

Applying artificial neural networks to create a helicopter dynamic mathematical model on the basis of flight test data

Victor A. Anikin¹, Yurii N. Sviridenko²

¹ OAO "Kamov"

8 8 Marta Str., Lybertsy, Moscow reg., 140007, Russian Federation

e-mail: kb@kamov.ru

² Central Aerohydrodynamic Institute (TsAGI)

1 Zhukovsky Str., Zhukovsky, Moscow reg., 140160, Russian Federation

e-mail: sviriden@progtech.ru

Key words: artificial neural net, rotorcraft, flight test

Abstract: The task of creating a mathematical helicopter dynamic model is very important while designing new flying machines and improving the existing ones. Both number and experimental models are widely used in this case. The artificial neural nets (ANN) usage to form mathematical models of flying machines' characteristics while designing has proved to be a rather worth-while trend, a properly set neural network requiring little calculating resources. While the information necessary to set a network may be based on data acquired earlier during the study of similar machines, and may be enriched in the course of designing.

This research includes the study of using artificial neural networks to create mathematical models of a helicopter dynamics based on the flight experiment data. Flight test data processing and creating on this basis rotorcraft's mathematical model characteristics is a rather involved process due to a large dimension of variables which has to be taken into consideration while creating the model. Using ANN to solve such problems is very convenient as the networks easily endure the task dimension increase, they do not demand that the data be sorted beforehand, allow to effectively process large amounts of experiment information and find out what data is missing.

As a data set for setting network coefficients and a test of helicopter dynamic models calculated on this basis the records of two helicopter Ka-226 flight tests with a total length of about 80 minutes were used. This data was used to set a series of neural networks that allow calculating a helicopter's trajectory and its angular position in accordance with a control device position. The research includes the evaluation of calculated trajectory parameters in comparison with the flight test data.

This work also deals with using artificial neural networks to calculate the law of piloting a helicopter according to a given trajectory.

On the basis of a suggested method helicopter's balance characteristics were calculated and compared with real balance characteristics.

INTRODUCTION

Nowadays artificial neural nets are successfully applied to solve a wide range of problems concerning rotorcraft dynamics and aerodynamics. [1-4]. Minimal computing requirements make it possible to use them at on-board calculating complexes while creating modern rotorcraft control systems. This work deals with creating a mathematical model of helicopter dynamics on the basis of test flight results.

1. PROBLEM STATEMENT

The rotorcraft trajectory can be defined with the following system of equations:

$$\dot{\vec{X}} = A\vec{X} + B\vec{U}$$

where \vec{X} – is a flight parameters vector;

\vec{U} –controlling vector.

Within the traditional approach this system of equations is either solved with applying the set controlling or defined by the rotorcraft control (considering the restrictions), which (the control) ensures the set rotorcraft trajectory. Matrix A and B coefficients are defined within aerodynamic experiments and calculations.

A neural net “learned” with the flight (wind-tunnel) experiment of flight simulator modelling is applied to solve similar tasks. In this case there is no need in defining the equations that describe the object dynamics and the same approach is used to define both the rotorcraft trajectory and the controlling that would ensure the set trajectory. The general scheme of applying neural nets to solve dynamic problems is shown in Fig 1a).

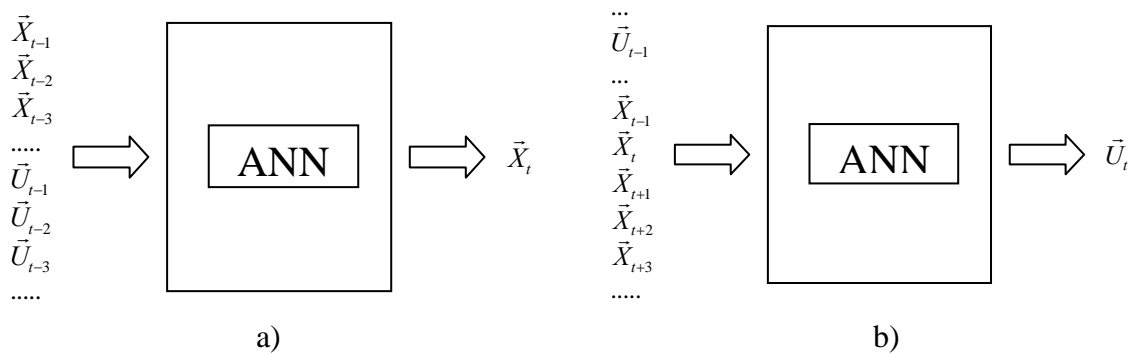


Figure 1.

