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ARTIFICIAL NEURAL NETWORK AND MATHEMATICAL MODELING OF AUTOMATIC SHIP BERTHING

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Abstract. Automatic berthing has been known as one of the most challenging problems in ship control. During port approach and berthing maneuvers, the ship master takes into account many factors before any maneuver action, i.e. ship speed, wind speed, wind direction, current water direction, available power, heading angle, and ship response. Many methods related to automatic berthing were developed by recent research, such as Artificial Neural Network, Adaptive Backstepping, Nonlinear Programming, and Proportional-Integral-Derivative. However, most of these researches adopted a simplified dynamic model that reduces the validity of the optimal solution and may lead to dynamics that do not express real-time conditions. In this paper, a feed-forward controller using a non simplified mathematical model is developed. Numerical simulations were performed to verify the effectiveness of the proposed controller and test its ability to control the ship safely to reach the goal points of the berthing plan. The agreement between the ANN model results and experimental data is impressive.

Keywords: automatic ship berthing; maneuver action; mathematical modeling; artificial neural network; feed-forward controller.

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1. INTRODUCTION

Despite the development of the marine industry in our present, automatic ship berthing is still one of the most challenging problems in ship control, since large ship maneuvering in harbor areas is still done manually with the assistance of tugboats in order to ensure a safe operation. When the ship moves from open seas into confined waters, the ship engine must be set to dead slow, which characterizes the berthing operation by the following: significant reduction of controllability, complicated and nonlinear differential equations of motion and high effect of environmental disturbances. Therefore, during port approach and berthing maneuvers, many factors must be taken into consideration before any maneuvering action, such as ship speed, available power, heading angle and ship response, wind speed and direction, water current speed and direction as well as the condition of tugboats [14].

For these reasons, the automatic berthing operation has attracted the attention of many researchers since late 1980s. Given the difficulties in determining the exact modeling of the system and the unsatisfying results of the traditional control algorithms (feedback control, linear and non linear control), it is not surprising that recent research efforts have focused on developing intelligent control strategies (Neural Networks, Bayesian probability, fuzzy logic, genetic algorithms, etc.) independent of the dynamic model. Among them, Artificial Neural Networks (ANN) has proved to be one of the most effective and attractive options for automatic ship berthing [2], [1], since it is developed to mimic the actions of the human brain by mathematically modeling its neurophysiological structure [13]. Artificial Neural Networks was first applied, by Yamato et al. [24], as the main controller for ship berthing where its inputs included ship position, ship heading, ship velocities, and beam distances. This work, although showing excellent results, was replaced later by an expert system proposed by Yamato et al. [12]. J. Y. park et al. designed an adaptive controller adopting backstepping method [7]. Using the neural network theory, Hasegawa [18], [19], [21] developed auto-berthing controllers that consider the nonlinear characteristics of the ship motion at low speed. Later, Im and Hasegawa [15], [16], [5] proposed a parallel hidden layer neural network controller to obtain better results comparing to the centralized neural network. Thereafter, Im et al. [1],[2] developed an application of ANN for ship berthing using selective controller and considering that the ship can start from any point around the berthing areas. On the other hand, Nguyen et al. [3] developed two ANN controllers using an adaptive interaction learning technique and a predetermined berthing route to control the ship heading and ship speed simultaneously.

However, many issues have reduced the effectiveness of these solutions. Firstly, the simplified dynamic model used in most of the previous researches does not express the real conditions of the berthing operation. Many simulation techniques sometimes give inaccurate estimations of the hydrodynamic coefficients for mathematical models of ship motion, since one technique used for a model may not be applicable for other models in general. To avoid this, we used the MMG method proposed by the Japanese Mathematical Modeling Group (JMMG) [8]. This method can fulfill the requirements better than the simplified dynamic model because each component of the ship, such as the hull, rudder, propeller, and engines, is considered as a separate module that can be developed and tested separately. Therefore, changing the parameters of one component does not alter other modules, e.g. a change in rudder size or propeller geometry could be done without having to change other modules [6]. Secondly, using a linear programming calculation to solve a problem involving some degree of non-linearity may cause errors that reduce the validity of the optimal solution and may lead to dynamics that do not express real time conditions [10].

This paper is organized as follows: First, we propose a mathematical model for ship maneuvering that expresses real time conditions of the berthing operation. Next, we introduce the automatic ship berthing concept, then we present the research goals and objectives. Then, we present the numerical simulations and results that verify the effectiveness of the proposed mathematical model. Next, we introduce the ANN concept and architecture used in this research. Then, numerical simulations were carried out to demonstrate the effectiveness of the proposed ANN controller. After that, we discuss all the research results, then we introduce a new perspective that will be the focus of our future work. Finally, we conclude this paper.

