Transforming Maritime Safety: Data-driven Applications for the Real-Time Detection and Mitigation of Maritime Incidents

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ABSTRACT

Critical maritime events have significant social, environmental and economic consequences. This paper presents a suite of applications that utilize big data streams to early forecast and automate mitigation procedures of critical maritime events effectively. Key innovations include an automated collision avoidance system using real-time AIS data and a hazardous weather rerouting solution that integrates fleet intelligence based on historical vessel mobility patterns with weather forecasts. These novel solutions aim to enhance the efficiency of vessel traffic monitoring systems, support autonomous vessel integration in the global fleet, and minimize global supply chain disruptions caused by maritime incidents.

1 INTRODUCTION

Maritime safety is crucial for the global shipping industry, particularly as international trade continues to expand, reaching 12,292 million tons in 2023. This growth, driven by a 2.7% global economic expansion, is threatened by persistent uncertainties such as extreme weather events and accidents, which disrupt maritime supply chains and increase market volatility [15]. Increasingly severe weather conditions due to climate change pose significant risks to maritime operations, especially for critical commodity trade routes. In 2023, 2,510 accidents were recorded, influenced by high traffic density and adverse weather conditions [3, 23] and vastly attributed to human error [7].

Kpler leverages a network of 6,600+ AIS receivers to collect information from vessels equipped with AIS transponders. Processing over 10^9 AIS messages daily, the MarineTraffic Service by Kpler offers real-time vessel tracking globally through its website and apps [11]. The widespread coverage and volume of AIS messages that Kpler has archived and is able to fuse and process in real time has the potential to enable big-data driven solutions to improve maritime operations [2] and support the development of new innovative products and services focusing on compliance, fleet management and route forecasting, effectively generating high added value for Kpler customers.

In the context of this work, we present innovative solutions for the early forecasting and the automation of the decision-making process for resolving critical situations at sea that leverage big data processing pipelines and distributed computing frameworks. Specifically, we demonstrate an automated vessel collision avoidance system that leverages the real-time AIS feed of the MarineTraffic Service to generate compliant and navigable collision avoidance routes for forecasted vessel collision events. Additionally, we utilize collective fleet intelligence by fusing weather data and forecasts with historical mobility information to develop a hazardous weather rerouting solution for manned and autonomous vessels.

2 SYSTEM ARCHITECTURE

In previous work, we presented a highly scalable digital twin for maritime situational awareness integrated with a distributed actor model-based system architecture [8, 9]. This system has been migrated from Akka [10] to Apache Pekko and deployed on Amazon Web Services (AWS). Real-time data processing is performed through the ingestion of AIS data streams from Apache Kafka [12] from MarineTraffic (Kpler), satellite services, and other providers. The data stream is partitioned to assign each vessel, identified by its Maritime Mobile Service Identity (MMSI), to a unique actor. Furthermore, the system employs event detection and prediction models, customized for the individual vessels (actors) and spatial actor classes, that facilitate vessel-specific event forecasts. Actor states are persistently stored in a Redis database [13] via a writer actor, ensuring efficient data access and integration. A Middleware API bridges the backend and user interface, enabling the interactive visualization of forecasts and event monitoring. The Collision Avoidance and Hazardous Weather Rerouting applications, are integrated as independent services on the middleware level utilizing the data ingestion components and the actor outputs from the Pekko Processing Engine.

3 AUTOMATED VESSEL COLLISION DETECTION AND AVOIDANCE SYSTEM

Current research in maritime collision mitigation focuses on the evaluation and planning of vessel route-based collision risk assessment metrics [14, 21]. The need for the compliant and collaborative resolution of vessel-to-vessel interactions is also highlighted [1, 7]. In previous work [8], we have proposed a highly scalable systematic approach for forecasting probable vessel collision events based on the actor model [9]. Leveraging the streaming outputs of vessel collision events, a vessel collision avoidance solution is adapted from [18], which is based on the Frenét Frame Optimal Trajectory Generation algorithm presented in [22]. The algorithm provides an optimal control-based approach to motion planning, seamlessly integrating path

