Original Scientific Paper/Original naučni rad UDC/UDK: 004.85:[005.334:620.9
Paper Submitted/Rad primljen:31.12.2025.
Paper Accepted/Rad prihvaćen:10.01.2026.
DOI: 10.5937/SJEM2601070A

Primena mašinskog učenja u industrijskoj bezbednosti: digitalne inovacije i nove bezbednosne paradigme u rafinerijskim procesima

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Summary in Serbian: U savremenim rafinerijskim postrojenjima, složeni industrijski procesi zahtevaju visok nivo bezbednosti kako bi se smanjili rizici po ljudske živote, imovinu i životnu sredinu. Tradicionalni sistemi nadzora i sigurnosne procedure sve češće pokazuju ograničenja u detekciji anomalija i predviđanju potencijalnih incidenata. Primena mašinskog učenja (ML) u industrijskoj bezbednosti omogućava transformaciju bezbednosnih paradigma kroz analizu velikih količina podataka sa senzora, SCADA sistema i drugih industrijskih izvora. Ovaj rad istražuje aktuelne digitalne inovacije u oblasti ML algoritama za prediktivnu analitiku, automatsko prepoznavanje anomalija i optimizaciju sigurnosnih procedura u rafinerijskim procesima. Poseban fokus je stavljen na integraciju ML modela u postojeće sisteme upravljanja rizicima, izazove u implementaciji i mogućnosti unapređenja industrijske bezbednosti kroz proaktivni pristup. Rezultati istraživanja ukazuju da primena mašinskog učenja značajno doprinosi smanjenju incidenata, poboljšava efikasnost bezbednosnih operacija i otvara nove perspektive za digitalnu transformaciju u industrijskoj bezbednosti.

Keywords: mašinsko učenje, industrijska bezbednost, rafinerijski procesi, digitalne inovacije, prediktivna analitika

Application of Machine Learning in Industrial Safety: Digital Innovations and New Safety Paradigms in Refinery Processes

Abstract in English: In modern refinery facilities, complex industrial processes require a high level of safety to minimize risks to human lives, property, and the environment. Traditional monitoring systems and safety procedures increasingly show limitations in detecting anomalies and predicting potential incidents. The application of machine learning (ML) in industrial safety enables a transformation of safety paradigms through the analysis of large volumes of data from sensors, SCADA systems, and other industrial sources. This paper explores current digital innovations in ML algorithms for predictive analytics, automatic anomaly detection, and optimization of safety procedures in refinery processes. Focus is placed on integrating ML models into existing risk management systems, implementation challenges, and opportunities for enhancing industrial safety through a proactive approach. The research results indicate that the application of machine learning significantly contributes to reducing incidents, improving the efficiency of safety operations, and opening new perspectives for digital transformation in industrial safety.

Keywords: machine learning, industrial safety, refinery processes, digital innovations, predictive analytics

