Developing a Model for Real-Time Decision Support Integration in FPSO-Based Deepwater Production Operations

ANDREW TOCHUKWU OFOEDU[1], JOSHUA EMEKA OZOR[2], OLUDAYO SOFOLUWE[3], DAZOK DONALD JAMBOL[4]
[1]*Shell Nigeria Exploration and Production Company, Nigeria*
[2]*First Hydrocarbon, Nigeria*
[3]*TotalEnergies Nigeria*
[4]*Shell Petroleum Development Company of Nigeria Ltd*

Abstract- Floating Production, Storage, and Offloading (FPSO) units are critical assets in deepwater oil and gas production, offering flexible and efficient solutions for hydrocarbon extraction in remote and challenging environments. However, the operational complexity, dynamic conditions, and safety-critical nature of FPSO-based deepwater production present significant challenges to effective decision-making. Real-time decision support systems (DSS) have emerged as essential tools to enhance situational awareness, optimize processes, and mitigate risks by integrating data from multiple sources and providing timely, actionable insights. Despite advances in automation and data analytics, the integration of real-time DSS tailored specifically for FPSO operations remains underdeveloped. This proposes a novel conceptual model for real-time decision support integration within FPSO-based deepwater production operations. The model is designed to assimilate heterogeneous data streams—including process measurements, environmental conditions, asset health indicators, and operational parameters—into a unified framework. Leveraging advanced technologies such as Internet of Things (IoT) sensors, edge computing, and artificial intelligence/machine learning (AI/ML), the model facilitates real-time data processing, predictive analytics, and visualization to support operators and engineers in making informed decisions rapidly. Key features of the model include multi-layered data integration, predictive maintenance forecasting, anomaly detection, and automated alert generation, all embedded within an intuitive human-machine interface. The architecture emphasizes scalability, interoperability with existing control systems, and adaptability to varying FPSO configurations. Validation approaches, including simulation and pilot implementation, are discussed to demonstrate the model's potential to improve operational efficiency, safety, and reliability. By providing a structured and technology-enabled framework for decision support, this model addresses the unique challenges of deepwater FPSO operations and contributes to the digital transformation of offshore production. Future research directions include empirical validation, integration of autonomous control capabilities, and extension to other offshore asset types, ultimately enhancing resilience and sustainability in complex marine environments.

Indexed Terms- Developing, Model, Real-time, Decision support, Integration, FPSO-based, Deepwater production, Operations

I. INTRODUCTION

Floating Production, Storage, and Offloading (FPSO) units have become a cornerstone in offshore oil and gas production, particularly in deepwater and ultra-deepwater environments (Awe, 2017; Oyedokun, 2019). FPSOs provide a versatile solution by combining production, processing, storage, and offloading capabilities within a single floating vessel, enabling hydrocarbon extraction from remote and challenging reservoirs without reliance on fixed infrastructure (Awe *et al*., 2017; ADEWOYIN *et al*., 2020). Deepwater production refers to hydrocarbon extraction activities conducted at water depths typically exceeding 500 meters, where subsea wells connect to FPSOs through complex riser and flowline systems (Akpan *et al*., 2017; OGUNNOWO *et al*., 2020). These operations are characterized by high capital expenditure, operational complexity, and stringent safety requirements due to harsh environmental conditions, including extreme weather, strong currents, and variable subsea pressures (Omisola *et al*., 2020; ADEWOYIN *et al*., 2020). The integrated nature of FPSOs—encompassing subsea systems, topside processing, and offloading operations—necessitates robust operational control to maintain efficiency, safety, and environmental compliance (Solanke *et al*., 2014; Chudi *et al*., 2019).

In the context of deepwater FPSO operations, the ability to make informed decisions in real time is critical. Real-Time Decision Support Systems (DSS) facilitate this by integrating data acquisition, processing, and analytics to provide actionable insights to operators and engineers (Magnus *et al*., 2011; Chudi *et al*., 2019). These systems enhance situational awareness, allowing timely responses to process deviations, equipment malfunctions, or environmental changes. The high degree of automation within FPSOs generates vast amounts of operational data, which, when effectively harnessed, can optimize production rates, improve safety margins, and reduce operational costs (Awe *et al*., 2017; Akpan *et al*., 2019). Real-time DSS thus serve as a critical interface between complex process data and human decision-makers, enabling proactive management of production processes, maintenance scheduling, and emergency response (Nuzzolo and Lam, 2017; Terziyan *et al*., 2018).

