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REVIEW ARTICLE

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Importance measure-based maintenance strategy optimization: Fundamentals, applications and future directions in AI and IoT

Abstract Numerous maintenance strategies have been proposed in the literature related to reliability. This paper focuses on the utilization of reliability importance measures to optimize maintenance strategies. We analyze maintenance strategies based on importance measures and identify areas lacking sufficient research. The paper presents principles and formulas for advanced importance measures within the context of optimizing maintenance strategies. Additionally, it classifies methods of maintenance strategy optimization according to importance measures and outlines the roles of these measures in various maintenance strategies. Finally, it discusses potential challenges that optimization of maintenance strategies based on importance measures may encounter with future technologies.

Keywords maintenance strategy, importance measure, reliability, maintenance cost

1 Introduction

A maintenance strategy refers to a set of action plans implemented when equipment experiences failures or requires maintenance. The advancements in this field contribute to a deeper understanding of maintenance practices and offer opportunities for innovative solutions to meet the evolving challenges and demands across industries (Pintelon and Gelders, 1992). The maintenance strategy optimization (MSO) problem involves the application of optimization methods and techniques to achieve optimal maintenance effectiveness (de Jonge and Scarf, 2020). In practice, MSO considers technical, economic, and organizational aspects. The operating environment of a system is complex, incorporating numerous interconnected factors. This complexity often leads to MSO with resource constraints and conflicting objectives. Effective decision-making is crucial, considering the uncertainties associated with faults and maintenance. Hence, research in MSO poses a significant yet complex challenge (Garg and Deshmukh, 2006). The MSO model serves as a mathematical tool to determine the optimal maintenance strategy within a given context (Dekker, 1996). It is applicable to systems in various domains, including manufacturing, energy, transportation and logistics, facility management, and communication networks. For instance, it plays a vital role in textile manufacturing systems (Ilangkumaran and Kumanan, 2012), railway track-beds (Bressi et al., 2021), gas turbine engines (Mancuso et al., 2021), and cellular networks (Wu et al., 2021a), among others.

Maintenance strategies include a variety of rules for optimization. Previous research has categorized these rules into several types: A) Minimizing maintenance resources; B) Maximizing performance recovery; C) Minimizing maintenance resources while meeting performance recovery requirements; D) Maximizing performance recovery with maintenance resource constraints; E) Multi-objective optimization (Wang, 2002). The classification of MSO problems can be subdivided into three categories: optimization of corrective, preventive, and predictive maintenance strategies. The optimization of corrective maintenance strategies (Fu et al., 2019; Golari et al., 2014; Groenevelt et al., 1992;

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Xing and Levitin, 2018) involves taking prompt measures to repair faults and restore system operation after failure. The goal of optimization is to minimize the impact of failures, effectively restoring system reliability and stability. On the other hand, optimization of preventive maintenance strategies (Wu and Castro, 2020; Wang et al., 2020; Levitin et al., 2021; Shi et al., 2022) involves proactive measures to avoid failures. Finally, optimization of predictive maintenance strategies (Grall et al., 2002; Ming Tan and Raghavan, 2008; Ren, 2021) employs real-time monitoring and fault prediction models to preemptively apply maintenance measures. Both preventive and predictive MSO aim to reduce the probability of failures.

Reliability Importance Measures (IMs), as exemplified by Birnbaum (1968), Dui et al. (2015), and Meng (1996), quantify the contribution of various components to different effective indicators of the overall system. Critical components are identified based on diverse indicators to optimize system design, operation, and maintenance strategies. During the system design phase, IMs are commonly employed for reliability optimization, which includes tasks such as component selection and layout, redundancy design, component allocation, invariance optimal designs (Zuo and Kuo, 1990), and risk-informed regulatory applications (Cheok et al., 1998). IMs have found applications in inventory systems design (Dui et al., 2019a), command post systems (Dui et al., 2022a), and wind turbine systems (Dui et al., 2023a). In operational processes, IMs are utilized to guide system monitoring and resilience optimization, ensuring that resources and attention are focused on the most critical components, thereby enhancing awareness and responsiveness to potential risks. IMs can be applied in maritime transport systems (Dui et al., 2023b; Dui et al., 2021a), main coolant systems (Dui et al., 2022b), and reactor protection systems in nuclear power plants (Marseguerra and Zio, 2004), wind power generation systems (Dui et al., 2022c), multi-lock cargo door systems (Lyu and Si, 2020), and feeding control systems of CNC lathes (Xiahou et al., 2018), among others. Regarding resource allocation and maintenance strategies, IMs can identify the weakest components to minimize the likelihood of system failures. IMs also find applications in aircraft hydraulic systems (Dui et al., 2022d), urban transportation networks (Dui et al., 2023c), simplified gas-detection systems (Andrews and Beeson, 2003), nuclear power plant systems (Dui et al., 2023d), and reactor coolant systems (Dui et al., 2023e).

This study explores two methods for Maintenance Strategy Optimization based on Importance Measures (IMMSO), including rules and algorithms of IMMSO. The rest of this paper is organized as follows. Section 2 provides an overview of MSO and IMs, elucidating the relationship between the two through literature collection and analysis. Section 3 presents the extension and application of IMs in three different types of maintenance strategies. Section 4 summarizes the MSO methods based on IMs, including optimization rules and algorithms. Finally, Section 5 concludes the paper, outlining the challenges that IMMSO problems may face in future research.

2 Relationships between maintenance strategy optimization and importance measures

Since the 1940s, maintenance strategies have undergone a transformation from specificity to generality and then back to specificity in new fields (Garg and Deshmukh, 2006). In the 1960s, the research focus shifted to MSO, building upon the foundation of early corrective maintenance (McCall, 1965). Figure 1 depicts the literature retrieval process in this field. Relevant papers were acquired through a carefully crafted search query and screening process, outlined in Fig. 1, culminating in a data set. The analysis of this data set outlined the characteristics of MSO during its evolutionary process. Numerous significant MSO techniques were proposed throughout this evolution, including the analytic hierarchy process, Bayesian methods, Galbraith information processing model, and genetic algorithm (GA). An overview of these techniques and an analysis of their new trends were provided in (Sharma et al., 2011). The evolving landscape of maintenance strategy studies reflects an increasing diversity in the aspects and dimensions considered within the field.

Researchers have expanded their focus beyond traditional perspectives. They have also investigated novel dimensions, methodologies, and applications in the field of maintenance. The study of imperfect maintenance has led to a diversification of maintenance behavior choices, marking a significant breakthrough in maintenance and reliability theory (Pham and Wang, 1996). In MSO studies of multi-component systems, it is essential to consider the interaction between components. These interactions are categorized as economic dependence, structural dependence, and stochastic dependence (Dekker et al., 1997). Due to a strong interest in dependence relationships, Olde Keizer et al. (2017) proposed a new classification of dependencies in multi-component systems, defining new types of structural dependencies. In modern maintenance decision-making, environmental multi-level and multi-objective optimization has become increasingly important. They assist in effectively addressing multiple conflicting criteria (Syan and Ramsoobag, 2019). Extensive research on maintenance strategies has generated significant interest in MSO models in academia and engineering. These models not only play a crucial role in addressing failures

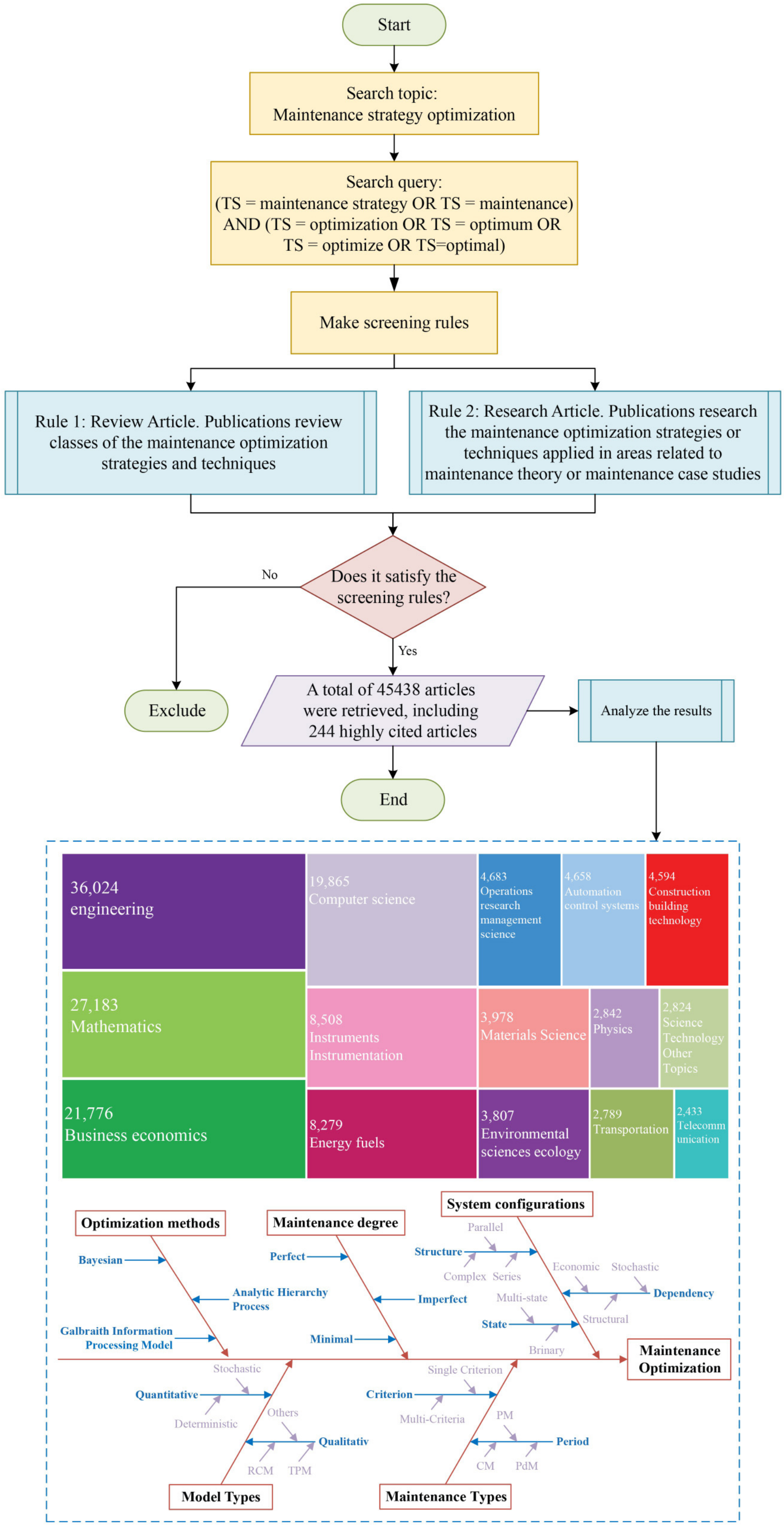

Fig. 1 The retrieval process and result analysis of MSO.

but also achieve noteworthy accomplishments in improving system performance recovery (Alaswad and Xiang, 2017; Cao et al., 2018; Cho and Parlar, 1991). With the ongoing refinement of mathematical models, dynamic maintenance strategies can be articulated and subsequently optimized using reinforcement learning processes, allowing them to adapt to changing environmental conditions and system states (Hu et al., 2022; Seites-Rundlett et al., 2022).

