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Neural Network Identification of Marine Ship Dynamics

Dmitry A. Oskin, Alexander A. Dyda, Vasily E. Markin

Laboratory of Nonlinear and Intelligent Control Systems,
Department of Automatic and Information Systems,
Maritime State University
50a, Verhneportovaya str., Vladivostok, Russia, 690059
daoskin@mail.ru, adyda@mail.ru, vasily_markin@mail.ru

Abstract: Recurrent neural network (RNN) – based approach to identification of ship dynamics is considered and investigated in the paper. It was shown that even rather simple RNN models can be successfully trained both to linear and nonlinear behaviour of a ship. Experiments carried out with data taken from hardware - software simulator of the ship also confirmed effectiveness and perspectiveness of the approach considered.

Keywords: marine ship dynamics, identification, neural network, control system.

1. INTRODUCTION

Marine ships belong to the class of uncertain dynamical objects. The features of their mathematical models consist of a poor knowledge of ship's parameters and even a functional structure of system differential equations.

For marine ships, factors of uncertainties are unknown masses and moments of inertia, including added masses of water, ship's load and its distribution coefficients of viscous forces and torques, effectiveness of rudders etc (Fossen, T.I.,1994, Vaguschenko L.L., 2002, Lukomsky J.A., 2002) .

To reduce these two main kinds of uncertainties – parametric and functional ones and to provide control system design, a number of approaches are developed.

Among them, one can point out the methods of adaptive control, robust control, variable structure systems with sliding modes, neural network systems and others (Narendra K. S., Parthasarathy K., 1990, Fradkov A.L.,1990, Dyda A.A., Oskin D.A., 2004).

Of course, the design of ship's control system would be essentially facilitated if its adequate mathematical model is available. The identification of a controlled object can be implemented as a separate preliminary procedure. Another possible way is to "embed" a block of identification into control system, as it takes place in particular kinds of adaptive system.

In this case, the identification and control processes exist simultaneously. No doubts, most convenient form of the controlled object mathematical model has analytically determined structure of differential (or different) equations with known parameters. But derivation of mathematical models, in particular, for new types of moving marine objects, can take long period and expensive experimental research.

In the same time, many important tasks can be set and successfully solved without usage of explicit ship's mathematical model. For instance, on the basis of an adequate model, a movement of a ship can be predicted for any time horizon (tasks of predictive control). Comparison of real and adjusted model dynamics can help to discover any system failure (the problems of fault detection and fault tolerant control). High quality model of a ship can be used as its dynamic simulator, for example, in the process of autopilot's design, to evaluate some of state space vector components and so on (Meihong Wang, Sutton R., 2004, Tianhao Tang, Gang Yao., 2004)

In this paper, neural network approach to ship's dynamics identifications is considered. The paper is organized as follows. In the introduction (Section 1) common questions of marine ship modelling are briefly discussed. In Section 2 a number of simple ship's course movement models are considered and discussed. Section 3 is devoted to construction of recurrent neural networks and learning procedures of them to identify marine ship dynamics that was described in previous section. In Section 4, neural networks identification procedure is demonstrated on the basis of data taken from ship's simulator.

Conclusion remarks are also given.

2. SHIP COURSE MOVEMENT MODELS

To demonstrate flexibility and perspectives of neural networks (NN) for purposes of modeling and control, we first consider simple mathematical models of a ship course movement

As well known, most general ship dynamics models are strongly nonlinear, multi-dimensional and uncertain. Their differential equations take into account a behaviour of properly ship as rigid body, steering machine, influens of environment (wind, waves, currents) etc.

Direct usage of full complex mathematical model for analysis and synthesis of ship control system is practically impossible. To reduce a complexity of the tasks solving, one uses methods of decomposition of rather large system into separated subsystem of lower order.