Despite technological advancements, deepwater FPSO operations face numerous challenges that complicate decision-making. The complexity and interdependence of subsea and topside systems create dynamic process interactions that are difficult to predict and control (Puecher *et al*., 2017; Monteverde *et al*., 2019). Harsh offshore environments contribute to equipment degradation and unforeseen failures, increasing operational risks. Data integration challenges arise from diverse sensor networks, varying communication protocols, and legacy systems, often resulting in fragmented information silos. Moreover, latency in data transmission and processing can hinder timely interventions. Human factors, such as operator workload, cognitive overload, and situational awareness limitations, further complicate decision-making under pressure (Aricò *et al*., 2017; Kim and Seong, 2019). Regulatory constraints and stringent safety standards add layers of operational complexity. These challenges highlight the necessity for advanced, integrated decision support solutions tailored to the unique context of deepwater FPSO production.

This aims to develop a conceptual model for real-time decision support integration specifically designed for FPSO-based deepwater production operations. The primary objective is to create a framework that seamlessly integrates heterogeneous data sources, advanced analytics, and user-centered interfaces to enhance operational decision-making. The model seeks to address existing challenges by improving data interoperability, reducing latency, and incorporating predictive and prescriptive analytics to anticipate and mitigate risks (Bhattarai *et al*., 2019; Osman, 2019). Additionally, the framework emphasizes scalability and adaptability to accommodate varying FPSO configurations and operational scenarios. The scope encompasses process data acquisition, environmental monitoring, asset health assessment, and integration with existing control systems. Ultimately, the model aspires to support operators in making faster, more accurate decisions, thereby enhancing production efficiency, safety, and asset integrity in complex deepwater offshore environments.

II. METHODOLOGY

The methodology for this followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure a systematic and transparent literature review process. An extensive search was conducted across multiple academic databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect. The search strategy utilized a combination of keywords such as "real-time decision support," "FPSO," "deepwater production," "automation integration," and "offshore oil and gas," applying Boolean operators to refine results.

Inclusion criteria were established to focus on peer-reviewed articles, conference papers, and technical reports published from 2000 to 2025, available in English, and specifically addressing real-time decision support systems, integration frameworks, or operational challenges in FPSO and deepwater production contexts. Exclusion criteria eliminated studies unrelated to offshore production, those focusing on non-real-time systems, or lacking substantive conceptual or empirical content.

The initial search yielded a significant number of records, which were imported into reference management software to remove duplicates. Titles and abstracts were screened against the inclusion criteria to identify relevant studies. Subsequently, full-text reviews were conducted on the shortlisted articles to confirm their relevance and quality. The screening and selection process was independently performed by multiple reviewers to ensure objectivity and reduce bias.

Data extraction from the selected studies captured key elements such as decision support methodologies, integration approaches, system architectures, operational contexts, and reported outcomes related to FPSO-based deepwater production. The synthesized data allowed for thematic analysis and identification of gaps in current real-time decision support models applicable to FPSO operations.

This systematic review provided a foundation for developing a comprehensive, domain-specific model for real-time decision support integration tailored to the unique challenges and operational requirements of FPSO-based deepwater production systems. The PRISMA methodology ensured a rigorous and replicable approach to literature synthesis, facilitating the creation of a robust conceptual framework grounded in current research.

2.1 Overview of FPSO-Based Deepwater Production Operations

Floating Production Storage and Offloading (FPSO) units have become a cornerstone technology in the development of offshore deepwater oil and gas fields (D'Souza *et al*., 2019; LaGrange and Maisey, 2019). These sophisticated vessels enable the extraction, processing, storage, and offloading of hydrocarbons directly at sea, particularly in regions where fixed platforms are impractical due to water depth, remoteness, or environmental constraints. FPSOs offer unmatched operational flexibility, allowing oil companies to tap into deepwater reservoirs with enhanced efficiency and adaptability. This provides an overview of FPSO systems, the key processes involved in deepwater production, and the operational complexities and risks unique to FPSO operations in challenging marine environments.

FPSO systems are essentially ship-shaped floating vessels equipped with topside processing facilities, storage tanks, and offloading infrastructure. Their primary advantage lies in their ability to operate independently without reliance on fixed infrastructure or permanent pipelines. This makes them ideally suited for deepwater environments where subsea wells are connected to the FPSO via risers and flowlines. The operational environment for FPSOs is highly dynamic, characterized by deep ocean depths, strong currents, waves, and extreme weather conditions such as hurricanes or cyclones (Zanganeh and Thiagarajan, 2018; Armstrong *et al*., 2019). Additionally, FPSOs are often moored using turret mooring systems that allow the vessel to rotate freely with the prevailing weather and sea conditions, reducing structural stress and improving operational stability. The modular design of FPSOs also enables relocation and redeployment to different fields, further enhancing their utility in the offshore industry.

