Need for a Smart Autonomous Bilge Management System: A Review

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Abstract

The discharge of bilge water from ships, regulated under MARPOL regulations, presents significant environmental and operational challenges. Despite stringent regulations, compliance remains inconsistent due to economic pressures and the limitations of current monitoring technologies, which rely heavily on rudimentary automation that, in turn, depends largely on human intervention and interpretation. This paper explores the application of artificial intelligence (AI) and machine learning (ML) in water level management and related fields, drawing parallels to their potential application in bilge water management. A novel concept for a Smart Autonomous Bilge Management System (SABIMS) is introduced.

Keywords

Bilge water management,MARPOL compliance, AI/ML, SABIMS, Autonomous systems

1. Introduction

The International Convention for the Prevention of Pollution from Ships (MARPOL), adopted by the International Maritime Organization (IMO), sets mandatory regulations to reduce ship-induced pollution, addressing oil, hazardous substances, sewage, garbage, and air emissions.

Drainage, leakages, and maintenance in merchant ship engine rooms result in water mixed with oil traces, to collect in bilges. MARPOL requires that Bilge water, containing oil traces from ship engine room operations, must be discharged only in non-restricted areas via an Oily Water Separator (OWS) with oil content below 15 ppm, monitored by an Oil Alarm Monitor (OAM). Alternatively, it must be stored in bilge tanks or discharged to authorized shore reception facilities, with all activities recorded in the Oil Record Book (ORB). Emergency discharges are permitted at the Master's discretion for securing the safety of life at sea[1].

Violating MARPOL regulations can lead to severe penalties, including ship detentions, fines, and criminal charges, with many violations linked to false ORB entries and evidence of improper discharges[2].MARPOL Compliance is challenging due to economic pressures, high maintenance costs, and operational demands, often leading to circumvention of regulations[3].

Artificial Intelligence (AI) and Machine Learning (ML) are revolutionizing the maritime industry enhancing efficiency and safety. Autonomous ships, such as Yara Birkeland, use AI for navigation, collision avoidance, and decision-making, reducing the need for human intervention [4].AI/ML has also been widely used in the field of water level management, including flood forecasting, reservoir control, rainfall prediction, and water quality monitoring and so on.

Despite these advancements, application of AI in shipboard bilge water management systems remains largely unexplored. To bridge this gap, the author proposes a Smart Autonomous Bilge Management System (SABIMS) that leverages AI/ML for real-time monitoring, predictive analytics, and autonomous compliance with MARPOL regulations. SABIMS with AI integration provides a promising solution to improve compliance rates and reduce reliance on human intervention.

2. Regulatory Landscape and Compliance Challenges

2.1. Overview of MARPOL Requirements

MARPOL provides a global framework for minimizing ship-induced pollution. It includes six annexes addressing various types of pollution, with Annex I specifically focusing on oil pollution prevention. MARPOL requires that bilge water discharges occur only under strict conditions:

1. Ship is proceeding on a voyage
2. Bilge water is being pumped through an OWS
3. Oil concentration in discharged water is not more than 15 ppm
4. Discharges to be monitored via an Oil Alarm Monitor (OAM) to provide alarm and automatic shutdown in case of oil content exceeding 15 ppm
5. Bilge water must have originated from within Engine Room

In addition to above conditions, there maybe restriction to discharges in special areas, territorial waters and Particularly Sensitive sea Areas (PSSAs).Bilge water generation, internal transfers, overboard discharges, Equipment malfunction or breakdown and emergency overboard discharges need to be meticulously recorded in an Oil Record Book (ORB). Emergency discharges are permitted only to secure the safety of the vessel and crew, at the discretion of the Master. Digital record of OWS operational data is required to be maintained for a period of 18 months[1].

2.2. Illegal Discharges: Motivation and Incentives

Despite the stringent regulatory framework for environmental compliance, adherence remains a persistent challenge due to economic pressures and practical constraints, often resulting in violations.

2.2.1 Economic Incentives and Cost Savings

The OECD 2003 report highlights significant cost-saving opportunities that continue to drive non-compliance with MARPOL regulations:

2.2.1.1 Avoidance of Waste Management Costs

Disposing of bilge water to port reception facilities costs USD 20/m^3 to USD 115/m^3, translating to annual savings of USD 50,000–400,000 for medium-sized ships avoiding these expenses [5].

2.2.1.2 Reduced Maintenance Costs

The annual maintenance of oily water separators (OWS) costs USD 3,000–5,000, but non-compliant operators bypass these expenses entirely [5].

2.2.1.3 Savings on Equipment and Training

With OWS systems costing USD 10,000–100,000 and additional crew training expenses, operators cutting these costs achieve significant savings [5].

2.2.1.4 Operating Cost Reductions

Avoiding regulatory compliance eliminates the operational downtime and labor costs required for proper bilge water treatment [5].

2.2.1.5 Avoidance of Equipment Replacement

Skipping replacement of worn-out OWS membranes (USD 10,000 per set) adds further financial incentives for violators [5].

These cost-driven motivations, first documented in 2003, persist in the industry even today.

2.2.2 Case Study: Carnival Corporation

Jonathon Brun's Jan. 2023 report illustrates ongoing compliance failures among major players like Carnival Corporation:

2.2.2.1 Minimal Deterrence

Carnival fines of USD 60 million in 2019, represented just 0.3% of Carnival's USD 20.8 billion revenue, failing to deter non-compliance [6].

2.2.2.2 Cost-Saving Practices Carnival circumvented waste management protocols and engaged in illegal discharges to save operational expenses, despite repeated penalties

[6].

2.2.2.3 Lax Oversight

Despite a USD 40 million fine and a probation for illegal discharges in 2016, Carnival continued to violate environmental laws, leading to an additional USD 20 million fine in 2019 [6].

2.2.2.4 Corporate Culture Issues

Carnival Corporate Culture did not pay much attention to alter their unlawful practices. The lack of prioritization for environmental compliance within corporate governance perpetuated violations [6].

This persistence of violations over two decades underscores the ineffectiveness of penalties and enforcement measures.

2.2.3 Broader Motivations Behind Illegal Discharges

Illegal discharges persist globally primarily due to economic and operational incentives:

2.2.3.1 Economic Advantage

Compliance costs account for 3.5–6.5% of daily operating expenses, while fines remain negligible in comparison; for instance, Carnival's penalties were only 0.4% of its revenue [7].