Our aim is the investigation of abilities of NN to identify a marine ship dynamics. As a generator of data that are

necessary to teach NN, three simple models of ship course movement were used.
These are the following (Amerongen, J. 1982, Pomirski J., 2004):
Linear models: Nomoto 1st and 2nd order

$$T\dot{\omega}_y + \omega_y = K\delta,$$

$$T_1T_2\ddot{\omega}_y + (T_1 + T_2)\dot{\omega}_y + \omega_y = K(\delta + T_0\dot{\delta})$$

Non-linear modifications:
Norrbin 1st order: $T\dot{\omega}_y + H(\omega_y) = K\delta$
Bech 2nd order:

$$T_1T_2\ddot{\omega}_y + (T_1 + T_2)\dot{\omega}_y + H(\omega_y) = K(\delta + T_0\dot{\delta}),$$

where ω_y - the yaw rate of the ship, δ - the rudder angle, T, T_0, T_1, T_2, K - dynamic parameters, $H(\omega_y) = a_3\omega_y^3 + a_2\omega_y^2 + a_1\omega_y + a_0$ - nonlinear function.
Linear models can be represented as simple transfer functions 1st and 2nd orders (fig. 1). The parameters of the transfer function depend on the speed and load of the ship. Non-linear models are given on Fig.2.

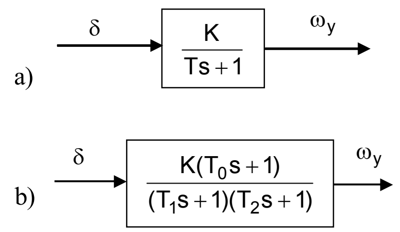
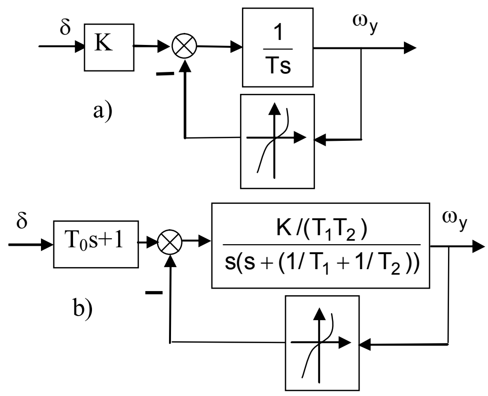


Figure 1. Linear models: a) Nomoto 1st and b) 2nd order



Fugure 2. Non-linear models: a) Norrbin 1st and b) Bech 2nd order

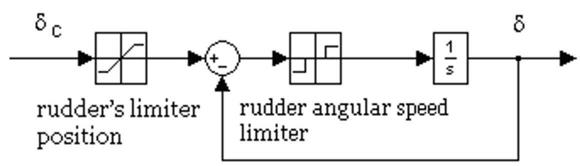


Figure. 3. Steering machine model

Full mathematical description of a ship should also include steering machine model, for instance, as shown on Fig. 3.Taking into account the provided description, mathematical model of the steering machine can be presented in the form:

$$\dot{\delta} = \mathrm{Fun}(F(\delta_c) - \delta), \tag{3}$$

where δ_c - a signal of the regulator (autopilot), $F(\cdot)$ - saturation function, $\mathrm{Fun}(\cdot)$ - relay function (in given case).
The model of environmental disturbances such as sea waves, wind and currents can be presented in the form of the sum of harmonious components, for example, as in (Viorel N., 2004).

$$f(t) = A_0 + A_1\sin(\omega_1 \cdot t) + A_2\sin(\omega_2 \cdot t), \tag{4}$$

Fig.4 shows full model of a ship.

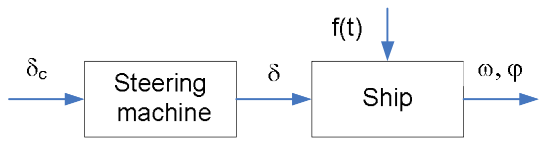


Figure 4. Full maritime ship model

3. RECURRENT NEURAL NETWORKS

Among different kinds of NN, one should be pointed out the class of recurrent neural networks (RNN) which are principally oriented to represent dynamical systems. RNN can be implemented on the basis of multi-layers or single-layer feed forward NN equipped with feedbacks. RNN operates in discrete time. Fig.5 represents a structure of RNN. Mathematical description of RNN can be written as follows:

$$x(k+1) = f\,[x(k),\ \ x(k-1),\ldots,\ \ x(k-n+1);$$
$$u(k),\ \ u(k-1),\ldots,\ \ u(k-m+1)]$$

where $u(k)$, $x(k)$ - a pair of values characterizing the state of input-output of the object at time k, $m \le n$. Function f[…] is realized by feed forward (in general case) multi-layers NN.

