International Journal of Scientific Research in Science and Technology
Available online at : www.ijsrst.com
OPEN ACCESS
Print ISSN: 2395-6011 | Online ISSN: 2395-602X
doi : https://doi.org/10.32628/IJSRST

Toward a Real-Time Decision Support System for Drilling Operations: Conceptual Architecture and Field Feasibility

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Article Info

Publication Issue
Volume 10, Issue 6
November-December-2023

Page Number
679-692

Article History
Accepted: 20 Dec 2023
Published: 30 Dec 2023

ABSTRACT

The increasing complexity of modern drilling operations, driven by deeper wells, tighter financial margins, and elevated subsurface uncertainties, has necessitated the development of real-time decision support systems (DSS) to enhance operational responsiveness and risk mitigation. This paper proposes a structured and modular conceptual framework for a real-time DSS tailored to drilling operations. The model comprises three core architectural layers—data acquisition, analytics, and decision support—designed to enable seamless integration of surface and downhole data, diagnostic analytics, and decision logic. Functional modules support event detection, risk scoring, trajectory correction, and rig performance optimization, while collaborative interfaces foster cross-disciplinary communication and rapid intervention. Implementation considerations address IT infrastructure, cybersecurity, organizational readiness, and governance. The system promises to improve decision speed, reduce non-productive time, and align drilling practices with digital transformation goals. Future pathways include integration with machine learning models, support for autonomous drilling, and advancement toward intelligent, adaptive well delivery systems. The framework establishes a foundation for safer, more efficient, and data-driven drilling operations in an increasingly complex energy landscape.

Keywords: Real-Time Decision Support, Drilling Optimization, Digital Oilfield, Drilling Data Analytics, Operational Risk Mitigation, Intelligent Well Delivery Systems

1. Introduction

1.1 Background

The drilling industry is undergoing a transformative shift, fueled by the demand for deeper targets, narrower economic margins, and mounting geological uncertainties. These operational realities call for heightened precision in execution and planning [1]. With increased technical challenges—such as wellbore instability, pressure anomalies, and equipment wear—traditional decision-making timelines no longer suffice. Drilling teams must adapt to a faster, more uncertain environment that rewards real-time awareness and responsiveness [2].

Conventional decision-making approaches often rely on retrospective analyses, where field data is interpreted long after critical events have occurred [3]. This time lag can lead to missed opportunities for intervention, escalating operational risk, and, in many cases, financial loss [4]. The gap between event detection and corrective action has become a major source of non-productive time and cost overruns. As drilling complexity rises, so does the inadequacy of static decision models, creating an urgent need for solutions that are dynamic, scalable, and intelligent [5, 6].

To address this gap, the industry is increasingly exploring digital transformation strategies, including the use of real-time data analytics and decision automation. Integrating sensors, telemetry, and intelligent algorithms into a cohesive architecture offers a pathway to improve both safety and performance. Such systems can enhance human decision-making with timely alerts, actionable insights, and predictive capabilities. The envisioned decision support system aims to serve as a central nervous system for drilling operations—assimilating data and distributing intelligence across functions and disciplines.

1.2 Problem Definition

One of the persistent challenges in drilling operations is the fragmented nature of information flow between different teams, such as subsurface, engineering, operations, and HSE personnel. These silos inhibit timely decision-making and often result in delayed responses to developing issues at the rig site [7, 8]. When data is collected but not shared or analyzed effectively in real time, opportunities for intervention are frequently lost. This disjointed communication framework increases the likelihood of operational inefficiencies, equipment failure, and safety incidents [9-11].

Moreover, while vast volumes of drilling data are now collected through advanced sensors and digital tools, there remains a significant deficiency in systems that can interpret this information coherently and generate useful recommendations [12, 13]. Most existing workflows are reactive, built around predefined thresholds and manual interpretations. These systems often fail to correlate multi-dimensional data streams or anticipate emerging risks before they materialize. As a result, operators struggle to convert real-time data into timely, high-quality decisions [14, 15].

The crux of the issue lies in the widening gap between the availability of real-time data and the industry's capacity to utilize it intelligently. Without an integrated platform to process, contextualize, and act upon live information, operators are left navigating complex scenarios with incomplete situational awareness [16, 17]. This paper identifies the absence of unified, decision-enabling systems as a major constraint on drilling efficiency and safety. The proposed solution—a real-time decision support system—seeks to close this gap by providing a structured, intelligent, and proactive approach to operational decision-making.