1. Introduction

Industrial safety represents one of the fundamental pillars of sustainable and reliable operation of refinery facilities. Oil and gas refineries belong to the most complex industrial systems due to a high level of technological integration, continuous process flows, and the handling of flammable, toxic, and highly reactive substances. Any disruption in the operation of such systems can have serious consequences for employee safety, the integrity of facilities, and the environment, as well as significant economic and reputational losses for the organization. Therefore, industrial safety in refinery processes has traditionally been regarded as a strategic priority within risk and process management. Traditional industrial safety systems in refineries are based on a combination of procedural measures, engineering safeguards, and conventional monitoring systems, such as alarm systems, protective logic, periodic inspections, and incident analysis based on historical data (Omoarebun, 2023). Although these systems have formed the foundation of safety practice for decades, contemporary industrial conditions reveal their limitations. Above all, traditional approaches are predominantly reactive, rely on predefined thresholds and rules, and are often unable to identify complex system behavior patterns that preceded incidents. In addition, the growing volume of data generated by modern SCADA and IIoT systems further complicates timely analysis and decision-making when relying solely on conventional methods. In the context of industrial digital transformation and the development of the industry 4.0 paradigm, there is an increasing need for more advanced, adaptive, and predictive approaches to industrial safety. Machine learning (ML), as a subfield of artificial intelligence, enables the analysis of large volumes of heterogeneous data in real time, the identification of hidden patterns, and the prediction of potential anomalies before they escalate into serious safety incidents (Sarker, 2023). The application of ML algorithms creates the opportunity to transition from a reactive to a proactive safety management model, in which risks are identified and mitigated at early stages of their emergence. The motivation for applying machine learning in refinery processes arises from the need to increase system reliability, reduce the number of false alarms, improve decision-making, and achieve more efficient use of available resources. ML models, such as anomaly detection algorithms, predictive analytics, and incident classification techniques, enable continuous learning from operational data and adaptation to changing operating conditions (Omol et al., 2024). In this way, safety systems become more intelligent, resilient, and capable of responding to the complex and dynamic risks characteristic of the refinery industry. The aim of this paper is to analyze the role of machine learning in enhancing industrial safety in refinery processes, with a particular focus on digital innovations and new safety paradigms emerging from their application. The paper seeks to present the possibilities for integrating ML algorithms into existing safety management systems, identify implementation challenges, and highlight potential benefits in terms of incident reduction, increased operational efficiency, and overall improvement of safety levels. The scientific contribution of this paper lies in the systematization of contemporary approaches to the application of machine learning in industrial safety, while its practical contribution is reflected in providing guidelines for their implementation in real refinery environments.

2. Industrial Safety and Digital Transformation of Refinery Systems

Industrial safety in refinery facilities represents an interdisciplinary field encompassing engineering, organizational, and technological aspects aimed at preventing undesirable events and minimizing their consequences. Contemporary refinery systems are characterized by a high degree of automation, continuous processes, and complex interdependencies among technological units, making safety one of the key factors of operational reliability (Olaizola et al., 2022). In such an environment, the theoretical framework of industrial safety must be considered through the lens of process safety, digital transformation, and the application of advanced analytical methods based on machine learning.

Process safety constitutes the fundamental concept of industrial safety in refinery processes and refers to the identification, control, and management of risks arising from the handling of hazardous substances and energy flows (Klein and Vaughen, 2017). Unlike occupational safety, which is primarily focused on the individual protection of employees, process safety is oriented toward the integrity of the entire system, including equipment, processes, control systems, and organizational procedures. Its primary purpose is the prevention of major industrial accidents that may have catastrophic consequences for people, assets, and the environment. Refinery facilities are particularly exposed to risks due to high temperatures and pressures, the presence of flammable and toxic substances, and complex chemical reactions occurring in real time. Typical risks in refinery processes include leaks of hazardous substances, fires and explosions, mechanical equipment failures, as well as risks associated with the human factor (Delshah et al., 2023). Gas or liquid leaks often represent the initiating event that can escalate into a serious incident if not detected in a timely manner. Explosions and fires result from a combination of technical failures and inadequate process control, while the human factor includes operational errors, incorrect assessments, and non-compliance with procedures. Traditional process safety systems rely on methods such as HAZOP analysis, Failure Modes and Effects Analysis (FMEA), alarm systems, and safety instrumented systems. Although these methods remain essential, their effectiveness is limited in dynamic environments where process parameters continuously change and the volume of data grows exponentially (Kim et al., 2018). These limitations create opportunities for integrating advanced digital solutions that can enhance existing safety mechanisms.

The digital transformation of industry, embodied in the Industry 4.0 concept, has brought significant changes in the way refinery processes are designed, managed, and monitored. The introduction of smart sensors, the Industrial

Internet of Things (IIoT), and advanced data acquisition and processing systems has enabled the creation of highly interconnected and information-rich industrial environments. SCADA systems represent a central element of refinery digital infrastructure, enabling real-time process monitoring and remote control of key technological parameters. In addition to SCADA systems, IIoT technologies enable continuous data collection from a large number of sensors distributed along production lines, storage tanks, and critical equipment (Babayigit and Abubaker, 2023). These data, combined with historical records of system operation and incidents, form the basis for the development of Big Data analytics in industrial safety. However, data availability alone is not sufficient to improve safety; it is necessary to apply advanced analytical methods capable of extracting relevant information from large and heterogeneous datasets. Digital innovations within the industry 4.0 framework enable a transition from static safety models to dynamic and adaptive systems capable of adjusting to changes in processes and the operating environment (Korytko and Piletska, 2022). In this context, industrial safety becomes an integral part of the digital strategy of refinery companies, where safety aspects are considered in parallel with system efficiency, reliability, and sustainability.