Table 1: OECD Report Cost Savings (2003 vs. 2025)

Incentive/Cost Saving	**Savings in 2003 (USD, Per Year)**	**Equiv. Savings in 2025 (USD, Per Year)**
Avoidance of Waste Management Costs	50,000–400,000	75,000–600,000
Reduced Maintenance Costs	3,000–5,000	4,500–7,500
Savings on Equipment and Training	10,000–100,000 (one-time)	15,000–150,000 (one-time)
Avoidance of Equipment Replacement	10,000 per set (one-time)	15,000 per set (one-time)

Table1, based on the OECD 2003 report, estimates that Carnival Cruise saved approximately USD 52 million fleet-wide in 2003, with an average fleet size of 100 ships. By 2025, this figure is projected to reach roughly USD 77 million annually, highlighting the significant financial benefits of deliberate non-compliance. Over 25 years, fleet-wide savings are estimated at approximately USD 1.6 billion. The fines imposed on Carnival Cruise to date are negligible compared to the massive financial gains achieved through non-compliance.

2.2.3.2 Inadequate Enforcement

Weak regulatory frameworks and limited enforcement mechanisms allow violators to operate with minimal risk of prosecution.

2.2.3.3 Low Risk of Detection

Discharges often occur in international waters, where jurisdictional and logistical challenges reduce the likelihood of detection.

2.2.3.4 Operational and Maintenance Shortcomings

Poor maintenance of OWS equipment and insufficient crew training continue to exacerbate violations as operators prioritize cost-cutting over compliance.

3. Existing 'Intelligent' OWS Control Systems

3.1. Overview

Several Oily Water Separator (OWS) systems currently available in the market claim to possess “Smart” or “Intelligent” functionalities. Examples include the CBM-LINK Intelligent System by RWO-VEOLIA, Bluebox SA by Alfa Laval, and Whitebox System with Enviropilot by Marinefloc, among others. These systems incorporate certain advanced features designed to enhance operational efficiency and regulatory compliance. However, despite their marketed sophistication, a detailed analysis reveals a critical limitation: none of these systems integrate Artificial Intelligence (AI) or Machine Learning (ML), which restricts their ability to operate autonomously or make independent decisions.

3.2. Smart Features in Existing 'Intelligent' Systems

While lacking true autonomy, these systems do incorporate a range of advanced features that elevate their functionality beyond standard OWS operations. Key smart features include:[8–11]

1. **Port Switch Mode (CBM-LINK):** Automatically locks the system in recirculation mode when the vessel is in port or restricted areas, preventing unauthorized discharge.

2. **Real-Time Visualization (CBM-LINK):** Provides real-time data visualization for system status and discharge parameters, ensuring better monitoring and control.

3. **Maintenance Prediction (CBM-LINK):** Predicts maintenance requirements, such as filter changes, by analyzing operational data, thus optimizing maintenance schedules.

4. **GPS Integration for Compliance (All Systems):** Logs vessel position during discharge operations for regulatory reporting and compliance verification.

5. **Stand-Alone Operation (BlueBox SA):** Operates independently and integrates with any OWS setup, providing enhanced flexibility for various configurations.

6. **Clean Drain Monitoring (BlueBox SA):** Monitors clean drain tanks to avoid unnecessary processing, thereby improving system efficiency.

7. **Two-Point Oil Content Measurement (CBM-LINK):** Measures oil content at two different points for enhanced accuracy and compliance assurance.

8. **Connectivity to Ship's AMS (CBM-LINK):** Enables integration with the vessel's Alarm Monitoring System (AMS) for centralized control and real-time alerts.

9. **Automatic Three-Way Overboard Valve (BlueBox SA):** Prevents overboard discharge unless specific monitored parameters are met, ensuring regulatory compliance.

10. **Tamper-Proof Logging (All Systems):** Includes secure logging features to record unauthorized access and ensure data integrity for compliance audits.

11. **Extended Data Storage (All Systems):** Stores operational data for extended periods (e.g., 18 months) to facilitate detailed historical analysis and reporting.

Table 2: Overview of Existing Intelligent OWS Control Systems

Trade Name	**Maker**	**Smart Capabilities**	**AI Integration**	**Market Status**
CBM LINK	VEOLIA	Yes	No	Available in Market
Whitebox	Marinefloc	Yes	No	Available in Market
BlueBox SA	Alfa Laval	Yes	No	Available in Market
Bilge-Guard	Wartsila	Limited	No	Available in Market

Table 2 provides an overview of existing intelligent OWS systems, highlighting their capabilities and limitations.

4. Literature Review

4.1. Introduction to AI and ML

Artificial Intelligence (AI) refers to the simulation of human intelligence in machines, enabling them to perform tasks such as learning, reasoning, and decision-making. Machine Learning (ML), a subset of AI, allows systems to learn and improve from data autonomously without explicit programming. Together, AI and ML are transforming industries and solving complex challenges by automating tasks, analysing large datasets, and delivering predictive insights.[12]

AI and ML are extensively applied across diverse domains, including natural language processing, robotics, environmental monitoring, maritime operations, transportation, disease diagnosis and drug discovery, agriculture, autonomous drones, threat detection, fraud detection, predictive maintenance, energy optimization, renewable energy optimization, personalized learning, automated grading, sports analytics, flood control, water level management, wildlife conservation, urban planning, cultural heritage preservation, support for learning disabilities, satellite monitoring, call analysis, remote sensing, weather prediction, energy demand forecasting, supply chain optimization, autonomous vehicles, cybersecurity, virtual assistants, sentiment analysis, language translation, climate modelling, social media analytics, human-computer interaction and so on. The application of

AI and ML is ever expanding in all domains and spheres of life.[13, 14]

4.2. History of AI and ML

The historical evolution of ML underpins its current capabilities and applications. Thomas Bayes introduced the Bayes theorem in 1763, later formalized by Pierre-Simon Laplace in 1812 [15]. The method of least squares (1805) [16] and Markov chains (1913) [17]laid the groundwork for statistical learning.

