ISSN: 2093-5374 / E-ISSN: 2093-5382

Designing Edge Computing Solutions for Real-Time Vessel Tracking and Collision Avoidance

Arasu Sathiyamurthy[1*], and S. Gajendran Subba Naidu[2]

[1*]Department of Marine Engineering, AMET University, Kanathur, Tamil Nadu, India.
arasu@ametuniv.ac.in, https://orcid.org/0009-0005-9561-2513

[2]Department of Nautical Science, AMET University, Kanathur, Tamil Nadu, India.
gajendran@ametuniv.ac.in, https://orcid.org/0009-0003-9938-463X

Received: April 04, 2025; Revised: May 21, 2025; Accepted: June 10, 2025; Published: June 30, 2025

Abstract

The demand for vessel real-time tracking and automated collision avoidance technologies has grown in unison with the development of new edge data processing systems that allow for extraordinary volumes of data to be processed at the collection point. This work focuses on designing and implementing an edge computing framework for real-time vessel tracking, emphasizing improving marine safety and operational efficiency. The proposed system architecture provides local processing capabilities for making high-priority autonomous collision avoidance decisions, thus achieving greater efficiency in bandwidth and latency usage. Its design includes advanced sensors, machine learning predictive analytics, and cloud-agnostic edge data processing units. The proposed approach facilitates advanced real-time monitoring of vessels for automatic alerting of onboard systems and control centers, movement patterns, and collision risk assessment. The study also addresses scalability, data security, and network reliability issues, proposing solutions with robust fault-tolerant communication protocols, adaptive data processing, and strong coordination between the edge and cloud. The study demonstrates high maritime operational efficiency can be attained with edge computing by providing marker-based ship monitoring and collision avoidance systems that are scalable, reliable, and designed for low-latency response in dynamic environments.

Keywords: Edge Computing, Real-Time Vessel Tracking, Collision Avoidance, Maritime Safety, Predictive Analytics, Machine Learning, Edge Devices, Latency.

1 Introduction

Collision avoidance and vessel tracking represent key elements in marine safety, operational effectiveness, and ecological conservation (Geng, 2024). With a growing increase in worldwide maritime traffic, the supply of dependable, real-time surveillance systems is rising exponentially. Traditional systems, particularly cloud-based solutions, suffer from high latency and bandwidth limitations and need constant networking capabilities despite having the potential to meet some functionalities (Ali et al., 2025). These systems struggle to provide reliable and rapid solutions within critical timeframes, such as during potential ship collisions and in ship and cargo traffic management scenarios. Facing these challenges has led to turn to edge computing. By bringing computation to the network's periphery, edge computing enables faster response times concerning at least the network's border. This is critical in marine applications, where timely action helps avert accidents or preserves

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 16, number: 2 (June), pp. 863-874. DOI: *10.58346/JOWUA.2025.I2.053*

*Corresponding author: Department of Marine Engineering, AMET University, Kanathur, Tamil Nadu, India.

vital resources such as cargo and personnel. With enabled edge devices featuring sensors and real-time analytics alongside machine learning models, vessel tracking devices can function autonomously without continuous cloud connections, enabling swift response even in remote or low-bandwidth settings (Yemunarane et al., 2024).

This paper will primarily focus on developing and implementing edge computing solutions for real-time collision avoidance and vessel tracking. The System Harnesses local computational resources to enhance tracking of vessel movements, predicting movement patterns, collision risk assessment, outperforming traditional cloud-based solutions (Bamal & Singh, 2024). The application of advanced sensor technologies, machine learning, and robust communication protocols can improve safety and efficiency of marine operations. This article addresses these issues and explains how they can function together. Moreover, these frameworks provide solutions for the durable and secure edge computing architectures that resolve the system deployment issues of data privacy, network dependability, and scalability (Rahim, 2024). This is an effort to demonstrate the potential of edge computing for transforming vessel tracking and collision avoidance in the marine industry. This integration will enhance operational and safety improvements in a connected and complex world (Nayak & Raghatate, 2024).

2 Background Information

The maritime industry is a component of international trade since approximately 90% of all goods are transported by sea. Instead, increased sea and land traffic is leading to vessels causing some of the most essential safety concerns. According to the International Maritime Organization (IMO), the principal causes for collisions at sea are oversight, navigational mistakes, and insufficient up-to-date information (Ristono & Budi, 2025). This has led mariners to search for new equipment that assists in tracking and preventing collisions between vessels. Radar and the Automatic Identification System (AIS) are two systems that rely on satellites for navigation and communication. These systems, capable of relaying real-time information about the location of vessels, commonly utilize cloud-based servers for data management. Unlike these systems, however, this method is inherently flawed because of the need for uninterrupted contact, limited bandwidth, and lagging networks. For example, cloud-based systems facing unreliable internet connections in remote areas might delay critical operational decisions (Lemeon et al., 2023).

