SYNTHESIS AND USE OF A NEURAL NETWORK MODEL OF A VESSEL TO SOLVE CONTROL PURPOSE

Cherniavskyi V.V., Ben A.P., Zinchenko S.M.
Kherson State Maritime Academy
(Ukraine)

Introduction. The characteristics of the vessel change significantly over time due to the aggressiveness of the environment, the overgrowth of the hull with plankton, mollusks, which leads to the need to periodically refine them by conducting field tests. At the time of field tests, the vessel is decommissioned, which is associated with financial costs. In addition, the characteristics of the vessel change between field tests, increasingly different from the passport at the time of the last tests, which increases the risk of error in various operations (divergence, maneuvering near dangerous facilities for ships servicing oil and gas platforms, etc.). The theoretical foundations of classical identification methods are set out, for example, in [1] and other sources. Classical methods of parametric identification are focused on obtaining estimates of individual parameters of the mathematical model of the control object. For complex dynamic systems, which is a ship, obtaining the mathematical model itself is problematic and is based on the use of empirical formulas and coefficients [2]. All this makes significant errors in the mathematical model. Many works have been devoted to improving maritime safety, in particular, the study of psychological effects on control processes, the use of ergatic systems and automatic modules in automated systems [3-12]. The aim of this article is to develop algorithms that allow to estimate with mathematical accuracy the maneuverability of the vessel taking into account its individual characteristics and real parameters of immersion (displacement, depth and trim) by identifying its mathematical model and its further use to assess maneuverability.

Relevance of research. Recently, neural networks have become increasingly used in control systems, which has allowed to perform a variety of vessel control tasks, including identification tasks. Unlike classical identification methods, neural networks can identify not only individual parameters of a mathematical model, but also the whole mathematical model as a whole. This is especially important for purely nonlinear control objects, for which knowledge of the nature of interaction with the immersion medium is approximate (interaction of the propeller with water, interaction of the jet of water from the propeller with the rudder and hull, shallow water, precipitation and trim, etc.). Therefore, the solution of this problem is relevant.

Problem statement. In the general case, the vector equation of motion of the ship, as a nonlinear control object, can be written as finite differences:

$$X(n+1) = F(X(n-j), U(n-j), P(n-j)),\ j = 1..m \tag{1}$$

where $F(*)$ is a nonlinear operator for converting a sequence of ship state vectors $X(n-j),\ j=0..m$, sequences of control vectors $U(n-j),\ j=0..m$ and sequences of immersion parameter vectors $P(n-j),\ j=0..m$, on the current and previous steps of calculation in the vessel state vector $X(n+1)$ in the next calculation step (mathematical model of the vessel).

To identify the mathematical model represented by equation (1), the neural network (2) is chosen:

$$[X(n+1)] = NN^{2}_{8,10,3}[X(n), U(n), P(n)] \tag{2}$$

consisting of input, output and one hidden layer. The input layer consists of 8 neurons, the input of which receives: 3 parameters of the state vector $X(n) = (Vx(n), Vy(n), \Omega z(n))$, 2 control parameters $U(n) = (\theta(n), \delta(n))$ and 3 dive parameters $P(n) = (d(n), h(n), \Delta(n))$.

The hidden layer consists of 10 neurons. The number of hidden layers and the number of neurons in the hidden layers were selected experimentally by training the neural network. The output layer consists of 3 neurons for deriving the parameters of the state vector:

$$X(n+1) = (Vx(n+1), Vy(n+1), \Omega z(n+1))$$

at the (n + 1) calculation step.

All parameters included in equation (2) are available for direct measurement using the ship's linear and angular velocity sensors, telegraph and rudder angle deflection sensors, as well as draft, depth of keel and trim sensors. Thus, it is possible to obtain all the necessary training and reference samples for training the neural network during the normal operation of the vessel.