The key production processes onboard an FPSO involve the separation, storage, and offloading of hydrocarbons extracted from subsea wells. The separation process is critical for isolating oil, gas, water, and impurities, ensuring that the produced fluids meet quality standards for export or further treatment. This typically involves multi-phase separators that operate under high pressure and temperature, given the challenging conditions of deepwater reservoirs. The separated oil is then stored in the vessel's large storage tanks, which can hold significant volumes of crude oil until offloading. Storage capacity is a vital aspect as it directly affects the FPSO's operational autonomy and economic efficiency. Offloading is the process of transferring stored oil to shuttle tankers or pipelines for transportation to onshore facilities. Offloading operations require precise coordination to manage the dynamic motions of the FPSO and shuttle tankers, often necessitating specialized offloading systems such as flexible hoses or tandem offloading arrangements (Xu *et al*., 2019; Utne *et al*., 2019).

Additionally, gas separated from the production stream may be re-injected into the reservoir, flared, or processed for export, depending on field development strategies.

Deepwater FPSO operations are inherently complex and fraught with numerous risks due to the harsh environmental and technical conditions. One of the primary operational complexities arises from the integration of subsea infrastructure with topside processing facilities, requiring advanced control systems and robust communication networks to ensure real-time monitoring and control. The dynamic motion of the vessel, influenced by waves and currents, affects the stability of risers and mooring systems, posing challenges for maintaining safe and efficient production. Environmental factors such as corrosion from seawater, biofouling, and extreme weather events necessitate rigorous maintenance regimes and contingency planning (Francis, 2019; Verma *et al*., 2019).

The risks specific to deepwater FPSOs are multifaceted. Safety hazards include the potential for hydrocarbon leaks, fires, and blowouts, which are exacerbated by the remote location and limited emergency response capabilities offshore. The complexity of handling multiphase flow and maintaining separation efficiency under fluctuating reservoir conditions further increases operational risk. Additionally, deepwater operations are capital intensive, and any unplanned downtime can lead to significant economic losses. Regulatory compliance and environmental protection standards impose additional operational constraints, requiring continuous risk assessment and mitigation strategies.

FPSO-based deepwater production operations represent a highly specialized and challenging sector within the offshore oil and gas industry. The unique combination of mobile processing capability, deepwater adaptability, and complex operational environment demands advanced engineering, stringent safety practices, and sophisticated automation systems (Wong *et al*., 2018; Max *et al*., 2019). Understanding the key processes and inherent risks associated with FPSOs is essential for optimizing their performance and ensuring safe, reliable, and efficient production in deepwater settings.

2.2 Real-Time Decision Support Systems: Concepts and Technologies

Real-Time Decision Support Systems (DSS) are integrated software frameworks designed to assist operators and engineers in making timely and informed decisions by continuously collecting, processing, analyzing, and presenting data as events unfold. Unlike traditional DSS, real-time DSS operate under stringent time constraints, enabling immediate responses to dynamic operational conditions. The primary functions of real-time DSS include situational awareness enhancement, anomaly detection, process optimization, risk mitigation, and predictive maintenance (Mishra *et al*., 2017; Ortiz *et al*., 2019). In offshore oil and gas production, these systems serve as critical intermediaries between complex process data streams and human decision-makers, translating raw data into actionable insights that improve safety, reliability, and efficiency.

A comprehensive real-time DSS comprises four main components; data acquisition, data processing, analytics, and visualization. Data Acquisition, this component involves the collection of data from diverse sources such as sensors, control systems, weather stations, and subsystems within the FPSO. Data can include process variables (pressure, temperature, flow rates), equipment status, environmental parameters, and safety alarms. Effective data acquisition requires robust communication protocols and sensor networks capable of delivering high-frequency, accurate data under harsh offshore conditions. Data Processing, after acquisition, raw data undergoes preprocessing steps such as filtering, normalization, synchronization, and validation to ensure accuracy and consistency (Pernet *et al*., 2018; Yin *et al*., 2019). Data processing transforms disparate data streams into a unified, reliable dataset suitable for analysis. This stage also involves real-time data integration across multiple subsystems and handling missing or noisy data. The analytics component applies statistical methods, machine learning algorithms, and rule-based logic to interpret processed data as shown in figure 1. Functions include pattern recognition, anomaly detection, predictive modeling, and optimization. Predictive analytics, for example, can forecast equipment failures or process upsets, enabling proactive interventions. Advanced prescriptive analytics provide recommended actions based on scenario simulations. Visualization translates analytic outputs into intuitive graphical user interfaces (GUIs) that enable operators to quickly comprehend complex data and trends. Dashboards, alarms, 3D process models, and augmented reality tools enhance situational awareness and support decision-making under time pressure (Franklin *et al*., 2017; Lee *et al*., 2018).