Over time, the demand for optimization of maintenance strategies in practical applications has driven advancements in both theory and practical implementations. The emergence of reliability-centered maintenance, total productive maintenance, business-centered maintenance, and risk-based maintenance has given rise to new maintenance concepts (Ahmad and Kamaruddin, 2012). Scholarly articles from 1961 to 2023 have been collected and used to thoroughly study the collection of papers on MSO spanning 63 years. This process aids in acquiring a comprehensive understanding of the key optimization focus in relevant application areas. Table 1 provides the objectives of MSO in key research areas. The quantity and variety of applications in the highlighted research areas in the table effectively demonstrate the practical value of MSO.

In many practical applications, maintenance requires a significant investment of resources. Reducing maintenance cost becomes a primary objective in MSO. Excessive or unplanned emergency maintenance can result in unnecessary cost expenditures (Velmurugan and Dhingra, 2015). Therefore, the rationality and effectiveness of maintenance strategy are crucial. Minimizing maintenance costs and maximizing system availability are the most common optimization goals in maintenance strategy. The diversity in maintenance research indicates that MSO is a multidimensional field involving technology, management, sustainability, and data-driven decision-making.

Importance analysis in reliability engineering is a critical and widely used approach. It helps identify the most vulnerable components within a system to enable effective measures for risk assessment and system optimization. The IM proposed by Birnbaum (Birnbaum, 1968) assesses how changes in component reliability impact the overall system reliability. This section provides a literature review on IMs following the method illustrated in Fig. 2. Relevant papers are collected using carefully designed search queries and screening rules as shown in Fig. 2, which generates another data set. Statistical analysis is conducted based on this data set. The analysis of the data set presents the publication count and trends of IMs between 2003 and 2022, indicating a rapid development in this field that is currently experiencing significant growth. Another section includes an association analysis of academic papers gathered in this review. The result of this association analysis is depicted in a network diagram where nodes represent academic papers, labeled with the first author and publication year. The presence of connections between nodes indicates a strong correlation between two academic papers. From this analysis, we can readily understand the ongoing progress in both theoretical and applied research aspects of IMs.

With the advancement of reliability theory, newer IM theories have been developed to take into account various factors such as reliability, structure, state transitions, and performance. These theories have been extended to provide more accurate and comprehensive assessment of systems (Dui et al., 2023g; Si et al., 2020), leading to their wide application in various fields. One early evaluation by Barlow and Proschan (Richard and Frank, 1975) focused on how components contribute to improving reliability during the development phase of coherent systems. They proposed a new importance measure $I_h(i)$ for basic events and their minimal cut sets in a fault tree. Another set of importance measures, known as Fussell–Vesely IMs, were developed based on the characteristics of system reliability. These measures evaluated the probability of system failure when a component fails (Fussell, 1975). Natvig (1979) provided dynamic and static

Table 1 Important research fields and objectives of MSO

Fields	MSO objectives	References
Engineering	Minimize downtime and cost consumption to the greatest extent, and extend the lifespan of the system, ensuring system reliability and performance	Carbonari et al., (2020); Guo et al., (2023); Wu and Li, (2021)
Mathematics	Optimize complex mathematical models, identify optimal parameter combinations based on practical considerations, achieve stability and precision in calculations, and reduce computational time and spatial complexity	Dui et al., (2023f); Liu, (2019)
Business Economics	Maximize economic benefits, including cost reduction, risk mitigation, enhanced production efficiency, and revenue maximization	Li et al., (2020a); Zhuang et al., (2023)
Computer Science	Optimize performance by enhancing security, reducing response time, and preventing malicious attacks and data leaks	Hu et al., (2022); Lin and Kumar, (2017)
Instruments Instrumentation	Enhance accuracy, sensitivity, and reliability, reduce noise and interference, and maximize instrument performance to meet various application requirements	Besnard and Bertling, (2010)
Energy Fuels	Improve energy production efficiency while minimizing adverse environmental impacts, ensuring sustainability and reliability in energy fuel production	Ikuzwe et al., (2020); Li et al., (2020b)
Operations Research Management Science	Enhance organizational and business process efficiency and improve decision quality, making the organization more agile, efficient, and sustainable	Huang et al., (2023); Wang et al., (2023)
Environmental Science Ecology	Optimize resource utilization, reduce environmental pollution, and adopt sustainable development practices, promoting the protection of biodiversity and the maintenance of ecological balance	Huang et al., (2022); Wang et al., (2022)

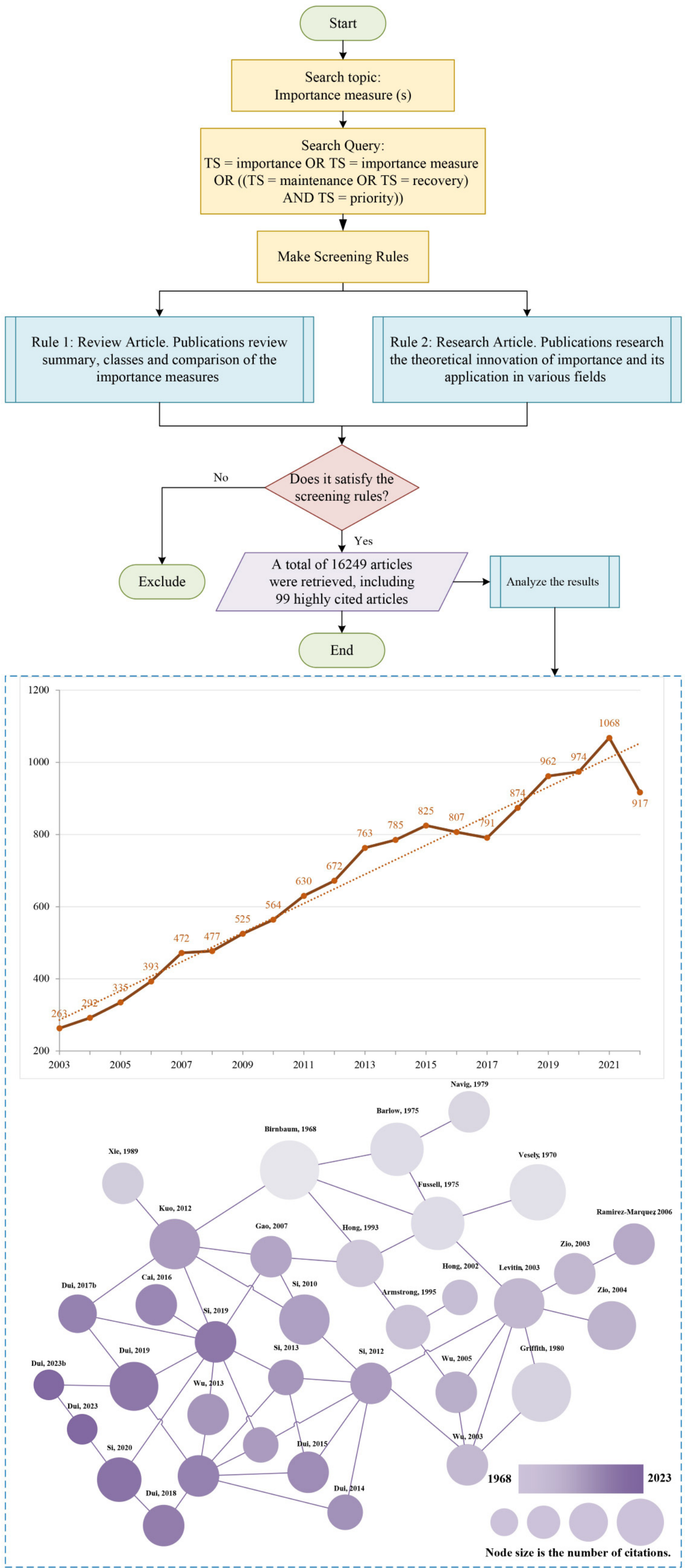

Fig. 2 The retrieval process and result analysis of importance measures.

importance measures for components through the analysis of the reliability of various structural multi-state systems. Griffith (1980) proposed a formula for the expected utility as a measure of system performance, which extended the Birnbaum importance measure by considering the importance measures of the states in a multistate system. This approach was used to assess how optimizing components contribute to enhancing system performance. Vesely and Davis (1985) proposed the concepts of risk achievement worth (RAW) and risk reduction worth (RRW) based on probabilistic risk analysis. These concepts were applied in risk analysis in the reactor safety study method application program. Xie and Shen (1989) proposed the Δ-importance measure to represent the influence of upgraded components on the reliability of the system. Zio et al. (Zio et al., 2004; Zio and Podofillini, 2003) extended the Birnbaum importance measure from binary systems to polymorphic systems and suggested employing a Monte Carlo (MC) simulation approach to evaluate the importance of multi-state components under different system performance levels. Wu and Chan (2003) addressed the limitations of the Griffith importance measure for multi-state systems and proposed a new utility importance measure for component states. This measure quantified the influence of components on the overall utility of the system. Ramirez-Marquez et al. (2006) proposed the marginal reliability importance (MRI) measure, which analyzes how states or state sets of components affect system reliability. They proposed enhancing system reliability through the allocation of redundant components. Levitin et al. (2003) proposed a generalized IM that determines the distribution of system performance by considering the performance of threshold-limited multi-state components.

Other extended variants included joint component IMs and their extensions for multi-state systems, as well as comprehensive IMs and their extensions, to name a few. Hong and Lie (1993) defined the impact of two interacting edges in an undirected network on network reliability, which was known as the joint reliability importance (JRI). Hong et al. (2002) analyzed the characteristics of JRI in k-out-of-n systems by computing the MRI for each edge and applied it to two-gate events in a fault tree (Hong et al., 2000). Armstrong (1995) derived JRI theorems and lemmas and demonstrated their applicability to failure scenarios with statistical dependencies, thereby expanding its scope of application. Wu (2005) proposed joint structure importance and joint reliability importance for polymorphic systems based on a system performance utility function, considering the interactions among components.

Traditional IMs primarily focused on the interplay among component reliability, structural characteristics, and overall system reliability. To describe the impact of component failures on the distribution of states in uncertain multi-state systems, Si et al. (2010) proposed a comprehensive importance measure called integrated importance measure (IIM), which was further expanded and refined by considering aspects such as state probability distribution, transition rates, and mutual influence between two components (Si et al., 2012a; Si et al., 2012b; Si et al., 2013). Zhao et al. (2013) elaborated on the characteristics of IIM in various types of systems. Its effectiveness was demonstrated through application in K-level multi-state coherent systems. Dui et al. (2014) analyzed the impact of component renewal functions on system performance and extended IIM from a unit time perspective to various life stages of the system. Dui et al. (2017a) improved the component state transition rates of IIM to be time-dependent, leading to the proposal of a new extended integrated importance measure (EIIM). Furthermore, Dui et al. (2017b) proposed an IM capable of quantifying the degree of external factors' influence on system performance and analyzed the regularity of system performance based on IMs as external factors vary. Dui et al. (2023h) provided a comprehensive attribute value, namely the multi-criteria importance measure (MCIM), for engineering systems and evaluated the overall impact of relevant multi-criteria components on the system. The extension to serial hierarchical systems and modular systems demonstrated its effectiveness in optimizing the performance of complex systems.

