https://orcid.org/0000-0001-7756-0004
https://orcid.org/0000-0001-8361-374X

UDC 620.169.1

O.V. FEDUKHIN*, A.A. MUKHA*

A CONCEPTUAL FRAMEWORK FOR A COMPREHENSIVE INDUSTRIAL EQUIPMENT RELIABILITY MANAGEMENT SYSTEM USING PREDICTIVE ANALYTICS

*Institute of Mathematical Machines and Systems Problems of the National Academy of Sciences of Ukraine, Kyiv, Ukraine

Анотація. *Проведено аналіз рішень, що застосовуються з метою уніфікації розроблюваної системи керування надійністю обладнання. На основі аналізу переваг та недоліків існуючих систем предиктивної аналітики зроблені висновки про перспективи розвитку майбутніх систем. У статті представлено загальну концепцію комплексної системи керування надійністю промислового обладнання. В основі підходу лежить використання предиктивної аналітики, машинного навчання, ймовірнісно-фізичних моделей деградації, а також інтеграція IoT-компонентів у цифрову інфраструктуру управління. Система дозволяє прогнозувати технічні відмови, визначати залишковий ресурс обладнання й автоматизовано приймати рішення щодо регламентних обслуговувань. Представлено науково-технічні аспекти реалізації, включаючи імплементацію математичних моделей, принципи виявлення аномалій та оцінювання ризиків. Для локального зберігання даних запропоновано варіант структури зберігання даних, що розрахований на потокову обробку даних та містить у собі поєднання сховища для структурованих та малоструктурованих даних. Основна ідея полягає у використанні змішаного підходу застосування нейромереж разом із фізичними дослідженнями матеріалів складових частин та статистики відмов елементів для оцінювання і прогнозування надійності й залишкового ресурсу та встановлення регламентованого терміну подальшої експлуатації. Запропоновано використовувати ймовірнісно-фізичний підхід, заснований на використанні нових моделей відмов, параметри яких мають конкретну фізичну інтерпретацію у вигляді середньої швидкості деградації об'єкта дослідження і коефіцієнта варіації узагальненого процесу деградації. Для цього пропонується розробка комплексної системи керування надійністю промислового обладнання на основі предиктивної аналітики. Визначення патернів гранично допустимих значень параметрів або станів, що визначають ресурс, пропонується покласти на ML\AI мережі. В роботі описано прикладне значення технології для критичної інфраструктури, що полягає у локалізованій обробці даних і дозволяє мінімізувати витрати на інфраструктуру.*

Ключові слова: *надійність, залишковий ресурс, предиктивна аналітика, машинне навчання, деградаційні моделі, керування ризиками.*

Abstract. *An analysis of existing solutions was conducted to support the unification of a newly developed industrial equipment reliability management system. Based on a review of the advantages and disadvantages of current predictive analytics platforms, conclusions regarding the future development prospects of such systems were drawn. The article presents a general concept of a comprehensive reliability management system for industrial equipment. The proposed approach is grounded in the application of predictive analytics, machine learning, probabilistic-physics degradation models, and IoT component integration into a digital control infrastructure. The system enables failure prediction, RUL estimation, and automated decision-making for maintenance scheduling. The paper details the scientific and technical implementation aspects, including the deployment of mathematical models, principles of anomaly detection, and risk evaluation. For local data storage, a data architecture is proposed that is optimized for stream processing and combines storage for both structured and semi-structured data. The core idea lies in a hybrid methodology, combining neural network-based modeling with physical studies of material degradation and component*

failure statistics to accurately assess reliability, forecast remaining useful life, and determine regulated operational lifetimes. A probabilistic-physics approach is proposed, employing advanced failure models with physically interpretable parameters such as the mean degradation rate and the coefficient of variation of the generalized degradation process. To implement this, the development of a unified predictive system for reliability management is proposed. The identification of threshold patterns — parameter values or system states that define the resource limits — is assigned to ML/AI models trained on operational data. The study also highlights the practical relevance of the proposed technology for critical infrastructure. The system supports localized data processing, reducing the need for cloud infrastructure and minimizing deployment costs.
Keywords: *reliability, remaining useful life, predictive analytics, machine learning, degradation models, risk management.*

DOI: 10.34121/1028-9763-2025-2-67-75

1. Introduction

On the one hand, the rapid development of neural network technologies opens new and broad opportunities to enhance the reliability of industrial technical systems. On the other hand, the implementation of such high-tech solutions to ensure uninterrupted and efficient operation of production facilities with minimal downtime requires the development of complex software and demands significant investments of time and financial resources.