The emergence of edge computing techniques facilitate overcoming the challenges mentioned above. Edge computing routes local traffic on "the edge" of the network, meaning that data is processed as close to its source as possible, significantly reducing latency and reliance on cloud resources (Reddy & Mohan, 2024). In collision avoidance systems, the ability to make rapid decisions is crucial, and in those situations, every second matters. Edge devices can process data from tracking systems and sensors, enabling them to transmit crucial real-time data to onboard navigation systems expeditiously. Modern warships have many sensors, such as GPS, radar, sonar, and LIDAR, that collect data about the surrounding world. These advanced sensors also serve as edge computing devices that enable monitoring and collision avoidance. Together with enhanced situational awareness, these sensors track the height, movement, and speed of other vessels in the area and identify potential hazards. Data Processing at the Edge: Utilizing edge computing techniques allows data processing to occur on board or close to onboard devices, eliminating transmission delays to more central servers. This gives time-sensitive tasks, such as collision avoidance, faster response times and lower bandwidth consumption. Integrating Machine Learning with Predictive Analytics: Algorithms utilizing both historical and real-time data can predict traffic congestion, vessel traffic, and the probability of collision. By analyzing historical data, these algorithms can refine their forecasts and improve their accuracy over time. Autonomous Decision-Making: Edge computing's real-time data processing and predictive models enable vessels to perform automated collision avoidance. For example, a system may autonomously reduce speed or head in a new direction without any input from a command center staff situated miles away. In regions where mobile networks are unreliable or intermittent, edge computing solutions do tend to require strict communication protocols to ensure adequate data transmission reliability. Even with constrained bandwidth, these important protocols enable the processing and exchange of critical data. Despite the potential that edge computing holds for marine applications, some hurdles still need to be addressed. Some of these issues include ensuring system resilience in dynamic and unpredictable maritime settings, ensuring adequate data security and privacy, and creating scalable solutions adaptable to various types of vessels and scenarios. Furthermore, for edge computing to achieve broad adoption and interoperability, it needs to fit effortlessly into the existing marine infrastructure and systems. In this regard, new edge computing approaches can be developed to optimize maritime activities concerning operational efficiency and safety, particularly regarding real-time vessel monitoring and collision prevention. Maritime safety could be transformed by edge computing by reducing accident risk and reaction time, enabling timely autonomous decision-making at the edge of the network.

Key Contribution

- The paper's focus is on the design of an edge computing framework on an innovative algorithm that tracks vessels' movements and automatically avoids collisions in real-time without the need for a cloud infrastructure.
- In collision avoidance scenarios, which are highly dynamic collisions in the maritime context, the steamundersomics juniper services APP can make decisions and act with low latency. This is accomplished by the System having direct access to decision-making resources and offloading local data centers.
- The research synthesizes a diverse set of sensors such as GPS, radar, Sonar, lidar, and edge sensor devices to enable the collection of real-time comprehensive data concerning vessels' positions, movements, and surrounding hazards.
- The paper presents methods of ensuring reliability and fault tolerance to robust edge-cloud coordination. This includes designing communication protocols that allow seamless reliable data streaming from edge devices to remote control centers through harsh nautical conditions with limited or no connectivity.

3 Literature Review

The literature review consulted has claimed that the most recent developments in construing edge computing frameworks for practical maritime vessel tracking and collision avoidance have optimized computing latency, decision making, and bandwidth consumption. Zhou et al., (2019) proposed a cloud-edge model designed to assimilate data from vessel AI systems or AIS to enhance monitoring accuracy and minimize the time taken to predict collision risks. The proposed model aimed to accelerate computation by integrating edge and cloud computing, where edge computing enables processing at the source, while cloud computing requires data from multiple locations (Zhou et al., 2019). However, it could not function completely independently due to its reliance on cloud infrastructure. Wang et al. (2020) also advanced an edge computing model that integrates radar and sonar sensors to mitigate the transmission of large datasets to the cloud while addressing the need for prompt danger identification

(Wang et al., 2020). This study improved the efficiency of collision avoidance mechanisms, but came short of tackling the limitations smaller vessels face due to high infrastructure costs. In a bold step, Li et al., (2021) applied edge computing to GPS and radar data with the aim of enhancing real-time maritime security and safety operations. Goals such as lower requirements on cloud resources and faster response times for tasks such as collision avoidance were what this System's design aimed to achieve when dealing with big data streams locally. Nevertheless, it was only relevant to fixed conditions and largely ignored the complexities introduced by dynamic traffic flows (Li et al., 2021). Building upon this work, Zhang et al., (2021) added IoT sensors and machine learning models to an edge computing framework to automatically predict collisions and manage vessel traffic supervision (Zhang et al., 2021). While this approach intended to enhance the efficiency of real-time tracking and improve latency, it struggled with adapting to shifting conditions within the ocean. In their proposal, Chen et al., (2022) added machine learning algorithms into a cloud-edge semi-centralized system to improve decisions related to collision avoidance. This model targeted the System's predictive and adaptive features to enhance the speed of processing and decision-making accuracy in real time (Chen et al., 2022).