2. Ship Dynamic Motion

In this study, the kinematic equations of the ship motion can be expressed using two coordinate systems: the space-fixed coordinate system O-xyz and the body-fixed coordinate system G-$x_b y_b z_b$. The origin G is located at the center of gravity of the ship, as described in Fig. 1,

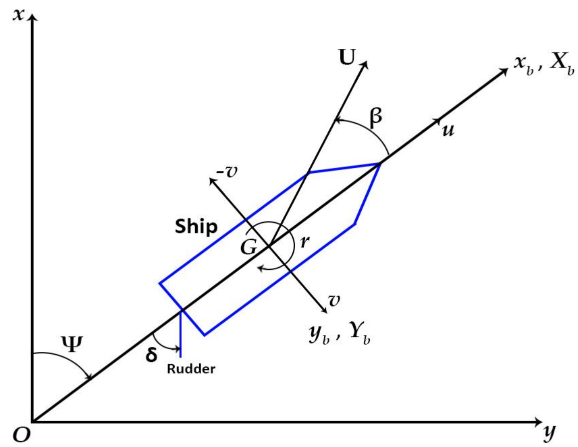

FIGURE 1. Coordinate systems for ship dynamic motion

and x_b-axis, y_b-axis point towards the ship's bow and towards the starboard, respectively. The z_b-axis is positive downward and all angles are positive in the clockwise direction. In most maneuvering studies, the ship motions in the three vertical degrees of freedom of heave, roll and pitch are assumed to be negligible. Therefore, the transformation between these two coordinate systems is expressed by Eq. 1 as follows:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\psi} \end{bmatrix} = J(\psi) \begin{bmatrix} u \\ v \\ r \end{bmatrix}, \quad \text{where } J(\psi) = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{1}$$

$J(\psi)$ is the rotation matrix that translates the body-fixed coordinate system into the space-fixed coordinate system. u and v are, respectively, the surge and sway velocities defined in the body-fixed coordinates, r is the yaw rate. ψ is the heading angle defined between the directions of y-axis and x-axis.

Using the Newtonian approach [9], the kinematic equations of the motion in the horizontal degrees of freedom of surge, sway, and yaw, described with respect to the selected reference system, in which the total hydrodynamic forces and angular moment are split into separate parts, are formulated as follows [4]:

(2)
$$\begin{cases} m(\dot{u}-v_G r) & = F_x \\ m(\dot{v}_G+ur) & = F_y \\ I_z\dot{r} & = M_z \end{cases}$$

Here, F_x, F_y and M_z are expressed as follows:

(3)
$$\begin{cases} F_x & = -m_x\dot{u}+m_y vr+X \\ F_y & = -m_y\dot{v}-m_x ur+Y \\ M_z & = -J_z\dot{r}+N-x_G F_y \end{cases},$$

where X and Y are the external forces in the x_b and y_b direction, respectively. N is the moment about z_b-axis through the center of gravity of ship.

Given that lateral velocity component at the center of gravity v_G is expressed as $v_G = v+x_G r$, the following equations are obtained:

(4)
$$\begin{cases} (m+m_x)\dot{u}-(m+m_y)vr-x_G mr^2 & = X \\ (m+m_y)\dot{v}+(m+m_x)ur+x_G m\dot{r} & = Y \\ (I_z+x_G^2 m+J_z)\dot{r}+x_G m(\dot{v}+ur) & = N \end{cases}.$$

Eq. 4 is the motion equations to be solved.

For better numerical simulations, the MMG method proposed by the Japanese Mathematical Modeling Group (JMMG) has been adopted. This method can fulfill the requirements better than the simplified dynamic model because it seperates the forces experienced by the hull, propeller, and rudder and also includes the interaction effects between the components of the ship that could be developed and tested seperately. Therefore, the terms on the right-hand side of Eq. 4 represent the external forces acting on the ship which are expressed as follows:

(5)
$$\begin{cases} X & = X_H+X_R+X_P \\ Y & = Y_H+Y_R \\ N & = N_H+N_R \end{cases}.$$

Subscripts H, R, and P denote hull, rudder, and propeller, respectively.

In these motion equations, the state variables are x, y, ψ, u, v, r. The external forces and moment on the right-hand side of Eq. 4 depend functionally on the state variables u, v, r, their derivatives $\dot{u}, \dot{v}, \dot{r}$, and the control variables η, δ. The control η (propeller revolution) converts engine horsepower into thrust by accelerating air and creating a low-pressure differential in front of the propeller and these forces are what helps move the propeller forward, thus moving the ship. The control δ associated with rudders that are hydrofoils which are pivoting on a vertical axis and produce a transverse force and steering moment about the ship centre of gravity [22].

In ship maneuvering, normalization is usually used to estimate the hydrodynamic coefficients in the mathematical model of ship motion [17]. Since the dimensions of the port area (longitude and latitude) and the length of the ship are reduced in numerical simulations, the port area and ship length must be normalized into a non-dimensional form by dividing the latitude and longitude by the length of ship (L) [23]. In addition, in trajectory optimization computation, it is convenient to normalize the kinematic equations [20]. Using the normalization factors, all variables become dimensionless. Of course, normalization is not really needed for quantities which are inherently dimensionless such as the yaw angle ψ.

For numerical simulations, a ship called SAE NURI of Mokpo National Maritime University was selected as training ship. The principal particulars of the training ship are given in Table 1. Using all these data, the equations of the developped MMG model were solved.

TABLE 1. Principal particulars of the model ship.

