Article history:
Received 06 February 2024
Revised 01 May 2024
Accepted 08 May 2024
Published online 20 June 2024

Journal of Resource Management and Decision Engineering

Volume 3, Issue 2, pp 62-72

Identifying the Components of Inventory Control and Maintenance with a Cost and Time Optimization Approach (Case Study: Mazandaran Province Water and Wastewater Company)

Meysam. Salavati[1], Hossein. Adab[1*], Ahmadreza. Kasraei[1], Jalal. Haghight Monfard[1]

[1] Department of Industrial Management, CT.C., Islamic Azad University, Tehran, Iran

*** Corresponding author email address**: adabhossein@iau.ac.ir

Article Info

Article type:
Original Research

How to cite this article:
Salavati, M., Adab, H., Kasraei, A., & Haghight Monfard, J. (2024). Identifying the Components of Inventory Control and Maintenance with a Cost and Time Optimization Approach (Case Study: Mazandaran Province Water and Wastewater Company). *Journal of Resource Management and Decision Engineering*, *3*(2), 62-72.
https://doi.org/10.61838/kman.jrmde.3.2.8

ABSTRACT

The purpose of this study is to identify the components of inventory control and maintenance with a focus on optimizing cost and time. By employing a systematic review and meta-synthesis approach, the researcher analyzed the results and findings of previous studies. Using the seven-step method of Sandelowski and Barroso, the influential factors were identified. Out of 198 articles, 35 were selected based on the CASP method. The validity of the analysis was confirmed using the Kappa coefficient, which was calculated at 0.775. The Kappa index was also used to assess reliability and quality control, indicating a high level of agreement for the identified indicators. Data collected were analyzed using MAXQDA software, resulting in the identification of six dimensions and 33 indicators for the model. To identify the components of the model, the meta-synthesis technique was applied. The identified dimensions include: inventory control, maintenance and repair, cost-related dimension, time-related dimension, technology and information systems, and planning and decision-making. Developing a comprehensive program based on risk analysis, forecasting future needs, analyzing failure trends, and allocating resources is essential for optimal management in this industry. Decision-making should be evidence-based and rely on multi-dimensional analyses to strike a balance between time, cost, service quality, and infrastructure sustainability. Stakeholder engagement, including operators, managers, engineers, and customers, in the decision-making process can facilitate a better understanding of priorities and challenges. Given the limited resources and complexity of water and wastewater service structures, the use of decision-support tools such as scenario analysis and decision support systems can enable more accurate planning and improved responsiveness in crisis situations.

Keywords: *Inventory control, maintenance and repair, cost and time optimization, Mazandaran Province Water and Wastewater Company.*

1. Introduction

In today's rapidly evolving industrial landscape, the effectiveness of inventory control and maintenance management is considered a cornerstone of operational excellence. As companies strive for leaner operations and competitive advantage, the pressure to optimize both cost and time in these domains has intensified. Inventory and maintenance decisions not only influence organizational performance but also significantly impact asset longevity, resource allocation, and customer satisfaction. Particularly in sectors such as water and wastewater management, where reliability and service continuity are critical, these functions must be strategically aligned to ensure optimal system performance and sustainable operations (Silva, 2023).

Inventory control, as a fundamental pillar of supply chain management, encompasses a wide array of decisions, including stock replenishment policies, demand forecasting, safety stock levels, and order scheduling. Poor inventory practices can lead to overstocking, stockouts, inflated holding costs, and disrupted service delivery (Basten & Ryan, 2019; Delnaz et al., 2023). Maintenance management, on the other hand, plays a pivotal role in sustaining equipment reliability and minimizing unplanned downtime. Whether preventive, predictive, or corrective, maintenance approaches must be strategically orchestrated to preserve equipment functionality at the lowest possible cost (Hajej et al., 2022; Wang et al., 2021). The integration of these two domains—inventory and maintenance—can yield synergistic benefits in terms of efficiency, risk reduction, and long-term value creation (Achamrah et al., 2022; Karabağ et al., 2020).

Recent developments in digitalization, artificial intelligence, and data analytics have transformed traditional practices into dynamic, responsive systems. For instance, reinforcement learning models now support predictive inventory management with real-time adaptability to demand fluctuations (Cuartas & Aguilar, 2023). Similarly, decision support systems using augmented reality and IoT facilitate rapid diagnostics and maintenance planning (Shirzadi & Tavakkolan, 2022; Sitompul & Rohmat, 2021). The adoption of integrated systems such as ERP and CMMS further strengthens data visibility and cross-departmental collaboration (Fakhimi Hosseinzadeh et al., 2023; Kaya & Ulutagay, 2023). These tools collectively enhance decision-making quality, reduce manual error, and contribute to a responsive supply-maintenance ecosystem (Dey & Seok, 2022; Xie et al., 2024).

A growing body of literature has emphasized the importance of adopting optimization-based approaches in inventory and maintenance strategy formulation. Multi-objective evolutionary algorithms, genetic algorithms, and fuzzy inference systems are increasingly applied to solve complex decision-making problems with multiple conflicting objectives—such as minimizing costs while maximizing service levels and equipment uptime (Adabbo et al., 2025; Cacereño et al., 2023; Kaya & Ulutagay, 2023). These advanced computational methods allow for the simultaneous consideration of constraints such as stochastic demand, lead time variability, equipment deterioration, and resource limitations (Yang et al., 2020; Zhang et al., 2021). As a result, hybrid models have emerged that jointly optimize inventory parameters and maintenance schedules, yielding solutions that are both efficient and resilient (Rivera-Gómez et al., 2019; Zhang et al., 2024).

