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CFD-Based Estimation of Sunken Vessel Position Using Environmental Data and Last-Recorded AIS Data

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ABSTRACT

This study proposes a fluid-dynamics–based approach for estimating the probable location of a sunken vessel. The last recorded position of the distressed ship from the Automatic Identification System (AIS) and environmental inputs—including wind direction, wind speed, and local bathymetric depth—are used as model drivers. A simplified Computational Fluid Dynamics (CFD) framework is adopted, in which the vessel is treated as a control volume subject to the primary forces of gravity, buoyancy, wave-induced drift, and the ship's initial velocity. The results indicate that fusing the last-recorded AIS data with environmental data enables an initial estimate of the final resting position of the sunken hull. In addition, Virtual Probability Circles (VPCs) are constructed around the estimated position to represent uncertainty and to delineate a practical search area. The model was applied to the Verity shipwreck case in the North Sea, yielding an estimated wreck position at 54.0254°N, 7.6446°E. The computed total probable error was 229 m, corresponding to 50% and 95% probability circles with radii of 229 m and 458 m, respectively. These numerical results demonstrate the model's practical capability for initial localization of sunken vessels and provide a decision-support tool for prioritizing search areas in maritime Search and Rescue (SAR) operations.

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1. Introduction

Maritime transport today constitutes a major component of global trade, with more than eighty percent of international commerce carried out by ships (Sirimanne, 2019). However, the increasing demand for waterborne transportation and the growing traffic in coastal zones and ports have elevated the likelihood of accidents such as collisions and vessel sinkings (Liu et al., 2021). In such circumstances, Search and Rescue (SAR) operations become critically important, where rapid response is the primary determinant of success (Wang et al., 2021). The central challenge in SAR operations is to delimit the potential area where a vessel may be located after an accident. Environmental factors such as currents, wind, and meteorological conditions can drastically alter the drift trajectory of a vessel, complicating accurate localization of the wreck (Röhrs et al., 2012). Although the Automatic Identification System (AIS) continuously transmits vessel positions to monitoring systems, in cases of signal loss or critical emergencies only the last recorded position is available. This last known position is then treated as the starting point for SAR planning. Under these conditions, modeling the vessel's behavior under environmental forcing by combining positional data and fluid dynamics can improve estimates of the probable final location of a sunken ship.

A variety of studies have been conducted on ship trajectory prediction, maritime safety, and the physical modeling of floating bodies. Some research, such as (Li et al., 2024) and (Jia et al., 2023), has focused on applying machine learning algorithms to AIS trajectory data for route prediction. Other studies, including (Wagner et al., 2022) and (Xiang et al., 2019), have investigated computational fluid dynamics (CFD) models to analyze the influence of wind and currents on drifting objects. These findings suggest that integrating environmental data with physical models can play a key role in improving the accuracy of estimating the final resting place of sunken vessels.

Previous studies have mainly focused on either AIS-based trajectory prediction under normal navigation conditions, CFD-based drift simulation of floating objects, or probabilistic SAR planning. AIS-based approaches are effective for normal route prediction but have limited applicability in accident scenarios, while CFD-based studies usually focus on the physical behavior of floating or drifting objects without integration with real AIS information. In addition, probabilistic SAR models are useful for representing uncertainty and prioritizing search areas, but they generally lack physical simulation of post-accident vessel drift. Therefore, a research gap remains in developing a unified framework that combines last-recorded AIS information, environmental data, and vessel physical characteristics for post-accident localization of sunken vessels.

In this study, last-recorded AIS information is integrated with environmental data and a simplified CFD-based model to simulate the post-accident movement of a sunken vessel and to compute its probable resting position. Environmental inputs, including wind and bathymetry, together with vessel physical characteristics, are used to better reconstruct real-world accident conditions. The main contribution of this research is to provide a multidimensional framework for estimating the probable location of sunken vessels when positioning systems fail, thereby offering a supporting tool for prioritizing search areas in SAR operations.

The remainder of this paper is structured as follows: Section 2 reviews related work. Section 3 outlines the theoretical foundations and governing equations of the proposed approach. Section 4 describes the research methodology and datasets employed. Section 5 presents the implementation process and case study. Section 6 presents the results. Section 7 discusses the findings. Finally, Section 8 concludes the paper and provides recommendations for future work.