Alan Turing's 1950 proposal for machine intelligence marked a critical milestone [18]. Subsequent breakthroughs include Arthur Samuel's Checkers-playing program (1952) [19], Frank Rosenblatt's neural network (1957), and foundational algorithms such as recurrent neural networks (1982), support vector machines (1995), and random forests (1995) [20]. Modern achievements like Google's AlphaGo (2016) [21] and generative AI models such as OpenAI's ChatGPT and Google's Gemini [21, 22] demonstrate the exponential growth and applicability of AI/ML in diverse and complex domains.

AI / ML models analyze oceanic patterns, pollutant levels, and underwater ecosystems, while at the same time they help monitor the health of marine environments, predict potential threats, and provide early warnings related to environmental degradation. Other notable applications of AI/ML in the maritime sector are the development of intelligent fleet management systems, predictive maintenance and repair, maritime traffic forecasting, vessel routing automation, navigation, docking management, enhancement of maritime security, optimal port operations, enhancing search and rescue missions, and enabling autonomous underwater vehicles (AUVs) for exploration and environmental assessments.

4.3. AI and ML Applications in Water Level Management

Research and application of AI/ML techniques in various fields of environmental and water management have made significant strides in recent years. However, research specifically focused on the application of AI/ML in bilge water management remains nonexistent. However, parallels can be drawn from studies on dam water level predictions, flood control, rainwater runoff, and groundwater level management, which have successfully employed AI/ML methodologies to address similar challenges.

The review of the literature revealed that no research has been done in the field of bilge

water management using AI / ML. However, there are many similar research studies done and parallels were drawn mainly from AI/ML application for Dam water level predictions, flood control, rain water run off, ground water level control and such similar works.
Mosavi et al. [23] reviewed various ML models with wide-ranging applications for predicting water levels, river floods, soil moisture, rainfall discharge, precipitation, river inflow, peak flow, river flow, rainfall runoff, flash floods, streamflow, seasonal streamflow, urban floods, plains floods, groundwater levels, etc. These models can be applied for short and long-term predictions.
German et al.(2024) [24] studied flood level predictions with Gradient Boosted Tree (GBT), SVM, Decision Tree (DT) and NN and found that NN model gave a better accuracy over GBT which in turn yielded better accuracy than the rest of the algorithms.
Hanh et al.(2024) [25] studied river water level with Support Vector Regression (SVR), DT, Random Forest (RF), Light Gradient Boosting Machine Regressor (LGBM) and Linear Regression (LR), using 20-year water level historical and found that SVR outperformed other models consistently followed by RF, DT and LGBM. Nash Sutcliffe efficiency (NSE), coefficient of determination (COD) Root-Mean Square Error (RMSE) and Mean Absolute Error (MAE) were the metrics used for comparison.
Wang et al.(2020) [26] predicted 5 minutes forecast of water level using previous 10 minutes data using Support Vector Machine (SVM) based model. Computation cost of SVM is high while the least-square SVM (LS-SVM) method highly improves performance with acceptable computation efficiency [27]. SVMs were applied in numerous flood prediction cases with better results and better performance when compared to ANN and Multi-Layer Regressor (MLR) [28–30].
Alvisi et al. (2006) [31] compared Artificial Neural Networks (ANN) and Fuzzy Logic (FL) for short-term water level forecasting. FL-Mamdani (FL-M) and FL-Takagi-Sugeno (FL-TS) outperformed ANN with Aggregated Rainfall Information (ARI) but were less reliable. With Distributed Rainfall Information (DRI), ANN showed significantly improved accuracy. ANN excels with large datasets, while FL performs better with limited data.
Adamowski et al.(2012) [32] demonstrated that the Wavelet-ANN (WA-ANN) method outperforms traditional methods like ANN, Autoregressive Integrated Moving Average (ARIMA), Multiple Linear Regression (MLR) and Multiple Non-Linear Regression (MNLR)

when used in short-term urban water demand forecasting.Valipour et al.(2013) [33] compared Autoregressive Moving Average (ARMA), AIMA, static ANN, and dynamic ANN to predict inflow in the Dez dam reservoir and found that dynamic ANN was the best over all models.

Lin et al. (2020) [34] used a feed-forward neural network (FFNN) with resilient backpropagation (RP) and conjugate gradient training algorithms (CGF) on a synthetic dataset and found that RP outperformed CGF based on the mean square error (MSE) metric. Xiong et al. (2021) [35] found that incorporating Ada-Boost optimization into a Back-Propagation Neural Network (BPNN) improved flood predictions for the Three-Gorges reservoir basin compared to traditional BPNN, Generalized Regression NN (GRNN), and Genetic BPNN.Yaseen et al.(2016) [36] found that streamflow forecasting using Extreme Learning Machine(ELM), which is an easy FFNN with only a single hidden layer, outperformed both the Support Vector Machine (SVM) and GRNN, with better computational efficiency.

Sahoo et al. (2005) [37] found that while radial basis function networks (RBFN) are easier to optimize for well-structured datasets, a well-optimized Back-Propagation Neural Network (BPNN) achieves higher prediction accuracy for Hawaiian stream forecasts.

The Adaptive Neuro-Fuzzy Inference System (ANFIS), based on the Takagi-Sugeno (T-S) Fuzzy Inference System (FIS), is a highly reliable estimator for complex systems, combining Artificial Neural Networks (ANN) and Fuzzy Logic (FL) with enhanced learning capabilities[38–40].Lafdani et al. (2013) [41] demonstrated its high accuracy in short-term rainfall forecasting, while Shu et al. (2008) [38] highlighted its ease of implementation and superior generalization ability.

The literature review highlights the potential of machine learning algorithms for water level prediction and their integration into bilge water management systems. These algorithms offer predictive accuracy, adaptability, and enhanced decision-making, essential for achieving autonomy. However, the absence of research specifically addressing their application in bilge water management presents a significant gap, offering opportunities for innovation to improve regulatory compliance and operational efficiency.

5. AI in the Maritime Domain: Current Landscape, Gaps, and Opportunities

5.1. Review of AI and ML Applications in Maritime Sector

The literature review highlights advancements in AI/ML across various domains but reveals limited applications in the maritime sector. Although these studies did not focus on bilge water management, related maritime studies were reviewed and summarized.