Another significant dimension in the optimization of inventory and maintenance systems is the economic impact of decision outcomes. Various studies have modeled the opportunity costs associated with unplanned downtime, backorders, and delayed maintenance interventions. For example, in the water utility sector, external costs of service interruptions have been shown to directly affect organizational efficiency and stakeholder satisfaction (Maziotis et al., 2020; Sarfaraz et al., 2023). These insights underscore the necessity of integrating cost metrics—such as holding cost, shortage cost, ordering cost, and maintenance cost—into strategic models (Alamri & Mo, 2023; San-José et al., 2023). As the industry shifts toward data-driven management, cost-benefit analysis and risk-based evaluation have become essential tools for evidence-based decision-making (Pasupuleti, 2025; Wang et al., 2024).

Moreover, maintenance decisions should not be viewed in isolation but rather as part of a holistic asset management framework. Advanced models now incorporate the life cycle costs of equipment and factor in wear-and-tear patterns, condition-based monitoring data, and service history to refine maintenance schedules and inventory allocations (Abdul-Malak et al., 2019; Hashemian et al., 2021). Joint optimization approaches, for example, account for equipment degradation rates and failure probabilities to align maintenance tasks with inventory availability (Dinh et al., 2022). The interplay between preventive and corrective strategies, and their dependence on the timely availability of spare parts, has also been a critical focus of optimization research (Dursun et al., 2022; Kalantari et al., 2020).

Importantly, decision-making in inventory and maintenance management must also incorporate planning and governance dimensions. Dynamic and uncertain environments—such as those characterized by supply chain disruptions, policy constraints, or fluctuating demand—require scenario-based analysis and contingency planning (Khoshnevis et al., 2023; Shahrjerdi, 2022). The inclusion of decision-making tools such as the Delphi method, fuzzy logic, and simulation modeling has significantly contributed to improving policy robustness and operational agility (Salmasnia & Talesh-Kazemi, 2022; Taheri et al., 2022). Additionally, digital transformation initiatives that aim to digitize records, enhance traceability, and automate warning systems for critical components are central to building a forward-looking and resilient asset management system (Ingemarsdotter et al., 2021; Sarhadi & Asraei, 2021).

The incorporation of artificial intelligence in maintenance and inventory optimization is gaining momentum in both research and practice. AI-based tools such as predictive analytics, machine learning models, and complex system simulators help in identifying patterns, predicting failures, and optimizing stock levels with minimal human intervention (Bukhsh et al., 2023; Delnaz et al., 2023). These technologies enable real-time updates, autonomous learning, and adaptive response mechanisms, all of which are crucial for managing complex supply and maintenance systems (Lönnrot, 2025; Wang et al., 2025). Consequently, organizations that embrace AI-driven approaches can expect to achieve higher levels of efficiency, reduced operational risk, and enhanced service quality.

From a practical standpoint, the application of integrated inventory-maintenance models is particularly valuable in utility services and critical infrastructure sectors. For instance, water and wastewater companies must maintain continuity of service despite aging infrastructure, budget constraints, and rising customer expectations (Shahrjerdi, 2022; Silva, 2023). In this context, decision-makers must balance the trade-offs between cost, availability, and risk—requiring frameworks that consolidate technical, economic, and operational considerations into a unified optimization model (Cacereño et al., 2023; San-José et al., 2023). This necessitates not only technological integration but also institutional commitment to proactive asset management and interdepartmental coordination (Alamri & Mo, 2023; Fakhimi Hosseinzadeh et al., 2023).

In summary, the convergence of digital technologies, advanced optimization techniques, and data-centric management philosophies is redefining the landscape of inventory and maintenance control. The evolution from reactive, siloed operations to integrated, strategic systems marks a paradigm shift in how organizations approach asset reliability and operational efficiency. The present study builds upon this foundation to develop a comprehensive model that identifies and classifies the key components of inventory and maintenance control through the lens of cost and time optimization.

2. Methods and Materials

The present study, which aims to identify the components of inventory control and maintenance with a cost and time optimization approach, follows a qualitative research design and applies a library-based research method using the meta-synthesis technique in the field of smart production. Meta-synthesis is a type of meta-study that systematically reviews sources to extract, assess, synthesize, and, if necessary, statistically summarize research that has been previously conducted on a specific subject area. In fact, in meta-synthesis, data and findings extracted from other related and similar studies are reviewed and analyzed. In this context, the data collected from these studies are qualitative rather than quantitative. Consequently, the sample selected for the meta-synthesis is formed based on its relevance to the research question. Meta-synthesis is not merely an integrated review of qualitative principles or secondary and primary data analysis from selected studies; rather, it involves the interpretation of the findings of those studies. In other words, meta-synthesis is the synthesis of interpretations of the primary data from selected studies. The ATLAS.ti software was used for the analysis.

3. Findings and Results

As previously mentioned, meta-synthesis analysis includes seven steps. In this section, the results for each of these steps are presented separately.

Step 1: Formulating the Fundamental Research Questions

The first step in the Sandelowski and Barroso method involves formulating the research questions. These questions are generally structured around four parameters: what, who, when, and how. After aligning the research questions with the study's objectives, the systematic literature review begins. Table 1 presents responses to these fundamental questions related to the meta-synthesis method:

Table 1

Research Questions

Parameter	Research Question
What	Identifying the components of inventory control and maintenance with a cost and time optimization approach
Who	Various works including books, articles, and reports on inventory control and maintenance with a cost and time optimization approach
When	Covers all works published between 2000 and 2024
How	Thematic analysis, identification and note-taking, key points extraction, and concept analysis

Table 2

Identification of Keywords for Step Two of the Meta-synthesis Method

Persian Equivalent of Key Concepts	English Keywords Used for Search
کنترل موجودی و نگهداری با رویکرد بهینه‌سازی هزینه و زمان	Inventory and maintenance control with a cost and time optimization approach
کنترل موجودی و نگهداری با رویکرد بهینه‌سازی هزینه و زمان در شرکت آب و فاضلاب	Inventory and maintenance control with a cost and time optimization approach in a water and wastewater company
کنترل موجودی و نگهداری در شرکت آب و فاضلاب	Inventory and maintenance control in a water and wastewater company

Step 2: Systematic Review of Literature

For data collection, secondary data in the form of previous documents and records were used. As previously mentioned, the two major databases selected for this purpose were Scopus and Web of Science.