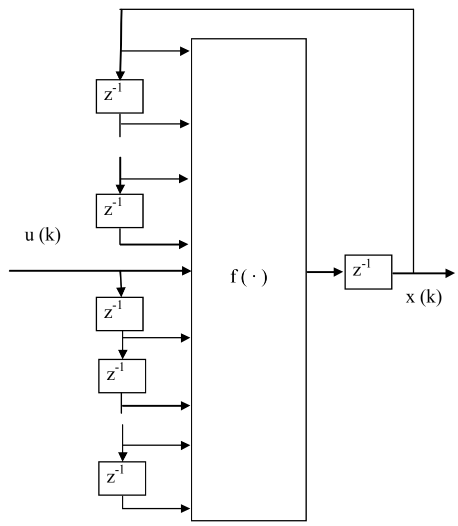


Figure 5 Structure of the recurrent multilayer NN

It should note that there are two different stages to deal with RNN models. First stage demands to train (to teach) RNN

using any input-output data. Scheme of RNN model is given on Fig. 5. When training procedure is finished, RNN are considered to be an adequate models which can used on second stage for purposes of control or another's.
It seems useful to define the notion of "neural network dynamics identification" as a procedure of design and training (adjustment) of RNN which dynamics are close to that of chosen dynamical object.

4. RNN IDENTIFICATION ON MODEL DATA

To investigate RNN approach to the problem of marine ship dynamics identification, multiple numerical experiments were carried. The scheme of RNN identification is given on Figure 6. Input-output training pairs of signals to teach RNN were generated by discrete modifications of ship dynamics models given in Section 2. Number of neurons and activation function types in RNN were varied. Computer modeling had demonstrated that even with small number of neurons (4-6 units) RNN identification of ship dynamics is of rather high quality. Figures 7 - 10 demonstrate results of RNN identification applied to the models of Nomoto (1-st and 2-nd orders), Norrbine and Bech respectively (all models with steering machine), with subpictures: a) training epoches and performance criteria, b) rudder angle (input), ship yaw rate and NNmodel output, error, respectively. Performance criteria are chosen as sum of squared difference of RNN and a model outputs.

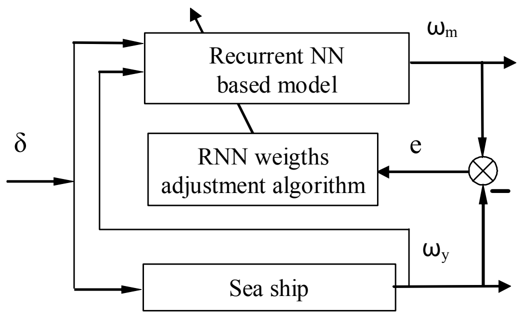
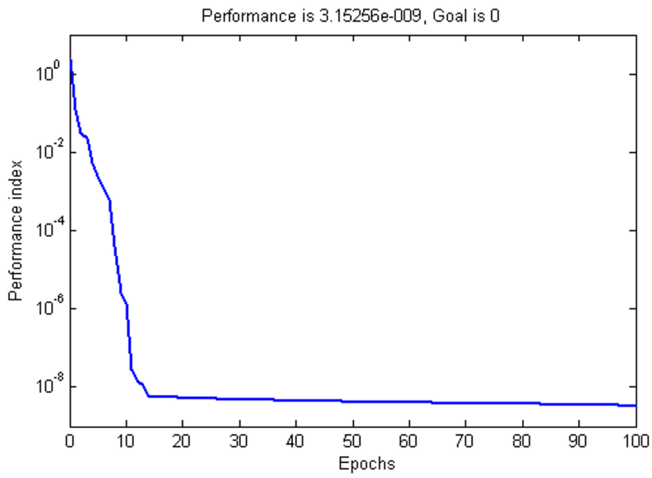