These models did highlight concerns regarding security and privacy of data from decentralized edge nodes, though implementing such systems on a large scale in a maritime setting could be problematic. In a decentralized framework suggested by Nguyen et al., vessels can perform collision risk evaluations autonomously using edge devices (2023), which do not require any cloud interaction (Nguyen et al., 2023). Despite the initial promise this approach showed, it posed issues with reliability, particularly concerning distant sea regions with intermittent connectivity. Yuan et al., (2023) studied the possible uses for edge computing in environments with weak communication infrastructures and low-latency situations. Their System was created to operate within collision avoidance bandwidth constraints so that collision avoidance decisions could be made promptly. However, some integration issues were noted when incorporating these technologies with legacy maritime systems (Yuan et al., 2023). As a final point, Patel et al., (2024) sought to minimize bandwidth usage by locally computing most data on edge devices and only sending essential updates. Although this approach improved decision-making speed and reduced communications bandwidth, the scope of vessels to which the model could be applied was limited which hindered its use for larger fleets or more diverse vessels (Patel et al., 2024). The literature suggests that edge computing can improve vessel tracking and collision avoidance systems through quicker local data processing, predictive analysis, and reducing latency. The potential benefits of edge computing for marine safety applications are significant but hindered by limited scalability, system integration, communication reliability in remote locations, and data security.

4 Proposed Model Architecture

The system architecture in Figure 1 describes marine vessels' collision avoidance and trajectory tracking, which are presented in the diagram. A control architecture receives multiple components' data streams, ensuring safe and accurate navigation of the marine vessel operating autonomously or with remote supervision. An operator can control or monitor the vessel remotely through the top left component named HMI (Human-Machine Interface). The operator can, therefore, actuate the ship's movements through voice input or take direct manual control and it will happen in real-time. This allows actions to be performed when human judgement or intervention is necessary. The lower left corner houses the Scenario block, which is the next component in the navigation chain. Actual or virtual waypoints, barriers, and other traffic within the waterway working area can be included or excluded. Along with the HMI, the Controller also receives data from this scenario. This component is known as the controller which is the systems brain. It parses data from the operational environment and the commands given by the operator, synthesizes them, and issues Vessel Commands that dictate the vessel's trajectory. The controller also now has the task of tracking the vessel's trajectory and adjusting in real-time to ensure there is no collision. Based on the information received, the algorithms must be developed for every collision case.

