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Calibration and validation for the Vessel Maneuvering Prediction (VMP) model using AIS data of vessel encounters

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Abstract

The Vessel Maneuvering Prediction (VMP) model, which was developed in a previous work with the aim of predicting the interaction between vessels in ports and waterways, is optimized in this paper by considering the relative position and vessel size (length and beam). The calibration is carried out using AIS data of overtaking vessels in the port of Rotterdam. The sensitivity analysis of the optimal parameters shows the robustness of the calibrated VMP model. For the validation, the optimal parameters are used to simulate the whole path of overtaken vessels and vessels in head-on encounters. Compared to the AIS data, the validation results show that the different deviations in longitudinal direction range from 33 m to 112 m, which is less than 5% of the waterway stretch. Both the calibration and validation show that the VMP model has the potential to simulate vessel traffic in ports and waterways.

Keywords: the VMP model, calibration, validation, overtaking encounter, head-on encounter

1. Introduction

With the development of international transportation, maritime traffic flows have increased substantially in recent decades. As both vessel number and size increase sharply, more and more concern is raised about the safety and capacity of maritime traffic, especially in ports and waterways. In these restricted areas, the interactions between vessels are more frequent than open waters. Many models have been developed to investigate maritime traffic, most of which focus either on the risk of collisions and groundings (Goerlandt and Kujala, 2011; Montewka et al., 2010; Qu et al., 2011), or on vessel hydrodynamics and maneuverability (Sariöz and Narli, 2003; Sutulo et al., 2002). Although progress has been made on the investigation of vessel behavior, such as vessel speed, course and path (Aarsæther and Moan, 2009; Xiao, 2014), few models have considered vessel characteristics, vessel encounters and traffic state, such as waterway geometry and external conditions including wind, visibility and current. Thus, vessel speed and course in ports and waterways cannot be accurately predicted.

To address this need, a new maritime traffic operational model was developed recently by applying differential game theory (Hoogendoorn et al., 2013). The approach of this model was adapted from an approach that was successfully applied to predict the behavior of pedestrians (Hoogendoorn and Bovy, 2003; Hoogendoorn and Bovy, 2004) as there are many similarities between vessels and pedestrians: both vessels and pedestrians (1) have specific origin and destination; (2) are constrained by boundary (bank for vessels, and wall or other obstacles for pedestrians); (3) can influence each other; (4) are influenced by external conditions, such as weather conditions. In this model, vessel behavior is described at two levels: a tactical level and an operational level. The tactical level includes vessel route choice (the desired course) and desired speed, which serve as the reference (guide) at the operational level. The desired course and desired speed represent the optimal course and speed when the vessel is not influenced by extreme external conditions and other vessels. The operational level includes the dynamics of the vessel sailing behavior, e.g. longitudinal acceleration and angular speed of the vessel. Although the route choice model is assumed to be very simple in the previous work (Hoogendoorn et al., 2013), the framework for the model was created. Based on this framework, the route choice model at tactical level was further developed (Shu et al., 2015b). The results of this study serve as an input into the operational model, which is called Vessel Maneuvering Prediction (VMP) model in this paper. The VMP model was introduced by considering the influence range in different directions of the vessel to be homogeneous and the model was only calibrated for unhindered vessel behavior (Shu et al., 2015a), in which the influence between encountered vessels is not considered.

The aim of this paper is to improve the VMP model by considering the relative position and vessel size (length and beam), and then calibrate and validate the improved VMP model using the AIS data of vessel encounters. To improve the model, we consider the distinct influence ranges of the vessel in longitudinal and lateral direction, which correspond to the findings of a recent study that the vessels keep larger distance in longitudinal direction than in lateral direction, and vessel speed is influenced for both overtaking and overtaken vessels (Shu et al., 2017). In the calibration, the VMP model is used to simulate overtaking vessel maneuvers for each path segment (60 seconds), and then to compare the final position of the overtaking vessel from the AIS data. For the validation, the VMP model is used to simulate the whole vessel path in the research area for overtaking, overtaken vessels and the vessels in head-on encounters, respectively. Then, these simulated paths are used to compare with the observed vessel path from the AIS data.