2. Literature Review

The first stream of related research concerns AIS-based ship trajectory prediction. Numerous studies have used AIS data to predict ship trajectories and support maritime navigation safety. For instance, (Li et al., 2024) developed a deep learning model based on Long Short-Term Memory (LSTM) for trajectory prediction using machine learning algorithms. Similarly, (Jia et al., 2023) applied deep learning architectures such as Bidirectional Long Short-Term Memory (BiLSTM) to capture temporal dependencies in vessel trajectory data and thereby improve prediction accuracy. (Bi et al., 2024) reviewed artificial-intelligence-based ship trajectory prediction methods using historical AIS data, including regression models, artificial neural networks, Kalman filtering, random forests, LSTM, Gated Recurrent Unit (GRU), and Sequence-to-Sequence (Seq2seq) models, and highlighted the strong potential of deep learning methods in intelligent maritime traffic systems. The integration of these approaches with optimization algorithms and attention mechanisms has further enhanced predictive performance. However, these models are primarily designed for normal navigation scenarios, as they rely on historical motion data, and therefore have limited applicability in critical conditions such as accidents, loss of propulsion, AIS signal loss, or vessel sinkings, where similar training data are scarce.

On the other hand, several studies have investigated physical modeling and CFD to analyze the behavior of floating or drifting bodies under environmental forcing. (Röhrs et al., 2012) evaluated the effects of surface waves on ocean currents and surface-drifter trajectories using in situ observations, showing that wave-induced Stokes drift can significantly improve the predictability of drift trajectories. (Wagner et al., 2022) examined the relative importance of water currents and wind in determining the drift of floating objects, while (Xiang et al., 2019) studied the dynamics of a freely falling horizontal cylinder entering the water. These works demonstrate that environmental forces such as currents, wind, and waves play a decisive role in controlling object drift and final displacement. They provide valuable insights into the physical mechanisms of object motion under environmental forcing. However, they generally do not integrate such physical modeling with real AIS information or last-recorded vessel data within a unified framework for post-accident localization.

Another body of research has focused on the optimization of SAR operations. The International Aeronautical and Maritime Search and Rescue (IAMSAR) Manual, Volume II (IMO & ICAO, 2019), provides standard guidance for SAR search planning and evaluation, including distress incident location estimation, survivor motion assessment, total probable position error, and search planning factors. (Otote et al., 2019) introduced indices such as Probability of Containment (POC), Probability of Detection (POD), and Probability of Success (POS) as key metrics for evaluating and designing search areas. Algorithms such as Monte Carlo simulations, Convex Hull methods, and GIS-based models have been employed to identify regions with the highest likelihood of target presence. In another study, (Wang et al., 2021) proposed an evaluation model of maritime SAR effectiveness using the concept of a Virtual Probability Circle (VPC), which represents a circular region centered at the incident location describing the probability distribution of vessel appearance. A systematic review of maritime transportation safety management also showed that recent studies have increasingly addressed maritime safety and emergency management through risk assessment, emergency resource optimization, resilience analysis, simulation, and data-driven methods (Xu et al., 2023). Nevertheless, although these probabilistic and GIS-based approaches are useful for representing uncertainty and prioritizing search areas, they generally lack a physical simulation of post-accident vessel drift under environmental forcing.

In summary, previous studies have generally addressed three related but separate problems: AIS-based trajectory prediction under normal navigation conditions, physical or CFD-based drift modeling of floating and drifting objects, and probabilistic or GIS-based SAR search-area planning. AIS-based models can achieve high predictive performance in normal navigation but are less reliable in emergency scenarios. Physical and CFD-based studies can represent environmental forcing and object motion, but they are generally not integrated with real AIS information or last-recorded vessel data. Probabilistic and GIS-based SAR approaches are useful for representing uncertainty and prioritizing search areas, but they usually lack a physical simulation of post-accident drift. Therefore, a research gap remains in developing a unified framework that combines last-recorded AIS information, environmental data, and simplified CFD-based modeling for post-accident localization of sunken vessels. The present study addresses this gap by integrating positional, environmental, and physical information to provide a physically grounded estimate of the probable wreck location and to support maritime SAR planning.

