

# Methodological foundations for forecasting economic benefits from the transition to condition-based predictive maintenance using the MACPOM methodology

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**Abstract.** The relevance of the study is determined by the growing complexity of industrial systems and the need to transition from time-based and reactive maintenance to condition-based approaches. Traditional strategies do not ensure alignment between technical parameters and economic performance, resulting in higher costs and productivity losses.

**The purpose** of the article is to develop and substantiate a methodological approach to forecasting the economic benefits of predictive maintenance through integrating technical monitoring, diagnostics, and prediction with economic evaluation, based on the MACPOM methodology.

**Methods** include system analysis, generalisation, modelling, and economic evaluation, combining sensor monitoring, digital modelling, and predictive analytics.

**Results** show that integrating technical condition data, remaining useful life, and cost parameters enables quantitative assessment of economic effects, including reduced downtime, maintenance costs, and operational losses.

**Conclusions** confirm that integrated cyber-physical approaches improve decision-making and reduce total costs.

**Future research** should focus on improving economic assessment under uncertainty and adapting models to industry-specific conditions.

**Keywords:** digital twin, sensor monitoring, asset management, adaptive control, remaining useful life, operational efficiency, cyber-physical systems, cost optimization, equipment reliability, intelligent analytics

## Методологічні засади прогнозування економічної вигоди від переходу до предиктивного обслуговування обладнання за фактичним станом на основі методики MACPOM

**Анотація.** Актуальність дослідження зумовлена зростанням складності промислових систем, підвищенням вимог до їх надійності та економічної ефективності, а також необхідністю переходу від регламентних і реактивних моделей технічного обслуговування до обслуговування за фактичним станом. Встановлено, що традиційні підходи не забезпечують достатнього рівня узгодження технічних і економічних параметрів функціонування обладнання, що призводить до втрат продуктивності, зростання витрат і підвищення виробничих ризиків.

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**Метою статті є** розроблення та наукове обґрунтування методологічного підходу до прогнозування економічної вигоди від переходу до предиктивного обслуговування обладнання за фактичним станом на основі інтеграції інженерних засобів моніторингу, діагностики та прогнозування технічного стану з економічними моделями оцінювання ефективності з урахуванням потенціалу методики МАСРОМ.

**Методи дослідження.** Використано методи системного аналізу, узагальнення та порівняння наукових підходів, методи моделювання технічного стану обладнання, а також елементи економіко-аналітичного оцінювання витрат і втрат виробничих систем. Застосовано підхід інтеграції сенсорного моніторингу, цифрових моделей і предиктивної аналітики.

**Результати.** Досліджено еволюцію підходів до технічного обслуговування обладнання та доведено доцільність переходу до предиктивних моделей. Встановлено, що інтеграція даних про технічний стан, прогнозу залишкового ресурсу та витратних параметрів дозволяє здійснювати кількісне прогнозування економічного ефекту. Обґрунтовано методичний підхід, який забезпечує трансформацію технічних прогнозів у показники зниження простоїв, оптимізації ремонтних витрат, мінімізації втрат продуктивності та скорочення операційних витрат. Виявлено, що застосування методики МАСРОМ підвищує достовірність прогнозів і забезпечує узгодження технічних і економічних рішень.

**Висновки.** Доведено, що використання інтегрованих кіберфізичних підходів створює науково обґрунтовану основу для прогнозування економічної ефективності предиктивного обслуговування. Встановлено, що запропонований підхід дозволяє підвищити ефективність управління виробничими активами та знизити сукупні витрати підприємства.

**Перспективи подальших досліджень.** Пов'язані з удосконаленням методів кількісного оцінювання економічного ефекту з урахуванням невизначеності даних, розвитком моделей прогнозування залишкового ресурсу та адаптацією підходу до галузевих особливостей функціонування промислових систем.

**Ключові слова:** цифровий двійник, сенсорний моніторинг, управління активами, адаптивне управління, залишковий ресурс, виробнича ефективність, кіберфізичні системи, оптимізація витрат, надійність обладнання, інтелектуальна аналітика.

### Introduction

The current stage of industrial system development is characterized by increasing complexity of technological equipment, intensification of production processes, and growing requirements for continuity and economic efficiency. Under such conditions, traditional maintenance approaches based on fixed schedules or reactive responses to failures prove insufficiently effective, as they do not account for the actual technical condition of equipment and the dynamics of its degradation. This results in inefficient resource utilization, premature maintenance interventions or, conversely, the occurrence of emergency failures accompanied by significant productivity losses, increased operating costs, and risks of disruption to production cycles.

