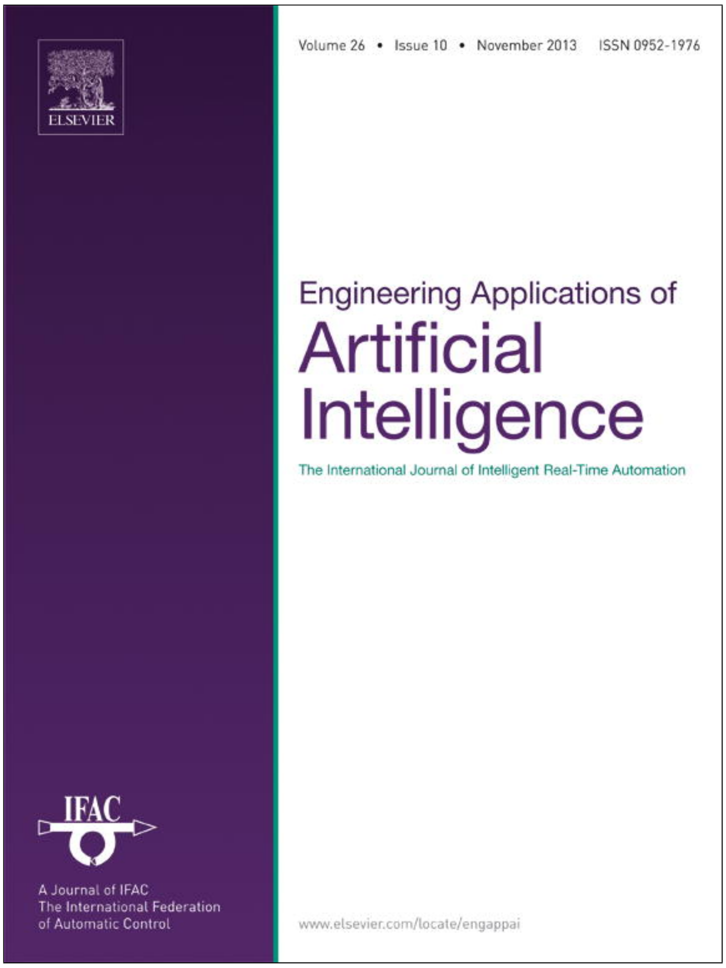
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Automatic ship berthing using artificial neural network trained by consistent teaching data using nonlinear programming method

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ABSTRACT

Ship handling during berthing is considered as one of the most sophisticated tasks that a ship master has to face. The presence of current and wind make it even more complicated to execute, especially when ship approaches to a pier in low speed. To deal with such phenomenon, only experienced human brain decides the necessary action taken depending on situation demand. So automation in berthing is still far beyond imagination. But, if the human brain can be replicated by any suitable artificial intelligence technique to perform the same action that human brain does during berthing, then automatic ship berthing is possible. In this research artificial neural network is used for that purpose. To enhance its learnability, consistent teaching data based on the virtual window concept are created to ensure optimal steering with the help of nonlinear programming language (NPL) method. Then instead of centralized controller, two separate feed forward neural networks are trained using Lavenberg–Marquardt algorithm in backpropagation technique for command rudder angle and propeller revolution output respectively. The trained ANNs are then verified for their workability in no wind condition. On the other hand, separate ANNs are trained with reconstructed teaching data considering gust wind disturbances. To deal with any abrupt condition, ANN followed by PD controller is also introduced in case of command rudder angle output whose effectiveness is well verified not only for teaching data but also in case of non-teaching data and different gust wind distributions.

1. Introduction

Ship berthing has always demanded a sophisticated controller due to the requirement of multiple input and output parameters including data of environmental disturbances. To achieve that purpose, different kinds of controllers like fuzzy theory and knowledge based system are tried by many researchers but each of such controllers has some limitations when using for berthing. Like in case of fuzzy theory, it is needed to define the fuzzy rule but to define proper rule is very tough for berthing since any unpredictable situation may arise including environmental disturbances which cannot be pre-implemented as a rule. On the other hand in case knowledge based system or expert system, every possible situation needs to be included as written statement with corresponding solution which makes the controller more rigid instead of robust. Thus human knowledge judgement should be regarded as a best alteration in such cases. That is why, among different kinds of controllers investigated for berthing, ANN has some privileges like it can be a good replicator of human brain and also has the ability to generalize and learn any nonlinear multi-input multi-output (MIMO) system. Moreover as the network learns from examples and adapts to situation based on its findings, it can generalize knowledge to produce adequate responses to any unknown situation. As a result ANN is expected to solve complex problems like automatic berthing that are difficult to manage by other controlling system.

In this research to ensure a safe and appropriate berthing manoeuvre, the whole manoeuvring plan is divided into three basic elementary manoeuvres which are course changing, step deceleration and stopping. For course changing manoeuvre, using NPL method, four virtual windows are founded where rudder angles are restricted within $\pm 10^\circ$, $\pm 15^\circ$, $\pm 20^\circ$ and $\pm 25^\circ$ respectively. Each of such windows ensures a ship with a particular heading angle passes through its allocated position to reach the imaginary line by actuating the corresponding rudder angle for which the window is constructed. In such cases, the NPL method ensures the command rudder angle taken to direct the ship with optimal time manoeuvre so as to merge with imaginary line well ahead which is 15 L from berthing point. Imaginary line is that line which most masters use to direct their ship course towards the berthing pier. After merging with imaginary line, ship commands to go straight by following sequential

Text for Footnote 1

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telegraph order which is constructed by maintaining speed response equation. Finally the engine idling time is tuned such that when engine idling followed by propeller revering, ship will stop as close as possible to the berthing point.

After preparing the teaching data, two separate feed forward multi-layered ANN controllers have been investigated to find the suitable number of hidden layers together with appropriate number of neurons in each layer which best suit to the teaching data for command rudder angle and propeller revolution output respectively and such suitability is determined by considering minimum squared error (MSE) as evaluation function. The famous back propagation which is gradient descent algorithm is used during training process where the network weights are moved along the negative of the gradient of the evaluation function.

In case of wind disturbances, same types of teaching data are reconstructed but this time considering gust wind of different velocities and from different directions. But in low speed, ship manoeuvrability reduces drastically. Therefore, when ship moves straight along with imaginary line and its velocity gradually reduces due to propeller revolution drop then the effect of such wind is very severe. If a ship motion is considered as signal and environmental disturbances as noises then in low speed straight running the signal-noise ratio becomes low enough for any controller to separate the noises from actual ship motion. Thus, even the ANN is trained to deal with wind disturbances, the differences in ship motion during low speed are quiet large and uncertain due to such high noises. As a result instead of ANN, more robust controller is preferable to take adequate rudder angle to guide the ship in correct path in such situation. In this research among different types of controllers, the more sophisticated PD controller is introduced to prevent ship's deviation from imaginary line by taking proper rudder angle and make the complete set of teaching data. While using the PD controller, the compensation for desired ship heading as well as minimizing the perpendicular distance from the imaginary line is given preference. As a result, even be a common PD controller, it plays a significant role due to its robust nature and works effectively than any other controller or rule based adjuster as Im and Hasegawa (2002) used during low speed running.

Finally, the effectiveness of ANN followed by PD controller is verified by performing automatic berthing simulations even under different initial conditions with teaching data and wind disturbances.

2. Background of this research

Considering the advantages of artificial neural network, it has a great applicability to use as a controller for any suitable nonlinear system or to assist some other controller to form a hybrid one. The first research using ANN as a controller was started by Yamato et al. (1990) for automatic ship berthing and found good results. Fujii and Ura (1991) then used both supervised and non-supervised learning system to construct neural network based controller for AUVs and compared the results. After him ANN had been used in different controlling aspects like temperature control (Cui et al., 1992), process control (Lee et al., 1994), paper mill wastewater treatment control (Zeng et al., 2003), and engine air/fuel ratio control (Zhau et al., 2009). ANN together with Fuzzy logic also created another field of research for hybrid controller like Aoyama et al. (1995) used it for process control, Di et al. (2001) used such for arc welding.

For automatic ship berthing, after Yamato et al., Hasegawa and Kitera (1993) and Im and Hasegawa (2001, 2002) have continued the research. Hasegawa considered neural network controller combined with expert system where Im proposed two separate nets to control rudder angle and propeller revolution instead of using centralized controller. In case of wind disturbances, Im also proposed motion identification method using ANN for detecting ship's lateral velocity and yaw rate. Then based on the two rule based adjusters for the corresponding, the necessary action was taken. Using this procedure, although he succeeded in limited wind velocity but in case of wind blowing parallel to the ship's direction, results were not fruitful. Later on, his research was tried to update by putting weights on creation of teaching data. Some adopted human knowledge for creating teaching data and some used standard manoeuvring plan. But in both cases consistency was not there. Thus the problems regarding how to create teaching data in more consistent way and whether proper trained ANN has the ability to cope with any possible wind disturbances remain unsolved. As a continuation of research, recently Im et al. (2007) proposed a new algorithm for automatic berthing using selective controller. In his proposed algorithm he divided the approaching ship area into several zones and used separately trained ANN to guide the ship from one zone to another. The main intention of this research was to make ANN independent of particular port shape and predetermined approaching pattern. On the contradictory, Nguyen et al. (2007) tried non-supervised learning system using adaptive ANN for automatic ship berthing where neural network controller is trained online using adaptive interaction technique without any teaching data and off-line training phase. Therefore, none of the mentioned researches put weight on creation of consistent teaching data and judge the effectiveness of trained ANN with such teaching data. In the meanwhile, Ohtsu et al. (2007) proposed a new minimum time ship manoeuvring method using nonlinear programming. Using his proposed method, first attempt to make consistent teaching data for berthing was made by Xu and Hasegawa (2012). But in such research even NPL method for creating teaching data was used but usage of too many constraints as termination conditions, resulted fluctuation in command rudder angle output which also provided difficulties during training net. As a result even in absence of disturbances, ANN results are not good enough during low speed manoeuvre. Moreover, such research also considered limited direction of wind blowing together with uniform wind disturbances up to certain small limit while investigating ANN's effectiveness in wind condition. But, in real case wind blows in gust form rather than uniform and severe wind may also expected to blow from any possible direction during travelling with reduced velocity which have not been investigated yet in case of berthing problem. Moreover, in case of wind disturbances he also adjusted the propeller revolution according to the requirement manually rather than by ANN. So to improve such lackings, current research is highly concentrated on creating consistent teaching data using NPL method with almost no fluctuating command rudder angle based on virtual window concept. Consideration of such virtual window concept in teaching data also eliminates the use of selective controllers as it covers almost all possible ship approaching and adjustable to any suitable pier configuration. After training, the effectiveness of ANNs are checked in case of no wind and gust wind condition where maximum wind velocity is considered as 1.5 m/s (15 m/s for full scale) from different directions which is also considered as maximum one in most ports in Japan for berthing.

3. Subject ship and mathematical model

3.1. Subject ship model

In this research, 3 m model ship of Esso Osaka is used as subject ship. Principal particulars of the corresponding model ship are shown in Table 1.

Moreover, the coordinate system used to formulate the equations of motions together with the wind direction consideration is shown in Fig. 1.

Table 1
Principal particulars and parameters of model ship.

Hull		Propeller		Rudder	
L (m)	3	D_p (m)	0.084	b (m)	0.083
B (m)	0.48	P (m)	0.06	h (m)	0.1279
D (m)	0.2	Pitch ratio	0.7151	A_R (m^2)	0.0106
C_b	0.831	Z	5	Λ	1.539

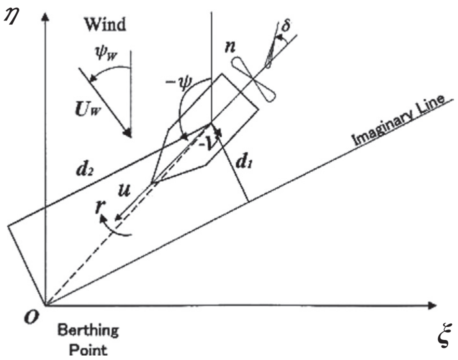

Fig. 1. Coordinate system.