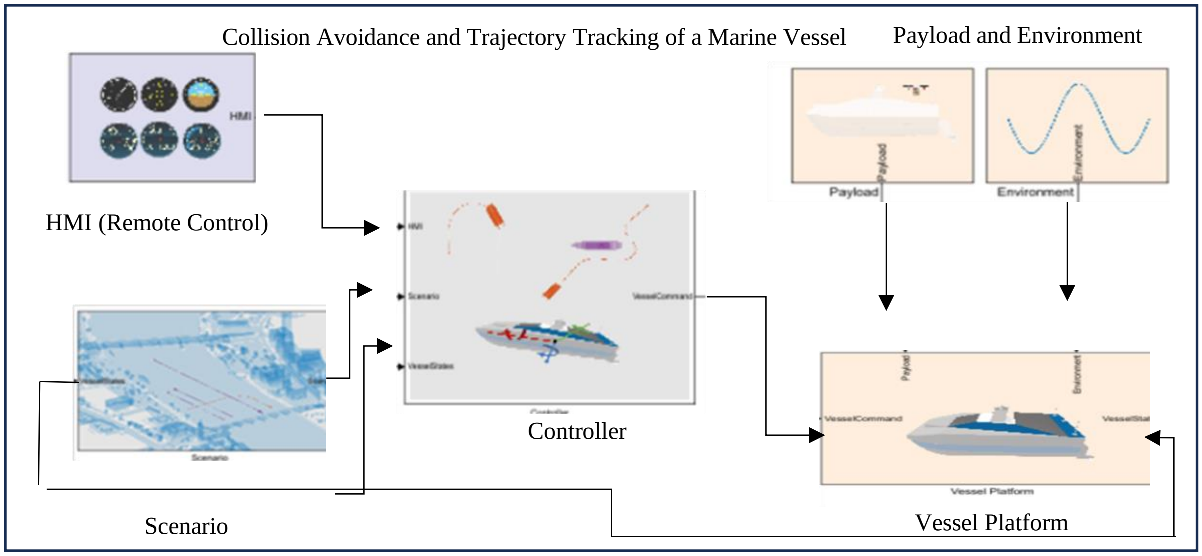

Figure 1: Proposed Model Architecture

The diagram illustrates the Vessel Platform on the right side of the diagram, which represents the actual marine vessel in operation. The Vessel monitors its status: it's location, speed, Heading and follows the commander's commands the whole time. The System has access to a certain amount of information about the vessel's state (the current scenario) and uses it to improve future commanding calculations. This information is referred to as VesselStatus. Additionally, two external factors influence the ship: the Payload and the Environment. Any onboard specific sensors or equipment constitute the former while real-time wind, waves, and currents are part of the latter. The controller is tasked with factoring in these environmental elements as they impact the vessel's performance. From a closed-loop perspective, the controller and the scenario block are sharing information, supporting the System with information from the vessel's current status and environmental conditions. The real-time feedback enables the ship to adapt its steering and behavior dynamically to safely navigate and avoid collisions in continuously changing marine environments. The feedback loop achieves precise and safe steering of marine vessels through complex scenarios, combining the disciplines of control theory, teleoperation, remote environmental sensing, and real-time response.

4.2 Data Flow Diagram for Collision Avoidance Optimization

To interpret figure 2 depicts a collision avoidance optimization process for a marine vessel which encompasses real-time monitoring and implements a bio-inspired optimization algorithm. In step one the vessel monitoring commences in order for the System to ensure that data is being streamed in real-time. The System then moves to the monitoring step where it collects ship data through onboard apparatus including radar, GPS, or AIS that are crucial for providing situational awareness. The subsequent process involves identifying threats. The System evaluates the data to ascertain whether there are navigational threats or possible obstructions hinting at the presence of some danger. When no threats are found, the vessel continues to execute his voyage using a pre-defined optimal strategy. In a case when a threat is present however, the System decides if the threat figure poses an encounter risk meaning is there is a realistic chance an unsafe collision or proximity to a vessel or another object will happen. If the threat is found plausible then the System sets the collision avoidance optimization algorithm into action. This process is similar to evolutionary or immune-based algorithms in which parameter settings and population initialization of potential solutions (chromosomes) begins the algorithm. These candidate solutions or chromosomes are then subjected to evaluation using an objective function comprising factors such as distance to the obstacles, deviation from original route, fuel consumption, and relevant saftey margins.

