Safe Speed for Maritime Autonomous Surface Ships – The Use of Automatic Identification System Data

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Introduction: All vessels are required by law to proceed at a safe speed while at sea. However, there is no acceptable method of determining what value of speed could be considered safe. One way of determining safe speeds in different conditions could be the utilization of Automatic Identification System (AIS) data to create a safe speed model that maritime autonomous surface ships (MASS) could follow.
Objectives: Investigate if MASS can determine the safe speed without human support by utilizing historic AIS speed data of other vessels. Investigate further if AIS and visibility data show a strong relationship between visibility and vessel speeds, and if vessels generally show a reduction of speed in restricted visibility.
Methods: AIS and visibility data was collected and merged in an area off Western Norway in the period between 27 March 2014 and 31 December 2020. A simple linear regression was calculated and supplemented by two graphical methods for revealing relationships between two variables.
Results: A significant regression equation between visibility and speed was found. This relationship was not strong. Average transit speed was highest when visibility was below 1,000 meters.
Conclusion: The problem of quantifying the safe speed of a vessel in different conditions does not seem to be solvable by only using historic AIS data to create a model of normalcy which a MASS can follow.

Keywords: MASS, AIS, Safe, Speed, COLREG, Visibility.

1. Introduction

The International Regulations for the Prevention of Collisions at Sea (COLREGs) lay out the basis of agreed practices for avoiding collisions at sea. They have to be followed by all vessels upon the high seas and in all waters connected therewith navigable by seagoing vessels (IMO 1972). As such, the COLREGs would apply to any maritime autonomous surface ship (MASS) navigating the seas in the future.
The COLREGs include a large number of qualitative terms such as "early" and "substantial" (Porathe 2019) which leaves much of the rule-system up to the interpretation of the navigator. This ambiguity is said to be the necessary price of applicability, as a completely prescriptive and rigid rule-system would be infinitely complicated (Taylor 1990). The ambiguity of the COLREGs can be seen as problematic, as collision avoidance to a large extend depends on each ship understanding the actual, likely and potential actions of the other (Taylor 1990). Collision avoidance is seen as a game of co-ordination where navigators on different vessels have to independently choose mutually compatible strategies (Cannell 1981). Already today, the interaction between traditional ships is seen as problematic (Porathe 2019), and collisions do still occur. It is warned that autonomous ships following a machine interpretation of the COLREGs may lead to even more uncertainty in the future, possibly causing more navigational problems (Porathe 2019).

One particular point of concern is the requirement of Rule 6 of the COLREGs, requiring every vessel to proceed at a safe speed at all times (Dreyer and Oltedal 2019). Nowhere in the rules is it further quantified what speed could be considered "safe". While attempts have been made, no acceptable method of determining what value of speed could be considered to be "safe" has been put forward by the International Maritime Organization (IMO) (Cockcroft and Lameijer 2012). It is therefore up to the navigator to determine the "safe" speed in the prevailing conditions.

As unsafe speed has been highlighted as either the immediate or contributory cause in 11.6% of 248 analyzed collision, close quarters & contact cases between 2002 and 2016 (Acejo et al. 2018), it is important to find a reliable way autonomous ships can determine the safe speed in the absence of a human navigator.

One tool that could help extract the knowledge of which speeds navigators consider to be safe in different conditions could be the Automatic Identification System (AIS). AIS is a communications system that provides automatic reporting between ships and to shore by exchanging information such as identity, position, time, course and speed (IALA 2016). Other researchers have already utilized historic AIS data to build models of normalcy for traffic patterns (Yan et al. 2020). These models are being used both to generate what is described as "safe paths" that MASS can follow (Xu, Rong, and Guedes Soares 2019), as well as to identify so-called "high risk" vessels that do not follow the predicted pattern (Yan et al. 2020). Historic AIS data can therefore be utilized to create a model of normalcy for the speed of different types of vessels.

