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Application of PID controller based on adaptive artificial neural network for ship control system

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Abstract

Traditional control methods for designing advanced control systems such as Proportional Integral Derivative (PID) controllers are for typical ships still popular because of their simple structure and with a sustainable calculation. This paper tries to develop application of PID controller based on adaptive neural network for ship navigation control system, thereby improving the quality of PID controller of this control system. At the same time, experimental design of the adaptive neural PID controller according to simulation and experiment are performed. Design of a ship model identifier using the input-output signal method is introduced and applied. The recognizer uses a multi-layer feedforward neural network, but the author trains the network online, enhancing it with good adaptation speed, capable of identifying nonlinear ship models that change over time, not just a static linear model like previous studies. By combining this neural recognition model, the control method is conducted in a real-time predictive control style, improving adaptation and control quality. PID controller with the proportional, integral, differential parameters K_p, K_i and K_d adjusted using a back-propagation neural network that is explicitly calculated and simulated. The online synthesis and modeling ability of the neural network helps the parameters of the PID control map to be fine-tuned and selected directly over time, and the adaptability of the neural network in control is utilized and promoted.

Keywords: Proportional Integral Derivative controller; Ship; Neural network; Control quality.

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1. Introduction

Improving the quality of the PID controller of the ship control system is always a topical issue for researchers, because when designing a controller for a ship, a PID controller is often required that must have a kinetic model of the ship. In fact, the dynamics of ships are often highly nonlinear and influenced by many external perturbations. The external perturbation factor itself also has nonlinear and undefined properties. This leads to the construction of unknown structures and parameters that requires advanced control techniques.

As a maritime country, Vietnam implements the policy of strongly developing the shipping industry and shipbuilding industry in the direction of international integration and meeting the transport needs of society with the goal of building and developing the shipping industry. Vietnam's shipbuilding industry to 2020 and development orientation to 2030, in order to meet the requirements of marine economic development in accordance with the Vietnam Maritime Strategy to 2020, serving the needs of socio-economic development. festival; contributing to consolidating national defense and security and protecting national sovereignty over the seas and islands of the Fatherland.

In Vietnam, the research on advanced control systems for ships has not been widely applied. Research to improve the quality of ship control systems will be one of the important issues for modernizing the shipbuilding industry in Vietnam, especially during the Industrial Revolution 4.0. This research focuses on the following parts according to the defined objectives:

- Research adaptive control algorithms based on the combination of artificial neural networks and conventional PID control.
- Develop algorithms and apply them to the design of autopilots using adaptive neural PID controllers for ship navigation control (Nguyen *et al*., 2015)
- Using Matlab software to simulate the proposed controller. Evaluating the quality of adaptive neural PID controller with conventional PID controller.
- Experiment on a miniature model ship in a test tank.

In this study, the scientific and practical significant issues are investigated that are represented below:

- Build a theoretical basis combining PID controller and artificial neural network to design a ship navigation control system. Since then, it has contributed to completing part of the scientific theoretical basis for PID controllers combined with artificial neural networks;
- Propose algorithm development, taking advantage of the advantages of PID controller and artificial neural network, to improve the quality of the navigation control system, increase adaptability and navigation accuracy;

- Improved PID controller and backpropagation neural network with enhanced training algorithm and neuron identifier for the controller to increase navigation accuracy and adapt to environmental disturbances.
- Closely combine the theoretical basis of automatic control and apply it to the practice of designing ship autopilots;

Finally, this paper has developed theory and applied PID control techniques with artificial neural networks in ship control. Specifically take advantage of the controllability and ease of development of the PID controller for preliminary design, combined with the neuronal controller, to control the ship's direction.

1.1. Overview of artificial neural networks in control

An overview and details of the research situation in the world and in the country related to the research on the application of artificial neural networks and Proportional Integral Derivative (PID) maps in controlling ship navigation are represented.

Research situation in the world related to the field of automatic control, scientists often tend to continue researching and developing new control methods based on the old methods to overcome existing shortcomings or search for completely different methods. Based on old, existing methods, this strongly promotes applications in the field of wide-ranging automatic control (Bennett, 1984; Moradi, 2003; Andrasik *et al*., 2004).

Despite strong advances, so far new control methods have not completely replaced common techniques, such as traditional PID control (Visioli, 2012; Lin *et al*., 2000; Brandt and Lin, 1999; Dong *et al*., 2012; Vagia, 2012; Martins and Coelho, 2000; Fang *et al*., 2010; Omatu *et al*., 2009; Hernández-Alvarado *et al*., 2016). PID controllers still account for more than 90% of applications in industrial systems (Visioli, 2012).

In recent years, control techniques using artificial neural networks have developed very rapidly. Many neural network systems with different structures have been proposed and widely applied in engineering. Neural networks are very useful and effective in this regard because they have the following characteristics: (1) the network has a large parallel structure; (2) has inherent nonlinear characteristics; (3) have extremely strong learning ability; (4) capable of generalization; (5) has guaranteed stability for certain control systems (Nguyen *et al*., 2008).

The adaptive PID controller based on adjusting the parameters K_p, K_i and K_d by an adaptive artificial neural network is called neural PID control and is widely researched and applied by scientists in industrial systems. Developing ship control systems is the research goal of many scientists (Visioli, 2012; Brandt and Lin, 1999; Aström and Hägglund, 1995; Martins and Coelho, 2000; Widrow and Streans, 1985). Furthermore, systematizing the theoretical basis of artificial neural networks; network structure; and neural network application method in identification and control.

There are many different methods to turn artificial neural networks into adaptive maps for control objects and can be divided into two types: indirect control and direct control (Brandt and Lin 1999; Mindell, 2002). The direct control method is simpler than the indirect method, and it does not require pre-training to identify the parameters of the control object and provides adaptive laws to update the weight functions of the neural network.

A number of research projects on PID controller based on the artificial neural networks for ship navigation control are analyzed. Typically, back propagation neural networks and radial basis functions are applied to ship control systems.

2. Materials and methods

Theoretical research methods are combined with experimental research to highlight the scientific and practical nature of the problem to be specifically solved:

Theoretical research:

- Analyze and synthesize conventional PID control systems and artificial neural networks;
- Research and develop adaptive neural PID control algorithm for ship navigation control system;
- Building a ship identification model using artificial neural networks;
- Designing an autopilot using a PID algorithm based on a feedforward neural network to control the ship's direction; Computer simulation.

Experimental study:

- Designing ship models and applying neural PID controllers to control in real environments;
- Comparison with conventional PID controller to demonstrate the effectiveness of adaptive neural PID controller.

2.1 Adaptive neural PID controller based on Back-propagation neural network for ship direction control system

2.1.1 Recognition-free back-propagation network-based neural PID controller for ship navigation control system

The theory of the method used in this research are fully explained by Hai (2020), but herein a summary is represented.

1) Principle diagram

The structure of the PID controller based on back propagation neural network (Figure 1) includes two parts: 1) Conventional PID controller and 2) Back propagation neural network (BPNN). PID controller is used to control the ship's direction. The control quality depends on the setting of the K_p, K_i, K_d parameters of the PID controller that is controlled by the BPNN network. The BPNN uses an online training algorithm based on the gradient descent method to update the weights and ensure that the designed neural network can calculate the desired PID parameters. Therefore, in this method, by combining conventional PID controller and intelligent BPNN network, the control quality is desired and stable (Fossen, 2002; Fossen, 2011).