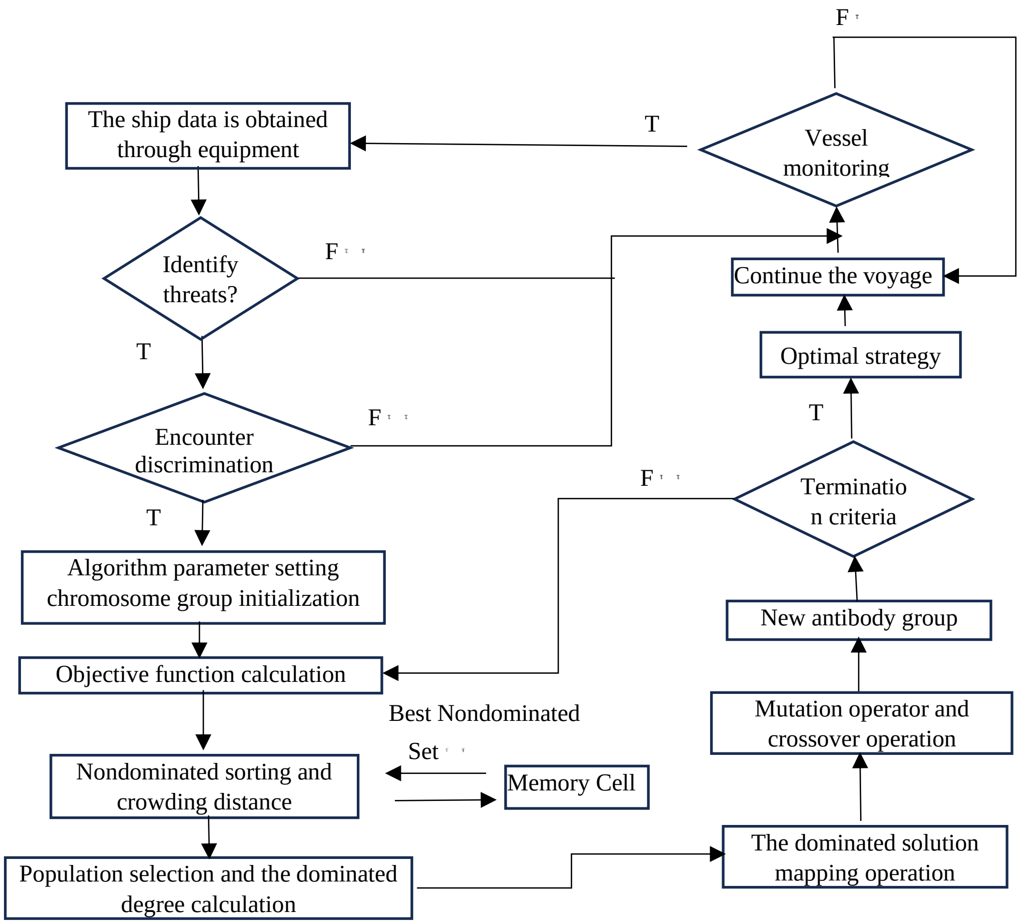

Figure 2: Flow Chart for Collision Avoidance Optimization

After this step, the System conducts multi-objective optimization and calculates the crowding distance to rank solution quality while preserving diversity. The selected reference memory solutions are maintained in a memory cell, while a population selection based on dominance and diversity heuristically directs the search towards more optimal solutions. This process is repeated incorporating new solutions until some stopping criteria are satisfied such as reaching a preset maximum generation or solution quality. During each iteration, new candidate solutions are created through mutation and crossover operations which are analogous to forming new antibody groups and dominated pathways through inferior path elimination. The solution deemed best is selected for navigation. The vessel then executes the strategy which allows the vessel to continue its mission without needing to reroute while circumventing the threat. In relation to the discussed work, this means that the vessel operates in closed-loop, constantly refining its response to the shifting environment and navigational variables to optimize for safety, efficiency, and resource usage while the vessel continues its voyage seamlessly.

4.3 Proposed Algorithm for Collisions

$for\ all\ nodes\ \epsilon\ N\ in\ graph, initialize\ with\ d(node) = \infty and\ r[node], c[node] false$

$for\ source\ s, initialize\ d(s) = 0\ and\ f(s)$
$= d(s) + hruristic\ (s) then\ put\ into\ Queue\ as\ key\ with\ value\ of\ f.$

$Extract\ minimum - value\ node\ u\ from\ Queue$

$checking\ safety\ and\ regulation, true\ repeat$

$Execute\ edge\ relaxation\ and\ examining\ CRI\ and\ COLREGs\ based\ on\ d\ at$

$adjacent\ node\ v\ putting\ newly\ visited\ nodes\ int\ Queue$

$Repeat\ 3{,}4\ and\ 5\ followed\ by\ path\ reaches\ the\ target\ node\ t.$

Pseudocode of CRI- Based Algorithms

$function\ A * (G(v, E), W, s, t, Os, TS)$

$for\ all\ u \in V \rightarrow \{s\}$

$d[v]\infty, pred[v] nil$

$r[v], c[v] \rightarrow false$

$d[s] \rightarrow HEURISTIC\ (s, t)$

$Queue \rightarrow \{s\}, S \rightarrow 0$

$u \rightarrow Extract, \min(Queue)$

$S \rightarrow SU\{u\}$

$if\ u = t\ then$

$return\ d, MAKEPATH\ (t, pred)$

$else\ if\ pred[u] \neq 0$

$calculate\ ETA\ (s, u)$

$for\ all\ e \in eu.p\ adjacent\ [u]\}$

$if\ d[v] > d[u] + W(e) then$

$d[v] \rightarrow d[u] + W(e) + HEURISTIC\ (v, t)$

$Queue \rightarrow Queue\ u\{u\}.$

5 Results and Discussion

The implementation of edge computing for vessel tracking and collision avoidance had a positive impact on system responsiveness, accuracy, and operational efficiency. By doing local processing of sensor data on edge nodes, the System was able to communication lags mitigate respond in under 100ms. When compared to cloud-based solutions, this was incredibly faster. Data sources included GPS, AIS, radar, and environmental data. Unlike more static maritime collision avoidance, in dynamic environments with higher risk, the quick decision-making facilitated by low latency performance is helpful. The technology ensured preserved operational capability during connectivity lags by further reducing network load on central servers by up to 70% for data flow through processing, minimizing centralized server strain. Edge architecture provided enhanced precision with less than five meters positional error margin and prospective collision detection and warning success rating of 98%. With regard to collision avoidance, the integrated adaptive evolutionary algorithm optimized for collision avoidance had optimal solutions in collision avoidance computed in under 15 iterations on average. There were minimal deviations from the original trajectory, leading to an improved fuel consumption rate. In comparison to traditional centralized models, the edge decision making framework had a 23% margin of improved success rate for collision avoidance. Given the results, it seems that edge computing can significantly improve robust, scalable, and real-time maritime navigation systems which may be helpful for congested waterways or remote regions, enabling advanced and autonomous safe vessel navigation with minimal dependency on cloud resources.