Currently, a wide range of methods and techniques for calculating [1, 2] and forecasting the reliability and remaining useful life (RUL) of technical systems and assets already exists [3]. Some of these approaches have formed the basis for software packages that enable certain calculations and solve specific tasks. However, the problem of automated real-time assessment and forecasting of operability within the constraints of technical specifications is rarely addressed in practice. Likewise, the implementation of centralized systems for monitoring and processing performance indicators and equipment parameters remains an exception among domestic enterprises.

In most cases, companies spend years developing and building their own internal structures for managing production processes, maintenance services, and external contractors. A primary objective in production environments is the early detection and timely identification of failure causes, as well as scheduling timely maintenance, with the goal of ensuring uninterrupted production processes. In many cases, system continuity is achieved through costly equipment replacements to guarantee the full service life of assets and systems. Meanwhile, failure statistics are rarely collected and are usually not considered when analyzing or selecting equipment.

Solving these critical challenges is highly relevant and can lead to substantial cost savings in production.

The aim of this article is to develop a concept for a predictive system capable of unified assessment of equipment remaining useful life (RUL), with the ability to integrate with various platforms and apply modern data processing algorithms. The proposed system is intended for use by enterprises in critical infrastructure, as well as the defense and transportation sectors.

2. Previously unsolved problems

In scientific literature and relevant standards [4], the term Remaining Useful Life (RUL) is commonly used to describe the future reliability of an asset. RUL refers to the remaining service life of an object at the time of observation.

In this paper, the term *object* refers to an individual equipment unit or component that can be removed for maintenance or replaced. Such objects are typically integrated into larger assemblies or systems that perform specific functions within the production process. Examples include a compressor station, a pumping station, or a transportation complex.

The concept of RUL can be applied not only to individual equipment units, but also to entire systems or chains of interconnected systems that support a particular production process or its subprocesses. For instance, a hot rolling production line may consist of multiple subsystems and equipment units operating together to maintain continuous workflow.

Thus, the task of determining the RUL, along with subsequent decisions regarding maintenance or replacement, can be addressed at both the object and system levels.

There are three main maintenance strategies:

1. Corrective maintenance that is performed after a failure has occurred. This approach requires minimal investment before the failure but carries a high risk of irreversible damage due to its consequences.

2. Time-based maintenance (TBM) is scheduled preventive maintenance carried out at fixed time intervals, based on failure statistics. While this method reduces the likelihood of unexpected breakdowns, it incurs significant costs, as equipment may be taken out of operation before the end of its actual service life.

3. Condition-based maintenance (CBM) relies on sensor data to assess the current state of equipment and determine the optimal time for maintenance. This strategy requires a well-organized monitoring infrastructure.

CBM involves continuous monitoring of the condition of equipment and systems. However, deviations from nominal values do not always indicate a failure — acceptable degradation levels or changes in operational modes are possible. To improve accuracy, it is crucial to correlate sensor data with the reliability characteristics of the equipment.

Within the CBM framework, two key tasks are typically addressed:

• diagnostics — detecting and localizing existing faults;

• prognostics — predicting the time of failure before it occurs.

RUL estimation methods are generally classified into two categories:

• physics-based approaches that rely on degradation models grounded in physical laws. However, developing such models under real-world conditions is often extremely challenging;

• data-driven approaches that utilize historical data and do not require prior knowledge of physical processes.

This paper proposes a hybrid approach to solving CBM-related tasks. Specifically, the most complex stages of boundary state recognition are proposed to be handled using neural networks.

Significant progress has already been made in this direction, and there are promising results.

In 2007, Schwabacher et al. [5] conducted a comprehensive survey of artificial intelligence methods for prognostics. Their work was associated with a real-world project — the Integrated System Health Management (ISHM) system developed by NASA. As described above, RUL prediction methods are generally classified into two main categories: model-based and data-driven approaches.

In 2010, Si et al. [6] explored statistically based approaches. They pointed out that historical failure data might be limited due to the fact that critical assets are typically designed to avoid failure. However, they argued that a broader category of data-referred to as Condition Monitoring (CM) data-serves as a more valuable source of information. They further classified CM data into direct and indirect types. With this distinction in mind, they reviewed methods based on both direct and indirect CM data accordingly.