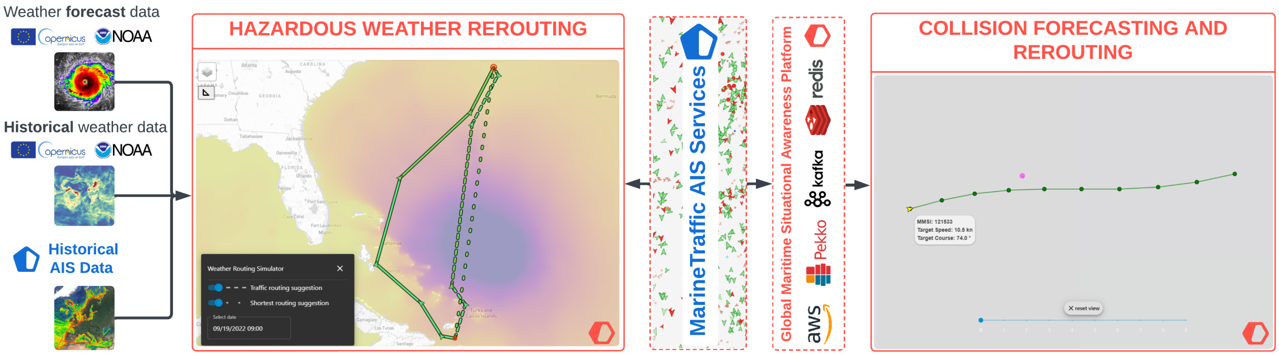

Figure 1: Visualization of the key components for critical situation detection and management at sea.

planning with path tracking to address dynamic routing challenges. Consequently, it is a robust solution for both manned and unmanned vessel routing, offering navigable paths that resolve collision avoidance problems in dynamic scenarios.

In the context of the maritime domain, vessel-to-vessel interactions are regulated by the COLREGs (International Regulations for Preventing Collisions at Sea) [16]. Thus, it is essential to integrate the COLREG framework within the Frenét Frame Optimal Trajectory Generation algorithm so that generated paths are compliant and navigable by vessels according to the International Maritime Organization (IMO) [7]. Specifically, the integration of COLREG involves modeling and incorporating vessel safety zones, detected based on the forecasted vessel positions vessel-to-vessel interaction cases, and filtering out non-COLREG compliant trajectories during the frenét path generation process.

Figure 2 presents an example output of the collision avoidance algorithm given two vessels that are forecasted to collide head on at the detected collision position. First, the collision detection output is ingested from the Redis database of the Pekko processing engine. The input includes the information on the collision detection event and vessel specific dynamic and static information as it is ingested from the Pekko vessel actors. Subsequently, the type of COLREG case is identified according to the vessel speeds and courses. Finally, compliant trajectories are identified in the possible paths generated by the path planning algorithm. The resulting output includes the longitudinal and longitudinal positions, speed and course as a function of time for the respective optimal collision avoidance path. In cases where the COLREG interaction type (e.g. crossing or overtaking) indicates that no rerouting action is required by the second vessel, a collision avoidance path will not be generated for that vessel.

4 HAZARDOUS WEATHER VESSEL REROUTING SYSTEM

4.1 Solution Space Generation and Weather Forecast Ingestion

To address the hazardous weather routing problem, the entire global sea area must be considered during the route planning process. To achieve this, we build a comprehensive spatiotemporal solution space leveraging Uber's hexagonal H3 grid [20], a robust and widely adopted methodology previously applied in the *Patterns of Life* approach [19]. The H3 grid features six uniform neighboring cells per hexagon and multi-resolution subdivision