Machine learning represents a key technology enabling intelligent processing of data generated in digitally transformed refinery systems. In industrial applications, ML algorithms are used for pattern recognition, event classification, fault prediction, and anomaly detection in system operation. Depending on the availability of labeled data, supervised and unsupervised machine learning models are applied. Supervised learning relies on historical data with clearly defined outcomes, such as recorded incidents, failures, or alarm events (Sun et al., 2022). These models enable the classification of risk states and the prediction of incident likelihood based on current process parameters. On the other hand, unsupervised learning is particularly suitable for anomaly detection in refinery processes, where incidents are rare and data are often unlabeled. Algorithms such as clustering and autoencoders enable the identification of deviations from normal operating regimes, allowing potential problems to be detected at early stages. The application of machine learning in industrial safety enables the development of predictive safety models that overcome the limitations of traditional approaches. Instead of relying on fixed thresholds and rules, ML systems continuously learn from data and adapt to changes in processes. In this way, it is possible to reduce the number of false alarms, increase the reliability of critical state detection, and improve real-time decision-making. In refinery processes, where timely response is crucial, this approach represents a significant step toward new safety paradigms based on proactive risk management.

3. Application of Machine Learning in Refinery Safety

The application of machine learning in refinery safety represents the practical operationalization of digital innovations within high-risk industrial systems. Unlike theoretical models, the real-world implementation of ML solutions in refineries must be adapted to process complexity, data availability, and existing safety architectures. In this context, effective application of machine learning requires careful consideration of data sources, algorithm selection, and their integration into existing safety and risk management systems.

The foundation for applying machine learning in refinery safety lies in the data continuously generated during plant operation (Erinjogunola et al., 2020). Modern refineries are equipped with a large number of sensors measuring process parameters such as temperature, pressure, flow, level, vibration, and chemical composition. These sensors are integrated into SCADA systems that enable real-time data acquisition, storage, and visualization. SCADA systems represent the central source of operational data and a key element for applying ML algorithms for safety purposes (Enemosah and Ifeanyi, 2024). Data from SCADA systems include both real-time process parameter values and records of alarms, shutdowns, and operator interventions. Analysis of these data enables the identification of system behavior patterns that precede abnormal states or incidents. In addition to operational data, historical data on incidents, failures, and safety events are of exceptional value for the development of predictive models. These data typically originate from safety management systems, incident reports, maintenance databases, and audit records. Although incidents in refineries are relatively rare, their analysis enables the training of supervised learning models capable of recognizing risk patterns and estimating the likelihood of similar events recurring. A key challenge in working with these data sources lies in their heterogeneity, incompleteness, and differing temporal resolutions. Therefore, data preprocessing is essential and includes noise filtering, time-series synchronization, and identification of relevant features to ensure the reliability of ML models under real refinery operating conditions.

Various ML algorithms are used in refinery safety systems depending on the analysis objectives, data availability, and requirements for interpretability. One commonly used algorithm is Random Forest, which has proven effective in classifying risk states and predicting incidents (Zhen et al., 2023). The advantage of this algorithm lies in its robustness to data noise and its ability to handle many input variables, which is particularly important in complex refinery processes. Support Vector Machines (SVM) are applied in cases where precise separation between normal and abnormal process states is required (Cuentas et al., 2017). In refineries, SVM algorithms are used to detect deviations in the operation of critical equipment such as compressors, reactors, and distillation columns. Their ability to operate in high-dimensional spaces makes them suitable for analyzing complex datasets generated by SCADA systems. Neural networks, particularly deep neural networks, enable modeling of nonlinear relationships among process parameters, which are common in refinery systems. Their application includes fault prediction, analysis of system behavior under boundary conditions, and simulation of scenarios that may lead to incidents. Although these models are often less interpretable, their high accuracy makes them extremely valuable in safety applications where early detection is critical. Autoencoders, as a form of unsupervised learning, are especially significant for anomaly detection in refinery processes (Zheng and Zhao, 2020). These models learn normal system operating patterns and identify deviations that may indicate leaks, equipment degradation, or unforeseen process changes. In practice, autoencoders provide early warnings of potential safety risks even in situations where no historical data on similar incidents exist.