In recent years, importance analysis has become a widely researched method for optimizing maintenance strategies, proving to be highly effective. Its origins can be traced back to the fields of reliability engineering and systems engineering. Over time, it has been recognized that applying importance analysis to MSO can greatly assist in determining the priorities for components that require maintenance. More recently, importance analysis has been extended to include predictive maintenance (PdM) and modern maintenance management, expanding its application. The introduction of importance analysis into the maintenance domain has sparked the development of various extended metrics based on IMs. These measures have not only resulted in the creation of new mathematical and computational models for MSO, but they have also suggested a paradigm shift in maintenance strategy. Furthermore, importance analysis has proven to be valuable in modern maintenance management, aiding in the identification of critical data sources that are vital for accurately predicting equipment failures or conducting health monitoring. In summary, the frequency and thoroughness of MSO activities are directly related to the importance of assets. Critical equipment and systems require greater attention and resources to ensure smooth operation, value delivery, and the fulfillment of objectives when needed. Consequently, maintenance management is a critical practice in numerous fields.

Corrective maintenance, which involves addressing failures, requires a swift and efficient response to rectify the issue and prevent further damage. Therefore, when faced with limited maintenance resources, it is crucial to employ IMs to promptly identify the most critical components for system recovery. To mitigate system downtime losses caused by unexpected problems, preventive maintenance strategies are typically implemented. These strategies are based on specific criteria, such as maintenance cycles or state thresholds, which correspond to periodic maintenance and condition-based maintenance, respectively. Within this framework, IMs are utilized to identify potential faults and select maintenance components, thus preventing issues in advance. Preventive maintenance measures are implemented alongside corrective maintenance, as they provide an opportunity to address other potential failures during the maintenance period. This approach helps to avoid the impact on system reliability and associated cost losses that may result from conducting preventive maintenance individually, leading to system downtime. The optimization problem of PdM can be regarded as condition-based preventive maintenance, where maintenance activities always align with the system's current state. According to the importance theory of components, high-importance equipment undergoes more frequent and comprehensive monitoring. The integration of importance theory and intelligent predictive information aids in formulating more precise maintenance strategies. This ensures the reliability of critical equipment and systems while minimizing downtime and maintenance costs. The method presented in Fig. 3 outlines the careful use of retrieval and screening rules to gather a collection of papers. Selected key papers from this data set underwent content analysis and critical review to identify current research challenges and opportunities. The search query and screening rules can be found in detail in Fig. 3.

3 Extensions of importance measures on maintenance

Extensions of IMs in the field of MSO provide valuable insights. Importance analysis, as a method for optimizing

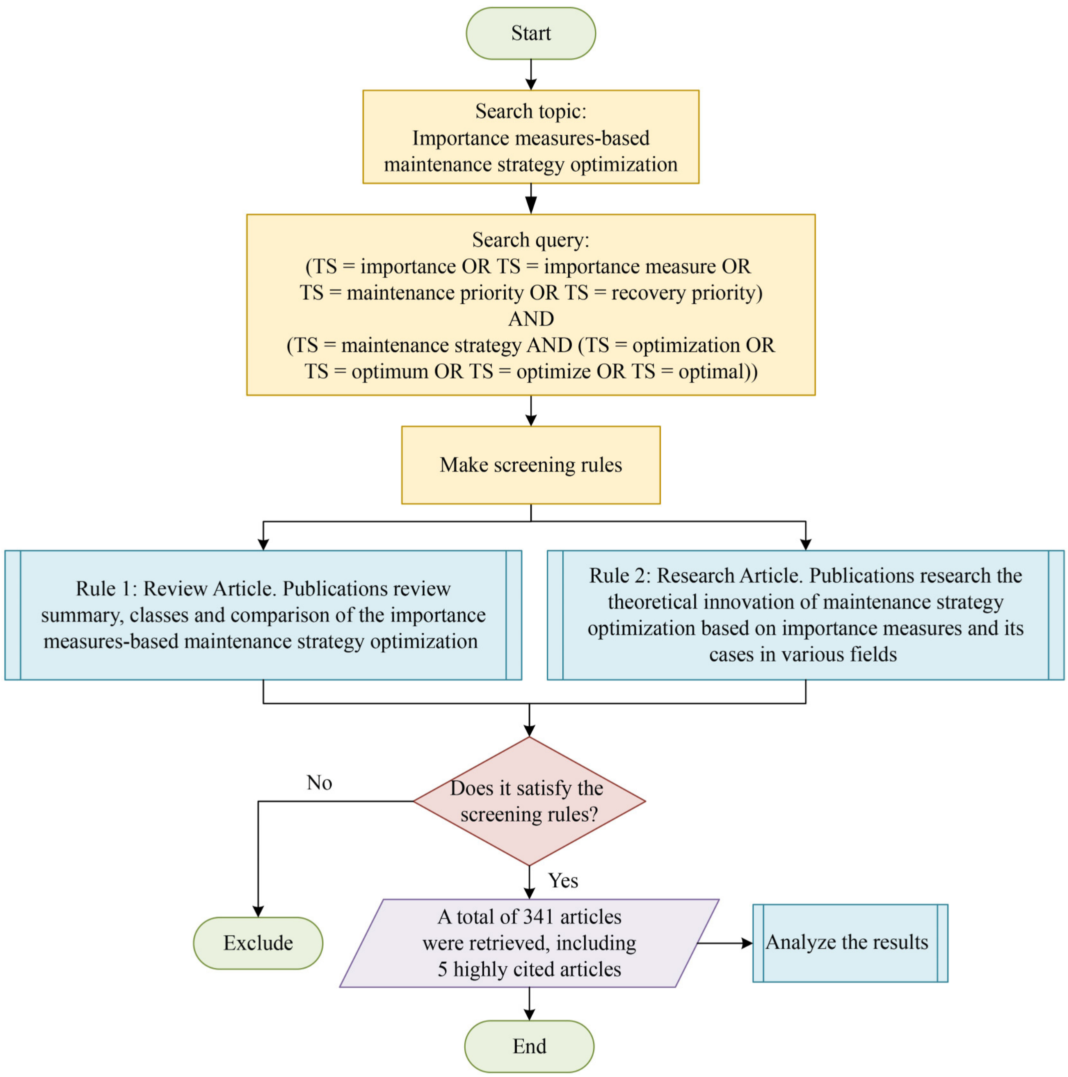

Fig. 3 The retrieval process of papers of IMMSO.

maintenance strategies, has evolved and expanded into various maintenance domains, ranging from traditional maintenance management to modern PdM and data-driven approaches. The application of this method allows maintenance strategies to accurately reflect the needs of equipment and systems, thereby improving the efficiency and effectiveness of maintenance activities. When optimizing maintenance strategies, it is crucial to consider the dependencies between components and engage in multi-objective optimization. This means giving attention not only to the performance of individual devices or components, but also to how they interact with each other and how they can meet multiple optimization goals. Achieving this requires a comprehensive use of engineering, risk assessment, and data analysis methods, enabling us to find the optimal maintenance solution. This approach simultaneously ensures the reliability, availability, and performance of the system. Within this procedure, balancing and optimizing different objectives, as well as assessing the importance of components, are critical factors. The following are noteworthy extensions of IMs for various scenarios.

3.1 Corrective maintenance

Wu and Coolen distinguished between the costs of component failures and system failures (Wu and Coolen, 2013). Based on the Birnbaum reliability importance, it proposed a novel maintenance cost-based importance measure I_k^C for binary systems:

$$I_k^C(t) = -\frac{\partial C(t)}{\partial R_k(t)}.$$

Its engineering implication lay in how alterations in component reliability over the time interval $(0, t)$ affected the system maintenance cost. The formula for maintenance cost importance was provided based on different scenarios, aiming to assist in optimizing maintenance decision-making.

Gupta et al. (2013) proposed a cost-effective importance measure (CEIM) by considering the influence of component failures on both reliability and cost. The formula was as follows:

$$I_i^{CEIM}(t) = \frac{I_i^{GI}(t)}{C_{f,i}},$$

where $I_i^{GI}(t)$ was the ratio of the change in the system failure probability caused by the change in component probability to the system baseline probability, and $C_{f,i}$ was the proportion of the total expected failure costs for all components to the expected failure cost of the ith component.

The achieved availability importance measure $I_{a,i}$ studied the influence of vital components on the system's achieved availability (Gravette and Barker, 2015). It determined the optimal inspection frequency, given by the following formula:

$$I_{a,i} = \frac{\partial A_a}{\partial A_{ai}},$$

where A_a was the availability achieved by the system, and A_{ai} was the achieved availability of the ith component.

Dui et al. (2022e) defined the total revenue considering the time value as the performance for the maintenance of cascading failures in subway networks. They put forward the performance importance measure I_i^P:

$$I_i^P = P_{\text{profit}}^i \ \ t = t_{\text{recover}}^i + T_i \ \ - P_{\text{profit}}^i(\mu_i = 0),$$

where $P_{\text{profit}}^i(\mu_i = 0)$ represented the total revenue when the node state completely failed, and $P_{\text{profit}}^i \ \ t = t_{\text{recover}}^i + T_i$ represented the restored total revenue of the subway station after maintenance for a time duration T_i.

Similarly, to accurately assess the importance of farmland in irrigation water networks under drought, Dui et al. (2023i) utilized maintenance efficiency as a performance metric to calculate the priority I_j for the allocation of irrigation network resources:

$$I_j = M \ \ \xi_j = 1, t_{2_j} \ \ - M \ \ \xi_j = 0 \ \ ,$$

where M was the network maintenance efficiency, t_{2_j} was the maintenance time for farmland node j, and the decision parameter $\xi_j = \begin{matrix} 0 \\ 1 \end{matrix}$ represented the maintenance decision for farmland node j.

3.2 Preventive maintenance

For multiple interdependent competing processes and maintenance activities, Lin et al. (2016) employed a piecewise deterministic Markov process to represent the degradation process considering component dependencies. By extending the mean absolute deviation, the importance measure CI_{O_q} at time t for component O_q was introduced to optimize strategies for two maintenance tasks. This importance could be calculated using the following method:

$$CI_{O_q}(t) = E \ \ P \ \overrightarrow{Z'}(s) \notin \mathcal{F}, \forall_s \ 6 \ t \ \overrightarrow{D_{O_q}}(q) \ \ - R(t) \ \ ,$$

where $\overrightarrow{Z'}(s)$ was the random process of system failures, $\mathcal{F}$ denoted the set of states corresponding to system failures, $\overrightarrow{D_{O_q}}(q)$ was the time-dependent continuous variable representing the degradation state of the component, and $R(t)$ was the system reliability.

Based on the maintenance cost function, the IIM $I_{l,q}^{IIM}(i)$ of component i was provided, which considered the probability distribution of the component states and the state transition rates and determined the extent of the influence of component states on the maintenance process (Si et al., 2012c). The IIM of component states could be calculated using the subsequent expression:

$$I_{l,q}^{IIM}(i) = P_{il} \times \mu_{l,q}^{i} \times I_{l,q}(i) = \frac{\partial I_l^C(i)}{\partial P_{il}} - \frac{\partial I_q^C(i)}{\partial P_{iq}},$$

where P stood for the probability of component i being in a certain state, $I^C(i)$ for the impact of a specific state of component i on the system maintenance cost, $\mu_{l,q}^{i}$ for the transition rate of component i from state l to state q, and $I_{l,q}(i)$ for the importance of component i improving from state q to state l, where $q > l$.