Figure 1: Components of DSS

Several emerging technologies underpin the development and effectiveness of real-time DSS in offshore FPSO operations. Internet of Things (IoT) technologies facilitate extensive sensor deployment across FPSOs, enabling continuous monitoring of process conditions and asset health. IoT networks support high data volumes and ensure connectivity between subsea equipment, topside modules, and control centers, despite challenging offshore environments. Edge Computing, given the latency and bandwidth limitations of offshore communication, edge computing is critical. By processing data locally at or near the data source (e.g., on the FPSO), edge computing reduces response times and dependence on remote data centers. This allows real-time analytics and decision-making without delays caused by data transmission. Artificial Intelligence and Machine Learning (AI/ML), algorithms enhance DSS capabilities by learning from historical and real-time data to detect complex patterns and predict future events (Mehmood *et al*., 2019; Gubbi *et al*., 2019). These techniques improve anomaly detection sensitivity, optimize control strategies, and automate routine decisions. AI-driven DSS adapt continuously, increasing accuracy and reducing operator workload.

Real-time DSS have been successfully deployed in various upstream oil and gas applications such as well monitoring, drilling optimization, production forecasting, and asset integrity management. Onshore and fixed platform installations have leveraged these systems to improve operational performance and safety. However, unique challenges in FPSO environments—such as constrained onboard computational resources, communication bandwidth limitations, and complex subsea-to-topside integration—have limited the full realization of real-time DSS benefits.

Existing DSS solutions often lack seamless integration across the diverse systems on FPSOs, resulting in fragmented data views and delayed decision-making (Bole *et al*., 2017; Ribotti *et al*., 2018). Additionally, many systems focus on specific functions, such as predictive maintenance or process control, rather than providing a holistic, multi-dimensional decision support platform. There is also limited incorporation of advanced AI/ML tailored to the dynamic and stochastic nature of deepwater production.

These gaps highlight the need for specialized real-time DSS models that address FPSO-specific constraints, emphasize data interoperability, and incorporate adaptive analytics. Such systems would enable operators to manage the complexity and risk inherent in deepwater FPSO operations more effectively, ultimately improving operational resilience, safety, and productivity.

Real-time DSS integrate advanced technologies and multi-source data processing to transform offshore operational management. While substantial progress has been made in oil and gas, targeted development and integration efforts are required to meet the unique demands of FPSO-based deepwater production operations (Gulas *et al*., 2017; Lu *et al*., 2019).

2.3 Requirements for Decision Support in FPSO Deepwater Operations

Floating Production Storage and Offloading (FPSO) units operating in deepwater environments present unique challenges that necessitate robust and adaptive decision support systems (Meng *et al*., 2018; Whyte *et al*., 2018). These systems assist operators in making timely and informed decisions critical to ensuring safety, optimizing production processes, and maintaining asset integrity. The complex interplay of operational demands, data diversity, real-time constraints, and human factors shapes the specific requirements for decision support in FPSO deepwater operations as shown in figure 2.

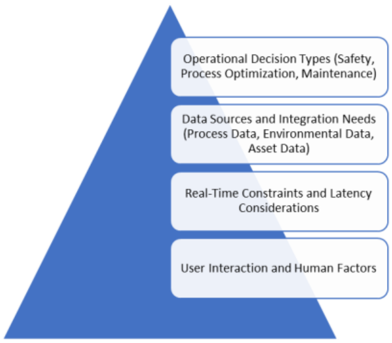

Figure 2: Requirements for Decision Support in FPSO Deepwater Operations

Operational decisions in FPSO contexts span multiple domains, each with distinct priorities and urgency levels. Safety decisions are paramount, as the offshore environment is inherently hazardous due to the presence of flammable hydrocarbons, extreme weather conditions, and limited emergency response capabilities. Decision support systems must enable rapid detection and response to abnormal events such as leaks, fire outbreaks, or equipment failures to prevent catastrophic incidents. Next, process optimization decisions focus on maximizing hydrocarbon recovery while minimizing operational costs and environmental impact. These involve adjusting process parameters like flow rates, pressure, temperature, and chemical dosing to maintain optimal separation and production efficiency. Lastly, maintenance decisions are critical for asset longevity and reliability. Predictive maintenance strategies require decision support systems that can analyze condition monitoring data to forecast equipment degradation and schedule timely interventions, thus reducing unplanned downtime and costly repairs.

A fundamental requirement for effective decision support is the integration of diverse data sources that collectively represent the operational state of the FPSO. Process data includes measurements such as pressure, temperature, flow rates, and valve positions collected from sensors distributed across subsea wells, risers, and topside processing equipment (Sotoodeh, 2019; Hansen *et al.*, 2019). This data provides real-time insight into production dynamics and equipment performance. Environmental data, encompassing wave height, wind speed, sea currents, and weather forecasts, is essential for assessing operational risks and planning activities such as offloading or emergency shutdowns. Asset data, including maintenance records, equipment specifications, and historical failure modes, informs reliability assessments and maintenance planning. Integrating these heterogeneous data streams in a coherent manner is challenging but vital for holistic situational awareness and decision accuracy.