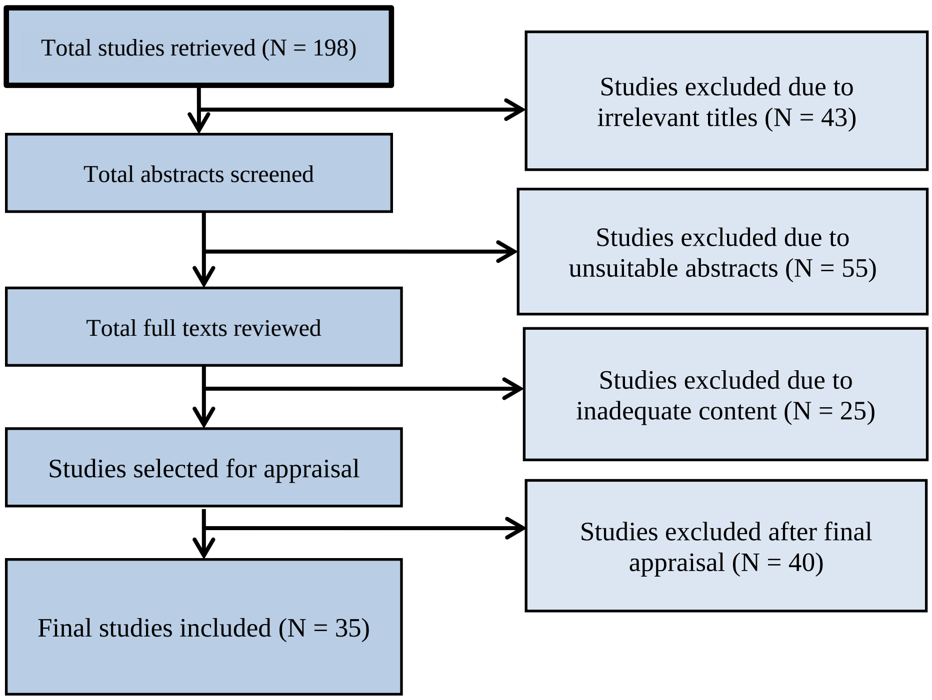
Additionally, in regard to Persian-language articles, the Scientific Information Database (SID) and the Comprehensive Portal of Humanities were utilized.

Step 3: Searching and Selecting Literature

Table 3 outlines the steps taken to refine the extracted articles. Based on this table, four stages were followed to refine the articles drawn from the literature. The final stage relied on the opinions of five expert reviewers involved in this research. These experts evaluated the final quality of the selected articles based on a specific evaluation approach (introduced below). Articles that did not meet the established threshold were excluded from the process.

Figure 1

Review and Selection Process



After eliminating studies that were inconsistent with the research objectives and questions, the researcher evaluated the methodological quality of the remaining studies. The aim of this step was to remove studies whose findings were deemed unreliable. The tool commonly used for evaluating the quality of primary qualitative studies is the Critical Appraisal Skills Programme (CASP). This tool includes ten questions that help assess the rigor, validity, and relevance of qualitative research. These questions focus on the following criteria:

1. Research objectives
2. Methodological rationale
3. Research design
4. Sampling method
5. Data collection
6. Reflexivity (referring to the researcher-participant relationship)
7. Ethical considerations
8. Accuracy of data analysis
9. Clear articulation of findings
10. Research value.

Table 3

Selected Articles

Article Code	Title	Score
S01	Optimisation of Preventive Maintenance Regime Based on Failure Mode System Modelling Considering Reliability	44
S02	A Proposed Optimization Model for Maximizing the Mean Time Between Failures in Urban Water Networks Considering Cost and Environmental Aspects	42
S03	The Value of Maintenance Delay Flexibility for Improved Spare Parts Inventory Management	38
S04	Simultaneous Optimization of Design and Maintenance for Systems Using Multi-Objective Evolutionary Algorithms and Discrete Simulation	39
S05	Improving Inventory and Procurement Management Through Business Intelligence	43
S06	A Framework for Assessing Maintenance System Performance in Water and Wastewater Companies: Case Study of Alborz Province Water and Wastewater Company	42
S07	A Maintenance Planning Framework Using Online and Offline Deep Reinforcement Learning	41
S08	Hybrid Algorithm Based on Reinforcement Learning for Smart Inventory Management	40
S09	Integrating Inventory Planning, Pricing, and Maintenance for Perishable Products in a Two-Component Parallel Manufacturing System with Common Cause Failures	38
S10	Joint Production and Preventive Maintenance Scheduling for a Single Degraded Machine Considering Machine Failures	32
S11	A Decision Support System Model to Enhance Equipment Maintenance Management Based on Augmented Reality Considering Maintenance Priorities	40
S12	Profit Maximization in an Inventory System with Time-Varying Demand, Partial Backordering, and Discrete Inventory Cycle	43
S13	Joint Integrated Production-Maintenance Policy with Production Plan Smoothing Through Production Rate Control	39
S14	A Heuristic Multi-Criteria Classification Method for Spare Parts Management Policy Selection: Case Study of East Azerbaijan Province Water and Wastewater Company	40
S15	Asset Management Analytics for Urban Water Mains: A Literature Review	40
S16	Pathology of the Maintenance Structure Regarding the Foundation for Physical Asset Management in East Azerbaijan Province Water and Wastewater Company	44
S17	Maintaining Systems with Heterogeneous Spare Parts	32
S18	Intelligent Inventory Management with Autonomation and Service Strategy	32
S19	Joint Condition-Based Maintenance and Inventory Optimization for Systems with Multiple Components	31
S20	Impact of External Costs of Unplanned Supply Interruptions on Water Company Efficiency: Evidence from Chile	37
S21	Multi-Level Opportunistic Predictive Maintenance for Multi-Component Systems with Economic Dependence and Assembly/Disassembly Impacts	31
S22	Evaluation of Preventive Maintenance (PM) System Performance with an Optimal Operation Approach in Distribution Networks	33
S23	Joint Optimization of Preventive Maintenance and Inventory Management for Standby Systems with Hybrid-Deteriorating Spare Parts	32
S24	Optimal Production, Pricing, and Substitution Policies in Continuous Review Production-Inventory Systems	38
S25	Reliability-Based Opportunistic Maintenance Modeling for Multi-Component Systems with Economic Dependence Under Base Warranty	31
S26	Spare Parts Inventory Routing Problem with Transshipment and Substitutions Under Stochastic Demands	39
S27	Age-Based Maintenance Under Population Heterogeneity: Optimal Exploration and Exploitation	40
S28	Challenges and Solutions in Condition-Based Maintenance Implementation – A Multiple Case Study	41
S29	IoT-Based Running Time Monitoring System for Machine Preventive Maintenance Scheduling	44
S30	An Integrated Model of Production, Maintenance, and Quality Control with Statistical Process Control Chart of a Supply Chain	32
S31	Integrated Optimization of Maintenance Interventions and Spare Part Selection for a Partially Observable Multi-Component System	32
S32	Inventory and Maintenance Optimization of Condition-Based Maintenance Using Fuzzy Inference System	40
S33	A Theoretical Framework for Risk–Cost-Optimized Maintenance Strategy for Structures	40
S34	Assessing Repair and Maintenance Efficiency for Water Suppliers: A Novel Hybrid USBM-FIS Framework	42
S35	Joint Optimization of Maintenance, Buffer, and Spare Parts for a Production System	44