1.3 Objectives and Significance

The principal objective of this paper is to propose a robust conceptual framework for a real-time decision support system tailored to the specific demands of drilling operations. The model aims to synthesize multiple data sources—including surface parameters, downhole measurements, and historical performance records—into a single, coherent architecture. By leveraging advanced analytics and intelligent rule engines, the system is designed to provide real-time recommendations, alerts, and insights that empower drilling teams to respond rapidly and effectively to unfolding events.

To achieve this, the paper outlines the critical components of the proposed system: data ingestion and processing layers, analytical engines, user interfaces, and feedback mechanisms. It also explores how these components interact within an operational workflow to enable iterative, informed decision-making. Particular emphasis is placed on defining the functional relationships among system elements—such as alert logic, visualization tools, and decision hierarchies—that underpin its practical utility in a field environment.

Beyond the technical architecture, the significance of this model lies in its potential to transform how drilling teams interact with data and make decisions. By enabling more collaborative, informed, and rapid responses to dynamic conditions, the system stands to improve operational efficiency, reduce non-productive time, and enhance overall safety. Furthermore, the framework offers a scalable foundation for future integration of automation, machine learning, and digital twin technologies, positioning it as a strategic tool in the ongoing digital evolution of well construction.

2. Technical Foundations

2.1 Real-Time Drilling Data Ecosystem

A robust real-time DSS depends first and foremost on a comprehensive and reliable data ecosystem. Drilling generates numerous high-frequency data streams from various sources, including surface sensors that measure parameters like hookload and pump pressure, downhole tools capturing temperature and inclination, and MWD/LWD services providing resistivity, gamma ray, and azimuthal imaging [18-20]. Mud logging systems further augment this ecosystem with lithological and gas composition data. These disparate inputs must be collected, processed, and interpreted cohesively to ensure operational relevance [21, 22].

Time-series data integrity is a critical factor in maintaining decision accuracy. Latency—delays in data transmission or processing—can reduce the usefulness of even the most detailed datasets, especially in dynamic drilling scenarios where seconds can make a difference. Data standardization using industry protocols such as WITSML (Wellsite Information Transfer Standard Markup Language) enables interoperability among platforms and service providers. Without such standards, integrating multiple tools and systems into a cohesive DSS becomes a technical bottleneck [23-25].

Challenges in the data environment include issues of reliability, synchronization, and calibration. Sensor drift, telemetry dropouts, and mismatched time stamps can corrupt datasets, leading to erroneous interpretations and flawed decisions. Addressing these challenges requires both hardware-level precision and software-driven validation techniques [26, 27]. A successful DSS must incorporate real-time filtering, error detection, and adaptive smoothing algorithms to maintain data fidelity. Ultimately, a well-designed data pipeline underpins the entire functionality and trustworthiness of a real-time decision framework [28, 29].

2.2 Drilling Decision Domains

To be effective, a real-time DSS must address the key decision domains that define drilling success or failure [30, 31]. These domains include wellbore stability, where data is used to detect early signs of collapse or breakout; pressure control, where ECD and formation pressure gradients are monitored to prevent kicks or losses; and trajectory correction, which involves geosteering decisions based on real-time borehole and formation data. Each domain presents specific challenges and requires targeted insight delivery to the appropriate decision-makers [32, 33].

The value of a DSS lies in its ability to integrate real-time insights at strategic decision points. For example, early detection of cuttings loading combined with torque and drag anomalies may signal developing hole cleaning issues [34, 35]. Integrating these observations allows the system to recommend mitigative actions—such as adjusting flow rate or ROP—before problems escalate. Similarly, timely data on pressure fluctuations and influx detection can enable faster choke adjustments or well control activation. These real-time interventions significantly improve operational safety and efficiency [36-38].

Key performance indicators such as rate of penetration (ROP), torque, weight on bit (WOB), and ECD are central to this dynamic decision-making process. These metrics provide quantifiable insights into downhole conditions and mechanical performance [39, 40]. A DSS that continuously monitors these indicators can identify deviations from expected norms, triggering alerts or recommendations for corrective action. Embedding these metrics into the system's feedback loop ensures that every decision is grounded in the current state of the operation, rather than historical or assumed models [41, 42].