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An important assumption of the approach described above is that that historic AIS data – on average – shows safe vessel behaviors. It is taken for granted that the common patterns extracted from historic AIS data resemble safe speeds. This assumption can be tested by comparing the common patterns of vessel speeds observed from AIS data with accepted interpretations of what constitutes a safe speed.

Research on what speeds can be considered "safe" in different conditions is rather sparse. The COLREGs themselves define safe speed by the vessels ability to "take proper and effective action to avoid collision and be stopped within a distance appropriate to the prevailing circumstances and conditions" (IMO 1972). They also provide a number of factors that shall be taken into account when determining the safe speed, with the state of visibility listed first (IMO 1972).

The importance of visibility is echoed in the available guides and commentary to the COLREGs. Kavanagh (2001) concludes his inquiry into safe speed by stating that the primary consideration in determining safe speed is visibility. Cockcroft and Lameijer (2012) state that visibility is "obviously of major importance" and that the need to moderate speed generally applies in restricted visibility. Rutkowski (2016) simply states that it is dangerous to go fast when visibility is poor.

For this paper, visibility is classified according to the national meteorological service of the United Kingdom, the Met Office. The definitions of their marine forecasts glossary can be seen in Table 1.

Table 1. Definition of visibility terms (Met Office 2021).

Term:	Meaning:
Very poor	Visibility less than 1,000 meters
Poor	Visibility between 1,000 meters and 2 nautical miles (3,704 meters)
Moderate	Visibility between 2 and 5 nautical miles (3,704 meters and 9,260 meters)
Good	Visibility more than 5 nautical miles (9,260 meters)

If speed patterns extracted from historic AIS data are to be used to aid MASS in determining safe speed, it must first be verified that the extracted speed patterns themselves represent safe speeds. Referring back to the contemporary guides and commentary on the COLREGS, a pattern which indicates the safe speed in different circumstances requires a strong correlation with visibility and should generally show a reduction of speed in restricted visibility.

This paper therefore combines historic AIS data with visibility data for the area to answer the following research question: **Can MASS autonomously determine the safe speed by utilizing historic AIS speed data of other vessels?**

This is done by investigating if speed data gathered through AIS show speeds that contemporary research would consider to be safe. To do so, the following research sub-questions were formulated:

(i) Does AIS and visibility data show a strong relationship between visibility and vessel speeds?

(ii) Does AIS data show a trend of vessels proceeding at a reduced speed in restricted visibility?

2. Description of Study Area, Collected Data, and Research Approach

This section introduces the reader to the study area, gives an overview of the collected data and describes the research approach of this study.

2.1. *Study area*

To decide which area this paper would utilize as the study area, the following requirements were set: The area had to be in open sea close to normal shipping routes and have both historic AIS- and visibility data.

The study area used in this study is located off Bulandet, an archipelago in the sea off the mainland coast of Western Norway, as shown in Figure 1. It is to the east of the "Gjøa A" platform – where the historic visibility data utilized in this study is measured – between the traffic separation scheme (TSS) Off Stad in the north and TSS Off Sotra in the south. The study area is approximately 4.2 by 4.2 nautical miles in size.

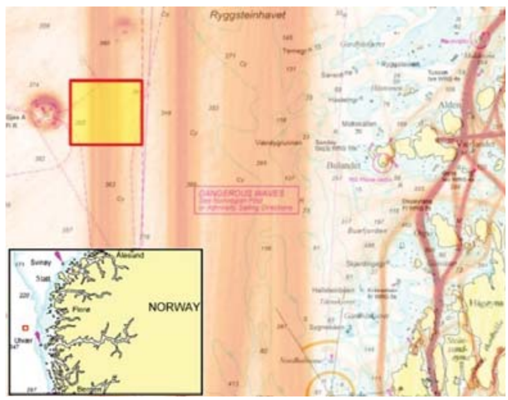

Fig. 1. Location of study area: West of Bulandet, off the mainland coast of Western Norway. AIS density plot overlay shows common shipping routes.