Type	Training ship
Length overall	103 $[m]$
Length between perpendicular	94 $[m]$
Breadth	15.6 $[m]$
Draft	5.4 $[m]$
Thruster (Bow)	49000 $[N]$
Tranverse projected area	183.3 $[m^2]$
Lateral projected area	1053.7 $[m^2]$

3. Automatic Ship Berthing Concept and Goals

3.1. Berthing plan. To control the ship into berth safely, the whole berthing operation is specifically divided into three basic elementary maneuvers that are course changing, step deceleration and engine stopping. Therefore, the berthing plan concept can be described as shown in Fig. 2. Firstly, the berthing master will guide the ship from any giving starting point to the first goal point $G1$ in which the ship will be aligned to a berthing approach line known as imaginary line. In most researches on berthing control, for simulation purposes, the imaginary line was chosen to form an angle of 30 deg with the berth direction. Secondly, after merging to the imaginary line, the ship will keep its path and reduce its speed until the engine resumes its idling speed to stop the ship at the second goal point $G2$. Finally, the ship will be controlled step by step to the last goal point $G3$, alongside the quay and ready for safe mooring operation. In the meantime, it is difficult to control the position of the ship only by means of rudder and main engine. In case of a large ship with speed of fewer than 2–3 knots, its position cannot be controlled by adjusting the rudder and main engine. In this case, it is necessary to use the equipment such as tugboats and thrusters to assist the ship maneuvering.

In this research, the supposed berthing final goal is assumed to be at some interval distance before the berth direction instead of approaching the pier board to board. In most cases, this distance between the ship and the pier is 1.5 times of ship length.

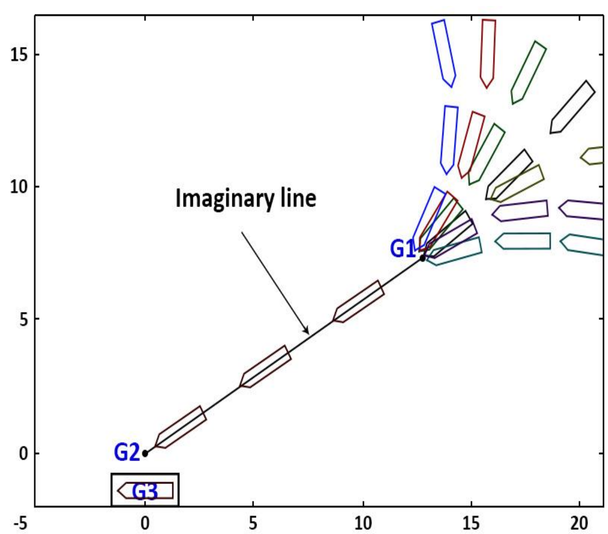

FIGURE 2. Berthing plan concept

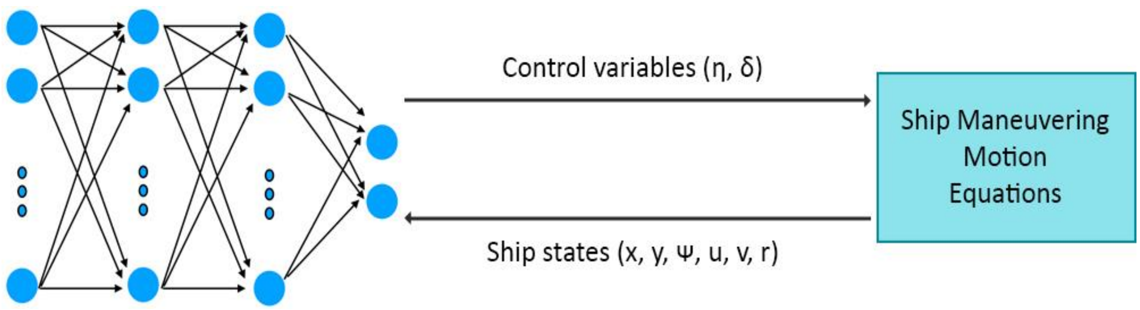

FIGURE 3. Control strategy of automatic ship berthing using neural controller

3.2. Basic facts and assumptions. To reduce the complexity of the procedure, some basic facts and assumptions, needed to be made before describing automatic ship berthing using ANN, are summarized as follows:

(1) Automatic ship berthing was performed using a computer simulation. Then, parameters such as the ship position, ship heading, and the ship velocities were calculated with respect to time using Eq. 1 and Eq. 4. These parameters were used as inputs for the ANN controller as shown in Fig. (3). Nowadays, the development of high technologies in navigation equipment provides us with various kinds of navigation aids such as a gyro-compass, ECDIS, AIS, GPS and RADAR. This makes navigators easily acquire more accurate ship states.

(2) The port area was assumed to contain sufficient water depth and no obstacles to ensure the ship dynamics and the ship motion are not affected by these factors.

3.3. Research goals and objectives. The primary goal of this research is to validate the effectiveness of our proposed mathematical model of ship motion by using a non linear programming calculation in order to express real time berthing operation of the ship. Once the effectiveness of the proposed mathematical model is verified, it will be used as the basic model in future works in which the environment conditions will be included. In Addition, a feed-forward neural network controller will be implemented with the proposed mathematical model. Once the effectiveness of the proposed controller is validated by the numerical simulations, the controller will be a part of a comparative analysis of methods related to automatic ship berthing.