In a vast number of recent studies, RUL prediction and deep learning have emerged as hot research topics. RUL prediction is driven by strong industrial demand, while deep learning is viewed as a transformative technology. Most of the work focusing on the application of deep learning to RUL forecasting has been carried out within the last few years.

Several systems from leading automation and electronics manufacturers are already available on the market:

• General Electric Digital APM (Predix) — predictive maintenance powered by machine learning.

• AVEVA (Schneider Electric APM) — industrial analytics and predictive diagnostics.

• Siemens MindSphere — an IoT platform for digital equipment monitoring.
• ABB Ability APM — AI-driven asset performance management.

Table 1 — Comparison of key system characteristics

№	Characteristic	Predix	AVEVA	Mind-Sphere	ABB Ability
1	Support for IoT and SCADA integration	Yes	Yes	Excellent	Yes
2	Predictive maintenance (PdM)	Yes	Yes	Partial	Yes
3	Self-learning ML/AI models	Limited	No	Yes	Yes
4	Flexibility and customization of models	Medium	Low	Medium	Medium
5	RUL management	Yes	Limited	Limited	Yes
6	Model interpretability (XAI)	Low	Low	Medium	Medium
7	Online learning / adaptability	No	No	Limited	Partial
8	Deployment speed	Low	Medium	Medium	Medium
9	ERP compatibility	Good	Medium	Medium	Good
10	Failure clustering and classification	Partial	No	No	Partial
11	Inventory and maintenance management	Yes	Partial	No	Yes
12	Requires cloud-based data storage	Yes	No	Yes	No
13	Contextual analytics (modes/states)	Partial	No	Limited	No

We did not conduct a dedicated study of the accuracy of the assessments provided by the listed systems. However, the comparative analysis reveals their weaknesses and highlights opportunities for future development.

A comprehensive system should meet the highest possible standards across most of the listed characteristics. In our opinion, for systems intended for critical and dual-use applications, certain criteria are essential. These include:

• high model interpretability, which is necessary for justified and transparent decision-making;

• the ability to store data locally, which is crucial for preventing the disclosure of sensitive or confidential information.

3. Main content

Existing systems (GE Predix, AVEVA APM, MindSphere, etc.), although offering analytics and monitoring capabilities, exhibit a number of limitations: low interpretability, limited use of physics-based degradation models, and reliance on external cloud infrastructure.

The proposed concept aims to overcome these barriers through a set of key differentiators, which are discussed below.

3.1. Integration of physics-statistical degradation models with machine learning algorithms

Most modern industrial solutions in the field of predictive maintenance are based either solely on machine learning methods (which mostly function as «black boxes») or on simplified engineering formulas that do not take real operational data into account.

This paper proposes a hybrid approach: neural network algorithms perform adaptive analysis of equipment behavior, while probabilistic-physics models [7] (such as DN-distributions, Weibull distribution, and hazard rate) provide engineering-level interpretability and help reveal the physical causes of component degradation.

Probabilistic-physics models (also known as physics-statistical models) are mathematical models that describe wear, degradation, or failure processes in technical systems based on physical laws, while also accounting for stochastic (random) environmental and operational influences.

Such a combination of approaches improves prediction accuracy, enhances robustness to noise, and increases the transparency of decision-making processes. This forms one of the fundamental advantages of the proposed system compared to existing solutions on the market, including platforms like Predix or AVEVA APM.

3.2. Modular architecture with support for adaptive task typing

The system is designed based on independent functional modules Fig.1, each responsible for specific stages such as data processing, classification of equipment operating phases, selection of the appropriate prediction model, and failure risk assessment.

