



Algorithmic Approach to Prescriptive Maintenance in Industry 4.0

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Abstract

Prescriptive maintenance extends predictive maintenance by not only forecasting potential failures, but also recommending concrete maintenance actions, explicitly accounting for operational, organizational, and resource-related constraints. Existing approaches in this area are often fragmented, as they typically focus either on technical diagnostics or on isolated optimization criteria, without integrating production schedules, resource availability, and organizational decision constraints into a unified decision-making framework. This creates a research gap in the integration of diagnostic and organizational data, thereby limiting real-time decision-making. The aim of this study was to develop and validate a hybrid prescriptive maintenance algorithm, combining fuzzy logic, neural network classification, and Analytic Hierarchy Process (AHP)-based scenario evaluation, aligned with the principles of Industry 4.0. The algorithm was implemented in MATLAB. A central design feature was the integration of sensor-based measurement data with organizational inputs to dynamically generate decision scenarios, accounting for time, cost, and resource constraints. This integration enabled the algorithm to consistently generate recommendations that respected budgetary and temporal constraints, demonstrating its effectiveness in translating combined technical and organizational data into actionable maintenance decisions. The algorithm was validated using real-world production data, achieving decision accuracy in the range of 94–99%, defined as consistency with expert-validated reference decisions, with a relative prediction deviation below 0.05%. It was further observed that when organizational and contextual data were not considered (such as production schedules, resource availability, and personnel qualifications), over 85% of the recommended maintenance scenarios deviated from the reference decisions determined based on realized production outcomes, with deviation assessed in terms of completion time and cost. The findings demonstrate that the developed prescriptive maintenance algorithm significantly improves decision accuracy, optimizes resource utilization, and reduces both downtime and operational costs, highlighting its practical impact and value for industrial maintenance management.

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1. Introduction

Maintenance (commonly referred to as MRO – Maintenance, Repair, and Overhaul) encompasses all technical, administrative, and managerial actions undertaken to retain or restore equipment functionality. It constitutes a critical component of industrial operations, directly influencing productivity, reliability, and competitiveness of manufacturing enterprises (Al-Najjar et al., 2004; Maletic et al., 2014). A well-organized maintenance strategy enables the minimization of downtime-related losses and enhances both resource efficiency and product quality (Azizi 2015; Al-Najjar et al.,

2018). According to the EN 13306:2010 standard (European Committee for Standardization, 2010), maintenance encompasses all technical, administrative, and managerial actions undertaken to retain or restore the functional condition of equipment to its required operating state.

Maintenance systems may take various organizational forms, ranging from unit-level to enterprise-wide implementations (Mosyurchak et al., 2017; Gerbert et al., 2015). In all cases, ensuring the required availability of production resources is essential, which can only be achieved through systematic assessment of their technical condition (Najjar, 2007;



Márquez et al., 2009). Effective maintenance is widely recognized as a key factor in reducing production losses and limiting the frequency of unplanned downtime to an economically acceptable level (Peres et al., 2018; Souza et al., 2020).

In industrial practice, the assessment of machine condition typically relies on measuring selected physical parameters, followed by detailed analysis – both quantitative and qualitative. These measurements are carried out using sensor arrays and control-monitoring modules, enabling continuous supervision of critical operating parameters (Ruppert et al., Forcina et al., 2020). The data collected in this manner provides the basis for identifying early signs of technical degradation and implementing preventive measures as part of the adopted maintenance policy.

Four main maintenance strategies are distinguished: reactive (failure-based response) (Legutko 2009), preventive (scheduled maintenance) (Kamat et al., 2020), predictive (failure forecasting based on data) (Grubisic et al., 2020; Zonta et al., 2020; Sajid et al., 2021), and prescriptive (action recommendations informed by operational context) (Choubey et al., 2020; Padovano et al., 2021; Meissner et al., 2021). Recently, prescriptive systems have been increasingly developed—not only predicting failure occurrences, but also recommending optimal response scenarios tailored to the company's operational landscape (Fusko et al., 2018).