Research results. The research was conducted in the MATLAB environment. Neural network learning parameters: array of normalized training samples pn [8x3500], array size of normalized reference samples tn [3x3500], hidden tansig layer initialization function, purelin output layer initialization function, trainlm learning algorithm, m001 learning criterion, learning accuracy epochs 50. Figure 1 shows the results of neural network training on the collected training and reference samples. The training results showed a good quality of training for the selected structure.

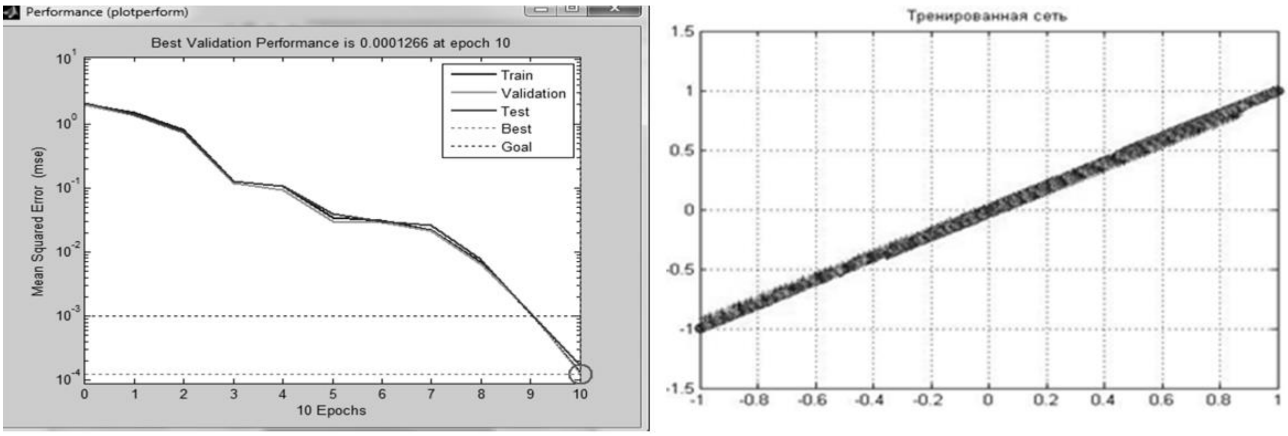

Figure 1 – The results of neural network training

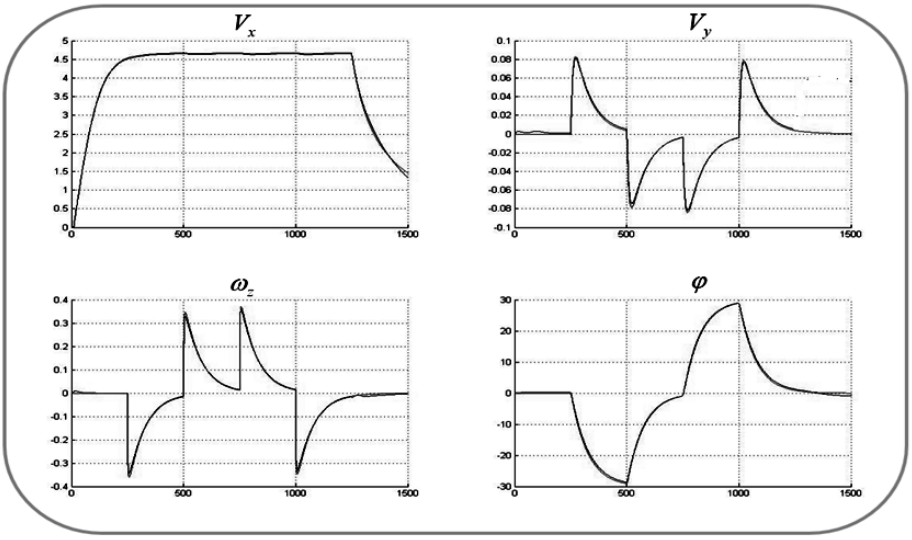

Figure 2 – Modeling results in MATLAB

Figure 2 shows the simulation results obtained using the original model (blue curve) and the simulation results obtained using the neural network (red line).