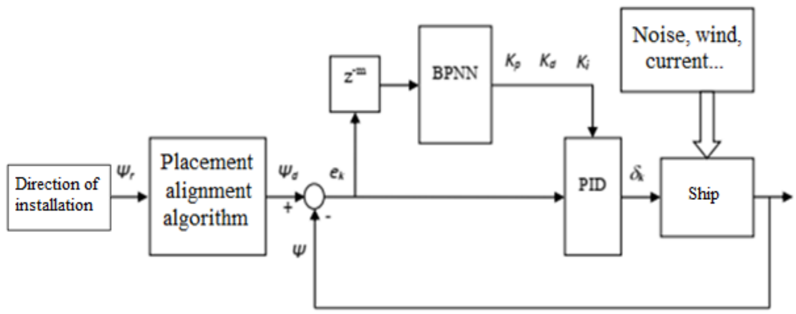

Figure 1. Principle diagram of PID back-propagation neural networks

2) PID remote control algorithm by Back-propagation neural network

Backpropagation has three layers; the structure of the map is illustrated in Figure 2. The number of input layer, hidden layer and output layer neurons are M, Q, 3, respectively (Lewis *et al*., 1998; Norgaard, 2000).

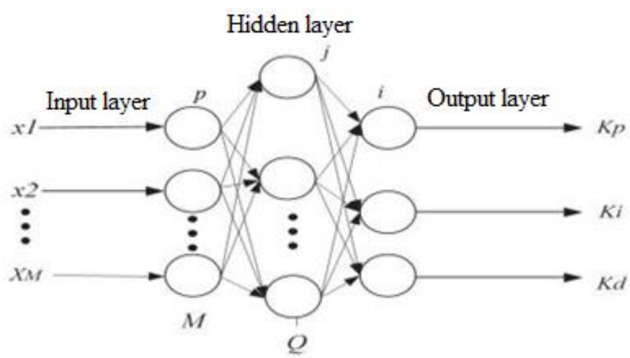

Figure 2. Backpropagation neural network (BPNN)

The algorithm of this BPNN-based PID control uses the reinforcement training method Hai (2020). Here the values of the number of training times in a cycle "n" and the learning coefficient "η" are fixed. At the beginning of the control cycle indicated by parameter k, the neural network weight is chosen to be a very small random value. The output signals of the hidden layer and output layer neurons are calculated based on these initial weights. Next, the weights of the neural network are updated using the backpropagation algorithm so that the value of E_k reaches a minimum value. This process is repeated n times before starting a new control cycle (k=k+1). The output signal of the neural network at the nth training round is the control signal output at the kth control cycle (Nguyen and Jung, 2005; Nguyen and Jung, 2006; Nguyen, 2007).

2.1.2 PID controller with neural identifier for ship navigation control system

1) Principle diagram

The proposed map has the structure as shown in Figure 3, supplemented with a second neural network (NN2) to predict the ship's turning speed (ψ_dot_k). This is a neural network with three feedforward layers and trained according to the augmented backpropagation algorithm (Figure 4). The input to the network is the ship's turning speed and the steering angle signal at certain times k-1, k-2, k-3. The predicted course of the ship is obtained by identifying the ship's turning speed, then these signals are transferred to the input of the first neural network (NN1).

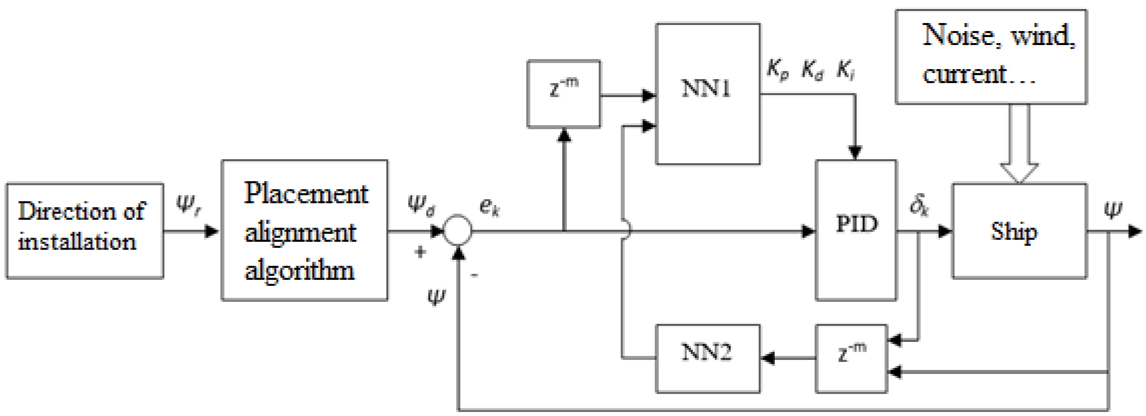

Figure 3. Schematic diagram of the NN1 neuron and NN2 neuron identifier with PID remote controller

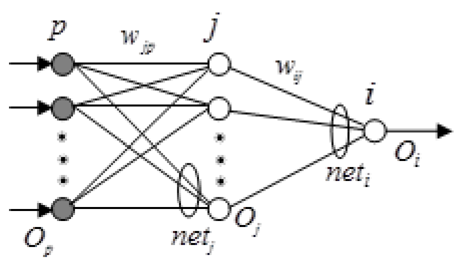

Figure 4. Neural network structure for recognizing NN2

2) Neural network recognition

A dynamical system can be described in two forms: input-output model and state space model. This project applies feedforward neural networks to learn and recognize ship models for control according to the input - output method.

The input-output model describes a dynamic system based on the input and output data of that system. Based on this principle, the input-output model assumes that the new output signal in the discrete time domain of the system can be predicted from the input and output data at the previous time period of the system, that is, is the system information obtained previously.

Actually, based on the above explanations, the study focused on the construction of a PID map based on a back-propagation neural network without and with a neuron identifier. In this neural

PID map, an enhanced training algorithm has been added to increase the system's adaptation speed, quickly and accurately adjust the parameters of the PID map.

Researching and building a neural pattern recognizer using the input-output signal method is introduced and applied. This recognizer uses a multi-layer feedforward neural network but is trained online, enhancing the adaptive speed and being able to identify nonlinear ship models that change over time. By combining this neural recognition model, the control method is conducted in a real-time predictive control style, improving adaptation and control quality. This application method was not new at the time of paper research, but few authors applied it to ship control.

3. Results and Discussion

3.1. Simulation results

In this study, a mathematical model of the ship is used, which is a model of the real ship Mariner Class Vessel. To be able to control the ship's rotation and respond well in the case of a large heading angle, a reference model of the ship's kinematics is used to create a course suitable for the ship's kinematics. for remote control. To test the stability and sustainability of these direction maps. The effect of wind on the ship's hull is based on research by Isherhood in 1972 (Fossen, 2011). The wind speed changes randomly in a 5-second cycle and is limited to the range [-60°, +60°] with a 30-second cycle. Noise in the direction measuring device is represented by a random signal distributed in the range [-0.1°, +0.1°]. The nonlinearity of the engine is also considered, the limited range of δ is in the range of steering angle [-35°, +35°] and the steering speed $\delta = r$ is in the range of [-2.5°/s, +2.5°/s]. In all situations, the ship's initial speed is 15 nautical miles/hour.