This paper starts with an introduction of the improved VMP model in Section 2. Then, the calibration and validation approaches are presented in Section 3, followed by the results of the calibration and validation in Section 4. Finally, this paper ends with discussion and conclusions in Section 5.

2. The improved VMP model of vessel traffic

In this section, the improved VMP model is introduced. As we know, the bridge team controls the vessel through the engine to accelerate or decelerate the ship and the rudder to change the vessel course. The longitudinal acceleration u_1 and angular speed u_2 are therefore considered as the controls on the ship by the bridge team in the VMP model of vessel traffic (Hoogendoorn et al., 2013). The vessel coordinate system and the control are defined in our previous research as follows (Shu et al., 2015a):

$$\dot{x} = v \cos\left(\frac{\pi}{2} - \psi\right) \tag{1}$$

$$\dot{y} = v \sin\left(\frac{\pi}{2} - \psi\right) \tag{2}$$

$$\dot{v} = u_1 \tag{3}$$

$$\dot{\psi} = u_2 \tag{4}$$

where the state of the vessel is defined as $\vec{\xi} = (x, y, v, \psi)$, in which *x* and *y* denote the position, and *v* and ψ denote vessel speed and course, respectively. In this coordinate system, Eqs. (1-2) represent the vessel speed in x-y coordinates and Eqs. (3-4) show the longitudinal acceleration and angular speed.

In the VMP model, it is assumed that the bridge team controls the vessel to maintain the desired speed and course as much as possible, to minimize the maneuvering effort and to keep sufficient distance to other vessels. In order to quantitively describe these control objectives and combine them into the VMP model, the concept “cost” is introduced. By minimizing the objective function (total cost), the controls could be optimized and an optimal vessel speed, course and path could be achieved. Thus, the control objectives could be turned into a cost minimization problem. The control objective function is defined as follows (Hoogendoorn et al., 2013):

$$J = \int_{t}^{t+H} L\left(s, \vec{\xi}, \vec{u}\right) ds + \Phi(t + H, \vec{\xi}(t + H)) \tag{5}$$

where H denotes the prediction horizon, which is assumed to be a time period in which the bridge team could predict the vessel behavior; L denotes the running cost (cost incurred in a small time interval $[\tau, \tau + \mathrm{d}\tau))$; $\vec{u} = (u_1, u_2)$ denotes the control, and Φ denotes the terminal costs at terminal conditions, which is the cost that is incurred when the vessel ends up with the state $\vec{\xi}(t + H)$ at time instant $t + H$. The terminal cost is assumed to be zero.

Corresponding to the control objectives, i.e. maintaining the desired speed and course as much as possible, minimizing the maneuvering effort and keeping sufficient distance to other vessels, the running cost L also includes three parts: costs for straying from the desired speed and desired course L^{stray}, propulsion and steering costs L^{effort} and the proximity costs L^{prox}:

$$L = L^{stray} + L^{effort} + L^{prox} \tag{6}$$

The straying costs and the propulsion and steering costs are defined as in our previous study (Hoogendoorn et al., 2013). The straying costs are defined as follows:

$$L^{stray} = \frac{1}{2}(c_2^{v}(v^0(\vec{x}) - v)^2 + c_2^{\psi}(\psi^0(\vec{x}) - \psi)^2) \tag{7}$$

where c_3^{v} and c_3^{ψ} are weight factors for straying from the desired speed and desired course, respectively. v and ψ denote the current speed and course, $v^0(\vec{x})$ and $\psi^0(\vec{x})$ denote the desired speed and the desired course at the position $\vec{x}$, which is the current position, respectively.

The propulsion and steering costs are defined by:

$$L^{effort} = \frac{1}{2}(c_3^{v}u_1^2 + c_3^{\psi}u_2^2) \tag{8}$$

where c_3^v and c_3^ψ are weight factors of the effort of the bridge team to accelerate (decelerate) and turning the vessel. So, these two factors correspond to the control (the longitudinal acceleration and angular speed).