The deepening digitalization of industry, along with the advancement of sensor technologies, data acquisition systems, and analytical tools, creates the preconditions for transitioning to condition-based maintenance using predictive models. However, the scientific and practical problem lies not only in the technical implementation of such a transition, but also in the lack of comprehensive methodological approaches for quantitatively forecasting its economic feasibility. Existing studies are primarily focused on improving reliability or diagnostic accuracy, while the integration of technical condition parameters with enterprise-level economic performance indicators remains insufficiently developed.

Particular relevance is associated with the need to develop a methodology that ensures the integration of monitoring, diagnostics, and technical condition forecasting results with the evaluation of economic benefits derived from predictive maintenance implementation. In this context, the use of engineering approaches based on the integration of sensor data, digital models, and adaptive control algorithms is of particular importance, especially MACPOM method, developed by the author as an engineering framework for integrating sensor monitoring, digital modeling, adaptive control, and predictive analytics. This method enables consideration of parameter variability, external influences, and degradation processes. At the same time, the transformation of technical forecasts into economic indicators reflecting reduced downtime, optimized maintenance costs, and improved resource utilization remains insufficiently explored.

Thus, there is an objective scientific and practical need to develop methodological foundations for forecasting the economic benefits of transitioning to condition-based predictive maintenance, ensuring alignment between technical and economic parameters of industrial system operation. Addressing this problem is essential for improving asset management efficiency, reducing operational risks, and ensuring sustainable industrial development in the context of digital transformation.

An analysis of contemporary research in this field indicates the formation of a comprehensive scientific foundation that integrates conceptual, analytical, technical-technological, and economic approaches. N. Sakib and T. Wuest consider predictive maintenance as an evolutionary extension of condition-based maintenance, emphasizing the role of data and analytics in improving maintenance efficiency [1]. A. Bousdekis et al. highlight the significance of predictive maintenance within the context of Industry 4.0, substantiating its role in value creation and optimization of asset management [2]. M. Mołęda et al. investigate the transformation of maintenance approaches in the energy sector, demonstrating the advantages of condition-oriented models [3]. M. Achouch et al. summarize modern models and implementation challenges of predictive maintenance, emphasizing the need to integrate technical and managerial components [4].

A significant body of research is devoted to the development of information-analytical tools for forecasting equipment condition. T. Zhu et al. propose a systematization of predictive maintenance architectures, enabling structured data collection and processing [5]. J. Lee et al. examine intelligent maintenance systems as part of predictive manufacturing, where analytics is integrated with production processes [6]. V. Kumar and M. L. Garg analyze modern predictive analytics methods forming the basis for prognostic models [7]. W. Zhang et al. investigate data-driven approaches to failure prediction, emphasizing the role of big data [8].

Other studies focus on the technical and technological support of predictive maintenance and the formation of information bases for decision-making. J. Pech et al. emphasize the role of intelligent sensors as key elements in collecting data on equipment condition [9]. J. Dalzochio et al. explore machine learning methods for identifying degradation patterns and predicting failures [10]. D. Zhong et al. consider digital twin technology as a tool for integrating data and forecasting models [11]. A. Busse et al. propose an approach to evaluating predictive maintenance efficiency that accounts for both technical and economic parameters of industrial system performance [12].

At the same time, modern research increasingly addresses the evaluation of economic effects and risk management in the context of predictive analytics. A. Meddaoui et al., based on a practical case study, demonstrate the effectiveness of predictive maintenance in improving reliability and productivity [13]. M. Seyedan and F. Mafakheri analyze the potential of predictive big data analytics for supporting decision-making in complex systems [14]. A. Aljohani examines the application of machine learning to enhance flexibility and resilience in supply chains [15].

Despite the progress in predictive maintenance approaches, unresolved issues remain regarding the integration of technical forecasts with economic assessments, particularly the transformation of technical condition indicators and remaining useful life into financial outcomes. Methodological approaches for quantitatively assessing impacts on downtime, maintenance costs, productivity losses, and operational expenses are insufficiently developed, as is the issue of ensuring data reliability and accounting for uncertainty.