Step Four: Data Extraction

This step involves reviewing the remaining articles and extracting texts for coding in the next phase. It focuses on separating results, outputs, and the interpretations of those outputs, along with the final discussion and conclusions of the researchers. At this stage, 35 articles were imported into MAXQDA software. To conduct an initial examination, portions of the articles were reviewed selectively and randomly coded in a scattered manner to familiarize the researcher with the existing data. In this way, the researcher gained an understanding of the general themes and the overarching research environment. The codes and their meanings are specified in Table 3.

Table 4

Extraction of Initial Codes

Indicator	Concept
Safety Stock Level	The minimum inventory required to prevent stockouts under unforeseen circumstances.
Inventory Turnover Rate	The number of times inventory is sold or used during a specific period; indicates warehouse efficiency.
Average Lead Time	The average time between placing an order and receiving the goods.
Excess Inventory Rate	The percentage of items held in excess of actual demand.
Obsolete or Unused Item Rate	The percentage of items that remain unused or are no longer usable.
Inventory Holding Cost	Costs such as warehousing, insurance, depreciation, and capital lock-up for storing goods.
Forecast Accuracy	The degree of alignment between demand forecasts and actual demand.
Reorder Point Level	The inventory level at which a new order should be placed.
Equipment Failure Rate	The number of equipment breakdowns within a specified time period.
Mean Time Between Failures (MTBF)	The average time equipment operates without failure.
Mean Time to Repair (MTTR)	The average time spent repairing equipment.
Monthly/Annual Preventive Maintenance Cost	The cost of regular servicing to prevent equipment breakdown.
Ratio of Corrective to Preventive Maintenance	A measure of organizational dependence on reactive versus planned maintenance.
Downtime Due to Failures	The proportion of operational stoppage time caused by equipment failures.
Spare Part Availability Time	The time it takes to provide the required spare part for repairs.
Total Annual Equipment Maintenance Cost	The total of all direct and indirect maintenance costs for equipment in one year.
Annual Spare Part Consumption Cost	The cost of purchasing or using spare parts during the year.
Spare Part Inventory Holding Cost	Costs associated with storing and maintaining spare parts.
Downtime Cost	Losses incurred from production or service interruptions due to equipment failure.
Reorder Processing Cost	Administrative and operational expenses for each reorder of a spare part.
Breakdown Response Time	The time maintenance teams take from receiving a breakdown report to initiating the repair.
Order-to-Delivery Time for Spare Parts	The total time required to procure a part, from order placement to receipt.
Waiting Time for Scheduled Servicing	The time equipment remains idle awaiting scheduled maintenance.
Reordering Cycle Time for High-Use Parts	The average time between successive orders of frequently used parts.
Time Spent on Future Inventory Needs Analysis and Planning	The duration allocated to analyzing demand and developing supply plans.
Use of ERP/CMMS Systems for Maintenance and Inventory	The extent to which integrated maintenance or enterprise resource planning systems are utilized.
Traceability of Items in Inventory System	The system’s ability to track the movement of each item or spare part in and out of inventory.
Automation Level of Critical Item Alert Systems	The presence of automated systems that alert when critical inventory thresholds are reached.
Percentage of Digitized Records in Inventory and Maintenance	The degree to which paper-based processes in inventory and maintenance management are digitized.
Frequency of Inventory Level Reviews	The number of times inventory levels are reviewed and adjusted annually.
Coordination Rate Between Maintenance and Inventory Departments	The extent of operational alignment and collaboration between the supply and maintenance departments.
Number of Revised Policies for Resource Optimization	The number of updated policies aimed at improving operational performance.
Percentage of Predictive Model Usage in Maintenance	The extent to which algorithms and forecasting models are used in maintenance and reordering decisions.