The evolution of maintenance strategies is closely tied to successive industrial revolutions (Xu et al., 2018). The first industrial revolution relied on reactive repairs performed by machine operators. The second brought formalization of maintenance procedures and the emergence of dedicated maintenance departments. The third revolution enabled the implementation of predictive strategies through advances in sensing technologies and computer-based planning systems. Today, the fourth industrial revolution (Industry 4.0) integrates cyber-physical systems, the Internet of Things (IoT), big data analytics, and artificial intelligence, supporting the development of real-time prescriptive maintenance systems capable of recommending optimal actions (Wang et al., 2021; Ayvaz et al., 2021; Ayad et al., 2018).

The literature increasingly emphasizes the importance of integrating maintenance with production management systems. This perspective is consistent with the concept of global production systems, in which maintenance, production planning, and organizational decision-making are treated as interdependent elements of a unified operational strategy (Abele et al., 2008).

Synchronizing diagnostics with production schedules improves enterprise profitability and yields both economic and organizational benefits (Al-Najjar et al., 2016). The implementation of integrated maintenance strategies-via intelligent predictive and prescriptive systems powered by artificial intelligence-is regarded as the future of maintenance operations (Dinardo et al., 2018). Within this integrated perspective, real-time process monitoring plays a supporting role by enabling continuous alignment between equipment condition, production planning, and maintenance decision-making.

Despite technological advances and the availability of diagnostic tools, the implementation of prescriptive maintenance

strategies faces challenges related to data integration, lack of standardization, and insufficient adaptability to specific industrial contexts (Ansari et al., 2019). This underscores the need to develop decision-making algorithms that combine diagnostic data with the operational context of an enterprise (Grijalvo et al., 2020).

To address this gap, the present study introduces a decision-making algorithm for prescriptive maintenance, integrating sensor-based data with contextual information and employing artificial intelligence methods to generate alternative action scenarios. The model was validated using real-world data from a metalworking company, and the results confirm its effectiveness in producing budget- and time-compliant scenarios, ultimately enhancing process reliability and efficiency.

2. Literature review

The literature emphasizes the growing significance of artificial intelligence and Industry 4.0 in the field of maintenance; however, their practical application remains limited, and existing research does not fully explore the cognitive potential of these domains.

A systematic review of the available literature was conducted using two major databases – Scopus and Web of Science (WoS) – to identify key research directions associated with the development of maintenance concepts (Strozzi et al., 2017). The review revealed prominent thematic areas, core research trends, and major challenges faced by systems supporting prescriptive maintenance.

To define the scope of the analysis, the following search phrases were used: Prescriptive maintenance, Decision making, and Industry 4.0. The queries targeted article titles, abstracts, and author-defined keywords. Only peer-reviewed publications were included in the search. In total, 211 peer-reviewed scientific papers indexed in Scopus and WoS met the specified criteria.

Figure 1 presents a graph illustrating the number of publications over time. A clear upward trend is visible, particularly after 2020, indicating an intensification of research efforts focused on prescriptive maintenance within the context of Industry 4.0.

To visualize the collected data, a keyword co-occurrence analysis was conducted using the VOSviewer software. Two semantic networks were generated: a comprehensive map including all keywords appearing at least twice (Figure 2), and a reduced map limited to a curated set of the most significant terms (Figure 4).

At the center of the first visualization lies the term Industry 4.0, interconnected with other key concepts such as predictive maintenance, digital twin, maintenance, and smart factory. The density of linkages reflects a high degree of diversity and terminological dispersion within the examined research domain. Several conceptual clusters can be distinguished:

- the red cluster, encompassing topics related to digital modeling and simulation,
- the blue cluster, focused on Internet of Things (IoT) technologies and process optimization,

- the orange cluster, representing traditional maintenance approaches such as condition-based maintenance and reinforcement learning,
- the purple cluster, associated with distributed systems, semantic technologies, and decision-support systems.