Figure 6. Sceme of RNN identification



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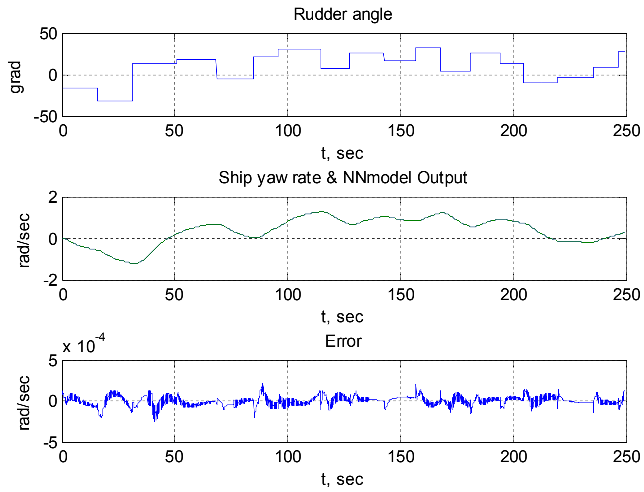

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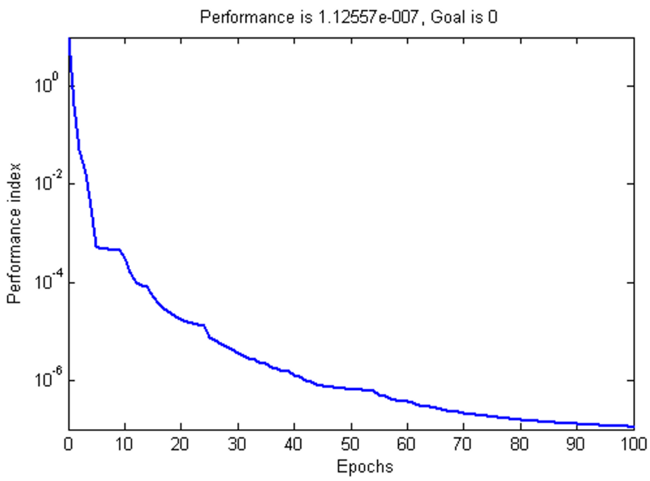
Figure 7. Nomoto 1st order model RNN training results



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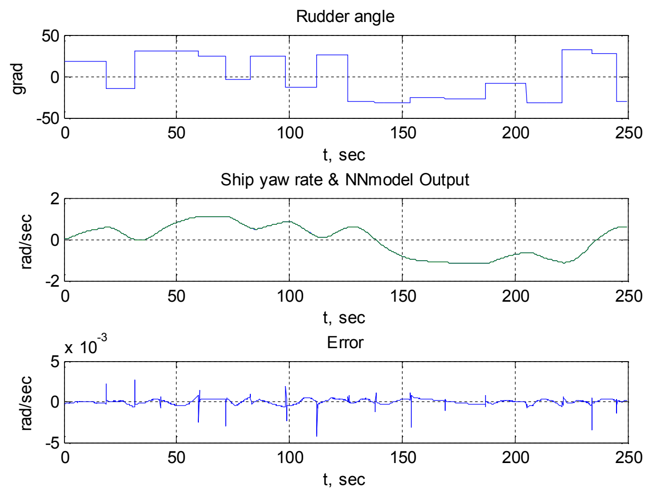

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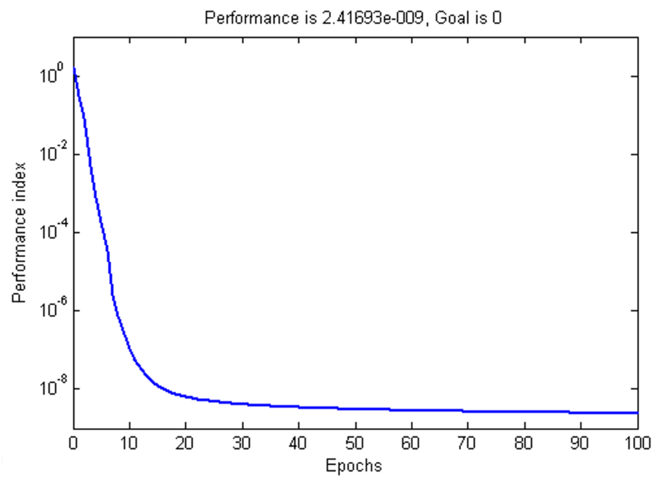
Figure8. Nomoto 2nd order model RNN training results