3.2. Mathematical model

A modified version of mathematical model based on the MMG (23rd ITTC meeting, The Specialist Committee on Esso Osaka, 2002) for describing the ship hydrodynamics in three degree of freedoms is used for Esso Osaka 3 m model ship. This mathematical model can predict the ship hydrodynamics for both advance and astern motions. The equations of motion as well as measured hydrodynamic forces are considered at CG (centre of gravity) of the ship. The corresponding equations of motions are expressed in the following form:

$$(m+m_x)\dot{u}-(m+m_y)vr = X_H+X_P+X_R+X_W$$

$$(m+m_y)\dot{v}+(m+m_x)ur = Y_H+Y_P+Y_R+Y_W$$

$$(I_{ZZ}+J_{ZZ})\dot{r} = N_H+N_P+N_R+N_W$$

X_H, Y_H, N_H: hydrodynamic forces and moment acting on hull
X_P, Y_P, N_P: hydrodynamic forces and moment due to propeller
X_R, Y_R, N_R: hydrodynamic forces and moment due to rudder
X_W, Y_W, N_W: hydrodynamic forces and moment due to wind

To verify the effectiveness of modified mathematical model, turning circles are compared with experiment results for both port and starboard turning as shown in Fig. 2.

The little variations existing in the comparison trajectories are believed due to wind disturbances since the tactical diameters of the corresponding circles are quiet same.

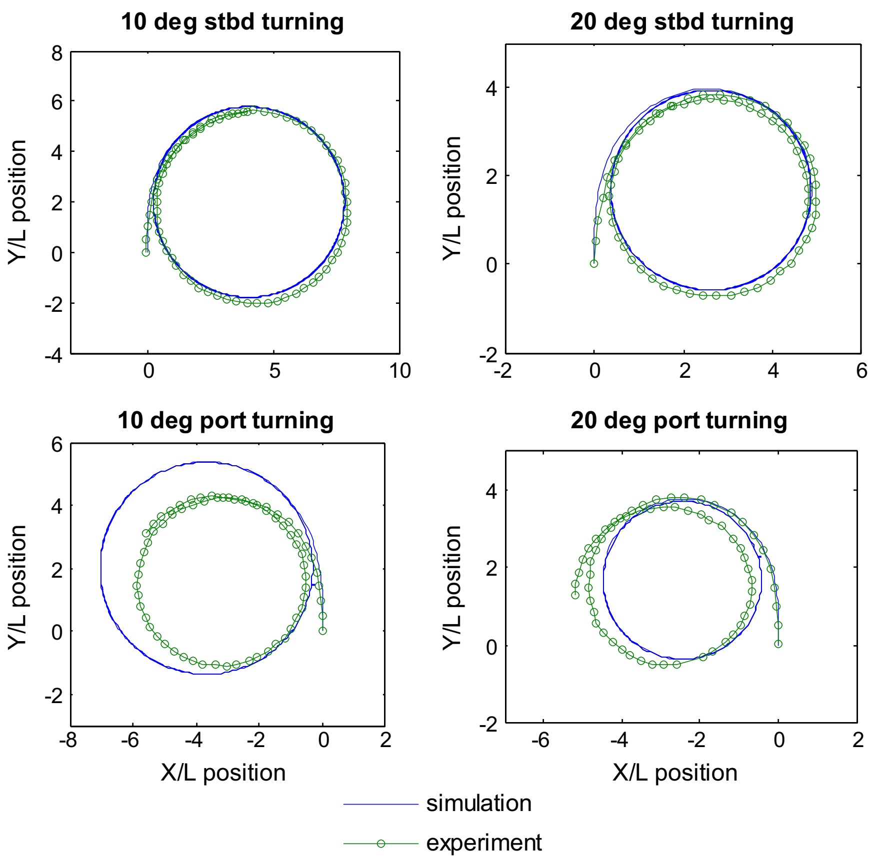

Fig. 2. Turning circles comparison.

3.3. Wind force model

To consider the influence of wind disturbances during ship manoeuvring, famous Fujiwara et al. (1998) wind model is used for calculating wind forces and moment. The following equations are used for such calculation:

$$X_W = \frac{1}{2} C_X \rho V_R^2 A_T$$
$$Y_W = \frac{1}{2} C_Y \rho V_R^2 A_L$$
$$N_W = \frac{1}{2} C_N \rho V_R^2 A_L L_{OA}$$

L_{OA}, length over all of ship;
A_T, transverse projected area of ship;
A_L, lateral projected area of ship;
V_R, relative wind speed;
X_W, fore-aft component of wind force;
Y_W, lateral component of wind force;
N_W, yawing moment;
C_X, C_Y, C_N, coefficients calculated using Fujiwara's model.

3.4. Gust wind consideration

Simulation of manoeuvring motion in actual sea necessities wind effects consideration. A simple way of doing that is to apply uniform wind loads. Previous researches based on the berthing simulation mostly considered such uniform wind velocity. However, if we need a result which is closer to reality, we have to consider the fluctuation of the wind velocity. In this research, the following equation is used to make irregular wave pattern by using power spectral density function $S(\omega)$:

$$\zeta(t) = \sqrt{2I(\infty)/M} \sum_{m=1}^{M} \cos(\omega_m t + \varepsilon_m)$$

where

$$a_m^2 = 2I(\infty)/M,\ I(\omega) = \int_0^{\omega} S(\omega) d\omega$$

ω_m satisfies $I(\omega_m) = (2m-1)I(\infty)/2M$

The power spectrum of wind expressed by Davenport (1967) is used as follows:

$$S(\omega) = 8\pi k \frac{U_{10}^2}{\omega} \frac{x'^2}{(1+x'^2)^{4/3}} \left(= 14.4 U_{10} \frac{x'^2}{(1+x'^2)^{4/3}} \right)$$

M	assigned integer number
K	0.003 above water surface
U_{10}	average wind velocity at 10 m high above water surface
x'	nondimensional frequency $= (600\omega/\pi U_{10})$

Thus by using inverse Fourier transform, the time series of fluctuating wind is found.

4. Teaching data creation

4.1. Manoeuvring plan for berthing

In order to ensure safe and appropriate berthing manoeuver the whole berthing procedure is divided into three basic elementary manoeuvres, such as minimum time course changing where virtual window concept is used, step deceleration and finally propeller reversing to stop the ship. In case of no wind condition, during straight running along with imaginary line, no rudder angle is taken. But in case wind disturbances, ship deviation from imaginary line is adjusted by more sophisticated PD controller.

Kose et al. (1986) proposed two concepts by analysing the manoeuvring procedure followed by the captain in case of real large ship to ensure safety. One is that the goal of berthing manoeuver is supposed to be at some interval distance before pier instead of approaching the pier board to board. The second one is planning a manoeuvre which allows a well-to-do operation in case of any critical situation.

In this research, to ensure Kose's two proposed concepts, the supposed berthing goal is assumed to be at a distance 1.5 times of ship length from the pier. However, the ship approaches the pier along with an imaginary line which makes an angle 30° with the pier. Other one is that, to cope with any un-expected situation rudder angle is restricted within $\pm 10°$, $\pm 15°$, $\pm 20°$ or $\pm 25°$ depending on its initial position on virtual window for course changing and in case of wind disturbances, the PD controller during straight running is restricted to take rudder angle within $\pm 5°$.

4.1.1. Virtual window creation for minimum time course changing manoeuvre

Virtual window denotes that safety window which ensures ship with any particular heading angle passing through its desired position to reach imaginary line via course changing so that it can continues with further deceleration to make successful berthing. In this research, four different types of rudder restrictions are considered as non-equality constraints to get their corresponding virtual windows.

Nonlinear programing method is used in such cases to get optimal steering which satisfies the constraints given in form of termination conditions during course changing. Here, the objective function is time which ensures minimum time steering and optimal variable is command rudder angle. The constraint conditions used in nonlinear programming method are shown in Table 2.

Virtual window construction is basically based on the findings of several points where each point indicates a particular ship heading angle to reach the imaginary line. To find such points repeated optimisation technique is used where in each optimisation, ship's initial heading angle is changed by certain amount keeping the termination conditions same. Fig. 3 demonstrates the technique adopted in this research to find several points on a particular virtual window.

Fig. 4 verifies the virtual window concept where ships with different heading angles start from different points on a particular window and merge with the imaginary line well ahead.

Table 2
Constraints used in optimal course changing.

Objective function	Course changing time	
Optimal variable	Command rudder angle, δ-order	
Initial conditions	Ship velocity	Half Ahead
	Heading angle	ψ
	Position	(x, y)
	Others	$v=0$; $r=0$; $\delta=0$
Termination conditions/equality constraints	Heading angle	240 (deg)
	Position	On the imaginary line
	Ship velocity	Free
Non-equality constraints	Rudder restriction	$\lvert\delta\rvert \le 10/15/20/25$ (deg)

4.1.2. Deceleration and stopping manoeuvre

As Endo et al. (2003) have surveyed the contents of deceleration manoeuvring during the real navigation cases, ships usually approach the berthing goal by dropping the ship velocity step by step as a standard deceleration manoeuvring. In this research, deceleration manoeuvring is performed by dropping ship speed from Half Ahead → Slow Ahead → Dead Slow Ahead → Stop Engine step by step in a straight course. The step changing time is as much as time constant T_p of ship speed response equation which is shown in the following:

$$T_P\frac{dU(t)}{dt}+U(t)=K_P n(t)$$

$U(t)$, ship velocity (m/s)
$n(t)$, propeller revolution (rps);
T_p, time constant;
K_p, gain.

In case of stopping manoeuvre, slow astern is used as telegraph order. Since engine idling is followed by propeller reversing thus engine idling time is also adjusted such that the ship can reach as close as possible to the berthing point during propeller revering stage. The total available distance considered during deceleration and stopping manoeuvre is 15 times of ship length according to IMO standard. Fig. 5 shows the execution of complete berthing plan. Here, 1st and 2nd rows indicate the command ruder and propeller revolution respectively and 3rd row is the corresponding trajectory due to such action.

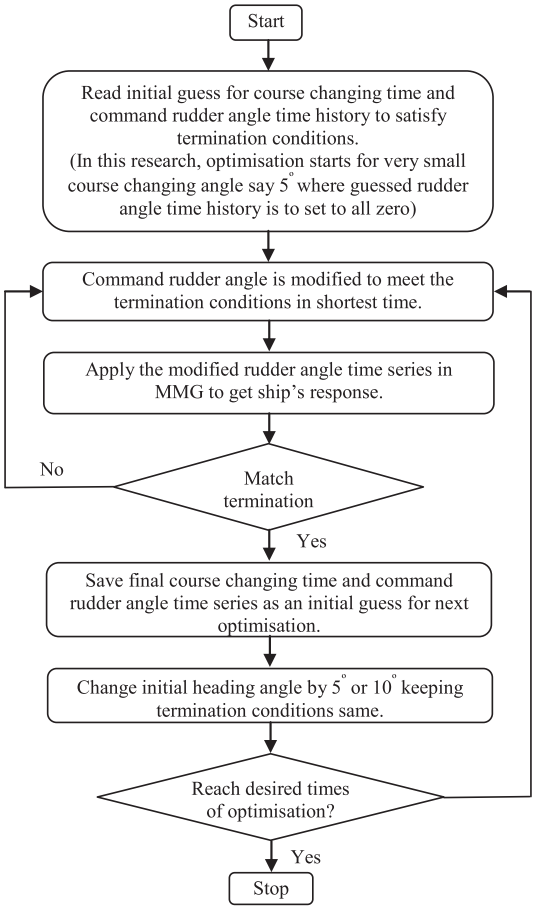

Fig. 3. Repeated optimisation technique.