2.3 Digital Technologies and Enablers

Several emerging technologies serve as critical enablers of real-time decision support. Edge computing allows data processing to occur closer to the source—at the rig site—thus minimizing latency and enabling faster response times. AI and ML algorithms enhance the system's ability to identify patterns, forecast events, and suggest optimal responses [43]. These technologies allow the system to evolve and improve over time, offering a level of adaptability that traditional rule-based systems cannot match. Digital twins also play a growing role by providing a live, virtual representation of the wellbore and drilling system [44-46].

The shift from post-well analysis to real-time analytics marks a significant evolution in operational philosophy. Traditional analysis models often rely on hindsight to improve future wells, but they fail to impact the current operation [47, 48]. By contrast, a real-time DSS transforms drilling from a reactive to a proactive discipline. It empowers teams to act on current data, avoid potential hazards, and optimize performance as conditions change. This agility is a defining advantage in today's high-stakes drilling environments [49, 50].

Open architecture and vendor-neutral design principles are essential for scalability and long-term viability. A closed system, tied to a specific vendor or proprietary format, limits integration and customization. An effective DSS must interface with a variety of data sources, software platforms, and operational protocols [51, 52]. Designing for openness ensures that the system can evolve with technological advances and operational demands, facilitating seamless upgrades, module expansions, and multi-vendor interoperability. These qualities are not just technical luxuries—they are strategic necessities in a rapidly digitizing industry [53-55].

3. Conceptual Framework and Architecture

3.1 Core Architectural Layers

The foundational architecture of the DSS can be organized into three primary layers: data acquisition, analytics and diagnostics, and decision support. The data acquisition layer interfaces directly with rig-based hardware, capturing real-time data from surface sensors, downhole telemetry (e.g., MWD/LWD tools), and mud logging systems. This layer must ensure continuous, secure data ingestion with high fidelity and time synchronization, creating a dependable data pipeline for downstream processing [56, 57].

The analytics and diagnostics layer processes incoming data using advanced algorithms to recognize trends, detect anomalies, and assess operational states . Pattern recognition tools—enabled by machine learning—can identify early indicators of dysfunction such as drillstring vibration or downhole pressure anomalies. This layer acts as the system's brain, interpreting sensor readings in real time to detect deviations from optimal performance or emerging risks requiring intervention [58, 59].

The decision support layer delivers synthesized insights to human operators through logic engines. These engines apply rule sets, probabilistic models, and decision trees to determine the likelihood of adverse events and suggest mitigation strategies [60]. Alerts, warnings, and recommendations are channeled to human operators for validation, maintaining a human-in-the-loop model. This ensures that high-stakes decisions remain under human oversight while benefiting from the speed and consistency of algorithmic support [61, 62].

3.2 Functional Modules

The DSS is composed of a series of functional modules, each targeting a specific operational challenge. A risk scoring module continuously quantifies the probability and severity of undesirable events, offering prioritized alerts to drilling teams. Event detection modules monitor for conditions such as kicks, stuck pipe, or loss circulation using predefined thresholds and learned behaviors from historical data. A trajectory management module supports directional drilling by integrating geological targets, toolface orientation, and real-time inclination data to maintain optimal wellpath execution [63-65].

To present these insights in an intuitive and accessible way, a visualization interface is included. This interface provides real-time dashboards populated with control charts, predictive indicators, and traffic-light systems to highlight performance status [66, 67]. Graphical representations of downhole conditions and operational trends enable rapid situational awareness, essential for minimizing response latency during drilling disruptions [68, 69]. Furthermore, a collaboration interface supports distributed decision-making by connecting field teams with remote operation support centers [70, 71]. This module provides live communication tools—such as annotation-enabled chat, voice/video conferencing, and shared dashboards—to ensure that subject matter experts can contribute to real-time problem-solving regardless of location. These interfaces are critical for enabling multidisciplinary collaboration in high-risk environments, aligning decisions across geoscience, engineering, and operations [72, 73].