Conclusions. As the results of mathematical modeling show, assessment of the maneuverability of the vessel using a neural network model synthesized during its normal operation on the measured parameters of the state and control vector, is possible for all types of maneuvering (acceleration, braking, change of course, circulation) with high accuracy.

REFERENCES

1. V.A. Antonov, M.N. Pis'mennyj. Teoreticheskie osnovy upravleniya sudnom. – Vladivostok: MGU im.admirala G.I.Nevel'skogo, 2007. - 78 s.

2. Perez, T. Dynamic Positioning Marine Manoeuvring (2017). DOI: 10.1002/9781118476406.emoe110

3. Zinchenko, S.M., Nosov P.S., Mateychuk, V.M., Mamenko, P.P. & Grosheva, O.O. (2019). Automatic Collision Avoidance with multiple targets, including maneuvering ones. Radio Electronics, Computer Science, Control, № 4, pp. 211-221. DOI 10.15588/1607-3274-2019-4-20

4. Zinchenko S., Ben A., Nosov P., Popovych I., Mateichuk V., Grosheva O. The vessel movement optimisation with excessive control // Bulletin of University of Karaganda. Technical Physics, 2020. - № 3(99). P. 86-96. DOI: 10.31489/2020Ph3/86-96

5. Zinchenko S., Mateichuk V., Nosov P., Popovych I., Solovey O., Mamenko P., Grosheva O. Use of simulator Equipment for the development and testing of vessel control system // Electrical, Control and Communication Engineering. Sciendo. Riga technical university. 2021. Vol. 16, Nom. 2, P. 58-64. DOI:10.2478/ecce-2020-0009

6. Zinchenko S., Moiseienko V., Tovstokoryi O., Nosov P., Popovych I. (2021) Automatic Beam Aiming of the Laser Optical Reference System at the Center of Reflector to Improve the Accuracy and Reliability of Dynamic Positioning. In: Hu Z., Petoukhov S., Dychka I., He M. (eds) Advances in Computer Science for Engineering and Education IV. ICCSEEA 2021. Lecture Notes on Data Engineering and Communications Technologies, vol 83. Springer, Cham. https://doi.org/10.1007/978-3-030-80472-5_1.

7. Zinchenko S.M., Tovstokoryi O.M., Nosov, Popovych I.S., Kobets V., Abramov G. Mathematical support of the vessel information and risk control systems P. 335-354. // CEUR Workshop Proceedings, 2805. http://ceur-ws.org/Vol-2805/paper25.pdf

8. Zinchenko S.M., Nosov P.S., Mateichuk V.M., Mamenko P.P., Grosheva O.O. Use of navigation simulator for development and testing ship control systems. МНПК пам'яті професорів Фоміна Ю. Я. і Семенова В. С. (FS - 2019), 24-28 квітня 2019, Одеса-Стамбул-Одеса. Pages 350-355.

9. Zinchenko, S.M., Mateichuk, V.M., Nosov, P.S., Popovych I.S. & Appazov, E.S. (2020). Improving the accuracy of automatic control with mathematical meter model in on-board controller. Radio Electronics, Computer Science, Control, pp. 197-207. DOI: https://doi.org/10.15588/1607-3274-2020-4-19

10. Zinchenko, S.M., Mamenko, P.P., Grosheva, O.O., Mateichuk, V.M. (2019). Automatic control of the vessel's movement under external conditions. Науковий вісник ХДМА, №2(21), s.10-15. DOI: 10.33815/2313-4763.2019.2.21.010-015

Zinchenko, S., Tovstokoryi, O., Ben, A., Nosov, P., Popovych, I., Nahrybelnyi. Ya. (2021) Automatic optimal control of a vessel with redundant structure of executive devices. In: Babichev S., Lytvynenko V. (eds) Lecture Notes in Computational Intelligence and Decision Making. ISDMCI 2021. Lecture Notes on Data Engineering and Communications Technologies, vol 77. P. 266-281, Springer, Cham. https://link.springer.com/chapter/10.1007/978-3-030-82014-5_18