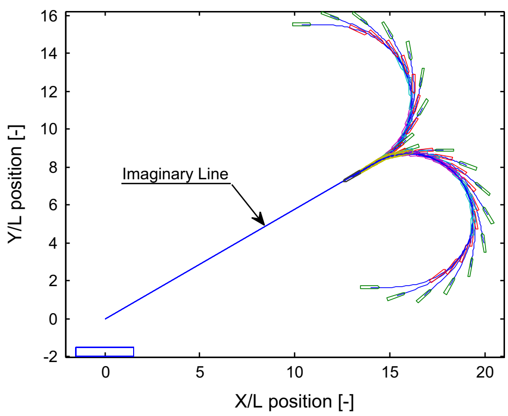

Fig. 4. Verification of virtual window concept.

4.2. Teaching data creation

Initially no wind disturbances are consider while making teaching data and such teaching data are used to train ANN in no wind condition. But, since such teaching data does not include any rudder angle during straight running, thus using the same teaching data to train ANN in wind condition does not make any sense as slow speed ship has high possibility to deviate from its original path due to any small wind disturbances. As a result, new set of teaching data are constructed including PD controller to take appropriate rudder angle during straight running and make successful berthing even in wind condition.

4.2.1. Teaching data for no wind condition

Considering the mentioned manoeuvring plan, teaching data are created based on the ship's initial heading angle staring from 90° to 230° (for ±10° restricted rudder angle) at 20° interval when ship comes from left hand side of imaginary line and −270° to 230° at

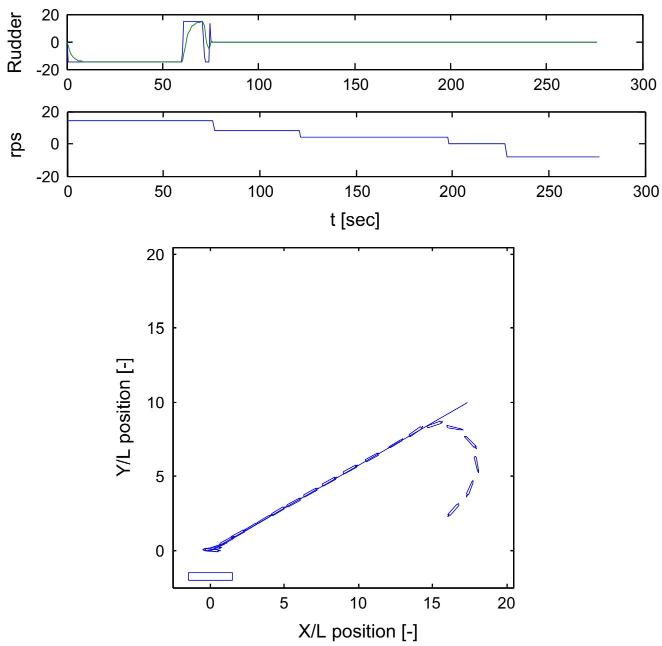

Fig. 5. Execution of complete berthing plan.

same interval in case of right hand side. Maximum rudder angle taken in the teaching data is fully dependent on ship's initial position and the corresponding virtual window. Fig. 6 shows the set of constructed teaching data used to train ANN in no wind condition.

4.2.2. *Teaching data for wind condition*

To make ANN understand about the influence of wind disturbances, teaching data are reconstructed considering wind speed as 0.2, 0.6 and 1.0 m/s and wind direction as 45°, 135°, 225° and 315°. Such teaching data also include PD controller during straight running to cope the deviated ship position in low speed. But, the command rudder angle during turning and the telegraph order remains same as in no wind condition. Because, such command rudder angle during turning as well as telegraph order are expected to be modified by ANN itself after training depending on wind influences.

5. Construction of neural network

Two separate feed forward neural networks are constructed for command rudder angle and propeller revolution output respectively instead of centralized controller as its effeteness has already proved by Im and Hasegawa (2001) in previous researches.

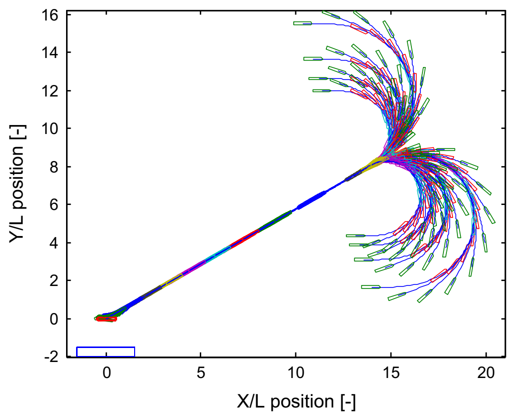

Fig. 6. All teaching data for no wind condition.

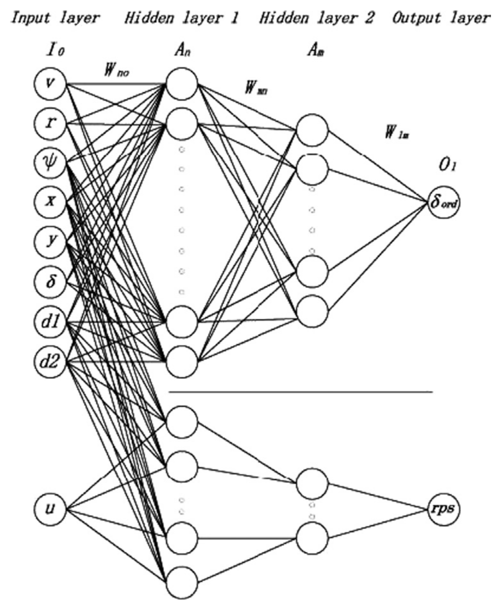

Fig. 8. Artificial neural network construction.

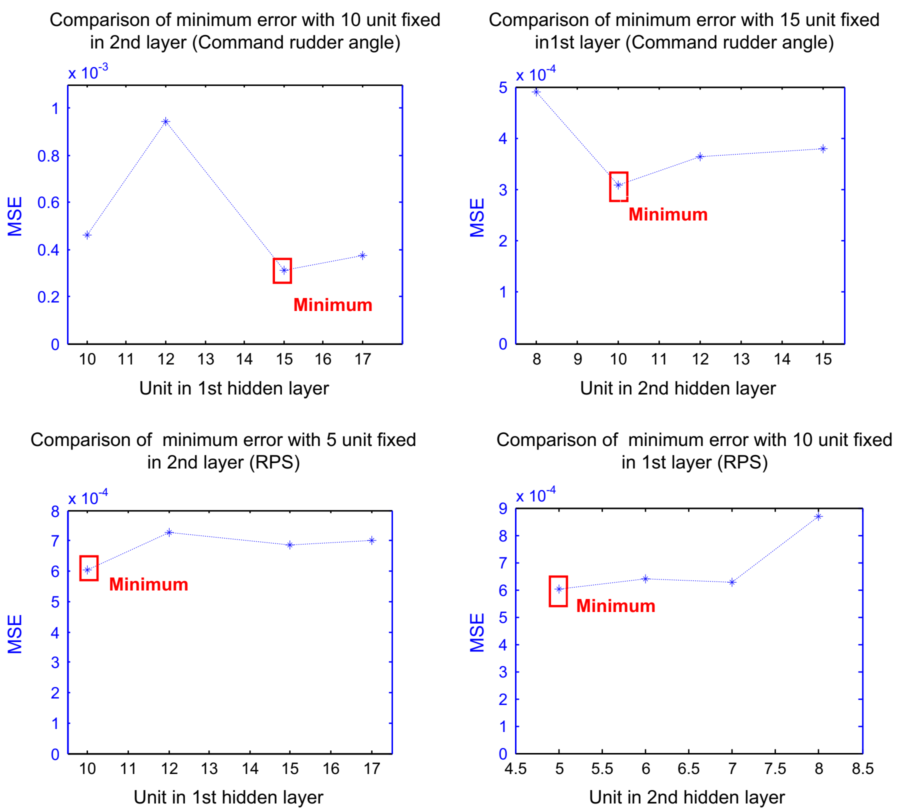

Fig. 7. Neurons determination for hidden layers.

5.1. Training function, transfer function and performance function

Famous back propagation technique which is gradient descent algorithm is used where the network weights are moved along the negative of the gradient of the performance function. In this research MATLAB Neural Network Toolbox is used where varieties of training functions with different basic algorithms are available to train the net. Among them training function based on Lavenberg–Marquardt algorithm is used. This algorithm is designed to approach second-order training speed without having to compute the Hessian matrix like in quasi-Newton method. When the performance function has the form of a sum of squares, then the Lavenberg–Marquardt algorithm uses the following approximation to the Hessian matrix in order to follow Newton-like update:

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e$$

J, the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases
e, a vector of network errors
μ, a scalar value.

If μ becomes zero, algorithm is same as Newton's method and when large, it results gradient descent with a small step size. Thus μ is decreased after each successful step when performance function is also reduced and vice versa. In this way, the performance function will always be reduced at each iteration of the algorithm.

In case of transfer function, log-sigmoid is found suitable which is given as

$$f(x) = \frac{1}{1+e^{-x}}$$

And performance of the trained network is judged depending on calculated mean squared error value (MSE). If the normalized teaching data are considered in the following form:

$$\{p_1, q_1\}, \{p_2, q_2\}, \ldots \{p_n, q_n\}$$

P, input of network; q, target output.

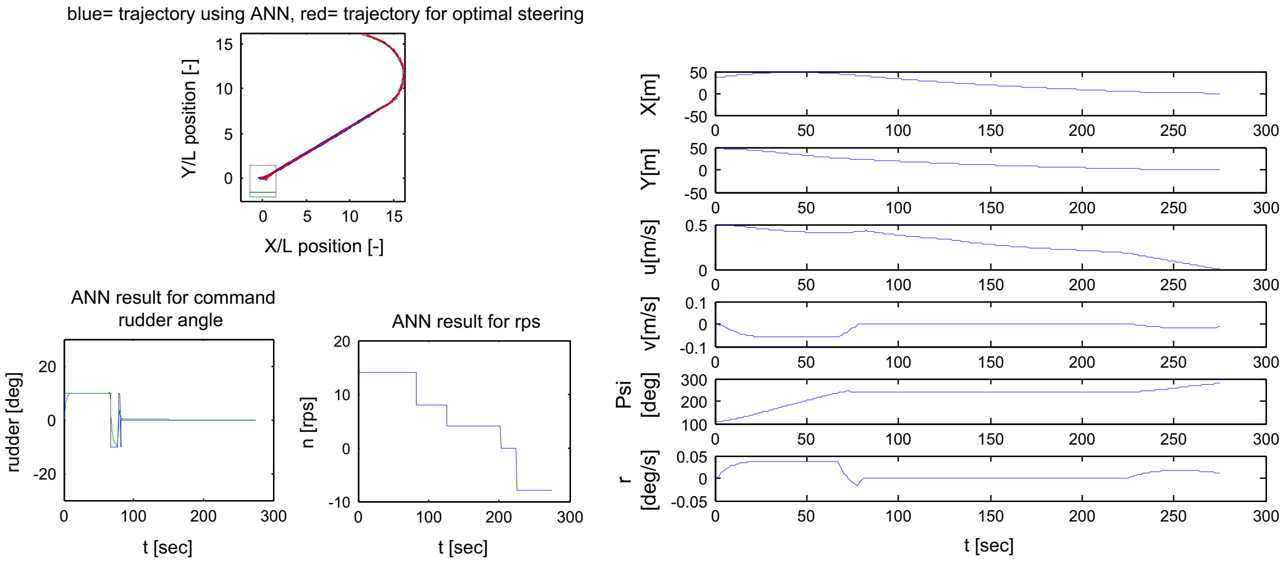

Fig. 9. Initial heading 110° with rudder restriction ±10°. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