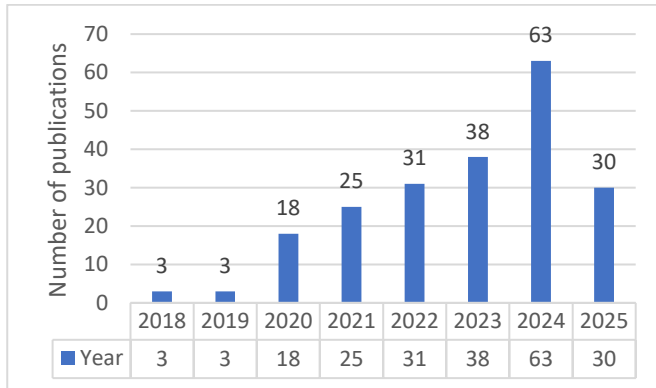


Fig. 1. Number of Publications from 2018 to 2025

Figure 3 presents the most frequently occurring keywords from the publications analyzed in Figure 2. The most prominent terms are Industry 4.0 (52 occurrences) and predictive maintenance (35), highlighting a strong association between the concept of the Fourth Industrial Revolution and intelligent methods for supporting the operation of production systems.

Other frequently occurring keywords include artificial intelligence (23), machine learning (22), and digital twin (21), confirming a clear research shift toward leveraging AI techniques, machine learning algorithms, and digital modeling as decision-support tools in maintenance strategies.

Notably, the presence of terms such as prescriptive maintenance (15), smart factory (10), sustainability (8), and decision making (7) indicates growing interest in predictive-prescriptive approaches augmented by decision-support mechanisms, particularly in the context of sustainability, automation, and alignment with Industry 5.0 paradigms.

Figure 3 further confirms that the research domain of prescriptive maintenance within the digital industrial environment is predominantly shaped by themes related to computational intelligence, digital twin modeling, and the correlation of cyber-physical systems with data analytics and decision-making.