4. Numerical Simulations and Results of the Proposed Mathematical Model

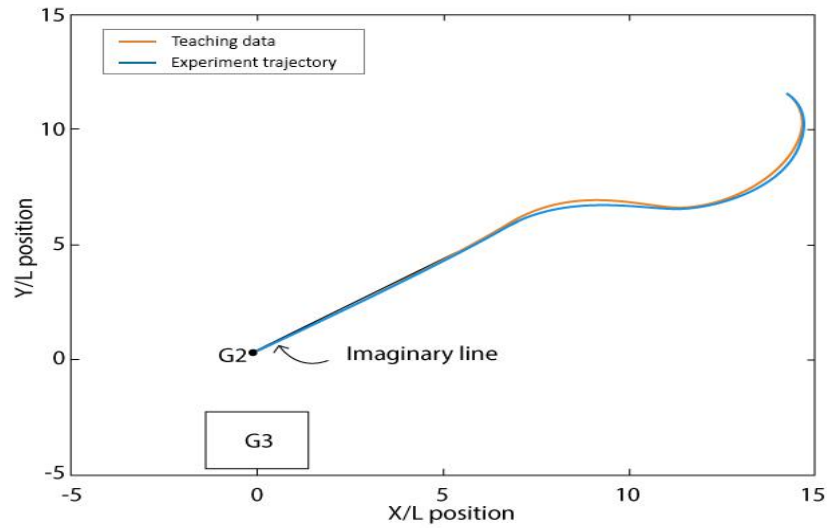

FIGURE 4. Control strategy of automatic ship berthing using neural controller

In order to validate the effectiveness of the proposed mathematical model of ship motion, the trajectory resulted from the numerical simulation is compared with the ship master performance, as shown in Fig. 4. Generally, the proposed mathematical model is believed to have the ability to control the ship safely to reach the goal point G2 due to its dynamics that are based on MMG method, the non-use of hypotheses that may simplify the model and the nonlinear resolution of the equation system. All these points lead the model to have the ability to express real time conditions [11]. In particular, the numerical simulation results presented in Fig. 5 demonstrated the effectiveness of the proposed model. The first spans of the simulation describe the course-changing maneuver as it was the first course taken for the ship berthing in this case. And as we took the deceleration course, the ship was controlled to the berth within $0.25\,m/s$ and with a heading that is parallel to the berth as possible.

The little variations, existing between the experiment trajectory and the trajectory performed by the ship master, are explained by the presence of wind disturbances. In case of no obstacles, during the course deceleration along the imaginary line, no rudder angle is taken. But in case of the presence of obstacles such as environmental disturbances, the ship may deviate from the imaginary line. Thus the necessity of some sophisticated controller that can deal with the ship deviation.