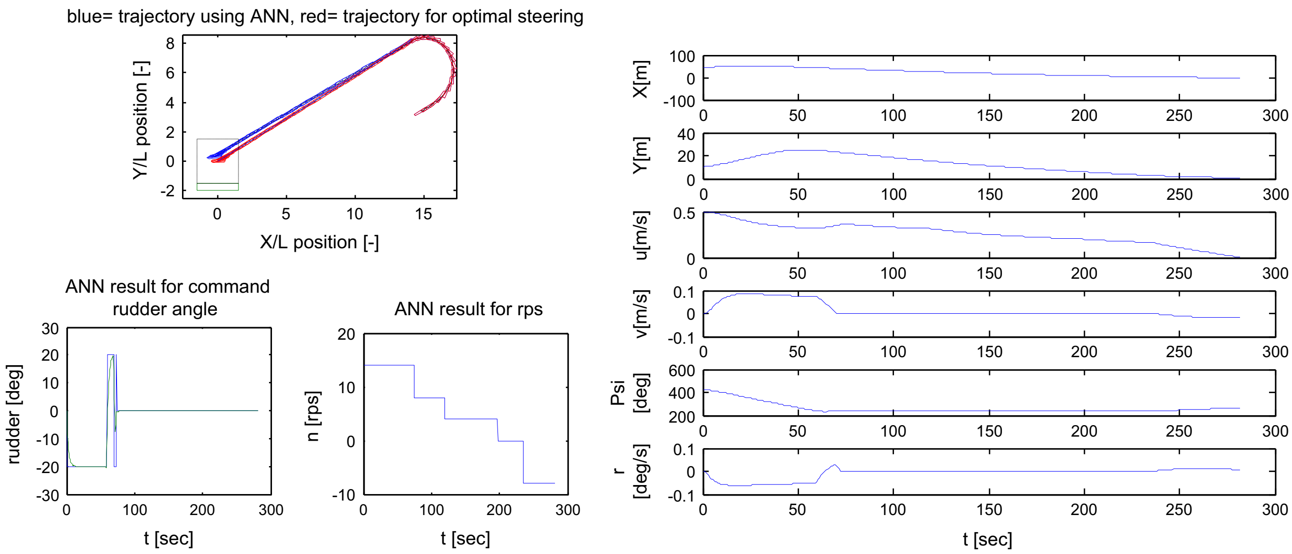

Fig. 10. Initial heading −240° with rudder restriction ±20°. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

Consequently, MSE can be calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e(i)^2 = \frac{1}{n}\sum_{i=1}^{n} (q(i) - O(i))^2$$

O, output of network.

5.2. Construction of artificial neural network

In order to construct well trained net first we need to investigate appropriate inputs for that net as well as number of hidden layers and the corresponding number of neurons in each hidden layer. In order to determine the suitable inputs, different parameters are tested depending on the previous researchers' preference and found the followings as suitable one.

For command rudder output, input parameters for the net are v, sway velocity; r, yaw rate; ψ, heading angle; (x, y), ship's position; δ, actual rudder angle; d_1, distance to imaginary line; d_2, distance to berthing point.

For propeller revolution, input parameters are u, surge velocity; ψ, heading angle; (x, y), ship's position; d_1, distance to imaginary line; d_2, distance to berthing point.

Since there are no any existing rules how to select the hidden layers and neurons, thus in this research such numbers are determined by trial and error and observing the minimum MSE value after each training period. In previous researches very

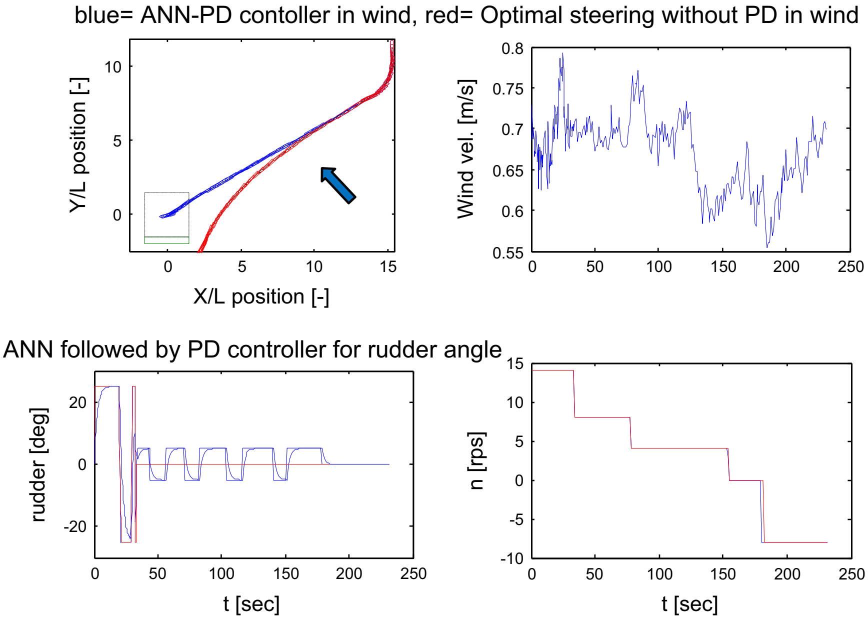

Fig. 11. Average wind velocity 0.6 m/s, wind direction 225°, initial ship heading 180° with rudder restriction ±25°. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

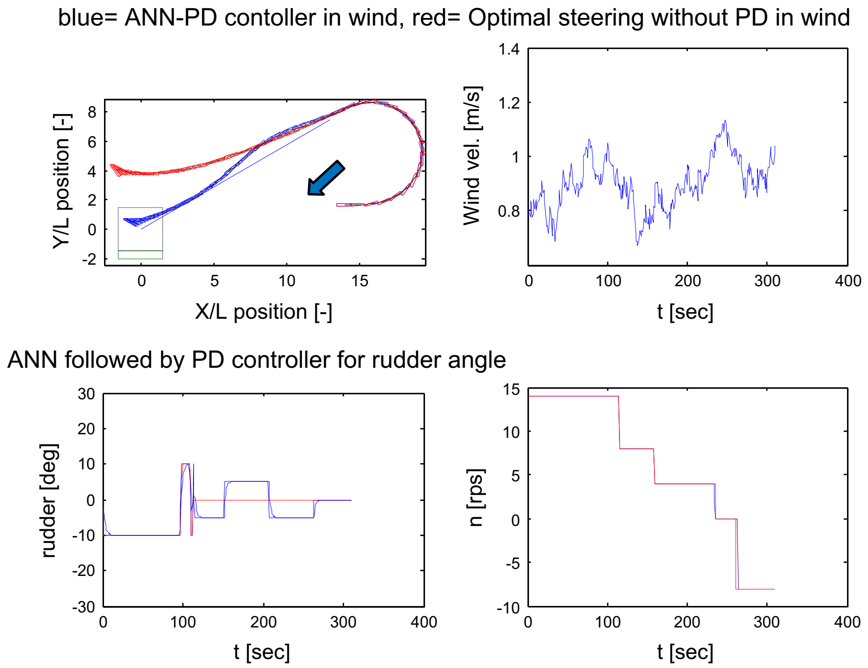

Fig. 12. Average wind velocity 1.0 m/s, wind direction 315°, initial ship heading −270° with rudder restriction ±10°. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

limited set of teaching data were used to train which resulted a very simple neural network construction with single hidden layer. But here to learn the complex pattern of teaching data, two hidden layers are found suitable enough with appropriate neurons to ensure minimum MSE value. Different combinations of neurons for the two hidden layers are investigated and that particular combination which gives less MSE value is chosen. Fig. 7 demonstrates the determination of neurons in each hidden layers for minimum MSE value.

And the resulting multi-layered ANN can be demonstrated in Fig. 8.

Here, the outputs from the hidden layers are given by

$$A_n = sig\left(\sum_{n=1}^{n} W_{n,o} I_o + b_n\right) \quad A_m = sig\left(\sum_{m=1}^{m} W_{m,n} I_n + b_m\right)$$

Finally, our respective output for rudder angles and propeller revolution is given by

$$O_l = purelin\left(\sum_{l=1}^{l} W_{l,m} A_m + b_l\right)$$

O, number of input parameters; n, number of neurons in 1st

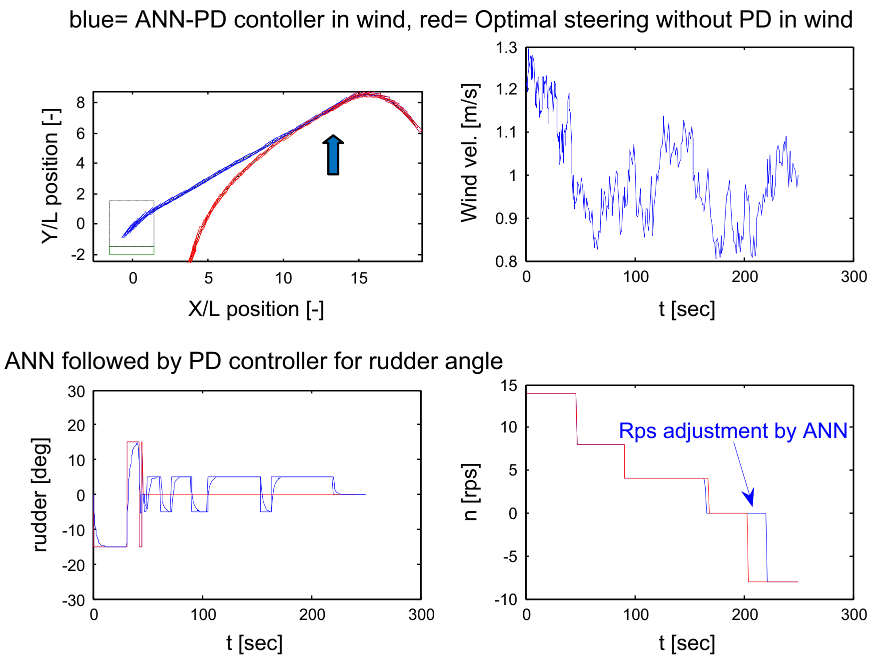

Fig. 13. Average wind velocity 1.0 m/s, wind direction 180°, initial ship heading 320° with rudder restriction ±15°. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

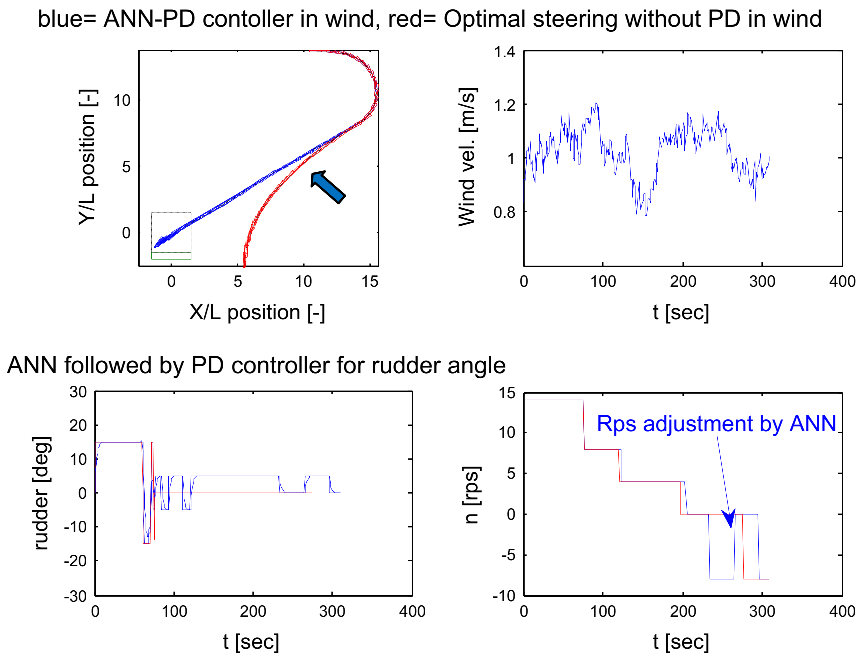

Fig. 14. Average wind velocity 1.0 m/s, wind direction 225°, initial ship heading 90° with rudder restriction ±15°. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

hidden layer; *m*, number of neurons in 2nd hidden layer; *l*, number of output; *sig*: log sigmoid function.