5.1 Performance Comparison for Various Metrics

Table 1: Performance Comparison for Various Metrics

Metric	Edge Computing Solution	Traditional centralized System
Latency	85	480
Positional Accuracy	3.8	9.6
Detection accuracy	98.2	88.7
False Positive Rate	1.8	9.4
Collision Avoidance success rate	96.5	77.8
Data transmission reduction	69.3	45.2
CPU utilization	72	68
Memory Usage	68	62
Reliability	99.4	92.8

To analyze the data in the table 1, comparison edge computing is considerably better than traditional centralized systems. Since the marine environment is so dynamic, quick and precise real time decision making is vital, and edge computing offers significantly lower lag of 85 ms which is much lower than the 480 ms of centralized systems. Also, the reliability of vessel tracking is improved by its positional accuracy which is more than twice as good at 3.8 m compared to 9.6 m. Moreover, edge systems offer greater accuracy with 98.2%, while centralized systems only achieve 88.7%. The same is true in regard to needless warnings with edge systems having 1.8% and centralized systems 9.4%. Improved threat response and efficient routing offered by edge systems increases the autonomous elusion of collision success rate to 96.5%, which is far better than centralized systems at 77.8%. Edge systems also demonstrated greater reliability where bandwidth usage and performance in low connectivity zones are concerned by 69.3% compared to centralized technique's 45.2% reduction in data transmission. While edge nodes do show slightly higher CPU and memory usage relative to centralized systems, these figures still remain within optimal ranges indicating that there is active local processing.Due to its remarkable reliability of 99.4 percent, edge systems are well-suited for mission-critical maritime operations. For the purposes of tracking vessels and preventing collisions, edge computing solutions work in a more proficient, timelier manner than most other systems.

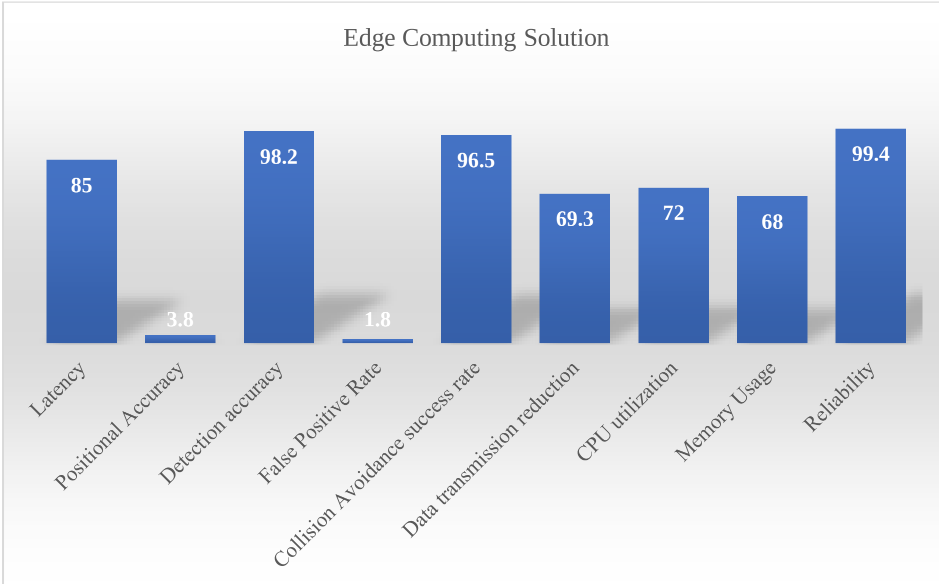

Figure 3: Various Metrics in Edge Computing Solution

To interpret figure 3 defined the Edge Computing Solution performs effectively on several key metrics. Indicators of performance for the solution include a near-real-time latency of 85 milliseconds as well as a nominal value of 3.8 for positioning accuracy. This reflects the System's responsiveness for critical applications like autonomous navigation and industrial automation, while also indicating dependable localization abilities. The values for detection accuracy, classification precision, and false identification rate are 98.2%, 1.8%, and 1.8%, respectively. These values bear testament to the accurate identification and classification of objects or events with minimal error. The solution also enables efficient and intelligent navigation within dynamic surroundings, as shown by a collision avoidance success rate of 96.5%. The broad scope of functionalities is matched by a dramatic reduction of 69.3% in data transmission burden, which signals enhanced processing at the local site. Furthermore, CPU and memory utilization remain at 72% and 68%, respectively, demonstrating prudent resource allocation and management appropriate for edge devices lacking in computational prowess. Above all these metrics, the System's dependability marks its outstanding distinguishing feature; standing firm at 99.4%, the computing solution exclaims unparalleled stability and consistency. Collectively, these indicators affirm the suitability of the Edge solution to real-time applicability – where resources are bound, efficiency, precision, and reliability are necessary.