Note that the weather measuring station is located outside the study area. While this may result in visibility data reported by the measuring station differing slightly from the actual visibility within the study area, this decision was taken due to two reasons. Firstly, to reduce the possible disturbing effects of having large navigational hazards located inside the study area, and secondly to ensure that the study area is located within a normal shipping lane. As can be seen from the AIS density plot overlay in Figure 1, the study area covers traffic transiting southbound along the Norwegian west coast, while avoiding most of the non-transit traffic around the Gjøa A platform. Collected data

The data utilized in this study consists of two parts and covers the period from 27 March 2014 to 31 December 2020. Firstly, vessel speeds were drawn from AIS data, which was collected via the Kystdatahuset service provided by the Norwegian Coastal Administration (NCA).

Secondly, the visibility data – which was collected on the Gjøafeltet platform – was accessed via the Norwegian Climate Service Center. This section introduces the AIS data first, then gives more information on the visibility data, and finally explains how the two were merged.

2.1.1. *AIS data*

The AIS data used for analysis in this study was collected via the Kystdatahuset AIS tool by the NCA. The NCA has established an AIS receiving infrastructure consisting of approximately 70 base stations for receiving AIS data from vessels sailing within 40 to 60 nautical miles from the Norwegian baseline. It registers three types of information, namely dynamic (position, course, speed), static (identity, vessel type, dimensions) and voyage related (destination, estimated time of arrival, cargo, draught) (The Norwegian Coastal Administration 2011).

AIS data that can be accessed via the Kystdatahuset website is “cleaned”, meaning that positions that are almost certainly erroneous are removed. The service includes historic AIS data going back to 2013 (Kystdatahuset 2021).

Since its inception, AIS data has become more accurate. While in 2004 10.4% of all vessels transmitted errors, this value decreased to 3.5% in 2007 (Shu et al. 2017; Harati-Mokhtari et al. 2007; Bailey, Ellis, and Sampson 2008). Furthermore, Shu et al. (2017) have concluded that dynamic vessel data was generally more accurate than static and voyage related data, with speed over ground only making up 0.8% of the errors.

Vessel speed data was extracted for the study area depicted in Figure 1 in the period from 27 March 2014 to 31 December 2020, resulting in a total of 38,820 data points.

This data was provided in form of a Microsoft Excel sheet, and included the following information: Start and end time, Maritime Mobile Service Identity Number (MMSI)[a], IMO Number[b], ship name, ship type, gross tonnage (GT)[c], length, draft, minimum- average- and maximum speed and number of transmissions received. Presumably due to interferences in transmission, some datapoints did not include all information. Where possible, missing information was added manually by the researcher. This included actions like utilizing a vessels IMO number to look-up and add information like the ship type to the dataset.

Ship type information was then utilized to filter the dataset to only include cargo ships such as bulk carriers, tankers, containerships, general cargo ships and ro-ro vessels in the dataset. This resulted in the removal of other types of vessels such as anchor handling vessels, cable layers, diving support ships, fishing vessels, dredgers and standby safety vessels. These vessels are expected to be constrained more by the nature of their assignment, then by external conditions such as visibility. For example, an increase in visibility is not expected to result in a standby safety vessel increasing its speed while standing by next to a platform.

While it was noted that most vessels had one datapoint for each time they passed the study area, this was not always the case: In some instances, a single passing would result in several datapoints being created. To prevent a skewed dataset, datapoints were merged in these instances, resulting in a dataset with a single datapoint for each unique transit of the study area. In practice this meant that all AIS transmissions received from a vessel transiting the study area within a period of five hours were combined to give a single datapoint for the whole transit. This datapoint included information of the vessel, the average transit speed, as well as the times of when the transit started and ended.

After removing datapoints showing dubious speeds (such as 102.3 knots), and datapoints where no visibility data was available, the final amount of AIS datapoints was 14,420.

2.1.2. *Visibility data*

The visibility data was collected by the Gjøafeltet measuring station, which is located approximately 1.6 nautical miles west of the study area. It was extracted utilizing the observations and weather statistics tool provided by the Norwegian climate service center.

