex technical systems, it is not possible to train such models and provide a given level of their accuracy.

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