The cost-based comprehensive importance $I_i^{IIM,C}(t)$ of component i emphasized the combined impact of component reliability and maintenance costs on system reliability (Dui et al., 2017c). It was obtained by taking the ratio of the total maintenance cost of component i to the comprehensive importance of component i. The expression was as follows:

$$I_i^{IIM,C}(t) = \frac{C(i,t)}{I_i^{IIM}(t)},$$

where $C(i,t)$ was obtained as the sum of the maintenance cost of component i at time t and the economic losses caused by the system's unavailability due to the failure of component i at time t.

In literature, similarly based on comprehensive importance, considering both component maintenance costs and failure-related costs, a new MCIM $I_i^{MCIM}(t)$ was proposed (Chen et al., 2022). It could be calculated as follows:

Its engineering implication was the trend of change in maintenance costs relative to IIM within a certain period. This measure was used for selecting the component with the minimum maintenance cost and assigning the highest priority.

To obtain general preventive maintenance decisions, considering the mean remaining useful life (MRUL) and the mean remaining system profit (MRSP) relative to MRUL, Zhu et al. (2021) proposed a new time-dependent lifetime importance measure, which included MRUL-based importance $IM_i^{MRUL-\pi}$ and MRSP-based importance $IM_i^{MRSP-\pi}$ regarding the maintenance action π and were used to assess the percentage increment in system MRUL and MRSP caused by the maintenance operation of a component respectively. The definitions were given by:

$$IM_i^{MRUL-\pi} = \frac{MRUL_i^{\pi}(t) - MRUL(t)}{MRUL(t)},$$

and

$$IM_i^{MRSP-\pi} = \frac{MRSP_i^{\pi}(t) - MRSP(t) - MC_i^{\pi}(t)}{MRSP(t)},$$

where $MRUL(t)$ was the expected remaining useful life (RUL) derived from the failure time distribution under the condition that all components have been functioning normally up to time t. $MRUL_i^{\pi}(t)$ represented the MRUL of the system after time t. $MRSP(t)$was the average of the system profit relative to the RUL. $MRSP_i^{\pi}(t)$ was the MRSP conditioned on performing preventive maintenance π on component i at time t. $MC_i^{\pi}(t)$ stood for the preventive maintenance cost for component i at time t.

Lin and Wang (2010) proposed an IM called unit-cost extended life (UCEL), designed for optimizing non-scheduled preventive maintenance costs in series-parallel systems. It emphasized the interval between two adjacent maintenance execution time points.

$$UCEL(t_k, i) = \frac{EL_{t_k,i}}{C_{t_k,i}},$$

where $i = 1,\ldots,n$; $k = 1,\ldots,m$; $t_m < T_M$. $EL_{t_k,i}$, $C_{t_k,i}$ represented the extended system life and the corresponding cost of the ith component at any point in time within the maintenance time, respectively.

Zhang et al. (2022a) proposed the importance-based maintenance priority (IBMP) for the selection of preventive maintenance components. IBMP was used to measure the impact of component state changes at a given time on the expected rate of change in system maintenance costs. It was calculated by the following formula:

$$I_i^{IBMP}(t) = P_{i,m} \times \lambda_{m,0}^{i} \times \sum_{j=0}^{M-1} c_j\{Pr\ \Phi(0_i, X(t)) = j - Pr[\Phi(m_i, X(t))] = j\},$$

where $P_{i,m}$ was the probability of component i being in state m, $\lambda_{m,0}^{i}$ was the transition rate of component i from state m to failure, and $Pr[\Phi(m_i, X(t))]$ represented the probability that component i was in state m while the remaining components were in state j.

Zhang et al. (2022a), in the context of opportunistic maintenance component selection, proposed joint importance-based maintenance priority (JIBMP) based on IBMP. It achieved the goal of increasing the expected rate of change in system maintenance costs. It was calculated by the following formula:

$$I_i^{JIBMP}(t)_{X_k(t)} = I_i^{IBMP}(t)_{X_k(t)=0} - I_i^{IBMP}(t)_{X_k(t)=1}.$$

When component k was in a faulty state compared to its ideal state, the IBMP value of component i was the difference denoted by $I_i^{JIBMP}(t)_{X_k(t)}$.

Similarly, an extension of the IIM based on system performance degradation, called the joint integrated importance measure (JIIM) I_i^{IIM}, was proposed. It was used for the selection of components for preventive maintenance. It measured the relative importance of one component to the system performance when another component underwent maintenance (Dui et al., 2019b). The derived formula was:

$$I_i^{IIM}(t)_{X_m(t)} = I_i^{IIM}(t)_{X_m(t)=1} - I_i^{IIM}(t)_{X_m(t)=0},$$

where $I_i^{IIM}(t)_{X_m(t)=1}$ and $I_i^{IIM}(t)_{X_m(t)=0}$ represented the contribution of component i to the system's performance change per unit time when component m failed and when it operated normally, respectively.

Chen and Feng (2022), aiming for a more precise selection of maintenance actions for components, redefined the criticality level of components. A new group importance measure was proposed. This measure was the ratio between the system's reliability and cost after the replacement of all components in a preventive maintenance group.

$$IB^{G_r}(T_r) = \frac{R_{\text{sys}}^{G_1}(T_r)}{C^{G_1}},$$

where $R_{\text{sys}}^{G_1}(T_r)$ could be obtained from the cumulative distribution function of component i; C^{G_1} was the difference between the cost of preventive replacement group and the cost savings of group maintenance considering economic dependence.

Dui et al. (2023j) combined the system's variable maintenance costs with the consideration of state transitions in the IIM to propose the recovery importance measure based on variable costs (RIM-VC). This measure was used to select component maintenance behaviors to form a group maintenance strategy.

$$\Delta U_m = \frac{RIM_i(t)}{C_i(t)} = \frac{IIM_{i,X_m}(t) - IIM_{i,X_f}(t)}{C_i(t)},$$

where RIM_i represented the importance of component i in descending from state X_f to 0 and recovering to state X_m through maintenance or replacement; C_i represented the cost required for the restoration of component i.

Different fault scenarios caused by external environmental impacts were considered in the maintenance strategy. Dui et al. (2023k) innovatively combined the proposed k-dimensional Wiener degradation process with environmental importance measure and joint importance measure. This approach provided a preventive component maintenance priority (CMP) when repairing component i:

$$CMP_{i|j}(t;e_t) = H_{j|i}\frac{\partial^2 R(t;e_t)}{\partial R^{(i)}(t;e_t)\,\partial R^{(j)}(t;e_t)},$$

where e_t was the external impact at time t; $R(t;e_t)$ was the system reliability at time t under the external impact e_t; $R^{(i)}(t;e_t)$ was the reliability of component i at time t under the external impact e_t; was the reliability of component j at time t under the external impact e_t; $H_{j|i}$ represented the system state.

3.3 Predictive maintenance

A novel importance measure based on the mean residual life (MRL), denoted as IM_{MRL}^i, described the improvement in the MRL of systems when replacing the components in the systems (Do and Bérenguer, 2022). It showed the dynamically changing component states over time and served to better assist MSO. It was defined through the following method:

$$IM_{MRL}^i(t) = MRL\ \ t|\mathrm{Z}_t, \Im_t^i = 3\ \ - MRL(t|\mathrm{Z}_t),$$

where $MRL(t|\mathrm{Z}_t)$ represented the MRL of the system at time t, $\Im_t^i = 3$, representing the replacement of component i with a new component, and $MRL\ \ t|\mathrm{Z}_t, \Im_t^i = 3$ denoted the MRL of the system at time t when only component i was replaced. $IM_{MRL}^i(t)$was then extended by considering maintenance costs, benefits gained from maintenance operations, and economic dependencies among components. The mathematical definition of $IM_{MRL-c}^i(t)$ was follows:

$$IM_{MRL-c}^i(t) = \frac{h\ \ IM_{MRL}^i(t)}{C^i},$$

where $h\ \ IM_{MRL}^i(t)$ represented the benefits linked to the replacement of component i at time t, and C^i was the replacement cost for component i, obtained by summing the costs of downtime during the replacement period for component i and all other relevant costs.

The functional dependence between components and product quality was under investigation. Han et al. (2021) proposed a functional importance measure I_i^{FB} of manufacturing components based on the mission reliability considering product quality for polymorphic manufacturing systems:

$$I_l^{FB} = \frac{\sum_{j}^{n_l} Pr\ \ \ddot{\Xi}(R_m(T_c - t_{PdM})) > R_0|R_{l,j}\ \ - Pr\{\ \ddot{\Xi}(R_m((T_c - t_{PdM}))) > R_0\}}{|N_i| - 1},$$

where $R_{l,j}$ represented the reliability of component l in state j, and $R_m(T_c)$ denoted the mission reliability of the manufacturing system during the remaining time $T_c - t_{PdM}$ in the production cycle.

To make up for the fact that the traditional maintenance priority does not fully consider the actual impact of risk, a cost-based risk importance was proposed (Dui et al., 2024). This approach considered both the cost of maintenance and the potential risk posed by the maintained areas to fully assess maintenance prioritization. It was defined through the following method:

$$I_{\alpha}^{R}(t)=\mu R_{\text{risk}}^{\alpha}(t)-(1-\mu)\frac{lC(t)}{lC'_{\alpha}(t)},$$

where $R_{\text{risk}}^{\alpha}(t)$ was the risk function for the αth observation, μ was a weight between 0 and 1, $C(t)$ was the sum of the risk costs of all regions that need to be maintained at the same time, and $C'_{\alpha}(t)$ represented the cost of performing preventive maintenance on the area.

3.4 Comparative analysis

Recent advancements in extensions of importance measures focus on providing solutions for coherent, multi-component systems. To ensure computational tractability, studies often assume that all components are new at the initial time and that their behaviors are statistically independent. To simplify the optimization problem of complex maintenance strategies, maintenance time is disregarded, and maintenance activities are simplified to support only one component repair at a time. Faulty components are typically assumed to be detectable and maintain their state unchanged after waiting for maintenance, without aging or deterioration. Building upon these conditions, importance measures are utilized for optimizing maintenance strategies in finite-period repairable systems and replacement strategies in non-repairable systems.

To facilitate a more intuitive review of the existing extensions of importance measures on maintenance, Table 2 has been provided for comparative analysis. The table extensively addresses the limitations and advantages of different importance measures, aiding in the assessment of their applicability in specific contexts. Additionally, it stimulates deeper reflection on research methodologies and conclusions, thereby driving advancements in related problem areas.

Researchers often engage in innovation by addressing simplified systems, such as binary systems, to overcome early research limitations when proposing new importance measures. Notable references in this regard include Wu and Coolen (2013), Gravette and Barker (2015), Dui et al. (2022e), Do and Bérenguer (2022), and Chen and Feng (2022). These novel importance measures typically focus on core factors crucial to the research problem. For example, $I_{k}^{C}(t)$ focused on costs, $I_{a,i}$ emphasized availability, I_{i}^{P} introduced time value, $IM_{MRL}^{i}(t)$ and $IM_{MRL-c}^{i}(t)$ investigated remaining useful life, and $IB^{G_r}(T_r)$ transcended the issue of component type singularity. The purpose of simplifying systems is to assist researchers in better understanding and controlling variables, as well as to more clearly study the impact of specific factors on research results.