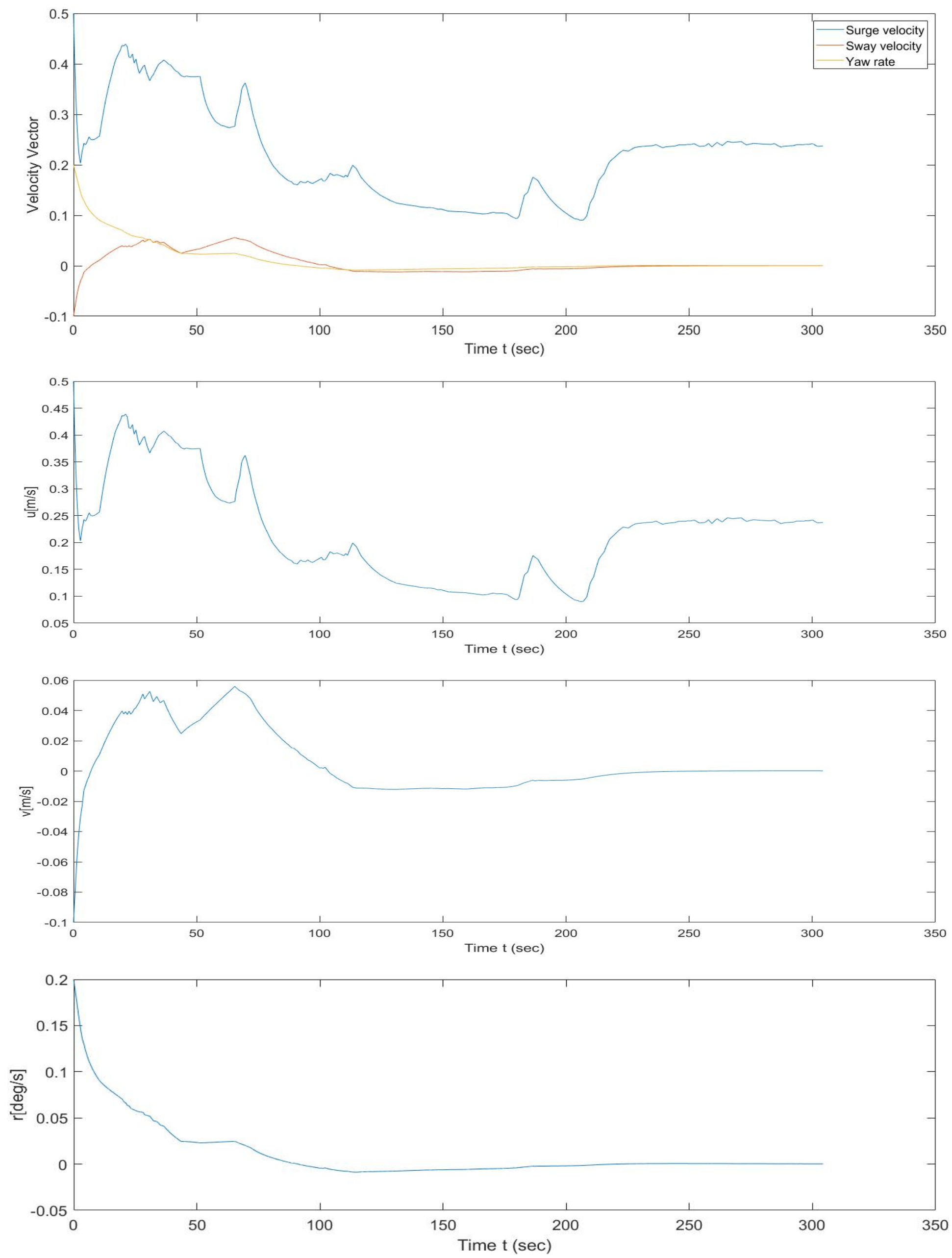

FIGURE 5. Control strategy of automatic ship berthing using neural controller

5. Artificial Neural Network Concept

5.1. Teaching data creation. In this section, numerical simulations were carried out to prove the above berthing plan and concept. The teaching data used to train the proposed ANN controllers is obtained from a real ship berthing performance that is manually controlled by the ship master. It is known that ship berthing is performed by skilled local captains who have the experience in manually maneuvering a ship into a berth and also who better know the port conditions. Therefore, due to their skills and experience, the teaching data is supposed to contain a set of time series of successful berthing maneuvering process that is able to control the ship from a starting point and reach the goal point $G2$ within 0.2 m/s of speed and 250-270 deg of the true heading angle.

In this research, the teaching data is constructed without taking in consideration the disturbances. In case of environmental disturbances such as wind and current, new teaching data must be created by a new ship berthing maneuvering process in which the environmental disturbances are included. Fig. 6 shows the time history of the teaching data used in this research, while Fig. 7 and Fig. 8 show, respectively, the propeller values and rudder values for ship automatic berthing best performance.

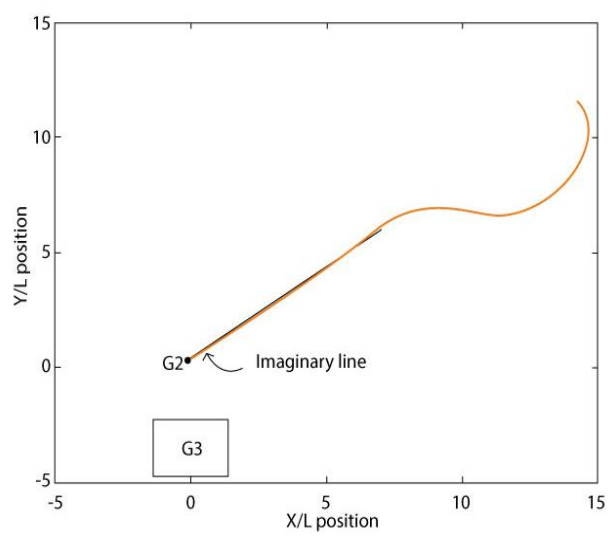

FIGURE 6. Time history of the teaching data.

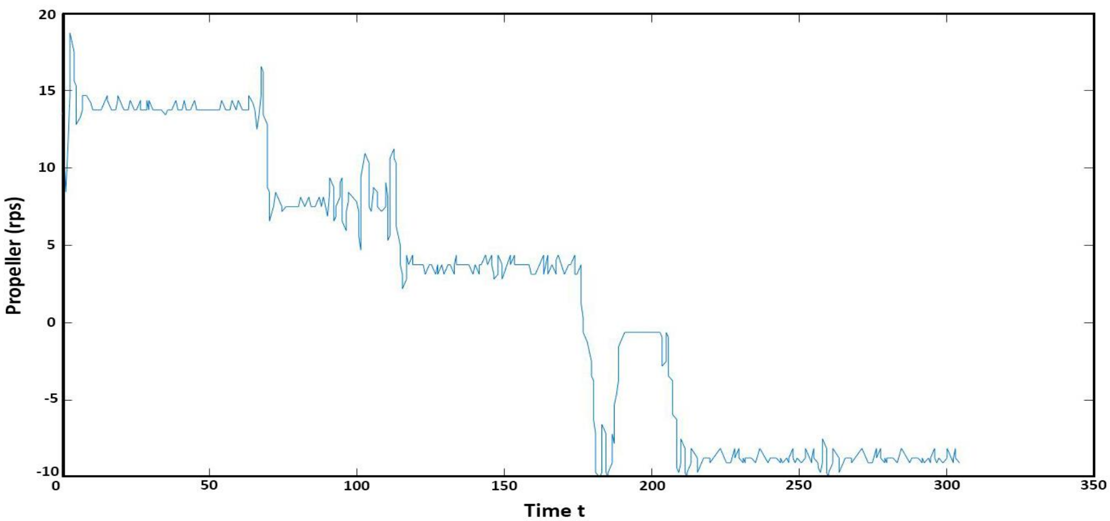

FIGURE 7. Propeller values for ship automatic berthing best performance.