The weather element selected for visibility data was “MOR visibility 1 min”, which gives a visibility value between 0 and 20,000 meters every 10 minutes. MOR stands for meteorological optical range, which is an objective measurement of the transparency of the atmosphere. Instruments for the measurement of MOR sample a relatively small region of the atmosphere, and therefore provide an accurate measurement of MOR only when the volume of air they sample is representative of the atmosphere around the point of measurement. While the measurement can therefore be misleading in situations of patchy fog or rain, experience has shown that such situations are not frequent (World Meteorological Organization 2018).

2.1.3. *Merging of research data*

As each AIS datapoint was provided with a start and an end time, it was possible to look-up the average visibility for that time frame from the visibility dataset. This information was then merged with the AIS dataset, resulting in a dataset combining vessel speed with information on the prevailing visibility conditions. Table 2 in section 3.2.3 provides an overview of the different average transit speeds in various visibility ranges.

2.2. *Research approach*

Research data was handled in Microsoft Excel, and the tools available within the program were used to analyze the data. To get an overview of the data, the first step in the research was the creation of several graphs to visualize the contents of the dataset.

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[a] An MMSI is a unique nine digit number used by certain marine radio communications equipment (such as AIS) to uniquely identify a ship (Navigation Center 2021).

[b] An IMO number is a unique reference number permanently associated to the hull of a ship (Retsch 2021).

[c] Gross tonnage is a measure of the overall size of a ship (Pearn 2000).

A commonly used graphical method for revealing relationships or associations between two variables is the scatter plot (NIST/SEMATECH 2013). Average transit speeds and average visibility during transit are therefore initially visualized in a scatter plot, with visibility on the x-axis, and average vessel speeds on the y-axis. The Pearson correlation coefficient is plotted as a trendline on the scatter plot, indicating the strength of the association between visibility and speed. If the vessel speeds collected from AIS data represent our current understanding of safe vessel speeds, a clear relationship should be visible, with a clear reduction of vessel speeds in restricted visibility.

Following the graphical representation of the research data in a scatter plot, a simple linear regression was then calculated in Microsoft Excel to predict vessel speeds based on visibility. Regression analysis is the study of relationships between two or more variables, and is usually conducted when we either want to know whether any relationship between two or more variables actually exists, or when we are interested in understanding the nature of the relationship between two or more variables (McIntosh, Sharpe, and Lawrie 2010).

Finally, datapoints were sorted into 20 different visibility groups, each covering a different range of 1,000 meters from 0 to 20,000. This allowed for the calculation of the average transit speeds of vessels in different visibility conditions, and the comparison of – for example – the average transit speed of vessels passing the study area in visibilities between 1,000 and 2,000 meters, and 12,000 and 13,000 meters. An X/Y scatter plot with straight lines was created to visualize the difference in average speeds in different visibility conditions.

3. Results

This section presents the results of this study. In the first subsection general findings are presented, followed by more detailed findings with regards to the effect of visibility on the average transit speeds in the second subsection.

3.1. *General findings*

In the period from 27 March 2014 to 30 December 2020, a total of 14,420 unique transits by 3,438 unique cargo ships through the study area were recorded. The highest number of unique transits by a single vessel was 230, while the lowest was 1. The vessels differed greatly in size, with the smallest vessel having a gross tonnage of 532 and the largest vessel having a gross tonnage of 176,490.

Transits took an average of 22:05 minutes (standard deviation: 09:17 minutes) and happened in visibilities between 88 and 20,000 meters. The recorded average transit speeds through the study area were between 1.4 and 21.6 knots, with an average of 11.2 knots and a standard deviation of 2.4 knots.

Histograms representing the distribution of gross tonnage (Figure 2), transit time (Figure 3), visibility (Figure 4) and average transit speed (Figure 5) can be seen below. Interestingly, even though both the gross tonnage (Figure 2) and visibility distributions (Figure 4) are extremely skewed, the average transit speed histogram (Figure 5) seems to be close to normally distributed.