A learned artificial net is given a vector containing the object description and controlling parameters during previous time steps, and the output vector contains the object parameters during the next time step. This vector may again be given to the net, and we get the parameters for the time step (t+1). It must be said that a learned net is a function with a large number of parameters (weight coefficients) and requires very little computing resources.

While training a neural network forming a set of patterns becomes the cornerstone, as the training set quality and quantity ensures the solution of the problem. For the existing rotorcrafts the simplest method of forming a set of patterns is using the flight tests data. This practically means forming a mathematical model of a real rotorcraft.

While defining the control parameters to ensure the set object trajectory the following scheme of neural net using is applied, see Fig. 1b. In this case the input vectors are vectors defining the trajectory parameters during the current $X(t)$, previous $X(t-1)$, $X(t-2)$... and following $X(t+1)$, $X(t+2)$, $X(t+n)$ time moments (the set trajectory) and controlling parameters within the previous step $U(t-1)$, $U(t-2)$, and the output vector is the one of control parameters $U(t)$ during the time moment t . The number of time steps is defined by the controlling system delay.

2. MAKING THE MODEL BASED ON KA-226 FLIGHT TEST DATA

The research to model the helicopter Ka-226 trajectory is given here as an example of this method application. The set of patterns for learning the neural nets was formed with the help of 2 helicopter transmitters records with a total time of ~5000 seconds. The data was recorded with a regular time interval of 0.125 seconds.

The vector of flight parameters contained the following variables:

$$\vec{X} = (\omega_x, \omega_y, \omega_z, n_x, n_y, n_z, \beta, \vartheta, \gamma, V_{ind}, H_{geom}, \psi)$$

$\omega_x, \omega_y, \omega_z$ – angular velocity

n_x, n_y, n_z – accelerations

β, ϑ, γ – angles of yawing, pitching, rolling

V_{ind} – indicator velocity

H_{geom} – geometrical height

ψ – angle of course

The control parameters vector contained the following variables (the position of control devices):

$$\vec{U} = (X_B, X_H, X_K, \varphi)$$

X_B, X_H, X_K – the position of control devices

φ – the collective pitch of rotor angle

While using the neural net to solve flight equations (Fig. 1) the input vectors were $\vec{X}_{t-1}, \vec{X}_{t-2}, \vec{X}_{t-3}, \vec{U}_{t-1}, \vec{U}_{t-2}, \vec{U}_{t-3}$ within three previous time steps, $\Delta t=0.125c$, and the output vector then was \vec{X}_t

For learning and testing the neural net all the set of patterns was divided into two parts: the learning set (about 75%) which was used to adjust the net coefficients and the testing set used to check the approximation accuracy.

The results after comparing flight parameters and the ones calculated with the help of a neural net (solid – flight results, dash – neural net) for a typical 30-second flight are shown in Fig. 2