Step Five: Qualitative Findings Analysis

During the analysis process, the researcher seeks themes that emerge across the studies included in the meta-synthesis. This is known as *thematic analysis*. Once themes are identified and clarified, the reviewer constructs a classification framework and places related or similar categories under a theme that best describes them. These themes form the foundation for constructing explanations, patterns, theories, or hypotheses. In this study, all extracted factors from the reviewed studies were initially considered as codes. Subsequently, based on the meaning of each, the codes were grouped into similar conceptual categories. These similar concepts were then organized into explanatory categories, which led to the identification of the core and sub-components of the research indicators. In Table 4, each article is cited by the letter "S" followed by its assigned number.

Table 5

Main Categories and Related Codes

Dimension	Indicator	Source
Inventory Control	Safety stock level	S22, S17, S29, S30, S31
	Inventory turnover rate	S14, S16, S19, S22, S26, S35
	Average lead time	S1, S17, S19, S22, S28
	Excess inventory rate	S3, S4, S6, S17, S30
	Obsolete or unused item rate	S2, S4, S8, S9, S18, S28, S31, S34, S35
	Inventory holding cost	S23, S34, S35
	Demand forecast accuracy	S3, S18, S20, S22, S25
	Reorder point level	S16, S17, S27, S29, S30, S33, S34, S35
Maintenance and Repair	Equipment failure rate	S22, S26, S27, S29, S30, S31
	Mean time between failures (MTBF)	S1, S6, S10, S20, S30, S33
	Mean time to repair (MTTR)	S1, S6, S9, S19, S21, S23
	Monthly/Annual preventive maintenance cost	S2, S5, S7, S9, S17, S18, S32
	Corrective-to-preventive maintenance ratio	S27, S29, S30, S31, S33
	Downtime due to failures	S1, S2, S3, S4, S6, S19, S20, S22, S24, S27, S28, S29
	Spare part availability time	S10, S14, S16, S33, S35
Cost-Related	Total annual equipment maintenance cost	S2, S5, S7, S9, S18, S24
	Annual spare part consumption cost	S15, S17, S22, S23, S34
	Spare part inventory holding cost	S1, S6, S10, S20, S30, S33
	Downtime cost	S1, S3, S6, S8, S10, S11, S17, S22
	Reorder processing cost	S15, S18, S22, S25, S26
Time-Related	Breakdown response time	S22, S17, S29, S30, S31
	Spare part order-to-delivery time	S4, S6, S8, S10, S11, S12
	Waiting time for scheduled servicing	S3, S16, S19, S32, S33, S34
	Reordering cycle time for high-use parts	S2, S14, S18, S19, S21
	Time for future inventory planning and analysis	S25, S26, S31, S33
Technology and Information Systems	Use of ERP/CMMS systems for maintenance and inventory	S2, S4, S8, S11, S17, S23
	Traceability of items in inventory system	S10, S16, S27, S9, S21, S22, S31
	Automation level of critical item alert system	S18, S19, S24, S26, S28
	Percentage of digitized records in inventory and maintenance	S13, S17, S18, S22, S28, S29, S30
Planning and Decision-Making	Inventory level review frequency	S5, S7, S23, S26, S12, S15, S18
	Coordination between maintenance and inventory departments	S4, S9, S10, S17, S18, S30, S32, S34
	Number of revised policies for resource optimization	S4, S6, S8, S10, S11, S12
	Percentage use of predictive models for maintenance	S3, S16, S19, S32, S33, S34

Step Six: Quality Control of the Analysis

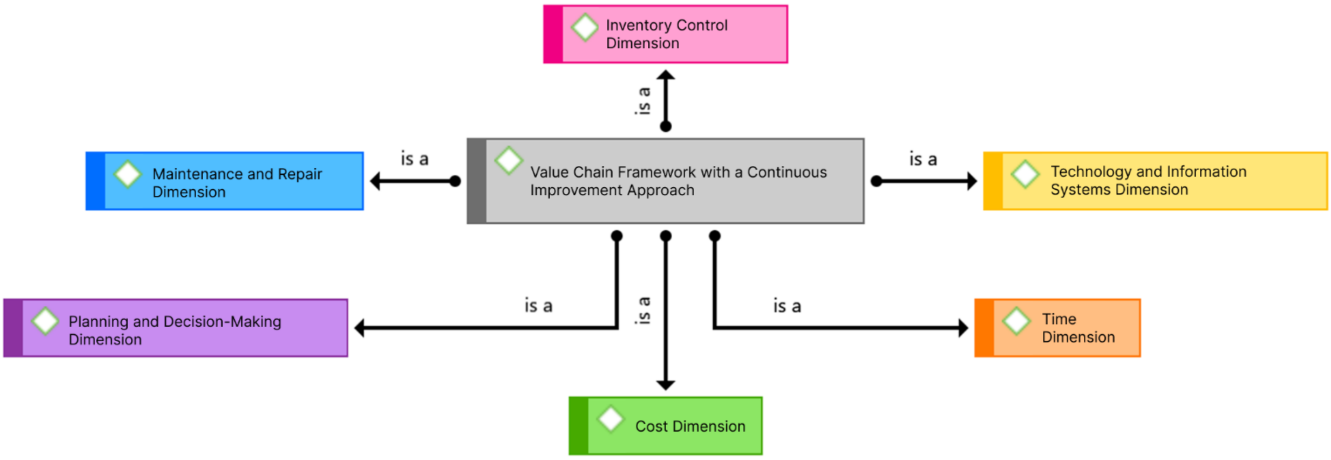
To evaluate the reliability of the meta-synthesis, one selected document was reviewed by an expert. Following the assessment, a Kappa coefficient of 0.755 was calculated. A Kappa coefficient above 0.60 is considered satisfactory.

Step Seven: Presentation of Report and Research Findings

At this stage, the findings are presented graphically. A total of 6 dimensions and 33 indicators were identified for the model. The dimensions are illustrated in the figure.