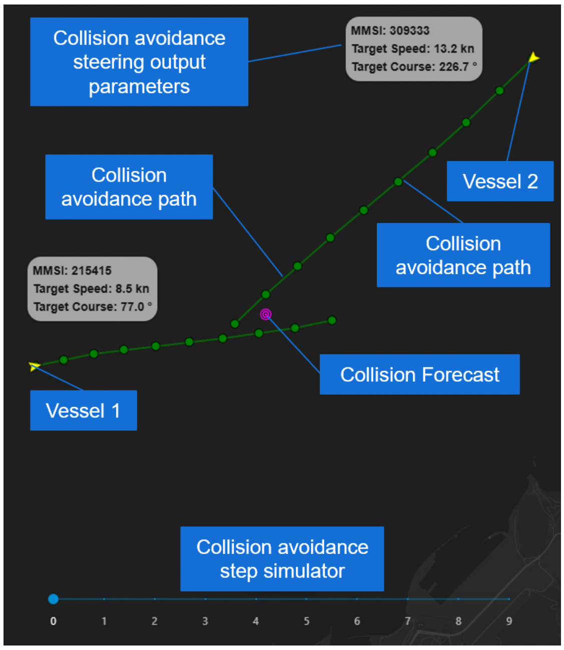

Figure 2: Vessel collision avoidance user interface.

capabilities and enables the systematic exploration of optimal and feasible paths.

In order to incorporate weather forecasts into the hazardous weather rerouting solution, we utilize the open-access NOAA Global Forecast System (GFS) to update the wind forecast layer [6], the Copernicus Marine Service Global Ocean Waves Analysis and Forecast product for high-resolution sea wave data [5] and the Copernicus Marine Service Global Ocean Physics Analysis and Forecast supplying sea current data [4]. However, these products vary in spatial and temporal resolution and recording intervals. To integrate these datasets efficiently, an ETL (Extract, Transform, Load) pipeline is implemented using Apache Airflow. Scheduled to run daily, the pipeline automates batch processing tasks to update and fuse weather forecasts with the H3 grid.

4.2 Routing Graph Creation

Rather than explicitly modeling weather events as obstacles to be avoided, our approach processes and scales weather features that inherently describe weather conditions. First, vessel mobility patterns corresponding to specific weather feature values, as derived from historical AIS (MarineTraffic (Kpler) platform) and weather datasets from 2022 (Copernicus, NOAA). These are mapped across the H3 grid, defining common vessel mobility patterns as functions of prevailing weather conditions at sea. Finally, vessel traffic graphs are constructed for each distinct weather category and serve as the foundation for generating safe and efficient rerouting paths under varying weather conditions.

4.3 Vessel Rerouting

The implemented routing solution uses the A* algorithm for route definition, where weather forecasts and vessel traffic patterns are scaled and introduced as edge weights. In order to extract a navigable path for the vessels, following steady course and speed, the Douglas-Peucker algorithm is leveraged to simplify the graph-based route output and extract a series of waypoints. As a post-processing step, additional operational attributes are assigned to each point of the resulting path, including speed as derived for the corresponding live AIS messages and course with respect to the proposed path. The estimated time of arrival (ETA) at each waypoint is iteratively calculated from the origin to the destination.

Users are provided with multiple routing options to compare and assess alternative scenarios for vessel navigation, facilitating informed and explainable decision-making in maritime operations (Figure 3). The first option, the *Weather-Optimized Route*, is generated using a modified A* algorithm that minimizes weather-related penalties, ensuring safer and more efficient navigation under adverse conditions. The second option, the *Traffic-Optimized Route*, incorporates traffic-based weights, prioritizing routes commonly followed by vessels. Lastly, the *Shortest Route* calculates the shortest navigable route to the destination, providing a baseline for comparison against the optimized alternatives.

5 DEMONSTRATION PLAN

The interactive demonstration for users aims to showcase the main functions of the two applications based on specific use cases. A demo video with guided interactive use case scenarios using both historical and streaming AIS data is available **here**.

The demo for the Automated Vessel Collision Detection and Avoidance System is based on live streaming AIS data from the MarineTraffic (Kpler) Platform. Users detect and visualize probable collision event forecasts. Subsequently, users can select the specific events and view the route(s) provided by the collision avoidance system. Also users are able to simulate the progression of the vessel(s) along the collision avoidance paths and visualize key navigation information such as the required vessel speed and course.