AI/ML has significantly transformed the maritime industry, enhancing efficiency, cost savings, and impproving operational capabilities such as navigation, route optimization, anomaly detection, and predictive maintenance. Vu et al. (2024) [42] ehighlighted advancements in predictive maintenance, ship routing, and port logistics, noting that Random Forest outperformed Tweedie regression in fuel consumption prediction. Autonomous ships leveraging advanced ML algorithms optimize routing, enhance safety, reduce fuel consumption, and ensure regulatory compliance,contributing to sustainability and cost efficiency. Despite these achievements, gaps remain in AI adoption for autonomous ports and the development of hybrid models. However, gaps persist in AI adoption for autonomous ports and hybrid model development.

Popescu et al. (2024) [43] reviewed AI and IoT applications in pollution monitoring across air, water, and soil, focusing on AI-powered sensors, UAVs, and remote sensing. They identified gaps in standardization, integration with legacy systems, and data privacy concerns.

Panda et al. (2021) [44] investigated ML applications in wave forecasting, Autonomous Underwater Vehicle (AUV) control, docking, offshore structure analysis, and turbulence modeling in CFD. They identified gaps in physics-informed constraints, validation methods, and robustness in untested environments.

Singh et al. (2022)[45] examined AI applications in oil spill detection using satellite and radar imaging with ML models such as ANN, SVM, and Random Forest. They identified gaps in classification standardization, noisy data handling, and model robustness.

Karakostas et al. (2024) [46] investigated digital twin technologies for decarbonization and emissions reduction through real-time data and simulations, identifying gaps in framework standardization, interoperability, and lifecycle modeling.

Xiao et al. (2024) [47] reviewed AI applications in shipping, emphasizing AIS data use for trajectory prediction and anomaly detection. Identified gaps include AIS data reliability, real-time anomaly detection, and trajectory classification.

Statheros et al. (2008) [4] examined ship collision avoidance using neural networks, fuzzy logic, and hybrid systems. Gaps include real-time environmental adaptation, system integration, and model complexity.

Simion et al. (2024) [48] highlighted AI-driven predictive maintenance for maritime systems, reducing downtime and optimizing maintenance schedules. Gaps include challenges in legacy system integration, installation complexity, and fault detection reliability.

Yoshioka et al. (2022) [49] evaluated AI-based collision avoidance using deep Q-learning with Dangerous Area of Collision (DAC). Gaps include algorithm refinement, validation, and real-world trials.

5.2. Research Gaps

As highlighted in the literature review, AI/ML has shown promising advancements in maritime applications, yet their integration into bilge water management systems remains unexplored. Existing "Smart" OWS systems, discussed earlier, rely on predefined logic and manual intervention, limiting their adaptability and autonomy. High maintenance costs, inadequate real-time monitoring, and weak enforcement further hinder MARPOL Annex I compliance. Integrating AI/ML can address these gaps by enabling predictive analytics, real-time monitoring, and automated decision-making, enhancing efficiency and ensuring robust regulatory compliance.

5.3. Technological Opportunities to Address Gaps

5.3.1 AI and ML Integration

AI/ML can provide predictive analytics to anticipate maintenance needs, detect anomalies, and optimize bilge water discharge using historical and real-time data. These technologies can enable autonomous decision-making, reducing human intervention and enhancing real-time monitoring to prevent MARPOL violations. By improving compliance, minimizing environmental violations, and optimizing operations, AI/ML can enhance cost savings, operational efficiency, and regulatory adherence.

5.3.2 IoT and Advanced Sensor Integration

IoT-enabled sensors monitor water quality, oil content, and discharge rates in real time, ensuring continuous oversight and seamless data transmission for remote monitoring and decision-making.

5.3.3 Enhanced Data Integration

Real-time integration with satellite and AIS data improves the detection of illegal discharges, while historical data enhances predictive models, making bilge water management more accurate and reliable.

The limitations of current bilge water management technologies underscore the need for more intelligent, adaptive, and autonomous solutions. By leveraging advancements in AI, IoT, and automation, these gaps can be bridged, paving the way for innovative systems that address regulatory and environmental challenges effectively.

6. Smart Autonomous Bilge Management System (SABIMS): Proposing A Step Toward Intelligent Sustainability

6.1. Overview

The Smart Autonomous Bilge Management System (SABIMS) is a novel solution proposed to address the limitations of current bilge water management systems and Oily Water Separator (OWS) control systems. SABIMS is made of hardware and control components to autonomously and dynamically control the operations of Bilge Management System. SABIMS Logic Operations Module (SLOM) acts as hardware while AI Driven Decision Module (AIDDM) acts as its AI control unit.

SLOM integrates level, pressure and temperature sensors connected to various components like bilge wells, tanks, pumps, valves, OWS, ship's location(GPS), ship's condition(List/trim), ship's motion(rolling/pitching), enroute status (Port/Anchorage/Sailing) providing real time data input to the AIDDM to analyse, predict and make autonomous decisions.