3.1.1 The neural PID remote controller is based on a backpropagation network without an identifier

The neural network consists of 4 input layer neurons, 6 hidden layer neurons and 3 output layer neurons. The input to the network includes the desired direction ψ_r, the actual direction ψ, the direction error e(k), and the difference e(k)-e(k-1). The three output layer neurons correspond to the parameters K_p, K_i and K_d of the PID remote controller. The learning coefficient and number of training times in a cycle are fixed (n=50, γ= 0.5), the momentum value added during backpropagation training η = 0.025. Variations of direction range from -25° to +25° with the simulation time of 900 seconds.

1) No wind and signal interference impact

Figure 5 shows that the BPNN-PID remote control has a very small overshoot, good stability and high stability, a faster setting time and a smaller steering angle than a conventional PID remote control. Figure 6 shows the changes of the parameters K_p, K_i and K_d adjusted by the proposed neural network.

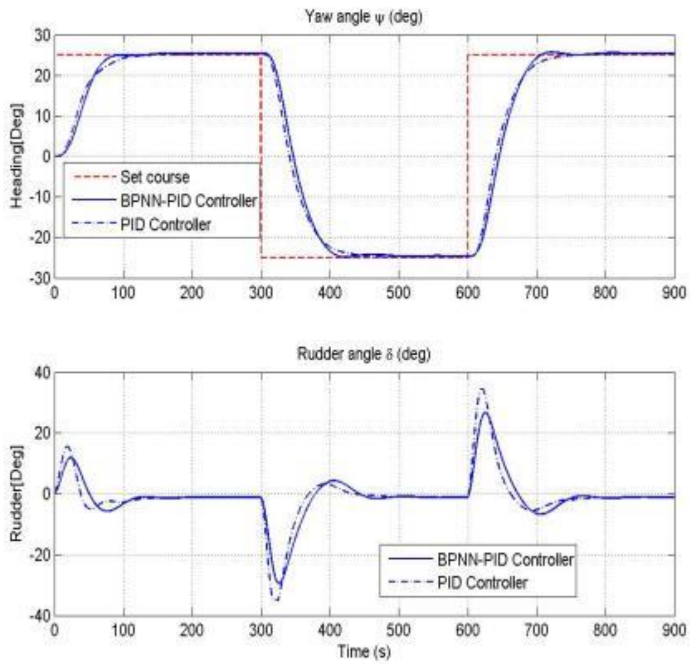

Figure 5. Ship direction and steering angle in the absence of wind and interference

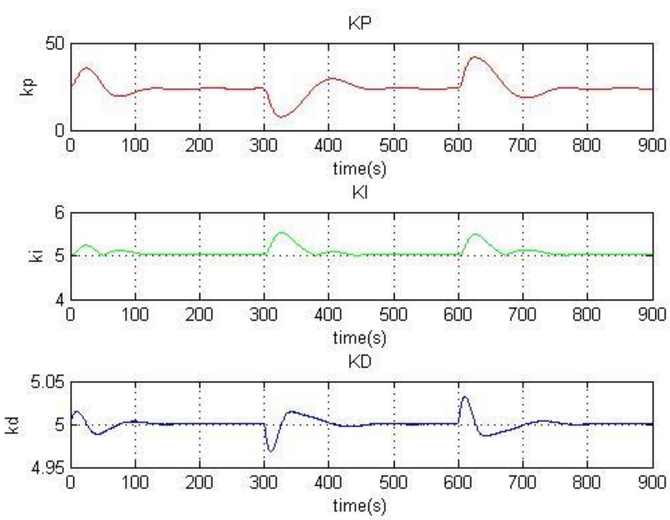

Figure 6. Variations of parameters K_p, K_i and K_d

Figure 7 illustrates the error of the ship's course, the speed and the acceleration to return to the bow. It shows the effectiveness and sustainability of the proposed BPNN-PID convolution (Table 1).

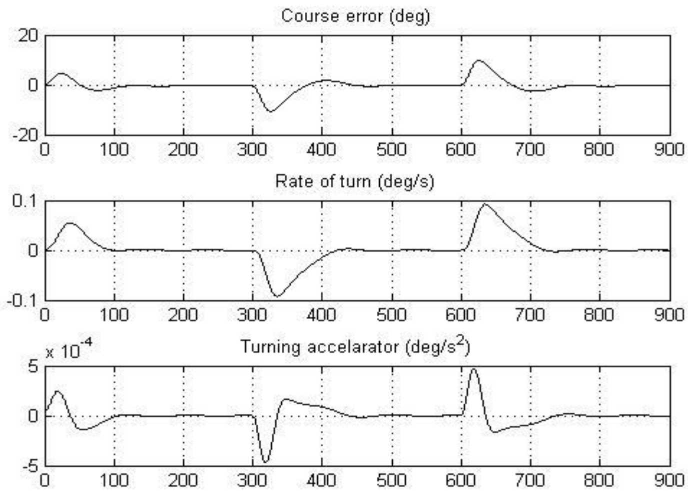

Figure 7. Errors of course, speed and acceleration of turning to the bow of the ship

Table 1. Sum of squares of deflection (E_ψ) and sum of squares of steering angle (E_δ) in the absence of wind and noise

		No wind
PID remote controller	E_ψ	23.72
	E_δ	156.28
BPNN-PID remote controller	E_ψ	20.98
	E_δ	148.27

2) Wind and noise/ interference impact

Figure 8 shows that when there is wind and interference, the autopilot using BPNN-PID has less oscillation, ensuring sustainability and stability throughout the simulation period. The steering angle is smaller than that of conventional PID control, which ensures that the steering motor is not overloaded in the presence of environmental noise.

