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# Adaptive neural network motion control for aircraft under uncertainty conditions

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**Abstract.** We need to provide motion control of modern and advanced aircraft under diverse uncertainty conditions. This problem can be solved by using adaptive control laws. We carry out an analysis of the capabilities of these laws for such adaptive systems as MRAC (Model Reference Adaptive Control) and MPC (Model Predictive Control). In the case of a nonlinear control object, the most efficient solution to the adaptive control problem is the use of neural network technologies. These technologies are suitable for the development of both a control object model and a control law for the object. The approximate nature of the ANN model was taken into account by introducing additional compensating feedback into the control system. The capabilities of adaptive control laws under uncertainty in the source data are considered. We also conduct simulations to assess the contribution of adaptivity to the behavior of the system.

## 1. Introduction

We need to provide motion control of modern and advanced aircraft under diverse uncertainty conditions [1, 2]. The aircraft control system should be able to adapt quickly to the current changes in the situation to ensure flight safety in such conditions. We analyze in this article the capabilities of adaptive control algorithms concerning aircraft motion for the two well-known types of such systems, namely, MRAC (Model Reference Adaptive Control) and MPC (Model Predictive Control) [3-5]. Both these schemes of adaptive control (Figure 1) require a model of the control object. As shown in [6-12], in the case of a nonlinear control object, the most effective solution to the problem of adaptive control is the use of neural network technologies. These technologies are suitable for the development of both a control object model and a control law for the object.

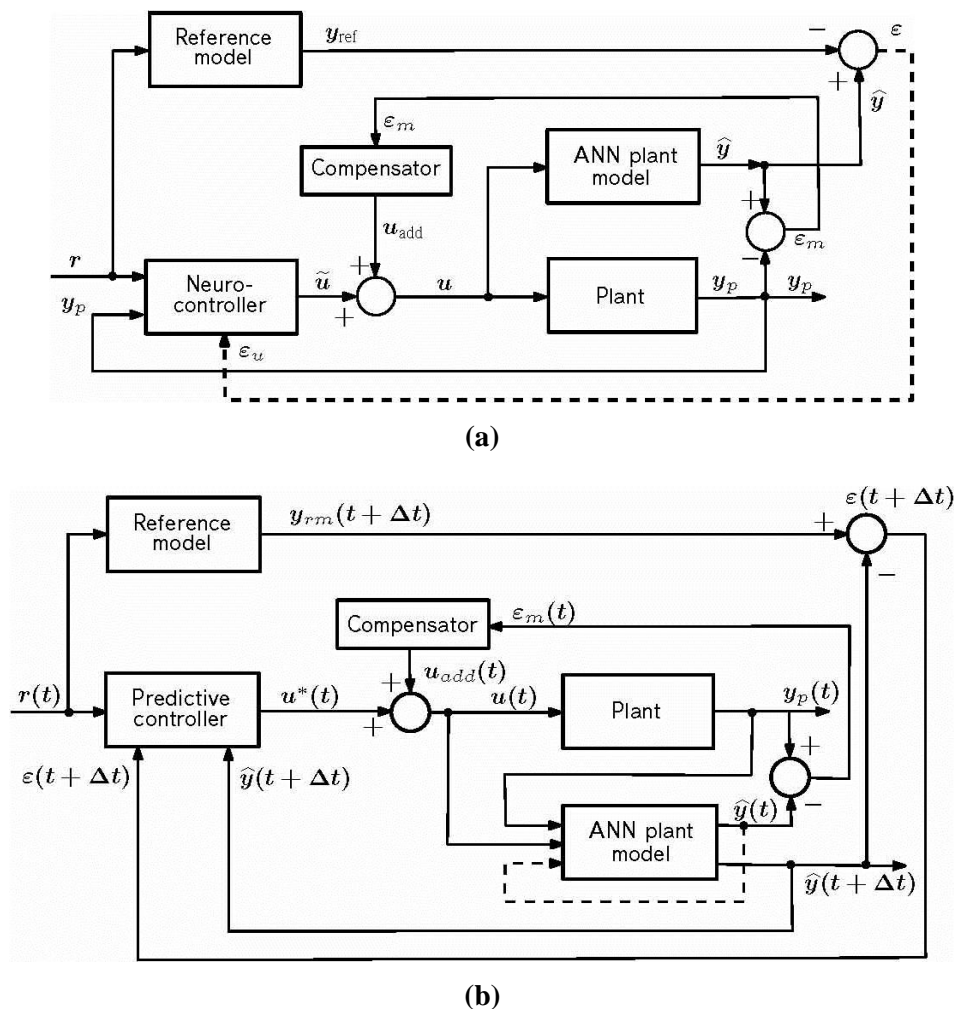
## 2. Ensuring robustness of adaptive control system