The decision support system must operate within stringent real-time constraints to be effective in FPSO deepwater environments. Many operational decisions, particularly those related to safety and process control, require near-instantaneous data processing and response capabilities. Latency in data acquisition, transmission, or analysis can lead to delayed actions, potentially compromising safety or reducing production efficiency. Therefore, system architectures must prioritize low-latency communication protocols, edge computing for local data processing, and high availability to ensure continuous operation. Additionally, the system should support varying time horizons for decision-making—from immediate emergency responses measured in seconds, to longer-term maintenance planning over days or weeks.

User interaction and human factors are critical considerations in the design of decision support systems for FPSOs. Operators typically work in control rooms under high cognitive load, managing multiple alarms and complex system interdependencies. Decision support interfaces must present information clearly and intuitively, emphasizing critical alerts and actionable recommendations while minimizing information overload. Visualization tools such as dashboards, trend graphs, and scenario simulations aid comprehension and support rapid decision-making. Furthermore, systems should be customizable to accommodate varying operator expertise and preferences (Sarikaya *et al.*, 2018; Kalliski *et al.*, 2018). Incorporating user feedback mechanisms and ergonomic design principles improves usability and acceptance, ultimately enhancing operational effectiveness.

Effective training and familiarization with decision support tools are also essential to ensure that human operators can trust and efficiently utilize these systems during routine and emergency situations. Additionally, the system should support collaborative decision-making, allowing multiple stakeholders—such as offshore operators, maintenance engineers, and remote experts—to share situational awareness and coordinate responses.

Decision support systems in FPSO deepwater operations must address a multifaceted set of requirements. They must support diverse operational decisions encompassing safety, process optimization, and maintenance. Integration of heterogeneous data sources into a unified framework is essential for comprehensive situational awareness. Real-time processing capabilities with minimal latency are critical to timely and effective decision-making. Lastly, user-centric design that accounts for human factors ensures that operators can efficiently interpret and act upon system recommendations. Meeting these requirements is vital for enhancing safety, reliability, and efficiency in the challenging deepwater FPSO environment.

2.4 Proposed Model for Real-Time DSS Integration

The proposed model for real-time decision support system (DSS) integration in FPSO-based deepwater production operations is designed as a multi-layered architecture that addresses the complexities of data acquisition, processing, analysis, and decision dissemination. At its core, the architecture facilitates seamless interaction between physical assets, data infrastructures, analytics engines, and human operators (Morgan and O'Donnell, 2017; Trakadas *et al*., 2019). The architecture consists of four primary layers: the sensing layer, data integration layer, analytics layer, and user interface layer. The sensing layer comprises heterogeneous sensors and instrumentation across subsea systems, topside processing units, and environmental monitoring stations. Data collected at this level is transmitted to the data integration layer, which consolidates and harmonizes data from diverse sources into a unified, real-time data repository. The analytics layer leverages this integrated dataset to perform advanced computations, including predictive and prescriptive analytics. Finally, the user interface layer delivers actionable insights through visualization dashboards and alerting systems to support timely decision-making by operators and engineers.

One of the central challenges in FPSO operations is managing the vast array of data originating from heterogeneous sources, each with distinct formats, protocols, and update frequencies. The model incorporates a robust integration framework that standardizes data exchange using open communication protocols such as OPC UA and MQTT. This framework supports both batch and streaming data integration, ensuring high-velocity data flows are managed without loss or latency. Middleware components handle data normalization, error checking, and timestamp synchronization, enabling real-time cross-referencing of process data, environmental parameters, and asset condition monitoring. Moreover, the framework supports interoperability with legacy control systems and newer IoT platforms, allowing incremental integration and minimizing operational disruptions (Givehchi *et al*., 2017; Lilis *et al*., 2017). Secure data transmission and role-based access controls are embedded to maintain cybersecurity and data integrity.

The analytics layer is the intellectual core of the DSS, implementing multiple modules that perform real-time and predictive analysis. Real-time analytics continuously monitor operational parameters to detect anomalies and deviations from expected behavior. Predictive modules employ machine learning algorithms—such as neural networks, support vector machines, and ensemble models—to forecast equipment failures, process bottlenecks, or environmental threats based on historical and real-time data trends. These models are trained on comprehensive datasets that include historical incident logs, sensor readings, and operational conditions. Prescriptive analytics further extend these capabilities by simulating potential interventions and recommending optimized actions to mitigate risks or enhance performance. The modular design allows for adaptive learning, where models are updated dynamically as new data becomes available, improving accuracy over time.