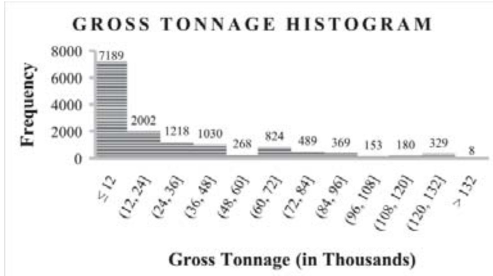

Fig. 2. Gross Tonnage Histogram. Number on top of each bar represents the total number of transits of vessels with different GT.

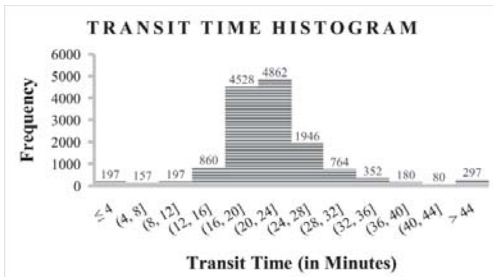

Fig. 3. Transit Time Histogram. Number on top of each bar represents the total number of transits of different length.

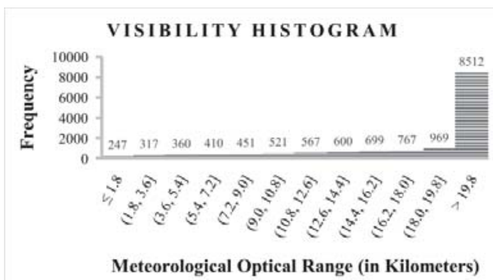

Fig. 4. Visibility Histogram. Number on top of each bar represents the total number of transits in different visibility conditions.

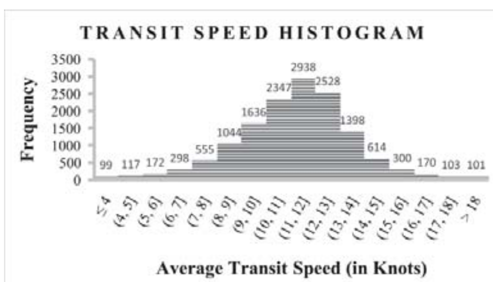

Fig. 5. Transit Speed Histogram. Number on top of each bar represents the total number of transits at different average speeds.

3.2. *Effect of visibility on average transit speed*

As described in section 2.2 above, three different methods were utilized to investigate the effect of visibility on the average transit speed of vessels through the study area. The results of the scatter plot, the regression analysis, and the representation of average transit speeds in different visibility ranges are presented below.

3.2.1. *Scatter plot*

Figure 6 shows a scatter plot of the average transit speed of vessels passing through the study area in different visibility conditions. The Pearson correlation coefficient – sometimes referred to as Pearson's r – was calculated to be 0.18. This value is displayed as a dashed line in Figure 6.

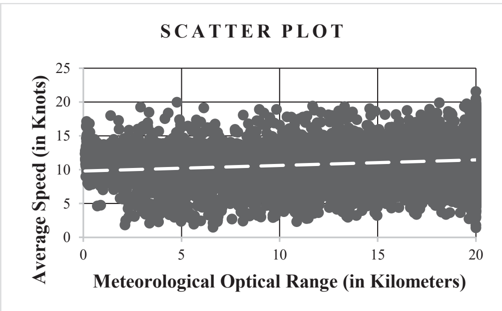

Fig. 6. Scatter plot. The different dots represent the average speeds and visibilities for each transit. Pearson correlation coefficient displayed as a dashed line.

3.2.2. *Regression analysis*

The result of the simple linear regression calculated in Microsoft Excel, with average speed as the dependent variable, and visibility as the independent variable was as follows: A significant regression equation was found ($F(1, 14{,}418) = 489.647$, $p < 0.000$), with an R^2 of 0.033. The predicted average speed is equal to $9.807 + 0.0822$ (MOR) knots when MOR is measured in kilometers. Average speed increased by 0.0822 knots for each kilometer of MOR.