Figure 2

Components of Inventory Control and Maintenance with a Cost and Time Optimization Approach



4. Discussion and Conclusion

The present study aimed to identify the key dimensions and indicators of inventory and maintenance control with an emphasis on cost and time optimization, using a meta-synthesis of 35 relevant studies. The results revealed six major dimensions—inventory control, maintenance and repair, cost-related, time-related, technology and information systems, and planning and decision-making—encompassing a total of 33 specific indicators. These findings offer a comprehensive and multidimensional framework that integrates operational, technological, and strategic components of inventory and maintenance systems.

The inventory control dimension included indicators such as safety stock levels, inventory turnover rate, lead time, excess inventory, obsolete items, and forecast accuracy. These findings are consistent with prior research that highlights the importance of balancing inventory availability with demand uncertainty to avoid both stockouts and overstocking (Basten & Ryan, 2019; San-José et al., 2023). For instance, accurate demand forecasting and real-time inventory tracking have been emphasized as critical for reducing holding costs and improving replenishment efficiency (Cuartas & Aguilar, 2023; Dey & Seok, 2022). The identification of reorder point levels and inventory review frequency aligns with models that integrate dynamic inventory planning and probabilistic demand management (Achamrah et al., 2022; Salmasnia & Talesh-Kazemi, 2022). These indicators, collectively, demonstrate the necessity for continuous monitoring and adjustment of inventory strategies, particularly in capital-intensive sectors like water and wastewater utilities.

The maintenance and repair dimension included critical performance metrics such as equipment failure rate, mean time between failures (MTBF), mean time to repair (MTTR), the cost of preventive maintenance, and the ratio of corrective to preventive interventions. These indicators mirror the consensus in the literature regarding the role of predictive and condition-based maintenance in reducing downtime and enhancing asset reliability (Dinh et al., 2022; Karabağ et al., 2020; Yang et al., 2020). Studies have shown that improving MTBF and reducing MTTR can directly lower operational disruptions and support cost minimization objectives (Wang et al., 2021; Zhang et al., 2021). The emphasis on access time to spare parts also supports earlier findings on the interdependence between maintenance scheduling and spare parts logistics (Abdul-Malak et al., 2019; Alamri & Mo, 2023). Moreover, integrating maintenance metrics with ERP/CMMS platforms enables real-time performance tracking and better prioritization of interventions (Fakhimi Hosseinzadeh et al., 2023; Kaya & Ulutagay, 2023).

The cost dimension was found to be cross-cutting and deeply interconnected with the other dimensions. Key cost-related indicators identified included total maintenance cost per year, cost of spare parts, inventory holding cost, cost of downtime, and reorder costs. These findings are supported by studies that advocate for total cost of ownership (TCO) approaches in maintenance and inventory decisions (Adabbo et al., 2025; Hashemian et al., 2021). Specifically, prior research has shown that poor inventory planning can lead to hidden costs such as backorders, service delays, and unscheduled downtime (Bukhsh et al., 2023; Maziotis et al., 2020). The integration of cost indicators into performance evaluation frameworks is critical to achieving economic sustainability, particularly in public infrastructure settings where resource constraints are common (Sarfaraz et al., 2023; Shahrjerdi, 2022).

In the time dimension, indicators such as breakdown response time, part order-to-delivery time, waiting time for scheduled maintenance, and lead time for high-consumption items were identified. These temporal factors directly influence operational continuity and customer service levels (Cacereño et al., 2023; Delnaz et al., 2023). Aligning with previous studies, the findings suggest that time efficiency is not only a logistical issue but also a strategic imperative that influences broader performance outcomes (Ingemarsdotter et al., 2021; Sitompul & Rohmat, 2021). For example, IoT-based monitoring systems can significantly reduce the response and repair cycle times by providing real-time alerts and enabling remote diagnostics (Shirzadi & Tavakkolan, 2022; Wang et al., 2025).

The technology and information systems dimension emerged as a key enabler of integration and efficiency. Indicators such as the use of ERP/CMMS systems, item traceability, digitalization of records, and automation of alert systems for critical components are consistent with the digital transformation trends in asset management (Pasupuleti, 2025; Wang et al., 2024). The digitization of inventory and maintenance data enhances decision accuracy and enables predictive modeling capabilities (Dey & Seok, 2022; Xie et al., 2024). Furthermore, traceability and automation help reduce administrative workload, prevent errors, and improve compliance with safety and performance standards (Fakhimi Hosseinzadeh et al., 2023; San-José et al., 2023).

Lastly, the planning and decision-making dimension incorporated indicators such as inventory review frequency, cross-functional coordination, number of revised policies, and the use of predictive models. This highlights the shift from reactive to strategic asset management, where continuous improvement, stakeholder engagement, and scenario planning are central (Kalantari et al., 2020; Taheri et al., 2022). Prior research emphasizes that effective governance structures and decision-making processes are vital for the successful implementation of optimization strategies (Khoshnevis et al., 2023; Shahrjerdi, 2022). The findings also echo calls for enhanced coordination between maintenance and inventory departments to reduce lead times and resource redundancies (Alamri & Mo, 2023; Sarhadi & Asraei, 2021).

Collectively, the six dimensions and 33 indicators identified in this study present a validated, multi-dimensional framework for analyzing and improving inventory and maintenance systems with a cost-time optimization lens. The alignment of findings with the broader literature confirms the robustness and applicability of the proposed framework across various industrial contexts. It also reinforces the importance of integrating operational metrics with technology adoption and strategic planning to achieve sustainable performance outcomes.

Despite its contributions, the study is not without limitations. First, the reliance on secondary data from published literature may introduce selection bias, as only peer-reviewed and accessible sources were included. Some relevant studies or case-specific insights may have been excluded due to database restrictions or publication language. Second, although meta-synthesis allows for the integration of qualitative findings, it lacks the empirical granularity provided by field data or quantitative simulations. As such, the practical applicability of the indicators may vary across industries with different operational constraints. Finally, the coding and classification processes, while systematic, remain inherently interpretive, which may affect the generalizability of the categorization.