Effective visualization is critical for bridging the gap between complex analytics and operational decisions. The model incorporates customizable dashboards tailored to different user roles, such as operators, engineers, and management, offering varying levels of detail and interactivity. Visual elements include real-time process flow diagrams, trend graphs, heatmaps, and 3D models of the FPSO and subsea infrastructure. Alerting mechanisms are integrated to notify users of critical events through color-coded alarms, sound notifications, and mobile alerts. These alerts prioritize based on severity and potential impact, helping operators focus on the most urgent issues. Interactive visualization tools also support scenario analysis and drill-down capabilities, enabling users to investigate root causes and evaluate the effectiveness of past decisions (Wu *et al*., 2017; Basole *et al*., 2018).

To ensure sustained performance and system adaptability, the model incorporates feedback loops that close the gap between system outputs and operational reality. User feedback, incident reports, and operational outcomes are fed back into the analytics layer to refine predictive models and update decision rules. This continuous learning mechanism enables the DSS to evolve with changing operational conditions, new equipment, and updated regulatory requirements. Automated logging of decisions and system responses facilitates audit trails and supports post-event analysis. Additionally, periodic system performance reviews and retraining sessions are scheduled to validate model accuracy and incorporate domain expert insights. This iterative approach fosters a learning organization culture and enhances the long-term resilience and effectiveness of real-time decision support in FPSO deepwater production operations.

The proposed model integrates advanced data handling, analytics, and human-centric design within a scalable architecture tailored for the unique complexities of FPSO environments. By harmonizing multi-source data, leveraging predictive intelligence, and facilitating intuitive user interactions, the model aims to elevate operational decision-making, improve safety, and optimize production in deepwater offshore settings (Sivils *et al*., 2019; Thomas *et al*., 2019).

2.5 Model Validation and Implementation Considerations

Developing a robust decision support model for Floating Production Storage and Offloading (FPSO) units in deepwater production necessitates thorough validation and careful implementation planning. The complexity of FPSO systems, their dynamic operational environments, and the critical nature of decisions require that models be rigorously tested before deployment and seamlessly integrated with existing control infrastructures (Mastrangelo *et al*., 2019; Aalberts *et al*., 2019). This discusses key considerations for model validation, performance assessment, integration challenges, and scalability to ensure successful implementation in diverse FPSO settings.

A fundamental step in model validation involves simulation and pilot testing approaches. Simulation provides a controlled environment to evaluate the model's behavior under a variety of operational scenarios without risking real assets or production downtime. High-fidelity dynamic simulations replicate the FPSO's process conditions, environmental interactions, and control responses, enabling detailed analysis of model accuracy and robustness. These simulations often incorporate real-time data feeds and stochastic elements such as equipment failures or weather disturbances to test the model's resilience and adaptability. Pilot testing extends validation by deploying the model on a limited scale within an operational FPSO, often in a shadow mode alongside existing decision support systems. This approach allows comparison between model recommendations and operator decisions under live conditions, identifying discrepancies and areas for improvement while minimizing operational risks. Iterative cycles of simulation and pilot testing build confidence in the model's reliability and performance.

Defining performance metrics and success criteria is essential for objective evaluation during validation and subsequent monitoring in operational use. Metrics typically include accuracy, precision, and recall of event detection in safety-critical scenarios, as well as production optimization indicators such as throughput enhancement and downtime reduction. Latency—the time delay between data input and decision output—is another critical metric, especially for real-time decision support in rapidly changing deepwater environments. User acceptance and usability measures, obtained via operator feedback and system interaction logs, also serve as important success criteria (Bano *et al*., 2017; Alexandre *et al*., 2018). Success is often defined by the model's ability to improve operational outcomes while maintaining or enhancing safety and regulatory compliance. Establishing clear benchmarks enables ongoing performance tracking and continuous improvement post-implementation.

Seamless integration with existing FPSO control and automation systems represents a significant implementation challenge. FPSOs typically employ complex, multi-vendor distributed control systems (DCS), supervisory control and data acquisition (SCADA) platforms, and specialized subsea control systems. The decision support model must interface effectively with these systems to access real-time process data and to communicate actionable recommendations or automated control actions. Integration requires adherence to industry communication standards such as OPC-UA and support for legacy protocols common in offshore facilities. Cybersecurity considerations are paramount to protect against unauthorized access or data manipulation. Additionally, integration should preserve system redundancy and fail-safe features critical for offshore safety. Close collaboration with control system vendors and operational teams is necessary to ensure that the decision support model complements rather than disrupts existing workflows.