The present study aims to address these gaps by developing an integrated approach that combines engineering and economic parameters based on the MACPOM methodology. This approach enables quantitative forecasting of economic effects and enhances the justification of managerial decisions regarding the implementation of predictive maintenance.

The aim of the article is to develop and scientifically substantiate a methodology for forecasting the economic benefits of transitioning to condition-based predictive maintenance through the integration of engineering approaches to monitoring, diagnostics, and forecasting with economic evaluation models, taking into account the potential of the MACPOM methodology as an engineering foundation for such a transition.

The objectives of the study are:

1. To investigate the evolution of maintenance approaches and substantiate the prerequisites for integrating sensor monitoring, digital models, and predictive analytics based on the MACPOM methodology;
2. To develop a methodological approach for forecasting the economic benefits of predictive maintenance by transforming technical condition indicators and remaining useful life into measurable economic parameters;
3. To identify scientific and practical challenges in assessing the economic feasibility of transitioning to predictive maintenance and to formulate recommendations for addressing them using the MACPOM methodology.

### Results

Modern approaches to organizing equipment maintenance are formed under conditions of increasing complexity of industrial systems and growing requirements for their economic efficiency. The evolution from reactive and time-based models to condition-based and predictive approaches reflects a transition from a focus on maintaining operability to managing costs and risks based on data. This transformation is driven by the ability to utilize sensor monitoring, digital models, and analytical tools for assessing the technical condition of equipment and forecasting its degradation (table 1).

Table 1

Evolution of equipment maintenance approaches and their economic characteristics

Approach	Main content	Economic consequences
Reactive maintenance (run-to-failure)	Repair after failure occurs	High downtime losses, unpredictable costs
Time-based maintenance	Scheduled maintenance at fixed intervals	Excessive maintenance costs, inefficient resource utilization
Condition-based maintenance (CBM)	Use of diagnostics to assess technical condition	Reduced unnecessary repairs, partial cost optimization
Predictive maintenance (PdM)	Failure forecasting based on data and models	Minimization of downtime, cost optimization, improved efficiency
Integrated cyber-physical approaches (including MACPOM)	Integration of sensor monitoring, digital models, and adaptive control	System-wide cost optimization, increased reliability, and long-term efficiency

*Source: compiled by the author based on [1, p. 269; 3; 4; 2, p. 59; 6]*

A comparative analysis of these approaches demonstrates that the economic efficiency of maintenance is directly dependent on the extent to which the actual condition of equipment is taken into account and on the system's ability to predict its changes. In industrial practice, the transition from time-based to condition-based maintenance allows avoiding unnecessary repair operations, which is particularly evident in equipment with uneven load patterns, such as electric drives or pumping units, where actual wear may significantly differ from standard estimates [1, p. 269]. The further implementation of predictive models enables not only the detection of deviations but also the estimation of remaining useful life, allowing maintenance activities to be synchronized with production cycles and preventing critical failures. In metallurgical and chemical industries, this is reflected in a reduction in emergency failures without disrupting technological processes, while in the energy sector it contributes to operational stability and reduced costs for reserve capacity.

The most significant economic effect is achieved when predictive maintenance is integrated with adaptive control algorithms, where equipment condition data are used not only for maintenance decision-making but also for optimizing operating modes [6]. In this context, the application of MACPOM methodology enables the integration of sensor data, digital models, and forecasting algorithms into a unified decision-making system. The practical implementation of such an approach ensures a reduction in total costs through simultaneous minimization of downtime, reduction in emergency repairs, and improved equipment utilization, confirming the feasibility of transitioning to predictive models as a key direction for enhancing industrial competitiveness [3].

The integration of sensor monitoring, digital modeling, and predictive analytics into equipment condition management systems is most comprehensively realized within the MACPOM framework, which represents an engineering concept for constructing multi-level control systems for complex industrial objects. Its essence lies in combining data acquisition, modeling, analytical processing, adaptive control, and forecasting into a unified closed-loop system. This approach not only improves equipment reliability but also creates an information basis for economically justified maintenance decisions. The generalized logic of this methodology can be represented as a sequence of interrelated stages (Fig. 1).