Future research should focus on empirically validating the proposed framework across diverse industries and geographical regions. Case studies or field experiments involving utility companies, manufacturing firms, or logistics providers can provide real-world insights into the implementation feasibility and outcomes of the framework. Additionally, integrating real-time data analytics and digital twin models could enhance predictive accuracy and decision support. Researchers may also explore the development of industry-specific key performance indicators (KPIs) and customizable dashboards to support continuous monitoring and dynamic policy adjustment.

Practitioners should prioritize the integration of inventory and maintenance management functions through centralized digital platforms such as ERP and CMMS. Emphasis should be placed on data quality, real-time tracking, and the use of predictive analytics to enhance responsiveness. Organizations should also invest in staff training and cross-departmental collaboration to ensure alignment of operational and strategic objectives. Finally, the continuous review and revision of inventory and maintenance policies based on performance data and environmental changes will be essential for sustaining competitive advantage and service excellence.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

References

Abdul-Malak, D. T., Kharoufeh, J. P., & Maillart, L. M. (2019). Maintaining systems with heterogeneous spare parts. *Naval Research Logistics (Nrl)*, *66*(6), 485-501. https://doi.org/10.1002/nav.21864

Achamrah, F. E., Riane, F., & Limbourg, S. (2022). Spare parts inventory routing problem with transshipment and substitutions under stochastic demands. *Applied Mathematical Modelling*, *101*, 309-331. https://doi.org/10.1016/j.apm.2021.08.029

Adabbo, G., Andreozzi, A., Iasiello, M., Napoli, G., & Vanoli, G. (2025). A multi-objective optimization framework through genetic algorithm for hyperthermia-mediated drug delivery. *Computers in Biology and Medicine*, *189*, 109895.

Alamri, T. O., & Mo, J. P. T. (2023). Optimisation of Preventive Maintenance Regime Based on Failure Mode System Modelling Considering Reliability. *Arabian Journal for Science and Engineering*, *48*, 3455-3477. https://doi.org/10.1007/s13369-022-07174-w

Basten, R. J. I., & Ryan, K. J. (2019). The value of maintenance delay flexibility for improved spare parts inventory management. *European Journal of Operational Research*, *278*(2), 646-657. https://doi.org/10.1016/j.ejor.2019.04.023

Bukhsh, Z. A., Molegraaf, H., & Jansen, N. (2023). A maintenance planning framework using online and offline deep reinforcement learning. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-023-08560-7

Cacereño, A., Greiner, D., & Galván, B. (2023). Simultaneous optimization of design and maintenance for systems using multi-objective evolutionary algorithms and discrete simulation. *Soft Computing*. https://doi.org/10.1007/s00500-023-08922-2

Cuartas, C., & Aguilar, J. (2023). Hybrid algorithm based on reinforcement learning for smart inventory management. *Journal of Intelligent Manufacturing*, *34*, 123-149. https://doi.org/10.1007/s10845-022-01982-5

Delnaz, A., Nasiri, F., & Li, S. S. (2023). Asset management analytics for urban water mains: a literature review. *Environmental Systems Research*, *12*(12). https://doi.org/10.1186/s40068-023-00287-7

Dey, B. K., & Seok, H. (2022). Intelligent inventory management with autonomation and service strategy. *Journal of Intelligent Manufacturing*. https://doi.org/10.1007/s10845-022-02046-4

Dinh, D. H., Do, P., & Iung, B. (2022). Multi-level opportunistic predictive maintenance for multi-component systems with economic dependence and assembly/disassembly impacts. *Reliability Engineering & System Safety*, *217*, 108055. https://doi.org/10.1016/j.ress.2021.108055

Dursun, İ., Akçay, A., & van Houtum, G. J. (2022). Age-based maintenance under population heterogeneity: Optimal exploration and exploitation. *European Journal of Operational Research*, *301*(3), 1007-1020. https://doi.org/10.1016/j.ejor.2021.11.038

Fakhimi Hosseinzadeh, S., Alavi Matin, Y., & Iranzadeh, S. (2023). An Innovative Multi-Criteria Classification Method for Determining Spare Parts Management Policies: A Case Study of East Azerbaijan Water and Wastewater Company. 17th International Conference on Management, Economics, and Development,

Hajej, Z., Nyoungue, A. C., Abubakar, A. S., & Kammoun, M. A. (2022). An Integrated Model of Production, Maintenance, and Quality Control with Statistical Process Control Chart of a Supply Chain. *Applied Sciences*, *11*(9), 4192. https://doi.org/10.3390/app11094192

Hashemian, S. E., Shafahi, Y., & Moghaddasnejad, F. (2021). Life Cycle Cost Analysis of Maintenance Decisions Using Markov Prediction Model Output Based on Railway Track Measurement Machine Data. *Amirkabir Journal of Civil Engineering*, *53*(2), 555-574.

Ingemarsdotter, E., Kambanou, M. L., Jamsin, E., Sakao, T., & Balkenende, R. (2021). Challenges and solutions in condition-based maintenance implementation - a multiple case study. *Journal of Cleaner Production*, *296*, 126420. https://doi.org/10.1016/j.jclepro.2021.126420

Kalantari, M., Haghighat Monfared, J., & Keramati, M. A. (2020). Explaining the Requirements of a Smart Water Management System in Iran. *Smart Business Management Studies*, *34*, 95-136.

Karabağ, O., Eruguz, A. S., & Basten, R. (2020). Integrated optimization of maintenance interventions and spare part selection for a partially observable multi-component system. *Reliability Engineering & System Safety*, *200*, 106955. https://doi.org/10.1016/j.ress.2020.106955

Kaya, B., & Ulutagay, G. (2023). *Inventory and Maintenance Optimization of Conditional Based Maintenance Using Fuzzy Inference System* (F. Calisir, Ed.). Springer, Cham. https://doi.org/10.1007/978-3-031-25847-3_18

Khoshnevis, M., alami, f., & Sarraf, A. (2023). Risk analysis of water and wastewater infrastructure projects based on publicprivate partnership (3P) approach by combining Fuzzy Delphi (FD), FMEA and artificial fuzzy assessment (FSE) techniques. *Journal of Structural and Construction Engineering*, *9*(11), 77-100. https://doi.org/10.22065/jsce.2022.315454.2644

Lönnrot, P. (2025). *Portfolio optimization with AI: Evaluating Performance Beyond Traditional Techniques*.