Effective application of machine learning in refinery safety requires its integration into existing risk management and decision-making systems (Erinjogunola et al., 2020). ML models do not function as standalone solutions but rather as support tools for traditional safety mechanisms. Integration into Risk Management Systems enables risk quantification based on predictive analyses and dynamic updating of safety assessments in real time. Within Decision Support Systems, ML models provide operators and management with additional information for decision-making, such as incident probability estimates, recommendations for preventive measures, and maintenance prioritization (Arinze et al., 2024). Such systems help reduce subjectivity in decision-making and increase the consistency of safety decisions in complex situations. An important aspect of integration also concerns compliance of ML solutions with regulatory requirements and safety standards applicable in the refinery industry. Model transparency, explainability of results, and system reliability are key factors for acceptance in industrial practice. When properly integrated, ML systems become an integral part of the refinery safety architecture and enable a transition toward a proactive and predictive model of industrial safety.

4. Challenges and Limitations of Implementing Machine Learning in Refinery Safety

Although the application of machine learning in refinery safety offers significant opportunities to improve risk management processes and incident prevention, its implementation in real industrial environments faces numerous challenges and limitations. These challenges are not exclusively technical in nature; they also encompass organizational, regulatory, and security aspects that can significantly affect the effectiveness and sustainability of ML solutions in refinery systems.

One of the key challenges relates to the quality and availability of data used for training and validating ML models. Although modern refineries generate large volumes of data through sensors and SCADA systems, these data often contain noise, missing values, or inconsistencies resulting from diverse sources and technologies (Olaizola et al., 2022). An additional issue is the relative rarity of major incidents, which makes it difficult to collect representative datasets for supervised learning. Under such conditions, ML models may become biased or insufficiently generalized, thereby reducing their reliability in detecting real safety risks.

Data security and cyber risks represent another significant challenge in the implementation of ML systems in refinery facilities. Integrating ML models into industrial networks requires access to sensitive operational data, which increases system exposure to cyberattacks (Pani and Soofastaei, 2025). Potential attacks on SCADA systems, data manipulation, or compromise of ML models can have serious consequences for process safety. Therefore, it is essential to ensure high standards of information security, including network segmentation, data encryption, and continuous system monitoring, in order to minimize cyber risks associated with the use of advanced analytical technologies.

Model interpretability constitutes a particular challenge in the context of industrial safety, where transparency of decision-making is of critical importance. Many advanced ML algorithms, such as deep neural networks, operate as so-called “black boxes,” whose decisions are not easily explainable to end users. In refinery systems, where operators and management must understand the rationale behind specific recommendations or warnings, a lack of interpretability can reduce trust in ML solutions and hinder their practical adoption. Consequently, increasing attention is being paid to the development of explainable models and techniques for interpreting machine learning results in safety applications.

In addition to technical and security challenges, the implementation of ML systems also faces organizational and regulatory barriers. The introduction of new technologies requires changes in organizational culture, additional employee training, and adaptation of existing safety management procedures (Maseda et al., 2021). Resistance to change, lack of interdisciplinary knowledge, and limited resources can slow down or complicate the implementation process. Moreover, the refinery industry is subject to strict regulatory frameworks that require demonstrable reliability and compliance of safety systems with applicable standards. The integration of ML solutions must therefore be carefully aligned with regulatory requirements to ensure their acceptability and long-term sustainability.

Considering these challenges, it is evident that successful application of machine learning in refinery safety requires a holistic approach that integrates technical solutions, organizational change, and regulatory compliance. Understanding and addressing these limitations represents a crucial step toward effective and responsible digital transformation of industrial safety in refinery processes.