The main improvement of the model focuses on the proximity costs, which are defined based on the relative position between the simulated vessel and the encountered vessel as follows:

$$L^{prox} = \begin{cases} c_1\left(e^{-d/R} - e^{-1}\right), & d < R \\ 0, & d \geq R \end{cases} \tag{9}$$

where c_1 is the weight factor for this proximity cost, d denotes the distance between the simulated vessel and the encountered vessel, and R is the scaling parameter, which indicates the range within which the simulated vessel is influenced by the other vessel and this parameter is determined by the relative position between the simulated vessel and the encountered vessel. As shown in Eq. (9), the proximity costs increase when the encountering vessels approach each other, and the proximity costs equal to zero when the distance is larger than the scaling parameter. In the data analysis of vessel encounters, it was found that the influence distance between encountering vessels in longitudinal direction is much larger than in lateral direction (Shu et al., 2017). This results in an elliptical influence area. As an example, the elliptical influence area of an overtaking vessel is shown in Fig. 1.

As shown in Fig. 1, the elliptical influence area has a semi-major axis a and a semi-minor axis b. The scaling parameter R could be interpreted as the radius of the ellipse, which is a function of the parameters a, b and the angle θ (the angle between the course of the own vessel and the line connecting the locations of the two encountering vessels):

$$R(\theta) = \frac{ab}{\sqrt{a^2 \sin^2\theta + b^2 \cos^2\theta}} \tag{10}$$

In the VMP model, it is also assumed that a larger vessel size will lead to larger influence distances. Then, the major axes a and minor axes b depend on the vessel length and beam of the own vessel and the other vessel as follows:

$$a = p * (L_A + L_B)/2 \tag{11}$$

$$b = q * (B_A + B_B)/2 \tag{12}$$

where p and q are scaling coefficients of the vessel length, L_A and L_B are the lengths of the two vessels in encounter, and B_A and B_B correspond to vessel beam. Thus, the VMP model is improved by considering the different influence range of the vessel in longitudinal and lateral direction and the proximity costs are improved with three parameters: the weight factor c_1, and scaling coefficient p and q.

3. Research approach

In this section, the calibration and validation approaches are presented. The aim of the calibration is to find the model parameters that result in the best prediction of the model, and the purpose of the validation is to confirm that the model and its optimized parameters can generalize the calibration data. The data used in both approaches come from the Automatic Identification System (AIS) system, which is used to record vessel data between vessels and shore stations. In recent decades, it has been developed and implemented as a mandatory tool on all ships by 1 July 2008 (Eriksen et al., 2006).

In this paper, the AIS data of 146 overtaking encounters and 162 head-on encounters are used. These data are provided by Maritime Research Institute Netherlands (MARIN) and analyzed using dedicated software called “ShowRoute”, which is developed by MARIN and used to investigate AIS data. These data were selected in the Botlek area in the port of Rotterdam and used to analyze the vessel behavior in previous studies (Shu et al., 2017). The waterway stretch is around 2.5 km and the sailing time in the research area approximately equals 500 seconds, given the average vessel speed of 5 m/s (Shu et al., 2013).

In this paper, the VMP model is assumed to be generic for different types of encounters, which means that the parameters determined by calibrating for data from overtaking vessels are applicable for overtaken vessels and vessels in head-on encounters. As overtaken vessels and vessels in head-on encounters are in many cases in the equilibrium situation (without longitudinal acceleration and angular speed) (Shu et al., 2017), the overtaking vessels are more suitable for the calibration because they normally have a larger deviation from their desired speed and path. The vessels that are in equilibrium situation cannot be used for the calibration because the resulting model parameters would be equal to zero.

In addition, it is assumed that the bridge team has enough experience to predict the speed and course of the other vessels, and they can use it in their decision-making procedure. Based on this assumption, the AIS data of the encountered vessel is considered as a known input in this research. This assumption is made in this first step to calibrate and validate the VMP model, with the aim to simultaneously simulate multiple vessels in future research.

3.1 Calibration approach

In this section, the calibration including calibration set-up, objective function and sensitivity analysis is presented.

3.1.1 Calibration Set-Up

The parameters of the VMP model, consisting of weight factors $c_1, c_2^v, c_2^\psi, c_3^v$ and c_3^ψ, and the scaling coefficients p and q need to be calibrated. It should be noted that all weight factors cannot be uniquely determined from the data, since only the relative importance of the weights can be determined. Without loss of generality, we set $c_1 = 1$. Then, the parameters to be calibrated are $\beta^T = (c_2^v, c_2^\psi, c_3^v, c_3^\psi, p, q)$.