3.2.3. *Average speeds in different visibility ranges*

Table 2 shows how the dataset was divided into different groups based on the visibility range during transit.

For each different visibility range, the total number of transits, and the average transit speed of all transits in that visibility range is shown. Details regarding how the AIS and visibility data were combined to create this table were given in section 2.1.3.

The information contained in Table 2 is visualized in Figure 7. Note that the number of datapoints per visibility range is not constant. Only 94 transits occurred in the visibility range of 1 – 2 kilometers, while the visibility range of 19 – 20 kilometers had a total of 9,019 transits.

In the maximum visibility range of 19 – 20 kilometers the average transit speed was 11.53 knots. The data shows that average transit speeds lessen as visibility is reduced, reaching its lowest value in the visibility range of 4 – 5 kilometers. After this, average transit speeds increase sharply even as visibility is further reduced. The highest average transit speed of the whole range of visibility from 0 – 20 kilometers was in the visibility range of 0 – 1 kilometers, with an average transit speed of 11.75 knots.

Table 2. Table showing the average transit speeds in different visibility ranges.

Visibility Range (in Meters):	Number of Transits:	Average Transit Speed (in Knots) in This Visibility Range:
0 – 1,000	174	11.75
1,001 – 2,000	94	11.33
2,001 – 3,000	164	10.08
3,001 – 4,000	211	10.15
4,001 – 5,000	199	9.75
5,001 – 6,000	224	9.98
6,001 – 7,000	220	10.16
7,001 – 8,000	256	10.07
8,001 – 9,000	243	10.23
9,001 – 10,000	267	10.46
10,001 – 11,000	317	10.58
11,001 – 12,000	329	10.49
12,001 – 13,000	286	10.47
13,001 – 14,000	364	10.65
14,001 – 15,000	348	10.74
15,001 – 16,000	400	10.90
16,001 – 17,000	409	10.84
17,001 – 18,000	434	10.85
18,001 – 19,000	462	11.23
19,001 – 20,000	9,019	11.53

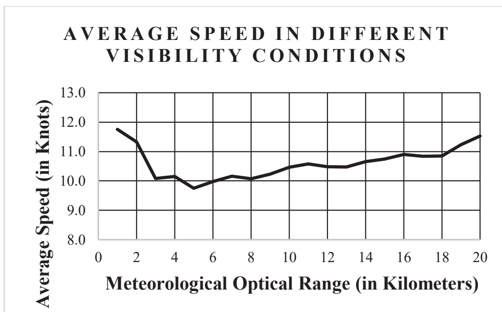

Fig. 7. Graph showing the average transit speeds in different visibility ranges.

4. Discussion

Contemporary commentary on safe speed at sea designates visibility as the primary influencing factor. Furthermore, it is generally agreed that the safe speed in restricted visibility is lower than in perfect visibility. If historic AIS data is to be used to aid MASS in determining the safe speed for the prevailing conditions without human intervention, it must first be ascertained that speed data taken from AIS represents speeds that can be considered safe. This section will discuss whether trends from AIS data can be classified as safe speeds under the contemporary understanding of what constitutes safe speed at sea.

4.1. ***Scatter plot***

No clear relationship between visibility and speed can be readily ascertained from the scatter plot (Figure 6), something that is manifested in the lack of predictability in determining the average transit speed from a given visibility value. Looking at the scatter plot, the average transit speed of a vessel passing when the MOR is 10 kilometers could be anywhere between 7 and 18 knots.

Pearson's correlation coefficient was calculated as being 0.18. While a positive value of Pearson's correlation coefficient generally indicates that both visibility and speed increase and decrease together, the strength of relationship is generally judged to be non-existent or very weak when it is below 0.3 (Moore, Notz, and Fligner 2021).