5. Discussion and Future Perspectives

The application of machine learning in refinery safety enables a transition from a reactive to a proactive approach to risk management, representing one of the most significant transformations in modern industrial systems. Traditional safety systems primarily responded after incidents had occurred, whereas the integration of ML algorithms enables the prediction of potential problems and their prevention before they escalate into critical events. Such a proactive approach contributes to reducing the number of incidents, minimizing economic losses, and protecting human lives and the environment, thereby significantly improving the overall safety of refinery processes.

One of the key aspects concerns the role of machine learning as an integral component of the Safety Management System (SMS) in refineries (Bramantyo et al., 2022). By integrating ML models into SMS, it becomes possible to continuously assess risks, monitor the performance of protective systems, and support real-time decision-making by operators and management. Predictive models enable dynamic adjustment of safety procedures and optimization of preventive maintenance, which further contributes to reducing the risk of incidents. In this way, ML technologies are not treated merely as an add-on to existing systems, but as an element in the evolution of modern industrial safety paradigms. Looking to the future, there is significant potential for the development and integration of additional digital technologies into refinery systems. One promising perspective is the application of digital twins – virtual replicas of physical facilities and processes that enable scenario simulation, risk analysis, and testing of safety procedures in controlled digital environments (Al-Jlibawi et al., 2020). Digital twins, combined with ML algorithms, allow for the identification of potential system weaknesses and the evaluation of the effectiveness of preventive measures before their implementation in actual facilities. Furthermore, the synergy of AI and IoT technologies offers opportunities for continuous process monitoring and adaptive responses to changes in system operation. The use of distributed sensors, edge computing, and predictive analytics algorithms enables continuous learning and real-time adaptation of ML models, significantly enhancing the efficiency and flexibility of safety operations. These technologies also support the integration of diverse data sources, including physical, process, and organizational parameters, thereby creating a holistic view of a facility's safety status.

Nevertheless, future application of these technologies requires careful balancing between innovative capabilities and practical constraints. Issues such as model interpretability, standardization of procedures, data protection, and cybersecurity remain critical factors determining implementation success. Effective integration of ML and digital technologies requires a multidisciplinary approach, collaboration among engineers, IT specialists, and management, as well as continuous monitoring of regulatory and industry standards.

In conclusion, this discussion demonstrates that machine learning and digital innovations represent key drivers of the transformation of industrial safety in refinery systems. Proactive approaches, integration into SMS, and the prospects of digital twins and AI–IoT technologies open new horizons in incident prevention, operational optimization, and overall enhancement of safety system effectiveness. Given the rapid pace of technological development, it is expected that future generations of refinery facilities will rely on comprehensive digital models, with machine learning functioning as a central element of safety architecture.

6. Conclusion

The application of machine learning in refinery safety represents a significant step toward the digital transformation of high-risk industrial systems. The analysis presented in this work demonstrates that ML algorithms, through predictive analytics and anomaly detection, enable a transition from a reactive to a proactive risk management approach, thereby enhancing the protection of personnel, the integrity of facilities, and environmental safety. Integration of ML models into existing risk management systems and the Safety Management System (SMS) contributes to the optimization of preventive procedures, reduction of incidents, and improvement of operational efficiency, while simultaneously supporting informed real-time decision-making.

Beyond technical advantages, the study highlights implementation challenges, including data quality and availability, cybersecurity, model interpretability, and organizational and regulatory barriers. Addressing these challenges requires a multidisciplinary approach, continuous employee training, development of explainable models, and alignment with applicable industrial standards and regulations.

The discussion on future perspectives emphasizes the considerable potential of advanced digital technologies, such as digital twins, IoT integration, and edge computing, which, combined with ML, enable holistic process monitoring, scenario simulation, and adaptive management of safety risks. These technologies facilitate the creation of intelligent and resilient refinery systems, where ML becomes a central element of the safety architecture, and industrial safety transitions toward proactive and predictive management.

In conclusion, this work demonstrates that the application of machine learning in the refinery industry not only improves safety and operational reliability but also opens new avenues for digital innovation and modernization of safety paradigms, laying the foundation for sustainable, safe, and technologically advanced refinery systems of the future.

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