The studied schemes of adaptive control essentially use the ANN models of the control object as a source of information about the behavior of this object. Since, due to the approximate nature of the ANN model, the real values of the variables describing the motion of the object inevitably differ from those obtained as the outputs of the ANN model, an error appears that reduces the quality of control. One possible approach to compensate for this error is that the inaccuracy of the ANN model we can interpret as some disturbance on the system. This disturbance causes the deviation of the trajectory of the real object from the reference trajectory. We can reduce the impact of this effect by introducing a compensating loop into the control system.



In the schemes shown in Figure 1, a PD-compensator is used. It realizes, through additional feedback, a correction signal of the form  $u_{add} = K_p e + K_d \dot{e}$ , where  $e$  is the difference between the outputs of the control object and the ANN model of this object. The simulation results show that, despite the simplicity, the compensating loop reduces the tracking error (the difference between the outputs of the control object and the reference model) about an order of magnitude.

As a model of the control object, a neural network such as NARX (Nonlinear AutoRegression with eXternal inputs) is used in the MRAC and MPC schemes [6-8]. The same network we use in the MRAC scheme as the neural controller. In the MPC scheme, the predictive controller implements the parametric optimization algorithm.



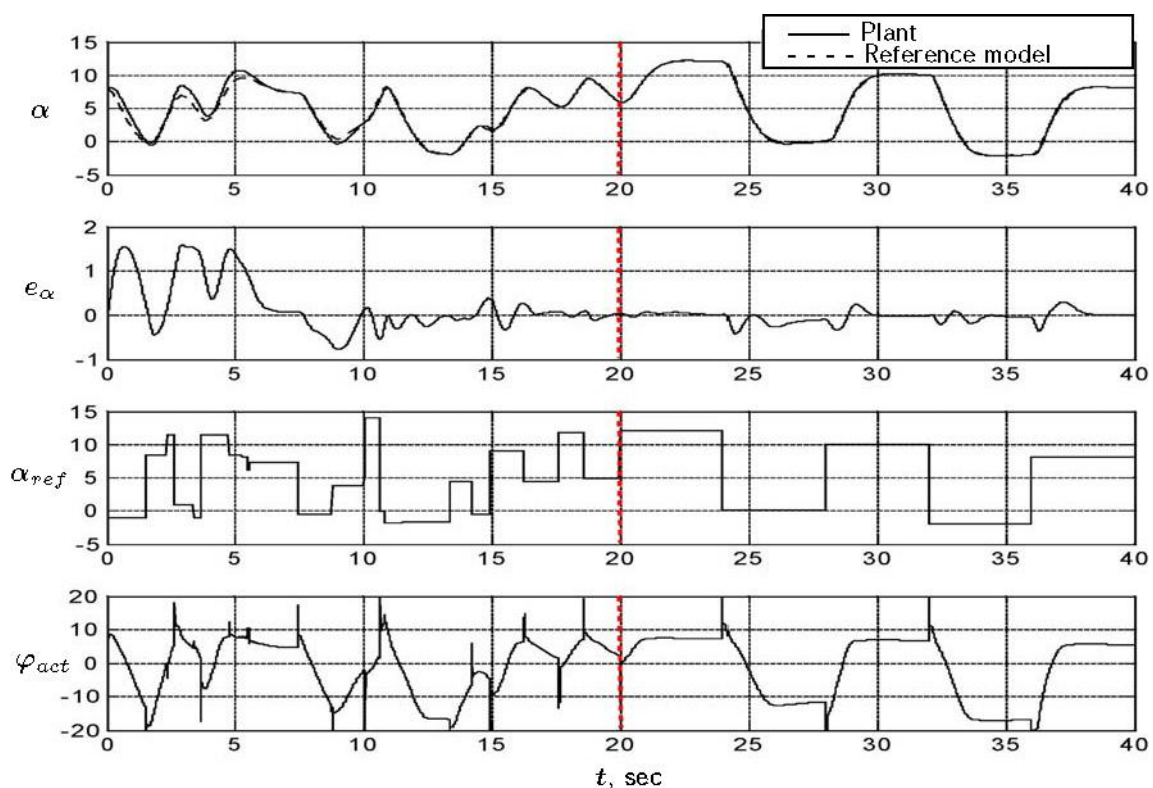
**Figure 1.** Adaptive control schemes: (a) Model Reference Adaptive Control (MRAC); (b) Model Predictive Control (MPC).