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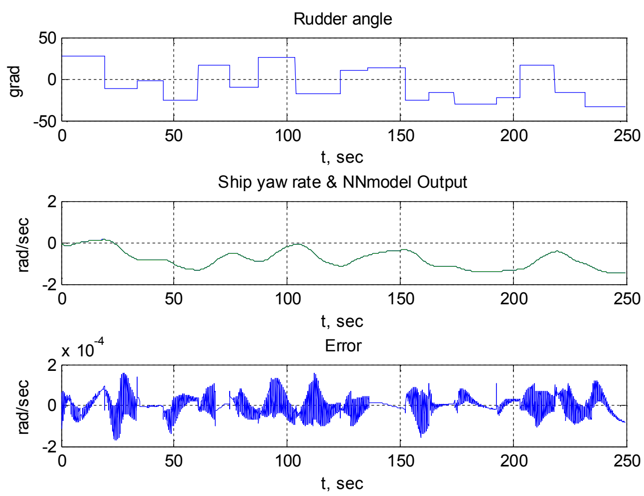

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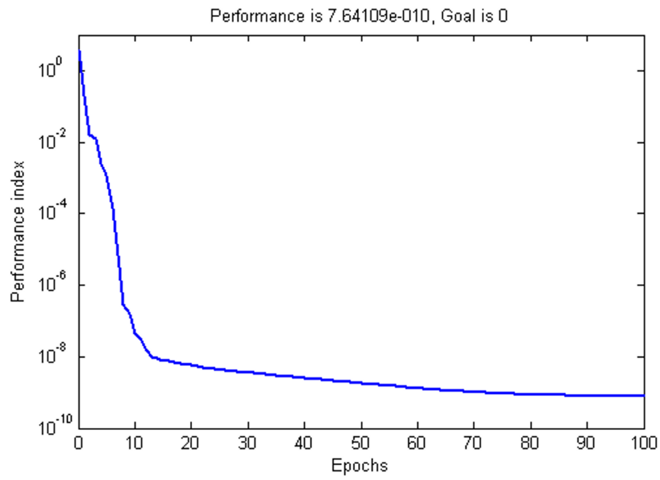
Figure 9. Norrbine model RNN training results



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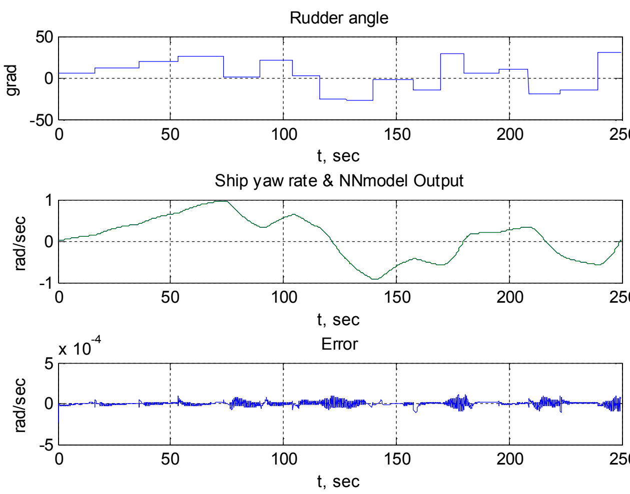


b)

Figure 10. Bech model neural net model training results

As results of numerical experiments had shown, RNN accurately approximate the dynamics of taken linear and nonlinear marine ship models.

One can see that even rather small number of RNN teaching epochs leads to fast reduction of performance index. Behaviour of RNN model tends to that of chosen ship model.

Main drawback of RNN identification as mentioned above is that derived neural network models have non-analytical form.

Flexiibility of RNN models as dynamics identification tool is their principal advantage and achieved by enough rich computational structure.

Conventional decisions to problem solving of dynamics identification are usually based on *a priori* chosen analytical form of differential equations. Researcher tries “to embed” available data describing an object into model by adjusting its parameters. Taken form of model equations, in fact, is itself constraint that can be essentially relaxed by RNN usage. Namely this feature of RNN makes possible to construct dynamical object models practically using only its input-output data.

