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

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14   **Abstract**

15   The Vessel Maneuvering Prediction (VMP) model, which was developed in a previous work with the

16   aim of predicting the interaction between vessels in ports and waterways, is optimized in this paper by

17   considering the relative position and vessel size (length and beam). The calibration is carried out using

18   AIS data of overtaking vessels in the port of Rotterdam. The sensitivity analysis of the optimal

19   parameters shows the robustness of the calibrated VMP model. For the validation, the optimal

20   parameters are used to simulate the whole path of overtaken vessels and vessels in head-on encounters.

21   Compared to the AIS data, the validation results show that the different deviations in longitudinal

22   direction range from 33 m to 112 m, which is less than 5% of the waterway stretch. Both the calibration

23   and validation show that the VMP model has the potential to simulate vessel traffic in ports and

24   waterways.

25

26

27   **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

51 dynamics of the vessel sailing behavior, e.g. longitudinal acceleration and angular speed of the vessel.

52 Although the route choice model is assumed to be very simple in the previous work (Hoogendoorn et al.,

53 2013), the framework for the model was created. Based on this framework, the route choice model at

54 tactical level was further developed (Shu et al., 2015b). The results of this study serve as an input into

55 the operational model, which is called Vessel Maneuvering Prediction (VMP) model in this paper. The

56 VMP model was introduced by considering the influence range in different directions of the vessel to be

57 homogeneous and the model was only calibrated for unhindered vessel behavior (Shu et al., 2015a), in

58 which the influence between encountered vessels is not considered.

59   The aim of this paper is to improve the VMP model by considering the relative position and vessel

60 size (length and beam), and then calibrate and validate the improved VMP model using the AIS data of

61 vessel encounters. To improve the model, we consider the distinct influence ranges of the vessel in

62 longitudinal and lateral direction, which correspond to the findings of a recent study that the vessels

63 keep larger distance in longitudinal direction than in lateral direction, and vessel speed is influenced for

64 both overtaking and overtaken vessels (Shu et al., 2017). In the calibration, the VMP model is used to

65 simulate overtaking vessel maneuvers for each path segment (60 seconds), and then to compare the final

66 position of the overtaking vessel from the AIS data. For the validation, the VMP model is used to

67 simulate the whole vessel path in the research area for overtaking, overtaken vessels and the vessels in

68 head-on encounters, respectively. Then, these simulated paths are used to compare with the observed

69 vessel path from the AIS data.

70   This paper starts with an introduction of the improved VMP model in Section 2. Then, the

71 calibration and validation approaches are presented in Section 3, followed by the results of the

72 calibration and validation in Section 4. Finally, this paper ends with discussion and conclusions in

73 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):

5

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

90   where H denotes the prediction horizon, which is assumed to be a time period in which the bridge team

91   could predict the vessel behavior; L denotes the running cost (cost incurred in a small time interval

92    $[\tau, \tau + d\tau)$); $\vec{u} = (u_1, u_2)$ denotes the control, and Φ denotes the terminal costs at terminal conditions,

93   which is the cost that is incurred when the vessel ends up with the state $\vec{\xi}(t + H)$ at time instant $t + H$.

94   The terminal cost is assumed to be zero.

95   Corresponding to the control objectives, i.e. maintaining the desired speed and course as much as

96   possible, minimizing the maneuvering effort and keeping sufficient distance to other vessels, the running

97   cost L also includes three parts: costs for straying from the desired speed and desired course L^{stray},

98   propulsion and steering costs L^{effort} and the proximity costs L^{prox}:

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

99   The straying costs and the propulsion and steering costs are defined as in our previous study

100   (Hoogendoorn et al., 2013). The straying costs are defined as follows:

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

101   where c_3^v and c_3^ψ are weight factors for straying from the desired speed and desired course, respectively.

102   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

103   course at the position $\vec{x}$, which is the current position, respectively.

104   The propulsion and steering costs are defined by:

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

105 where c_3^v and c_3^ψ are weight factors of the effort of the bridge team to accelerate (decelerate) and turning

106 the vessel. So, these two factors correspond to the control (the longitudinal acceleration and angular

107 speed).

