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A Probability-Based Reliability Model for Evaluating Ro-Ro Ferry Sailing-Speed Compliance on an Indonesian Short-Sea Route Using AIS Data

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Abstract: Automatic Identification System (AIS) data provide continuous operational records that can be transformed into computational indicators for evaluating maritime service performance. This study aims to develop an AIS-based probabilistic model for assessing Ro-Ro ferry service-speed reliability through sailing-speed compliance. Speed over Ground (SOG) observations were used to determine whether vessels operated within a predefined reliable speed range during sailing. The reliable speed range was defined as 7–9 knots based on the performance indicator required by the local transportation authority responsible for route licensing, while sailing observations were identified using a 3–15-knot SOG filter. From 32,358 raw AIS messages collected between 1 January and 31 March 2026, 11,166 sailing observations were retained. Observation-based reliability was 35.63%, while duration-based reliability was 36.63%, indicating that 324.76 of 886.64 estimated sailing hours were spent within the reliable speed range. Vessel-level analysis showed substantial variation, with two vessels recording duration-based reliability above 50% and two others below 10%. The Weibull distribution provided the best parametric fit, with an Akaike Information Criterion (AIC) of 44,051.48, the lowest among the fitted distributions. The cumulative distribution function indicated a 35.88% probability of operating within the 7–9-knot range. Monte Carlo bootstrap resampling with 10,000 iterations produced 95% confidence intervals of 34.75–36.53% and 35.38–37.88% for observation-based and duration-based reliability, respectively. These findings indicate that AIS data can support a reproducible screening approach for evaluating aggregate and vessel-level ferry service-speed reliability.

Keywords: Automatic Identification System (AIS); Service-Speed Reliability; Probability Distribution; Weibull Distribution; Monte Carlo Simulation; Ro-Ro Ferry

1. Introduction

Ro-Ro ferry services are essential components of short-sea transport systems because they support passenger mobility, vehicle transfer, and regional logistics connectivity. In short-sea corridors, service performance can be affected by vessel availability, terminal operations, sailing regularity, and the ability of vessels to maintain an expected operating condition during a crossing. Among these operational variables, Speed over Ground (SOG) is one of the most directly observable indicators available from Automatic Identification System (AIS) data. Although SOG does not represent the overall quality of ferry service, it provides a measurable basis for evaluating whether a vessel operates within a predefined service-speed envelope while sailing.

AIS data have been widely used in maritime analytics because they provide repeated records of vessel identity, timestamp, position, course, and speed. Recent studies have applied AIS data to maritime anomaly detection, trajectory prediction, operational monitoring, and port-efficiency measurement. Nguyen *et al.* (2020) demonstrated the operational relevance of AIS-based detection of abnormal vessel behaviour, while Singh and Heymann (2020) used AIS-derived position, speed, course, and timing features for maritime anomaly detection. Capobianco *et al.* (2021) showed that historical AIS observations can support vessel trajectory prediction using deep learning, while Martinčič *et al.* (2020) emphasized the role of validated AIS data in constructing vessel and port-efficiency metrics. Li *et al.* (2023a) also demonstrated the use of AIS data for ship trajectory prediction using machine learning and deep learning methods. These studies demonstrate that AIS data can support not only navigation-related analysis but also the assessment of vessel and maritime transport performance.

Despite these developments, most AIS-based maritime studies focus on trajectory prediction, anomaly detection, traffic monitoring, and port-efficiency indicators rather than threshold-based service reliability. In ferry operations, reliability is commonly associated with schedule adherence, travel-time variability, headway regularity, and terminal performance. Transportation reliability research also indicates that performance consistency can be evaluated using probability-based and distribution-based measures when an acceptable operating range or threshold is defined. Zang *et al.* (2022) reviewed methodological developments in travel-time reliability and emphasized the use of distributional and probability-based approaches for evaluating transport-system performance under variable conditions. However, limited attention has been given to AIS-derived reliability measures that assess ferry service-speed compliance using both observation-based and duration-based indicators.

This study addresses this gap by developing a simplified observation-level probabilistic model for evaluating Ro-Ro ferry service-speed reliability from AIS data. The model defines reliable operation as compliance with a sailing-speed interval of 7–9 knots and applies a 3–15 knot filter to identify sailing observations. The 7–9 knot interval was not selected as an arbitrary statistical threshold; it was defined based on the performance indicator required by the local transportation authority responsible for route licensing. Therefore, the threshold represents an operational service-speed envelope used to assess whether observed Ro-Ro ferry operations comply with the expected sailing-speed condition on the permitted route. Reliability is measured using two complementary indicators: observation-based reliability, which estimates the proportion of AIS observations within the reliable-speed range, and duration-based reliability, which estimates the proportion of valid sailing time spent within that range. The second measure accounts for differences in the spacing of AIS observations and provides a time-based complement to the observation-count measure.

In contrast to AIS studies that mainly use SOG as an input feature for trajectory prediction, anomaly detection, or traffic monitoring, this study treats SOG as an operational compliance variable. The focus is therefore on whether a vessel operates within the expected service-speed envelope while sailing, rather than on trajectory characteristics alone. This approach provides a link between AIS-based maritime analytics and probability-based assessment of service-speed compliance. The main contribution of this study is the formulation of ferry service-speed compliance as a reproducible AIS-derived probabilistic indicator rather than as a conventional trajectory-prediction, anomaly-detection, or schedule-adherence problem. The proposed approach combines speed filtering, binary service-compliance classification, duration-based reliability estimation, reliable-segment analysis, parametric distribution fitting, CDF-based probability estimation, and bootstrap-based uncertainty assessment within a screening-level framework. The term "first-stage diagnostic tool" refers to an AIS-exclusive screening method for identifying aggregate, temporal, and vessel-specific speed-compliance patterns before more detailed berth-to-berth service-leg reconstruction is undertaken. The method is not intended to provide a causal diagnosis of service delays or operational failures, but to identify patterns that may warrant further operational investigation.

