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# Consistently Trained Artificial Neural Network for Automatic Ship Berthing Control

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ABSTRACT: In this paper, consistently trained Artificial Neural Network controller for automatic ship berthing is discussed. Minimum time course changing manoeuvre is utilised to ensure such consistency and a new concept named 'virtual window' is introduced. Such consistent teaching data are then used to train two separate multi-layered feed forward neural networks for command rudder and propeller revolution output. After proper training, several known and unknown conditions are tested to judge the effectiveness of the proposed controller using Monte Carlo simulations. After getting acceptable percentages of success, the trained networks are implemented for the free running experiment system to judge the network's real time response for Esso Osaka 3-m model ship. The network's behaviour during such experiments is also investigated for possible effect of initial conditions as well as wind disturbances. Moreover, since the final goal point of the proposed controller is set at some distance from the actual pier to ensure safety, therefore a study on automatic tug assistance is also discussed for the final alignment of the ship with actual pier.

## 1 INTRODUCTION

The ever-increasing modern technologies often demand a promising solution of highly demanding control problems. Although conventional approaches are proposed for many control problems, however the successful applications can only be found within well-constrained environment. Therefore, numerous advancements have been made in developing intelligent systems like artificial neural network (ANN). ANN consists of several interconnected simple non-linear system that are typically modelled by the transfer function. Therefore, ANN is suitable enough for system without clear and known structure. Regarding the potential of neural network for learning complicated behaviour of any nonlinear multi-input multi-output system, researchers from several disciplines are now designing the ANN to solve different problems in pattern recognition, prediction, optimisation, associative memory or control. Yamato *et al*. (1990) was the first who considered the application of ANN as a controller and he used it for automatic ship berthing. Later on, Fujii and Ura (1991) confirmed the effectiveness of ANN as a controller using both supervised and non-supervised learning system for autonomous underwater vehicles (AUVs). ANN was also tried as a controller in different controlling aspects like temperature control, wastewater treatment control, engine air/fuel ratio control, process control, etc. Regarding ship berthing, after Yamato, Hasegawa and Kitera (1993) and Im and Hasegawa (2001, 2002) had continued the research. Hasegawa and Kitera proposed ANN combined with the expert system to assist ANN, while Im and Hasegawa proposed separate controller instead of a centralised one for command rudder and propeller revolution output respectively. Both proposals played a vital role individually for further development of this research. However, the teaching data used for these research studies were not consistent, i.e. not in similar pattern. As a result, in the presence of wind disturbances, the ANN often failed to guide the ship.

On the other side, Ohtsu *et al.* (2007) proposed a new minimum time ship manoeuvring method using nonlinear programming. The method is used to create teaching data consistent and a concept named 'virtual window' is proposed by Ahmed and Hasegawa (2013a). Such window consists of gradually changing ship's position as well as ship's heading. To ensure minimum time manoeuvre, a ship with its initial heading is expected to start from a desired starting point of that window. Then by taking the calculated rudder as proposed by the optimal method, it is guaranteed for each ship with different heading to reach the so-called imaginary line. Such line is usually imagined by most ship operators during the berthing manoeuvre to ensure safe guidance of their ships. For the first time, Kose *et al.* (1986) mentioned about such strategy when he analysed the manoeuvring of ships in harbours. This imaginary line serves as a goal during optimisation and acts as a reference line for further descent. In this research, four of such virtual windows are constructed for minimum time course changing. Each window has its limitation of maximum usage of rudder angle used as non-equality constraint during optimisation. Following the imaginary line, ship will drop propeller revolution according to speed response equation and stop at the end of it. Considering the effect of wind disturbances during slow speed running along the imaginary line, in this research a modified version of PD controller is chosen to deal with it. Such controller can correct not only ship's heading, but also the distance between the ship's CG (centre of gravity) and the imaginary line. Finally, by combining the course changing and track keeping trajectories, a complete set of consistent teaching data are created. Using the set of teaching data, two multi-layered feed forward neural networks are trained for the minimum mean squared error (MSE) value. Several simulations are then done to judge the effectiveness of the trained controller for wind up to 1.5 m/s for an Esso Osaka model ship that would be 15 m/s for full scale considering the same Froude number. To analyse the success of the proposed controller, Monte Carlo simulations are also performed.

Although neural network is becoming widely used in complex control problems, however the effectiveness of such controller cannot be judged only by doing simulations. Many unknown situations may arise which cannot be simulated well before to judge the behaviour of controller. The first attempt to perform automatic ship berthing experiment using ANN was made by Nakata and Hasegawa (2003) but unfortunately the success rate was very low due to improper training. Considering this fact and to demonstrate the virtual window concept, the consistently trained neural networks are then implemented for the free running experiment system to perform automatic ship berthing experiment. Initially, a few experiment results are published by Ahmed and Hasegawa (2013b) in a scattered way. Later on, more experiments are done in different unknown situations and gathered depending on the network's behaviour. This paper contains such interesting experiment results that will also focus on how the ANN behaves in different situations. To understand the possible causes of network's behaviour, the effect of initial conditions and wind disturbances are then tried to discuss. Moreover, the goal point of the proposed controller is set at 1.5L distance from actual pier. Therefore, to execute the crabbing motion as a last stage of berthing operation, automatic side thrusters are also introduced.

## 2 MODEL SHIP AND MATHEMATICAL MODELS

### 2.1 *Model Ship*

In this research, among the different types of model available, 'Esso Osaka' 3-m model is chosen. The main reason of choosing this model is the availability of large amounts of captive model test results as well as a physical model itself. Its details are given in Table 1.