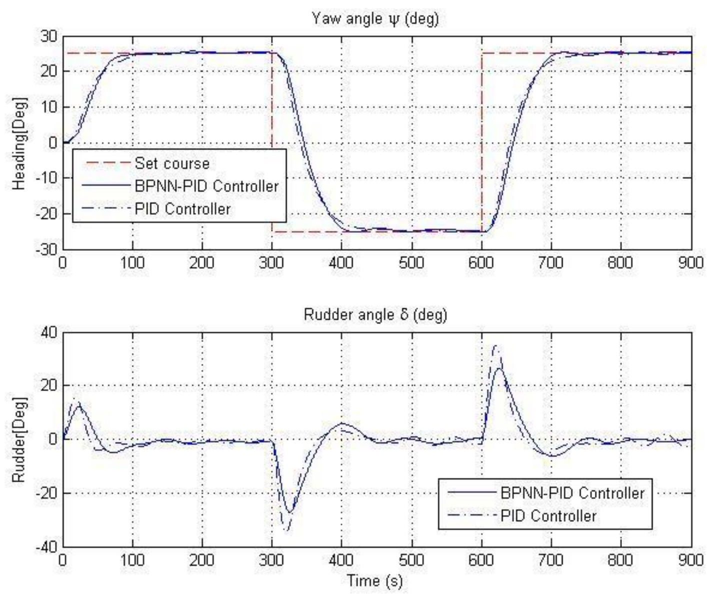

Figure 8. Direction and steering angle in the presence of wind and interference

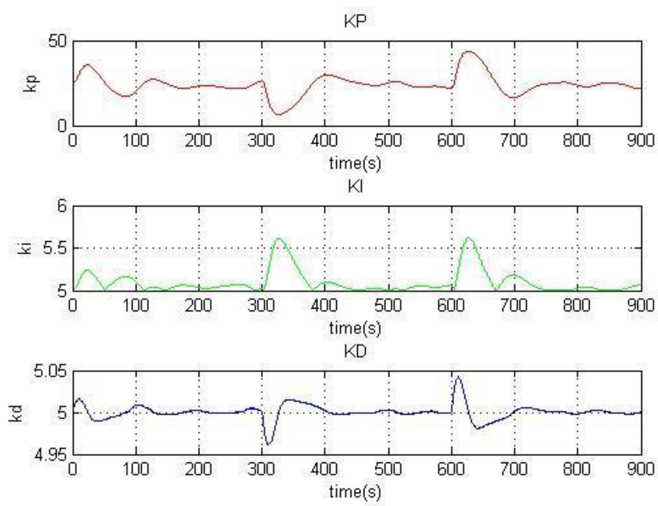

Figure 9. variations of parameters K_p, K_i and K_d due to noise impact

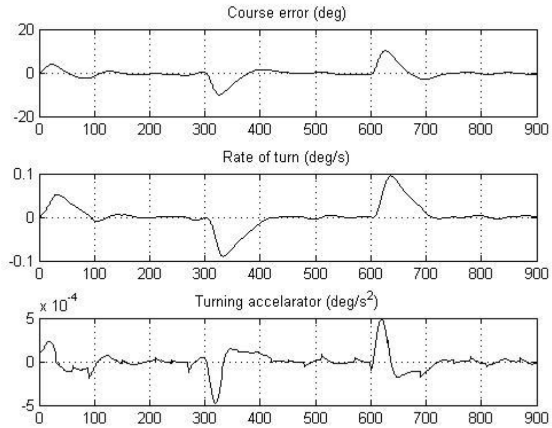

Figure 10. Errors of course, speed and acceleration of the ship's bow turn

Figure 9 illustrates the parameters K_p, K_i and K_d which are adjusted automatically during the simulation by the neural network under the influence of noise and wind to the ship's direction (Table 2).

Table 2. Sum of squares of deflection (E_ψ) and sum of squares of steering angle (E_δ) in the presence of noise and wind

		Windy
PID remote controller	E_ψ	28.32
	E_δ	171.24
BPNN-PID remote controller	E_ψ	26.43
	E_δ	159.45

3.1.2 Neural PID controller based on back-propagation neural network with recognition network

Neural network used to adjust PID parameters (NN1) includes 6 neurons in the input layer, 9 neurons in the hidden layer and 3 neurons in the output layer. The input to the network consists of the desired path ψ_r, the actual path ψ, the direction error e(k), and the difference e(k)-e(k-1). The three output neurons correspond to the parameters K_p, K_i and K_d of the PID controller. The recognition neural network (NN2) consists of 6 input layer neurons, 9 hidden layer neurons and one output layer neuron. The learning coefficient and the number of training times in a cycle are fixed (n=150, γ= 0.5), the added momentum value during back-propagation training η = 0.025. Redirect range from -25° to +25°with the simulation time of 900 seconds.

1) *No wind and impact measurement signal interference*

Figure 11 shows that the BPNN-PID convolution with neural recognition network has a very small overshoot of the control value, good stability and high stability, a faster setting time and a fast response steering angle compared to conventional PID control. Figure 12 shows the change of parameters K_p, K_i and K_d adjusted by remote controller with the neural network for recognition (Table 3).

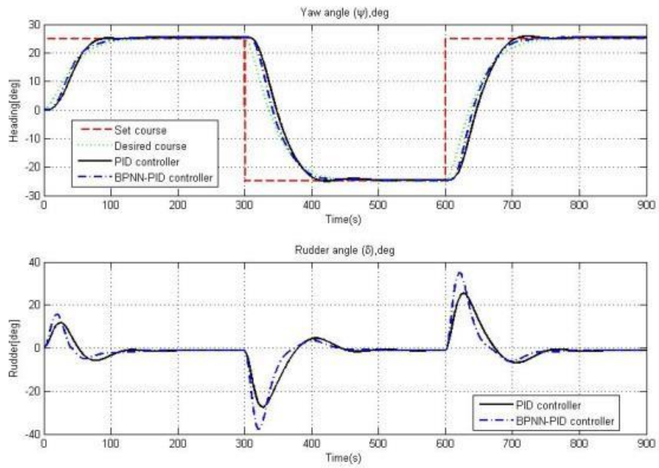

Figure 11. Ship direction and steering angle in the absence of wind and interference

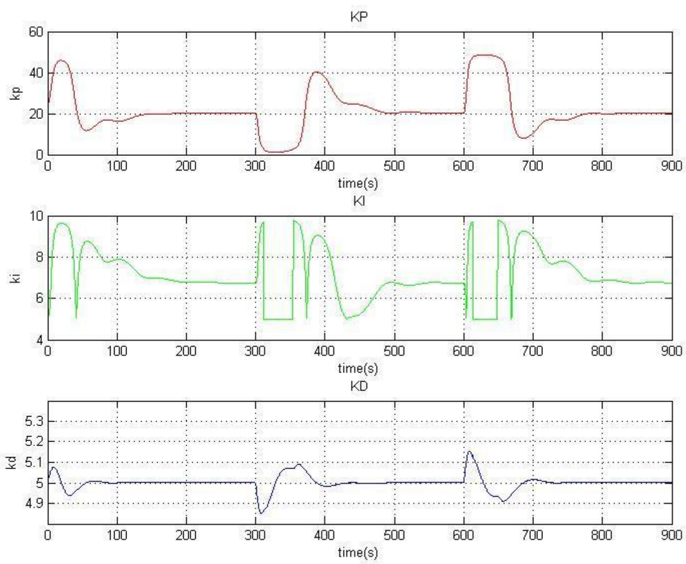

Figure 12. Variations of parameters K_p, K_i, K_d

Figure 13 illustrates the error of the ship's course, the speed and the acceleration to return to the bow. It shows the efficiency and sustainability of the BPNN-PID convolution with the neuron recognizer.