The layout of the proposed SABIMS system components in the Engine Room of a

Case ship (53100 DWT Bulk Carrier) is shown in Figure 1

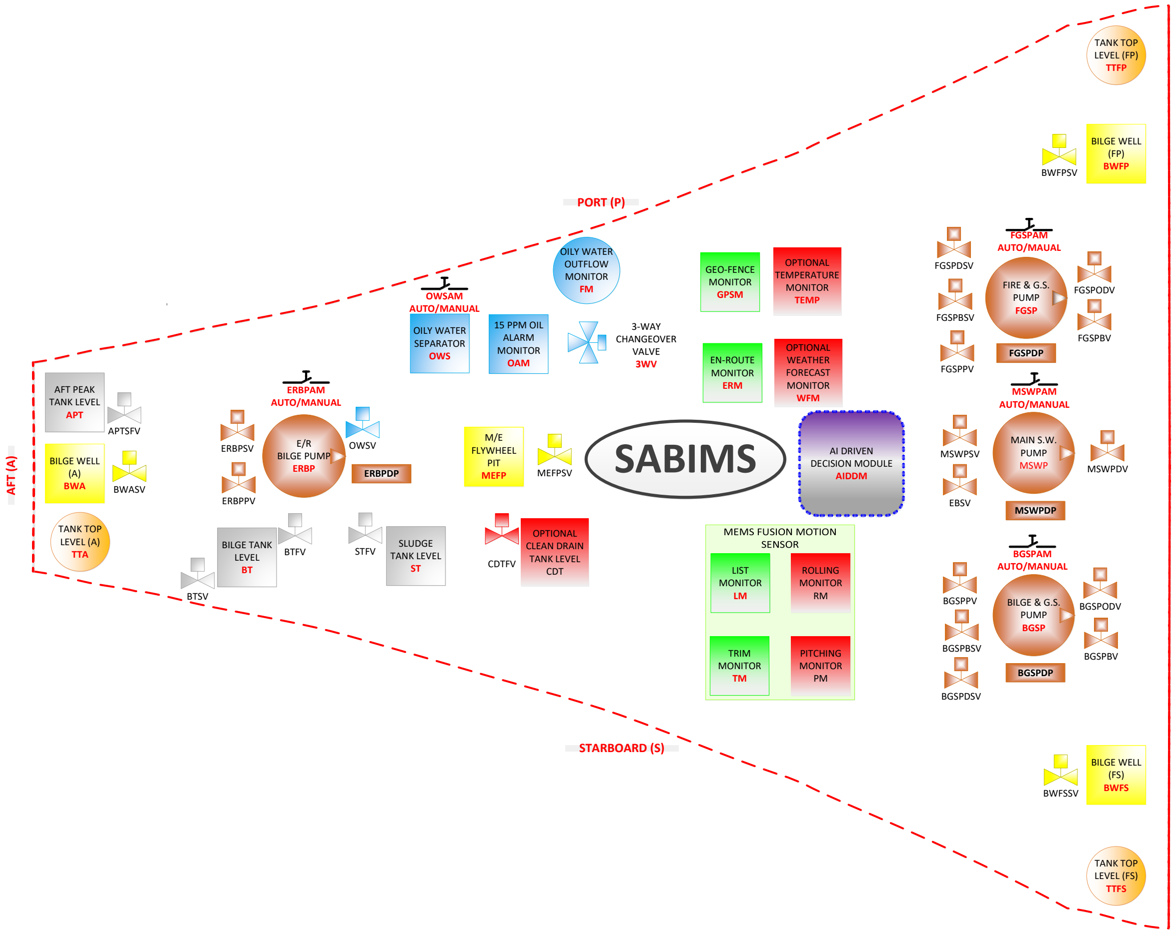


Figure 1: SABIMS Components Layout in Engine Room

6.2. Main Components of SABIMS

Figure 1 illustrates the main components of SABIMS, displayed in the plan view of the engine room tank top of the case ship. Due to space constraints, all abbreviations used in Figure 1 are expanded in Appendix 1. SABIMS consists of the **SABIMS Logic Operations Module (SLOM)**, which serves as the hardware module, and the **AI-Driven Decision Module (AIDDM)** as the control unit. Its key components include bilge wells, system-associated tanks such as bilge and sludge tanks, bilge system pumps, the Oily Water Separator (OWS), and various sensors. These sensors monitor bilge well and tank levels, oil content (ppm), pump discharge pressures, and ship parameters such as GPS location, weather, speed, temperature, list, and trim. The system also includes valves for controlling pumps and the OWS, enabling seamless and autonomous operation.

6.2.1 SABIMS Logic Operations Module (SLOM)

The **Smart Autonomous Bilge Management System (SABIMS)** incorporates the **SABIMS Logic Operations Module (SLOM)**, a high-level automated control module designed to integrate with AI capabilities for autonomous predictions and dynamic decision-making. Figure 2 shows the Logic Diagram of SLOM operations. While SLOM represents a deterministic control structure, its integration with AI transforms it into an advanced solution for enhanced environmental compliance, efficient decision-making, and operational optimization.

6.2.1.1 Core Functions of SLOM

1. Bilge Well and Tank Level Monitoring: SLOM uses high-level alarms in bilge wells to trigger pumps, transferring water to the bilge tank when thresholds are exceeded. Bilge tank levels are continuously monitored, initiating actions such as rerouting to alternative tanks when critical levels (e.g., >75%) are reached.

2. Environmental Compliance Checks: The module performs automated checks to ensure adherence to MARPOL regulations, including verifying distance from shore (e.g., beyond 12 Nm), avoiding restricted zones (e.g., Antarctic or Local Area Restrictions), and assessing ship status (e.g., in port or en route). These checks determine whether bilge water should be discharged to shore reception facilities or stored onboard.

3. Weather and Operational Adjustments: Operations are guided by predefined thresholds that account for weather conditions (normal, moderate, extreme) to ensure safe pump and Oily Water Separator (OWS) operations. The OWS activates only under conditions such as oil content below 15 PPM and equipment readiness.

4. Fallback Mechanisms: In scenarios like high bilge tank levels or unavailable shore reception facilities, SLOM reroutes bilge water to alternative storage tanks (e.g., sludge tank, waste oil tank, clean drain tank). Alarms and fail-safes ensure compliance and system reliability.