Table 1. Principal particulars of model

| Hull | | Propeller | | Rudder | |
|---|---|---|---|---|---|
| L (m) | 3.0 | Dp (m) | 0.084 | b (m) | 0.0830 |
| B (m) | 0.48 | P* (m) | 0.06 | h (m) | 0.1279 |
| D (m) | 0.20 | Z | 5.0 | $A_R$ ($m^2$) | 0.0106 |
| $C_b$ | 0.831 | P_ratio | 0.7151 | $\Lambda$ | 1.5390 |

* Pitch

Here, the Esso Osaka ship model used for berthing experiment is made of FRP (fibre-reinforced plastic) and scaled as 1:108.33.

### 2.2 *Mathematical models*

In this research, a modified version of mathematical model based on manoeuvring mathematical group (MMG) is used to describe the ship hydrodynamics in three degrees of freedoms. This MMG model can predict both forward and astern motion of ship for any particular rudder angle and propeller revolution. The corresponding equations of motions at the CG of the ship are expressed in the Equation 1.

$$\begin{aligned} (m+m_x)\dot{u}-(m+m_y)vr &= X_H+X_P+X_R+X_W \\ (m+m_y)\dot{v}+(m+m_x)ur &= Y_H+Y_P+Y_R+Y_W \\ (I_{ZZ}+J_{ZZ})\dot{r} &= N_H+N_P+N_R+N_W \end{aligned} \quad (1)$$

where, $X_H$, $Y_H$, $N_H$ are hydrodynamic forces and moment acting on a hull, $X_R$, $Y_R$, $N_R$ are hydrodynamic forces and moment due to rudder, $X_P$, $Y_P$, $N_P$ are hydrodynamic forces and moment due to propeller and $X_W$, $Y_W$, $N_W$ are hydrodynamic forces and moment due to wind. Details of such mathematical model can be found in the 23rd ITTC meeting report on Esso Osaka.

To consider the wind disturbances, Fujiwara wind model (1998) is adopted and instead of steady wind, gust wind is considered.

## 3 TEACHING DATA CREATION & TRAINING OF ANN

### 3.1 *Berthing Plan and Execution*

In this research, similar to aircraft landing, the berthing manoeuvre is planned to make first course changing from any given initial heading to a final desired ship heading. This final heading with no sway speed and angular velocity will align the ship to a reference line known as imaginary line. To imagine such reference line during berthing operation is usually a common practice for most ship operators. After merging to this line, the ship will keep its path and drop its speed according to the speed response equation as proposed by Endo and Hasegawa (2003). In this research, the imaginary line is assumed 15L of length according to the IMO standard. The berthing goal point is also considered at a distance of 1.5L from the actual pier as proposed by Kose *et al.* (1986) to ensure safety. Figure 1 shows the details of the co-ordinate system used in this research together with other valuable information.

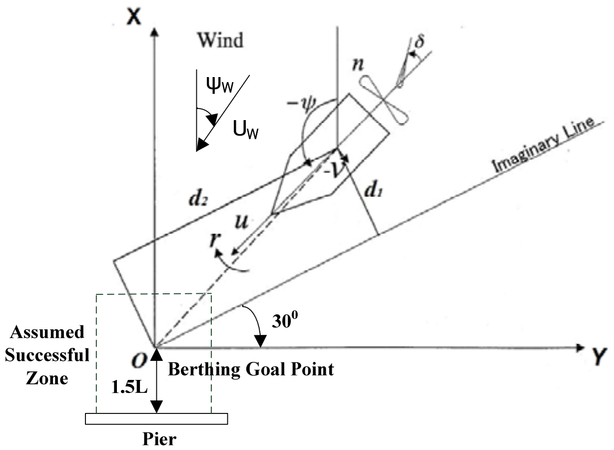


Figure 1. Coordinate system and other assumptions during berthing

#### 3.1.1 *Virtual Window Concept for Course Changing*

Maintaining consistency in the course changing trajectories while training neural network, would be a key factor to increase the robustness of the controller. In this research, nonlinear programming (NLP) method for minimum time course changing manoeuvre is utilised to do so. Then, considering the repeated optimisation techniques as explained by Ahmed and Hasegawa (2013a), several course changing trajectories are constructed for ship's different initial heading and one particular final heading which is 240º with no sway and angular velocity. Here, the final heading 240º means making an angle 30º with the pier i.e. the ship will align with the imaginary line after course changing.

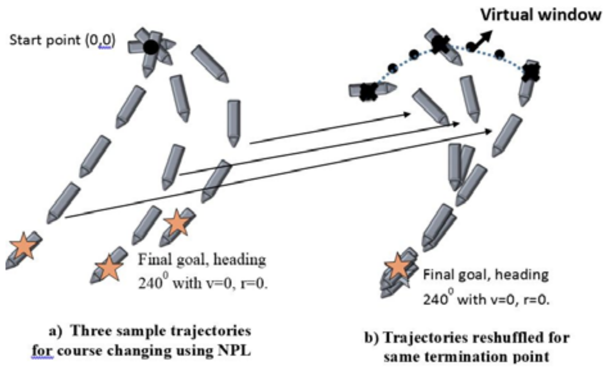


Figure 2. Idea of virtual window

During the optimisation process, the time is set as objective function and rudder angle as optimal variable. Moreover, four different rudder angles ±10º, ±15º, ±20º and ±25º are used as non-equality constraints. The repeated optimisation technique used in this research is to generate the course changing trajectories by altering only the initial heading and keeping the same starting point. Therefore, the plot of consecutive trajectories would be the same as shown in Figure 2 (a), i.e., each trajectory ends with a different endpoint. However, by following the reshuffling process as shown in Figure 2 (b), it is possible to align the trajectories for a particular endpoint that will coincide with the imaginary line. Such reshuffling process results a new set of starting points, each belongs to a particular ship heading and it is possible to draw a curvature through such points. Such curvature is named as 'virtual window'. In this research, four different windows are constructed, each result due to the constraint rudder angle used during the optimisation technique.