2. Related Work

2.1 AIS-Based Maritime Data Analytics

Automatic Identification System (AIS) data have become an important source for maritime data analytics because they provide spatio-temporal records of vessel identity, position, course, and speed. Recent studies have used AIS data for trajectory prediction, anomaly detection, route extraction, maritime monitoring, and operational decision support. Yang *et al.* (2024) reviewed machine-learning applications using AIS data and discussed the use of large-scale spatio-temporal vessel patterns for maritime decision-making (Liang *et al.*, 2024; D. Yang *et al.*, 2019). These studies indicate that AIS records can be processed beyond their original navigational purpose to support the analysis of vessel operations. Several studies have focused on trajectory prediction and movement modelling. An AIS-based Bi-LSTM trajectory prediction model showed that denoising, trajectory separation, and standardization can improve prediction accuracy in maritime traffic management (C.-H. Yang *et al.*, 2022). A systematic review of machine-learning and deep-learning methods for ship trajectory prediction found that AIS-based prediction is mainly directed toward navigation safety, collision prevention, and traffic management (H. Li *et al.*, 2023b). Historical AIS data have also been used for maritime route extraction by transforming vessel trajectories into semantic trip objects and directed traffic graphs (Yan *et al.*, 2020). These studies demonstrate the suitability of AIS data for identifying vessel movement patterns, but their primary focus is on trajectory modelling, route extraction, and navigational decision support. AIS data have also been widely applied to anomaly detection. Wolsing *et al.* (2022) reviewed 44 studies on maritime AIS anomaly detection and reported that AIS-based anomalies are commonly examined in relation to safety, security, collision risk, and abnormal vessel behaviour. This deviation-based approach is relevant to the present study because both approaches compare observed vessel behaviour with an expected condition. The difference is that the present study does not define deviation in terms of safety or security anomalies; instead, it evaluates compliance with a predefined sailing-speed requirement for Ro-Ro ferry operations.

2.2 Reliability and Probabilistic Assessment in Maritime Transportation

Reliability-oriented approaches have been applied in maritime and waterway transportation to evaluate system performance, resilience, and operational risk. Wang and Yuen (2022) developed a resilience assessment model for waterway transportation systems by combining system performance with recovery cost, while AIS data were used as an input to a discrete-event simulation. Their study demonstrates that AIS-derived operational information can support performance assessment when vessel delays and system recovery are considered. This perspective is relevant to the present study because it shows that vessel movement data can be linked to quantitative measures of transportation-system performance. Probabilistic approaches provide another means of representing uncertainty in maritime operations. Xin *et al.* (2021) proposed a probabilistic conflict-detection approach for multi-ship collision risk under spatio-temporal movement uncertainty and applied Monte Carlo simulation for risk estimation. Vukša *et al.* (2022) similarly combined Monte Carlo simulation with AIS-based traffic and route information to estimate ship collision probability. Other reliability studies have also applied Monte Carlo methods to quantify uncertainty in operational systems (Arekar *et al.*, 2021; Labeau & Zio, 2002). These studies indicate that probability-based methods can be used to represent variability in observed or simulated operational conditions rather than relying only on deterministic performance measures.

In a threshold-based assessment, reliability can be defined by first specifying an acceptable operational condition and then estimating the proportion or probability of observations that satisfy that condition. In the present study, the acceptable condition is defined by compliance with a prescribed sailing-speed range. The distinction between compliance and reliability is therefore important: compliance refers to whether an individual observation or time interval satisfies the prescribed speed condition, whereas reliability refers to the proportion of observations or operating time that satisfies this condition. This definition allows AIS-derived vessel speed to be converted into a measurable operational indicator while maintaining a clear distinction between an individual compliant state and the aggregate reliability measure. Parametric probability distributions can also be used to characterize the variability of continuous operational measurements. Rather than assuming a particular distribution in advance, distribution fitting can be used to identify whether a parametric model provides an adequate representation of the observed sailing-speed data. The selected distribution can then be used to estimate probabilities associated with the predefined operating range. This approach provides a complementary perspective to direct observation-based and duration-based reliability measures because it describes the observed speed pattern through its probability distribution.

Bootstrap methods provide an additional approach for evaluating uncertainty in empirical reliability estimates. By repeatedly resampling the available observations, bootstrap analysis can provide an empirical assessment of the stability of an estimated reliability value without requiring the reliability indicator itself to follow a predetermined theoretical distribution. In the context of AIS-based ferry analysis, this approach can complement probability-based modelling by indicating how sensitive the estimated reliability is to variation in the available observations. Although these studies provide useful methodological foundations, their applications mainly concern collision risk, resilience, route prediction, or safety-related operational conditions. Less attention has been given to defining ferry service reliability specifically through compliance with a prescribed sailing-speed range derived from AIS observations. The present study therefore extends the use of probability-based operational assessment toward Ro-Ro ferry service-speed compliance, using observation-based and duration-based indicators together with distributional analysis and bootstrap-based uncertainty assessment.

2.3 Position of the Present Study

The present study differs from previous AIS-based maritime analytics in three main respects. First, it uses AIS-derived Speed over Ground (SOG) as an operational compliance variable rather than primarily as an input feature for trajectory prediction or anomaly detection. Second, it formulates Ro-Ro ferry sailing-speed compliance as a service-speed reliability measure by classifying AIS observations according to a configured 7–9 knot operating range. Third, it complements observation-based reliability with duration-based reliability and reliable-speed segment analysis, thereby reducing the dependence of the assessment on the number of AIS messages alone. This positioning is relevant because AIS observations may be recorded at unequal intervals. A measure based only on observation counts can therefore be sensitive to differences in message-reporting frequency. The present study addresses this issue by combining observation-based reliability with duration-based reliability and by examining the distribution of observed sailing speeds. PDF fitting, CDF-based probability estimation, and bootstrap resampling are used as complementary analytical procedures within the proposed AIS-based screening framework. The model is intended as a first-stage assessment of ferry service-speed compliance rather than as a replacement for full berth-to-berth service-leg reconstruction.