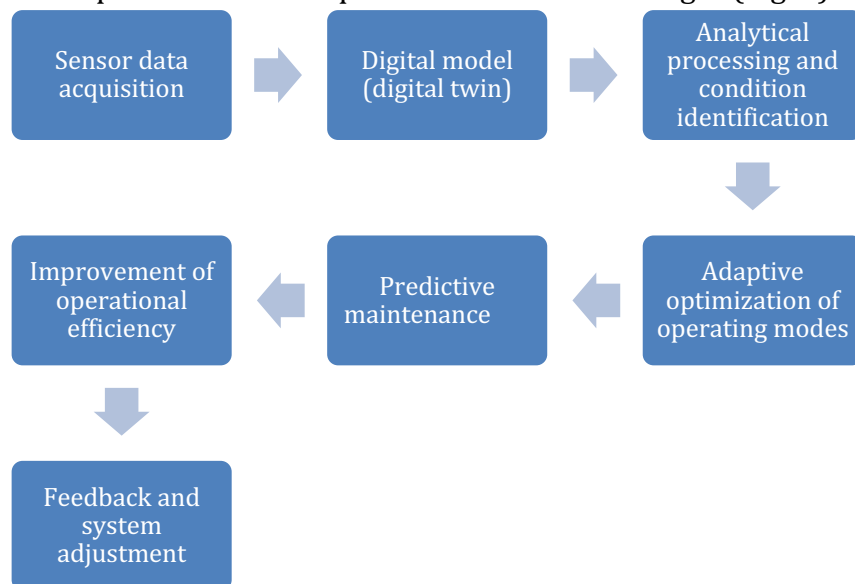


Рис. 1. Generalized logic of the MACPOM methodology functioning  
*Source: author's own development*

The presented sequence reflects the transition from the physical level of equipment operation to analytical and managerial levels, where economically justified decisions regarding operating modes and maintenance are formed. A key feature is the presence of a feedback loop

that ensures continuous system adaptation to changes in operating conditions, load levels, and equipment degradation. The characteristics of the MACPOM methodology levels in equipment condition management systems are presented in table 2.

Table 2

Functional characteristics of MACPOM methodology levels in equipment condition management systems

Level	Main content	Technological implementation	Practical significance
Sensor	Acquisition of equipment operating parameters	Temperature, vibration, pressure, and electrical sensors	Formation of a reliable information base on system condition
Model	Creation of a digital representation of processes	Mathematical models, digital twins	Reproduction of equipment behavior under various conditions
Analytical	Data processing and condition assessment	Statistical methods, machine learning, state observers	Detection of deviations and early signs of degradation
Optimization	Formation of control actions	Model Predictive Control (MPC), adaptive algorithms	Optimization of operating modes and load reduction
Predictive	Forecasting future condition	Forecasting algorithms, Remaining Useful Life (RUL) estimation	Maintenance planning and failure prevention

*Source: compiled by the author based on [9; 11; 10; 6; 8, p. 2216]*

Under modern production conditions, such an architecture operates as an integrated digital ecosystem, where each level not only performs a specific function but also provides an informational basis for subsequent decision-making stages. In industrial automation, continuous sensor data acquisition enables the formation of digital operational profiles, which at the modeling level are transformed into digital twins that account for the physical laws governing processes [8, p. 2216]. This allows for more accurate analysis of the impact of loads, temperature regimes, and vibration characteristics on component degradation rates.

The analytical level ensures the transition from simple parameter monitoring to intelligent data interpretation, enabling the identification of anomalies at early stages. In practice, this is reflected, for example, in detecting gradual increases in vibration in bearing units or changes in electrical characteristics of motors, indicating potential failures. The optimization level uses this information to adaptively adjust operating modes, reducing wear intensity and improving energy efficiency. At the final stage, the predictive level generates estimates of remaining useful life, allowing maintenance activities to be synchronized with production schedules and minimizing downtime.

The practical implementation of such a model, particularly in water treatment systems, energy systems, and automated production lines, ensures not only increased equipment reliability but also creates the basis for justified forecasting of the economic effects of predictive maintenance implementation [11]. This is achieved through reduced emergency shutdowns, optimized repair costs, and more efficient utilization of production resources, confirming the practical significance of the integrated approach implemented in the MACPOM methodology.