3.3 Feedback and Learning Loop

An effective DSS must not only support decisions but also continuously learn and improve over time. This is achieved through a feedback and learning loop, in which user interactions and system outcomes inform future behavior. Operators are encouraged to provide qualitative feedback on alert relevance, recommendation accuracy, and system usability. This feedback is captured and used to refine underlying models, improve algorithm tuning, and update alert thresholds [74, 75].

Each event that occurs during drilling—whether it is a near-miss or an incident—is tagged and documented within the system. A structured root cause analysis is linked to the event, creating a lessons-learned repository that can be referenced during future planning and execution phases. This historical database supports institutional knowledge retention and reduces the likelihood of repeating previous mistakes [76, 77].

As the system accumulates feedback and contextual learning, it transitions from a reactive decision aid to a predictive intelligence tool. Closed-loop improvement ensures that the DSS adapts to both technological advancements and field-specific nuances. Over time, it becomes increasingly proficient at identifying early-warning signals, supporting a proactive drilling culture that enhances safety, efficiency, and cost-effectiveness [78, 79].

4. Implementation Considerations

4.1 Infrastructure and Connectivity

A real-time DSS is highly dependent on seamless data transmission between rig sites, cloud environments, and control centers. This requires high-bandwidth, low-latency rig-to-cloud connectivity capable of handling continuous streams of time-sensitive drilling data. Satellite and LTE technologies may be leveraged, but they must be designed with sufficient bandwidth redundancy and signal stability to prevent interruptions that can compromise decision accuracy or delay critical alerts. Ensuring low latency is particularly important when dealing with dynamic wellbore conditions requiring immediate action [80, 81].

Cybersecurity is another essential concern. Drilling systems are increasingly connected and vulnerable to cyber threats, making it critical to implement comprehensive access control, robust data encryption protocols, and compliance with industrial standards such as ISA/IEC 62443 [82, 83]. The integrity of real-time operational data must be preserved against tampering, and access should be limited through role-based authentication mechanisms. Continuous monitoring and periodic audits can further safeguard sensitive drilling information and uphold operational trust [84-86].

Moreover, redundancy and fault tolerance must be built into the system to withstand failures in harsh drilling environments. This includes local data buffering, failover protocols, and backup communication lines that ensure data capture and system operation continue even during network outages or equipment failure. Ruggedized hardware, secure edge devices, and cloud redundancy strategies collectively enhance resilience and maintain system availability—crucial for uninterrupted decision support during high-stakes drilling operations.

4.2 Organizational Readiness and Change Management

Effective implementation of a DSS is as much an organizational transformation as it is a technical deployment. A critical first step is ensuring cross-functional alignment among drilling engineers, geologists, IT teams, and HSE personnel. This alignment ensures that all stakeholders understand their roles in interacting with the system, interpreting alerts, and contributing to collective decision-making. The DSS must be positioned as an enabler of collaboration, not as a replacement for domain expertise or human judgment [87, 88].

Training requirements must also be considered in detail. Users need to understand how to interpret real-time alerts, interact with dashboards, and respond appropriately to evolving operational scenarios [89, 90]. This includes familiarity with the visual interface, thresholds that trigger warnings, and escalation protocols. Interactive training programs, simulation exercises, and on-the-job support help foster user confidence and reduce resistance to system adoption. The goal is to embed the DSS into daily operational workflows without overwhelming field personnel [91, 92].

Finally, clearly defined governance structures are required to manage real-time decision rights and responsibilities. It must be transparent who has the authority to act on system-generated recommendations, who validates model outputs, and how conflicting signals are resolved. This involves both strategic policies and procedural clarity, supported by documentation that outlines escalation hierarchies, inter-team communications, and accountability mechanisms. Formalizing these aspects helps ensure that decision support becomes integrated and trusted across the organization [93, 94].

4.3 Performance Metrics and Validation

To ensure the DSS delivers value, it must be measured against well-defined performance benchmarks. Success criteria often include improvements in drilling efficiency, reductions in non-productive time, and enhancements in safety performance. These outcomes must be linked to system functionality through observable indicators such as early event detection, quicker response times, and reduced frequency of severe incidents. Real-time systems must therefore be evaluated not only for technical reliability but also for operational impact [95, 96].