Table 1. Research Gap

Study / Literature Group	Data / Method	Main Focus	Limitation Relative to This Study	Position of the Present Study
Yang *et al.* (2024); Yang *et al.* (2019)	AIS-based maritime data mining and machine learning	AIS analytics, maritime data, and operational knowledge extraction	Does not explicitly address ferry service-speed compliance	Uses AIS-derived SOG as an operational compliance variable
Wolsing *et al.* (2022)	Review of AIS anomaly-detection studies	Abnormal vessel behaviour and safety/security anomalies	Focuses on anomaly detection rather than service-standard compliance	Applies deviation logic to service-speed compliance
Yang *et al.* (2022); Li *et al.* (2023b)	AIS denoising, Bi-LSTM, ML/DL trajectory prediction	Vessel trajectory prediction and navigational decision support	Treats SOG primarily as a trajectory variable	Converts SOG into compliant/non-compliant service states
Yan *et al.* (2020)	Historical AIS and route extraction	Maritime route extraction and traffic-pattern construction	Does not explicitly evaluate compliance with a service-speed envelope	Evaluates sailing-speed compliance against an operational threshold
Wang and Yuen (2022); Zohoori *et al.* (2023)	AIS-based simulation and resilience assessment	Waterway resilience and system-level performance	Focuses on system resilience rather than vessel-level ferry speed compliance	Provides aggregate and vessel-level speed-compliance diagnostics
Xin *et al.* (2021); Vukša *et al.* (2022)	Probabilistic risk assessment and Monte Carlo simulation	Collision risk and maritime safety uncertainty	Applies probability and simulation to safety risk rather than ferry service performance	Applies probabilistic estimation and bootstrap resampling to service-speed reliability
Betz *et al.* (2022); Labeau and Zio (2002); Arekar *et al.* (2021)	Reliability theory and Monte Carlo methods	Reliability estimation and uncertainty quantification	Provides methodological foundations but not a ferry-specific AIS compliance model	Combines reliability estimation, candidate distribution fitting, CDF interpretation, and bootstrap uncertainty assessment

Present study	AIS-derived SOG, threshold-based compliance, duration weighting, distribution fitting, CDF estimation, and bootstrap	Ro-Ro ferry service-speed reliability	—	Provides a reproducible AIS-based screening model for aggregate, temporal, and vessel-level speed compliance

The reviewed studies show that AIS data have been extensively used for trajectory prediction, route extraction, anomaly detection, collision-risk analysis, and waterway resilience assessment. However, these applications rarely transform AIS-derived sailing speed into a service-standard compliance indicator for ferry operations. The specific gap addressed in this study is therefore methodological and operational: existing AIS analytics can describe vessel movement or detect abnormal behaviour, but they provide limited direct assessment of how consistently Ro-Ro ferry vessels operate within a predefined service-speed envelope. The present study addresses this gap by combining observation-based compliance, duration-based reliability, distribution fitting, CDF-based probability estimation, and bootstrap resampling within a single AIS-based screening framework.

3. Methodology

3.1 Dataset and Preprocessing

The dataset consisted of AIS records from Ro-Ro ferry operations. The raw dataset contained 32,358 messages from four vessels. The created_at field was used as the timestamp, while Speed over Ground (SOG) was used as the main operational variable. Records with missing timestamps or SOG values were removed, together with records outside the initial SOG quality-control range of 0–30 knots. A subsequent sailing-state filter retained observations with SOG values between 3 and 15 knots (Deriba & Yang, 2025; Liang *et al.*, 2024). The 0–30 knot range was used for initial data-quality control, whereas the 3–15 knot range was used to identify observations considered representative of sailing conditions.

Table 2. AIS dataset and preprocessing summary

Stage	Number of records	% of raw AIS records
Raw AIS messages	32,358	100.00
After timestamp and SOG cleaning	32,352	99.98
Sailing observations (3.0–15.0 knots)	11,166	34.51
Reliable observations (7.0–9.0 knots)	3,978	12.29
Non-compliant observations	7,188	22.21

The percentages in Table 2 are calculated relative to the raw AIS dataset. The observation-based reliability reported later is calculated relative to the retained sailing observations. All analyses were conducted in Google Colab using Python. The computational workflow used pandas for data processing, NumPy for numerical operations, SciPy for distribution fitting and statistical computation, Matplotlib for visualization, and openpyxl for table export. The software and library versions were recorded in the analysis notebook to support reproducibility.

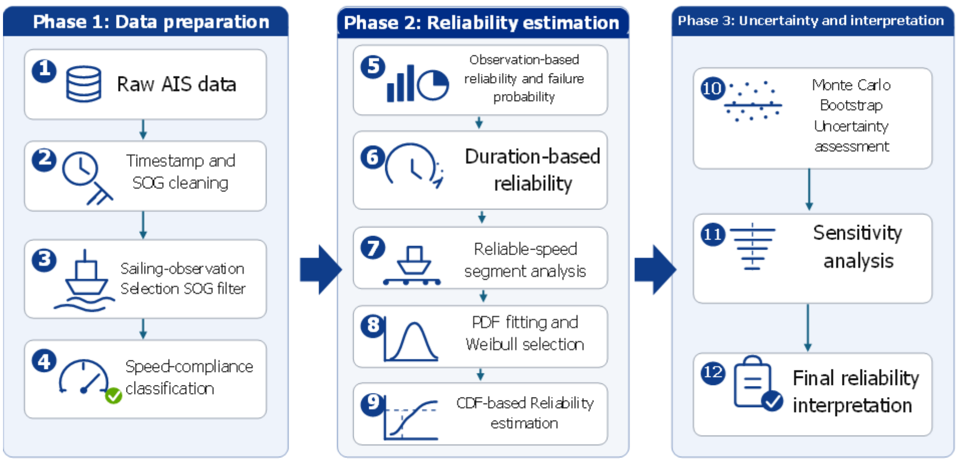

Figure 1. Stage of Processing AIS data

Figure 1 summarizes the analytical workflow, beginning with raw AIS preprocessing and sailing-observation filtering, followed by service-speed compliance classification, empirical reliability estimation, duration-based reliability calculation, distribution fitting, CDF-based probability estimation, and bootstrap-based uncertainty assessment. This workflow was designed to maintain a transparent and reproducible transformation from raw AIS observations to the resulting reliability indicators.