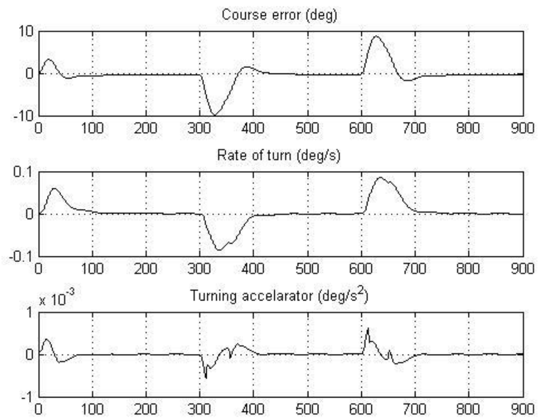

Figure 13. Error of course, speed and acceleration of ship's turn in the absence of wind and interference

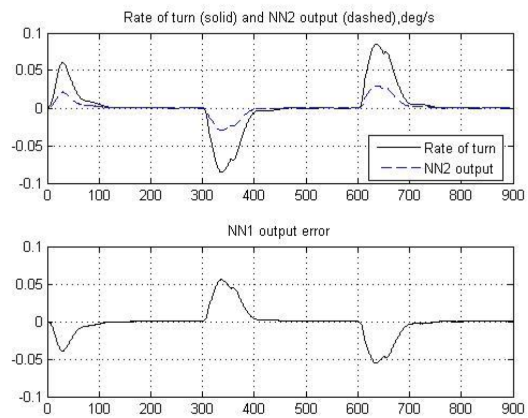

Figure 14. Output of neuron recognizer NN2 in the absence of wind and noise

Table 3. Sum of squares of deflection and sum of squares of steering angle in the absence of wind and noise

		No wind and noise
PID remote controller	E_ψ	23.91
	E_δ	149.41
BPNN-PID	E_ψ	17.44
(has an identifiable NN)	E_δ	149.33

2) Wind and interference impact

Figure 15 illustrates the direction and steering angle of a ship using a neural PID controller with a recognizer, so it shows that the course is stable, the setting time is fast and the steering angle is suitable, and the stability is high (Table 4).

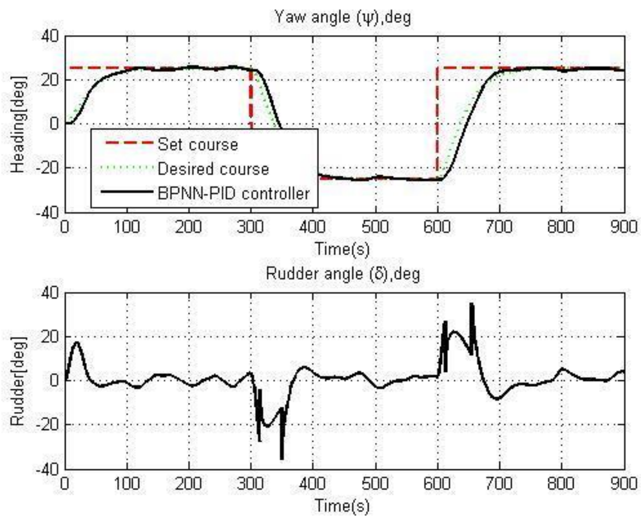

Figure 15. Vessel direction and steering angle in the event of wind and disturbance impact

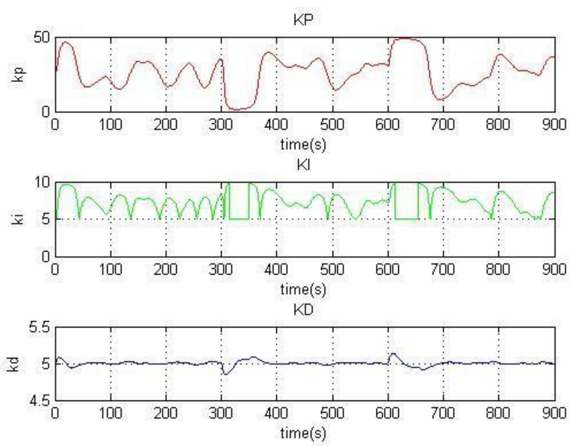

Figure 16. Changes of parameters K_p, K_i, K_d

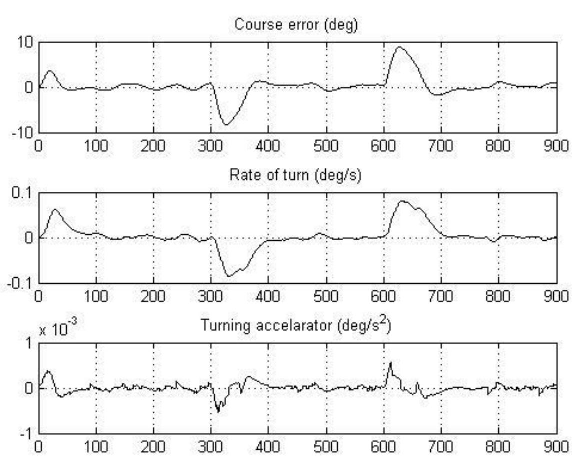

Figure 17. Errors of course, speed and acceleration of ship's turn in the presence of wind and noise

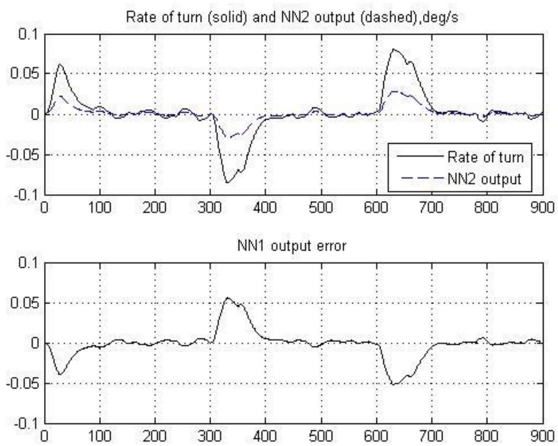

Figure 18. Output of neuron recognizer NN2 in wind and noisy conditions

Table 4. Sum of squares of deflection and sum of squares of steering angle in the presence of noise and wind

		Wind and noisy
PID remote controller	E_ψ	31.32
	E_δ	195.76
BPNN-PID (has an identifiable NN)	E_ψ	18.35
	E_δ	154.39

Through the simulation results, it is found that the neuron PID controller with the neuron recognizer has a smaller direction error and a smaller steering angle than a normal PID controller that is active and the parameters are adjusted more adaptively than the PID controller. That proves the feasibility and effectiveness of the proposed remote controller.

This section represents the results of the computer simulation of a remote controller. The mathematical model of the ship is a nonlinear model of a real ship used in the simulation situation. The random noise in the signal and the effect of wind on the direction keeping process are used to test the feasibility as well as the response of the control conditions.

The wind is changed during the simulation to check the adaptation of the climatic conditions to the change of the external impact. The results show the stable and efficient operation of the neural PID controller compared with the traditional PID and the ability to adapt to the changes of the environment. The recognition neural network also gives positive results when combined with the neural PID controller.

The results show the stable and efficient operation of the neural PID controller compared with the traditional PID and the ability to adapt to the changes of the environment. The recognition neural network also gives positive results when combined with the neural PID controller.

3.2. Experimental results

3.2.1 Experimental conditions

The ship model was experimentally conducted at the swimming pool of the University of Transport in Ho Chi Minh City with a pool size of 9m x 25m. The author proceeds to control the ship to follow the contour of the pool as pointed out in Figure 19. The desired trajectory of the ship is described by five turning points and the ship will make three turns with the following values of 90°- 90°- 90°, respectively. At the initial moment the ship is positioned along the width of the pool corresponds to an initial bow angle of 10°. The desired orbital length (Figure 19) is $L_{trajectory}$ = 57(m).