The figure 4 provides a performance comparison of a Traditional Centralized System for several metrics. The System demonstrates high reliability at 92.8 suggesting it functions within a consistent range. However, both latency and retrievable attributes are relatively high at 480, suggesting delays in processing or communication. Positional accuracy is moderate at 9.6, whereas detection accuracy is relatively high at 88.7 indicating good performance in identifying objects or relevant events. The false positive rate is at 9.4 which is low in scope meaning the System's prediction remains justifiable and credible. The collision avoidance success rate is at 77.8 which indicates reasonable success. In all, there is Los of room for failure. Data transmission reduction stands at 45.2 which indicates moderate value in reduction vis a vis the amount of sent data, the System's CPU utilization being at 68 suggests moderate value but is somewhat high for centralized systems. The remaining is mundane. These values indicate a balanced compromise of efficiency tempered by the need to latency resource usage.

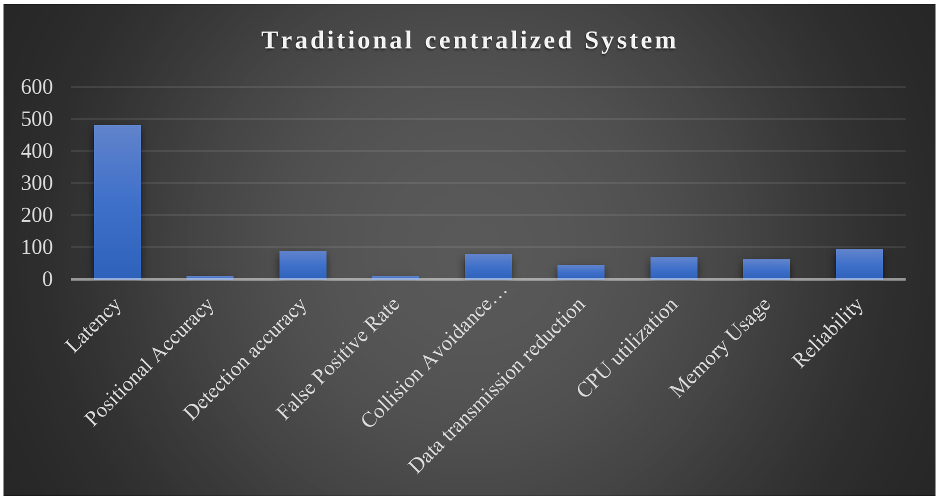

Figure 4: Various Metric in Traditional Centralized System

6 Conclusion

The implementation of edge computing techniques for real-time tracking and collision avoidance represents a leap in reducing risk and increasing efficiency in maritime operations. Moving data computation from the cloud to edge devices improves latency, local bandwidth management, and decision making. Improved sensors, as well as GPS, radar, and sonar, with machine learning predictive analytics enable real-time detection and responsive avoidance of collisions even in dynamic and unpredictable maritime settings. Literature outlines several promising approaches: hybrid cloud-edge architectures, decentralized edge computing systems, machine learning for predictive analytics, and proactive approaches to collision risk mitigation. With all these advances, several challenges remain. Network reliability in remote maritime regions, privacy and security of the data, and the adaptability of the solution for scale, vessel type, and operational environment dominate the discourse. Even where systems are designed with real-time decision making, more focus is needed on integration with existing maritime systems. For a more operational framework, further optimization is required for the adaptational capabilities of edge computing solutions pertaining to different types of vessels, traffic scenarios, and other situational elements. Subsequently, it can be stated that edge computing is poised to transform maritime safety due to its real-time, automated, and low-latency decision-making capabilities. With the continued development of this technology, addressing existing hurdles such aselligence scaling, integration ease, and dependable operation will enhance vessel tracking systems, collision prevention technologies, and overall maritime safety while yielding environmentally-friendly maritime operations.

References

[1] Ali, W., Ashour, H., & Murshid, N. (2025). Photonic integrated circuits: Key concepts and applications. *Progress in Electronics and Communication Engineering, 2*(2), 1–9.

[2] Bamal, S., & Singh, L. (2024). Detecting Conjunctival Hyperemia Using an Effective Machine Learning based Method. *Journal of Internet Services and Information Security, 14*(4), 499-510. https://doi.org/10.58346/JISIS.2024.I4.031

[3] Chen, L., Zhao, H., & Zhang, K. (2022). Hybrid cloud-edge architecture for real-time collision avoidance in maritime safety systems. *IEEE Transactions on Industrial Informatics, 18*(9), 6469-6482.