3.2 Speed-Compliance Indicator

The reliable sailing-speed range was defined as 7–9 knots based on the performance indicator required by the local transportation authority responsible for route licensing. This range was used as the operational compliance threshold for evaluating whether each retained AIS-derived sailing observation satisfied the prescribed service-speed condition. The 7–9 knot interval was therefore not treated as an arbitrary statistical threshold but as an operational service-speed envelope for the permitted route. The use of AIS-derived SOG is consistent with previous AIS-based maritime studies in which vessel speed, position, course, and timestamp are used to characterize vessel behaviour and operational patterns (Wolsing *et al.*, 2022; Y. Yang *et al.*, 2024). Each sailing observation was classified using a binary compliance indicator. An observation was assigned a value of 1 when its SOG was within the 7–9 knot range and 0 otherwise. The compliance indicator is defined as:

$$I_i = \begin{cases} 1, & 7 \leq SOG_i \leq 9 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Where I_i denotes the reliability state of the i-th sailing observation, and SOG_i denotes the Speed over Ground value of that observation. The observation-based reliability was then calculated as the proportion of sailing observations that satisfied the reliable-speed criterion:

$$R_{obs} = \frac{\sum_{i=1}^{N} I_i}{N} \tag{2}$$

Where N is the total number of sailing observations after filtering. The corresponding failure probability, representing the proportion of observations outside the reliable speed range, was computed as:

$$P_f = 1 - R_{obs} \tag{3}$$

In this study, non-compliance probability refers to the proportion of retained sailing observations outside the predefined 7–9 knot service-speed envelope. It does not indicate mechanical failure, accident occurrence, or complete service failure. The formulation therefore defines reliability specifically as the proportion of observed sailing states that comply with the prescribed service-speed condition. A sensitivity analysis was conducted to examine whether the reliability estimates were affected by the selected sailing-filter and service-speed parameters. The baseline configuration used a 3–15 knot sailing filter and a 7–9 knot reliable-speed range. Alternative sailing filters with lower boundaries of 2 and 4 knots were also tested, together with wider service-speed ranges of 6.5–9.5, 7–9.5, and 6.5–9 knots. For each scenario, observation-based and duration-based reliability were recalculated using the same computational procedure.

Table 3. Sensitivity analysis of sailing filter and reliable-speed range

Scenario	Sailing Filter (Knots)	Reliable-Speed Range (knots)	Sailing Obs.	Reliable Obs.	R_obs (%)	Sailing h	Reliable h	R_time (%)
Baseline	3–15	7–9	11,166	3,978	35.63	886.64	324.76	36.63
S1	2–15	7–9	11,823	3,978	33.65	948.82	337.57	35.58
S2	4–15	7–9	10,503	3,978	37.87	818.90	310.93	37.97
S3	3–15	6.5–9.5	11,166	5,549	49.70	886.64	458.57	51.72
S4	3–15	7–9.5	11,166	4,493	40.24	886.64	369.99	41.73
S5	3–15	6.5–9	11,166	5,034	45.08	886.64	413.34	46.62

The sensitivity analysis showed that modifying the lower boundary of the sailing filter produced only moderate changes in the reliability estimates. Using a 2–15 knot filter resulted in observation-based and duration-based reliability values of 33.65% and 35.58%, respectively, while the 4–15 knot filter resulted in 37.87% and 37.97%. These values remained relatively close to the baseline duration-based reliability of 36.63%. In contrast, widening the reliable-speed range increased the estimated reliability because a larger proportion of observations satisfied the compliance criterion. For example, extending the range to 6.5–9.5 knots increased duration-based reliability to 51.72%. The baseline 7–9 knot range was retained because it represents the operational service-speed indicator for the observed route, while the alternative configurations were used only for robustness assessment.

3.3 Duration-Based Reliability

Reliable sailing duration was estimated after AIS records were sorted separately by vessel identity and timestamp. For each vessel, the time interval between consecutive AIS observations was calculated as:

$$\Delta t_{v,i} = t_{v,i} + 1 - t_{v,i} \quad (4)$$

where v denotes the vessel and i denotes the index of the consecutive observation pair. Only positive intervals not exceeding the maximum allowable AIS gap of 20 minutes were retained as valid sailing intervals. This restriction was applied to reduce the risk of interpreting long AIS transmission gaps as continuous sailing activity. The 20-minute maximum gap was selected based on the operational characteristics of the observed Ro-Ro ferry route. The total crossing time was generally within approximately 40–60 minutes, while the effective sailing-zone interval was approximately 20 minutes. An AIS reporting interval longer than this threshold may bridge unobserved manoeuvring, terminal approach, waiting, or transition periods and therefore may not represent continuous sailing activity.

A gap-threshold sensitivity analysis was also conducted. The 15-, 20-, and 30-minute thresholds produced duration-based reliability estimates of 36.86%, 36.63%, and 36.40%, respectively. These results indicate that the estimate was relatively stable around the selected 20-minute threshold. Shorter thresholds reduced the number of valid temporal intervals and could fragment continuous reliable-speed periods, whereas longer thresholds increased the possibility of treating extended periods without AIS observations as continuous sailing activity. The 20-minute threshold was therefore retained as the baseline setting. The total estimated sailing duration was calculated by summing the valid consecutive intervals across all vessels:

$$T_{sailing} = \sum_{v=1}^{v} \sum_{i=1}^{nv-1} \Delta t_{v,i,} \quad (5)$$

Where v denotes the number of vessels and nv denotes the number of retained observations for vessel v. The reliable sailing duration was calculated by summing the valid intervals associated with observations classified as compliant with the prescribed 7–9 knot range:

$$T_{reliable} = \sum_{v=1}^{v} \sum_{i=1}^{nv-1} c_{v,i,} \Delta t_{v,i,} \quad (6)$$