3. Theoretical Foundations

The modeling of the motion of sunken vessels in this study is based on the fundamental laws of fluid mechanics (Pritchard and Mitchell, 2015). The governing equations employed are summarized as follows.

3.1. Gravity Force

This force arises from the total mass of the vessel, acts downward, and is used in calculating the net vertical forces acting on the vessel. Equation 1 expresses this relation:

$$F_g = m.g = \rho_{ship}.Vg \tag{1}$$

Where:

F_g = gravitational force,

m = vessel mass,

g = gravitational acceleration,

ρ_{ship} = vessel density,

V = vessel volume.

3.2. Buoyancy Force

This force results from the displaced fluid, acts opposite to gravity, and is used in evaluating the net vertical force:

$$F_b = \rho_{water}.V.g \tag{2}$$

Where:

F_b = buoyancy force,

ρ_{water} = water density,

V = submerged volume,

g = gravitational acceleration.

3.3. Net Vertical Force

The difference between buoyancy and gravity determines the sinking acceleration:

$$F_z = F_b - F_g \tag{3}$$

Where:

F_z = net vertical force,

F_b = buoyancy force,

F_g = gravitational force.

3.4. Newton's Second Law for a Control Volume

This relation describes the balance between body and surface forces acting on a control volume, used to compute net forces in the horizontal direction:

$$\vec{F} = \overrightarrow{F_S} + \overrightarrow{F_B} = \frac{\partial}{\partial t}\int_{CV} u\rho dV + \sum_{CS} u\rho\vec{V}.\vec{A} \tag{4}$$

Where:

$\vec{F}$ = resultant force,

$\overrightarrow{F_S}$ = surface forces,

$\overrightarrow{F_B}$ = body force (gravity),

CV = Control Volume,

u = velocity in considered direction,

ρ = density,

dV = differential volume element within the control volume,

CS = Control Surface,

$\vec{V}$ = relative velocity (wave–ship difference),

$\vec{A}$ = effective surface area.

3.5. Horizontal Forces under Steady Flow

The horizontal drift due to wave impact on the effective surface is modeled as:

$$\overrightarrow{F_S} = u\rho V^2 A \tag{5}$$

Where:

u = velocity in considered direction,

ρ = density,

V = relative velocity (wave–ship difference),

A = effective cross-sectional area.

3.6. Newton's Second Law

For computing accelerations in both vertical and horizontal directions:

$$F = m.a \tag{6}$$

Where:

m = vessel mass,

a = acceleration (a_x, a_y , a_z).

3.7. Kinematic Relations

By integrating acceleration over time, velocity is obtained, and by integrating velocity, displacement is derived:

$$\int a(t)dt = V(t) \tag{7}$$

$$\int V(t)dt = X(t) \tag{8}$$

3.8. Total Probable Error (TPE)

To account for positional uncertainty, the total error is computed as:

$$E = \sqrt{X^2 + D_e^2 + Y^2} \tag{9}$$

Where:

E = total probable error,

X = initial position error,

D_e = drift-estimation error,

Y = navigation error of search unit.

Together, these relations form the theoretical framework of the model. The subsequent section presents the proposed solution approach built upon this framework.

4. Methodology

The aim of this research is to develop a model for estimating the final resting position of sunken vessels using environmental data and last-recorded AIS information. The overall workflow is illustrated in Figure 1.

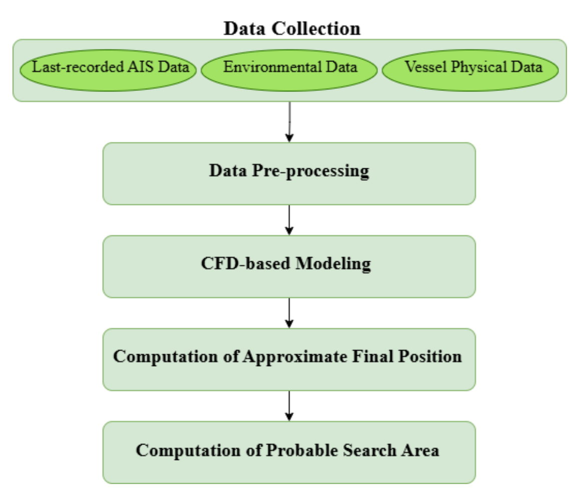

Figure 1. Flowchart of the research procedure.