6. Verification of ANN in no wind condition

Verification of ANN has been done using not only the same initial ship position and states with teaching data but also with those different from the teaching data. Fig. 9 illustrates such verification for same initial position and sates with teaching data where Fig. 10 illustrates for completely different one. Considering the left hand side of such figures, 1st row represents the trajectory due to ruder action and propeller revolution change as shown in 2nd row, decided by the ANN itself. The right hand side of such figures describe the time history of several parameters. Among them the 3rd row represents the velocity drops and it clearly ends with zero in both cases, i.e. ship stops near the pier successfully. In those figures the squared dotted line around pier ensures the assumed successful zone for berthing.

7. Reconstructed net for gust wind

The teaching data used in training net for no wind condition do not contain any effect of wind disturbances, thus ship does not

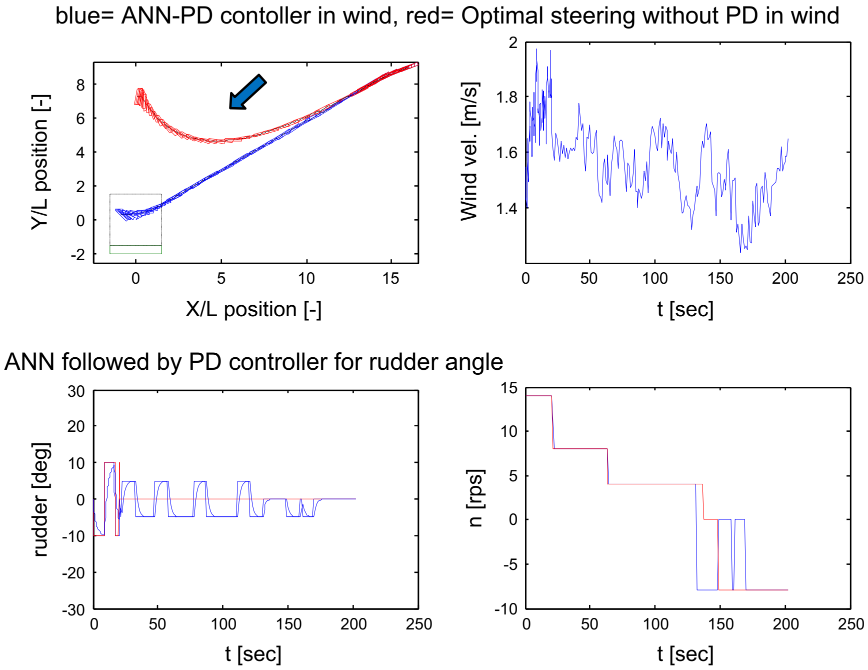

Fig. 15. Average wind velocity 1.5 m/s, wind direction 315°, initial ship heading 250° with rudder restriction $\pm 10°$.

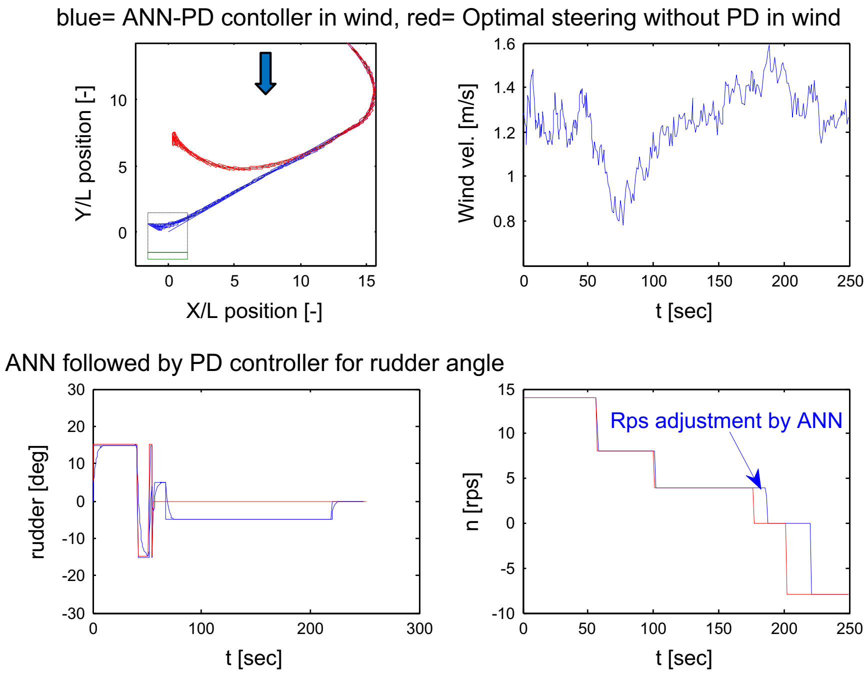

Fig. 16. Average wind velocity 1.3 m/s, wind direction 0°, initial ship heading 140° with rudder restriction $\pm 15°$. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

take any rudder angle while going straight along imaginary line. But, it is not real while considering wind where ship must take rudder angle to compensate its deviation from desired path. In case of berthing, such action is very necessary as ship's velocity is comparatively low enough to cause its deviation due to any small wind disturbances from any direction. For that reason, teaching data are reconstructed considering wind effect to train new set of nets which can deal with any possible wind disturbances while more sophisticated PD controller is used to prevent ship's deviation during straight running.

Reconstruction of such teaching data also creates the opportunity to investigate new set of input parameters to make understand how situation differs for different wind speeds and directions keeping other condition same. In such situation, surge velocity has found to be suitable one to be added in addition as an input parameter when training net for command rudder angle and for propeller revolution output as it already contains the surge velocity, no any extra parameter is needed.

7.1. Controllers throughout the berthing process in wind

Proper trained ANN with reconstructed teaching data is used for course changing in case of command rudder angle output. After merging with the imaginary line when going straight, as ship's velocity is gradually reduced thus maintaining its desired straight course becomes more sensitive than in course changing. As a result instead of using ANN, more sophisticated PD controller is introduced for the first time in berthing case. In this research the following expression for PD controller is used where the corresponding coefficients are decided by trial and error to ensure earlier response during deviation:

$$\delta_{order} = C_1 * (\psi_d - \psi) - C_2 * \dot{\psi} - C_3 * d_1$$

$$\Rightarrow \left\{ \begin{array}{ll} \text{if } \delta_{order} > 0^0, & \delta_{order} = 5^0 \\ \text{if } \delta_{order} = 0^0, & \delta_{order} = 0^0 \\ \text{if } \delta_{order} < 0^0, & \delta_{order} = -5^0 \end{array} \right\}$$

ψ_d, desired heading angle; d_1, deviation from imaginary line; $C_1=0.30$; $C_2=0.08$; $C_3=0.010$

Another aspect which is very important in berthing case is the telegraph order which is based on the speed response equation. In case of no wind, it is very easy to determine correct timing of propeller revolution change but in case of gust wind disturbances, velocity drop curve is no longer predictable as it changes with wind velocity together with its direction of

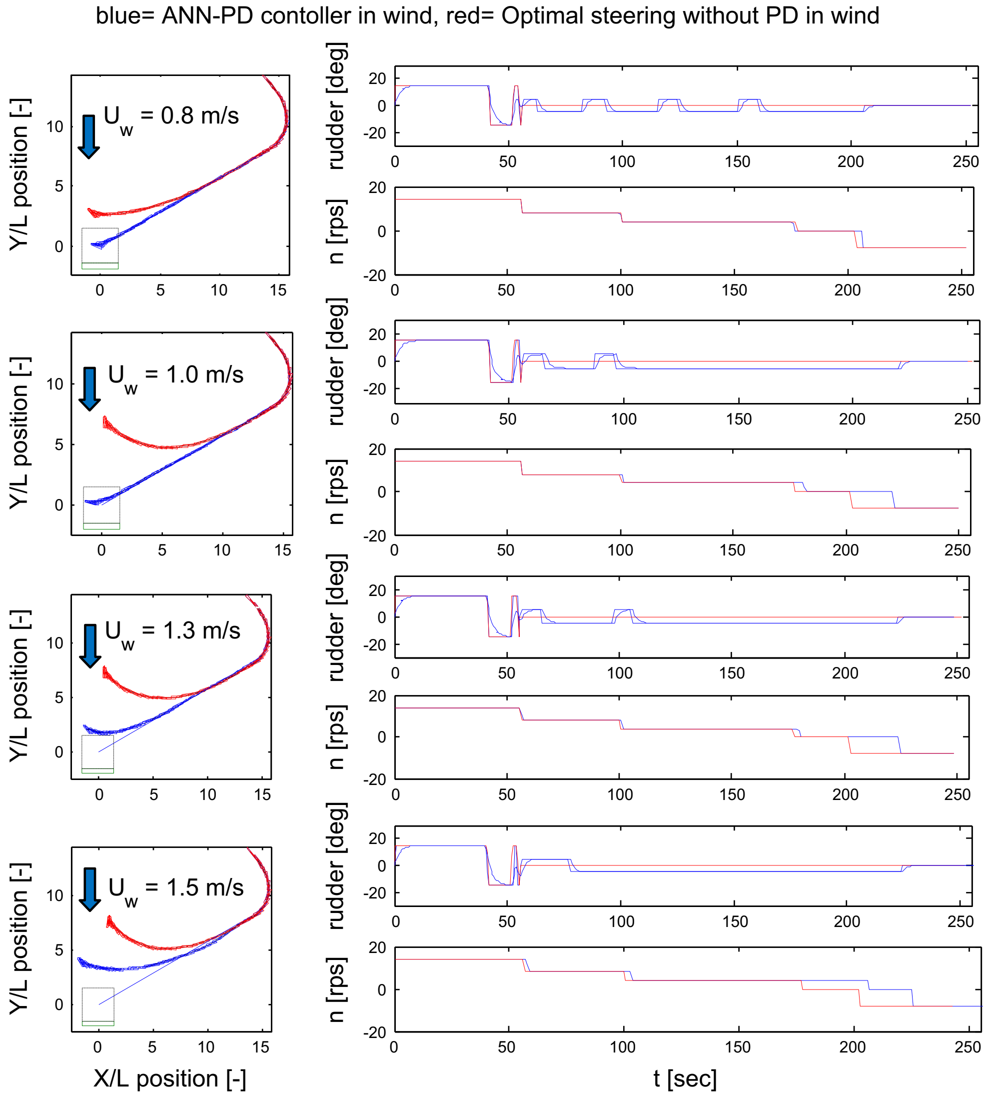

Fig. 17. Wind direction 0°, initial ship heading 140° with rudder restriction $\pm 15°$. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

blowing. So, correct timing of changing propeller revolution need to be determined by a proper trained ANN during the whole berthing process i.e. in case of both course changing and straight running. Such trained ANN in this research can ensure final ship velocity reduction considerably low enough which is less than 0.05 m/s.