Where $C_{v,i}$ denotes the compliance indicator associated with the observation at the beginning of the i- th valid interval for vessel v. The duration-based reliability was then calculated as:

$$R_{time} = \frac{T_{reliable}}{T_{sailing}} X 100\% \quad (7)$$

This metric estimates the proportion of valid sailing time associated with the reliable-speed condition and therefore complements the observation-based reliability measure when AIS observations are not uniformly distributed over time. Reliable-speed segments were also identified to describe the continuity of compliant operation. Consecutive reliable observations from the same vessel were grouped into the same segment when the time interval between observations did not exceed the 20-minute threshold. A new segment was initiated when the vessel identity changed, the observed SOG moved outside the 7–9 knot range, or the time gap exceeded the maximum allowable threshold. The duration of each reliable segment was calculated from its valid consecutive intervals. This segment-level measure provides additional information on whether compliant operation occurred as short isolated periods or as sustained sailing periods.

3.4 Probability Distribution Fitting and CDF Analysis

The empirical distribution of sailing speed was first examined using a histogram and kernel density estimation (KDE). These non-parametric representations were used to describe the observed SOG pattern before fitting candidate parametric distributions. Four candidate distributions—Normal, Lognormal, Gamma, and Weibull—were fitted to the retained sailing-speed observations. These distributions were selected as candidate models for representing continuous operational measurements and for enabling probability estimation through their cumulative distribution functions. The best-fitting distribution was determined using the Akaike Information Criterion (AIC), which considers both model fit and the number of estimated parameters. A lower AIC value indicates a more parsimonious model among the candidate distributions. The AIC is calculated as:

$$AIC = 2k - 2\ln(L) \tag{8}$$

Where k denotes the number of estimated parameters and L denotes the maximum likelihood of the fitted model. After the best-fitting distribution was identified, its cumulative distribution function F(x) was used to estimate the probability that the observed sailing speed fell within the prescribed 7–9 knot range:

$$P(7 \leq SOG \leq 9) = F(9) - F(7) \tag{9}$$

This distribution-based probability provides a complementary estimate of service-speed compliance and can be compared with the empirical observation-based and duration-based reliability measures.

3.5 Bootstrap Uncertainty Assessment

Bootstrap resampling was used to assess the sampling uncertainty of the estimated service-speed reliability. The procedure consisted of 10,000 bootstrap iterations with a sampling fraction of 1.0, meaning that each bootstrap sample contained the same number of units as the original dataset. For observation-based reliability, retained sailing observations were resampled with replacement, and the reliability indicator was recalculated for each iteration. For duration-based reliability, the resampling procedure was designed to preserve the temporal structure required to calculate consecutive AIS intervals. The resampling unit was therefore defined according to the temporal structure of the sailing observations rather than treating individual AIS records as independent time intervals. The resulting bootstrap distribution was used to estimate a 95% confidence interval. The lower and upper confidence limits were obtained from the 2.5th and 97.5th percentiles of the bootstrap reliability distribution. This procedure provides an empirical uncertainty range without requiring the reliability estimates themselves to follow a predetermined theoretical distribution. The bootstrap procedure was applied separately to observation-based and duration-based reliability.

4. Result and Discussion

4.1 Results

The descriptive analysis was conducted to determine the distribution of AIS-derived sailing-speed observations relative to the predefined 7–9 knot service-speed envelope. A total of 11,166 AIS observations satisfied the baseline sailing filter of 3–15 knots. Of these observations, 3,978 were within the 7–9 knot reliable-speed range, while 7,188 were outside the prescribed range.

Table 4. Descriptive statistics and observation-based reliability

Statistic	Value
Sailing observations	11,166
Reliable observations (7–9 knot)	3,978
Non-compliant observations	7,188
Mean SOG (knot)	6.74
Median SOG (knot)	6.70
SOG standard deviation (knot)	1.74
Minimum SOG after sailing filter (knot)	3.00
Maximum SOG after sailing filter (knot)	12.30
Observation-based reliability (%)	35.63
Non-compliance probability (%)	64.37

The observation-based reliability was 35.63%, calculated from 3,978 reliable observations out of 11,166 retained sailing observations. The complementary non-compliance probability was 64.37%. The mean SOG was 6.74 knots, while the median was 6.70 knots. Both values were below the lower boundary of the prescribed 7–9 knot range. The observed SOG values ranged from 3.00 to 12.30 knots, with a standard deviation of 1.74 knots. Duration-based analysis was used to quantify the proportion of valid estimated sailing time associated with the 7–9 knot reliable-speed condition. After applying the vessel-specific temporal filtering and maximum AIS-gap criterion, the total estimated sailing duration was 886.64 hours.

Table 5. Duration-based reliability and reliable-segment statistics

Measure	Value
Total estimated sailing duration (hours)	886.64
Total reliable duration, 7–9 knot (hours)	324.76
Total non-compliant duration (hours)	561.88
Duration-based reliability (%)	36.63
Non-compliance probability (%)	63.37
Reliable segments (count)	1,285
Mean reliable segment duration (minutes)	15.16
Median reliable segment duration (minutes)	13.10
Maximum reliable segment duration (minutes)	40.93

A total of 324.76 hours were classified as reliable-speed duration, corresponding to a duration-based reliability of 36.63%. The remaining 561.88 hours, or 63.37% of the estimated sailing duration, were outside the reliable-speed range. The reliable-speed observations formed 1,285 reliable segments. The mean segment duration was 15.16 minutes, the median was 13.10 minutes, and the maximum was 40.93 minutes.