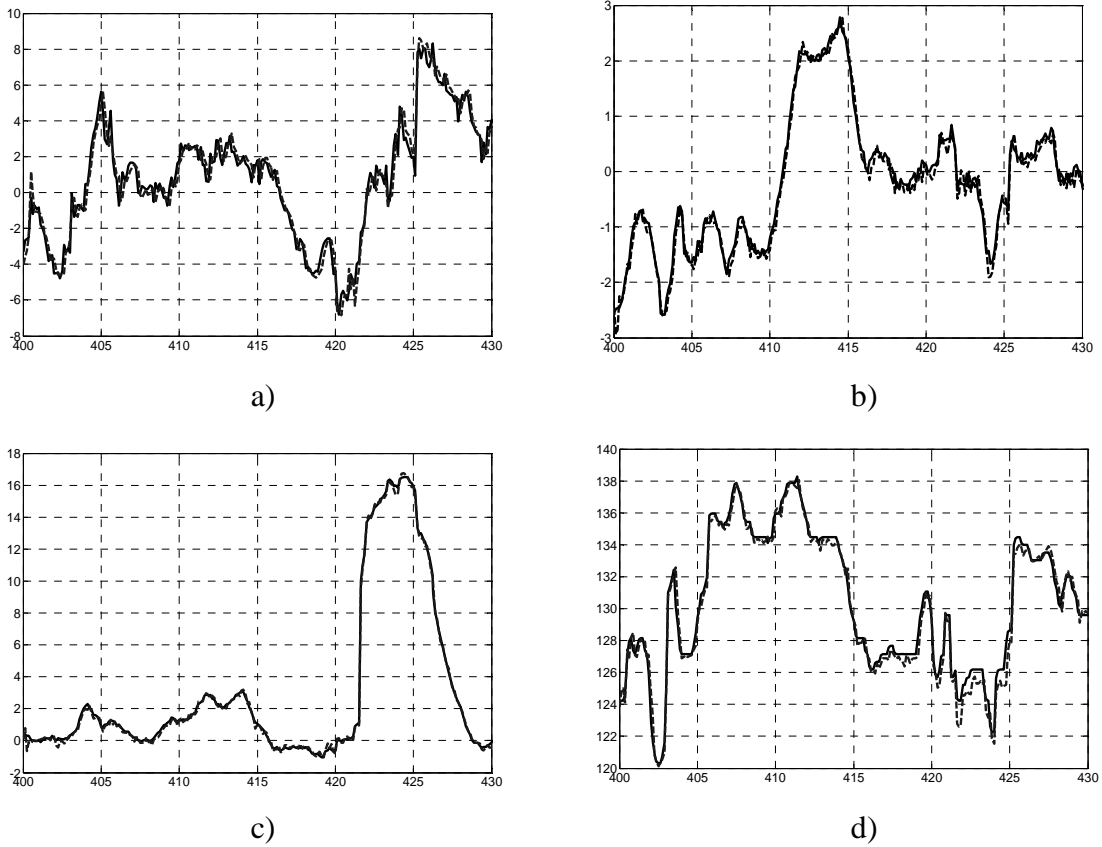


Figure 2, a) angle of yawing, b) angle of pitch, c) angle of rolling, d) indicator velocity, solid – flight results, dash - ANN

The scheme of applying ANN to define control parameters within the set trajectory parameters is shown in Fig. 1 b). The results of comparing real data with the data calculated by an ANN are shown in Fig. 3. The comparison was made on a basis of a flight interval (from the 400th to the 430th second) chosen at random.