108 The main improvement of the model focuses on the proximity costs, which are defined based on the

109 relative position between the simulated vessel and the encountered vessel as follows:

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

110 where c_1 is the weight factor for this proximity cost, d denotes the distance between the simulated vessel

111 and the encountered vessel, and R is the scaling parameter, which indicates the range within which the

112 simulated vessel is influenced by the other vessel and this parameter is determined by the relative

113 position between the simulated vessel and the encountered vessel. As shown in Eq. (9), the proximity

114 costs increase when the encountering vessels approach each other, and the proximity costs equal to zero

115 when the distance is larger than the scaling parameter. In the data analysis of vessel encounters, it was

116 found that the influence distance between encountering vessels in longitudinal direction is much larger

117 than in lateral direction (Shu et al., 2017). This results in an elliptical influence area. As an example, the

118 elliptical influence area of an overtaking vessel is shown in Fig. 1.

119 As shown in Fig. 1, the elliptical influence area has a semi-major axis a and a semi-minor axis b.

120 The scaling parameter R could be interpreted as the radius of the ellipse, which is a function of the

121 parameters a, b and the angle θ (the angle between the course of the own vessel and the line connecting

122 the locations of the two encountering vessels):

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

123   In the VMP model, it is also assumed that a larger vessel size will lead to larger influence distances.

124   Then, the major axes a and minor axes b depend on the vessel length and beam of the own vessel and

125   the other vessel as follows:

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

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

126   where p and q are scaling coefficients of the vessel length, L_A and L_B are the lengths of the two vessels

127   in encounter, and B_A and B_B correspond to vessel beam. Thus, the VMP model is improved by

128   considering the different influence range of the vessel in longitudinal and lateral direction and the

129   proximity costs are improved with three parameters: the weight factor c_1, and scaling coefficient p and

130   q.

131   **3. Research approach**

132   In this section, the calibration and validation approaches are presented. The aim of the calibration is

133   to find the model parameters that result in the best prediction of the model, and the purpose of the

134   validation is to confirm that the model and its optimized parameters can generalize the calibration data.

135   The data used in both approaches come from the Automatic Identification System (AIS) system, which

136   is used to record vessel data between vessels and shore stations. In recent decades, it has been developed

137   and implemented as a mandatory tool on all ships by 1 July 2008 (Eriksen et al., 2006).

138   In this paper, the AIS data of 146 overtaking encounters and 162 head-on encounters are used. These

139   data are provided by Maritime Research Institute Netherlands (MARIN) and analyzed using dedicated

140   software called "ShowRoute", which is developed by MARIN and used to investigate AIS data. These

141   data were selected in the Botlek area in the port of Rotterdam and used to analyze the vessel behavior in

142   previous studies (Shu et al., 2017). The waterway stretch is around 2.5 km and the sailing time in the

143   research area approximately equals 500 seconds, given the average vessel speed of 5 m/s (Shu et al.,

144   2013).

145   In this paper, the VMP model is assumed to be generic for different types of encounters, which

146   means that the parameters determined by calibrating for data from overtaking vessels are applicable for

147   overtaken vessels and vessels in head-on encounters. As overtaken vessels and vessels in head-on

148   encounters are in many cases in the equilibrium situation (without longitudinal acceleration and angular

149   speed) (Shu et al., 2017), the overtaking vessels are more suitable for the calibration because they

150   normally have a larger deviation from their desired speed and path. The vessels that are in equilibrium

151   situation cannot be used for the calibration because the resulting model parameters would be equal to

152   zero.

153   In addition, it is assumed that the bridge team has enough experience to predict the speed and course

154   of the other vessels, and they can use it in their decision-making procedure. Based on this assumption,

155   the AIS data of the encountered vessel is considered as a known input in this research. This assumption

156   is made in this first step to calibrate and validate the VMP model, with the aim to simultaneously

157   simulate multiple vessels in future research.

158   *3.1 Calibration approach*

159   In this section, the calibration including calibration set-up, objective function and sensitivity analysis

160   is presented.

161   *3.1.1 Calibration Set-Up*

162   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

163   coefficients p and q need to be calibrated. It should be noted that all weight factors cannot be uniquely

164 determined from the data, since only the relative importance of the weights can be determined. Without

165 loss of generality, we set $c_1 = 1$. Then, the parameters to be calibrated are $\beta^T = (c_2^v, c_2^\psi, c_3^v, c_3^\psi, p, q)$.

166   In this calibration, all paths of overtaking vessels have been broken down into multiple small

167 segments, which have the same time period as the prediction horizon. The prediction horizon H is taken

168 as 60 seconds, which is a reasonable time period for the bridge team to maneuver the vessel. The

169 calibration is performed for each path segment and the final position of the predicted vessel path is

170 compared with the AIS data.