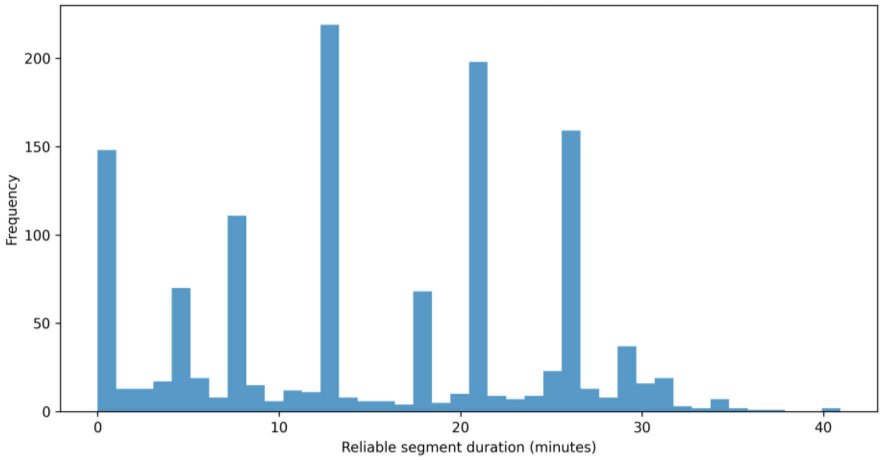

Figure 2. Distribution of reliable sailing segment duration.

The distribution of reliable-segment duration is presented in Figure 2. The figure illustrates the temporal distribution of periods during which the vessel operated within the prescribed reliable-speed range. The reliability indicators were further calculated separately for each vessel to identify differences in operating performance within the observed fleet.

Table 6. Vessel-level observation and duration reliability

Vessel	Sailing obs.	Reliable obs.	Mean SOG	R_obs (%)	R_time (%)	Sailing h	Reliable h
KMP BN	3,569	2,034	7.21	56.99	61.52	279.26	171.79
KMP SP	3,298	1,655	7.76	50.18	53.68	236.96	127.20
KMP SD	3,491	247	5.59	7.08	7.40	284.84	21.09
KMP MP2	808	42	5.39	5.20	5.47	85.58	4.68

The vessel-level results showed substantial differences among the four vessels. KMP BN recorded the highest observation-based reliability at 56.99% and duration-based reliability at 61.52%. KMP SP recorded 50.18% observation-based reliability and 53.68% duration-based reliability. In contrast, KMP SD recorded 7.08% observation-based reliability and 7.40% duration-based reliability, while KMP MP2 recorded 5.20% and 5.47%, respectively. The mean SOG was 7.21 knots for KMP BN and 7.76 knots for KMP SP, compared with 5.59 knots for KMP SD and 5.39 knots for KMP MP2. Four candidate probability distributions were fitted to the retained sailing-speed observations: Normal, Lognormal, Gamma, and Weibull. Their fitting performance was evaluated using log-likelihood, AIC, and BIC.

Table 7. Parametric distribution fitting for sailing speed

Distribution	n parameters	Log-likelihood	AIC	BIC
Weibull_min	3	-22,022.74	44,051.48	44,073.44
Normal	2	-22,053.14	44,110.28	44,124.92
Gamma	3	-22,177.56	44,361.13	44,383.09
Lognormal	3	-22,411.42	44,828.85	44,850.81

The Weibull distribution produced the lowest AIC (44,051.48) and BIC (44,073.44) among the four candidate distributions. The Normal distribution produced the second-lowest AIC of 44,110.28. The difference in AIC between the Weibull and Normal distributions was 58.80. The fitted Weibull distribution had a shape parameter of 4.3276 and a scale parameter of 7.4030.

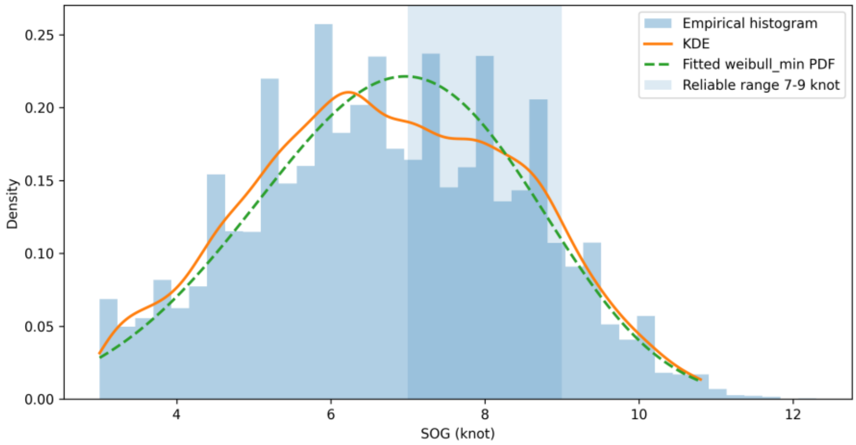

Figure 3. PDF of sailing speed using empirical histogram, KDE, and fitted Weibull distribution.

Figure 3 presents the empirical histogram, KDE, and fitted Weibull probability density function for the retained sailing-speed observations. The selected Weibull distribution was subsequently used to estimate the probability that sailing speed fell within the 7–9 knot service-speed range.

Table 8. CDF-based interpretation of sailing-speed compliance

CDF measure	Value
Selected distribution	Weibull_min
F(7)	0.5438
F(9)	0.9026
P(7 ≤ SOG ≤ 9)	0.3588
CDF-based reliability (%)	35.88
CDF-based probability outside range (%)	64.12

The fitted Weibull CDF gave F(7) = 0.5438 and F(9) = 0.9026. The resulting probability within the 7–9 knot range was 0.3588, corresponding to a CDF-based reliability of 35.88%.

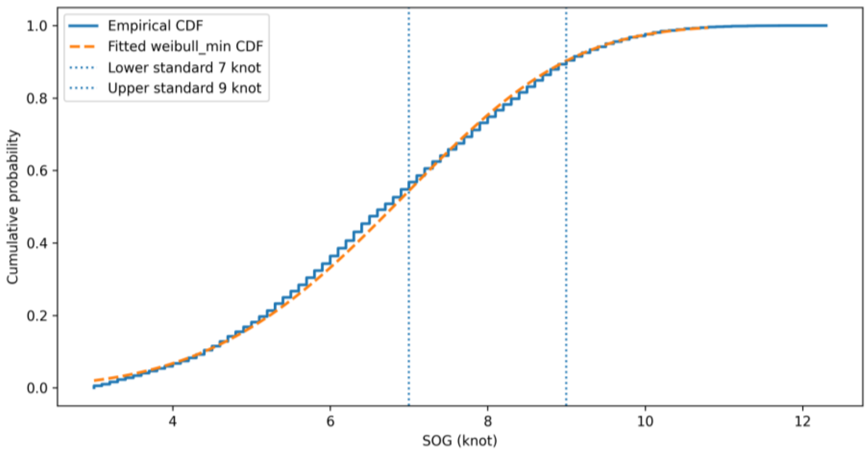

Figure 4. CDF of sailing-speed distribution.