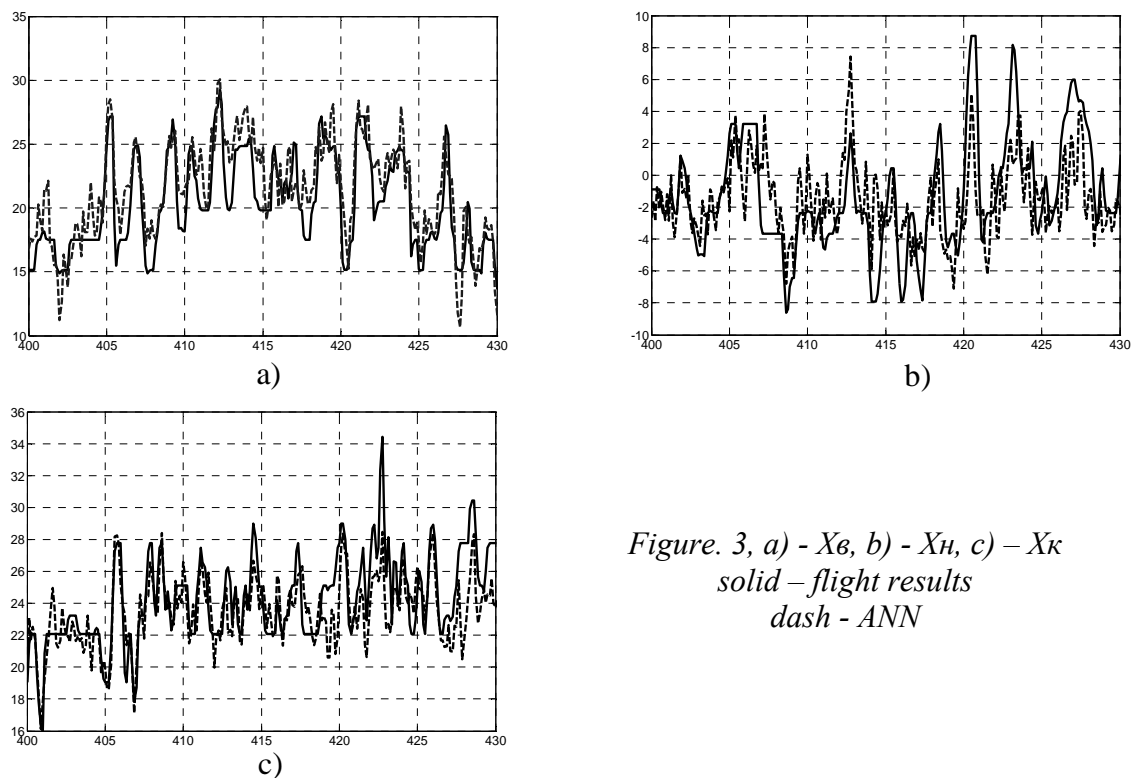


Figure. 3, a) - X_{θ} , b) - X_H , c) - X_{κ}
solid – flight results
dash - ANN

3. INTEGRATING THE FLIGHT TRAJECTORY WITH THE HELP OF A NEURAL NET

The task of applying neural nets to integrate flight equations at set control parameters is discussed in this chapter. The trajectory piloting is known (the flight experiment data), the basic and required within previous time steps flight parameters are known (from flight results), then we are able to define new flight parameters and turn them into input vectors. At the next integrating stages we use the trajectory parameters calculated by a neural net, and thus calculated flight trajectory is compared with the real (flight results) trajectory.

To solve this problem neural nets were learned to approximate each of the following flight parameters:

- pitching, rolling and course angles
- indicator velocity
- pitch rates
- course angle
- geometrical height

Further on the ANNs were used to calculate the trajectories with the help of the foregoing algorithm. In Fig. 4 we can see the results of research for a flight interval: blue lines stand for flight results, red ones stand for the ANN.