The scalability and adaptability of the model to accommodate different FPSO configurations and field-specific conditions are crucial for widespread applicability. FPSOs vary in size, processing capacity, mooring arrangements, and subsea architecture, influencing the nature and complexity of decision support requirements. A modular model design facilitates customization, allowing operators to enable or disable features according to asset specifics. Adaptability extends to evolving operational contexts such as field life-cycle stages, changing production profiles, and integration of new technologies like digital twins or advanced sensors. Cloud-based or edge computing architectures enhance scalability by supporting distributed data processing and allowing updates without extensive downtime (Taleb *et al*., 2017; Qi and Tao, 2019). Additionally, models should be designed to learn and improve from historical operational data, enhancing their predictive capabilities and relevance over time.

Effective model validation and implementation for decision support in FPSO deepwater operations demand a comprehensive approach. Simulation and pilot testing provide rigorous, risk-mitigated environments for performance evaluation. Clearly defined metrics guide objective assessment and continuous improvement. Careful integration with existing control and automation systems ensures operational compatibility and safety. Finally, scalability and adaptability enable the model to serve diverse FPSO assets and evolving operational demands. Addressing these considerations holistically is vital to harnessing decision support models' full potential to enhance safety, efficiency, and reliability in the challenging offshore deepwater domain.

2.6 Challenges and Mitigation Strategies

Implementing real-time decision support systems (DSS) in FPSO-based deepwater production operations faces substantial technical challenges, primarily related to data quality and integration complexity as shown in figure 3. Data quality issues stem from sensor inaccuracies, communication disruptions, and environmental interference common in harsh offshore conditions. Sensor degradation, calibration drift, and intermittent connectivity often result in missing, noisy, or inconsistent data streams. Such poor data quality compromises the reliability of analytics and decision-making, potentially leading to erroneous actions or missed alarms. Furthermore, integrating heterogeneous data sources—ranging from subsea sensors, topside instrumentation, control systems, to third-party environmental monitoring—poses significant complexity (Munafờ *et al*., 2019; Gayes *et al*., 2019). Differences in data formats, communication protocols, and update frequencies create interoperability barriers, complicating real-time data fusion. Legacy systems often lack standard interfaces, necessitating bespoke adapters or middleware solutions. To mitigate these challenges, robust data validation and cleaning algorithms must be embedded within the DSS to filter out anomalies and fill data gaps using imputation techniques. Adoption of industry standards like OPC UA can streamline interoperability. Additionally, modular middleware architectures can abstract system heterogeneity and enable scalable integration, while redundant communication pathways improve data availability.

Beyond technical constraints, organizational and cultural factors significantly influence the successful deployment of real-time DSS on FPSOs. Resistance to change is common in mature offshore operations, where entrenched workflows and traditional decision-making processes prevail. Operators may distrust automated recommendations or fear job displacement, leading to underutilization of DSS capabilities. The cognitive overload resulting from new interfaces or alert systems can also reduce acceptance. Furthermore, interdisciplinary collaboration between IT, operational, and engineering teams is often insufficient, hindering holistic implementation. To overcome these barriers, stakeholder engagement and comprehensive training programs are critical. Transparent communication about DSS objectives, benefits, and limitations fosters trust and aligns expectations. Participatory design approaches, involving operators in system development and customization, improve usability and ownership. Leadership must champion digital transformation efforts and incentivize adoption through performance metrics. Cultural change initiatives emphasizing human-machine collaboration and continuous learning cultivate an adaptive organizational mindset supportive of real-time decision support technologies (Raybourn *et al*., 2017; Metcalf *et al*., 2019).

Figure 3: Challenges and Mitigation Strategies

The integration of real-time DSS in FPSO operations introduces heightened cybersecurity and data privacy risks. Offshore facilities are increasingly digitized and interconnected, expanding the attack surface vulnerable to cyber threats such as hacking, ransomware, and data tampering. Compromise of critical operational data or control systems could lead to catastrophic safety incidents, production losses, or environmental harm. Protecting sensitive proprietary and personal data collected through monitoring systems is also essential to comply with privacy regulations and safeguard commercial interests. Mitigation strategies include implementing multi-layered cybersecurity frameworks that encompass network segmentation, encryption, intrusion detection, and secure authentication protocols (Meera, 2019; Mughal, 2019). Regular vulnerability assessments, penetration testing, and incident response planning strengthen resilience against cyberattacks. Employing edge computing for local data processing reduces dependence on external networks, limiting exposure. Furthermore, adherence to cybersecurity standards such as IEC 62443 and coordination with regulatory bodies ensure robust protection. Training personnel on cyber hygiene and establishing clear data governance policies are equally vital to prevent human-related breaches.