Maziotis, A., Villegas, A., Molinos-Senante, M., & Sala-Garrido, R. (2020). Impact of external costs of unplanned supply interruptions on water company efficiency: evidence from Chile. *Utilities Policy*, *66*, 101087. https://doi.org/10.1016/j.jup.2020.101087

Pasupuleti, M. K. (2025). AI in Global Trade and Economics: Predictive Modeling and Quantum-Enhanced Policy Optimization. 46-58. https://doi.org/10.62311/nesx/77517

Rivera-Gómez, H., Gharbi, A., Kenné, J. P., Montaño-Arango, O., & Corona-Armenta, J. R. (2019). Joint optimization of production and maintenance strategies considering a dynamic sampling strategy for a deteriorating system. *Computers and Industrial Engineering*, *140*, 106273. https://doi.org/10.1016/j.cie.2020.106273

Salmasnia, A., & Talesh-Kazemi, A. (2022). Integrating inventory planning, pricing, and maintenance for perishable products in a two-component parallel manufacturing system with common cause failures. *Operations Research International Journal*, *22*, 1235-1265. https://doi.org/10.1007/s12351-020-00590-6

San-José, L. A., Sicilia, J., González-de-la-Rosa, M., & Febles-Acosta, J. (2023). Profit maximization in an inventory system with time-varying demand, partial backordering and discrete inventory cycle. *Annals of Operations Research*, *316*, 763-783. https://doi.org/10.1007/s10479-021-04161-6

Sarfaraz, A. H., Yazdi, A. K., Hanne, T., Wanke, P. F., & Hosseini, R. S. (2023). Assessing repair and maintenance efficiency for water suppliers: a novel hybrid USBM-FIS framework. *Operations Management Research*. https://doi.org/10.1007/s12063-023-00347-2

Sarhadi, R., & Asraei, A. (2021). *Improving Inventory and Logistics Management Using Business Intelligence* Ghiyath al-Din Jamshid Kashani University].

Shahrjerdi, R. (2022). A Framework for Evaluating Maintenance Systems Performance in Water and Wastewater Companies: A Case Study of Alborz Province Water and Wastewater Company. *Water and Wastewater Science and Engineering*, *7*(4), 47-59.

Shirzadi, F., & Tavakkolan, M. (2022). *A Decision Support System Model for Enhancing Maintenance Management of Equipment Based on Augmented Reality Considering Maintenance Priorities* University of Tehran].

Silva, J. A. (2023). Wastewater treatment and reuse for sustainable water resources management: a systematic literature review. *Sustainability*, *15*(14), 10940-10940. https://doi.org/10.3390/su151410940

Sitompul, E., & Rohmat, A. (2021). IoT-based running time monitoring system for machine preventive maintenance scheduling. *Elkha Jurnal Teknik Elektro (Pontianak)*, *13*(1), 33-40. https://doi.org/10.26418/elkha.v13i1.44202

Taheri, M. T., Maki Al Agha, M., & Samadiyar, H. (2022). Prioritizing and managing industrial waste in the ninth refinery of South Pars Gas Complex. *Environmental and Water Engineering*, *8*(4), 842-855. https://www.jewe.ir/article_146971_c5df0e9b2abce6eb1af1e8d80c4a8780.pdf?lang=en

Wang, C., Lu, Z., & Yu, J. (2025). Biological Optimization of Sustainable Agricultural Systems Through Genetic Algorithms and Nitrogen Balance Management. *Molecular & Cellular Biomechanics*, *22*(3), 1073. https://doi.org/10.62617/mcb1073

Wang, R., Cheng, Z., Dong, E., Guo, C., & Rong, L. (2021). Reliability-based opportunistic maintenance modeling for multi-component systems with economic dependence under base warranty. *Discrete Dynamics in Nature and Society*, *52*, 1-16. https://doi.org/10.1155/2021/5541902

Wang, W., Chen, Y., Wang, Y., Deveci, M., Cheng, S., & Brito-Parada, P. R. (2024). A decision support framework for humanitarian supply chain management – Analysing enablers of AI-HI integration using a complex spherical fu zzy DEMATEL-MARCOS method. *Technological Forecasting and Social Change*, *206*, 123556. https://doi.org/10.1016/J.TECHFORE.2024.123556

Xie, S., Lim, Y. T., Wang, H., Yi, W., & Antwi-Afari, M. F. (2024). Location and Capacity Optimization of Waste Recycling Centers: Mathematical Models and Numerical Experiments. *Applied Sciences*, *14*(16), 7039-7039. https://doi.org/10.3390/app14167039

Yang, W., Baji, H., & Li, C. Q. (2020). A Theoretical Framework for Risk-Cost-Optimized Maintenance Strategy for Structures. *International Journal of Civil Engineering*, *18*, 261-278. https://doi.org/10.1007/s40999-019-00470-x

Zhang, J., Du, D., Si, X., Hu, C., & Zhang, H. (2021). Joint optimization of preventive maintenance and inventory management for standby systems with hybrid-deteriorating spare parts. *Reliability Engineering and System Safety*, *214*. https://doi.org/10.1016/j.ress.2021.107686

Zhang, Q., Xu, S., & Miao, K.-X. (2024). Research on Global Illegal Wildlife Trade Based on Integrated Optimization Methodologies. *Highlights in Science Engineering and Technology*, *115*, 230-236. https://doi.org/10.54097/r0v6np04