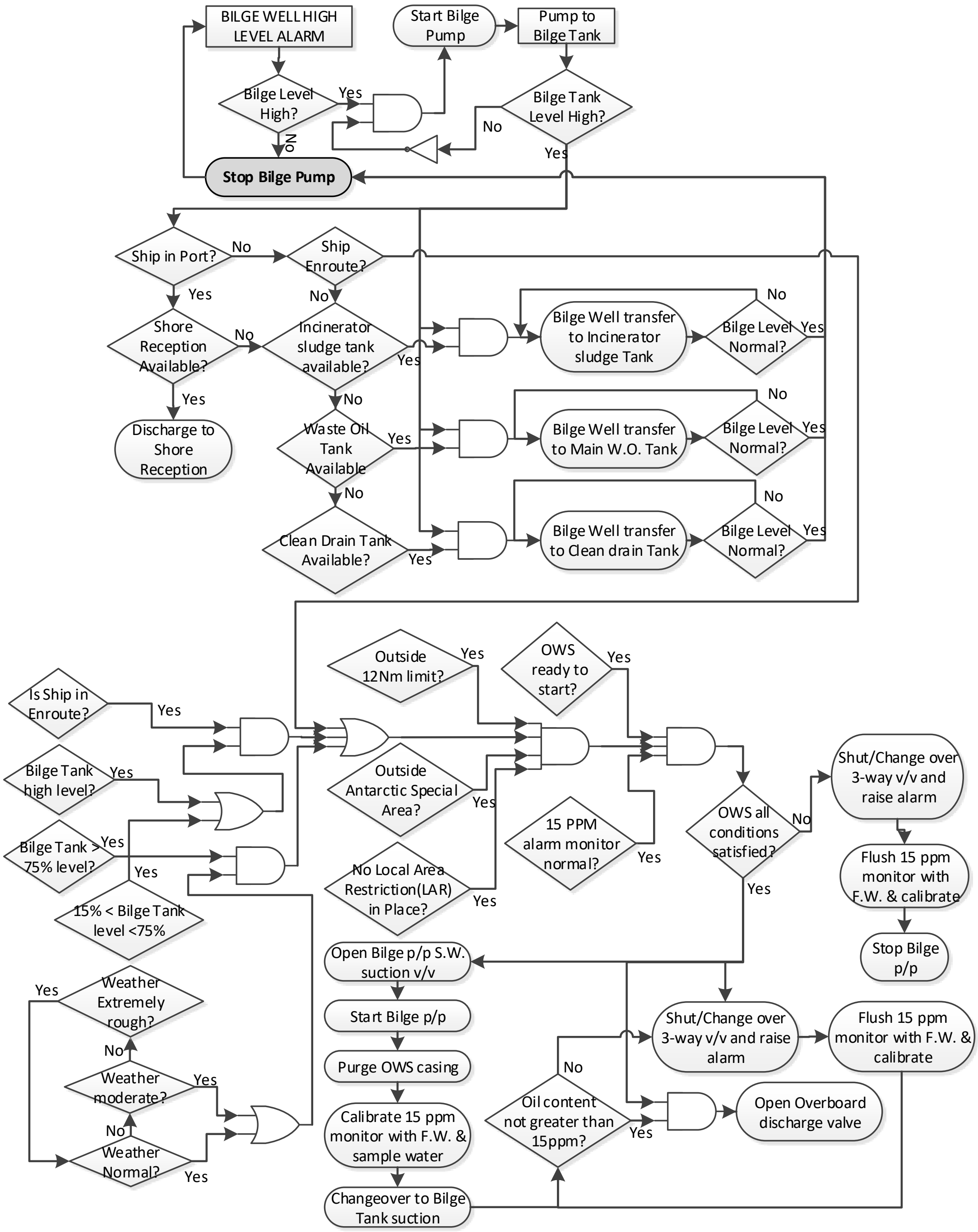


Figure 2: SABIMS Logic Operations Module (SLOM) Logic Diagram

This automated framework provides operational efficiency and regulatory compliance but is inherently limited by its reliance on static thresholds and predefined rules.

6.2.2 AI-Driven Decision Module (AIDDM)

AI integration into **SLOM** is done by **AI-Driven Decision Module (AIDDM)** which acts as the brain of SABIMS. AIDDM elevates the SLOM from a deterministic automated system to an adaptive, autonomous solution. By leveraging machine learning (ML), AIDDM enhances SABIMS' ability to analyze real-time data, predict outcomes, and enable proactive, real-time decision-making.

6.2.2.1 How AIDDM Enhances SLOM

1. **Dynamic Decision-Making:**
    - AIDDM analyzes real-time data (e.g., bilge levels, weather conditions, ship motion) to dynamically adjust operational thresholds and actions.
    - Predictive capabilities enable the AI to predict bilge well overfill, bilge tank overfill, pump failures, Port reception facilities requirement, anticipate bilge water generation and retention during a voyage, ,make adjustments for operational inefficiencies, alarms and unprecedented scenarios by ensuring proactive interventions.
2. **Prediction and Pattern Recognition:**
    - Using ML models trained on historical and synthetic data, AIDDM predicts:
        - **Bilge tank filling rates** based on current inflow and pumping capacity.
        - **Weather-induced risks**, such as extreme waves affecting pumping efficiency.
        - **Environmental compliance risks**, ensuring legal discharges.
    - These predictions allow SABIMS to take proactive steps, such as initiating bilge transfers earlier or rerouting discharge based on predicted delays.
3. **Autonomous Adjustments:**
    - AIDDM makes real-time adjustments to operational parameters, such as:
        - Modifying alarm thresholds based on ship motion (e.g., rolling and pitching).

  - Calibrating the OWS system autonomously for optimal performance.
  - Adjusting pump schedules to balance bilge tank levels and maintain suction efficiency.

4. **Feedback Loops and Retraining:**

   - AIDDM continuously improves its predictions and decision-making by integrating **live operational data** into the retraining loop.
   - Feedback mechanisms ensure that operational insights are incorporated into **model retraining**, enhancing accuracy and adaptability over time.

5. **Regulatory and Safety Compliance:**

   - While AIDDM autonomously manages operations, **hardcoded regulatory constraints** (e.g., 15 PPM oil content alarm, legal discharge limits) ensure compliance with MARPOL regulations.
   - AIDDM validates and adjusts its decisions by comparing predictions against these constraints.

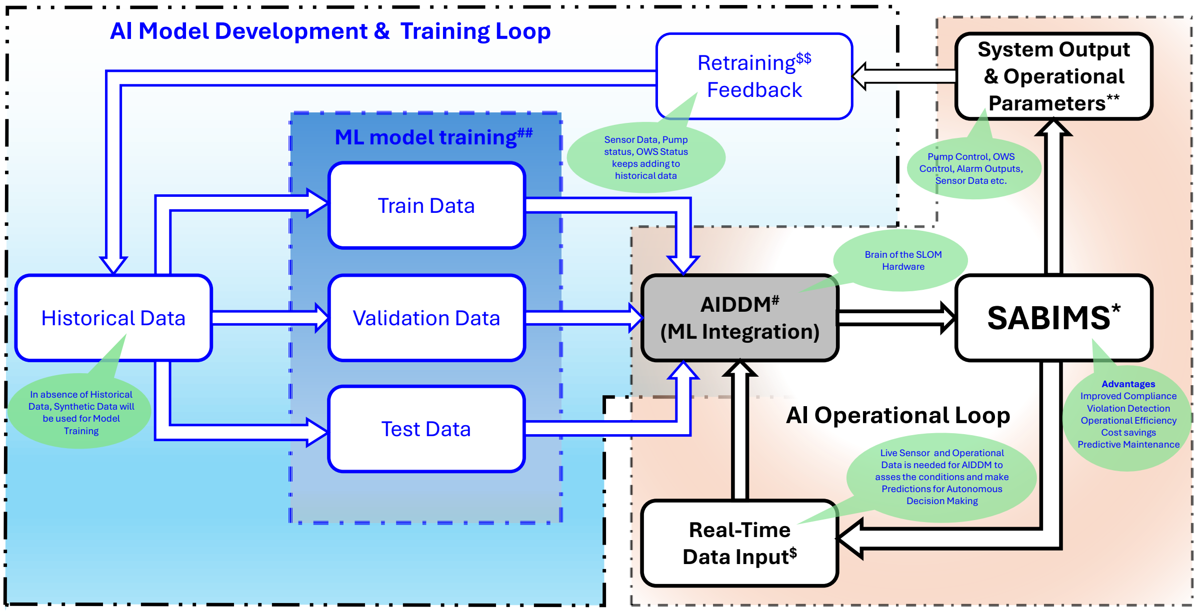
6.3. AI Training and Operational Workflow