#### 3.1.2 *Track Keeping using PD Controller*

After making a proper course change using the calculated command rudder for minimum time manoeuvre, the ship is expected to go straight if there would no wind disturbances. However, in real cases such disturbances exist. Therefore, after merging to the imaginary line while reducing the speed gradually, slight wind may cause drastic course changes if no action is taken to compensate such disturbances. Considering the difficulties in maintaining the course, especially in low speed under environmental disturbances, in this research as a feedback controller PD is used which is mentioned in the Equation 2. The coefficients used for the controller are tuned on a trial basis to ensure earlier response of the controller in any slight disturbances.

$$\delta_{order} = C_1 * (\psi_d - \psi) - C_2 * \dot{\psi} - C_3 * d_1$$
$$\Rightarrow if \begin{cases} \delta_{order} > 0^0, \delta_{order} = 10^0 \\ \delta_{order} = 0^0, \delta_{order} = 0^0 \\ \delta_{order} < 0^0, \delta_{order} = -10^0 \end{cases} \tag{2}$$

where, $\psi_d$ is desired heading, $\psi$ is current heading, $\dot{\psi}$ is yaw rate, $d_1$ is a deviation from the imaginary line, $C_1$~$C_3$ are coefficients.

Maintaining a proper telegraph order is also important to stop the ship within an available distance. The sequence of telegraph maintained here is half ahead during course changing, then it is followed by show ahead, dead slow ahead, engine idling and at last propeller reversing. To judge the proper timing of telegraph order without damaging the engine and propeller shaft, a time constant Tp is used which is mentioned in Equation 3.

$$T_P \frac{dU(t)}{dt} + U(t) = K_P n(t) \tag{3}$$

where, $U(t)$ is ship velocity, $n(t)$ is propeller revolution, $T_p$ is time constant and $K_p$ is gain.

### 3.2 *Teaching Data Creation and Training of ANN*

Combining the course changing and track keeping trajectories along the imaginary line, the whole set of teaching data is created. In order to include the wind effect in teaching data, each successful ship berthing trajectory is considered under three different wind velocities which are 0.2m/s, 0.6m/s and 1.0 m/s for model ship. Each velocity is again considered for four different wind directions that are 45º, 135º, 225º and 315º. Therefore, instead of using the wind information directly as input neuron, the influence of wind is considered in a way of somewhat deviated ship trajectories and at the same time using the PD controller to correct them during low speed running. The resulting set of teaching data considering the wind effect is given in Figure 3.

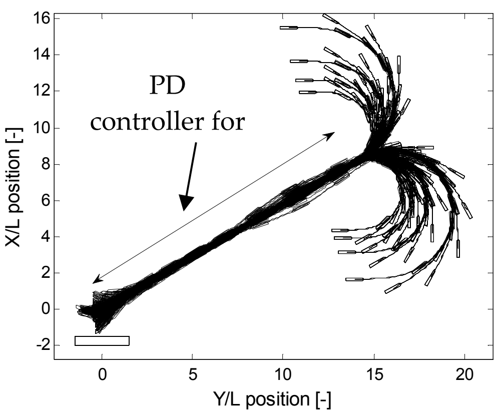


Figure 3. Teaching data including wind influence

The above mentioned teaching data are then divided for left hand side (LHS) and right hand side (RHS) approach to ensure similar course changing pattern (port or starboard). Using these two sets of teaching data, two multi-layered feed forward neural networks are constructed using Lavenberg-Marquardt algorithm as training function and mean squared error (MSE) as an evaluation function for each case. Figure 4 shows the constructed networks for command rudder and propeller revolution output. The number of neurons used in the hidden layers for LHS approach is (10, 6) for command rudder and (12, 8) for propeller revolution output. For RHS approach, this number would be (12, 5) for command rudder and (12, 8) for propeller revolution output.

Considering Figure 4, input parameters for command rudder output are $u$: surge velocity, $v$: sway velocity, $r$: yaw rate, $\psi$: heading angle, $(x, y)$: ship's position, $\delta$: actual rudder angle, $d1$: distance to imaginary line and $d2$: distance to berthing point. For propeller revolution, input parameters are $u$: surge velocity, $\psi$: heading angle, $(x, y)$: ship's position, $d1$: distance to imaginary line and $d2$: distance to berthing point.

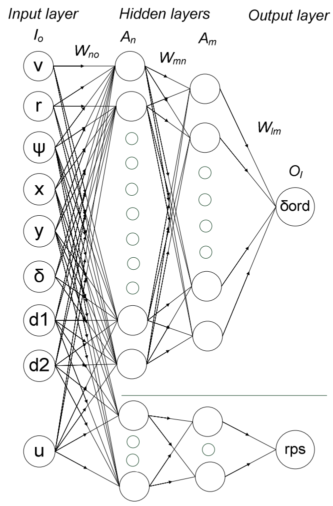


Figure 4. Teaching data including wind influence

In this research, the ANN controller for rudder is used only during course changing. Then, it will be followed up by the PD controller for low speed straight running. Here, the decisive factor to alter the ANN for PD controller is ship's position. Once the PD controller is activated, the rest of the task regarding the rudder controller is solely determined by the PD controller itself. On the other hand, the ANN controller for propeller revolution is used throughout the whole berthing process. Therefore, it would be a combined effort of both ANN and PD controller while considering the wind disturbances. Figure 5 shows the control strategy during the whole berthing process.