The substantiation of the methodological approach to forecasting the economic benefits of predictive maintenance is based on integrating technical parameters of equipment operation with enterprise economic performance indicators. In the context of digital transformation, the technical condition of equipment is no longer considered solely an engineering characteristic but acquires an economic dimension, as it determines the level of operational risks, stability of

technological processes, and cost structure. The use of sensor monitoring, digital models, and predictive analytics within the MACPOM framework enables forecasting of remaining useful life and estimation of failure probabilities, forming the basis for informed managerial decision-making regarding the timing and scope of maintenance. A key aspect in this context is the transformation of technical forecasts into economic indicators reflecting changes in costs and losses during equipment operation, particularly through their impact on downtime duration, repair volumes, productivity levels, and overall operational costs (table 3).

Table 3

Methodological approach to forecasting the economic benefits of predictive maintenance

Model component	Technical content	Economic interpretation	Expected effect
Condition monitoring	Continuous acquisition of parameters (vibration, temperature, load)	Formation of an information base for risk assessment	Reduction of uncertainty in cost planning
Condition assessment	Identification of deviations and degradation	Determination of failure risk level	Prevention of emergency costs
RUL forecasting	Estimation of time to potential failure	Evaluation of future losses and costs	Optimization of maintenance timing
Maintenance optimization	Determination of optimal intervention timing	Balancing repair costs and downtime losses	Reduction of total costs
Managerial decision	Formation of an action plan	Alignment of technical and economic parameters	Improvement of operational efficiency
Operational result	Implementation of maintenance actions	Change in cost and revenue structure	Increase in economic efficiency

*Source: compiled by the author based on [12, p. 693; 13, p. 3688; 7, p. 34; 14; 15]*

The proposed methodological approach reflects the cause-and-effect relationship between the technical condition of equipment and the economic performance of an enterprise, enabling a transition from descriptive analysis to quantitative forecasting of the effects of predictive maintenance implementation. Its practical value lies in the transformation of engineering parameters, particularly degradation characteristics and Remaining Useful Life (RUL) forecasts, into measurable economic indicators that directly influence cost structure and the level of production losses. Empirical evidence confirms the realism of such estimates: the implementation of predictive maintenance in medium-scale industrial systems leads to a reduction in total maintenance costs by 10–25%, a decrease in the frequency of emergency shutdowns by up to 35%, and an increase in Overall Equipment Effectiveness (OEE) by 10–15 percentage points [12, p. 693; 13, p. 3688]. Within the MACPOM framework, this is achieved through the integration of sensor monitoring, digital models, and predictive analytics, which enables not only the detection of equipment condition but also the forecasting of its evolution over time.

From a practical perspective, this implies that each stage presented in the table forms a distinct channel of influence on economic outcomes. In particular, accurate monitoring and timely identification of deviations allow for the detection of early-stage component degradation before it develops into critical failure, thereby reducing the likelihood of unplanned downtime [7, p. 34].

To quantitatively assess the expected effect, the following basic relationship is proposed:

$$E = \Delta D * C_h + \Delta R * k_r - C_{pdm} \quad (1)$$

where:  $\Delta D$  is the reduction in unplanned downtime (hours/year),  $C_h$  is the unit cost of downtime (UAH/hour),  $\Delta R$  is the reduction in emergency repair costs (UAH/year),  $k_r$  is the coefficient reflecting the reduction in their frequency, and  $C_{pdm}$  represents the annual costs of maintaining the predictive maintenance (PdM) system. According to conservative industry estimates [12; 13], even at  $\Delta D=25-30\%$  and  $k_r=0.15$ , the system reaches break-even within the first year of operation.

At the level of remaining useful life forecasting, the possibility arises to shift maintenance interventions from critical failure points to technologically optimal periods, thereby minimizing productivity losses. This is particularly important for continuous production systems, where even short-term interruptions may lead to substantial economic losses.

The application of optimization algorithms within the MACPOM framework ensures the selection of operating modes that slow down degradation processes without reducing production efficiency, which is reflected in reduced maintenance costs and extended asset life cycles. In industry practice, this is confirmed, for example, in water treatment systems, where timely detection of membrane contamination prevents premature replacement, or in energy systems, where monitoring vibration parameters helps avoid the destruction of critical equipment components [13, p. 3688]. In automated production lines, the use of predictive models enables synchronization of maintenance activities with production cycles, reducing downtime losses and increasing throughput. In addition, predictive analytics systems allow reducing excessive preventive maintenance by 20–30%, directly lowering operational costs without increasing failure risk [7, p. 34].