Figure 4 shows the cumulative probability of sailing speed based on the fitted Weibull distribution and indicates the probability mass accumulated below and above the prescribed service-speed boundaries. Monthly analysis was conducted to examine temporal variation in the service-speed reliability indicators during the observation period.

Table 9. Monthly sailing-speed reliability

Month	Sailing obs.	Reliable obs.	Mean SOG	R_obs (%)	R_time (%)	Reliable h
2026-01	2,652	1,022	6.87	38.54	39.88	103.23
2026-02	4,020	1,424	6.71	35.42	36.78	100.98
2026-03	4,494	1,532	6.68	34.09	34.13	120.55

Both reliability measures showed a decline during the three-month observation period. Observation-based reliability decreased from 38.54% in January to 35.42% in February and 34.09% in March. Similarly, duration-based reliability decreased from 39.88% in January to 36.78% in February and 34.13% in March. The number of sailing observations increased from 2,652 in January to 4,494 in March, while the mean SOG decreased from 6.87 to 6.68 knots.

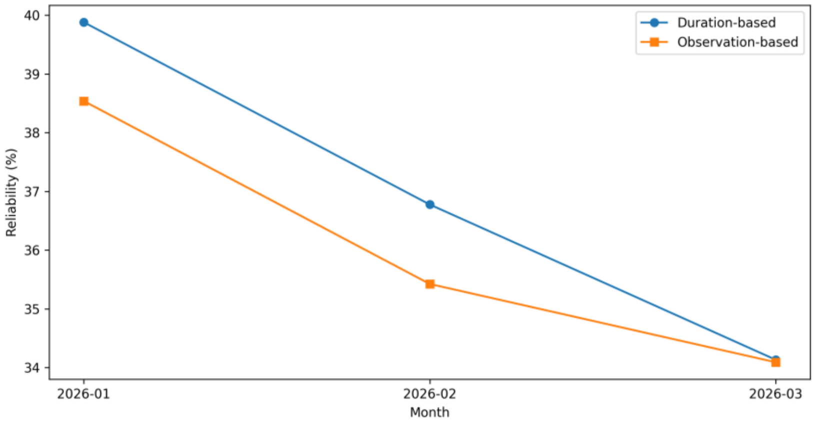

Figure 5. Monthly sailing-speed reliability.

Bootstrap resampling was conducted using 10,000 iterations to assess the uncertainty of the observation-based and duration-based reliability estimates.

Table 10. Bootstrap confidence intervals

Metric	Mean (%)	Std. dev. (%)	95% CI lower (%)	95% CI upper (%)
Observation-based reliability	35.63	0.451	34.75	36.53
Duration-based reliability	36.63	0.635	35.38	37.88

The bootstrap mean for observation-based reliability was 35.63%, with a standard deviation of 0.451 percentage points and a 95% confidence interval of 34.75–36.53%. For duration-based reliability, the bootstrap mean was 36.63%, with a standard deviation of 0.635 percentage points and a 95% confidence interval of 35.38–37.88%.

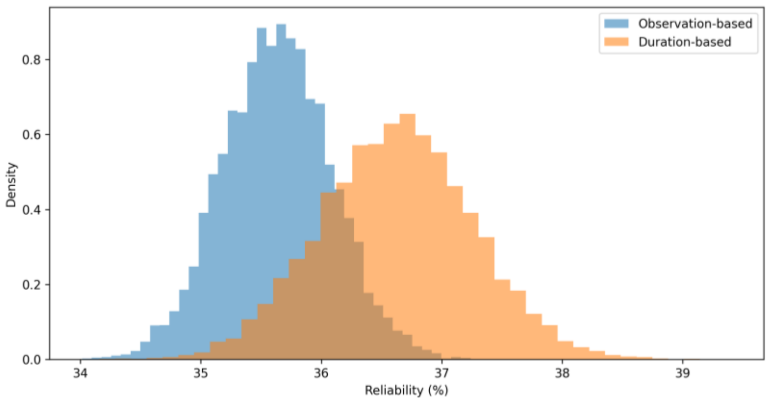

Figure 6. Bootstrap distribution of observation-based and duration-based reliability.

4.2 Discussion

The results show that compliance with the prescribed 7–9 knot service-speed range was relatively limited. Observation-based reliability was 35.63%, duration-based reliability was 36.63%, and the Weibull CDF produced 35.88%. The close agreement among these estimates, particularly the 1.00 percentage-point difference between observation- and duration-based reliability, indicates that the overall finding was relatively consistent across the analytical approaches. However, these values should be interpreted specifically as service-speed compliance, rather than mechanical reliability, accident probability, or complete ferry-service reliability. The observed non-compliance was predominantly associated with lower sailing speeds. The mean and median SOG were 6.74 and 6.70 knots, respectively, both below the lower threshold of 7 knots. This pattern is also reflected in the fitted Weibull distribution, where F(7) = 0.5438, indicating that approximately 54.38% of the fitted speed distribution was at or below 7 knots. Thus, the dominant direction of non-compliance was low-speed operation rather than excessive speed. Possible influences include vessel characteristics, maneuvering, loading conditions, route constraints, terminal approaches, traffic, or other operational factors; however, these cannot be established causally from the AIS-only analysis.