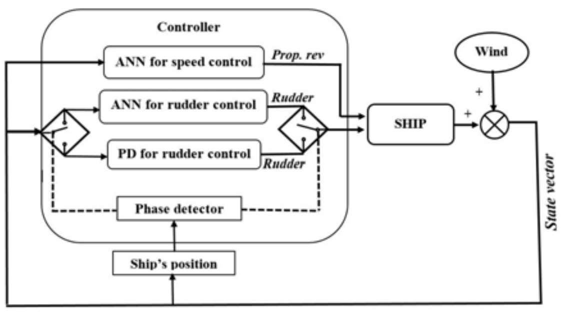


Figure 5. Control Strategy

## 4 SIMULATION RESULTS

As a next step after successful training of ANNs, several simulations are done by Ahmed and Hasegawa (2013a) where the ship starts from its desired virtual window point either used as teaching data or non-teaching data. However, the ship, staring from any arbitrary point within the constructed virtual window area is not yet considered. Such cases are studied in the following subsection.

## 4.1 *Berthing Simulations for arbitrary Staring Point*

Several combinations of ship's initial heading and starting point are possible to judge the robustness of the proposed controller. Figure 6 illustrates one of such results.

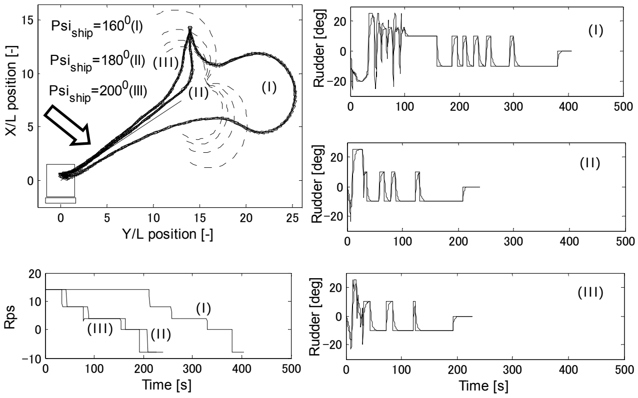


Figure 6. Ship with different heading and same initial point

Here, the ship starting with initial heading 160º, 180º and 200º respectively is tested for the same starting point. In case of initial heading 160º as shown in the first row of Figure 6, the ANN first decides to take a port turn. Later on, it starts its expected starboard turn, but very gradually. Therefore, the ship follows a long way of course changing and there exists a large gap between the ship and the imaginary line. This is a quiet unusual phenomenon and may sometimes occur due to starting from unexpected point. However, the PD controller works effectively to minimise such existing gap and at last, the ship successfully stops within the expected zone. For the other two cases, the ANN controller takes proper decision and after a slight port turn, the ship starts its expected starboard turn. Therefore, it takes a shorter path to travel as well as less time to complete the berthing process. The wind disturbances considered in all three cases are the same, which is average wind velocity of 1.5 m/s from 315º wind direction.

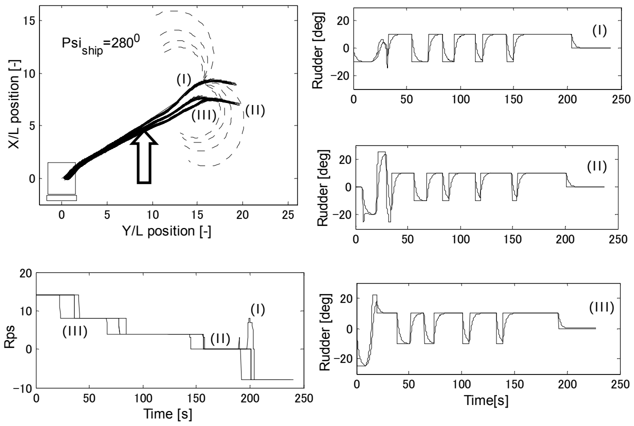


Figure 7. Ship with same heading and different initial point

Figure 7 illustrates the simulation results for ship starting with the same initial heading, but from three different arbitrary points. In all three cases, the controller takes different decisions based on surrounding situation and succeeded to guide the ship up to the expected safety zone. The PD controller gradually corrects the error regarding ship's position and heading after course changing during low speed running as mentioned before. In case 1, the controller also increases the propeller revolution during idling stage that is similar to boosting action. The wind disturbances considered in all three cases are the same, which is average wind velocity of 1.5 m/s from 180º wind direction.

## 4.2 *Monte Carlo Simulations*

In any closed loop system, it is very important to prove the stability in order to guarantee the success of the controller. In this research, to analyse the stability of the system, Monte Carlo simulations are performed. To generate the random numbers, uniformly distributed pseudorandom numbers are chosen. Such random numbers are generated for ship's staring points, headings, average wind velocities and angles. Then 970 cases are investigated which covers all virtual window areas.

As a success index, three parameters are considered. These parameters are sufficient to know the success of the controller in each run. The indexes are: non- dimensioned distance with respect to the ship's length from the target goal point, heading error from target value 240º and surge velocity error from target value 0.05 m/s. Figure 8 shows the frequency distribution table of these three success indexes.

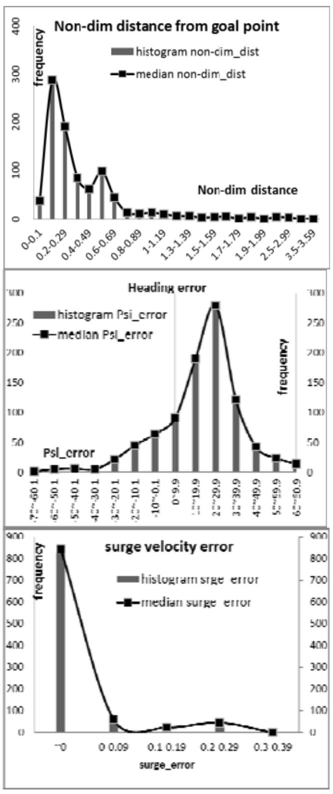


Figure 8. Frequency distribution for success indexes

#### 4.2.1 *Non-dimensionalized Distance from Final Goal Point*

In this research, the ship is assumed to be stopped if the surge velocity becomes less than 0.05 m/s during reversing. After the termination of each simulation case, error in ship position, i.e. $\Delta x$ and $\Delta y$ are calculated based on target goal point (0,0). In this research, the success of each ship berthing counts if the ship stops within the desired successful zone, which is 1.5L area around the goal point due to safety reason. After that, tugs will assist to align it with pier.