In another class of extensions of importance measures tailored to specific backgrounds, researchers restrict or control factors such as system structure, component dependencies, and maintenance behaviors that are not directly related to the research problem. This approach enables a better study of the impact of target factors. Relevant references in this context include Dui et al. (2023i), Han et al. (2021), and Dui et al. (2023j). In such study designs, researchers should make efforts to explain the differences between simplified systems and real-world conditions. This will help identify research limitations and propose recommendations for future research to enhance our understanding of the complexity of the real world.

4 Importance measures-based maintenance strategy optimization

In the field of MSO, IMs consistently play a significant role. The IMMSO approach aims to quantify the criticality of components or systems in relation to maintenance activities, ultimately optimizing the allocation of maintenance efforts. The core principle of IMMSO is to prioritize maintenance work on the most crucial components or systems that have the greatest impact on overall performance recovery. By addressing issues in these high-importance areas, asset managers can efficiently allocate resources to critical components while maximizing system availability. Numerous professionals and researchers have proposed various MSO methods, which have been widely utilized across diverse fields and industries.

4.1 IMs-based rules for maintenance strategy optimization

IMs are utilized in MSO to prioritize maintenance activities based on the importance of different components. This section examines the methods of MSO, drawing upon four categories of optimization rules identified in existing research: A) Minimizing maintenance resources; B) Maximizing performance recovery; C) Minimizing maintenance resources under performance recovery requirements; D) Maximizing performance recovery under maintenance resource constraint requirements; E) multi-objective optimization (Wang, 2002). Due to the immense difficulty and complexity of computing the optimal maintenance strategy under multi-objective rules, research in this area often involves proposing enhanced algorithms. The research methodology based on Rule E is discussed in Section 4.2. Figure 4 illustrates an MSO framework based on IMs under various optimization rules. The first step involves system modeling and failure analysis. Importance analysis methods serve as an optimization technique for different maintenance objectives. These IM-based optimization rules contribute to determining the most effective allocation of resources, aiming

Table 2 Contrastive analysis of extensions of importance measures on maintenance

References	IMs	Advantages	Limitations
Wu and Coolen (2013)	$I_k^C(t)$	Distinguishing between maintenance costs for faulty components and system failures; Investigating processes within finite periods; Considering different maintenance costs for various components; Applicable to diverse maintenance scenarios	Only applicable to binary systems with binary components; Only considering fixed costs; Neglecting economic dependence among components; Only considering minimal maintenance
Gupta et al. (2013)	$I_i^{CEIM}(t)$	Simultaneously considering operating time, severity of failures, system structure, and total failure cost; Applicable for prioritizing basic events such as inspections, fault detection, and maintenance activities; Considering different maintenance costs for various components	Only considering fixed costs; Neglecting economic dependence among components
Gravette and Barker (2015)	$I_{a,i}$	Considering the availability of maintenance-centric components; Considering the impact of maintenance activities; Applicable for determining optimal inspection frequencies	Only applicable to binary systems with binary components; Only analyzing systems related to series and parallel configurations; Only considering perfect maintenance
Dui et al. (2022e)	I_i^P	Considering the time value during the recovery process; Considering performance loss in the metro network due to cascading failures	Only applicable to binary networks with binary nodes; Neglecting realistic factors such as connection path length, transfer time, etc
Dui et al. (2023i)	I_j	Applicable to other network resource allocations with characteristics; Considering the impact of maintenance efficiency and degradation on yield loss	Neglecting realistic factors such as costs Only considering perfect maintenance
Lin et al. (2016)	$CI_{O_q}(t)$	Applicable to multi-state systems with multi-state components; Considering the impact of multiple interdependent degradation processes and maintenance tasks; Distinguishing between discrete and continuous degradation processes	Neglecting parameter uncertainty; Considering fixed detection intervals; Assuming corrective maintenance for component failures is immediate Only considering perfect maintenance
Si et al. (2012)	$I_{l,q}^{IIM}(i)$	Applicable to multi-state systems with multi-state components; Simultaneously considering the probability distribution of component states, transition rates, and system maintenance costs; Regarding maintenance costs as system performance; Considering imperfect maintenance	Only analyzing systems related to series and parallel configurations; Neglecting economic dependence among components
Dui et al. (2017c)	$I_i^{IIM,C}(t)$	Considering the joint impact of maintenance costs and time on system reliability; Considering different maintenance costs for various components Distinguishing between critical components and non-critical components	Neglecting economic dependence among components
Chen et al. (2022)	$I_i^{MCIM}(t)$	Distinguishing between maintenance costs for faulty components and system failures; Distinguishing between critical components and non-critical components	Only applicable to binary components; Neglecting economic dependence among components
Zhu et al. (2021)	$IM_i^{MRUL-\pi}$ $IM_i^{MRSP-\pi}$	Considering time dependency, remaining useful life, and maintenance behaviors (considering system reliability, average remaining system profit, and maintenance costs); Combining characteristics of time-dependent and time-independent life importance; Providing an extension of importance to incoherent systems; Considering imperfect maintenance	Only applicable to binary components; Assuming no loss of reliability within replacement intervals; Neglecting economic dependence among components
Lin and Wang (2010)	$UCEL(t_k, i)$	Considering economic dependence and structural dependence; Emphasizing the interval between two maintenance time points	Only applicable to systems related to series and parallel configurations
Zhang et al. (2022)	$I_i^{IBMP}(t)$ $I_i^{JIBMP}(t)_{X_k(t)}$	Applicable to multi-state systems; Considering the correlation between the two components; Considering the changes in maintenance costs (rate) resulting from component state changes; Considering different maintenance costs for various components	Only applicable to binary components; Neglecting economic dependence among components
Dui et al. (2019b)	$I_i^{IIM}(t)_{X_m(t)}$	Applicable to multi-state systems; Reflecting the relative importance of system performance between two components; Distinguishing between critical components and non-critical components	Only applicable to binary components; Neglecting constraints on maintaining resources
Chen and Feng (2022)	$IB^{G_r}(T_r)$	Introducing survival signature to calculate system reliability and reduce the number of calculations; Considering four different types of components; Considering different maintenance degrees for different maintenance types, including perfect maintenance and minimum maintenance; Considering replacement costs and maintenance costs with economic dependence	Only applicable to binary systems with binary components; Neglecting constraints on maintaining resources

(*Continued*)

References	IMs	Advantages	Limitations
Dui et al. (2023j)	ΔU_m	Applicable to multi-state systems with multi-state components; Distinguishing between critical components and non-critical components. Considering the probability of component state transition and the variable maintenance cost of the system; Considering the influence of wind speed and temperature	Neglecting economic dependence among components; Only applicable to direct-drive permanent magnet turbo systems with specific structures;
Dui et al. (2023k)	$CMP_{i\|j}(t;e_t)$	Applicable to multi-state systems with multi-state components; Distinguish between deterministic and stochastic external impact environment; Distinguishing between critical components and non-critical components; Considering different maintenance costs for various components	Neglecting economic dependence among components; Only considering perfect maintenance
Do and Bérenguer (2022)	$IM^i_{MRL}(t)$	Considering mean residual life, dynamic changes in component states, and system structure.	Only applicable to binary systems; Only applicable to non-repairable systems; Neglecting structural dependence among components; Only considering perfect maintenance
	$IM^i_{MRL-c}(t)$	Considering maintenance costs, improvements in mean residual life, and economic dependencies between components	
Han et al. (2021)	I^{FB}_l	Applicable to multi-state systems; Investigating large-scale and continuous production activities; Considering the functional dependencies of components; Considering component performance states and mission reliability	Assuming no starvation and blocking in production; Assuming component degradation follows a time-homogeneous Markov process. Neglecting constraints on maintaining resources; Only considering perfect maintenance

to maximize the quality of recovery.

A. Minimizing maintenance resources

"Minimizing maintenance resources" refers to achieving efficient and effective maintenance processes while utilizing the minimum possible resources to keep equipment in optimal operating condition. This approach is often associated with improving cost-effectiveness and operational efficiency in maintenance practices. Gao et al. (2007) proposed a state-based component conditional reliability importance to measure the JRI and joint failure importance (JFI) of extended multi-component systems. These measures were applied in the context of a k-out-of-n system to obtain information about the relationship between them for optimizing maintenance activities. For polymorphic systems, Si et al. (2012c) defined maintenance costs in terms of performance levels and introduced the importance of multi-state reliability to assess how enhancements in component states can influence the maintenance costs of the system. Chen et al. (2020) investigated cost-aware differential importance and Birnbaum importance in the context of inventory control models. Through importance ranking and identification of critical parameters, they effectively reduced total inventory costs and introduced novel analytical approaches to assess the impact of various parameters on inventory systems.

Minimizing the maintenance cost of a system can have a positive impact on an organization's production efficiency and sustainability. It is important for these strategies to thoroughly consider factors such as equipment type, operating environment, and maintenance requirements in order to develop an optimal maintenance strategy. By incorporating maintenance costs associated with system failures into the overall importance of the concept, three maintenance replacement strategies were proposed based on the new MCIM (Chen et al., 2022). These strategies include a failure-triggered replacement strategy, an age-based preventive replacement strategy, and a fusion strategy. In the context of a propeller aircraft system, the optimal maintenance strategy was found to be a fusion strategy that combines failure-triggered and age-based replacement strategies. Dui et al. (2022f) used IMs to evaluate the influence of initial fault nodes on traffic congestion scale, with the goal of minimizing maintenance time and optimizing strategies for congestion relief in traffic networks.