4.1. Data Collection

AIS information of the distressed vessel, including its last recorded position, speed, and heading, was gathered as the initial condition for the proposed model. Environmental data, including wind direction, wind speed, and local bathymetric depth, were extracted from climatic databases and bathymetric maps. In addition, the physical characteristics of the vessel (length, beam, draft, and mass) were obtained from maritime technical databases. These vessel parameters were required to estimate the forces acting on the vessel and to calculate its vertical and horizontal displacement. Information regarding the onboard cargo and the number of crew at the time of the accident was derived from official accident reports for use in the model.

4.2. Data Pre-processing

AIS records were checked to identify the last valid AIS information before sinking. The last valid AIS position, speed, and heading before sinking were selected as the initial conditions. Environmental data were temporally synchronized with the same period, and all inputs were mapped to a common spatiotemporal reference (the last recorded AIS position).

4.3. CFD-based Modeling

To simulate vessel dynamics after the accident, a simplified CFD framework was applied. The vessel was represented as a control volume subject to the principal forces of gravity, buoyancy, and wave-induced loads, with its motion initialized using the AIS-derived initial velocity. For simplification, wind was assumed to be a proxy for wave forcing. In the vertical direction, the difference between gravity and buoyancy generated downward acceleration leading to sinking (Fig. 2).

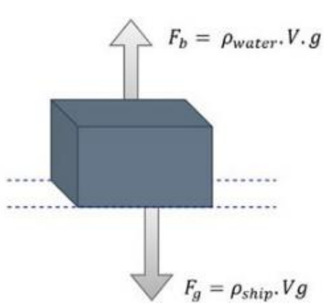

Figure 2. Forces acting in the vertical direction.

In the horizontal plane, wave-induced forces on the effective cross-sectional area and the initial velocity derived from the last-recorded AIS speed and heading were considered (Fig. 3).

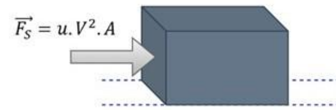

Figure 3. Resultant forces acting in the horizontal direction.

Based on these inputs, the governing equations of the simplified CFD framework were solved using Newton's second law to compute vertical and horizontal accelerations.

4.4. Computation of Approximate Final Position

By integrating the equations of motion, horizontal displacement was estimated, and the final seabed position of the vessel was calculated relative to the last-recorded AIS position.

4.5. Computation of Probable Search Area

Following the IAMSAR Manual, Volume II (IMO & ICAO, 2019), the total probable error (E) was obtained by combining initial position error (X), drift-estimation error (D_e), and navigation error of the search unit (Y). The 50% probability circle (radius = E) and the 95% probability circle (radius = 2E) were then drawn around the estimated location to delineate search zones. The outputs of this step include the estimated wreck datum and the corresponding probability-based search areas.

5. Implementation and Case Study

5.1. Case Study Description

In this implementation, the sinking of the cargo ship Verity (IMO 9229178) was selected as the case study. The vessel collided with the bulk carrier Polesie and sank on 24 October 2023 in the North Sea near the island of Heligoland, Germany.

5.2. Input Data for the Verity Shipwreck

The model inputs were categorized into three groups:

• Last-recorded AIS data: last recorded position at 54°01.50′ N, 7°38.40′ E, with speed 4 kn and heading 279° (west–northwest);

• Environmental data: wind from east-southeast (112.5°) with magnitude 12 m/s and seabed depth of 37 m (Bathymetric Maps);

• Physical vessel data: length 91.25 m, beam 14.01 m, and draft 5.2 m (from maritime databases).