### 3. Adaptation to uncertainty in source data

With the adaptive control schemes shown in Figure 1, a series of simulations were carried out to evaluate the capabilities of such systems. As the control object, Hyper-X research hypersonic vehicle was used [13-16]. The uncertainty that we simulated in these computational experiments is an inaccurate knowledge of the dynamics of the control object. For such an imitation, the synthesis of the control law we apply to one flight mode (Mach number and flight altitude), and then the control law began to work under significantly different conditions.

The simulation results are shown in Figure 2 for the problem of stabilizing the longitudinal angular motion of Hyper-X vehicle. We use here the following notation:  $\alpha$  is Hyper-X angle of attack;  $\alpha_{ref}$  is reference signal for the angle of attack;  $e_\alpha$  is the tracking error for the reference signal;  $\varphi_{act}$  is command signal for the elevator actuator. Here, we synthesize the control law for the  $M = 7$ ,  $H = 32$  km flight regime, and the testing was carried out for the  $M = 5$ ,  $H = 28$  km regime.

The results shown in Fig. 2, demonstrate the operation of the control system for two time intervals of 20 seconds each. On the first of them, the adaptation of the control law is carried out by feeding a perturbing signal on the input of the control system (this signal is an actively changing reference value  $\alpha_{ref}$  for the angle of attack  $\alpha$ ). In the second interval with the same duration, the system is tested with a sequence of step input signals spaced apart in time so that the disturbed motion caused by the applied signal can attenuate until the next signal is applied. If this condition is met, then we can assume that the system in one session is tested by a set of independent step input signals, differing in magnitude.