Here, the distance as a success index is calculated as $\Delta d = \sqrt{\Delta x^2 + \Delta y^2}$ and non-dimensionalised as $\Delta d' = \Delta d / L(ship)$. The frequency distribution of this success index in Figure 8 clearly shows the maximum frequency occurs at 0.1L~0.19L interval that is 29.66% of total sample cases. Then the frequency gradually decreases with the increment of non-dimensionalised distance value. Beyond 1.12L, the percentage gets less than 1.0. Here, the total success rate is 91.45%. However, the unsuccessful cases can be solved by including those initial conditions into the teaching data while training nets again.

#### 4.2.2 *Heading Error*

The error in final heading is calculated based on the target heading i.e. $\Delta\psi = \psi(final) - 240$. Here it noted that the expected heading to be kept by the PD controller during low speed running is 240º. However, due to the hydrodynamic properties that are acting on the ship during reversing, the ship with single rudder single propeller has the natural tendency to turn toward its starboard side. Thus, the frequency distribution for heading error is shifted towards the starboard side.

The frequency distribution of this success index in Figure 8, clearly shows the maximum frequency occurs at 20º~20.9º interval which is 28.73% of total sample cases. This will actually make the final ship heading parallel to the pier. Beyond that maximum frequency, in both positive and negative directions the frequency gradually reduces.

#### 4.2.3 *Surge Velocity*

One of the criteria for considering the berthing as successful in this research is final surge velocity ≤ 0.05 m/s. Thus, for each of the sample cases, the final surge velocity error is calculated to know its frequency distribution by considering the expression as $\Delta surge = surge(final) - 0.05$.

The frequency distribution of this success index in Figure 8 shows the maximum frequency occurs when the error is almost zero. Such cases occur as 86.92% of total sample cases. This clearly shows, the controller is effective enough in stopping the ship within a desired zone. Beyond that maximum frequency, it gradually decreases to a smaller value.

## 5 EXPERIMENT RESULTS

After getting promising simulation results, experiments are conducted by implementing the trained nets for free running experiment system. While performing the experiments, the model is accelerated first from the pier and then turned to enter the virtual window. As a result, every time while switching to auto mode, the ship experiences some sway velocity as well as initial yaw rate. For real ship operation, it is also very difficult to maintain zero sway and zero yaw rate in a straight course before entering to the virtual window. Therefore, the fact is also true for the real ship operation and it would be quite interesting to observe how the ANNs behave to such new situation by utilising the robustness.

In this research, experiments are carried out for both LHS and RHS approach. Desired virtual window points as well as arbitrary starting points are considered to judge the effectiveness of the controller. While doing such experiments, some similarities are found in the network's behaviour. Based on that, the experiment results are presented in some groups where the controller behaves in a similar way or the resulting trajectories look like it.

For LHS approach, three types of pattern are identified during the experiments. The representative trajectory belongs to each pattern is shown in Figure 9.

For the first type, while switching to auto mode, the ANN decides to take the starboard rudder first to ensure the ship's approach from left hand side. This is a usual case for the left hand side approach and ANN's action remains same irrespective of initial sway velocity or yaw rate. Here, in most cases within reasonable wind, the ship manages to merge with the imaginary line well ahead and proceeds along with the line without much deviation.

For the second type, due to the presence of some initial sway velocity and yaw rate while switching to auto mode, the ANN first decides to minimise them by taking the counter rudder. Doing so often distracts the ship from its safest place to approach. Therefore, the ANN realises such situation and continues with port rudder until the ship makes a complete port turn. At the same time, ANN also tries to adjust the ship's position to a safer place. Then it decides to take the desired starboard rudder to start the approaching. Here, during the turning and course changing stage, the controller keeps steady half-ahead speed.

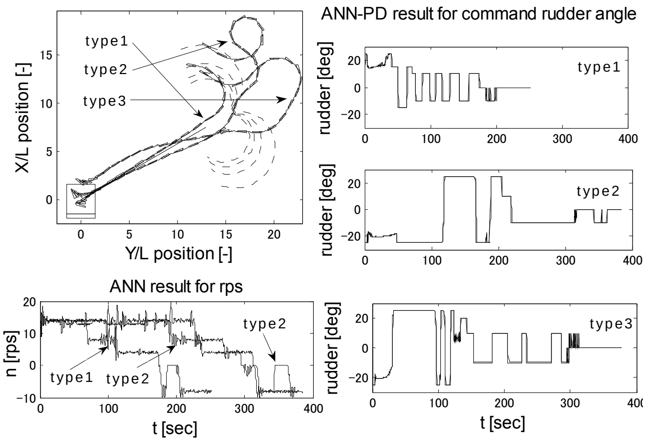


Figure 9. Berthing experiments for LHS approach

For the third type, ANN always tries to oppose the existing initial sway velocity and yaw rate while switching to auto mode. However, sometimes ANN may go with such existing values by taking the expected starboard rudder first like in type one. By doing so, if the sway velocity or yaw rate reaches some peak value depending on the ship's position, then the ANN finally decides to take the port rudder to oppose them. But this time, unlike as type two, the ANN prevents the complete turn of ship by taking the starboard rudder again as the ship is believed to be still in suitable positing to start its approaching to merge with the imaginary line. Therefore, all trajectories belong to this group is due to subsequent starboard to port or port to starboard rudder taken by ANN according to situations demand.