The duration-based analysis complements the observation-based indicator by accounting for unequal AIS reporting intervals. The relatively small difference between the two reliability estimates suggests that the overall conclusion was not strongly affected by observation density. In addition, the 1,285 reliable-speed segments had a mean duration of 15.16 minutes and a median of 13.10 minutes, indicating that compliant operation frequently occurred in relatively short and fragmented periods rather than being continuously sustained. Therefore, service-speed reliability should be understood not only in terms of whether vessels reached the prescribed speed range, but also in terms of how long they remained within that range.

Substantial vessel-level heterogeneity was also observed. KMP BN and KMP SP achieved duration-based reliability of 61.52% and 53.68%, respectively, whereas KMP SD and KMP MP2 achieved only 7.40% and 5.47%. Their mean SOG values showed a similar pattern, with 7.21 and 7.76 knots for KMP BN and KMP SP compared with 5.59 and 5.39 knots for KMP SD and KMP MP2. These differences demonstrate the diagnostic value of the proposed framework because aggregate reliability alone would conceal the variation among vessels. Nevertheless, the available AIS data cannot determine whether these differences resulted from vessel condition, loading, route assignment, operational practice, or other factors. The distribution analysis further supports the consistency of the reliability estimate. The Weibull distribution produced the lowest AIC and BIC among the tested Normal, Lognormal, Gamma, and Weibull distributions, with an AIC of 44,051.48 compared with 44,110.28 for the Normal distribution. Its CDF-based reliability of 35.88% was close to both empirical estimates. The CDF therefore provides a useful parametric representation of service-speed compliance through $P(7 \leqslant X \leqslant 9) = F(9) - F(7)$. Nevertheless, this value remains a model-based probability and depends on the adequacy of the selected distribution.

The monthly results indicate a gradual decline in reliability from January to March 2026. Observation-based reliability decreased from 38.54% to 34.09%, while duration-based reliability decreased from 39.88% to 34.13%. The parallel movement of both indicators suggests that the temporal pattern was not solely attributable to differences in AIS message counts. March recorded the largest number of retained observations but the lowest reliability percentage, demonstrating that the number of compliant observations must be interpreted relative to total sailing exposure. Because the present model does not include weather, tide, current, loading, maintenance, traffic, or terminal-operation variables, this temporal decline should be interpreted as a descriptive pattern rather than evidence of a specific causal mechanism.

The bootstrap analysis provides evidence of estimation stability. The 95% confidence interval was 34.75–36.53% for observation-based reliability and 35.38–37.88% for duration-based reliability. The relatively narrow intervals indicate that the approximately 36% estimates were stable under the applied resampling procedure. However, statistical stability should not be interpreted as operational adequacy. The bootstrap demonstrates the precision of the estimate under the specified resampling framework, not the quality of ferry service itself.

The findings demonstrate that AIS-derived SOG can be used as a screening-level indicator of ferry service-speed compliance. The framework provides complementary information on overall compliance, the direction of non-compliance, vessel-level differences, temporal variation, and estimation uncertainty. The approximately 36% reliability level indicates that only about one-third of the retained AIS-observed sailing states and valid sailing-time exposure fell within the configured 7–9 knot service-speed envelope. The framework therefore provides greater diagnostic information than a single aggregate reliability percentage and can support early-stage monitoring of Ro-Ro ferry operations where detailed trip-level operational data are unavailable. The findings should nevertheless be interpreted within the limitations of the observation-level design. AIS-derived SOG does not independently reconstruct complete berth-to-berth service trips and does not identify berth departure, port exit, destination entry, or destination berthing. It also does not distinguish normal maneuvering, waiting, terminal approaches, current effects, loading conditions, or other operational influences. Consequently, an observation outside the 7–9 knot range should not automatically be interpreted as a service failure. Furthermore, the 7–9 knot threshold represents a route-specific operational service-speed envelope, so the approximately 36% reliability estimate should not be generalized to other ferry routes without considering their respective operating standards. Future research should integrate AIS with route-leg reconstruction, terminal-event inference, weather, tide, current, vessel loading, traffic, and maintenance information to extend the present screening-level indicator toward a more comprehensive trip-level ferry service reliability model.

5. Conclusion and Recommendations

This study developed and demonstrated a simplified AIS-based probabilistic framework for evaluating Ro-Ro ferry service reliability through sailing-speed compliance. Using a sailing filter of 3–15 knots and a reliable-speed range of 7–9 knots, 11,166 sailing observations were retained from 32,358 AIS messages. The results showed an observation-based reliability of 35.63% and a duration-based reliability of 36.63%, with 886.64 estimated sailing hours, of which 324.76 hours fell within the reliable-speed range. The distribution analysis identified the Weibull distribution as the best-fitting model based on AIC, while its CDF estimated a 7–9 knot compliance probability of 35.88%. The close agreement among observation-based, duration-based, and CDF-based estimates indicates that the approximately 36% service-speed compliance level was consistent across the applied analytical approaches. Bootstrap resampling further produced relatively narrow confidence intervals, supporting the stability of the estimated reliability within the retained AIS dataset. The main contribution of this study is the development of a dual-metric AIS-based probabilistic framework that combines observation-based reliability and duration-based reliability with distribution-based probability estimation and bootstrap uncertainty assessment. This framework provides a practical screening-level approach for transforming AIS-derived SOG into an operational service-speed compliance indicator and enables additional diagnostic analysis at the vessel and temporal levels.

The proposed pipeline can be applied to other AIS datasets and ferry routes provided that route-specific service-speed thresholds and appropriate preprocessing criteria are established. However, the empirical findings remain specific to the observed route and dataset. The study did not incorporate ground-truth schedule data, loading records, terminal-operation information, weather, tidal conditions, or current measurements. Consequently, the model identifies speed-compliance patterns rather than providing a complete causal explanation of service-performance degradation. Future research should extend the present observation-level framework toward trip-level ferry service reliability by reconstructing service legs, terminal events, route direction, and berth-to-berth operating durations. Integrating these elements with contextual operational and environmental data would allow future studies to distinguish speed variations associated with normal maneuvering or terminal operations from genuine service-performance degradation and thereby provide a more comprehensive assessment of ferry service reliability.

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