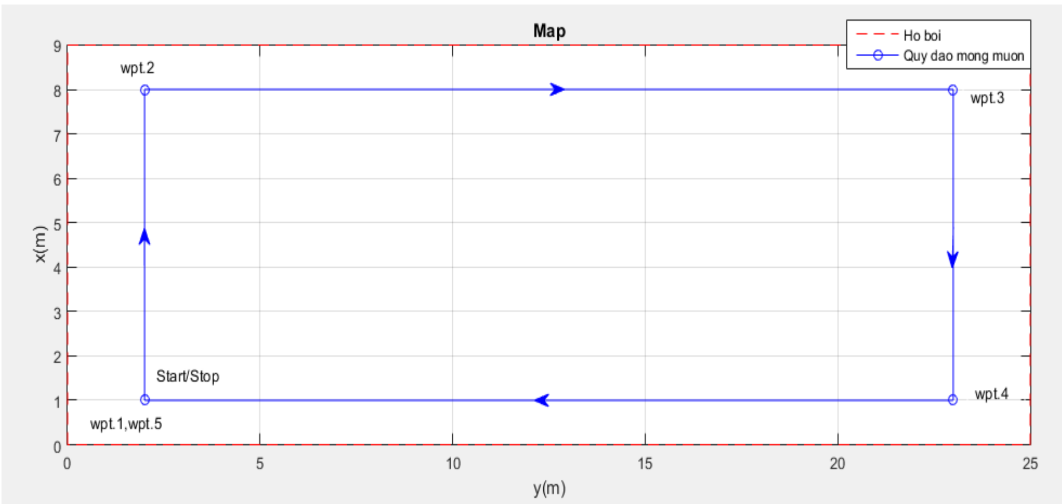

Figure 19. Desired trajectory of the ship

According to the study by Nguyen *et al*. (2015), the supposed ship has the following characteristics:

- The ship's carrying capacity is 4.5 kg;
- The draft is 100 mm, the length of the ship is 1500 m, the width is 250 mm;
- The rudder angle limit is from -20° to 20°. The rudder angular velocity limit is from -5°/s to +5°/s;
- The sampling time of the system is 0.1 s;
- The moving speed of the ship is constant 0.4 m/s;

During the simulation, to check the response of the controller, three types of noise were added as follows:

- Noise caused by waves in the Pierson–Moskowitz (PM) spectrum with dominant frequency ω_0 = 0.60625, relative damping coefficient ξ= 0.3, and constant K_ω= 0.1979;
- The disturbance of the flow is constant and deflects the bow angle by 10°;

- The noise due to the measurement process is a random number.

In addition, during the simulation, the position of the ship is determined by the integral method of the following formulas:

$$\begin{cases} x(t) = x_0(0) + \int_0^t U\cos\psi(t)\,dt \\ y(t) = y_0(0) + \int_0^t U\sin\psi(t)\,dt \end{cases}$$

3.2.2 Experimental outcomes

Figure 20 depicts the block diagram of the automatic ship steering system using neural PID-NN (PID Neural Network block). In which, the interference caused by sea waves will affect the system described in the Wind-wave effect block; The noise due to the currents is described in the Ocean current effect block and the noise due to the measurement is added directly to the bow angle. The PID neural network block is the controller of the ship steering system.

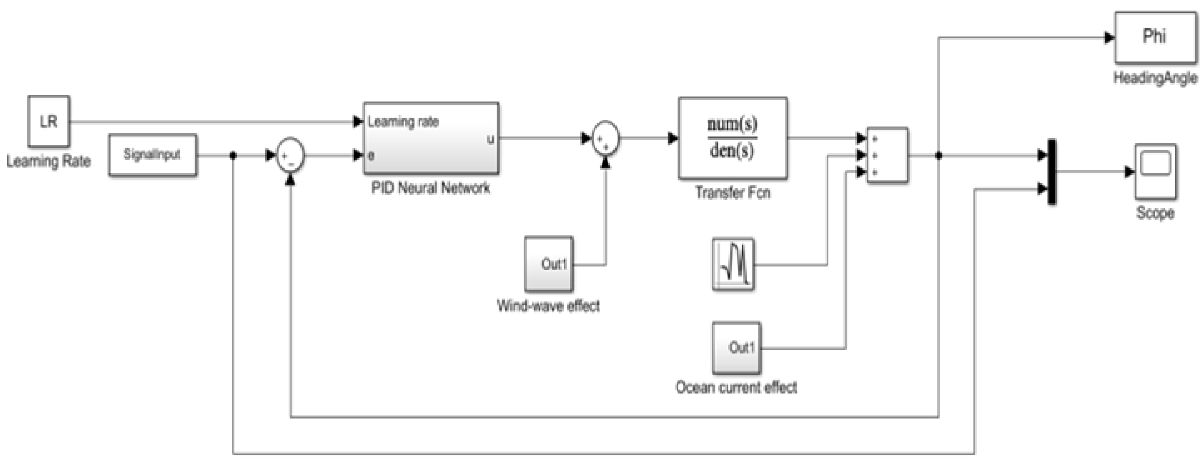

Figure 20. The block diagram of the ship direction control system using the neural network PID controller

During the movement, the ship will always have errors in position and angle. That is why the author gives two graphs of error, including a graph describing the trajectory tracking error-the distance from the ship to the desired line of the trajectory over time as shown in Figure 21 and a graph describing the angular error. The ship's bow is at an angle between the desired trajectory line and the ship's steering direction, or in other words, the ship's bow angle error is the difference between angle ψ and angle α in Figure 22 (LOS navigation algorithm) over time as shown in the Figure 21. Moreover, it also describes two graphs describing the rudder angle and bow angle obtained from the sensors as shown in Figures 22 and 23.