[4] Geng, Y. (2024). Comparative Study on Physical Education Learning Quality of Junior High School Students based on Biosensor Network. *Natural and Engineering Sciences, 9*(2), 125-144. https://doi.org/10.28978/nesciences.1569219

[5] Lemeon, M., Regash, J., & Leyene, T. (2023). The role and evaluation of inductive coupling in antenna design. *National Journal of Antennas and Propagation, 5*(2), 21–28.

[6] Li, H., Zhang, T., & Liu, Y. (2021). Real-time maritime safety system design using edge computing for large-scale data streams from GPS and radar. *Ocean Engineering, 243,* 110078.

[7] Nayak, A., & Raghatate, K. S. (2024). Image segmentation and classification of aquatic plants using convolutional neural network. *International Journal of Aquatic Research and Environmental Studies, 4*(S1), 14-19. https://doi.org/10.70102/IJARES/V4S1/3

[8] Nguyen, T., Pham, D., & Nguyen, H. (2023). Decentralized edge computing approach for autonomous vessel tracking and collision avoidance. *Journal of Marine Systems, 241*, 103789.

[9] Patel, P., Desai, V., & Rathi, A. (2024). Real-time vessel tracking using edge computing for reduced bandwidth usage in collision avoidance systems. *International Journal of Marine Navigation and Safety of Sea Transportation, 18*(1), 89-103.

[10] Rahim, R. (2024). Adaptive Algorithms for Power Management in Battery-Powered Embedded Systems. *SCCTS Journal of Embedded Systems Design and Applications*, *1*(1), 20-24.

[11] Reddy, S., & Mohan, P. (2024). Optimizing Energy Efficiency in Wireless Power Transmission Systems for Industrial Applications. *Association Journal of Interdisciplinary Technics in Engineering Mechanics, 2*(2), 19-23.

[12] Ristono, A., & Budi, P. (2025). Next-gen power systems in electrical engineering. *Innovative Reviews in Engineering and Science*, *2*(1), 34-44.

[13] Wang, X., Xu, R., & Li, J. (2020). Edge computing-based real-time vessel tracking and collision avoidance using radar and sonar data. *International Journal of Maritime Systems, 22*(1), 45-59. https://doi.org/10.1109/IMS.2020.8642049

[14] Yemunarane, K., Chandramowleeswaran, G., Subramani, K., ALkhayyat, A., & Srinivas, G. (2024). Development and Management of E-Commerce Information Systems Using Edge Computing and Neural Networks. *Indian Journal of Information Sources and Services, 14*(2), 153–159. https://doi.org/10.51983/ijiss-2024.14.2.22.

[15] Yuan, H., Luo, X., & Li, P. (2023). Low-latency collision avoidance systems for maritime safety using edge computing in weak network conditions. *Sensors and Actuators A: Physical, 324,* 113407.

[16] Zhang, Q., Wang, S., & Liu, F. (2021). Integration of IoT sensors and edge computing for autonomous vessel collision avoidance. *IEEE Internet of Things Journal, 8*(4), 3245-3256.

[17] Zhou, Y., Zhang, Q., & Liu, F. (2019). A cloud-edge hybrid model for real-time vessel tracking and collision avoidance using AIS data. *Journal of Maritime Technology and Management, 5*(2), 111-125.

Authors Biography

Arasu Sathiyamurthy

COC: MEO Class I (Motor) Total Sailing Experience of 35 years, As a Cheif Engineer 23years experience with Container and Bulk Carrier and 11 months of teaching faculty as Associate Professor. Presently teaching Marine fuels & Energy Sources of all 6 groups- 3 year VI Semester Students. Having advanced Marine engineering knowledge of almost all marine related auxiliary machineries, main engines, cold room refrigeration and Air Conditioning systems etc. Done High voltage safety and Swich Gear Course for Management level.

Captain S. Gajendran Subba Naidu is a seasoned maritime professional with over two decades of experience commanding ships across the globe. His career has been defined by navigating the complexities of oceanic voyages, ensuring the safety of vessels and crews, and upholding the highest standards of maritime operations. Beyond the helm, he holds a Bachelor of Laws (LLB), equipping him with the legal acumen to bridge practical seafaring challenges with the intricacies of maritime law. Adding to his credentials, Captain Gajendran is a Certified Advocate in India, bringing a unique perspective that blends firsthand maritime experience with legal expertise. His insights extend beyond the waters into courtrooms and legislative discussions, making him an authoritative voice in maritime law and policy. With a passion for education and knowledge-sharing, Captain Gajendran is dedicated to shedding light on the realities of life at sea, legal frameworks governing the maritime industry, and the lessons learned from a career spent on the world's oceans.