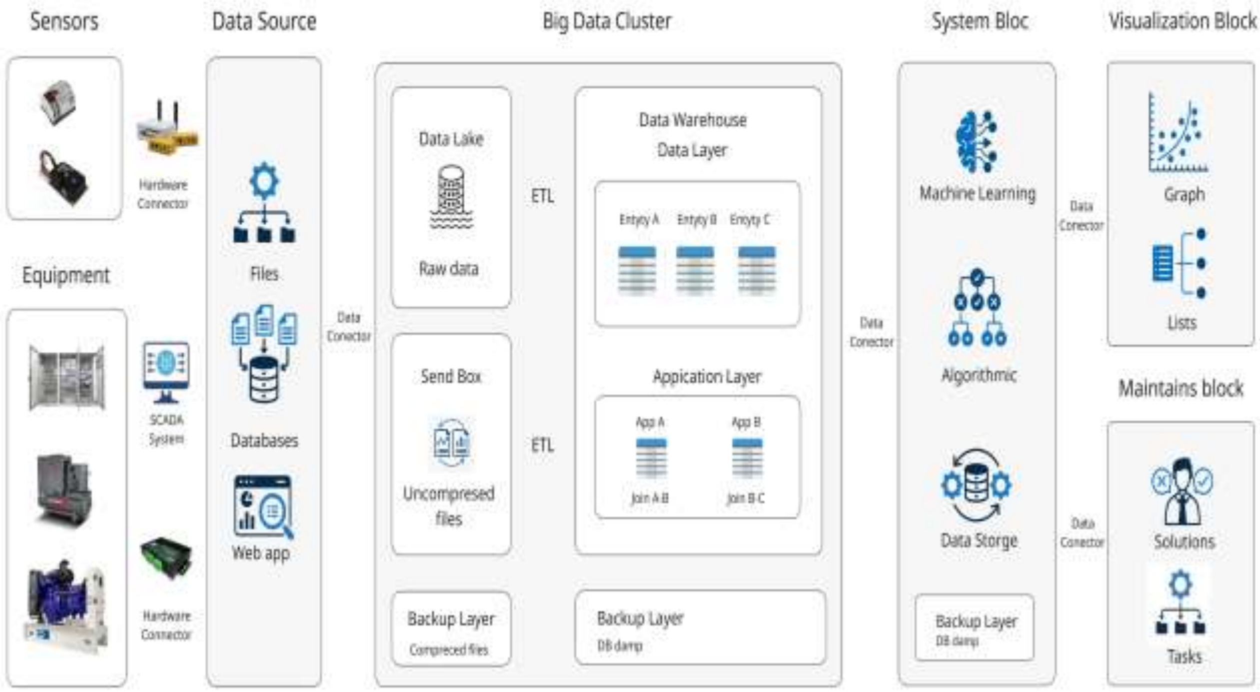

Figure 1 — System structure

This architectural approach provides the following advantages:

• connection to different types of equipment without requiring a complete system reconfiguration;

• flexibility in modifying algorithms without affecting other components of the system;

• independent model training for each specific operating mode or phase state.

Adaptive task typing makes it possible to account for the operational characteristics of equipment, which is critically important for systems operating under variable loads (e.g., compressor units, electric drives, and pumping stations), as well as for equipment used outdoors and exposed to environmental conditions, such as seasonal operating modes («summer/winter»).

3.3. Autonomous operation without the need for external processing environments

The system supports local data storage and model execution directly on the premises of the enterprise. This approach enables full operation without the need for external cloud services, which is particularly important for protected or classified facilities (e.g., defense industry, energy sector).

It helps prevent the leakage of technical or commercial information and eliminates reliability issues that may arise from the lack of a stable internet connection.

4. System architecture

4.1. Architectural concept of the system

Multilevel architecture of the proposed system

The proposed system features a multilevel architecture that enables the processing of large volumes of telemetry data in real time, supports adaptive analytics, and facilitates maintenance decision-making based on Remaining Useful Life (RUL) estimation. A detailed description of each level is provided below.

Hardware integration level (hardware connectors)

At the first level, a unified hardware connector is implemented, enabling the connection of various equipment types to the enterprise's digital infrastructure in a manner similar to IoT modules. This approach ensures scalability and simplifies the integration of both new and legacy assets. Additionally, a data connector is required for centralized data acquisition from multiple sources. Streaming tools, data buses, pipelines, or stream-processing solutions can be utilized at this level.

Data storage level (data source + big data cluster)

Sensor data (e.g., temperature, pressure, vibration, current) is transferred to a big data cluster, consisting of data lake (for unstructured telemetry records) and data warehouse (DWH) (for storing aggregated and processed data used in machine learning and analysis). The proper setup of the data storage scheme is critical, as this stage defines the data quality requirements that directly influence the reliability of future predictions. Errors at this level can block data consolidation and reduce the accuracy of ML models.