Figure 3 depicts the **AI Model Development & Training Loop** and the **AI Operational Loop** in SABIMS.

1. **Training AIDDM:** AIDDM is trained using historical or synthetic data divided into training, validation, and test datasets. Continuous retraining incorporates real-time operational data, improving prediction accuracy and adaptability.

2. **Operational Integration:** Real-time sensor data from system components feeds into AIDDM, enabling dynamic decision-making and autonomous SABIMS control, ensuring compliance, efficiency, and reliability.

This streamlined workflow combines continuous learning with real-time operations, optimizing SABIMS performance over time.



\## Historical Data is split into Training, Validation and Test Data for ML Model Training
** SABIMS components operational output and system parameters values
$$ Regular retraining for improving the model prediction accuracy through improved learning

\# AI Driven Decision Module
* Smart Autonomous Bilge Management System
$ Live Sensor Data from Bilge well, Tanks, Pumps, OWS, GPS for Real-Time Control

Figure 3: SABIMS Training & Operational Flowchart

6.4. Advantages of AI Integration in SABIMS

1. **Enhanced Decision-Making:** AI-powered predictions enable dynamic thresholds, optimizing operations and minimizing risks.

2. **Regulatory Compliance:** The system ensures adherence to MARPOL regulations by dynamically adjusting operations to meet environmental standards.

3. **Violation Detection:** Real-time anomaly detection prevents non-compliance through instant alerts and proactive measures.

4. **Predictive Maintenance:** AI forecasts equipment failures, enabling condition-based maintenance and reducing downtime.

5. **Time Optimization:** Efficient scheduling ensures bilge water discharge within limited timeframes during voyages.

6. **Cost Savings:** Reduced fines, optimized operations, and minimal manual intervention lower operational costs.

7. **Autonomy:** The system operates independently, reducing crew workload and enhancing safety.

6.5. Objective of SABIMS

The primary objective of SABIMS is to enable better environmental compliance through the use of AI. By seamlessly integrating deterministic automation and AI-driven adaptability, SABIMS enables proactive measures that go beyond simple regulatory compliance, enhancing MARPOL adherence, minimizing the risk of violations, and delivering tangible benefits to all stakeholders. This cutting-edge approach establishes SABIMS as a benchmark for smart, sustainable maritime operations.

7. Conclusion

This review has highlighted the significant challenges posed by existing bilge water management systems, including persistent MARPOL violations, operational inefficiencies, and the lack of dynamic adaptability in current solutions. While AI and ML applications are being implemented in the domain of water level management across various fields and have found increasing use in maritime applications, this paper reviewed the current landscape and identified a complete void in their application to engine room bilge management on ships. This gap presents a critical opportunity for innovation to address these pressing issues.

The Smart Autonomous Bilge Management System (SABIMS) is proposed as a novel solution to bridge this gap, integrating deterministic automation with advanced AI capabilities to deliver a transformative approach to bilge water management. SABIMS not only addresses operational inefficiencies and compliance risks but also introduces dynamic decision-making, ensuring strict regulatory adherence while enabling violation detection, predictive maintenance, and time-optimized bilge discharges. The system's ability to autonomously monitor, predict, and adjust operations results in enhanced environmental compliance, significant cost savings, and improved efficiency, all while functioning as a completely autonomous framework.

By addressing this critical AI technology gap, SABIMS has the potential to be a game changer for the maritime industry, setting a new standard for sustainable shipping practices. Its development offers a robust pathway toward smarter, more compliant maritime operations, addressing current limitations while paving the way for future innovations. Continued research and development will be essential to fully realize SABIMS' potential as a cornerstone for achieving global environmental objectives in the shipping sector.

8. Scope for Further Research

While the development of SABIMS represents a significant step toward autonomous and environmentally compliant bilge water management, several areas warrant further investigation to fully realize its potential. One critical aspect is the integration of advanced machine learning (ML) models into the AI-Driven Decision Module (AIDDM). This integration requires robust datasets to train and optimize the predictive capabilities of the system.

To address the challenges of limited real-world data availability and variability in operational conditions, future research should explore the generation of synthetic datasets. Synthetic data can replicate diverse scenarios and edge cases, enabling the development and fine-tuning of ML models to achieve highly accurate predictions under dynamic maritime environments.

By advancing these areas, SABIMS can transition from a conceptual framework to a fully functional system, equipped to handle complex real-world challenges with higher accuracy, adaptability, and compliance assurance. This evolution will contribute significantly to the broader goal of integrating AI for sustainable and autonomous bilge water management by enhancing environmental compliance, optimizing resource utilization, ensuring effectiveness across diverse operational scenarios, and reinforcing its role in achieving long-term sustainability in the maritime domain.

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- **Lead Author:** Conceptualization, Methodology, Data Analysis and Interpretation, Writing - Original Draft.
- **Co-Author:** Supervision, Guidance, Feedback , Review and Editing, Advised on Resources and Consultation.