171   To run the VMP model, the desired speed and desired course serve as inputs, while the vessel speed,

172 course and path are the outputs. We assume that the desired course generated by the Route Choice

173 model (Shu et al., 2015b) is applicable for all vessels in the research area, because it was found that

174 vessel course is hardly influenced by vessel size and type (Shu et al., 2013). In terms of the desired

175 speed, it was found that overtaking vessels increase their speed before the CPA (Closest Point of

176 Approach) and decrease the speed after the CPA (Shu et al., 2017). Therefore, the desired speed is set as

177 the maximum speed v_{max} before the CPA and set as the end speed v_{end} after CPA, as shown in Fig. 2.

178 This way, the variability of the desired speed is considered, which is closer to reality than setting a

179 constant desired speed.

180 *3.1.2 Objective function for calibration*

181   The calibration process aims at minimizing the difference between the vessel path predicted by the

182 VMP model and the observed path from AIS data. As shown in Fig. 3, an overtaking vessel sails from

183 left to right and the observed vessel position at the end of the prediction horizon is $\vec{x}_{data}$. The VMP

184 model predicts that the overtaking vessel is at position $\vec{x}_{sim}$ at the end of the prediction horizon. Then,

185   the parameters should be chosen such that the distance between the position $\vec{x}_{data}$ and the position $\vec{x}_{sim}$

186   is minimized.

187   Let m denote the number of vessel paths and let n_i denote the number of segments for vessel path i,

188   then we have the objective function for the calibration as follows:

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

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

190   follows:

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

191   *3.1.3 Sensitivity analysis*

192   Based on the calibration results, a sensitivity analysis is performed to get insight into the influence of

193   each parameter on the error and the robustness of the calibration, as well as the reliability of the optimal

194   parameter set. To this end, each model parameter is varied while keeping the other parameters constant

195   at their estimated value. The relationships between model parameters and the error provide insight into

196   the model's parameter properties and the sensitivity.

197   **3.2 Validation approach**

198   The validation is performed to see if the calibrated parameters could be used to predict the vessel

199   path for other datasets accurately (within the allowed error margin). Contrary to the path segments used

200   in the calibration, the validation simulates the whole path using the optimized parameters. In the

201   validation, the optimized parameters are applied for all three scenarios: overtaking vessels, overtaken

202   vessels and head-on vessels. Among these scenarios, the overtaking and overtaken vessels are from the

203   same dataset. Similar as in the calibration, the vessel is simulated while the encountered vessel path is

11

204   considered as a known input (described by the AIS data). Then, the calibrated parameters are used by

205   the VMP model to predict each vessel path every 10 seconds.

206   To evaluate the simulation quality, the comparison between the simulated path and the real path

207   focuses on four aspects in both the longitudinal and lateral direction: the final position of the whole path,

208   the maximum absolute deviation, the average absolute deviation and average percentage of good

209   predictions (within the allowed error margin). To quantify how well the simulated path fits the vessel

210   path from AIS data, 8 goodness of fit measures are defined. Considering the overtaking vessel as an

211   example, Fig. 4 shows the simulated vessel path for the overtaking vessel and the real path from AIS

212   data, as well as the parameters used to formulate the measures. It should be noted that the scheme to

213   determine the port side or starboard overtaking is not included in this VMP model yet, so the simulated

214   overtaking may happen on the other side than the real one, when the whole vessel path is simulated by

215   the VMP model. The results for these overtaking and overtaken paths will not be included in the

216   validation results and the choice of the overtaking side is left for further research.

217   As shown in Fig. 4, the origin of the simulated overtaking vessel is $\vec{x}_0^i$, in which i denotes vessel path

218   id. The maximum deviation happens when the overtaking and overtaken vessels are located at positions

219    $\vec{x}_{sim}^{i,max}$ 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

220   deviations E_{lo}^F and E_{la}^F are the average difference for the final position of simulated path and AIS path in

221   the longitudinal and lateral direction, respectively:

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

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

12

222 where m denotes the number of vessel paths, α_{end}^i denotes the angle between the longitudinal direction

223 for the last AIS data recorded and the line connecting the two end positions. This angle is used for the

224 projection of the error in the longitudinal and lateral direction.

225 The deviations E_{lo}^M and E_{la}^M correspond to the maximum deviation between the simulated path

226 and the AIS path in the longitudinal and lateral direction, respectively. These two are defined as:

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

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

227 where α_{max}^i denotes the angle between the longitudinal direction at the position where the maximum

228 deviation occurred and the line connecting the two compared positions.