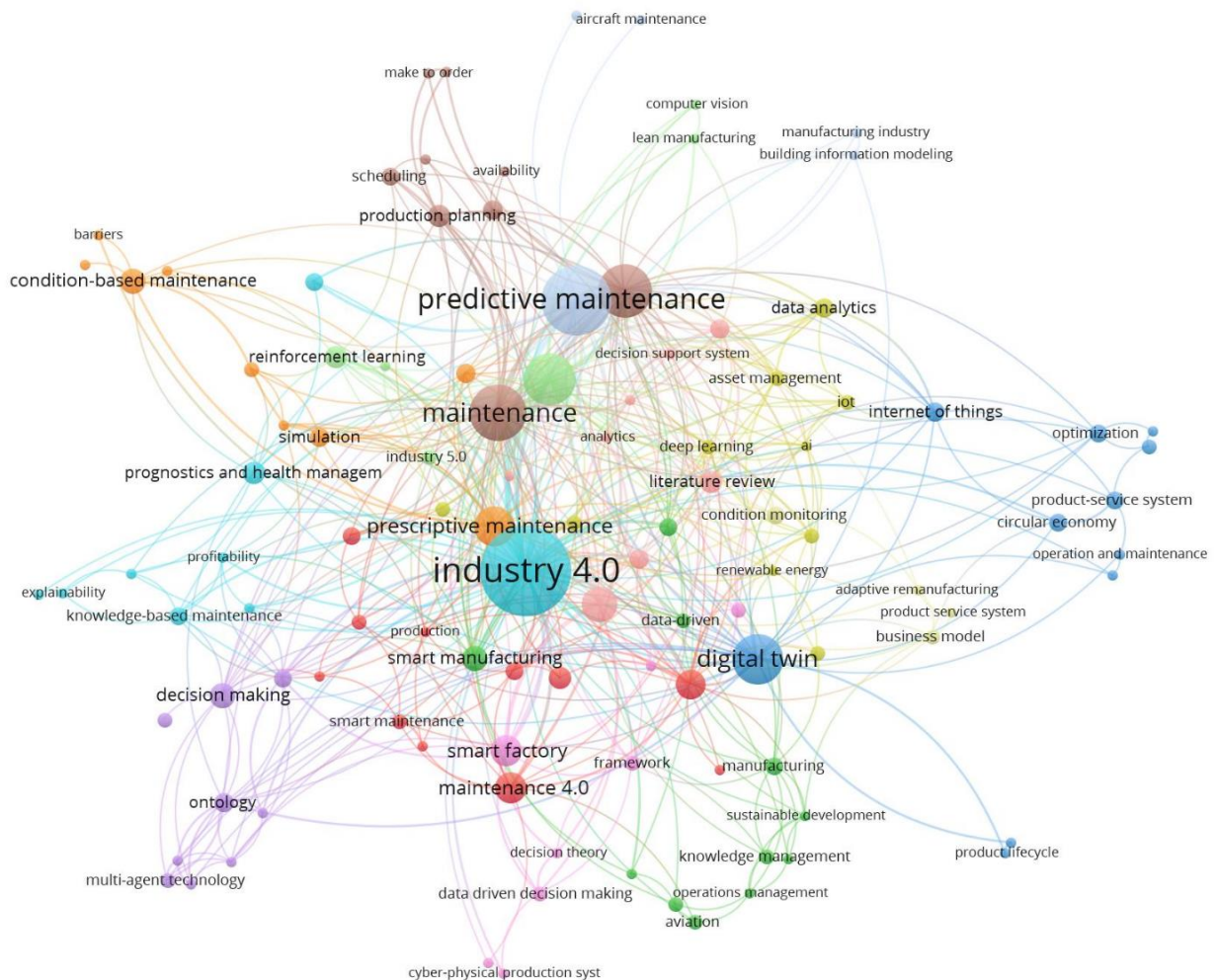


Fig. 2. Network map of all co-occurring keywords

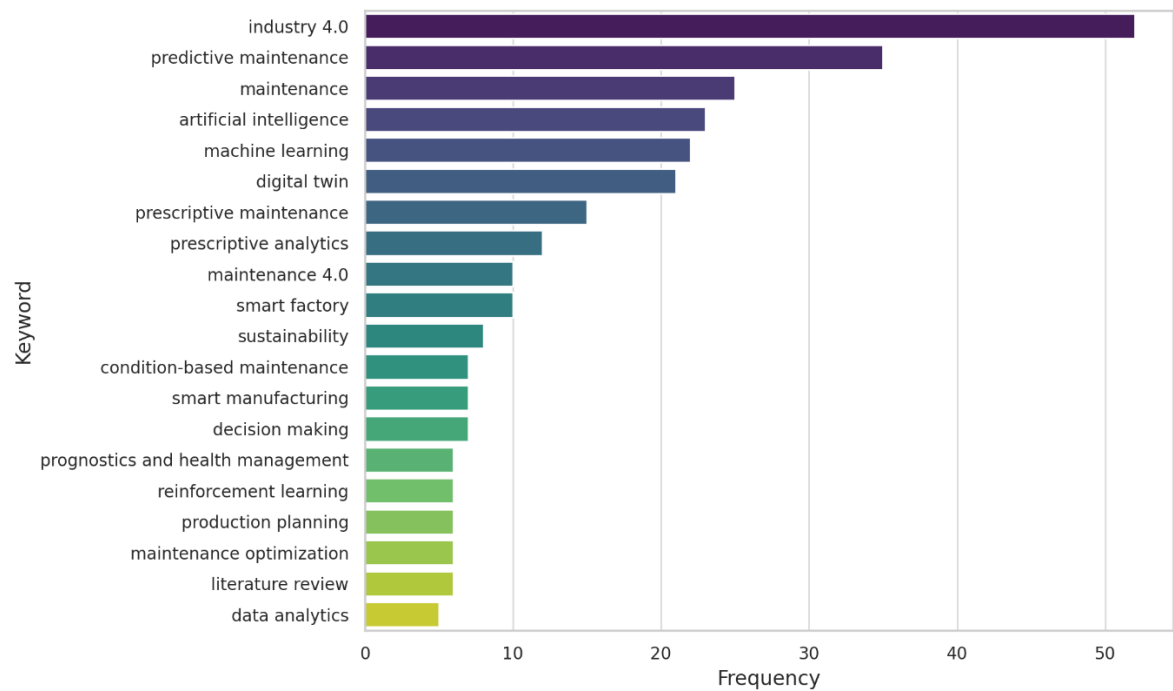


Fig. 3. Most frequently occurring keywords

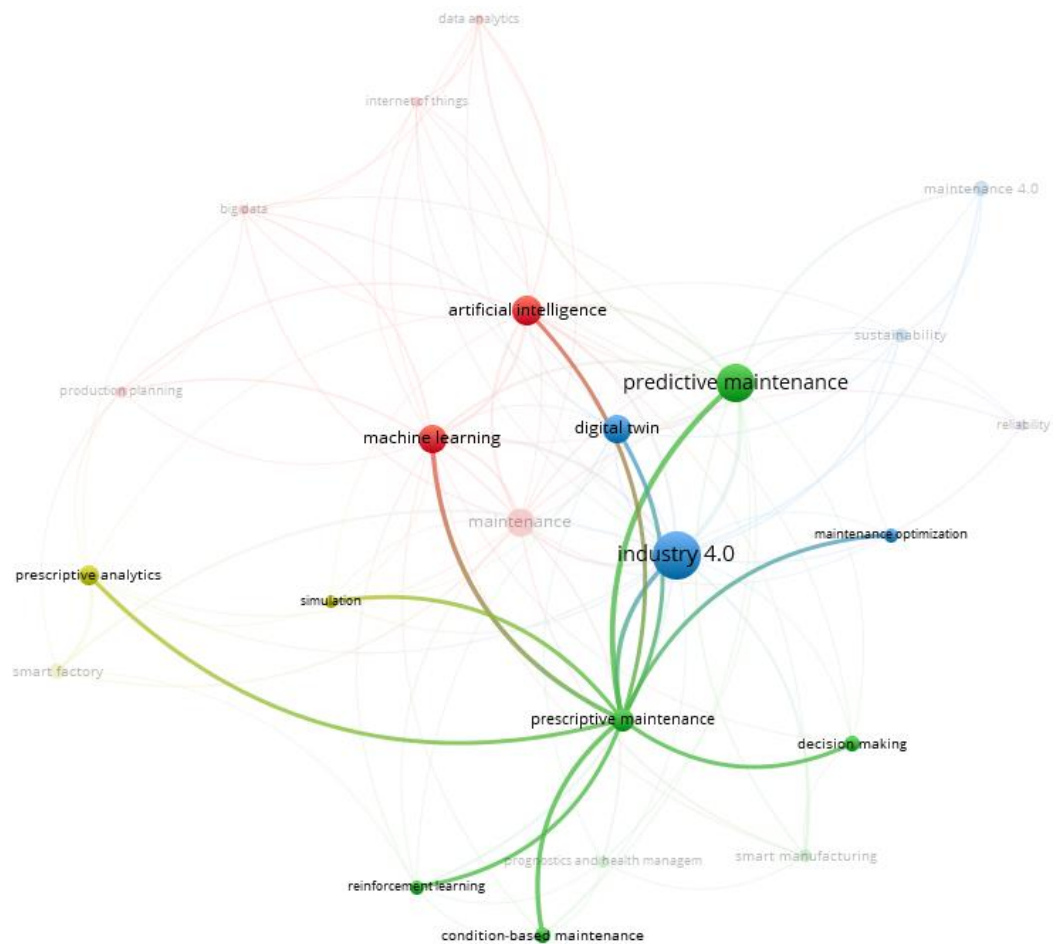


Fig. 4. Keyword map with a minimum occurrence threshold of 2

The second visualization presents a refined set of keywords, selected based on frequency criteria (threshold level 2). While Industry 4.0 remains at the center of the map, the overall network structure has been significantly simplified, enabling the identification of three main functional areas:

- computational intelligence, encompassing terms such as machine learning and artificial intelligence,
- integrated maintenance, represented by predictive maintenance, prescriptive maintenance, condition-based maintenance, and decision-making methods,
- digital infrastructure, with nodes such as digital twin and smart manufacturing, which serve as connectors between intelligent approaches and operational modeling.

The map presented in Figure 4 facilitates the identification of key concepts, relational structures, and research gaps within the examined topic area. An in-depth analysis of thematically selected publications enabled the classification of research domains (Table 1) and the formulation of emerging trends and research gaps. Additionally, recommendations for future research directions are provided.