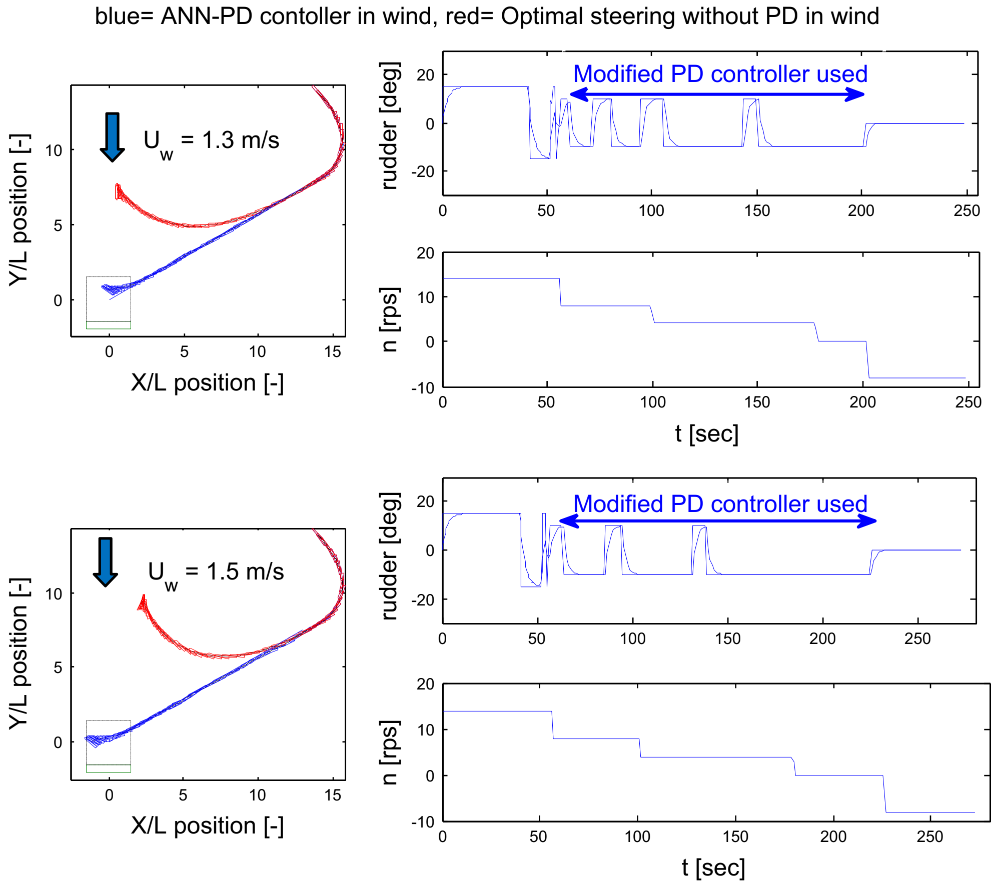

Fig. 18. Wind direction 0°, initial ship heading 140° with rudder restriction ±15°. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

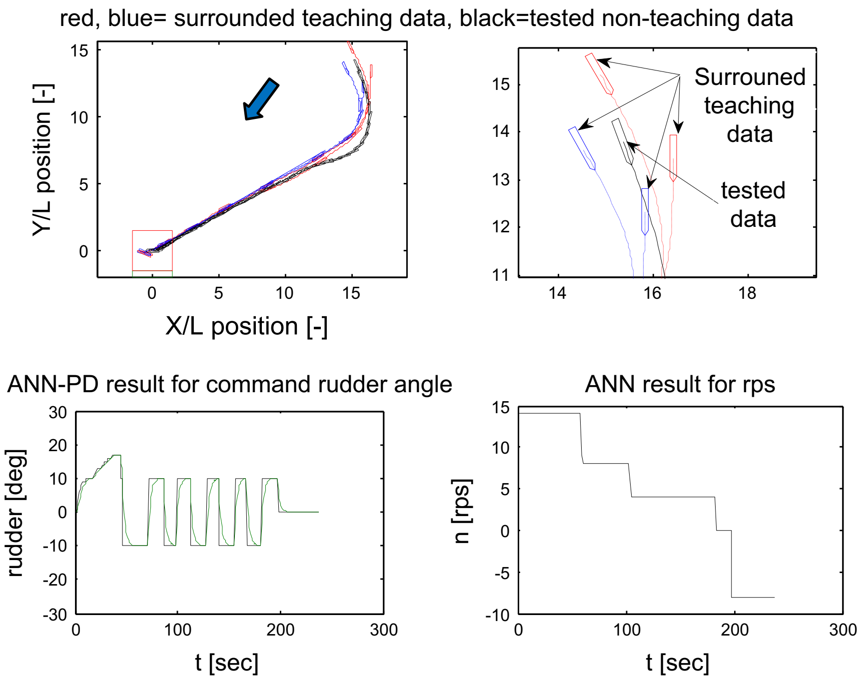

Fig. 19. Initial heading 160° from any arbitrary point. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

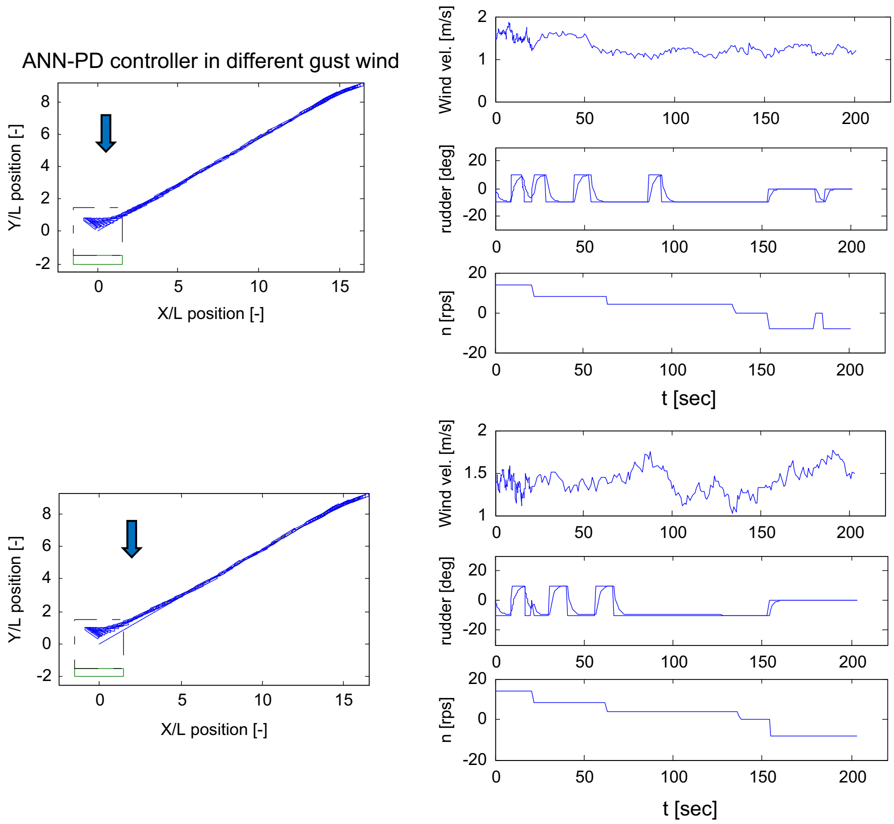

Fig. 20. Average wind velocity 1.5 m/s, wind direction 0°, initial ship heading 250° with rudder restriction $\pm 10°$.

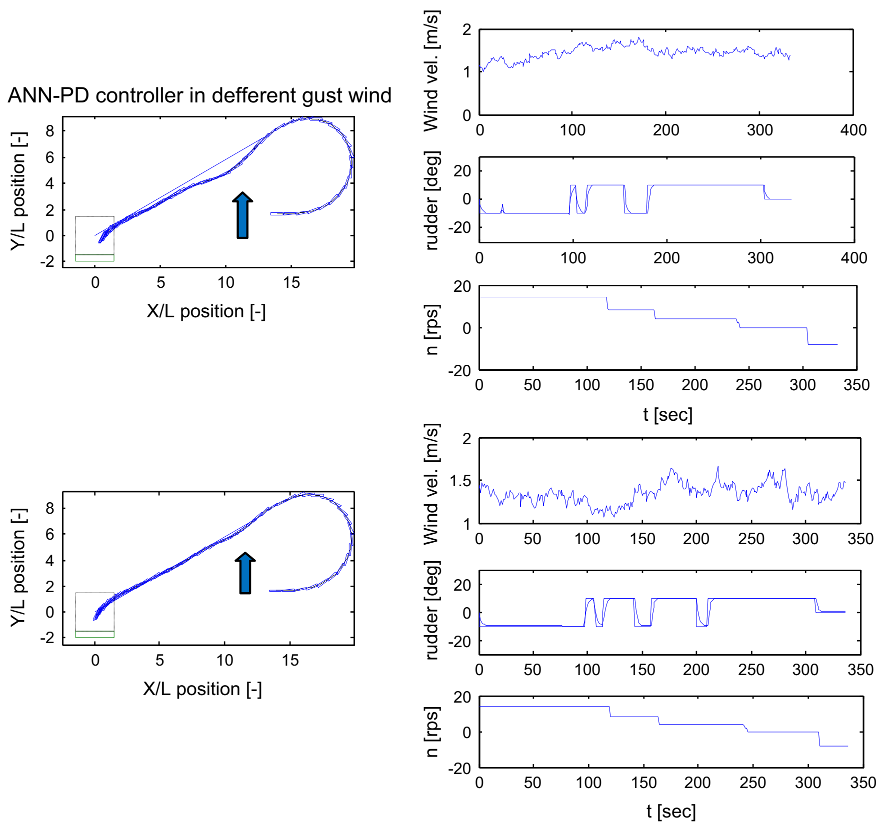

Fig. 21. Average wind velocity 1.3 m/s, wind direction180°, initial ship heading $-270°$ with rudder restriction $\pm 10°$.

8. Verification of ANN-Pd in gust wind condition

8.1. Verification for teaching and non-teaching data

To verify the effectiveness of trained ANN with PD controller during straight running, both teaching and non-teaching are tested. When considering teaching data, same ship's initial position and states are used with identical wind disturbances as used while training net. On the other hand, in case of non-teaching data, not only different ship states but also completely different wind velocities and directions are tried to judge whether the trained ANN can cope with such disturbances or not. And the results are quite satisfactory in both cases. Figs. 11 and 12 illustrate the effectiveness of ANN-PD controller when tested with same teaching data provided. In such figures, two types of trajectories are plotted. One is for ANN-PD controller in wind and other one is for optimal steering without PD in wind. It clearly shows when using PD controller, it succeed to prevent the ship's deviation even in low speed. On the other hand, the red trajectory results due to not using PD controller and ship simply deviates from its desired path. Although in course changing, such deviation is not noticeable due to high ship speed. Wind information is shown in 1st row 2nd column of each figure which is experienced by the ship during such berthing.

On the other hand, Figs. 13 and 14 illustrate the validation for ANN-PD controller when tested in completely different situations than used in teaching data during training net. In such figures, 2nd row 2nd column clearly shows how the ANN adjusts the propeller revolution by elongating idling time or by considering engine idling and reversing sequentially depending on situation demands, where 2nd row 1st column shows the rudder angle which is adjusted by ANN during course changing and PD controller during straight running.

In most of the previous researches, consideration of maximum wind velocity was very limited say 1.0 m/s for Esso Osaka model ship. So, in this research one of the most changing tasks is to make ANN-PD controller able to ensure successful berthing when considering severe wind over 1.0 m/s although teaching data contain information upto 1.0 m/s. To judge such workability, average wind velocities of 1.3 and 1.5 m/s are tested for different directions of blowing. Figs. 15 and 16 demonstrate such validation where ANN adjusts the propeller revolution and ANN-PD control the command rudder to ensure safe berthing.