4.2. ***Regression analysis***

While the scatter plot did not show a clear relationship between visibility and speed, the regression analysis was able to find a significant regression equation, with the P-value of $1.008x10^{-106}$ indicating a statistically significant relationship between visibility and speed. This is in line with the expectation that a reduction in visibility should cause a reduction in the speeds of vessels. Nevertheless, the regression equation only has an R^2 value of 0.033. R^2 is the fraction by which the variance of the errors in the model is less than the variance of the dependent variable, meaning that it indicates the percent of variance explained by the model (Nau 2020). This means that the regression analysis found that only 3.3% of variation in average speed can be explained by the variation in visibility.

This can hardly be interpreted as visibility being the primary influencing factor on vessel speeds. Instead, the data shows that there must be other, more influential factors influencing the speeds of vessels. These could be the other factors directly named in the COLREGs, such as traffic density, maneuverability, background light at night, the state of wind, sea and current, the proximity of navigational hazards and the draft in relation to the available depth of water. However, other factors that are unrelated to the goal of proceeding at a safe speed could also have large influences on the speeds that vessels proceed at.

From research into road safety, we know that almost all drivers want to drive faster than the speed that they themselves consider to be a safe speed (Goldenbeld and van Schagen 2007). Reasons for speeding in a road context are diverse and include – among others – temporary motives (such as being in a hurry or adapting the speed to the general traffic stream) and permanent personality characteristics (such as proneness to risk taking or general enjoyment of driving fast) (European Commission 2018). Human perceptual skills and limitations play a role as well, with some situations making it easy to underestimate one's own driving speed. These include situations when a high speed has been maintained for a long period, as well as situations where there is little peripheral visual information (ETSC 1995; Martens, Comte, and Kaptein 1997; Elliott, McColl, and Kennedy 2003). It is easy to find maritime examples for situations that provide little peripheral information, such as navigating in the open sea, at night, or – maybe most importantly in this context – in fog.

Additionally, we have learned from Rasmussen (1997) that "human behavior in any work system is shaped by objectives and constraints which must be respected by the actors for work performance to be successful". The navigators setting the speed on the different vessels are not only bound by safety related constraints, but by administrative and functional constraints as well. The decision at which speed a vessel will proceed is therefore not only influenced by factors relating to safety, but by factors relating to efficiency and reduction of effort as well. Speed decisions made by navigators on board a vessel can be seen as being under immense outside pressure, with standard ocean shipping contracts requiring vessels to proceed at 'utmost dispatch', and first-come, first-served berthing policies adding additional incentives for navigators to proceed at full speed (Alvarez, Longva, and Engebrethsen 2010).

With only 3.3% of the speed variation in the dataset being able to be explained by changes in visibility, it seems prudent to explore the possible impact of non-safety related influences on the speed that vessels proceed at, before utilizing speed data from AIS to teach MASS what constitutes safe speed.

The other interesting value of the regression equation is the coefficient of 0.0822. For each kilometer of increased visibility, vessel speed only seems to be increasing by 0.0822 knots. With the difference between what the Met Office describes as good and very poor visibility being 8.26 kilometers, this means that the regression equation predicts a vessel experiencing a deterioration of visibility from good to very poor to reduce its speed by approximately 0.7 knots (0.0822 x 8.26).

Cockcroft and Lameijer (2012), whose Guide to the Collision Avoidance Rules is described as the essential reference to safe operation of all vessels at sea, provide an example on safe speed in restricted visibility from the legal case of the collision between the *Hagen* and the *Boulgaria*. Here it was stated that a radar equipped vessel normally capable of proceeding at 13.5 knots would be expected to reduce its speed to about 8 to 9 knots when proceeding in visibility of approximately 1.1 kilometers. Note that this expected speed reduction was stated for a vessel equipped with radar, i.e. a vessel that was not solely reliant on human senses such as sight and hearing but could instead utilize technology to perceive its environment. This example is therefore well-suited for application to MASS, which will also rely on technology – and not on human senses – to perceive their surroundings. When comparing this expected speed reduction of 4.5 – 5.5 knots with the 0.7 knots expected by the regression equation of the AIS dataset, it becomes clear that the reduction of speed in reduced visibility observed in the AIS data is not nearly enough to be classified as sufficient by our current understanding of safe speed.