B. Maximizing performance recovery

Maximizing the recovery performance of a system is a crucial objective in the field of system maintenance. Dui et al. (2018) addressed the limitations in the study of structural changes in systems by utilizing IMs to determine the optimization problem of linear consecutive k-out-of-n systems. By modifying the structure in descending order of the suggested IM, the system's maximum reliability improvement could be achieved, resulting in an optimal configuration. Enhancing the efficiency of system performance recovery involved matching maintenance strategies with the optimal maintenance sequence. For complex multi-component and polymorphic systems, Zhang et al. (2022b) proposed the resilience efficiency importance measure (REIM) based on the JIIM to assess the impact of repairing individual components on the rate of system performance changes. Subsequently, this approach was extended to account for the interrelationships between components. They also proposed a maintenance efficiency measure (MEM) to quantify the comprehensive efficiency of system recovery. Specifically, when the performance

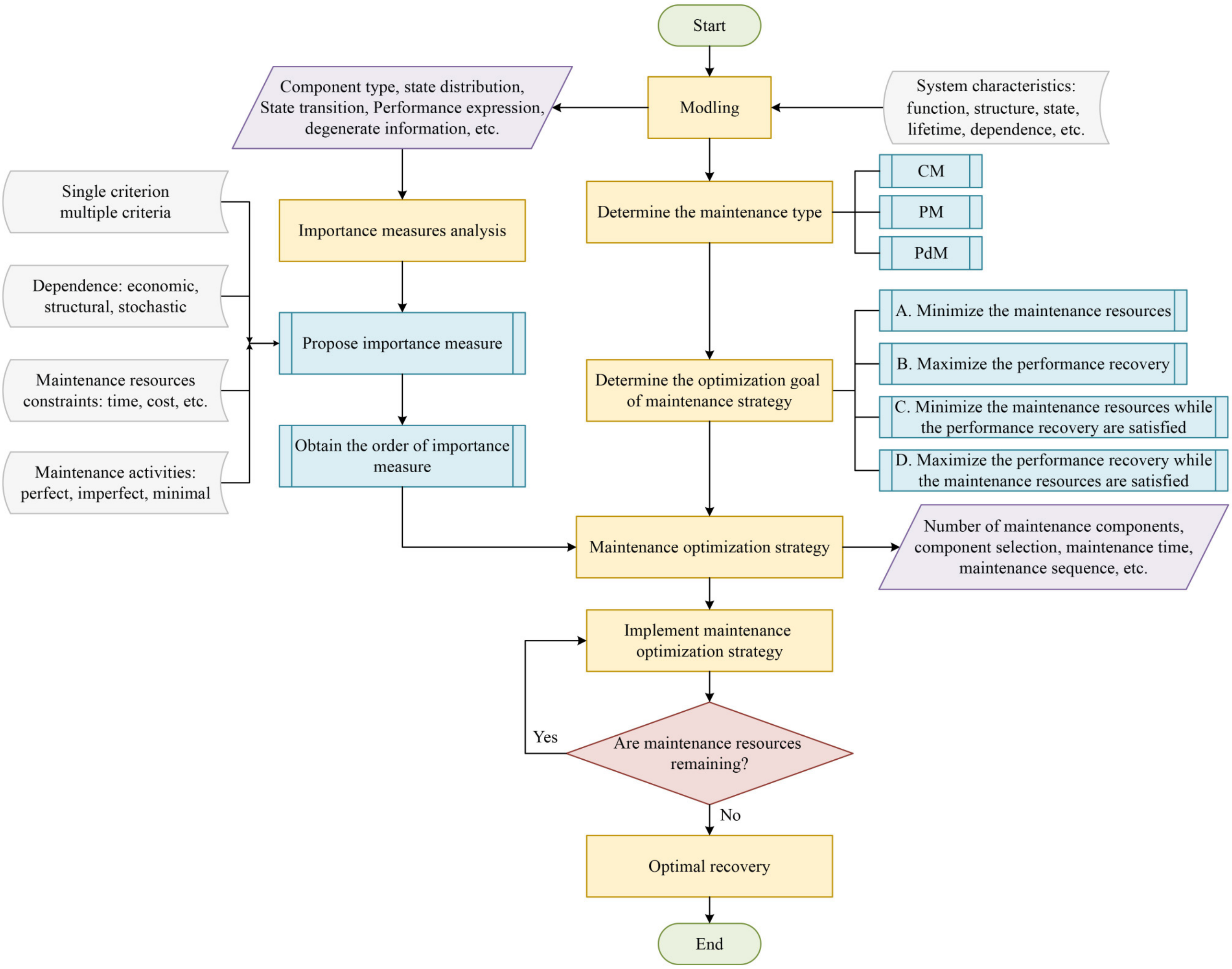

Fig. 4 IMs-based MSO process.

benefits from each maintenance strategy were equal, the maintenance sequence that achieved the maximum efficiency in system performance recovery was adopted. To tackle the challenging problem of dynamic maintenance strategy optimization in partially observable Markov decision processes (POMDPs), Zhang (2020) proposed two computationally tractable importance measures. These measures effectively define POMDPs and establish heuristic maintenance strategies based on system rankings. These strategies can be implemented at different stages during the decision-making process. Yan et al. (2021) utilized a stochastic Markov decision process to model the dynamic maintenance scheduling problem in power systems. They approximated the solution to this complex computation by introducing a look-ahead strategy approximation based on repair importance.

Maximizing the recovery performance of a system is of utmost importance for organizations that rely on the high availability of systems and equipment. This is because it can help reduce system interruptions and losses, ultimately maintaining the organization's profits and reputation. Informed by risk considerations, Zio et al. (2007) conducted an assessment of the importance of components within a network that exhibits stochastic degradation and multiple states. Their focus was specifically on the overall expected delay. This evaluation served as a guide for decision-making, enabling the relaxation of speed in certain segments to contribute to the reduction of delays. This, in turn, provided guidance for recovery and the reduction of congestion-related traffic delays. Dui et al. (2020) addressed the fault characteristics of the underwater submarine pipeline gate valve anti-spraying system by employing an extended JIIM. This approach allowed for the measurement of the relative importance of components toward the system's performance. The information gathered facilitated effective optimization efforts when formulating maintenance decisions. In the field of intelligent unmanned aerial vehicles (UAVs), Petritoli et al. (2018) placed a strong emphasis on considering intrinsic reliability and safety during the design phase. To assess the uncertainty of degradation processes, they utilized confidence intervals. By examining their findings, they were able to explore the relationship between reliability and preventive maintenance. This exploration provided a novel logistic approach for determining maintenance intervals. Dui et al. (2021b) rationalized the modeling of a polygonal formation of a UAV swarm using the continuous k-out-of-n: F system. They employed IMs to identify critical node positions, which allowed for prioritized preventive maintenance for UAVs positioned in those locations. Furthermore, they explored the prediction of communication reliability and the completion status of multi-stage missions for the UAV swarm. To maximize post-disaster grid electricity generation, Bai et al. (2021) proposed a residual elasticity analysis based on CMP. This analysis aimed to determine the optimal sequence for grid recovery, ultimately maximizing recovery capacity.

C. Minimizing maintenance resources under performance recovery requirements

The increasingly stringent economic requirements for MSO rules in long-term development have spurred the innovative development of theoretical knowledge. To minimize maintenance costs, especially when increasing reliability requirements, it is necessary to select components where changes in reliability have the greatest impact on maintenance costs. Wu and Coolen (2013) proposed maintenance strategies for two scenarios where faults were immediately detected and repaired. Through considering the maintenance costs caused by different types of component failures, a cost-based importance ranking was obtained. The cost-based joint importance analysis method, as suggested by Dui et al. (2017c), effectively achieves cost minimization while enhancing system reliability. This study addresses the maintenance time and cost impacts of components or component groups with varying maintenance costs, thus overcoming the shortcomings in previous joint studies. From a different perspective, preventive maintenance can be viewed as an opportunity to proactively address potential system failures. However, frequent preventive maintenance may result in higher costs due to increased manpower, time, and resource requirements. Wu et al. (2016) focused on the frequency of preventive maintenance for components, which is directly related to maintenance costs. The introduction of the CMP based on the Birnbaum importance aims to optimize the economic benefits of maintenance activities by optimizing the maintenance frequency. To bridge the research gap in dynamic fault analysis, Bayesian updating methods were employed to incorporate multi-source online state detection information. The literature proposed the dynamic modified Risk Achievement Worth Measure (RAWM), which quantifies the maximum achievable percentage increase in system reliability associated with a component (Shi et al., 2020). The study suggests that utilizing dynamic information can yield more accurate predictive results. Numerical experiments have validated that group maintenance based on dynamic priorities can achieve more optimal maintenance costs.

To further analyze actual maintenance costs in a logical manner, a cost model has been established, which incorporates economic dependencies among components. The study introduces preventive maintenance decision rules and adaptive opportunistic maintenance decision rules. Nguyen et al. (2014) derived two rules based on the structural importance of components, predictive reliability, criticality of components, and resource constraints. Similarly, Vu et al. (2016) formulated two rules by jointly considering the average remaining life and Birnbaum importance. Likewise, Nguyen et al. (2017) applied the aforementioned rules to joint maintenance decisions involving preventive maintenance and inventory activities, thereby validating their applicability and effectiveness.

The application of optimization criterion C can enhance resource utilization while ensuring the normal operation of various systems in different domains. To ensure the profitability and competitiveness of production systems, Gupta et al. (2013) addressed maintenance design for repairable production systems and proposed a CEIM. This measure was used for ranking the basic events and allocating the maintenance resources. Optimizing the design of manufacturing systems required overcoming the neglect of the functional dependence between equipment performance and product quality. Han et al. (2021) investigated equipment failures and product output failures stemming from this functional dependence. Building upon this, component functional importance and dynamic RUL were proposed. They played a crucial role in minimizing accurate PdM costs and time.

D. Maximizing performance recovery under maintenance resource constraint requirements

A comprehensive approach that considers both cost and benefit factors is significant in striking a balance between MSO and economic rationality. In their research, Dui et al. (2021c) proposed a new model to assess the influence of preventive maintenance on the reliability of system components, taking into account the detection of component states. The paper addressed dual-state coherent systems, incoherent multi-state systems, and continuous systems, providing extended formulas through mathematical derivation and practical application to validate their effectiveness. The criterion used in this study was to maximize system performance based on importance ranking under cost constraints, with preventive maintenance playing a crucial role in addressing maintenance cost constraints. The optimal solution between constraints and objectives was determined using integer programming methods. For general repairable systems, Dui et al. (2019b) solved integer programming problems for components with different maintenance costs and joint importance measures. The solution involved selecting the optimal combination of components for preventive maintenance under fixed costs, aiming to maximize system performance gains. Similarly, preventive replacements of different components resulted in varying costs and degrees of reliability improvement. Therefore, Dui et al. (2021d) investigated a renewal selection model under cost constraints to find the maintenance strategy with the maximum benefit. This model utilized joint importance measures to choose components for preventive replacement, aiming to maximize system reliability. Findings from the study on a hydraulic tension system indicated that, as the maintenance cost budget increases, the count of components available for preventive maintenance remained unchanged after reaching a certain level. To explore the impact of deterministic and stochastic environments on reliability in practical engineering systems, Dui et al. (2023k) proposed the environmental importance of impact effects into the joint importance. Under cost constraints, the research sought the optimal preventive maintenance component set that maximized the system's lifespan.

The utilization of optimization rule D offers a scientific approach to guide maintenance decisions, providing a balance between performance recovery and resource constraints. In the context of studying the pod slewing hydraulic system in vessel engineering, the corrective maintenance strategy was optimized using IIM to reduce the ship's failure maintenance time (Chen et al., 2021). The optimization analysis revealed that the redundant design of the weakest motor effectively decreased the system's failure rate. In a hydraulic system with a linear semi-active lift and sink compensation system, Griffith's importance and IIM were used to rank components for preventive maintenance, considering their performance in different system states. This ranking served as the basis for optimizing the maintenance strategy while considering cost constraints (Zhang et al., 2020). To minimize system failures, critical components with the greatest impact were designed with redundancy. In the modeling of a multi-state irrigation network, each water-demanding farmland was treated as a node in multiple states, and the replenishment of water resources after drought played a crucial role in crop productivity. Dui et al. (2023i) proposed an underwater resource constraint-based farmland irrigation priority to maximize crop productivity recovery and post-disaster agricultural food production.