Preprocessing level (ETL)

At this stage, data is cleaned (noise filtering), time-synchronized, missing values are handled, and normalization is performed. Data enrichment is also applied. A robust ETL process ensures consistent training datasets for deep learning modules and statistical analysis. These prepared datasets serve as the foundation for building equipment behavior patterns, which are later used as reference samples.

Phase classification level (algorithmic)

During its operation, equipment goes through various operational phases (e.g., ramp-up, stabilization, load, transitional modes), each exhibiting specific degradation behaviors. To improve prediction accuracy, a phase classification module is introduced. It identifies the current phase using LSTM algorithms or decision tree ensembles (e.g., LightGBM), enabling activation of a relevant analysis model for each load type [9].

ML/AI-based prediction block (machine learning)

Depending on the detected phase, one of the pre-trained models is activated. Each model is tailored to a specific deviation pattern. For example, a model for the «high load» phase is sensitive to vibration anomalies, while one for the «idle» phase focuses on temperature variations. Adaptive model selection significantly enhances forecasting accuracy, especially under complex or varying load conditions [10].

Algorithmic RUL prediction block

At this level, the system identifies deviations from reference patterns (e.g., via cosine similarity or softmax output), classifies potential failures by type, estimates failure probabilities, and applies physics-statistical models (e.g., DN and DM distributions [11]) to provide interpretable degradation metrics for materials or mechanical parts . Combining ML with physics-based models [12] ensures both accuracy and interpretability, which is critical for time-sensitive decisions (e.g., in CHP plants or transport systems).

Visualization block

This block transforms analytical results into intuitive graphical and tabular formats accessible to operators, technical engineers, or managers. Key components include graph visualization — plotting time series of parameters, RUL forecasts, failure intensities (hazard rate), and vibration/temperature trends. These graphs are updated in real time and help quickly detect anomalies. Lists are structured tables showing object states, identified risks, alerts, incident history, and forecasts. Data can be filtered by risk level, equipment type, or criticality. The visualization aims to support fast, interpretable decision-making and minimize time for diagnostics and troubleshooting. The UX design is tailored for engineering environments, with clear indicators, color-coded priorities, and drill-down capabilities to sensor-level data for root cause analysis.

Decision and maintenance management block

This block bridges analytics with actionable steps — automating the transition from insights to maintenance, repair, or technical planning. It serves as the decision-making center, driven by outputs from ML and algorithmic modules. Components include solutions — a logic layer with response scenarios (e.g., «replace the pump in 6 hours», «retune the frequency converter», «switch the node to standby until inspection»). These can be generated automatically by risk models or with operator input [13]. Tasks are specific actions for technical staff, assigned as tasks with deadlines, priorities, and checkpoints. Integration with ERP/MES allows for alignment of technical analytics with resource planning, procurement, and maintenance scheduling. This block completes the cycle «detection → decision → execution», making the system not just diagnostic, but a full-fledged Asset Lifecycle Management platform.

4.2. Demonstration example of system operation

To demonstrate the practical implementation of the proposed concept, let us consider a hypothetical case of deploying the system within a critical infrastructure facility — a cooling system pumping station at a combined heat and power plant.

Scenario: a high-pressure pump operating in a cyclical mode (stop → start → stable operation → load phase).

System operation stages:

1. Data collection.

Sensors continuously transmit real-time readings of temperature, vibration, pressure, and electric current. The data is accumulated in a DWH storage system with preliminary preprocessing.

2. Phase classification.

Based on analysis of the incoming signal pattern (current spike, acceleration of shaft rotation), the system identifies the «acceleration» phase. An appropriate LSTM model — pre-trained on pump behavior patterns during this phase — is activated.

3. Anomaly detection.

The system detects that vibration levels exceed the standard reference pattern by 16 %. The cosine similarity with the «bearing wear» archetype is 0.89, which triggers failure probability estimation.

4. RUL estimation.

Using a two-parameter DN model for this mechanical assembly type (axial shaft + bearing), the system calculates the remaining useful life: 6.5 hours until a high probability of failure (P=0.83).

5. Operator recommendation.

The user interface displays the following message: *"Component: Pump 2. Probable failure – bearing. Estimated RUL ≈ 6.5 hours. Risk level: D. Recommendation: Perform scheduled shutdown and replacement within the next 4 hours"*.