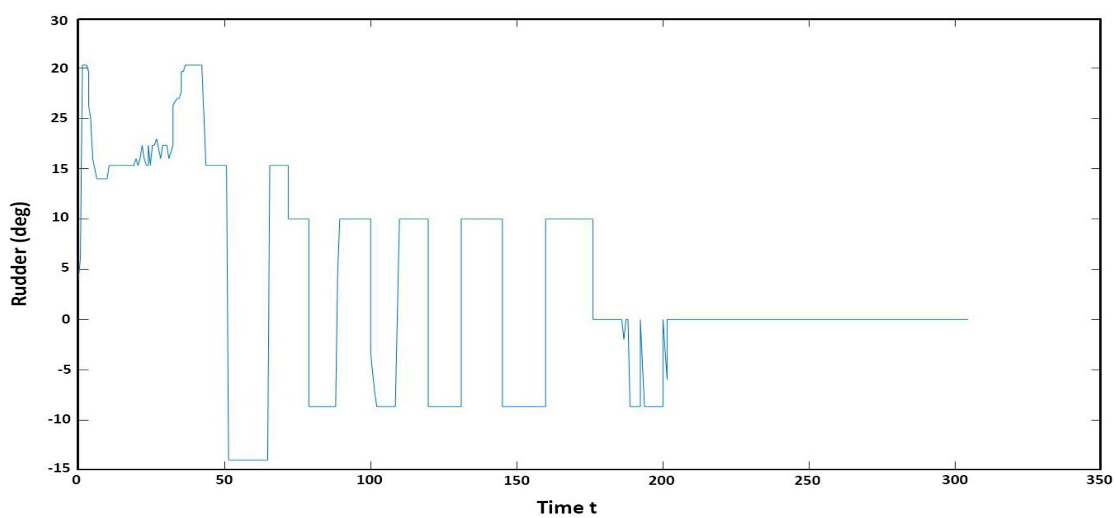

FIGURE 8. Rudder values for ship automatic berthing best performance.

5.2. Artificial neural network architecture. In this research, a feed-forward neural network, also known as deep feed-forward network or multi-layer perceptrons, is used instead of Centralized Neural Networks (CNN) as its effectiveness has already been proved in many previous researches and in which it is based on the fact that the hidden layer has a strong learning ability.

In order to design well-trained network, we first need to choose an appropriate number of hidden layers as well as the corresponding number of neurons in each hidden layer. Though there is no real concept or interpretation of how many hidden layer to use in the neural network model, yet, using one or two hidden layers show good results in previous automatic ship berthing studies. In addition, determining the appropriate number of neurons in the hidden layer is considered one of the greatest issues in designing NN model. The fewer the neurons in a network, the fewer the number of operations required and this proved to be the less time-consuming part in the implementation of the controller. In the case of too few hidden neurons, the controller will not be capable of modeling complex data. Conversely, in case of too many hidden neurons, the model will over fit the data. Therefore, our proposed controller presented in Fig. 9 is built by a three-layer feed-forward neural network (input layer, output layer and hidden layer). The input layer has 6 variables: ship position (x, y), surge u, sway v, yaw rate r, and ship heading ψ. The output layer has two variables: propeller revolution η and rudder angle δ, while in the hidden layer 21 neurons are constructed.

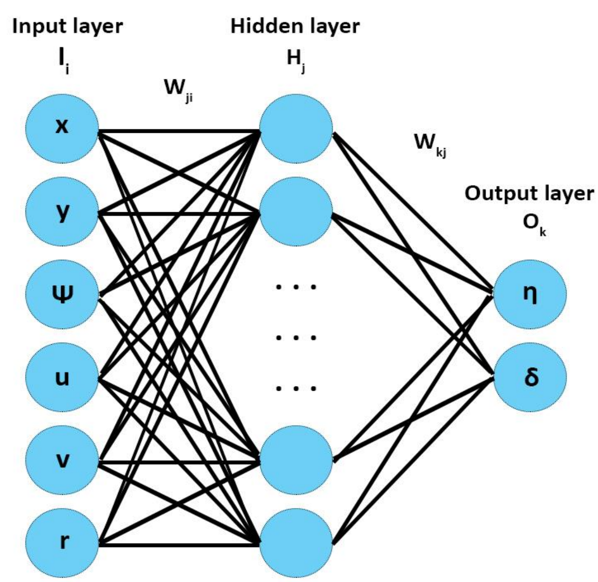

FIGURE 9. The structure of neural network controller.

5.3. Artificial neural network design. In machine learning, Back-Propagation (BP) algorithm is one of the most popular algorithms for training feed-forward neural networks. It aims to evaluate the outputs of the network against the desired outputs of the teaching data. In other words, if the results are not satisfactory, the back-propagation is used to compute the necessary corrections in order to modify the connection (weights) between layers. The process is repeated again and again until the value of the error function has become sufficiently small. The algorithm is decomposed in the following four steps:

(1) Feed-forward computation
(2) Back-propagation to the output layer
(3) Back-propagation to the hidden layer
(4) Weight updates

where the last step is happening through out the algorithm.