A detailed analysis of the reviewed articles clearly indicates that the use of artificial intelligence and decision-support systems in maintenance management is both timely and relevant from cognitive and practical perspectives. Ongoing research encompasses machine learning, AI components integrated with decision-making systems, and digital twin models – all of which are rapidly evolving and shaping new directions in the design of flexible and adaptive maintenance systems. The findings also demonstrate that implementing Industry 4.0 concepts not only enables the forecasting of pre-failure events but also supports the recommendation of specific action scenarios that take into account the internal environment of the enterprise.

Table 1. Literature overview by research domain, keyword, trends, research gaps, and future research directions

Research domain	Keywords	Key trends identified in the literature	Research gaps	Opportunities for development / future research
Predictive maintenance in manufacturing	Predictive Maintenance, Condition Monitoring, Fault Detection, Predictive Analytics, Maintenance Optimization	Use of machine learning for real-time monitoring of equipment condition.	Limited quality of available datasets and underrepresentation of unstructured data sources.	Integration of textual data with sensor-based inputs; development of XAI models to improve algorithm transparency.
Prescriptive analytics and decision support	Prescriptive Analytics, Decision Support Systems,	Implementation of advisory systems; real-	Lack of models incorporating socio-technical context	Design of adaptive systems with dynamic optimization of decision-

	Reinforcement Learning, Adaptive Optimization, Maintenance Strategy Planning	world applications; real-time decision process analysis.	and decision-making system components; difficulties in scaling current solutions.	making processes; application of reinforcement learning in MRO environments.
Artificial intelligence in maintenance	Artificial Intelligence, Federated Learning, Transfer Learning, Anomaly Detection, Ai-Based Maintenance	Application of AI in distributed data analytics; reduction of latency and computational resource usage.	Absence of unified AI standards; insufficient development of model lifecycle management methods.	Use of transfer learning and federated learning approaches for model updates.
Digital twin and smart infrastructure	Digital Twin, Smart Infrastructure, IoT-Enabled Maintenance, Cyber-Physical Systems, Semantic Data Models	Integration of digital twin with AI and IoT technologies.	Lack of standardized real-time data analysis frameworks; absence of unified data exchange protocols.	Development of interdisciplinary semantic models; advancement of Digital Twin 5.0 concepts with predictive and adaptive functionalities.

Source: 1 - Predictive maintenance in manufacturing: (Zonta et al., 2020; Ansari et al., 2019; van Dinter et al., 2022; Ucar et al., 2024; Pincirolì et al., 2023; Zonta et al., 2022; Ruiz Rodriguez et al., 2022; Nemeth et al., 2018; Shahin et al., 2023; Shaheen et al., 2022; Zhao et al., 2022; Rousopoulou et al., 2022; Zhang et al., 2021; Wang et al., 2021; Mallioris et al., 2024; Kaur et al., 2018; Kaur et al., 2018), 2 - Prescriptive analytics and decision support: (Ansari et al., 2019; Shahin et al., 2023; Mallioris et al., 2024; Lepenioti et al., 2020; Silva et al., 2021; Sheng et al., 2021; Consilvio et al., 2020; Longo et al., 2023; Liu et al., 2019), 3 - Artificial intelligence in maintenance: (Zonta et al., 2020; Zonta et al., 2022; Rousopoulou et al., 2022; Wang et al., 2021; Kaur et al., 2018; Cohen et al., 2021; Casini 2021; Peres et al., 2020; Bueno et al., 2020), 4 - Digital twin and smart infrastructure: (Ucar et al., 2024; Errandonea et al., 2020; Bueno et al., 2020; D'Amico et al., 2022; Hazrathosseini et al., 2023; Longo et al., 2023; Wang et al., 2021; Cohen et al., 2021; Piron et al., 2024)

The literature also reveals significant research gaps. In particular, there is a lack of comprehensive decision-making models that integrate all relevant analytical methods while aligning with the operational requirements of modern enterprises and the technological capabilities of Industry 4.0. These challenges include data integration from heterogeneous sources, process standardization, and the adaptation of solutions to the organizational specificity of individual facilities. The presented literature review confirms that the development of a decision-making algorithm for prescriptive maintenance

– one that incorporates both diagnostic data and the operational context – remains a critical area of research and is well aligned with current scientific trends.