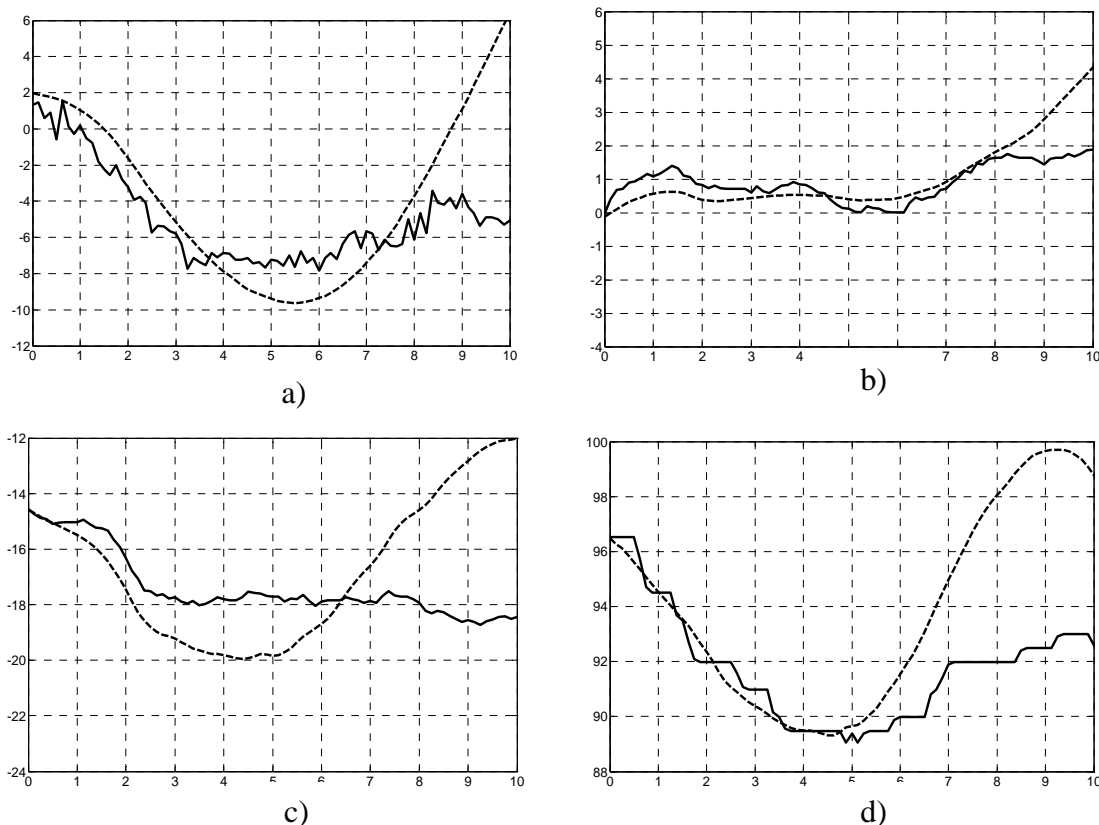


Fig. 4, a) yawing angle, b) angle of pitch, c) angle of rolling, d) Vind (km/h)
solid – flight results, dash – ANN

It can be seen that an accurate coinciding lies at the integrating with neural nets up to 2-4 seconds, further on the data becomes inexact as the integrating errors accumulate.

4. DEFINING BALANCING CHARACTERISTICS

In this chapter balancing characteristics are defined on the basis of calculated mathematical models of helicopter dynamics. To define them it was necessary to solve the problem of minimizing the following functional I. In fact the task was to define such controlling and stage variables vectors at which during the next time moment stage variables vector would stay the same.

$$I = (\vec{X}(t + \Delta t) - \vec{X}(t))^2$$

In this process of defining the stage vector at time moment $(t + \Delta t)$ neural net approximating the corresponding variables were used.

The functional was minimized only in case a part of stage variables was set. The results of defining balancing characteristics at different flight angles with a set speed of 120 km/h are shown in Fig. 5. For convenience, the points stand for the data calculated with traditional methods, when defining the balancing characteristics included special flight regimes.