Importance analysis is a highly effective technique for implementing optimization rules in maintenance strategies. By considering various influencing factors for different issues, researchers carefully design importance formulas to fully achieve optimization goals in diverse maintenance strategies. This approach allows decision-makers to gain comprehensive understanding of each factor's contribution to the system, thereby guiding the formulation of appropriate maintenance strategies. A reference analysis of MSO is conducted in Table 3 using system states, IMs, maintenance types, and optimization rules. Researchers have put forth methods tailored to different system types and maintenance characteristics, based on existing traditional importance measures. These methods demonstrate wide applicability across various industries, systems of different scales, and environmental conditions.

4.2 IMs-based algorithms for maintenance strategy optimization

When faced with the challenge of optimizing multi-objective maintenance strategies, it is important to recognize the inherent trade-off between system reliability and maintenance costs. Previous research has attempted to address this complex issue by utilizing classical algorithms or proposing enhanced optimization algorithms that merge Birnbaum importance with traditional approaches. However, making significant progress in innovation remains a formidable task. Existing multi-objective MSO algorithms based on IM are primarily focused on seeking optimal solutions for binary Lin/Con/k/n systems. Limited research has been conducted on the study of polymorphic complex systems.

For reconfigurable systems such as Lin/Con/k/n systems that take reconfiguration costs into account, Zhao et al. (2019) proposed three optimal reconfiguration methods that integrate replacement and reallocation: the reordering method, the integral method, and the replacement method for optimal reconfiguration. The selection of the optimal reconfiguration method and the quantity of replaced components utilized a two-stage method based on Birnbaum importance. A coarse-grained parallel genetic algorithm (CPGA) was employed to search for optimal feasible solutions. In the field of practical engineering, Cai et al. (2019) developed a multi-objective Birnbaum importance-based particle swarm optimization (MOBI-PSO) algorithm which resolves the Con/k/n conflict between enhancing system reliability and minimizing maintenance costs. This algorithm is applicable to generic practical engineering multi-objective MSO strategies. Furthermore, to address the multi-objective optimization problem for reconfigurable systems, Ma et al. (2022) developed a non-dominated sorting genetic algorithm II based on multi-objective Birnbaum importance. This algorithm provides optimal solutions for direct and switched maintenance of Con/k/n systems.

For the purpose of ensuring the structural safety of aging bridges, Kim et al. (2020) investigated the safety threshold of individual bridges' reliability within a bridge network perspective. Through the comparison of reliability metrics based on structural importance with those obtained under dual-objective, triple-objective, and quadruple-objective optimization rules, they demonstrated that classical algorithms could compute Pareto optimal solutions, enabling effective life-cycle management of bridge networks by considering multi-objective reliability optimization.

Table 3 Reference analysis of optimization rules based on IMs

References	IMs	Systems	Types of Maintenance Strategies	Rules
Si et al. (2012)	$I_{l,q}^{IIM}$	Multi-state	Condition-based maintenance	A
Chen et al. (2022)	MCIM	Binary	Opportunity maintenance	
Dui et al. (2022f)	I	Binary	Corrective maintenance	
Gao et al. (2007)	JRI & JFI	Binary		
Dui et al. (2018)	Birnbaum importance & IIM	Binary	Adaptive maintenance	B
Zhang et al. (2022)	REIM & MEM	Multi-state	Corrective maintenance	
Zhang (2020)	Approximate measure & rate measure	Multi-state		
Zio et al. (2007)	Performance achievement worth measure	Multi-state		
Dui et al. (2020)	JIIM	Multi-state		
Bai et al. (2021)	I^{RRW} & I^{RAW}	Binary		
Petritoli et al. (2018)	IM	Multi-state	Preventive Maintenance	
Dui et al. (2021b)	Birnbaum importance, IIM	Binary		
Wu and Coolen (2013)	I_k^C	Binary	Corrective maintenance	C
Gupta et al. (2013)	CEIM	Binary		
Han et al. (2021)	Functional importance	Multi-state	Predictive Maintenance	
Dui et al. (2017c)	$I_i^{IIM,C}$	Multi-state	Preventive Maintenance	
Wu et al. (2016)	CMP	Binary		
Shi et al. (2020)	RAWM	Multi-state	Condition-based maintenance	
Nguyen et al. (2014)	Birnbaum structure importance	Binary		
Vu et al. (2016)	Birnbaum structure importance	Binary	Opportunity maintenance	
Nguyen et al. (2017)	Birnbaum structure importance	Binary		
Zhao et al. (2019)	Birnbaum importance	Binary	Adaptive maintenance	
Dui et al. (2023i)	CMP	Multi-state	Corrective maintenance	D
Dui et al. (2019b)	JIIM	Binary	Preventive Maintenance	
Dui et al. (2023d)	Environmental importance	Binary		
Dui et al. (2021c)	CMP	Binary		
Dui et al. (2021d)	JIIM	Multi-state		
Zhang et al. (2020)	IIM	Multi-state		
Chen et al. (2021)	IIM & Griffith IM	Multi-state	Adaptive maintenance	

Many industrial and infrastructure systems are highly complex, consisting of numerous components and interconnected failure modes. Addressing the challenge of identifying the most effective maintenance strategies for such complex systems is a difficult task. IMMSO algorithms have been proposed to aid in problem-solving by reducing the solution space and simplifying the search complexity. Additionally, these algorithms have streamlined the challenges of solving complex system problems and considering the integration of multiple factors. Invariant optimal allocation is a classic problem in reliability optimization. To determine the relative allocation sequence, Lin and Kuo (2002) presented a robust LK heuristic algorithm that aligns with Birnbaum importance ranking. This algorithm takes into account the error term of the approximate solution, achieving an error rate of 1% in complex system cases. In the context of dynamic environmental information, Shi et al. (2020) proposed a heuristic maintenance grouping algorithm with dynamic priorities. This algorithm was applied to the selection of preventive maintenance components in Lin/Con/k/n systems. It also refined the state maintenance decision framework through a rolling time-domain approach.

To overcome the limitations of Markov decision processes when dealing with small-scale systems, Zhou et al. (2022) integrated an agent hierarchy based on the structural importance of components with agent coordination relationships derived from system reliability diagrams. This integration was used in distributed Q-learning (DQL) to propose a new Hierarchical Coordinated Reinforcement Learning (HCRL) algorithm. The HCRL algorithm is specifically designed for managing MSO in large-scale, multi-component complex systems. Under the optimization Rule C, Levitin and Lisnianski (2000) utilized a genetic optimization algorithm to solve combination optimization problems based on IMs. This approach aimed to reduce the search time while ensuring the excellence of the optimal solution and minimizing the effective service life (Levitin and Lisnianski, 2000).

Optimization algorithms based on Birnbaum importance are capable of generating highly effective solutions. The problem of determining the optimal solution for the component allocation problem is considered to be NP-hard. Yao et al. (2014) chose the BITA method as the foundation and developed a hybrid GA that incorporates Birnbaum importance-based local search. This approach significantly enhances local search for maximizing system reliability allocation problems. For the component allocation optimization problem in Lin/Con/k/n systems, a novel algorithm called Birnbaum importance-based genetic algorithm (BIGA) was proposed (Cai et al., 2016). BIGA was designed to find an approximate globally optimal solution for the component sequence. This optimization algorithm incorporates Birnbaum importance to control the randomness of the GA within the solution space, ultimately achieving the optimization solution of maximizing system reliability. Under Rule C, research has focused on preventive maintenance strategy optimization for series-parallel systems. Bris et al. (2003) proposed an algorithm for detecting time-first vectors for perfect maintenance degree that effectively incorporates time-related Birnbaum importance. The algorithm is efficiently computed through parallel simulation methods and integrated into a GA for achieving maintenance strategy objectives. The effectiveness and practicality of this method have been confirmed through its application in addressing related theoretical problems (Samrout et al., 2005).

Similarly, an improved genetic algorithm (IGA) was proposed by Lin and Wang (2012) and Wang and Lin (2010). The mechanism of IGA involves utilizing a conventional GA for cost optimization under a proposed new importance sequence to identify critical components. Subsequently, the response surface methodology is employed to determine optimal parameter combinations for crossover and mutation probabilities. Finally, IGA with an adjustment mechanism is used to shorten maintenance cycles, enabling periodic preventive maintenance strategy optimization under Rule C.

Heuristic and metaheuristic algorithms demonstrate remarkable effectiveness in addressing MSO problems. However, given the diversity and complexity of problems, it is often necessary to customize algorithms. The aim is to enhance both computational efficiency and accuracy when addressing specific issues. This customization is not only beneficial for better adaptation to the specific characteristics of the problem but also contributes to optimizing the algorithm's performance in practical applications.

In practical industrial equipment maintenance, Marseguerra and Zio (2000) used MC evaluation in the maximization process of the GA to obtain coupled algorithms. The algorithm efficiently computed the significant solution of the IM-based optimal maintenance. By coupling a simulation model and the GA, Cheng et al. (2017) solved the production schedule and the optimal maintenance strategy. The use of metaheuristic optimization algorithms was often required to address the mathematical modeling and data challenges in optimizing complex maintenance decisions for large networks. Zhang and Wang (2017) tailored the binary particle swarm optimization algorithm (BPSO) for bridge maintenance decisions. This algorithm was introduced to the proposed dynamic prioritization metrics. It could solve maintenance schedules that maximized the performance of the network while satisfying cost requirements. To reduce the risk of extensive power outages resulting from cyber-physical power system failures, Wu et al. (2021b) proposed a gene importance-based evolutionary algorithm (GIEA). The GIEA approach leveraged gene importance to solve the binary integer planning NP-hard problem and optimize the identification of crucial components. It was evaluated by considering performance contribution, coupled fault impact, and interdependencies for GIEA optimization.

IM-based optimization algorithms prove to be an efficacious approach to addressing MSO problems for complex systems. Heuristic and metaheuristic optimization algorithms exhibit versatile applicability across various systems and problem domains. By carefully adjusting and enhancing heuristic methods, we can better meet the requirements of diverse problem scenarios, achieving more reliable and efficient problem-solving solutions. This customized approach not only helps overcome the complexity of problems but also provides more accurate and rapid guidance for the computational processes involved in problem-solving. IMMSO algorithms are likewise varied because of the multiple factors that are considered differently in the synthesis of importance-based optimization rules. The differences that exist between MSO algorithms can be examined in Table 4, based on IMs, system type, and optimization algorithms.