In this calibration, all paths of overtaking vessels have been broken down into multiple small segments, which have the same time period as the prediction horizon. The prediction horizon H is taken as 60 seconds, which is a reasonable time period for the bridge team to maneuver the vessel. The calibration is performed for each path segment and the final position of the predicted vessel path is compared with the AIS data.

To run the VMP model, the desired speed and desired course serve as inputs, while the vessel speed, course and path are the outputs. We assume that the desired course generated by the Route Choice model (Shu et al., 2015b) is applicable for all vessels in the research area, because it was found that vessel course is hardly influenced by vessel size and type (Shu et al., 2013). In terms of the desired speed, it was found that overtaking vessels increase their speed before the CPA (Closest Point of Approach) and decrease the speed after the CPA (Shu et al., 2017). Therefore, the desired speed is set as the maximum speed v_{max} before the CPA and set as the end speed v_{end} after CPA, as shown in Fig. 2. This way, the variability of the desired speed is considered, which is closer to reality than setting a constant desired speed.

3.1.2 Objective function for calibration

The calibration process aims at minimizing the difference between the vessel path predicted by the VMP model and the observed path from AIS data. As shown in Fig. 3, an overtaking vessel sails from left to right and the observed vessel position at the end of the prediction horizon is $\vec{x}_{data}$. The VMP model predicts that the overtaking vessel is at position $\vec{x}_{sim}$ at the end of the prediction horizon. Then, the parameters should be chosen such that the distance between the position $\vec{x}_{data}$ and the position $\vec{x}_{sim}$ is minimized.

Let *m* denote the number of vessel paths and let n_i denote the number of segments for vessel path *i*, then we have the objective function for the calibration as follows:

$$E(\beta) = \frac{1}{m} * \frac{1}{n_i} * \sum_{i=1}^{m} \sum_{j=1}^{n_i} \left(\vec{x}_{data}^{i,j} - \vec{x}_{sim}^{i,j}\right)^2 \tag{13}$$

This way, the calibration problem becomes a multi-variable nonlinear optimization problem as follows:

$$\beta^* = \arg\min E(\beta) \tag{14}$$

3.1.3 Sensitivity analysis

Based on the calibration results, a sensitivity analysis is performed to get insight into the influence of each parameter on the error and the robustness of the calibration, as well as the reliability of the optimal parameter set. To this end, each model parameter is varied while keeping the other parameters constant at their estimated value. The relationships between model parameters and the error provide insight into the model's parameter properties and the sensitivity.

3.2 Validation approach

The validation is performed to see if the calibrated parameters could be used to predict the vessel path for other datasets accurately (within the allowed error margin). Contrary to the path segments used in the calibration, the validation simulates the whole path using the optimized parameters. In the validation, the optimized parameters are applied for all three scenarios: overtaking vessels, overtaken vessels and head-on vessels. Among these scenarios, the overtaking and overtaken vessels are from the same dataset. Similar as in the calibration, the vessel is simulated while the encountered vessel path is considered as a known input (described by the AIS data). Then, the calibrated parameters are used by the VMP model to predict each vessel path every 10 seconds.

To evaluate the simulation quality, the comparison between the simulated path and the real path focuses on four aspects in both the longitudinal and lateral direction: the final position of the whole path, the maximum absolute deviation, the average absolute deviation and average percentage of good predictions (within the allowed error margin). To quantify how well the simulated path fits the vessel path from AIS data, 8 goodness of fit measures are defined. Considering the overtaking vessel as an example, Fig. 4 shows the simulated vessel path for the overtaking vessel and the real path from AIS data, as well as the parameters used to formulate the measures. It should be noted that the scheme to determine the port side or starboard overtaking is not included in this VMP model yet, so the simulated overtaking may happen on the other side than the real one, when the whole vessel path is simulated by the VMP model. The results for these overtaking and overtaken paths will not be included in the validation results and the choice of the overtaking side is left for further research.