Key performance indicators (KPIs) can include the system's false alarm rate, decision accuracy compared to human benchmarks, and average time-to-decision [97]. False positives must be minimized to avoid alert fatigue, while false negatives must be critically low to ensure risks are not missed. Decision accuracy reflects how well system recommendations align with expert judgement or post-event analyses. A low time-to-decision, when supported by actionable intelligence, is indicative of the system's utility in high-pressure operational scenarios [98, 99].

Lastly, field validation strategies must be phased and systematic. Pilot deployments provide the opportunity to assess system functionality in live operations without full-scale rollout risks. These deployments should be monitored closely, with structured feedback loops to refine algorithms, dashboards, and workflows [100]. Once efficacy is demonstrated in controlled conditions, the system can be scaled incrementally, expanding across rigs and geographies. This phased approach ensures lessons learned are incorporated, securing organizational buy-in and reducing implementation friction [101, 102].

5. Conclusion

This work has articulated a structured and modular approach to real-time DSS tailored to the operational realities of modern drilling. The architecture presented comprises distinct layers—data acquisition, analytics, and decision support—each of which serves a critical function in ensuring timely, actionable intelligence. By framing the system as a layered ecosystem, this model enables flexibility in design and scalability across various drilling contexts, from conventional onshore to technically challenging offshore wells.

The integration of streaming data, advanced analytics, and decision logic into a unified and interactive system framework represents a fundamental shift from reactive, post-event analysis to proactive, in-the-moment decision-making. The model provides a foundation for continuous performance monitoring, event detection, and collaborative intervention—key elements for mitigating risk and optimizing drilling outcomes. It also enhances transparency and alignment across disciplines, fostering a more cohesive and accountable drilling operation.

Beyond immediate operational benefits, the proposed DSS framework is strategically positioned as an enabler of broader digital transformation within well construction. Its open architecture and compatibility with cloud, edge, and AI technologies make it a cornerstone for evolving toward intelligent drilling systems. This system not only improves day-to-day operations but also contributes to institutional learning by capturing data, outcomes, and insights that can be applied to future wells, fields, and teams.

At an operational level, the adoption of a real-time DSS substantially improves decision-making speed and accuracy under dynamic wellbore conditions. By aggregating and interpreting vast streams of surface and downhole data, the system enables drilling teams to identify anomalies early, assess risks more accurately, and respond with precision. This responsiveness minimizes unplanned events such as stuck pipe or kicks, enhances wellbore stability, and contributes to consistent drilling performance across complex formations.

From a cost and risk perspective, the system reduces inefficiencies linked to delayed or fragmented decision-making. Faster identification of drilling dysfunctions reduces non-productive time, while early detection of instability or pressure events can prevent costly incidents. The DSS also facilitates a shared operational picture among drilling engineers, geologists, and rig crews, improving interdisciplinary coordination and collective situational awareness—both of which are critical in time-sensitive drilling environments.

Strategically, this system aligns with the broader vision of the digital oilfield, in which data and automation are leveraged to optimize hydrocarbon development throughout the asset lifecycle. The integration of DSS with existing digital initiatives allows operators to extract more value from real-time monitoring infrastructure, data lakes, and analytics platforms. It also lays the groundwork for future-ready drilling programs that can adapt dynamically to evolving geological, technical, and economic constraints, enhancing long-term competitiveness.

The path forward for real-time DSS development involves deepening the integration of intelligent automation and adaptive analytics. One promising avenue is the deployment of advanced machine learning algorithms capable of learning from historical and real-time data to generate automated recommendations with high confidence levels. These models could augment or even automate certain decision domains, such as rate-of-penetration optimization or early kick detection, making the DSS more autonomous and responsive.

Additionally, the DSS can be expanded to support fully remote operations centers and semi-autonomous rigs. These capabilities would reduce reliance on on-site personnel, improve operational consistency across fleets, and enhance safety by enabling experts to monitor and intervene from centralized locations. The real-time DSS could serve as the nerve center for such operations, synthesizing sensor inputs, running diagnostics, and relaying insights to remote teams in real-time.

In the long term, the vision is to develop fully adaptive, intelligent systems that not only support but continually optimize drilling execution. These systems would leverage real-time learning, feedback from previous operations, and cross-well comparisons to enhance performance in a continuous loop. Ultimately, the integration of DSS into the drilling ecosystem represents not just an incremental improvement but a foundational shift toward smarter, safer, and more efficient hydrocarbon extraction.

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