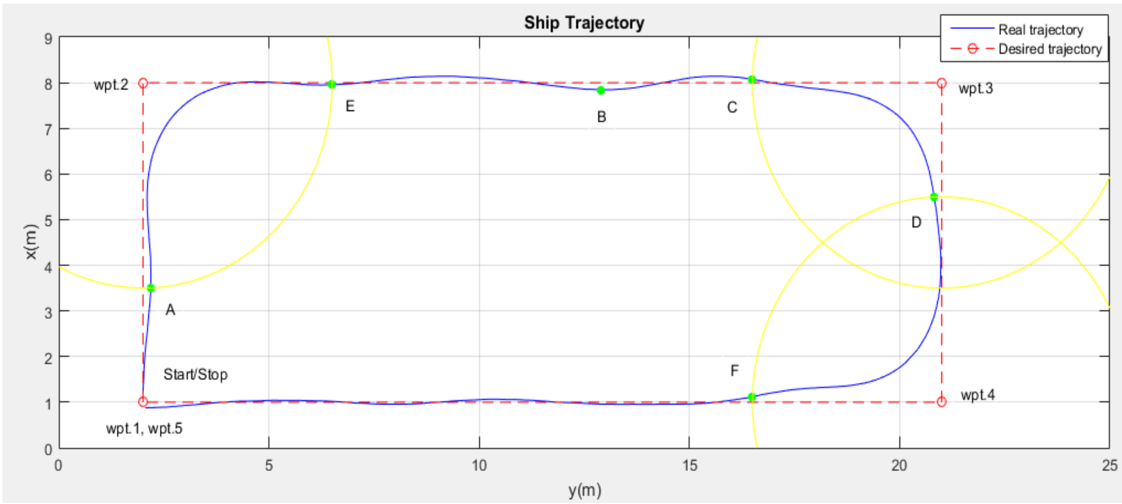

Figure 21. Trajectory of the ship with the neural PID remote controller

Figure 21 represents the moving trajectory of the ship when the automatic ship steering system uses neural PID. We see the appearance of limiting circles (yellow) with centers located at the turning points waypoint 2, waypoint 3, waypoint 4 with a radius equal to three times the length of the ship. These circles are used to determine the position where the ship begins to change course to follow the new trajectory line. In addition, from Figure 21, we see that when passing through the waypoint 2 diverting point, the ship does not deviate from the desired trajectory, but the ship oscillates around the trajectory line formed from waypoint 2 and waypoint 3. The maximum tracking error of the ship when going from waypoint 2 to waypoint 3 is 0.1557m, corresponding to point B in Figure 21 and Figure 22.

Furthermore, we find that because the response of the neuron PID is quite good, when it passes the waypoint 2, the ship quickly follows the desired trajectory. In addition, when passing waypoint 3, we found that the ship did not deviate from the desired trajectory, but because the steering radius was too large (R=3; L_{ship}= 4.5m), when passing the waypoint 3, the ship has entered the next limiting circle with the center at the waypoint 4 diversion point, so the ship must continue to change direction to follow the new trajectory line formed from waypoint 3 and waypoint 4. That's why on this straight line of the trajectory, the ship's tracking error has not yet reached zero.

Figure 22 shows the tracking error of the ship over time. It can be seen that at times t = 6.25s; 51.1s; 64.2s corresponding to the points A, C, D in Figures 21 and 22, the tracking error of the ship has a leap at the time of changing the waypoint. This jump in tracking error is explained similarly to the jumps in Figure 21. On the other hand, also Figure 21 represents that after the ship passes through the waypoint 3, the tracking error of the ship still cannot go to 0, but the tracking error reaches the minimum value of 0.1767m corresponds to point D in Figure 21 and Figure 22.

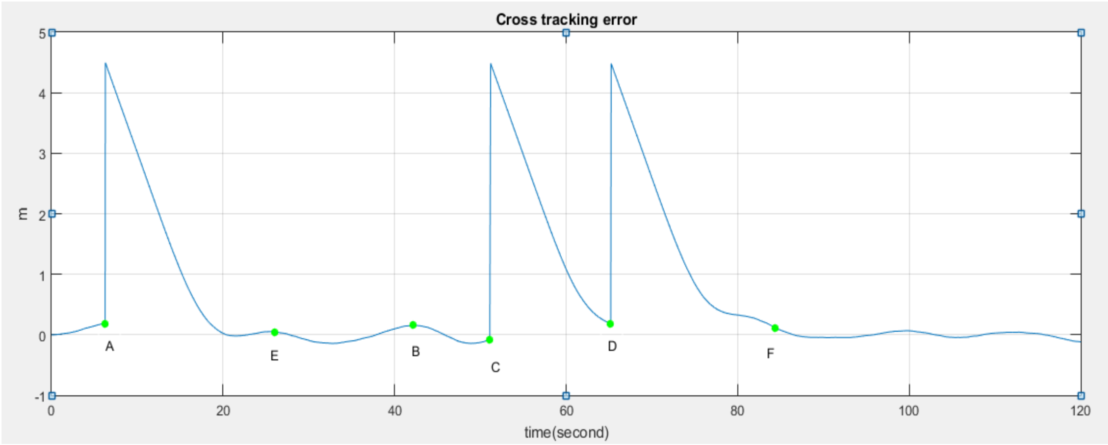

Figure 22. Error of tracking the ship's trajectory with the neuron PID control

In addition, as it is seen in Figure 21, the ship goes out of the bounding circle centered at waypoint 2, the tracking error in the stable region from point E to point C as shown in Figure 23 and Figure 24 has a tracking error of the oscillation around 0 with the largest tracking error in this region being 0.1557m. The establishment time of the ship from the time of starting to change direction from point A to follow the line segment of the trajectory made up of waypoint 2 and waypoint 3 is T = 11.97s (t_{100}-t_{10}=18.25-6.28=11.97s). Similarly, when the ship goes out of the limit circle centered at the waypoint 4 diversion point, we see that the tracking error in the stable area from point F to the point of waypoint 5 diversion also fluctuates around the value 0 and the value. The largest orbital tracking error value in this region is 0.1148m. The setting time of the ship from the moment of starting to change direction from point C to follow the trajectory line made up of waypoint 3 and waypoint 4 is T=17.54s (t_{280}-t_{190}=82.79-64.25=17.54s).

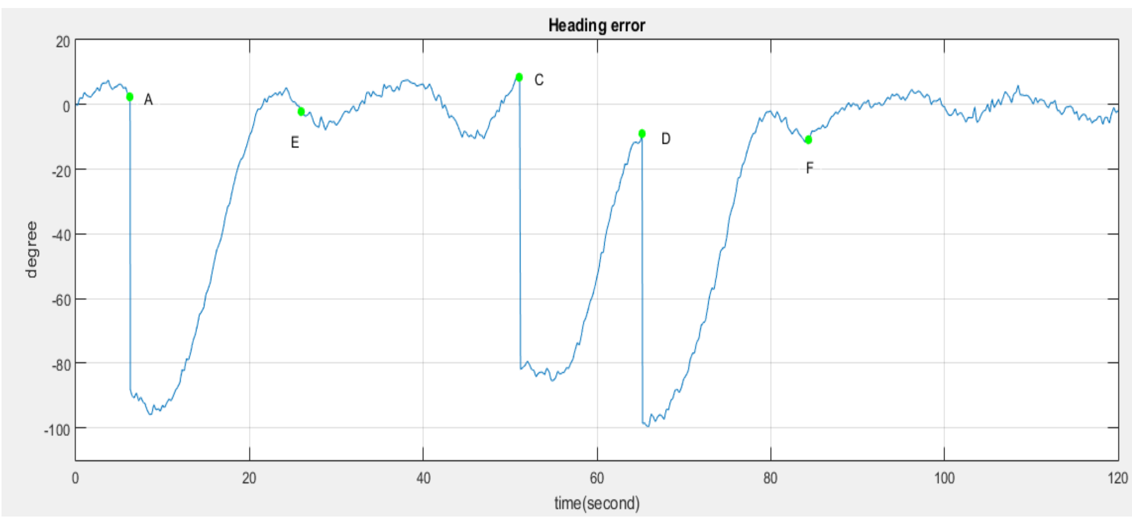

Figure 23. Error of ship's bow angle with neural PID control

Figure 23 shows the bow angle error over time. At time t = 6.25s; 51.1s; 64.2s, the bow angle error also has a similar jump as shown in Figure 24. In addition, we can see that after the ship leaves the limited circle centered at waypoint 2, the ship's bow angle error in the stable zone from point E to point C fluctuates around the value 0°, wrong. The largest bow angle in this section is 10.51°. Similarly, when the ship goes out of the limited circle centered at waypoint 4, the ship's bow angle error in the stability zone from point F to waypoint 5 also fluctuates around the value 0°. The largest bow angle error in this section is 10.82°.