As shown in Fig. 4, the origin of the simulated overtaking vessel is $\vec{x}_0^i$, in which *i* denotes vessel path id. The maximum deviation happens when the overtaking and overtaken vessels are located at positions $\vec{x}_{sim}^{i,max}$ and $\vec{x}_{data}^{i,max}$, while the simulated path and the real path end at $\vec{x}_{sim}^{i,end}$ and $\vec{x}_{data}^{i,end}$, respectively. The deviations E_{lo}^F and E_{la}^F are the average difference for the final position of simulated path and AIS path in the longitudinal and lateral direction, respectively:

$$E_{lo}^F = \frac{1}{m}\sum_{i=1}^{m}(\left|\vec{x}_{data}^{i,end} - \vec{x}_{sim}^{i,end}\right| * \cos\alpha_{end}^i) \tag{15}$$

$$E_{la}^F = \frac{1}{m}\sum_{i=1}^{m}(\left|\vec{x}_{data}^{i,end} - \vec{x}_{sim}^{i,end}\right| * \sin\alpha_{end}^i) \tag{16}$$

where m denotes the number of vessel paths, α_{end}^{i} denotes the angle between the longitudinal direction for the last AIS data recorded and the line connecting the two end positions. This angle is used for the projection of the error in the longitudinal and lateral direction.

The deviations E_{lo}^{M} and E_{la}^{M} correspond to the maximum deviation between the simulated path and the AIS path in the longitudinal and lateral direction, respectively. These two are defined as:

$$E_{lo}^{M} = \frac{1}{m}\sum_{i=1}^{m}(\left|\vec{x}_{data}^{i,max} - \vec{x}_{sim}^{i,max}\right| * \cos\alpha_{max}^{i}) \tag{17}$$

$$E_{la}^{M} = \frac{1}{m}\sum_{i=1}^{m}(\left|\vec{x}_{data}^{i,max} - \vec{x}_{sim}^{i,max}\right| * \sin\alpha_{max}^{i}) \tag{18}$$

where α_{max}^{i} denotes the angle between the longitudinal direction at the position where the maximum deviation occurred and the line connecting the two compared positions.

The deviations E_{lo}^{A} and E_{la}^{A} denote the average deviation of the simulated path and AIS path in the longitudinal and lateral direction, respectively. They are defined by:

$$E_{lo}^{A} = \frac{1}{m} * \frac{1}{n_i} * \sum_{i=1}^{m}\sum_{j=1}^{n_i}(\left|\vec{x}_{data}^{i,j} - \vec{x}_{sim}^{i,j}\right| * \cos\alpha_{i,j}) \tag{19}$$

$$E_{la}^{A} = \frac{1}{m} * \frac{1}{n_i} * \sum_{i=1}^{m}\sum_{j=1}^{n_i}(\left|\vec{x}_{data}^{i,j} - \vec{x}_{sim}^{i,j}\right| * \sin\alpha_{i,j}) \tag{20}$$

where n_i denotes the number of path segments of vessel path i, and j denotes the id of path segment.

The last two measures are defined to present the average percentage of good predictions, which are within the error margin. The error margin is taken as 5% of the relative error in the longitudinal direction, while 5% of the waterway width is used in lateral direction. The measures P_{lo} and P_{la} are calculated as follows:

$$P_{lo} = \frac{1}{m} * \sum_{i=1}^{m} P_{lo}^{i} \tag{21}$$

$$P_{la} = \frac{1}{m} * \sum_{i=1}^{m} P_{la}^{i} \tag{22}$$

where P_{lo}^{i} and P_{la}^{i} represent the percentage of good predictions (the prediction error less than the error margin) of the vessel path *i* at longitudinal direction and lateral direction, respectively.

Among these measures of fit, the first six measures are formulated as the average of the deviation of the final position, the maximum deviation and the average deviation. The histogram of these deviations is also shown in the result section to provide more insight into the simulation quality. In addition, some example paths have been randomly chosen from each scenario and presented in the next section to compare with the actual path from AIS data and unhindered path (generated by the desired course), for more in-depth discussion.

4. Results

In this section, the calibration results including the optimal parameters and sensitivity analysis are presented, followed by the validation results and example simulated paths.

4.1 Calibration results

By applying the optimization approach, the best fit of the VMP model to the AIS data of overtaking vessels is determined. The optimal model parameters are shown in Table 1. The obtained error is 458 m^2, which is the mean square of the distance of the final position between the simulated path and actual path from AIS data. This implies that the prediction error is around 21 meters while the prediction period is 60 seconds.