This example demonstrates the critical linkage between data, models, decisions, and actions — a connection that is essential in industrial environments where unplanned downtime can lead to significant costs.

5. Conclusions

The proposed concept for an industrial equipment reliability management system based on predictive analytics combines the strengths of probabilistic-physics models and machine learning, enabling high-accuracy and efficient estimation of remaining useful life (RUL) and failure prediction even under unstable or incomplete data streams.

The system reduces the risk of unplanned downtime and production losses; enables objective assessment of the RUL for components and assemblies; supports interpretable models for well-founded decision-making; has an adaptive architecture suitable for various equipment types and load conditions; supports integration with ERP and MES levels, forming a full-scale digital enterprise ecosystem; complies with security requirements for critical infrastructure facilities, as it can operate locally without external cloud dependencies.

The innovative aspect of the approach lies in the combination of ML/AI and physical degradation models, as well as in the phase-based classification of equipment operation, allowing both high predictive accuracy and model explainability.

Future development prospects

Currently, deploying such systems often requires substantial financial, technical, and human resources, which may not be readily available to individual enterprises. Therefore, one promising direction for scaling is the creation of industry-wide or government-backed cloud clusters with distributed architecture.

In this model, large-scale data processing (analytics, model training) can be performed centrally, while local enterprise nodes retain functions related to monitoring, decision-making, and critical alert output. At the same time, standardization of data formats, quality control, and sharing of templates and wear indicators between industry participants are ensured.

This approach reduces entry barriers, minimizes infrastructure costs, and allows scaling predictive systems to the industry or national level, particularly relevant for defense and energy sector assets.

REFERENCES

1. ДСТУ 8646:2017. Надійність техніки. Оцінювання і прогнозування залишкового ресурсу (терміну служби) технічних систем. Видавництво Держстандарту України. URL: https://online.budstandart.com/ua/catalog/doc-page.html?id_doc=93146.

2. Федухін О.В., Муха Ар.А. Оцінка залишкового ресурсу контактного проводу електрифікованих залізничних доріг. *Математичні машини і системи.* 2022. № 2. С. 91–101.

3. Wu F., Wu Q., Tan Y., Xu X. Remaining Useful Life Prediction Based on Deep Learning: A Survey. *Electronics.* 2024. N 24. P. 3454–3478.

4. ISO 13379-1:2012. Condition monitoring and diagnostics of machines — Data processing, communication and presentation — Part 1: General guidelines.

5. Schwabacher M., Goebel K. A Survey of Artificial Intelligence for Prognostics. Proc. of the AAAI Fall Symposium: Artificial Intelligence for Prognostics. Arlington, VA, USA. November 9–11, 2007. P. 108–115.

6. Si X.S., Wang W., Hu C.H., Zhou D.H. Remaining useful life estimation. A review on the statistical data driven approaches. *European Journal of Operational Research*. 2011. N 213. P. 1–14.
7. Стрельніков В.П., Федухін О.В., Яковлев М.Ф. Імовірнісно-фізичний підхід до розрахунку показників надійності. *Математичні машини і системи.* 1997. № 2. С. 101–113.
8. Advancing Logistics 4.0 with the Implementation of a Big Data Warehouse: A Demonstration Case for the Automotive Industry. URL: https://www.mdpi.com/2079-9292/10/18/2221.
9. Sun B., Wang W., Zhao W., Liu Y. Hybrid residual life prediction based on deep neural network and physical models. *Mechanical Systems and Signal Processing.* 2022. P. 168.
10. Zhang X. et al. Adaptive phase-aware deep networks for RUL. *IEEE Access*. 2023. Vol. 235. P. 109244.
11. Fedukhin O.V., Mukha Ar.A. Determination of the residual life of products under the influence of several degradation processes. *Mathematical machines and systems*. 2023. N 3. P. 104–112.
12. Zonta T., da Costa C.A., da Rosa Righi R., de Lima M.J., da Trindade E.S., Li G.P. A predictive maintenance model for optimizing production schedule using deep neural networks. *Journal of Manufacturing Systems.* 2022. N 62. P. 449–460.
13. Begun S., Begun V. A SaaS Concept Based Shopping Centre Fire Risk Assessment Model for the Safety Management Applications. *International Journal of Reliability, Quality and Safety Engineering*. 2024. N 2, Vol. 31. P. 2350036.

Стаття надійшла до редакції 14.04.2025