FPSO operations are subject to stringent regulatory frameworks designed to ensure safety, environmental protection, and operational integrity. Real-time DSS implementations must comply with relevant international and national regulations governing offshore oil and gas activities, such as API standards, OSHA regulations, and local maritime laws. Compliance challenges arise from the need to validate DSS outputs, maintain traceability of decisions, and ensure that automated interventions meet safety integrity levels (SIL) prescribed for critical control functions (Nicoletti 2018; Tolio *et al*., 2019). Regulatory bodies may also require transparency on algorithmic decision-making, posing challenges for proprietary or complex AI models. Additionally, evolving regulations on data management and cybersecurity necessitate ongoing system updates. To navigate these issues, DSS designs must incorporate audit trails that log data inputs, analytic results, and operator actions, enabling verification and forensic analysis. Collaborating early with regulators during development promotes alignment and facilitates certification processes. Implementing configurable safety envelopes within DSS ensures that automated recommendations adhere to predefined safety thresholds. Continuous monitoring of regulatory developments and incorporating compliance checks into system updates maintain operational legality and reduce liability risks.

The deployment of real-time DSS in FPSO deepwater production operations confronts multifaceted challenges spanning technical, organizational, cybersecurity, and regulatory domains. Addressing these through robust data management, inclusive organizational strategies, comprehensive cybersecurity protocols, and proactive regulatory compliance will be pivotal to realizing the full potential of decision support technologies in enhancing safety, efficiency, and resilience offshore (Choucri *et al*., 2017; Catota *et al*., 2019; Akinsanya *et al*., 2019).

CONCLUSION

This has presented a comprehensive exploration of decision support systems (DSS) tailored for Floating Production Storage and Offloading (FPSO) units operating in deepwater oil and gas environments. The research has focused on developing a conceptual model that integrates real-time data streams, operational decision-making needs, and system architecture considerations unique to FPSO deepwater production. This concluding section summarizes the key contributions, acknowledges inherent limitations, and outlines promising avenues for future research.

The primary contribution of this work lies in articulating a structured framework for real-time decision support integration specific to FPSO deepwater operations. By systematically reviewing operational requirements, data integration challenges, and human factors, the model addresses the multifaceted nature of offshore production decision-making. The framework emphasizes the convergence of safety-critical, process optimization, and maintenance-related decisions, underpinned by heterogeneous data sources such as process measurements, environmental monitoring, and asset health information. Additionally, it incorporates real-time constraints and latency considerations essential for timely and effective interventions. This also highlights practical implementation aspects, including simulation-based validation, integration with legacy control systems, and scalability across different FPSO configurations. Together, these contributions provide a holistic roadmap for advancing decision support capabilities that enhance operational efficiency, safety, and resilience in challenging deepwater contexts.

Despite its strengths, this acknowledges several limitations that constrain its immediate applicability. First, the proposed model, while comprehensive, has been primarily validated through simulation and pilot testing scenarios rather than extensive field deployment. This limits the understanding of its performance under diverse real-world conditions, including extreme weather events, unexpected equipment failures, or cyber-physical threats. Second, the integration strategies discussed focus predominantly on existing control and automation infrastructures, potentially overlooking emerging technologies or proprietary systems that vary across operators. Third, the human factors analysis, though informed by established ergonomic principles, would benefit from deeper empirical studies involving actual FPSO operators to refine interface designs and interaction protocols. Lastly, the model currently assumes relatively stable communication networks, an assumption that may not hold true in all offshore environments where bandwidth limitations and intermittent connectivity are common.

Looking forward, several promising research directions emerge to enhance and extend the current work. A foremost area is the integration of advanced artificial intelligence (AI) and machine learning (ML) techniques to improve predictive analytics, anomaly detection, and adaptive decision-making capabilities. AI-driven models can leverage vast historical and real-time datasets to identify subtle patterns and optimize operational strategies dynamically, reducing human cognitive load and improving response times. Additionally, there is growing interest in developing autonomous operation frameworks that enable FPSOs to operate with minimal human intervention, particularly in hazardous or remote conditions. This entails integrating robotics, autonomous control algorithms, and robust fail-safe mechanisms to maintain safety and continuity.

Furthermore, expanding decision support systems beyond individual FPSOs towards cross-asset integration represents a critical frontier. As offshore fields increasingly employ multiple interconnected assets—such as subsea infrastructure, drilling rigs, and floating units—decision support must evolve to provide holistic situational awareness and coordinated control across the entire ecosystem. This cross-asset DSS approach can facilitate optimized resource allocation, emergency response, and maintenance scheduling at the field or portfolio level.

In conclusion, this lays a foundational framework for real-time decision support in FPSO deepwater operations, addressing key technical and operational challenges. While limitations remain, ongoing advancements in AI, autonomy, and system integration promise to substantially enhance the effectiveness and scope of such models. Future research focused on these areas will be instrumental in realizing safer, more efficient, and resilient offshore production systems, ultimately supporting the sustainable development of deepwater hydrocarbon resources.

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