Table 1. Calibration results for the VMP model for three different datasets.

Parameters	$\boldsymbol{c_2^v}$	$\boldsymbol{c_2^\psi}$	$\boldsymbol{c_3^v}$	$\boldsymbol{c_3^\psi}$	$\boldsymbol{p}$	$\boldsymbol{q}$
Unit	$[s^2/m^2]$	$[1/rad^2]$	$[s^4/m^2]$	$[s^2/rad^2]$	-	-
Optimal value	0.59	0.32	682	257	8	3.9

It can be seen that all parameters have positive values, which is as expected because these parameters are weight factors and scaling parameters. Compared to c_2^v and c_2^ψ, c_3^v and c_3^ψ are much larger. Compared to vessel speed and course, the values of longitudinal acceleration and angular speed are normally very small. This will result in large values of c_3^v and c_3^ψ. The scaling parameters p and q equal to 8 and 3.9, which means that the influence range in longitudinal and lateral direction is around 8 times the vessel length and 3.9 times the vessel width, respectively. They are consistent with our expectation that vessels have stronger influence in the longitudinal direction than in the lateral direction, considering the fact that vessel length is much larger than vessel beam.

Based on the six optimal parameter values in Table 1, the relationships between each parameter and the error by varying each parameter while keeping the other parameters constant at their optimal value are shown in Fig. 5.

It is clear that all curves for these parameters are smooth. For parameters c_2^v, c_2^ψ, c_3^v, c_3^ψ and q, the curves have a single and clear minimum, which means the optimal values are taken at the global minimum. Thus, it also means that the calibration method is robust and the optimal values for these parameters are reliable. Regarding the parameter p, the error decreases with the increase of the scaling parameter up to 8, after which the p value remains stable. It means that the model is not sensitive to the p value and the optimal p value is difficult to be determined when the p value is larger than 8. However, it is not meaningful to investigate the situation for larger p value (p > 8), which leads to a unrealistically large influence range in longitudinal direction (exceeding the research area).

In addition, the optimal values of these two scaling parameters indicate that the influence range in longitudinal direction is much larger than in the lateral direction, which is consistent with our expectation. In general, this sensitivity analysis indicates the robustness of the calibration and the reliability of the optimal parameter set.

4.2 Validation results and examples

By applying the validation approach, the goodness of fit measures is calculated for overtaking vessels, overtaken vessels and head-on vessels, as shown in Table 2. As mentioned in section 3.2, the 23 vessel paths in which overtaking occurred on the other side of the overtaken ship than the actual side are removed from these validation results, and 10 vessel paths of simulated overtaken vessels are filtered in the same way.

Table 2. The goodness of fit measures for the validation of different scenarios.

	Overtaking vessels	**Overtaken vessels**	**Head-on vessels**
E_{lo}^{F}	102 m	79 m	58 m
E_{la}^{F}	50 m	51 m	78 m
E_{lo}^{M}	112 m	85 m	68 m
E_{la}^{M}	67 m	60 m	83 m
E_{lo}^{A}	62 m	44 m	33 m
E_{la}^{A}	29 m	27 m	34 m
P_{lo}	67 %	60 %	81 %
P_{la}	50 %	55 %	49 %

The deviations in longitudinal direction range from 33 m to 112 m. Considering the waterway stretch of around 2.5 km, all measures representing the error in longitudinal direction are less than the 5% of the waterway stretch. In the lateral direction, the deviations vary from 27 m to 83 m, which is relatively large given the waterway width of around 430 m. However, the deviation in lateral direction is also influenced by the deviation in longitudinal direction, as the vessel path is compared by time line. So it is difficult to judge the simulation quality based on the deviation in lateral direction here.

The data clearly showed that the best prediction in longitudinal direction is for head-on encounters, as all the deviations in longitudinal direction for head-on encounters are smaller than other scenarios, and the percentage of good prediction is around 81%, which is better than for the other scenarios as well. This may be caused by the fact that the speed is hardly influenced by the head-on encounters. However, the prediction in lateral direction for head-on encounters is obviously worse than for the other scenarios. This could imply that the elliptical influence area does not work well for head-on vessel encounters. It suggests to improve the cost function for vessel influence in the VMP model in future research, specifically for head-on encounters. As mentioned in Section 3.2, the histograms of the deviations for the first six goodness of fit measures are shown in Fig. 6-8.