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Appendix A:SABIMS Component Description

S.NO.	COMPONENT DESCRIPTION	NAME USED IN DIAGRAMS	ABBREVIATION	ACTUAL LOCATION ON SHIP
		LEVEL SENSORS - INSIDE BILGE WELLS		
1	E/R Bilge well level sensor aft	BILGE WELL (A)	BWA	E/R Aft
2	E/R Bilge well level sensor forward port	BILGE WELL (FP)	BWFP	E/R forward port
3	E/R Bilge well level sensor forward starboard	BILGE WELL (FS)	BWFS	E/R forward starboard
4	M/E flywheel pit level sensor	M/E FLYWHEEL PIT	MEFP	E/R Aft
		LEVEL SENSORS - ON E/R TANK TOP		
5	E/R Tank top flood level sensor aft	TANK TOP LEVEL (A)	TTLA	E/R Tank top aft
6	E/R Tank top flood level sensor forward port	TANK TOP LEVEL (FP)	TTFP	E/R Tank top forward port
7	E/R Tank top flood level sensor forward starboard	TANK TOP LEVEL (FS)	TTFS	E/R Tank top forward starboard
		LEVEL SENSORS - INSIDE GIVEN TANKS		
8	Bilge Tank Level Sensor	BILGE TANK LEVEL	BTL	Bilge Tank
9	Sludge Tank Level Sensor	SLUDGE TANK LEVEL	STL	Sludge Tank
10	Aft Peak Tank Level Sensor	AFT PEAK TANK LEVEL	APTL	Aft Peak Tank
		PUMP RUNNING STATUS		
11	E/R Bilge Pump	E/R BILGE PUMP RUN STATUS	ERBP	E/R Aft Port
12	Fire & Bilge Pump	FIRE & G.S. PUMP RUN STATUS	FGSP	E/R Forward port
13	Bilge & Ballast Pump	BILGE & G.S. PUMP RUN STATUS	BGSP	E/R Forward starboard
14	Main S.W. Pump	MAIN S.W. PUMP RUN STATUS	MSWP	E/R Forward starboard
		OWS & ANCILLARY EQUIPMENT STATUS		
15	Oily Water Separator	OILY WATER SEPARATOR STATUS	OWS	E/R Aft Port
16	15 Ppm Oil Alarm Monitor	15 PPM OIL ALARM MONITOR STATUS	OAM	E/R Aft Port
17	3-Way Changeover Valve-OWS Overboard discharge	3-WAY CHANGEOVER VALVE POSITION STATUS	COV	E/R Aft Port
18	Oily Water Outflow Flow meter	OILY WATER OUTFLOW MONITOR	FM	E/R Aft Port
		PUMPS AUTO/MANUAL MONITORING		
19	E/R Bilge Pump	E/R BILGE PUMP AUTO/MANUAL STATUS	ERBPAM	@ ECR Console
20	Fire & Bilge Pump	FIRE & G.S. PUMP AUTO/MANUAL STATUS	FGSPAM	@ ECR Console
21	Bilge & Ballast Pump	BILGE & G.S. PUMP AUTO/MANUAL STATUS	BGSPAM	@ ECR Console
22	Main S.W. Pump	MAIN S.W. PUMP AUTO/MANUAL STATUS	MSWPAM	@ ECR Console
23	Oily Water Separator	OWS AUTO/MANUAL STATUS	OWSAM	@ ECR Console
		OTHER COMPLIANCE MONITORING SENSORS		
24	Programmable Geo-Fencing GPS monitor	GEO-FENCE MONITOR	GPSM	Bridge ECDIS console
25	Main Engine Sub-Telegraph for ship condition	EN-ROUTE MONITOR	ERM	Bridge and ECR console
26	List angle measurement	LIST MONITOR	LM	Navigation Bridge/ECR
27	Trim value measurement	TRIM MONITOR	TM	Navigation Bridge/ECR
		VALVES		
28	E/R Bilge pump suction valve	----	ERBPSV	@ E/R bilge pump
29	E/R Bilge pump priming valve	----	ERBPPV	@ E/R bilge pump
30	Oily Water Separator inlet valve	----	OWSV	@ OWS
31	Fire & G.S. Pump Direct Suction Valve (from BWFP)	----	FGSPDSV	@BWFP
32	Fire & G.S. Pump Direct Suction Valve	----	FGSPBSV	@FGSP
33	Fire & G.S. Pump priming Valve	----	FGSPPV	@FGSP
34	Fire & G.S. Pump overboard discharge Valve	----	FGSPODV	@ Ship's side
35	Fire & G.S. Pump ballast line discharge Valve	----	FGSPBV	@FGSP
36	Bilge & G.S. Pump Direct Suction Valve (from BWFS)	----	BGSPDSV	@BWFS
37	Bilge & G.S. Pump Direct Suction Valve	----	BGSPBSV	@BGSP
38	Bilge & G.S. Pump priming Valve	----	BGSPPV	@BGSP
39	Bilge & G.S. Pump overboard discharge Valve	----	BGSPODV	@ Ship's side
40	Bilge & G.S. Pump ballast line discharge Valve	----	BGSPBV	@BGSP
41	Main Sea Water pump suction valve	----	MSWPSV	@ MSWP
42	Emergency Bilge Suction Valve	----	EBSV	@ MSWP
43	Main Sea Water pump discharge valve	----	MSWPDV	@ MSWP
44	Bilge Well Aft suction valve	----	BWASV	@BWA
45	Main Engine Flywheel Pit suction valve	----	MEFPSV	@ M/E Aft end, below flywheel
46	Bilge Well Forward Port suction valve	----	BWFPSV	@BWFP
47	Bilge Well Forward Starboard suction valve	----	BWFSSV	@BWFS
48	Aft Peak Tank suction valve	----	APTSV	@Aft Peak Tank
49	Bilge Tank suction valve	----	BTSV	@Bilge Tank
50	Bilge Tank filling valve	----	BTFV	@Bilge Tank
51	Sludge tank filling valve from E/R bilge pump	----	STFV	@Sludge Tank
		PUMP DISCHARGE PRESSURE SENSORS		
52	E/R bilge pump discharge pressure	----	ERBPDP	@ ERBP
53	Fire & G.S. pump discharge pressure	----	FGSPDP	@ FGSP
54	Bilge & G.S. pump discharge pressure	----	BGSDP	@ BGSD
55	Main sea Water pump discharge pressure	----	MSWPDP	@ MSWP