4.3. ***Average speeds in different visibility ranges***

Perhaps the most interesting finding of this study is visualized in Figure 7. While commentary on the safe speed requirement of the COLREGs states that the need to moderate speed generally applies in restricted visibility and that it is dangerous to go fast when visibility is poor, the AIS data shows that the average transit speed of vessels passing the study area in very poor visibility conditions was higher than that of any other visibility range.

Starting at the maximum measured MOR of 20 kilometers, average transit speeds in the different visibility ranges gets smaller as visibility is reduced. This trend continues until the measured MOR reaches 4 kilometers, at which point average transit speeds increase as visibility is reduced.

Referring to the visibility definitions by the Met Office stated in Table 1, we can see that the visibility range of 3,704 meters to 9,260 meters is called moderate visibility. The data therefore shows that in moderate to good visibility, the measured average transit speeds decreased as visibility deteriorated, while in very poor to poor visibility, the measured average transit speeds increased as visibility deteriorated.

This phenomenon of vessel speeds increasing as visibility decreases in very poor to poor visibility conditions is in direct opposition to our current understanding of safe speed. This is therefore another indicator that vessel speeds collected via AIS do not represent safe vessel speeds in the prevailing circumstances.

To understand why average vessel speeds are highest in very poor visibility conditions, more research is necessary. It is possible to hypothesize that more influential factors on vessel speeds – such as the influence of wind and waves – are greatly reduced in situations of very poor visibility. For example, light winds increases the likelihood of fog forming, while high wind generally prevents for from forming (Haby 2021).

5. Conclusion

This research paper had the following research question:
Can MASS autonomously determine the safe speed by utilizing historic AIS speed data of other vessels?
To find an answer to the research question, AIS speed data was scrutinized to ascertain if it could be taken to represent safe speed. As visibility is stated to be of major importance when determining the safe speed and the need to reduce speed generally applies in restricted visibility, this process was conducted by answering the following research sub-questions:

(i) Does AIS and visibility data show a strong relationship between visibility and vessel speeds?
(ii) Does AIS data show a trend of vessels proceeding at a reduced speed in restricted visibility?

The regression analysis conducted in this study found a statistically significant relationship between visibility and speed. However, the regression equation is only able to explain 3.3% of the speed variation in the dataset with changes in visibility. Factors other than visibility are therefore likely to have a larger influence on vessel speeds observed on AIS. Furthermore, the regression equation predicts the average speeds of vessels transiting the study area in good and very poor conditions to only differ by approximately 0.7 knots.

By dividing transits into different visibility groups, this study showed that average transit speeds in very poor visibility are the highest of any visibility group. Instead of showing a reduction of speed in restricted visibility, the data shows that the average transit speeds actually increase as visibility deteriorates in poor to very poor visibility conditions.

Vessel speed data taken from AIS therefore shows that while there is a statistically significant relationship between visibility and speed, it is not particularly strong. Moreover, vessels do not show a reduction of speed in restricted visibility. It can therefore be concluded that there is a difference between the predicted changes in vessel speeds – based on contemporary theoretical understanding of safe speed – and the actual differences in vessel speeds in different visibility conditions. This difference can be either due to our contemporary understanding of safe speed being flawed, or because speed data taken from AIS does not represent safe speeds in all conditions. This is because the speeds of vessels are not only influenced by factors relating to safety, but by factors relating to efficiency and reduction of effort as well.

The problem of quantifying the safe speed of a vessel in different conditions therefore does not seem to be easily solvable by simply using historic AIS data to create a model of normalcy which a MASS can follow. More research in this area is necessary to gain a deeper understanding of what a safe speed constitutes and how this knowledge can be transferred to any MASS sailing the seas in the future.

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