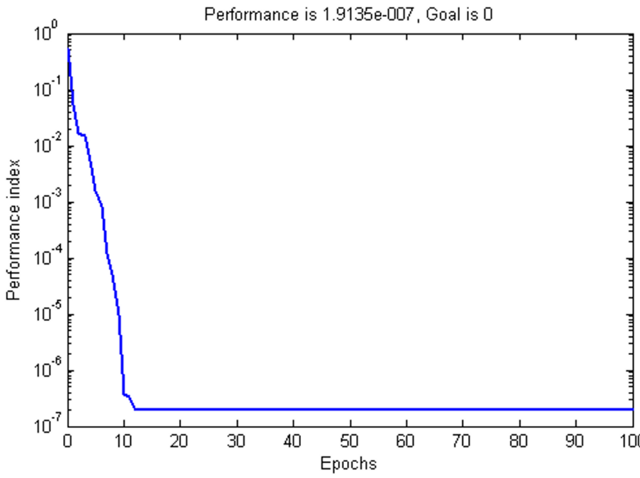
5. RNN IDENTIFICATION ON THE SHIP SIMULATOR'S DATA

Ship simulators have wide and various applications in engineering practice and professional education. In the research, the signals imitator SI-2005 (http://www.ec-ics.ru, 2005) was also used to generate data on ship dynamics, conditions and regimes of its movement and to analyze the effectiveness of RNN identification.

SI-2005 allows to simulate six different models of ships, such as a coastal passenger ship sailing, trawler, transport refrigerator, passenger ship, oil tanker and super tanker.

The data obtained in the simulation (the position of the rudder, the yaw rate of the ship, etc.) were saved to a text file with the sampling interval 0.1s and forther applied to adjustment of RNN ship models.

Figures 11 – 13 present results of RNN identification using simulator data(a) training epochs & performance criteria, b) rudder angle (input), ship yaw rate & NNmodel output, error, respectively).



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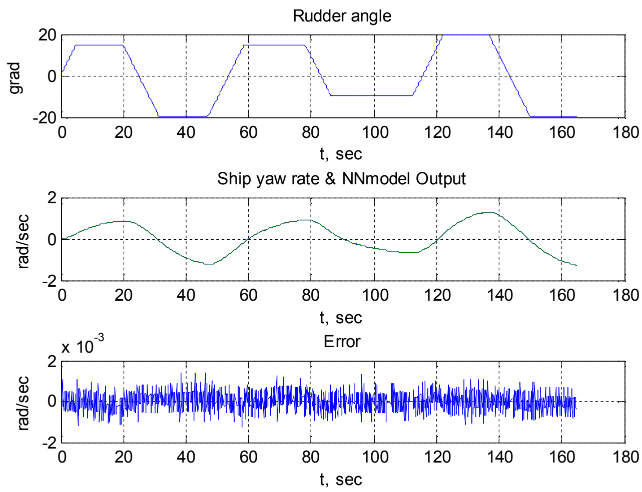

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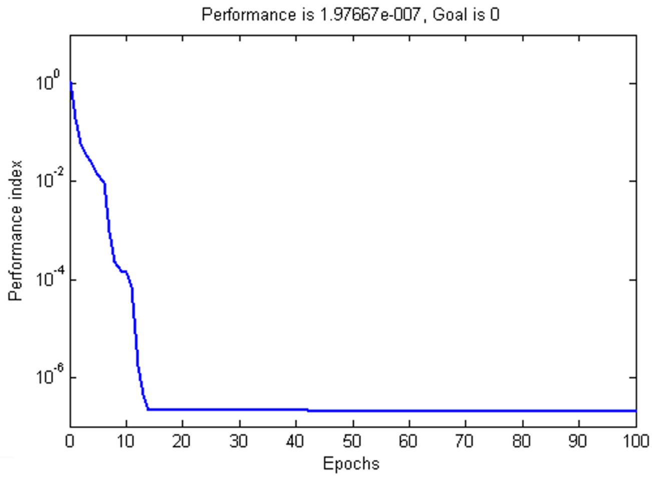
Figure 11. RNN model training results using simulator, ship speed 8 knots