5.3. Numerical Implementation

For simplification, wind velocity was assumed to act as a proxy for wave-induced forcing and was considered constant during the simulation period. The governing equations of the simplified CFD framework were implemented in Python. The last-recorded AIS speed and heading were used to initialize the vessel's initial horizontal motion, while the vertical and horizontal accelerations were computed from the corresponding force balances based on

Newton's second law. The resulting accelerations were then integrated to estimate velocity, displacement, and the final seabed position of the vessel.

5.4. Model Outputs

In this case study, the outputs of the model included the predicted seabed coordinates of the wreck and the probability-based search areas. The final estimated position was 54.0254°N, 7.6446°E, which served as the datum for the probability circles. For uncertainty quantification, the following values were assumed: X = 50 m, D_e = 200 m, and Y = 100 m. The total probable error was therefore calculated as E = 229.12 m. Consequently, a 50% probability circle with radius E and a 95% probability circle with radius 2E were plotted around the datum to indicate the most probable wreck location (Fig. 4).

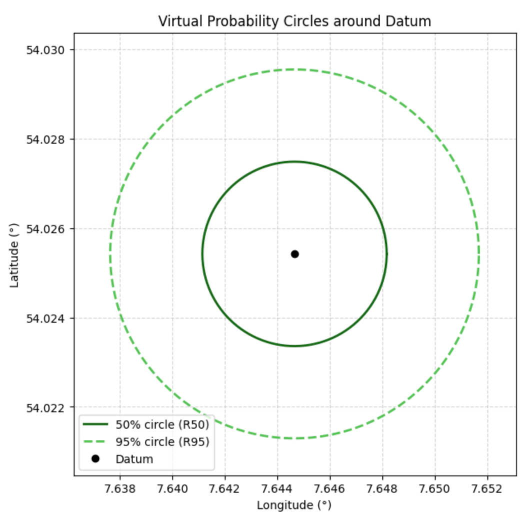

Figure 4. Probability circles of vessel presence at the 50% and 95% probability levels

According to the guidelines of the IAMSAR Manual, Volume II (IMO & ICAO, 2019), Figure 5 illustrates the probability map of each cell in a grid constructed over the standard initial hypothetical distribution around the sunken vessel's position. Assuming a circular normal distribution, the probability of the vessel being located within a circle of radius E is 50%. The remaining portion in the corners of the central cell accounts for an additional 7.91%, bringing the total probability of the central cell to 57.91%. The cells directly adjacent (top, bottom, left, and right) each have a probability of 9.08%, while the corner cells (northeast, northwest, southeast, and southwest) each have a probability of 1.42%.

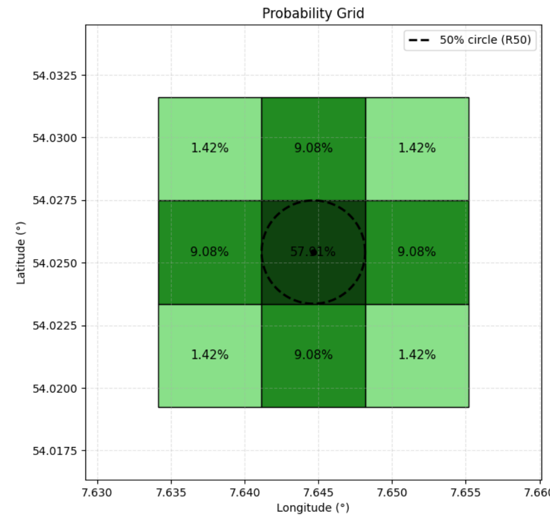

Figure 5. Probability map of the standard hypothetical distribution around the estimated wreck position.

6. Results

The simulation results demonstrated that when environmental data, including wind and waves, were incorporated, the final resting position of the vessel significantly deviated from its last recorded AIS location. The predicted horizontal displacement occurred in a west–northwest direction, which aligns with the observed east–southeast wind forcing. This indicates that the model successfully captured the influence of environmental forces.

If environmental data had not been considered, the final vessel location would have remained at the last AIS position, with no drift applied. Therefore, it can be concluded that environmental data play a decisive role in changing the estimated wreck location and providing a more physically realistic drift-based estimate.

Overall, the proposed model, despite its simplified computational structure, produced reasonable results consistent with the physical realities of the accident. Nevertheless, the absence of more complex parameters—such as wave spectra, temporal variability of currents, and turbulence—represents a major limitation of the current framework and should be addressed in future work.