Even though above figures show successful berthing results using ANN-PD controller but due to the difficulties of accurate prediction of wind disturbances and to verify the ANN-PD controller in more real world situation, further researches are done where three separate types of investigations are carried out. These are given as follows:

(a) The effectiveness of ANN-PD controller is tested for any particular ship's initial states and increasing the wind velocity gradually keeping the direction same in every case.
(b) Different gusts for same average wind speed and directions are tested for same ship's initial states.
(c) Eight different wind directions are tested for particular average wind velocity and ship's initial states.

The following subsections will explain about such investigation results.

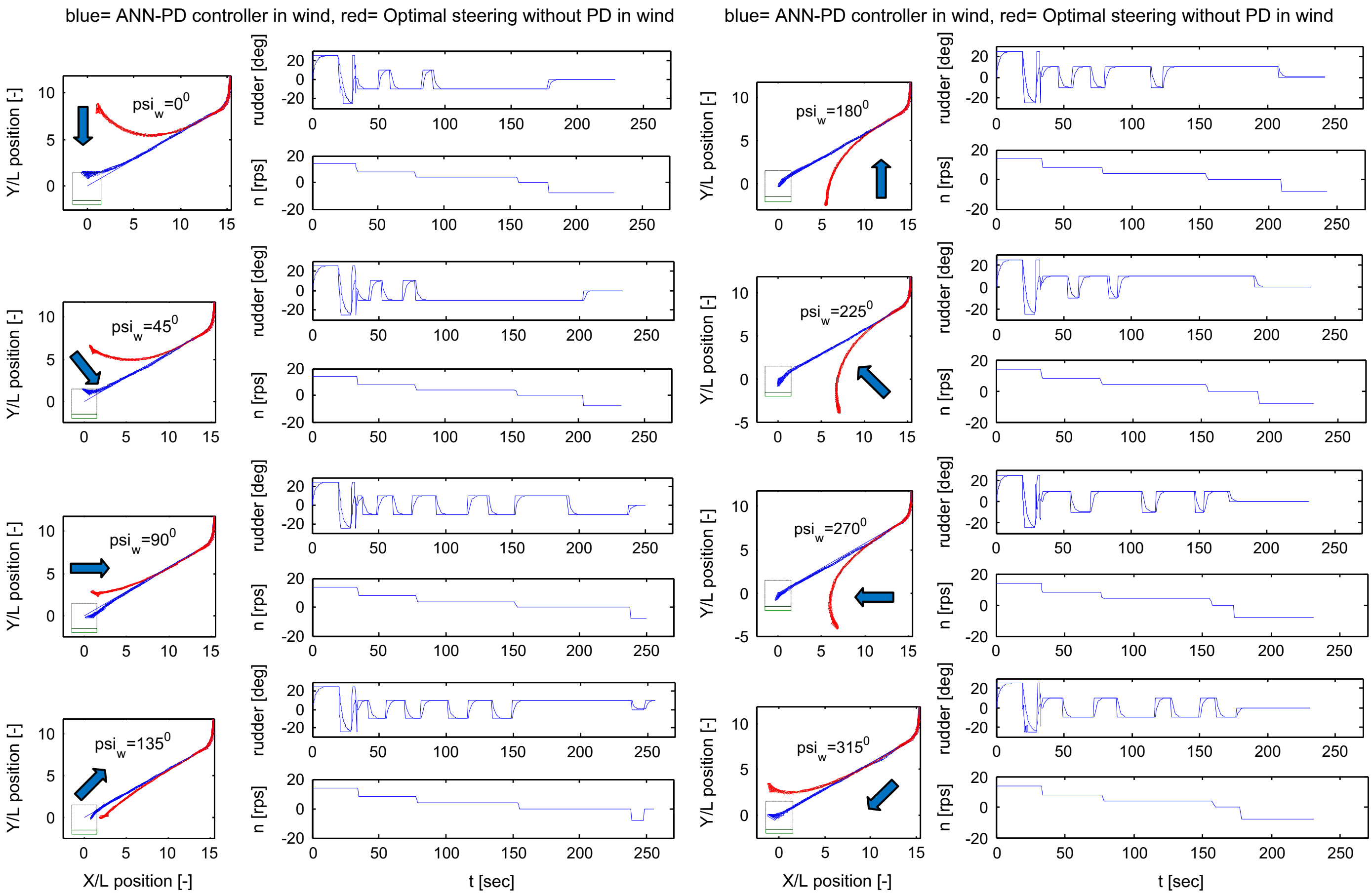

Fig. 22. Average wind velocity 1.5 m/s, initial ship heading 180° with rudder restriction ±25°. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

8.1.1. Verification for different wind speeds

To verify the controller's effectiveness for different wind speeds, ship with any particular initial states is tested for gradually increasing wind speed in each case. Although many successful results are found during such investigation but some rare cases are also found where ANN provides proper propeller revolution order but due to inappropriate rudder angle used in PD controller during straight running, ship cannot reach the pear successfully. Fig. 17 shows one such examples where ANN-PD controller is capable enough to guide the ship safely to the berthing zone upto 1.0 m/s but for 1.3 or 1.5 m/s it fails as shown in rows 3 and 4.

To deal with such rare situation which may arise in real cases, a revised rudder angle is proposed to use for PD controller during straight running which is $\pm 10^\circ$ instead of $\pm 5^\circ$. Fig. 18 demonstrates its effectiveness where successful berthing is ensured even in such cases where PD with $\pm 5^\circ$ fails as found in 3rd and 4th cases of Fig. 17 for average wind speed 1.3 and 1.5 m/s. Therefore for further investigation, ANN controller followed by newly proposed PD controller is used during straight running to judge the workability of ANN-PD controller.

Using that modified PD controller the following figure is also analysed to judge the interpolation ability of ANN. In Fig. 19 considering the 1st row, the red and blue lines indicate the surrounded teaching data when ANN is tested for any arbitrary point in mid of $\pm 10^\circ$ and $\pm 15^\circ$ virtual windows as shown in black line with initial ship heading 160°. It is also mentioned that teaching data contains only 150°and 180° ship heading information considering the nearest value of tested condition. Here the average wind velocity is 1.3 m/s and direction is 315° for the tested condition. It is clearly noticeable that the course changing pattern is similar to its surrounded teaching data and the rudder angle shown in 2nd row 1st column is a combination of 10° and 15° for course changing which is expected one.

8.1.2. Verification for different gust distributions

Different gust distributions for same average wind velocity are also investigated to judge the controller's effectiveness. Such investigation also provides importance to consider the gust wind instead of uniform one, as the resulting ship trajectories as well as controlling action may vary drastically for different fluctuating patterns of same average wind velocity. The following sets of figures illustrate such validation for ANN-PD controller. In such figures 1st and 4th rows of 2nd column show different gust distributions although the average is the same.

Here, Fig. 20 shows almost similar trajectories for different gusts but the PD controller's output as well as adjustment for propeller revolution by ANN are completely different. On the other hand, noticeable differences are found in trajectories for Fig. 21. But in both cases ANN-PD controller can ensure successful berthing by taking proper rudder angle and propeller revolution depending on situation demands.

8.1.3. Verification for different wind directions

Wind can blow from any possible direction thus the effectiveness of ANN-PD controller needs to be investigated for different wind directions together with different velocities. For that purpose, ships with different initial states are tested for any particular average wind speed and different wind directions. Fig. 22 shows the simulation results for different wind directions considerations while keeping the average wind velocity and ship's initial states same. During such investigation, maximum average wind velocity

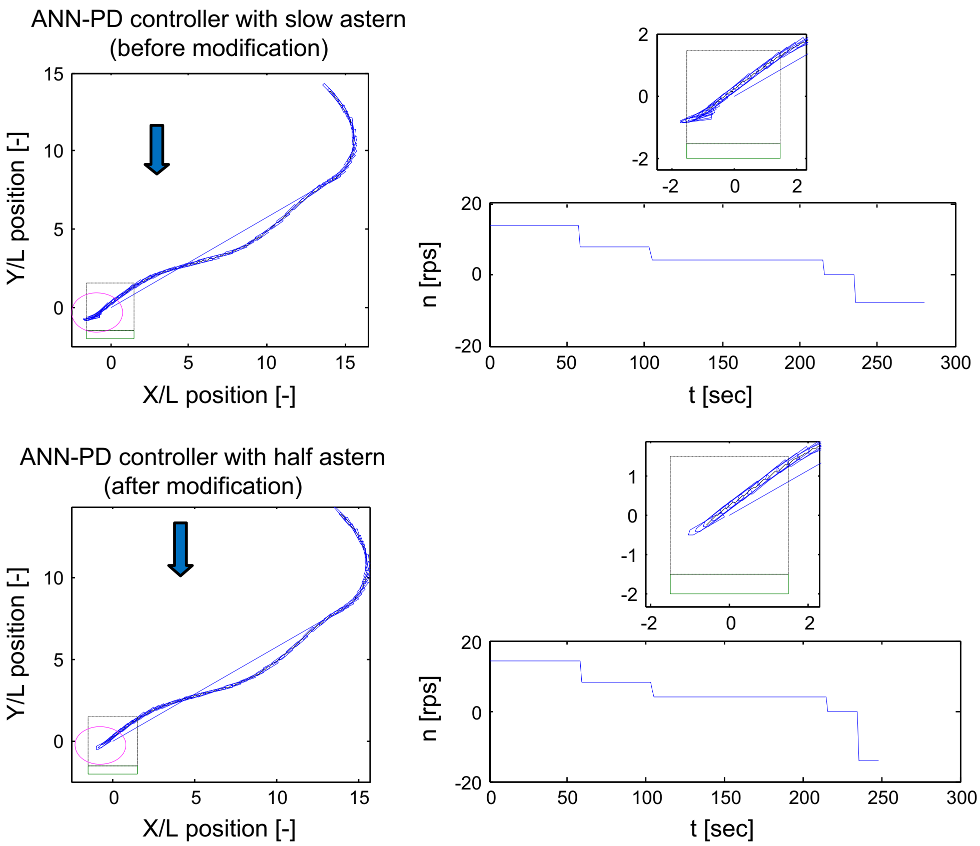

Fig. 23. Average wind velocity 1.3 m/s, wind direction 0°, initial ship heading 140° with rudder restriction $\pm 15^\circ$.

of 1.5 m/s is used with eight different directions of blowing at 45° interval.

8.2. ANN-PD controller in severe wind near pear

In the previous stages of this research, when using PD controller with restricted rudder angle $\pm 5^\circ$ it was investigated by Ahmed and Hasegawa (2012) that stopping with higher reversing propeller revolution may become necessary in some limited cases, depending on strong wind blowing near pear over 1.0 m/s average velocity. Since, the final position to stop the ship in case of berthing is very crucial, thus such criterion was investigated depending on ship's position before stating reversing and proposed as following:

If the ship's position before reversing propeller becomes less than 0.9 times of ship length from the berthing goal point then reversing with half astern is better than using slow astern. Thus in such cases, ANN result for slow astern are substituted by half astern value.

Considering such modification, the following figure demonstrates the simulation result while using half astern ensures earlier stopping of ship when compared with previous result.