3. Research methodology

The existing literature on prescriptive maintenance typically addresses the subject from a theoretical perspective or offers only a general outline of algorithmic operations. Relatively few studies attempt to apply these solutions in practical industrial contexts. For this reason, the author of this study undertook the development of a functional prescriptive maintenance algorithm and evaluated its performance under real-world industrial conditions. The dataset and the implementation code are restricted due to confidentiality agreements with the industrial partner and cannot be publicly released, ensuring compliance with company policies and protection of sensitive operational information.

The first step involved designing the decision-making framework of the algorithm, aimed at supporting corrective actions in maintenance operations. The algorithm comprises four decision-making paths that encompass monitoring, diagnostics, prediction, and prescription. The overall structure is illustrated in Figure 5, and its operation follows a seven-step sequence:

1. Data input: Import diagnostic data (D_diag) and contextual data (D_kont) from the current production cycle.
2. Fuzzy logic processing: Analyze D_diag using fuzzy inference rules to determine the failure risk level.
3. Neural network classification: Feed data into a neural network to classify the technical condition of equipment.
4. Scenario generation: Produce potential maintenance scenarios (e.g., repair, deferral, scheduled maintenance).
5. Scenario evaluation using FAHP, based on the following criteria:
 - Downtime duration,
 - Intervention cost,
 - Availability of personnel/materials,
 - Production schedule,
 - Equipment criticality.
6. Scenario prioritization: Rank the scenarios based on their computed priority scores.
7. Output: Generate the final output as a ranked list of recommendations (Lista_R).

where:

- D_diag – diagnostic data: real-time technical parameters of machines (e.g., temperature, vibration, operating time).
- D_kont – contextual data: availability of human and material resources, production schedules, and decision-making priorities.
- Lista_R – algorithm output: a list of possible maintenance scenarios with assigned priority levels.

All decision paths rely on a common set of input and database resources.

The developed prescriptive maintenance algorithm employs an integrated hybrid approach composed of three core components: technical diagnostics, equipment condition classification, and multi-criteria evaluation of maintenance scenarios.

The fuzzy logic module was designed to perform an interpretable diagnostic assessment of machine condition based on measured technical parameters. The input variables of the fuzzy inference system consisted of selected diagnostic indicators obtained from the monitoring layer, including vibration level, temperature, operating time, and failure-related historical indicators such as mean time between failures. These variables were treated as continuous inputs and normalized to a common range prior to inference.

The output variable of the fuzzy system was defined as the machine condition risk level, expressed as a linguistic variable with three states: low, medium, and high. For all input and output variables, triangular and trapezoidal membership functions were applied to represent gradual transitions between diagnostic states.

Inference was performed using a Mamdani-type rule-based system. The rule base combined multiple diagnostic symptoms to infer the overall risk level of technical degradation. Defuzzification was carried out using the centroid (center of gravity) method, resulting in a crisp risk value. The parameters of the membership functions and the structure of the rule base were adjusted empirically during system testing, based on consistency between inferred risk levels and observed machine behavior in real industrial conditions.

The defuzzified output was forwarded to the subsequent classification and decision-support modules as a quantitative representation of failure risk.

For full replicability, the fuzzy system employed the following parameters: triangular membership functions were defined with vertex points at 0–0.3–0.6 for low, 0.4–0.6–0.8 for medium, and 0.7–1.0–1.0 for high variables. Trapezoidal membership functions for selected indicators were set with lower and upper bounds determined from historical minimum and maximum sensor readings. The rule base included 18 empirically defined rules linking combinations of vibration, temperature, and operating time to risk levels; an example rule is: IF vibration is high AND temperature is medium THEN risk is medium. Prior to fuzzy evaluation, all diagnostic signals were preprocessed with a Daubechies-4 wavelet transform to extract time–frequency features relevant to early degradation.

The neural network module was used to classify the technical condition of equipment based on diagnostic data. A multilayer perceptron (MLP) architecture was employed, consisting of an input layer, two hidden layers with 10 neurons each, and an output layer representing machine condition classes.

The input dataset consisted of historical diagnostic measurements collected from machines of the same type operating within a single production cell. The target label was defined as the technical condition state of the machine, derived from maintenance documentation and inspection outcomes, distinguishing normal operation from degraded or pre-failure states.