Quantitatively, the modeling framework yielded a predicted wreck position at 54.0254°N and 7.6446°E. The estimated west–northwest offset corresponded well with the prevailing east–southeast wind conditions during the incident, confirming that the simplified CFD-based approach successfully captured the dominant environmental forcing. Incorporating wind and bathymetric data enabled the calculation of a total probable error of 229 m and the delineation of 50% and 95% probability circles with radii of 229 m and 458 m, respectively. These numerical results indicate that coupling last-recorded AIS information with a CFD-based physical representation provides a more physically grounded wreck-location estimate and supports its practical application in maritime SAR operations.

7. Discussion

The results demonstrate that incorporating environmental parameters such as wind and bathymetry changes the estimated final wreck position compared with estimations based solely on the last-recorded AIS position. Due to the unavailability of the exact geographic coordinates of the recovered Verity wreck, the absolute localization error could not be calculated in this study. Nevertheless, the west–northwest offset observed in the simulation is consistent with the prevailing east–southeast wind direction during the incident, indicating that the simplified CFD-based formulation produced a physically reasonable prediction of the vessel's drift behavior.

The proposed framework addresses a non-normal post-accident scenario in which normal AIS-based trajectory prediction is no longer applicable after the last valid AIS record. However, the present study focuses on sinking conditions that can be approximated using a simplified CFD-based formulation. More complex non-normal situations, such as severe storms, highly time-varying currents, progressive flooding, structural damage, and loss of stability, may strongly affect the vessel motion and are outside the scope of the current simplified model. These scenarios require more detailed hydrodynamic and flooding-mechanism models and should be investigated in future studies.

Despite these encouraging outcomes, several simplifying assumptions limit the model's precision. Wind velocity was adopted as a proxy for wave forcing, temporally varying surface currents were not explicitly represented, and an idealized hull geometry was used. These simplifications reduce the physical realism of the model but enable rapid computation, making the approach suitable for first-order SAR support when high-resolution environmental data are unavailable. From an operational perspective, deriving the total probable error (E = 229 m) and defining 50% and 95% probability circles provide a transparent and quantitative framework for delineating priority search zones. Future research should focus on integrating dynamic ocean current data, modeling time-dependent drag coefficients, and coupling the CFD-based outputs with standardized SAR probability indices to further improve localization reliability.

Compared with conventional VPC approaches, such as the method discussed in (Wang et al., 2021), which primarily rely on geometric probability distributions derived from AIS data, the present CFD–AIS fusion framework provides a more physically grounded estimation of wreck position. While VPC-based methods define search areas based only on statistical uncertainty, the proposed approach explicitly incorporates environmental dynamics—including wind and bathymetry—to simulate post-accident drift behavior. This integration enhances spatial realism and helps better constrain the probable search area, thereby offering an operational advantage for maritime SAR planning.

8. Conclusion

This study presented a fluid-dynamics–based approach for estimating the probable location of a sunken vessel. Last-recorded AIS information, together with environmental and vessel physical information, was employed as model inputs to reconstruct the accident conditions. Simulation outcomes showed that integrating spatial data with a simplified fluid-dynamics model can provide a first-order representation of vessel drift and its final position after sinking. Furthermore, the use of VPCs around the estimated wreck position provided a practical tool for visualizing uncertainty and defining search areas with specific probabilities.

However, several limitations remain. The model relies on simplified assumptions, including idealized hull geometry, steady and uniform flow, the use of wind speed as a proxy for wave forcing, and the omission of complex surface currents.

For future research, it is recommended that the model be extended to incorporate higher-resolution environmental data, including ocean currents and dynamic atmospheric conditions, as well as more complete AIS information. Future studies should also examine more complex non-normal sinking scenarios, including severe weather, progressive flooding, structural damage, and loss of vessel stability, using more advanced hydrodynamic and damage-flooding models. Additionally, integrating time-dependent drag coefficients and standardized SAR probability indices could further improve predictive accuracy. The development of advanced machine-learning models combined with physical modeling may also enhance the reliability of wreck-location estimation.

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