In the remainder of this section, some example paths have been randomly chosen for each scenario and plotted in Fig. 9, and compared to the actual path from AIS data and unhindered path (generated by the desired course). The first example is to simulate overtaking vessel sailing from left to right. It can be seen that the predicted path in the middle part of the stretch is closer to the starboard bank, meaning that the influence between two vessels in the VMP model is not strong enough during that period. In the right part of the stretch, the simulated vessel deviates from the desired path and then the simulated path is consistent with the AIS overtaking path, which implies the influence between two vessels is reasonably predicted in this situation. In the remaining two examples, the predicted paths are nearer to the shore, compared to both the AIS path and desired path. This could mean that the influence between vessels, as calibrated for overtaking vessels, is too strong for overtaken and head-on vessels. These findings based on example paths suggest that the further research should focus on the different influence range for different types of encounters.

5. Discussion and conclusions

In this paper, the VMP model is optimized by considering the relative position and vessel size (length and beam). Furthermore, the model is calibrated and validated using the AIS data of vessel encounters. The calibration results and the sensitivity analysis showed the robustness of the calibration and the reliability of the optimal parameters. In the validation of the three scenarios, it was found that the different goodness of fit measures in longitudinal direction are less than 5% of the waterway stretch.

It should be noted that several factors influence the calibration results. Firstly, the calibration results are influenced by the desired speed and desired course, which are important inputs to the model. As we can see in Eq. (7), the costs for straying from the optimal path were based on the difference between the real speed and the desired speed, as well as the real course and the desired course. In this research, the desired speed is based on empirical data. A better solution would be a derivation of the desired speed based on waterway geometry and vessel characteristics. For the desired course, the results of the Route Choice model for one representative vessel category is used. Since the dataset used for calibration comprises several vessel categories, this contributes to the error in the calibration of the VMP model.

Secondly, some differences between measured and simulated vessel paths can be attributed to non-constant maneuvering style and different experience of the bridge team. The encounter pattern, such as port side or starboard overtaking, is not regulated by international or local rules. The maneuvering behavior of the bridge team is normally determined according to the traffic situation at that moment based on their experience, which is difficult to be integrated in the model.

As far as we know, this is the first study on vessel maneuvering prediction including speed, course and path in ports and waterways using a simulation model. Based on the calibration and validation, it can be concluded that the VMP model has potential to simulate the vessel traffic in ports and waterways. This paper also provides a fundamental basis for better optimizing and simulating vessel traffic in future. The approach to determine the port side or starboard overtaking for overtaking encounters is not included yet and this is an important improvement for the VMP model in future research. In the validation, the example paths suggest that different influence range for different encounters should be considered. In addition, single vessel is simulated in this paper and the future research will focus on simulating multiple vessels simultaneously. Another future research direction is to determine different calibration parameters for different vessel categories.

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Figure captions

Fig. 1. Elliptical influence area of overtaking vessel and the definition of scaling parameter for the overtaking vessel.

Fig. 2. Definition of desired speed v^0 for an overtaking vessel. The curve indicates the speed track of overtaking vessel in overtaking encounters. Axis *x* and *y* represent the longitudinal distance and vessel speed, respectively.

Fig. 3. Vessel path of overtaking and overtaken vessel from AIS data (solid line) and simulation path of overtaking vessel (dashed line) within the prediction horizon.

Fig. 4. Simulated vessel path (solid line) of overtaking vessel and the observed path (dashed line) from AIS data.

Fig. 5. The relationships between each parameter and the error by varying each parameter while keeping the other parameters constant at their optimal value.

Fig. 6. Histograms of the deviations from the first six good of fit measures for overtaking vessels.

Fig. 7. Histograms of the deviations from the first six good of fit measures for overtaken vessels.

Fig. 8. Histograms of the deviations from the first six good of fit measures for head-on vessels.

Fig. 9. Example simulated vessel paths compared to the actual path from AIS data and unhindered path generated by the desired course.