4.3 Analysis of real cases

Previous research has demonstrated the significant impact of IMMSO methods on various systems through comprehensive exploration and analysis of real-world cases. These studies underscore the importance of maintenance strategies in improving system performance and reliability, offering valuable insights and references for both future engineering practices and academic research. Gravette and Barker (2015) utilized maintenance data from a year-long period to elucidate the benefits of IM-based optimal fault management strategies in enhancing the availability of practical series-parallel structured

Table 4 Reference analysis of optimization algorithms based on IMs

References	IMs	Systems	Algorithms
Shi et al. (2020)	Dynamic prioritization measure	Lin/Con/k/n system	Dynamic-priority-based heuristic algorithm
Lin and Kuo (2002)	Birnbaum importance	Coherent & complex system	LK strong heuristic algorithm
Bris et al. (2003)	Birnbaum importance	Series-parallel System	GA
Lin and Wang (2012); Wang and Lin (2010)	Birnbaum importance	Series-parallel system	Hybrid GA
Cai et al. (2016)	Birnbaum importance	Lin/Con/k/n system	BIGA
Marseguerra and Zio (2000)	Functional importance	Parallel–series system	GA
Zhang and Wang (2017)	Dynamic prioritization measure	Bridge network	BPSO
Cai et al. (2019)	Birnbaum importance	Lin/Con/k/n system	MOBI-PSO
Ma et al. (2022)	Birnbaum importance	Lin/Con/k/n system	Non-dominated Sorting GA II
Wu et al. (2021b)	Birnbaum importance	CPPS	GIEA

aircraft systems. By leveraging data from the 2019 Shandong Province Electricity Yearbook and annual industrial power generation and consumption figures, Bai et al. (2021) created a real-world data set for a grid case study. They analyzed IM-based grid restoration strategies in a simplified grid model across various fault scenarios. Experimental analysis results showed the feasibility and superiority of the proposed metrics: residual resilience and maintenance priorities. Dui et al. (2022e) modeled the Zhengzhou metro network, which includes 127 lines spanning 198 km and 147 stations. They demonstrated that prioritizing failure nodes based on metro network node importance models led to faster and more substantial recovery of system performance. In their research, Dui et al. (2023i) employed real historical drought data from the agricultural irrigation network in Henan Province, China to simulate the network's performance evolution. Detailed case studies affirmed the more pronounced effects of IM-based early intervention maintenance strategies on performance enhancement, maintenance duration, and maintenance efficiency.

These notable scholarly investigations underscore the essential significance of real-case analysis in the fields of science and engineering. Through the thorough examination of these cases, we gain insights into the complexities of system operation, the identification of critical components, and the importance of effective maintenance strategies. These insights and guidance provide invaluable support for cutting-edge technological and engineering practices.

In one study, Lin et al. (2016) examined a subsystem of the residual heat removal system (RHRS) in a nuclear power plant owned by Électricité de France (EDF). The study utilized the proposed PDMP to model the degradation process of the system. The experimental results demonstrated that the proposed IM accurately assessed components crucial to the reliability of the system. Another study by Kim et al. (2020) leveraged information from MOLIT to construct a bridge network between the cities of Goseong and Seocheon in South Korea. This network consisted of 57 independent bridges. The case study confirmed that the method of utilizing bridge group reliability to determine the reliability of individual bridge target reliability outperformed single-objective optimization in various aspects under the rules of multi-objective optimization. Dui et al. (2023k) utilized service data from household robots to simulate the degradation process parameters of repairable transportation robot systems. The case analysis indicated that the proposed method effectively calculated inspection intervals that minimized average maintenance costs. Additionally, the proposed preventive maintenance strategy based on environmental IM maximized system reliability. Based on extracted data packets, Wu et al. (2021b) demonstrated the effectiveness and superiority of the proposed importance-based evolutionary strategy in improving the convergence efficiency and accuracy of algorithms. This was illustrated through an example of a coupled Cyber-Physical Production System (CPPS) consisting of an IEEE 30-bus model and a communication network with a small-world structure.

In the domain of contemporary science and engineering, the investigation of MSO has emerged as a crucial topic. A wide range of research efforts span various domains, including nuclear power plants, urban infrastructure, aircraft hydraulics, network communications, and more. These studies not only reveal the important role of IMs in system maintenance and performance optimization, but also offer innovative approaches to improve system reliability. These findings not only provide valuable guidance for future engineering practices and system management, but also establish a strong theoretical framework for the development of more reliable and efficient systems. Continued exploration and innovation in this field will drive technological advancements, contributing to the creation of a safer and more stable future society.

5 Conclusions and future work

This paper represents the first comprehensive literature review on the significance of Importance-Based MSO. The study categorizes and critically analyzes existing literature, providing a systematic overview of the field. The paper begins by discussing the general development in the fields of MSO and reliability Importance Measures, exploring their relationship. It then summarizes the optimization role of Importance Measures in maintenance strategies for different types of maintenance. The paper also investigates IMMSO rules and algorithms, offering a foundation for future research.

5.1 Current research directions

The research on IMMSO methods primarily relies on the characteristics of maintenance strategies and the selection of optimization objectives. By considering different optimization features, IMs are utilized to identify components that have the greatest overall impact on maintenance recovery. Complex real-world problems are modeled by combining importance with optimization objectives.

In Section 4.1, where IMMSO rules are discussed, it is evident that the introduction of several new IMs has fully taken into account the relationship between the recovery performance and cost of maintenance strategies. The implementation of the optimization model also ensures attention is given to minimizing costs while maintaining recovery quality.

Another extensively researched area is the technical or theoretical study involving economic dependencies. However, these optimization studies typically only focus on a single type of dependence and seldom explore other dependencies. Similarly, optimization rules for maintenance resources usually revolve around cost-related indicators, with limited research on optimizing other maintenance resources. Future research should consider studies on structural dependence, stochastic dependence, and further integration of various types of dependencies. This includes extending and applying the importance of multiple criteria in the domain of MSO to provide a more advanced theoretical foundation for complex engineering systems, taking into account the correlation of multiple components.

In IMMSO research, models often assume that maintenance teams can immediately respond and execute required repair operations, without considering actual response time and maintenance duration. Moreover, some complex scenarios, such as constant degradation levels and known structures, might be overlooked. Similarly, perfect maintenance is used as a benchmark for an ideal state, accompanied by the same cost consumption. On the other hand, minimal maintenance is based on economic and resource considerations, aiming to maintain the fundamental operational capabilities of the system with the least amount of maintenance work. Although these simplified assumptions and model choices contribute to providing a clear analytical framework, more comprehensive considerations and complex models may be necessary in practical applications to accurately reflect real-world situations.

Intelligent algorithms have played a significant role in addressing the complex computational issues in IMMSO. The existing research in this field can be classified into three main types: (1) the direct utilization of heuristic and metaheuristic algorithms for solving IMs-based combinatorial optimization problems; (2) the improvement of mature heuristic and metaheuristic algorithms using Birnbaum importance, and (3) the customization of heuristic algorithms based on proposed IMs to address specific problems.

All three types of research aim to optimize the search for component sequences and ensure the quality of solutions. However, there is a need for further research to investigate algorithmic optimization considering more realistic maintenance features. Applying research models to real-world data cases remains a practical challenge, primarily due to the known conditions assumed in many studies. Such assumptions provide crucial information that cannot be overlooked in practical applications. Consequently, the application of advanced Internet of Things (IoT) technology can provide a more comprehensive understanding of IMMSO. Utilizing available data collected through IoT and machine learning techniques can assist in theoretical innovation. However, it is essential to consider the imperfections and errors in real-time detection information within the IoT. Monitoring devices used in practical applications may have limitations, leading to information that is not entirely accurate or complete. Hence, future research efforts should focus on developing more robust models and algorithms that can handle the uncertainty in real-time monitoring information, thereby enhancing the reliability of maintenance decision-making.

5.2 Research directions based on emerging technologies

Traditional PdM strategies are typically based on predetermined physical models, estimating or predicting the remaining useful life of systems. However, practical engineering systems often exhibit degradation patterns in diverse forms. Overreliance on physical models may result in lower prediction accuracy and failure to achieve optimal strategies. With the rapid advancement of artificial intelligence (AI), emerging technologies like the IoT, information technology (IT), and machine learning (ML) have gained prominence. PdM is a critical application scenario for these decision-support technologies. Maintenance strategies based on emerging intelligent technologies do not heavily rely on system degradation models. Instead, they utilize real-time monitoring data to predict the health status of systems, enabling more accurate maintenance decisions. This approach facilitates a shift from passive maintenance to proactive prediction and comprehensive planning management.

PdM strategies based on advanced decision support technologies heavily rely on the effective collection of system operational data. The cornerstone of these strategies is the utilization of sensor-based IoT technologies, which serve as the foundation for maximizing their effectiveness. IoT technologies, as an innovative method for monitoring industrial equipment, include both process monitoring and condition monitoring to ensure quality and prevent unplanned downtime. PdM strategies that leverage real-time data offer higher accuracy compared to those based on historical data, but they also require greater technological sophistication. Processing large volumes of data presents significant challenges for on-site equipment computing capabilities. Furthermore, the communication framework poses another significant challenge in facilitating communication between the industry and the IoT. Data-driven predictive models form the core of PdM decisions by predicting the probability of system failure and remaining useful life through the processing of substantial amounts of data. Although data-driven methods offer accuracy advantages, they necessitate a large amount of real data, which comes at a high collection cost and risks sensor failures during the collection process.

Predictive modeling serves as a crucial step, providing essential inputs for maintenance decisions, with its accuracy directly impacting the effectiveness of maintenance strategies.

Within this domain, both ML and deep learning (DL) emerge as highly scrutinized decision-support technologies. ML leverages IoT sensor data to facilitate intelligent enhancements through autonomous learning and continual training. It plays a pivotal role in predicting remaining useful life and offers support for MSO. However, ML typically requires substantial data for training, along with prolonged training and computation times, resulting in increased costs. Additionally, existing predictive models often only provide simple prediction values of remaining useful life, necessitating the integration of predictive outcomes with maintenance decisions to ensure system security and reliability. The inherent uncertainties in system prediction problems are frequently overlooked in practical engineering contexts.

In contrast to conventional ML, DL automatically extracts monitoring data features in an end-to-end manner, providing a solution for handling vast data sets. However, research on remaining useful life prediction and MSO based on DL is still relatively nascent, especially for systems that require elevated levels of security and task completion. The considerable security vulnerabilities inherent in DL raise concerns regarding data integrity, confidentiality, and system reliability.

The combination of edge computing and blockchain (BC) is emerging as an effective solution to address the challenges in data-intensive deep learning applications like PdM. Edge computing enhances the processing efficiency and real-time data processing capabilities of deep learning, while BC ensures secure data transmission and transaction verification, mitigating unauthorized data tampering and bolstering trustworthiness within IoT ecosystems. This amalgamation meets the demands for efficient data processing and secure storage, offering promising solutions.

To further optimize PdM strategies, there are several future research directions that can be explored. Integrating new intelligent algorithms and ML technologies can propose more precise and effective methods. Additionally, the advantages of integrating DL and degradation process models can be studied to improve the accuracy of fault detection in complex systems. Applying reinforcement learning to optimize the maintenance decision-making process would also be beneficial. Further research can focus on the combination of new data preprocessing methods and ML algorithms.

It is important to consider integrating importance analysis into PdM technologies to determine which equipment components have the greatest impact on system reliability and performance, and allocate maintenance priorities accordingly. Taking into account the preferences of decision-makers and the dynamic PdM strategies of complex systems with multiple objectives and multi-mission cycles can further improve the shortcomings of the research.

Another research direction involves integrating real-time data monitoring, data analysis, prediction, and maintenance strategy. This research can provide unprecedented insights into the remaining useful life of systems, promoting dynamic maintenance planning and resource allocation. Furthermore, exploring the potential of BC technology to improve inventory management efficiency, supply chain transparency, and traceability is of great importance. Research constraints on BC in large-scale networks can promote its role in a wider range of applications. By addressing these emerging trends and technologies, future research can lay the groundwork for more advanced and effective optimization methods for maintenance strategies in various industrial environments.

Competing Interests The authors declare that they have no competing interests.

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