The feed-forward computation is decomposed in two steps. The first step consists of calculating the values of the hidden layer by the following equation:

$$H_j = f_1(net_j) = f_1\Big(\sum_{i=1}^{i} W_{ji} I_i\Big), \tag{6}$$

where, H_j is the j-th node at the hidden layer, f_1 the transfer function at the hidden layer, net_j the input of the j-th node of the hidden layer, i the number of nodes in the input layer, j the number of nodes in the hidden layer, W_{ji} the weights or the connections between the node j and node i, and I_i is the value of the input of the node i of the input layer.

As a transfer function of the network at the hidden layer, sigmoid function was found very suitable and is given as:

$$f_1(x) = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1}. \tag{7}$$

Similarly, the p-th node at the output layer is determined as in the following equation:

$$O_k = f_2(net_k) = f_2\Big(\sum_{j=1}^{j} W_{kj} H_j\Big), \tag{8}$$

where, O_k is the k-th node at the hidden layer, f_2 the transfer function at the output layer, net_k the input of the k-th node of the hidden layer, j the number of nodes in the hidden layer, k the number of nodes in the output layer, W_{kj} the weights or the connections between the node k and node j, and H_j is the value of the node j of the hidden layer.

The transfer function of the network at the output layer was chosen as a satlins function and expressed as in the following equation. The selection of a satlins function to activate the output layer of the network both creates a network with sufficient capacity to fit the teaching data and saves time in training the network.

$$f_2(net_k) = \begin{cases} -1, & \text{if } (net_k) \leq -1 \\ net_k, & \text{if } -1 \leq (net_k) \leq +1 \\ +1, & \text{if } (net_k) \geq +1 \end{cases} . \tag{9}$$

Back-propagation and weights adjustment step consists of calculating the error of the nodes of the output layer. In this study, we used the Mean Squared Error (MSE) (or Mean Squared Deviation (MSD)). It measures the average of the squares of the errors between the output values of the trained network and the desired output. Depending on the calculated Mean Squared Error value (MSE), the performance of the trained ANN is evaluated.

Assuming for each target output T of the network, there is a corresponding desired output O, then the MSE is computed as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e(i)^2 = \frac{1}{n}\sum_{i=1}^{n}(T_(i) - O(i))^2. \tag{10}$$

The calculated mean squared error will be used for backward propagation and weights adjustment.

First, the error is propagated from output layer to the hidden layer. This is where learning rate and momentum are brought to equation. Before weights can be updated, rate of change needs to be found for each connection between the output layer and the hidden layer and it is calculated by multiplying the learning rate, error value and the value of the j-th node of the hidden layer. The process is repeated from hidden layer down to the input layer.

This paper has no ambition to explain the mathematical process step by step but concentrates on the concept of berthing and its results that are displayed by simulation procedures implemented in MATLAB.

During the training process of the neural network, the big challenge was to choose the number of the nodes in the hidden layer. This procedure is very important to guarantee that learning error converges to zero in the shortest time, which means it ensures that the outputs of the network always follow up the outputs of the teaching data. The parameters of the proposed ANN controller are listed in Table 2 and Table 3.

TABLE 2. The parameter of weights linked input layer to hidden layer (W_{ji}).

1	2	3	4	5	6
-2.4358	-1.0040	1.4569	0.7489	2.4569	2.8788
-2.8597	-0.2008	0.0089	-0.2500	-2.1255	-1.4089
-1.3066	-1.4059	-2.8788	-1.5455	2.5044	1.9528
-0.8001	0.7458	1.4587	2.4578	3.4785	2.5478
-1.8856	-0.4522	-0.5787	2.4545	1.9878	3.2544
-1.2545	-0.7800	1.2111	-2.0087	1.3005	2.1805
-1.0203	0.2545	-02005	-2.2121	0.4000	2.7588
2.3500	0.9455	-0.7810	-2.1205	2.0055	-2.0244
-1.5455	-0.6777	1.1345	-1.5455	1.0450	2.2240
0.4550	1.8789	2.0048	-1.4458	2.4540	1.0005
0.6788	-3.0055	2.6788	2.3445	1.9880	-0.7815
1.8880	-3.0227	-0.0545	0.2440	-0.4577	2.4578
-24608	0.9800	-3.0400	1.2455	2.4003	1.8313
3.0320	-4.0529	0.2332	-1.6873	-0.3240	-1.4320
-0.8627	-1.2754	-3.1900	-2.7070	-2.1950	-07895
-0.5537	-1.8054	-0.0274	0.2874	-1.7845	2.4563
-2.6012	-1.0458	1.2487	0.2345	2.7531	2.1458
1.7842	-3.2748	-0.4520	0.2009	-0.3128	2.4859
-2.1547	0.1247	-1.24r9	3.0058	1.2405	0.5482
-0.5142	-0.3258	1.0081	0.2385	2.7151	0.1478
0.9163	0.8452	-0.4520	-0.4753	2.4578	0.5426

6. ANN Numerical Simulations and Results

The numerical simulation results of the trained network presented in Fig. 10, after being trained by back-propagation and weights adjustment processes, demonstrated the effectiveness and the accuracy of the proposed ANN controller. Using the same teaching data constructed from the berthing ship performance of the ship master used in previous sections, the trajectory resulted from the numerical simulation is almost the same as the trajectory performed by the ship master.