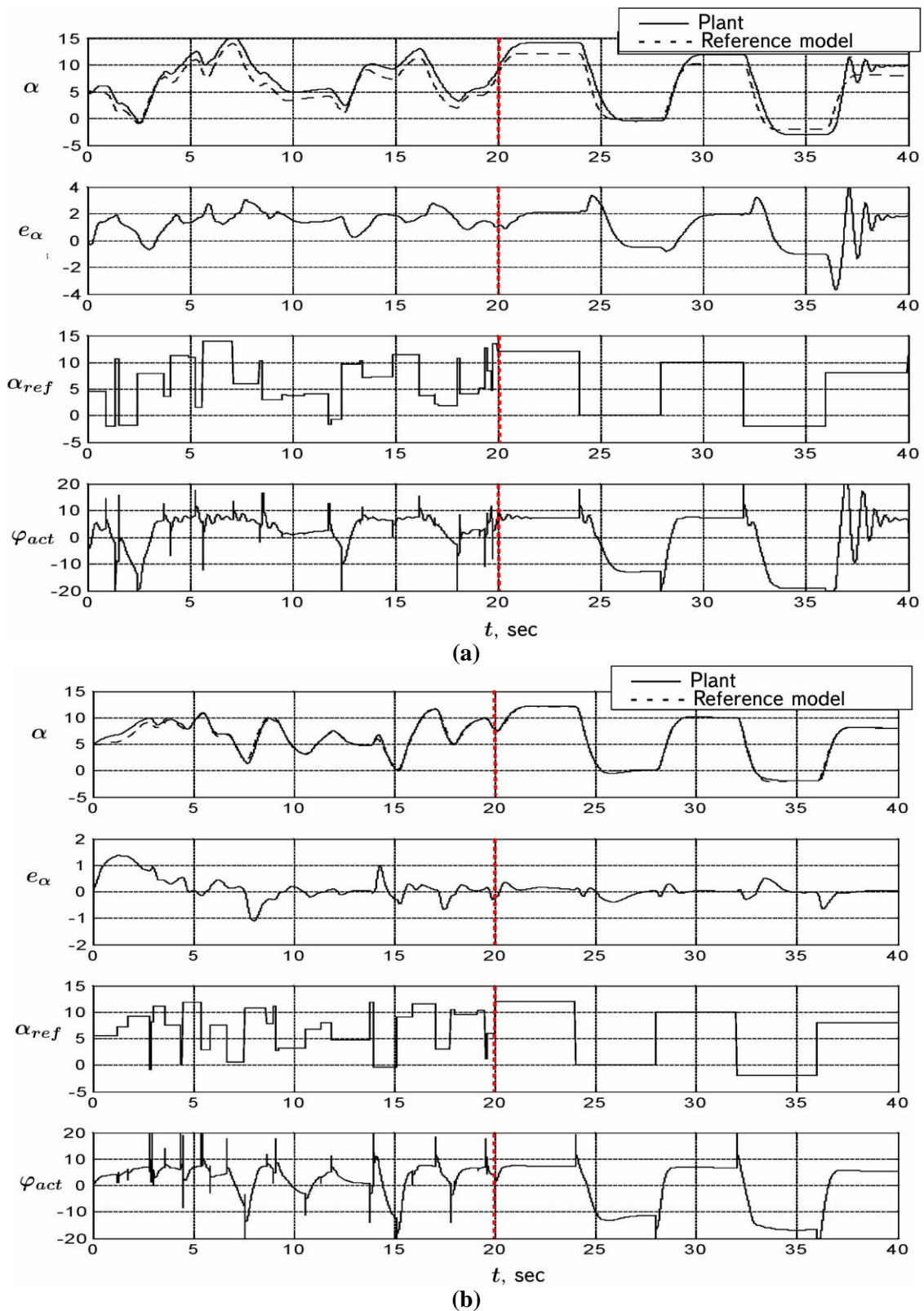


**Figure 2.** Adaptation to inexact source data for MRAC scheme (adaptation of the control law is for  $0 \leq t \leq 20$  sec and testing for  $20 \leq t \leq 40$  sec).

#### 4. Efficiency evaluation of adaptation mechanisms

To evaluate the contribution of adaptivity and robustness in the system behavior, we conduct experiments in which we disconnect the adaptation mechanisms. The mechanism to ensure robustness of the system in the form of a compensating loop (Figure 1) remained switched on.

In the performed experiments, the results of which for MRAC scheme are presented in Figure 3, the operation time of the system was divided, as in the experiments with robustness (Figure 2), into two segments with a duration of 20 seconds each. The nature of the signal  $\alpha_{ref}$  that is the reference value for the angle of attack is the same as in the previous case (Figure 2). Therefore, the first 20 seconds the reference signal is a random sequence of frequently changing values of the angle of attack. In this case, the perturbation from the input signal is not yet wholly damped, as the next reference signal acts on the object.



**Figure 3.** Efficiency evaluation of adaptation mechanisms for MRAC scheme: (a) the adaptation mechanism is disabled; (b) the adaptation mechanism is enabled (adaptation is for  $0 \leq t \leq 20$  sec and testing for  $20 \leq t \leq 40$  sec).

This kind of complicated reference signal allows us to estimate the cumulative effect of several disturbances, the reactions from the impact of which overlap in time. This approach makes it possible to test the control system under rather severe conditions. In the second time interval, the control system is tested using a more traditional input signal, which makes it possible to evaluate the behavior of the system for isolated step disturbances. As we can see from the results presented in Figure 3, the lack of adaptation mechanisms leads to a sharp deterioration in the quality of motion control. Namely, values of the tracking error  $e_\alpha = \alpha_{ref} - \alpha$  are within  $\pm 2^\circ$ , and, in some cases, even within  $\pm 4^\circ$ . For the MPC system, the results are similar.

Thus, the adaptation mechanisms significantly reduce the tracking error and expand the frequency band in which the error does not exceed some preset value. It follows that if a system has adaptive properties, this allows it to deal with a much broader class of parametric uncertainties in control objects.

## 5. Conclusion

The general conclusion, based on the results presented in this article, is that the methods of nonlinear adaptive-robust modeling and control in MRAC and MPC variants are a powerful and promising tool that allows us to efficiently solve the movement control tasks for aircraft under uncertainty conditions.

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