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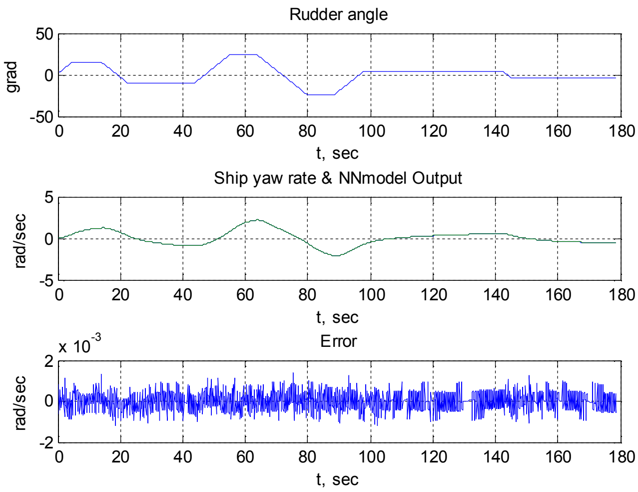

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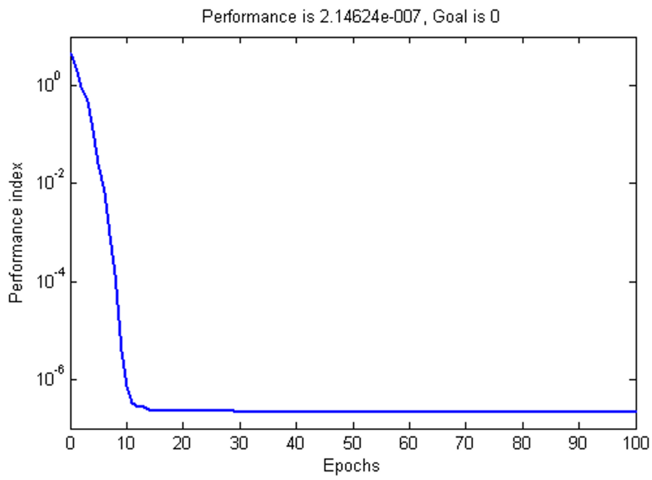
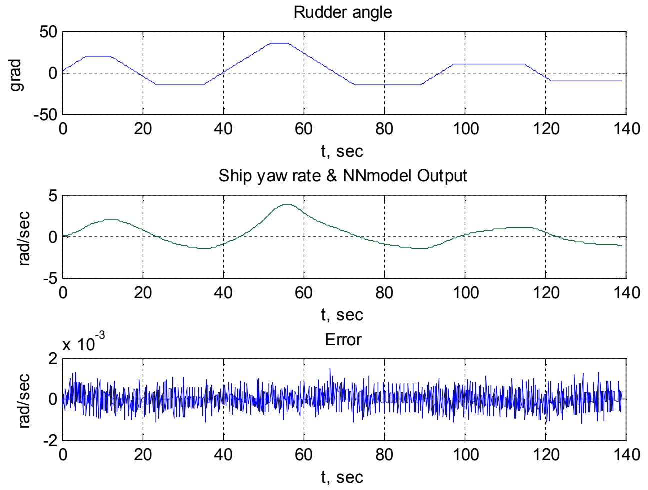
Figure 12. RNN model training results using simulator, ship speed 10 knots



a)



b)

Figure 13. RNN model training results using simulator, ship speed 12 knots

As seen from experiment results, the output of the trained RNN practically coincides with output data of the ship simulator as this took place when model-generated data were used to train RNN.

One should underline that only input-output data without any assumptions on ships mathematical models implemented in the simulator were used in the RNN ship dynamics identification procedure. These experimental results demonstrate that RNN approach can be extended and directly applied to identification of real marine ship dynamics.

6. CONCLUSIONS

The results of research carried out in the paper had demonstrated that recurrent neural networks are highly effective for presentation of ship dynamics. RNN identification essentially differs from conventional one when, as a rule, a structure of mathematical model equations are a priori postulated. RNN approach for ship dynamics approximation is much more flexible and has good perspectives to solve numerous problems in control theory and applications in marine systems.

The further research aims to extend the RNN approach to ship dynamics identification in area of multidimensional and full-scale experiments.

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