229 The deviations E_{lo}^A and E_{la}^A denote the average deviation of the simulated path and AIS path in

230 the longitudinal and lateral direction, respectively. They are defined by:

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

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

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

232 The last two measures are defined to present the average percentage of good predictions, which

233 are within the error margin. The error margin is taken as 5% of the relative error in the longitudinal

234 direction, while 5% of the waterway width is used in lateral direction. The measures P_{lo} and P_{la} are

235 calculated as follows:

13

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

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

236   where P_{lo}^i and P_{la}^i represent the percentage of good predictions (the prediction error less than the error

237   margin) of the vessel path i at longitudinal direction and lateral direction, respectively.

238   Among these measures of fit, the first six measures are formulated as the average of the deviation of

239   the final position, the maximum deviation and the average deviation. The histogram of these deviations

240   is also shown in the result section to provide more insight into the simulation quality. In addition, some

241   example paths have been randomly chosen from each scenario and presented in the next section to

242   compare with the actual path from AIS data and unhindered path (generated by the desired course), for

243   more in-depth discussion.

244   **4. Results**

245   In this section, the calibration results including the optimal parameters and sensitivity analysis are

246   presented, followed by the validation results and example simulated paths.

247   ***4.1 Calibration results***

248   By applying the optimization approach, the best fit of the VMP model to the AIS data of overtaking

249   vessels is determined. The optimal model parameters are shown in Table 1. The obtained error is 458 m^2,

250   which is the mean square of the distance of the final position between the simulated path and actual path

251   from AIS data. This implies that the prediction error is around 21 meters while the prediction period is

252   60 seconds.

253

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

Parameters	c_2^v	c_2^ψ	c_3^v	c_3^ψ	p	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

255

256   It can be seen that all parameters have positive values, which is as expected because these

257 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

258 larger. Compared to vessel speed and course, the values of longitudinal acceleration and angular speed

259 are normally very small. This will result in large values of c_3^v and c_3^ψ. The scaling parameters p and q

260 equal to 8 and 3.9, which means that the influence range in longitudinal and lateral direction is around 8

261 times the vessel length and 3.9 times the vessel width, respectively. They are consistent with our

262 expectation that vessels have stronger influence in the longitudinal direction than in the lateral direction,

263 considering the fact that vessel length is much larger than vessel beam.

264   Based on the six optimal parameter values in Table 1, the relationships between each parameter and

265 the error by varying each parameter while keeping the other parameters constant at their optimal value

266 are shown in Fig. 5.

267   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

268 curves have a single and clear minimum, which means the optimal values are taken at the global

269 minimum. Thus, it also means that the calibration method is robust and the optimal values for these

270 parameters are reliable. Regarding the parameter p, the error decreases with the increase of the scaling

271 parameter up to 8, after which the p value remains stable. It means that the model is not sensitive to the

272 p value and the optimal p value is difficult to be determined when the p value is larger than 8. However,

15

273   it is not meaningful to investigate the situation for larger p value ($p > 8$), which leads to a unrealistically

274   large influence range in longitudinal direction (exceeding the research area).

275   In addition, the optimal values of these two scaling parameters indicate that the influence range in

276   longitudinal direction is much larger than in the lateral direction, which is consistent with our

277   expectation. In general, this sensitivity analysis indicates the robustness of the calibration and the

278   reliability of the optimal parameter set.

279   *4.2 Validation results and examples*

280   By applying the validation approach, the goodness of fit measures is calculated for overtaking

281   vessels, overtaken vessels and head-on vessels, as shown in Table 2. As mentioned in section 3.2, the 23

282   vessel paths in which overtaking occurred on the other side of the overtaken ship than the actual side are

283   removed from these validation results, and 10 vessel paths of simulated overtaken vessels are filtered in

284   the same way.

285   **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 %

286

287   The deviations in longitudinal direction range from 33 m to 112 m. Considering the waterway stretch

288   of around 2.5 km, all measures representing the error in longitudinal direction are less than the 5% of the

289   waterway stretch. In the lateral direction, the deviations vary from 27 m to 83 m, which is relatively

290   large given the waterway width of around 430 m. However, the deviation in lateral direction is also

291   influenced by the deviation in longitudinal direction, as the vessel path is compared by time line. So it is

292   difficult to judge the simulation quality based on the deviation in lateral direction here.

293   The data clearly showed that the best prediction in longitudinal direction is for head-on encounters,

294   as all the deviations in longitudinal direction for head-on encounters are smaller than other scenarios,

295   and the percentage of good prediction is around 81%, which is better than for the other scenarios as well.