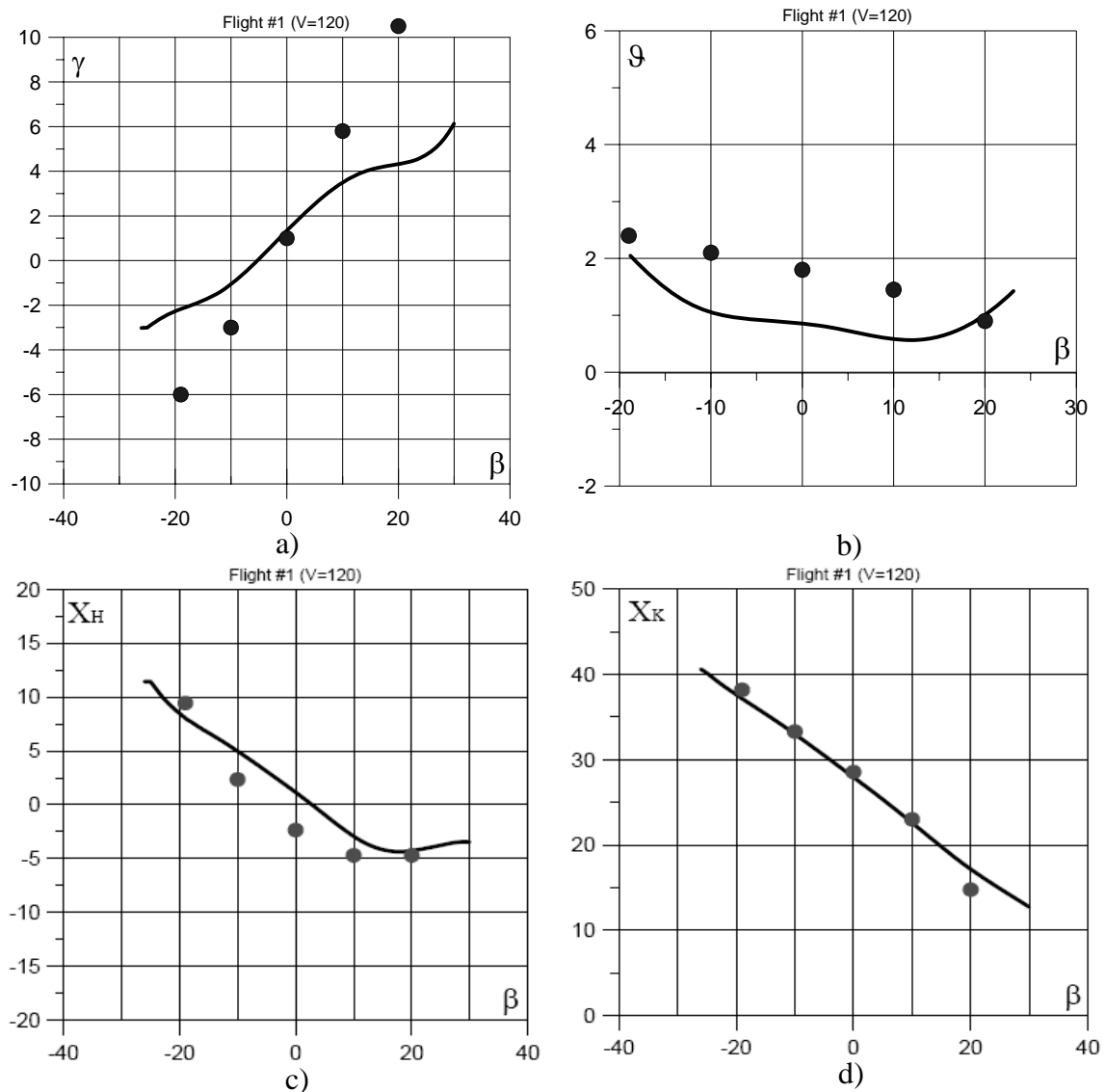


Figure 5, dependence of balance results on a) rolling angle, b) angle of pitch, c) X_H , d) – X_K on the yawing angle; points – flight, lines – ANN

CONCLUSION

This article dwells on the possibility of applying ANNs to form a mathematical model of a rotorcraft dynamics using the flight test results on the example of two recorded Ka-226 flights. The accuracy of the calculated model was defined. Also it states that this approach may be applied to define balancing characteristics of a helicopter based on flight test results without special regimes of flight.

REFERENCES

- [1] A. A. Bogdanov, E. A. Wan, M. Carlsson, Y. Zhang, R. Kiebertz, and A. Baptista. Model predictive neural control of a high fidelity helicopter model. In *AIAA Guidance Navigation and Control Conference*, Montreal, Quebec, Canada, August 2001. C.M. Bishop. Neural networks for pattern recognition, Clarendon press, Oxford, 1995.
- [2] A. Calise and Rysdyk. Nonlinear adaptive flight control using neural networks. In *IEEE Control System Magazine*, volume 18, No. 6, December 1998.
- [3] E.A. Dorofeev, V.V. Romanov, Yu.N. Sviridenko Application of Neural Networks Technology to Aerodynamic Problems. International Symposium on Aeronautical Sciences near Aviation Technologies of the XXI century, Flight Safety as a Pledge of Success. Zhukovsky, Russia, 17 – 22 August 1999.
- [4] Anikin V.A., Sviridenko Yu.N. Application of the neural networks for design and define aerodynamic characteristics rotor airfoils. VI Russian Rotorcraft Forum, Moscow, Russia, 2004.