For the RHS approach, separately trained networks are used and three different types of pattern are identified. The representative trajectory belongs to each pattern is shown in Figure 10. In the following figure, the ship starts from nearby starting point, however due to having different gust wind and initial conditions the resulting trajectories are different.

For type one, while switching to auto mode, the ANN may take starboard rudder first to oppose the existing surge velocity and yaw rate as shown in the figure. However, it may go with the existing one by taking the port rudder. While taking the port rudder, if surge velocity and yaw rate reach their maximum value as analysed by ANN, it takes the starboard rudder to minimise these values. After that, the ANN actuates the desired port rudder to start its final approach to merge with the imaginary line. The important concern belongs to this group is that after course changing, ANN in most cases manages to make it without much deviation.

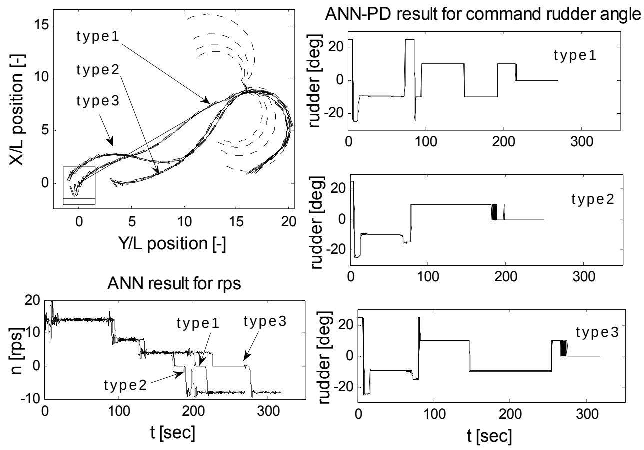


Figure 10. Berthing experiments for RHS approach

Most of the results belong to type two are due to the presence of high wind disturbances during course changing. Therefore, the ship fails to merge with the imaginary line in large extent. After that, the PD controller takes continuous counter rudder to compensate such deviation and it succeeds in some extent.

For type three, depending on ANN's response or due to the existence of wind disturbances, sometimes a ship fails to merge with the imaginary line, which is similar to type two. However, this time, the PD controller during steep deceleration successfully returns the ship to the imaginary line by taking the starboard rudder and the ship just passes through it. Then for such overshooting, the controller again takes the port rudder to correct the ship's heading and minimise its deviation from the imaginary line. Finally, the completed trajectories look like 'S' shape.

Figure 11 shows other experiment results for LHS and RHS approach while starting from different arbitrary points. However, the trajectory patters are same as explained above.

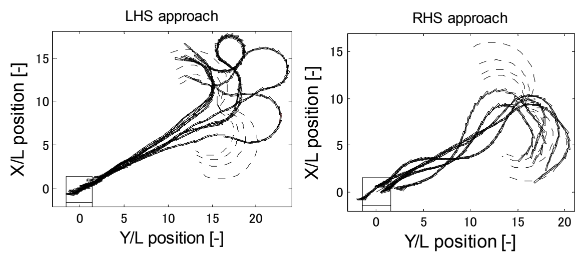


Figure 11. Berthing experiments for arbitrary starting point

## 6 ANALYSIS OF NETWORK'S BEHAVIOUR

In this research, the network's behaviour for command rudder is analysed depending on the initial sway velocity and yaw rate. During the experiment for LHS approach, the ship is expected to take a starboard turn to enter the window. Thus, while switching to auto mode, the initial sway velocity and yaw rate are likely to have negative and positive value respectively. On the contrary, for RHS approach the ship expected to a port turn to enter the window. Thus, the initial sway velocity and yaw rate are likely to have positive and negative value respectively. To analyse such situations, four different sway velocities are considered as found during the experiment. Then for each sway velocity, the yaw rate varies in a particular range. The corresponding plots of such analysis are given in Figure 12 for LHS and RHS approach.

Here, the responses for LHS approach are illustrated for varying yaw rate from 1.0 deg/s to 2.4 deg/s. Although in each case, the network possesses a pulsating characteristic, however the nature of the curves is almost similar. Here, each of the curves show a particular band of yaw rate, for which ANN decides to take the port rudder to oppose the existing sway velocity and yaw rate. Beyond that mentioned band, ANN takes the starboard rudder, which is usual for left hand side approach of a ship. Moreover, the defined band of yaw rate gradually shifts towards the right side with the increment of sway velocity. Although, these curves demonstrate the result for any particular ship's heading and initial position, however upon altering these values the ANN shows similar types of behaviour. In general, it means that if a ship has some drifted sway velocity while entering to the window, then depending on its initial yaw rate ANN may sometimes take counter rudder initially before activating its expected rudder action.