Thus, within this approach, the MACPOM methodology is demonstrated to perform not only the function of technically substantiating the transition to condition-based maintenance but also to serve as a tool for forecasting the economic effects of its implementation. This is manifested in the ability to quantitatively assess reductions in downtime, optimization of repair costs, minimization of productivity losses, and reduction of operational expenses, which collectively form the basis for improving enterprise performance and justifying the feasibility of implementing predictive maintenance in modern industrial systems.

The evaluation of the economic feasibility of transitioning to predictive maintenance is accompanied by a number of scientific and practical challenges arising from the complexity of integrating technical and economic parameters into a unified decision-making system. The key issue lies in transforming the results of diagnostics and technical condition forecasting into financial indicators that differ in nature, temporal structure, and level of uncertainty [11]. Technical models, focused on assessing degradation processes and remaining useful life, operate with probabilistic characteristics, whereas economic calculations require deterministic estimates of costs and revenues. This creates a methodological gap between engineering forecasts and financial outcomes, complicating the justification of investment decisions related to predictive maintenance implementation.

Additional challenges arise due to the limited reliability of input data generated through sensor monitoring and historical operational records. Variability in loads, external influences, and operating conditions leads to discrepancies between actual and predicted parameters, reducing the accuracy of economic assessments. In practice, this is reflected in uncertainty regarding the magnitude of potential benefits from downtime reduction or maintenance cost optimization, which restrains the adoption of innovative maintenance approaches [9]. At the same time, the lack of unified methodological approaches for assessing indirect effects, such as productivity losses or product quality impacts, limits the possibility of comprehensive economic efficiency analysis.

These challenges necessitate the use of integrated approaches capable of combining technical and economic aspects of industrial system operation. In this context, the MACPOM methodology serves as an effective tool for overcoming the identified limitations, as it provides

a unified architecture for data processing and decision-making based on the integration of sensor monitoring, digital models, and predictive analytics. Its application enhances the reliability of technical forecasts through the use of digital twins and adaptive algorithms that account for variability in operating conditions. This, in turn, creates the basis for more accurate evaluation of the economic consequences of different maintenance scenarios.

Practical recommendations for the application of the MACPOM methodology are based on the step-by-step integration of technical and economic data into the management process. First, it is advisable to implement continuous monitoring systems that ensure the formation of a reliable data foundation for further analysis. The next stage involves developing digital models of equipment that allow accounting for specific operational characteristics and simulating various degradation scenarios. The use of remaining useful life forecasting algorithms enables the determination of optimal maintenance timing aligned with production schedules, directly contributing to reduced downtime and productivity losses. Integrating these results into enterprise management systems ensures alignment between technical decisions and economic objectives, particularly through the optimization of maintenance and repair costs.

Under modern conditions, the implementation of such recommendations leads to the formation of an adaptive model for equipment condition management, where decisions are based on predictive assessments and economic efficiency criteria. This not only improves the reliability of industrial systems but also ensures the achievement of tangible economic effects, manifested in reduced downtime, lower maintenance costs, minimized productivity losses, and improved utilization of production resources. Thus, the MACPOM methodology serves not only as an engineering foundation for the transition to condition-based maintenance but also as an effective tool for substantiating its economic feasibility.

### **Conclusions**

The study demonstrates that the transition to condition-based predictive maintenance leads to improved economic efficiency of industrial systems through the integration of technical and economic parameters of their operation. It has been established that the MACPOM methodology provides the most comprehensive integration of sensor monitoring, digital modeling, and adaptive control, forming a reliable basis for quantitative forecasting of economic effects, which constitutes the scientific novelty of the research.

A methodological approach to transforming technical RUL forecasts into measurable economic indicators has been substantiated, including reductions in downtime, decreases in emergency repair costs, and minimization of productivity losses. Empirical evidence confirms the realism of such estimates: the implementation of predictive maintenance results in a 10–25% reduction in maintenance costs, up to a 35% decrease in emergency shutdowns, and a 10–15 percentage point increase in OEE.

It has been identified that the key scientific and practical challenges include the methodological gap between probabilistic technical forecasts and deterministic financial evaluations, limited reliability of sensor data under variable operating conditions, and insufficient formalization of indirect effects. The application of digital twins and adaptive algorithms within the MACPOM framework partially mitigates these limitations. The proposed approach has been validated at the level of model-based calculations; its empirical verification on real industrial systems, the development of industry-specific RUL models, and the improvement of evaluation methods under uncertainty define the directions for future research.

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