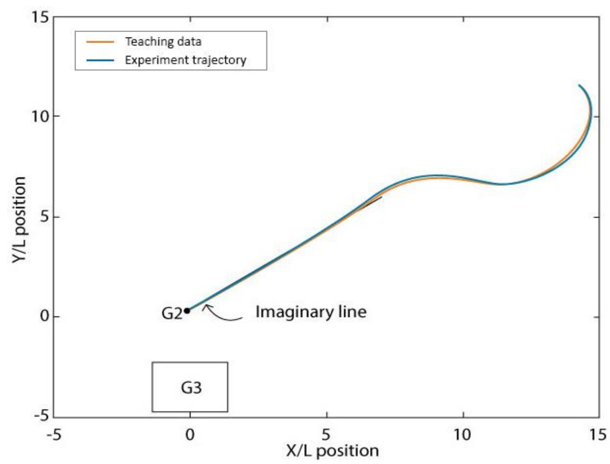

FIGURE 10. Control strategy of automatic ship berthing using neural controller

These numerical simulation results validated the learning ability of our proposed ANN controller. It is believed to be a very useful tool when faced with a situation that mimics that of a trained one. As presented in Fig. 10, having the same initial conditions at the starting time as those of in the teaching data, the numerical simulation results show that the proposed ANN controller is believed to have the ability to perform successful actions for controlling the ship safely to reach the goal point G2 within $0.25\,m/s$ and with a heading that is parallel to the berth.

7. Discussion and Perspectives

In this study, we used the MMG method proposed by the Japanese Mathematical Modeling Group (JMMG) that consists of developing and testing each component of the ship separately. This technique can give accurate estimations of the hydrodynamic coefficients for the mathematical model of the ship. The resulted mathematical model can express real conditions of the berthing operation better than the simplified dynamic model used in previous researches. In addition, the use of nonlinear programming calculation for the proposed mathematical model prevents us from errors that reduce the validity of the optimal solution and may lead to dynamics that do not express real time conditions. Therefore, the proposed mathematical model of the ship motion, as presented in the numerical simulation results, is believed to have the ability to provide us with accurate ship parameters such as ship position, ship heading, and ship velocities, that were used as inputs for the proposed ANN controller.

The ship model represented in the study is under condition of calm and deep water conditions, in the actual navigational situation, there are many kinds of environmental forces such as wind, wave and current. It will be proper in the future to investigate the mathematical formulas of such forces and add them as additional modules.

TABLE 3. The parameter of weights linked hidden layer to output layer (W_{kj})

1	2	1	2	1	2
-0.1231	-0.1294	1.2345	0.9485	-0.8107	-1.2874
0.4586	1.2389	-0.5458	-1.3777	-0.5527	-1.1554
-2.5447	1.2223	0.4250	2.1245	-2.6212	-2.0478
-0.2455	-0.5963	0.6588	-0.0855	2.7542	-3.2648
-2.1009	0.1200	1.8580	-3.2057	-0.5647	1.1487
-0.1254	1.2350	-24608	1.1200	-0.5142	-2.3998
2.4578	-0.1214	3.0120	-4.0529	1.9143	-1.8452

8. CONCLUSION

Even though the marine industry knew an important development, automatic ship berthing is still one of the most challenging problems in ship control. Many researches have been carried out to solve this problem. This study proposed a feed-forward neural network which its inputs are generated by a proposed mathematical model for ship maneuvering. The numerical simulation results showed that the ship could automatically reach the designated goal point in a safe distance and heading angle. The conclusions of this study can be summarized as follows:

(1) To express real time conditions of the berthing operation of the ship, MMG analysis method is adopted for determining the hydrodynamic force coefficients that used to create the proposed mathematical model for ship maneuvering simulations.

(2) To increase the validity of the optimal solution, the proposed mathematical model is solved using a nonlinear programming calculation with less hypotheses.

(3) To validate the effectiveness of the proposed mathematical model, the trajectory resulted from the numerical simulation is compared with the trajectory performed by the ship master. The comparison results are found quite satisfactory.

(4) The little variations, existing between the experiment trajectory and the trajectory performed by the ship master, are explained by the presence of environmental disturbances such as the wind.

(5) The outputs of the proposed mathematical model are used as inputs for the proposed feed-forward neural network that is adopted instead of centralized neural networks as its effectiveness has already proved in many previous researches and in which it is based on the fact that the hidden layer has a strong learning ability.

(6) Numerical simulations result demonstrated that the proposed neural network controller built for the proposed berthing system verified its effectiveness.

(7) In our future work, new controllers will be proposed to carry out a comparative analysis of methods related to automatic ship berthing. Adding the environmental disturbances modules into consideration in the berthing operation modeling will contribute to the enhancement of maritime safety.

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CONFLICT OF INTERESTS

The author(s) declare that there is no conflict of interests.

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