This kind of modification is proposed for emergency cases when ANN fails to make early reversing and the remaining distance to stop the ship becomes less than 0.9 times of ship length. But for further research, when same ANN-PD controller is tested for different wind speeds and different ship's initial sates as explained in previous subsections, it has been found in some cases even using PD controller with restricted rudder angle $\pm 5^\circ$ it may become difficult to make successful berth due to severe wind disturbances. In this research, such cases are investigated with newly proposed PD controller where $\pm 10^\circ$ instead of $\pm 5^\circ$ is used and found satisfactory results as shown in Fig. 18. Considering the newly proposed PD controller, cases with severe wind near pear are also investigated where half astern may become necessary if

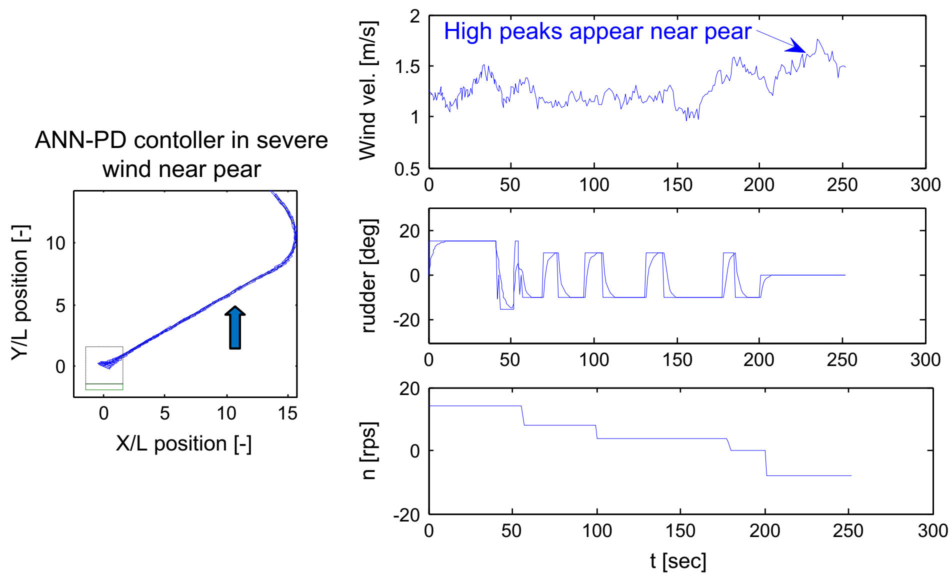

Fig. 24. Average wind velocity 1.3 m/s, wind direction 0°, initial ship heading 140° with rudder restriction $\pm 15^\circ$.

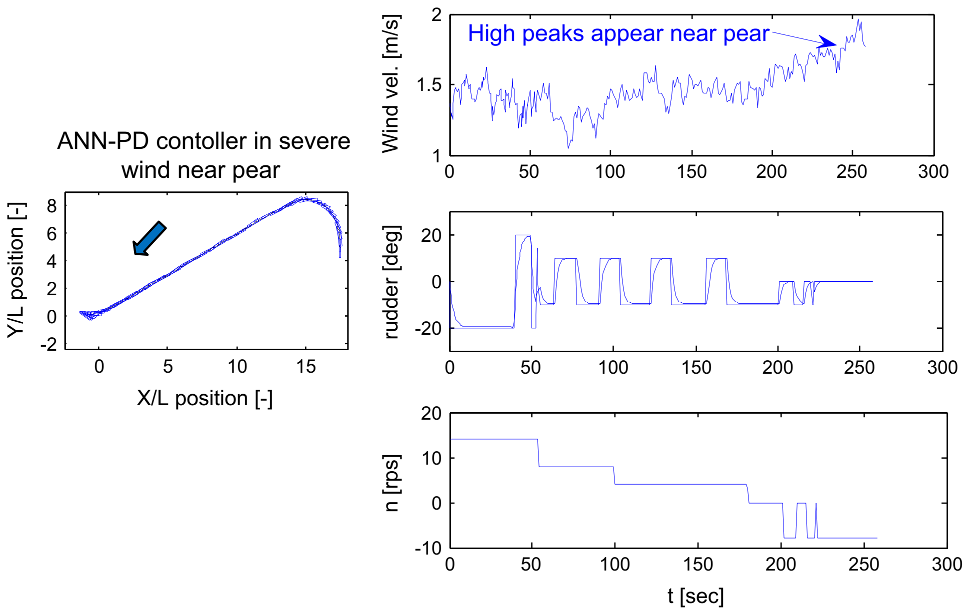

Fig. 25. Average wind velocity 1.5 m/s, wind direction 315°, initial ship heading 360° with rudder restriction $\pm 20^\circ$.

PD controller with $\pm 5^\circ$ is used during straight running as shown in Fig. 23. Figs. 24 and 25 demonstrate some results in case of severe wind near pear while modified PD controller is used during straight running.

The above figures clearly show that when using modified PD controller, there is no need of half astern although severe winds are observed near pear. This is because the PD controller here is sufficient enough to take adequate rudder angle to prevent much deviation and ANN adjust the propeller revolution according to demand to make successful berthing. Therefore, the ANN controller with modified PD may treat as alternative solution to avoid any possible higher reversing astern while berthing.

8.3. Optimal-PD controller versus ANN-PD controller

This kind of comparison emphasises the necessity of using ANN to judge correct timing of propeller revolution change online, while only PD controller to adjust the ship's deviation from imaginary line may fail for higher wind condition. In this research the created teaching data are so consistent that proper training with such set of

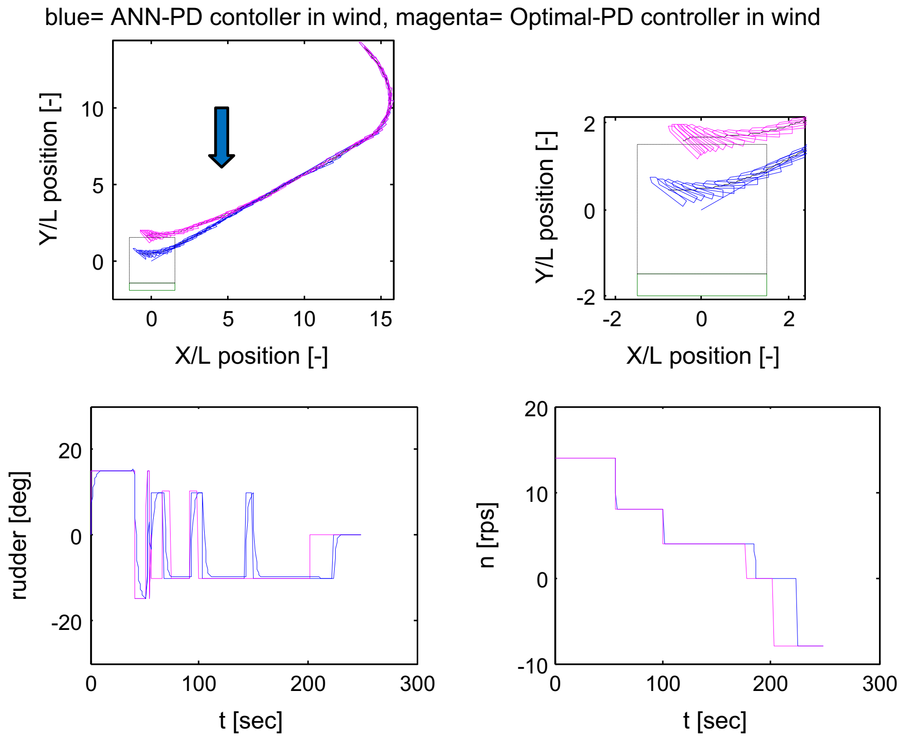

Fig. 26. Average wind velocity 1.5 m/s, wind direction 0°, initial ship heading 140° with rudder restriction $\pm 15^\circ$. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

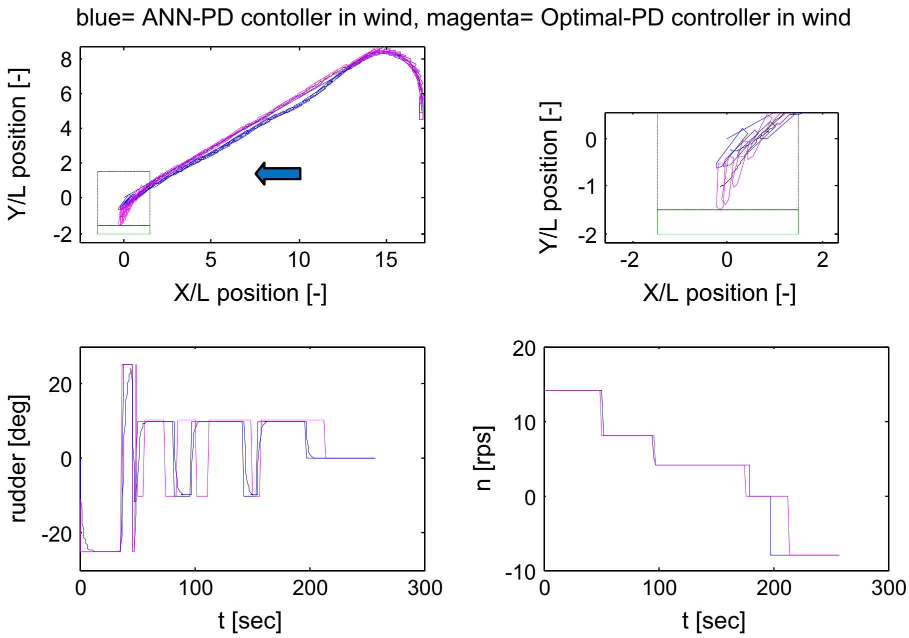

Fig. 27. Average wind velocity 1.3 m/s, wind direction 270°, initial ship heading 360° with rudder restriction $\pm 25^\circ$. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

teaching data enhances the ability of trained ANN to judge correct telegraph order depending on ship's velocity and other input parameters available. Therefore, ANN with PD controller works successfully in most cases where optimal with PD controller fails due to the failure of judging correct timing of propeller revolution change. Figs. 26 and 27 illustrate such comparison for severe wind disturbances like 1.3 m/s or 1.5 m/s. And the difference in the trajectories is shown in enlarged form as 1st row 2nd column of each figure.

Here, Fig. 25 shows how ANN elongates the engine idling time to allow the ship to go further and then finally followed by reversing to stop the ship within the successful berthing zone. On the other hand Fig. 26 shows ANN reduces the idling time as situation demands to make successful berthing where improper idling time causes berthing failure.

9. Conclusions

This research starts with an intention to create automatic and more consistent teaching data in order to train neural network for berthing cases and judge the ability of trained ANN in presence of gust wind disturbances which is more realistic one and not yet consider in previous researches. The main conclusions of this research are given as follows:

(a) To predict the hydrodynamic behaviour of subject ship while creating teaching data, mathematical model is modified and results from that modified model are compared with experiment results for both port and starboard turning. Such comparison results are found quite satisfactory.

(b) New way of creating teaching data using nonlinear programming (NPL) method is proposed to ensure optimal steering and by considering the technique of repeated optimisation, virtual windows are constructed to prepare whole set of teaching data. The concept of virtual window creation enable the teaching data to include not only variations in ship's initial heading angle and position but also in operated command rudder angle for the first time which offers greater flexibility to the created Net.

(c) To make the controller more robust and to learn such complex relationship, double hidden layer concept is introduced with minimum MSE value where more improved Lavenberg–Marquardt algorithm in back propagation technique is used as training function to create two separate feed forward nets for command rudder and propeller revolution output respectively instead of centralized controller.

(d) No wind conditions are tested with trained ANN where satisfactory results are ensured not only for teaching data used but also for non-teaching data.

(e) In order to consider wind disturbances during berthing, gust wind instead of uniform wind is investigated for the first time to train ANN. Such trained ANN is proposed to be followed by a more sophisticated PD controller with rudder restriction of $\pm 10^\circ$ during straight running for controlling command rudder and other separately trained ANN is used for judging propeller revolution change throughout the whole berthing process. The proposed ANN-PD controller is well verified to proof its combined effectiveness even in completely different situations than in training session where eight different directions of wind with maximum velocity 1.5 m/s (15 m/s for full scale) is considered which is also regarded as maximum one in most ports in Japan for berthing.

(f) Different gusts for same average speed are investigated for same wind direction to verify the ANN-PD controller's workability and found satisfactory.

(g) In case of severe wind blowing near pear, the ANN-PD controller is again proved by investigating different ship's heading angles and positions.

For further research, it is very important to perform experiment to judge the effectiveness of ANN-PD controller in real cases.

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