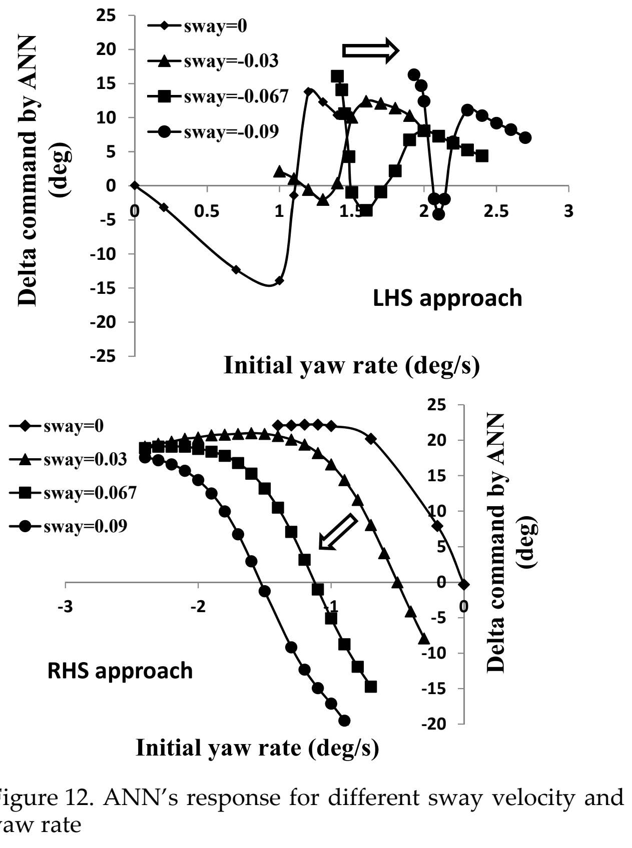


Figure 12. ANN's response for different sway velocity and yaw rate

On the other hand, for RHS approach, the low sway velocity curve does not have that much effect in altering the ANN's behaviour. As a result, the effect of having an initial yaw rate is more prone than having any low sway velocity in RHS approach. The ANN takes the port rudder only for smaller values of yaw rate. Otherwise, irrespective of any higher values of yaw rate as an initial condition, ANN always takes the starboard rudder. On the other hand, with the increment of sway velocity, the curves are gradually pulled down. Thus, the effect of having high sway velocity is dominant for small yaw rate. However, later on with the increment in yaw rate, the curve turns toward the positive value and the ANN starts to take starboard rudder. Each time with the increment of sway velocity, the graph is also little bit shifted towards the left. Finally, the analysis of the network for RHS approach can be concluded in a similar way as for LHS approach. That is if a ship has a low initial sway velocity while entering to the window, then in most cases the ANN will take the starboard rudder to oppose the expected turn except for low existing yaw rate.

Here, the analysis of the network's behaviour mainly demonstrates how the network behaves depending on existing initial sway velocity and yaw rate. Therefore, no matter how such existing initial sway velocity or yaw rate results from. Thus, the network will behave in a similar way in other experiment sites depending on the existing initial conditions.

## 7 AUTOMATIC TUG ASSISTANCE

After stopping the ship within the assumed successful zone as shown in Fig. 1, the final step would be the actual alignment of the ship to the pier. In this research, to execute the crabbing motion for a big ship like Esso Osaka with single rudder and single propeller, two lateral and one longitudinal thrusters are considered. First, the ANN controller is tried for the mentioned purpose as proposed by Tran and Im (2012). However, in the most unpredictable wind, there is no other easy way to create consistent teaching data that is important to ensure the effectiveness of ANN controller. As a result, the PD controller has given some preference over the ANN. Equations 4 to 8 demonstrate the PD controllers used for automatic thrust generation in lateral and longitudinal direction.

*if $\Psi<270^0$ and dis_fore>dis_rev*

$$\begin{aligned} T_{fore} &= C_1*(X_{fore}-1.5-X_{fore})+C_2*\text{sway} \\ T_{aft} &= C_1*(X_{fore}-1.5-X_{fore})+C_2*\text{sway}+C_3*\text{diff} \end{aligned} \tag{4}$$

*if $\Psi>270^0$ and dis_aft>dis_rev*

$$\begin{aligned} T_{fore} &= C_1*(X_{aft}-1.5-X_{aft})+C_2*\text{sway}+C_3*\text{diff} \\ T_{aft} &= C_1*(X_{aft}-1.5-x_{aft})+C_2*\text{sway} \end{aligned} \tag{5}$$

*if $\Psi<270^0$ and dis_fore<dis_rev*

$$\begin{aligned} T_{fore} &= C_1*(-1.5-X_{fore})+C_2*\text{sway} \\ T_{aft} &= C_1*(-1.5-X_{fore})+C_2*\text{sway}+C_3*\text{diff} \end{aligned} \tag{6}$$

*if Ψ >270⁰ and dis_aft<dis_rev*

$$T_{fore} = C_1 * (-1.5 - X_{aft}) + C_2 * \text{sway} + C_3 * \text{diff} \qquad (7)$$
$$T_{aft} = C_1 * (-1.5 - X_{aft}) + C_2 * \text{sway}$$

*Longitudinal thrust*

$$X_{tug} = C_4 * surge + C_5 * \text{Ypos} + C_6 * \text{distance} \qquad (8)$$

where, $\Psi$ is ship's heading, $X_{fore}$ and $X_{aft}$ are x-coordinate of ship's fore and aft peak respectively, *diff* is *abs*($X_{fore}$-$X_{aft}$), *distance* is the perpendicular distance of ship's CG from the actual pier, *dis_fore* and *dis_aft* are perpendicular distance of ship's fore and aft peak respectively from the actual pier, *dis_rev* is the perpendicular distance from the actual pier to start reverse thrust, $Y_{pos}$ is the y coordinate of ship's CG in the earth fixed coordinate, $C_1$~$C_6$ are the coefficients.

Considering Equation 4 and 5 for providing side thrusts, first part belongs to a constant value irrespective of ship's position to withstand the wind force up to 1.5 m/s. Second part is for controlling sway velocity and third part activates if a correction for ship's heading is needed. On the other hand, if ship reaches the zone to provide reverse side thrusts as given in Equation 6 and 7, the first part is no longer constant rather increases the thrust value gradually with the decrement of the distance value to minimise the sway velocity upon reaching the pier. Other parts remain same. Here, the value of *dis_rev* depends on the steady sway velocity while approaching to the pier using side thrusters in presence of wind disturbances form different direction. Considering longitudinal thrust given in Equation 8, the first part is for controlling forward velocity, second part is for controlling ship's position in longitudinal direction and the third part is for controlling thrust value with respect to ship's distance from actual pier. Now, by combining the proposed controller for side thrusters with the existing ANN-PD controller, simulations are done for the different unknown situation. Figure 13 and 14 demonstrate such results.