The demo of the Hazardous Weather Vessel Rerouting System is based on the Hurricane Fiona (formed in September 2022) [17] and is deployed at a sea area of 8,017,052.30 km^2, fusing 240,318,693 AIS positional records with weather data. Users can visualize and explore various weather forecast layers derived from the Copernicus wave and current products. Additionally, the system enables the visualization of rerouting plans for a vessel of interest within the affected sea area of Hurricane Fiona. The system also displays the traffic-optimized route and shortest route to the destination, allowing users to make informed route planning decisions. The system includes a departure time simulation feature, enabling users to explore alternative departure times for their vessel and minimize the deviation from the shortest route caused by weather conditions, thereby optimizing maritime operations and reducing costs.

6 CONCLUSIONS

This paper introduces a suite of applications that harness big maritime data for the detection and mitigation of critical events across large sea areas. These applications utilize the AIS streaming service provided by MarineTraffic (Kpler) and weather forecast products from NOAA and Copernicus and components from a distributed computing framework based on Pekko. The primary objective of these applications is to enhance the scalability and efficiency of current maritime operations and vessel traffic monitoring systems, enabling more effective planning, monitoring and response to critical maritime events. Additionally, they aim to facilitate the integration of autonomous vessels into the global maritime traffic framework. Future work will focus on enhancing the performance and usability of these applications by incorporating key vessel operational parameters and strategies.

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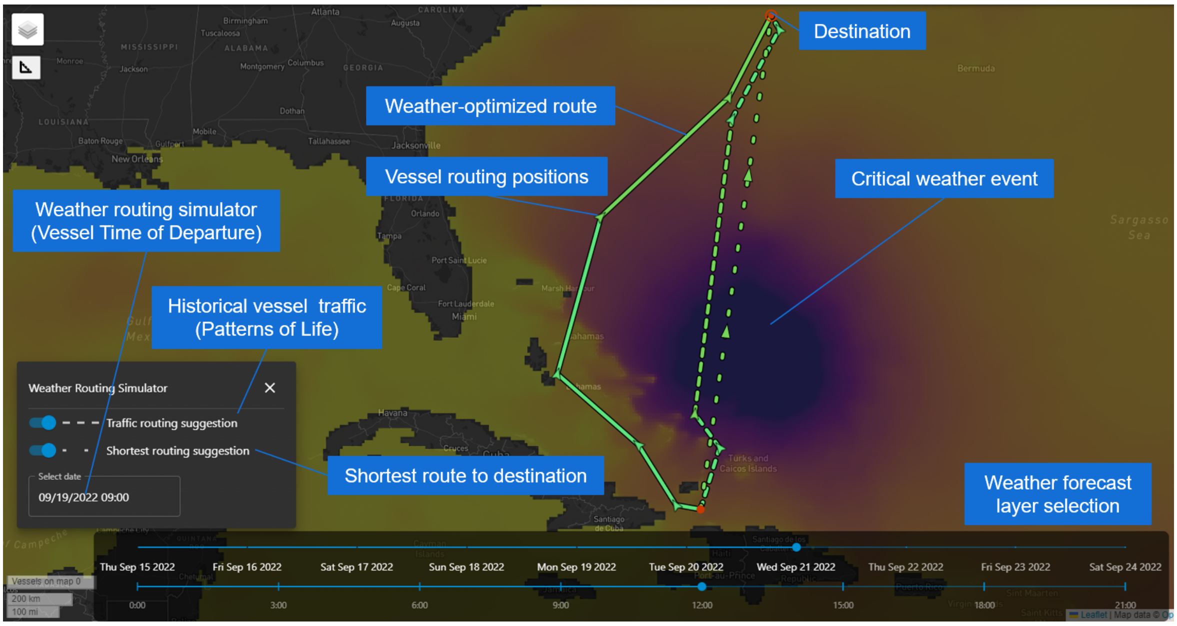

Figure 3: Hazardous weather rerouting user interface.

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