296   This may be caused by the fact that the speed is hardly influenced by the head-on encounters. However,

297   the prediction in lateral direction for head-on encounters is obviously worse than for the other scenarios.

298   This could imply that the elliptical influence area does not work well for head-on vessel encounters. It

299   suggests to improve the cost function for vessel influence in the VMP model in future research,

300   specifically for head-on encounters. As mentioned in Section 3.2, the histograms of the deviations for

301   the first six goodness of fit measures are shown in Fig. 6-8.

302   In the remainder of this section, some example paths have been randomly chosen for each scenario

303   and plotted in Fig. 9, and compared to the actual path from AIS data and unhindered path (generated by

304   the desired course). The first example is to simulate overtaking vessel sailing from left to right. It can be

305   seen that the predicted path in the middle part of the stretch is closer to the starboard bank, meaning that

306   the influence between two vessels in the VMP model is not strong enough during that period. In the

307   right part of the stretch, the simulated vessel deviates from the desired path and then the simulated path

308   is consistent with the AIS overtaking path, which implies the influence between two vessels is

309   reasonably predicted in this situation. In the remaining two examples, the predicted paths are nearer to

310   the shore, compared to both the AIS path and desired path. This could mean that the influence between

311   vessels, as calibrated for overtaking vessels, is too strong for overtaken and head-on vessels. These

17

312   findings based on example paths suggest that the further research should focus on the different influence

313   range for different types of encounters.

314   **5. Discussion and conclusions**

315   In this paper, the VMP model is optimized by considering the relative position and vessel size

316   (length and beam). Furthermore, the model is calibrated and validated using the AIS data of vessel

317   encounters. The calibration results and the sensitivity analysis showed the robustness of the calibration

318   and the reliability of the optimal parameters. In the validation of the three scenarios, it was found that

319   the different goodness of fit measures in longitudinal direction are less than 5% of the waterway stretch.

320   It should be noted that several factors influence the calibration results. Firstly, the calibration results

321   are influenced by the desired speed and desired course, which are important inputs to the model. As we

322   can see in Eq. (7), the costs for straying from the optimal path were based on the difference between the

323   real speed and the desired speed, as well as the real course and the desired course. In this research, the

324   desired speed is based on empirical data. A better solution would be a derivation of the desired speed

325   based on waterway geometry and vessel characteristics. For the desired course, the results of the Route

326   Choice model for one representative vessel category is used. Since the dataset used for calibration

327   comprises several vessel categories, this contributes to the error in the calibration of the VMP model.

328   Secondly, some differences between measured and simulated vessel paths can be attributed to non-

329   constant maneuvering style and different experience of the bridge team. The encounter pattern, such as

330   port side or starboard overtaking, is not regulated by international or local rules. The maneuvering

331   behavior of the bridge team is normally determined according to the traffic situation at that moment

332   based on their experience, which is difficult to be integrated in the model.

333   As far as we know, this is the first study on vessel maneuvering prediction including speed, course

334   and path in ports and waterways using a simulation model. Based on the calibration and validation, it

335   can be concluded that the VMP model has potential to simulate the vessel traffic in ports and waterways.

336   This paper also provides a fundamental basis for better optimizing and simulating vessel traffic in future.

337   The approach to determine the port side or starboard overtaking for overtaking encounters is not

338   included yet and this is an important improvement for the VMP model in future research. In the

339   validation, the example paths suggest that different influence range for different encounters should be

340   considered. In addition, single vessel is simulated in this paper and the future research will focus on

341   simulating multiple vessels simultaneously. Another future research direction is to determine different

342   calibration parameters for different vessel categories.

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382

383 **Figure captions**

384

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

386 overtaking vessel.

387

388 Fig. 2. Definition of desired speed v^0 for an overtaking vessel. The curve indicates the speed track of

389 overtaking vessel in overtaking encounters. Axis x and y represent the longitudinal distance and vessel

390 speed, respectively.

391

392 Fig. 3. Vessel path of overtaking and overtaken vessel from AIS data (solid line) and simulation path of

393 overtaking vessel (dashed line) within the prediction horizon.

394

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

396 AIS data.

397

398 Fig. 5. The relationships between each parameter and the error by varying each parameter while keeping

399 the other parameters constant at their optimal value.

400

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

402

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

404

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

406

407   Fig. 9. Example simulated vessel paths compared to the actual path from AIS data and unhindered path

408   generated by the desired course.