Considering Fig.13, the combined controller is tested for following wind. Here, the following wind brings the ship much closer to the pier than in Fig.14. Finally, the simulation ends with a ship heading 271º and sway velocity close to zero.

On the other hand, for Fig. 14, the controller also successfully manages to maintain the ship's heading against the wind during the crabbing motion. However, the ship takes a long time to reach the pier as the sway velocity is relatively low due to opposite wind direction. It is also noted that there is barely in need of any longitudinal thruster for position alignment. Here, the ship's final heading is 269º and sway velocity is almost zero.

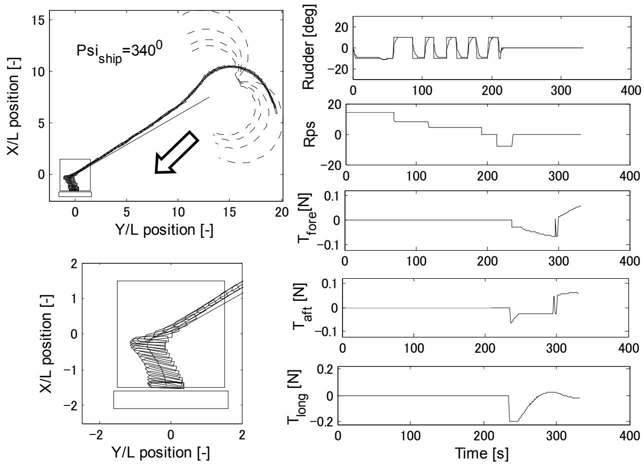


Figure 13. Initial heading 340º starting from an arbitrary point

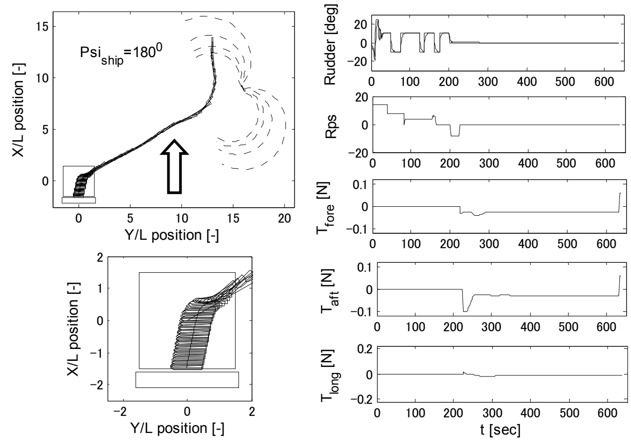


Figure 14. Initial heading 180º starting from an arbitrary point

Simulations are also done considering the end condition of different experiment results to judge the capability of the proposed PD controller in aligning the ship to the pier. Fig. 15 illustrates such results.

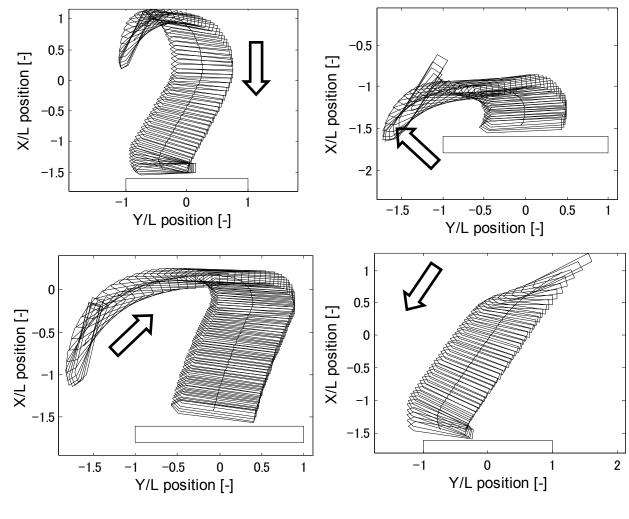


Figure 15. Simulations with different experiment end condition

Considering the above figure, in spite of dealing with the ship having different final heading and position, the controller is effective enough to guide it up to the pier. Only for the following wind, it poses some difficulties in correcting the ship heading.

## 8 CONCLUSIONS

In this research, repeated optimisation technique is utilised to create consistent teaching for training the ANN controller. The proposed repeated optimisation technique also demonstrates a new idea named 'virtual window', which is to start a ship with its particular heading from a desired point for minimum time course changing.

Following the control strategy mentioned in this research, several simulations are done for desired and arbitrary starting point to judge the robustness of the controller under gust wind disturbances. Stability of the closed loop system is also analysed using Monte Carlo simulations. This gives 91.45% success over 970 arbitrarily chosen cases. However, the success rate can be increased by including the initial conditions of the unsuccessful cases into the teaching data while training the net again.

After getting satisfactory percentages of success, ship berthing experiments are conducted and results are included in this paper. While performing the experiments, the controller has found to behave in some particular ways depending on different initial conditions and wind disturbances. Therefore, the experiment results are tried to gather in some groups depending on the similarities of network's behaviour or trajectories pattern. Such behaviours are also tried to analyse for different initial sway velocities and yaw rates.

The controller in this paper is proposed to stop the ship at some safe distance from actual pier. Therefore, as a final approach to the berthing operation, the PD controlled side thrusts is proposed and coupled with the current controller. Several simulations are done to check the compatibility of the controllers and found quite promising results.

Finally, it is clearly said that the existing environmental disturbance plays a vital role while using the proposed controller for automatic ship berthing. If the wind blows beyond permitted limit, then evenusing the proposed PD controller, it will no longer possible to keep the track due to reduced manoeuvrability at low speed.

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