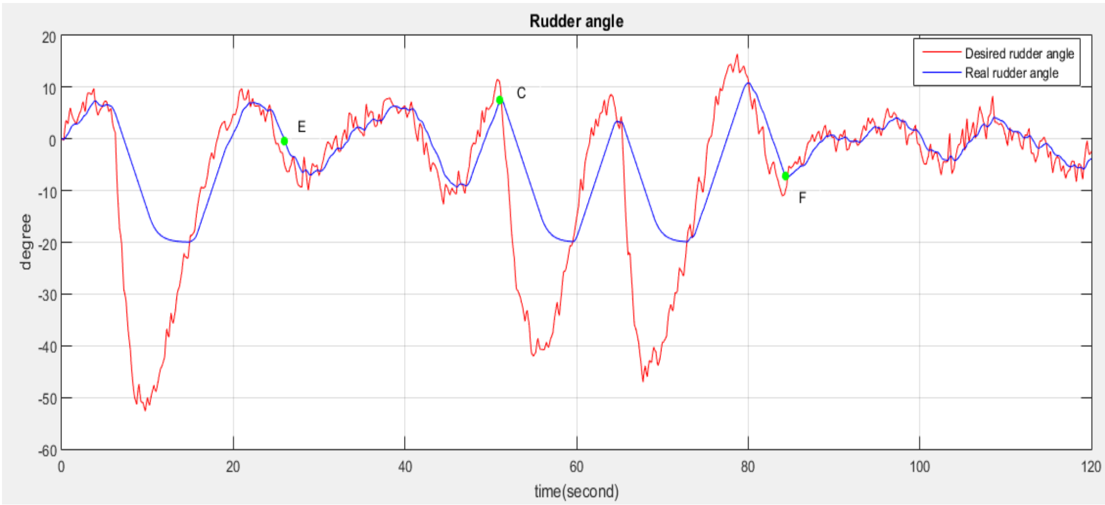

Figure 24. Steering wheel angle with neuron PID control

Figure 24 shows the ship's bow angle response when the automatic ship steering system uses a neural PID remote controller. Although the desired bow angle - the controller's output signal (desired rudder angle) (red line in Figure 24) has quite large jumps at times t = 6.25s; 51.1s; 64.2s, but the actual rudder angle response is still a smooth curve because the model ship's rudder is limited in angle and angular velocity, so the actual rudder angle response cannot have very large jumps.

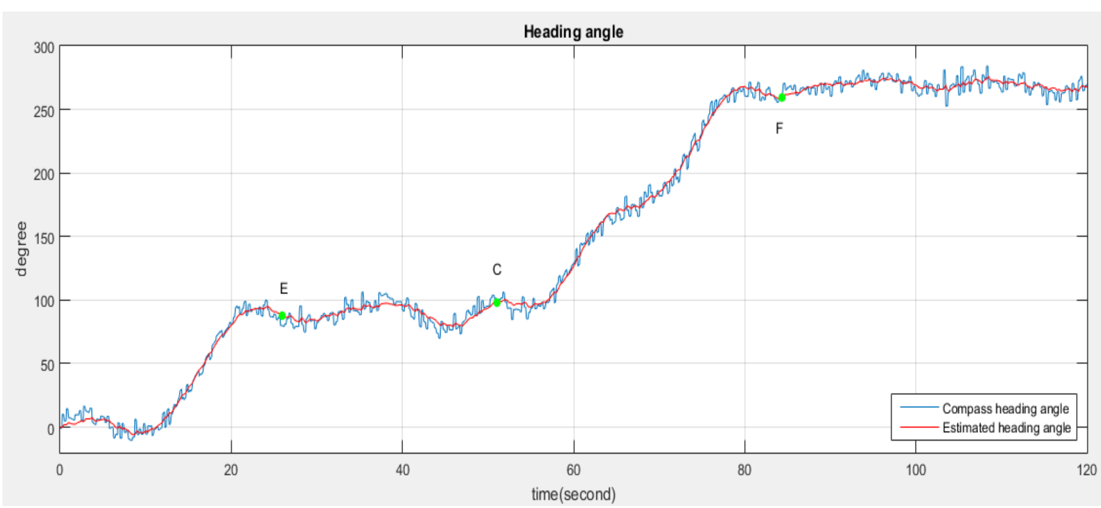

Figure 25. The bow angle of the ship with the neuron PID control

Figure 25 depicts the angle on the bow obtained from the compass sensor over time. After the ship passes through waypoint 2, in the stable area from point E to point C, the error of the bow angle does not approach 0° but fluctuates around this value. This can be explained because in the process of moving the ship is affected by noise from the environment, so the bow angle of the ship fluctuates. Similarly, when the ship passes through the waypoint 4 diversion point, in the stable zone from the point F to the waypoint 5 turning point, the bow angle also fluctuates around the value 0°.

Conclusions

The research has achieved the set research goals, with the following specific results:

1) Systematizing the theoretical basis of adaptive control algorithms based on the combination of artificial neural networks and conventional PID control theory. On that basis, it is proposed to develop an algorithm and apply it to the design of an autopilot using an adaptive neural PID controller for ship navigation control.
2) Programming application on Matlab to simulate the proposed controller, evaluate the quality of the neural PID controller adapted to the conventional PID controller.
3) Designing and simulating a neural PID map based on a backpropagation network, the author used a neural identifier to recognize the ship model. This recognizer uses a multi-layer feedforward neural network, but the author trains the network online, enhancing it with good adaptation speed, capable of identifying nonlinear ship models that change over time. By combining this neural recognition model, the control method is conducted in a real-time predictive control style, improving adaptation and control quality.
4) Experimental control of a miniature ship model in a test tank environment to verify the neural PID map and the response of the entire system to the impact of the external environment as well as the nonlinearity of the real ship model.

The Proportional - Integral - Differential parameters (K_p, K_i, K_d) of the PID controller are adjusted using a back-propagation neural network.

The novelty is demonstrated in the research through the following results:

- Proposing a model using augmented back-propagation neural networks combined with traditional PID maps to control ship navigation.
- Proposing a neural network to recognize ship models used in combination with a neural PID map to improve control quality and support the learning and adaptation process of the control neural network.

- The augmented back-propagation neural network training algorithm was used for the first time in combination with PID map applied to ship navigation control and gave good results.

The neural PID controller based on the artificial neural network proposed in the research shows the feasible options presented in the research and application of the PID controller based on the adaptive artificial neural network for ship control systems. The simulation and experimental results provide better results than the traditional PID map within the research scope of the research and demonstrate that the research goals have been achieved.

Research results can serve as a reference for further research projects, especially the application of intelligent control to ship navigation systems such as ship sway reduction, dynamic positioning.

Conflict of interest

With the specific scope and research object of the paper, the author's research problem has scientific and practical significance in the maritime industry and does not overlap with other published works.

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