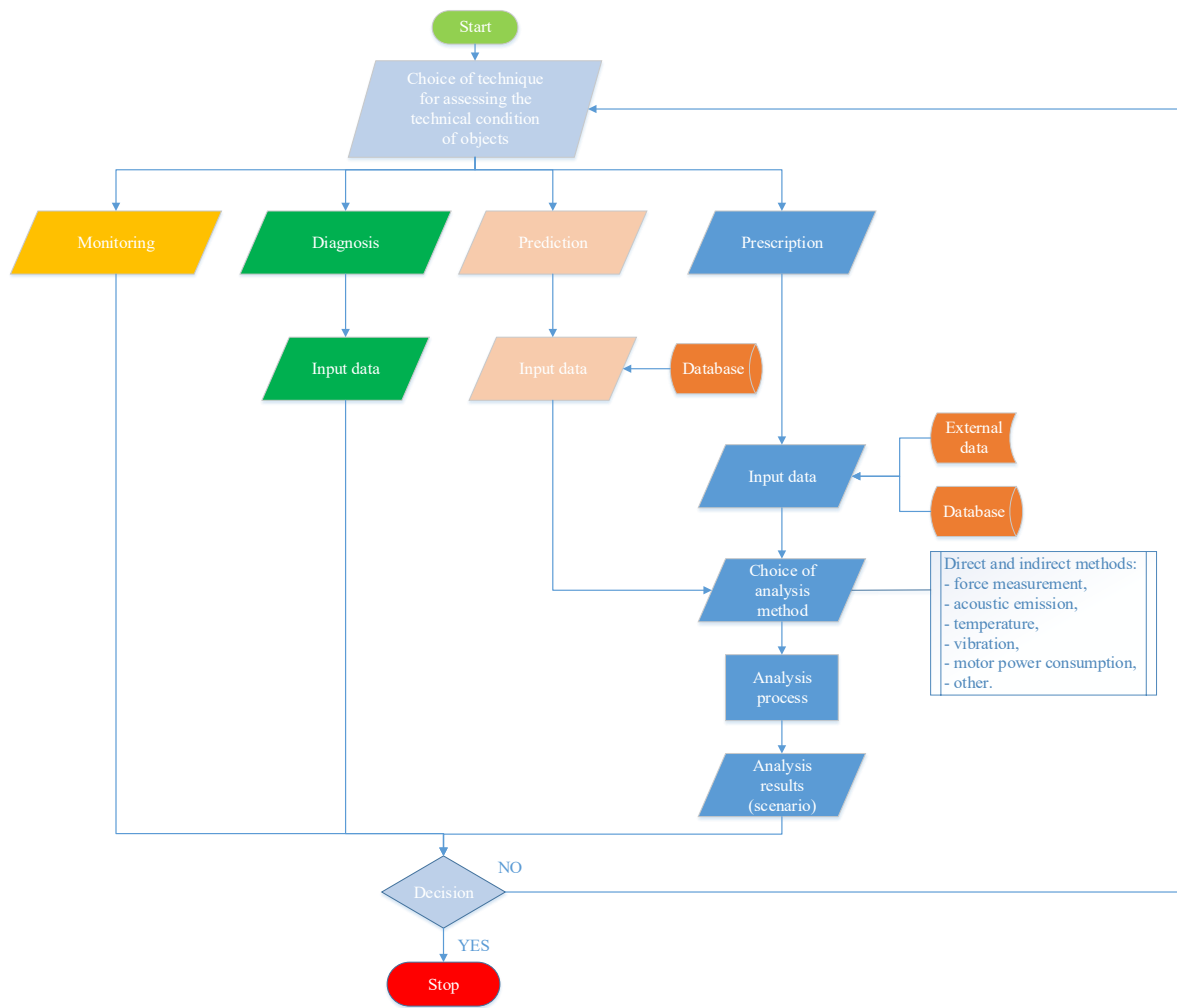


Fig. 5. Decision-making algorithm for prescriptive maintenance

Prior to network training, the diagnostic signals were subjected to preprocessing. This included normalization and feature extraction supported by wavelet-based signal analysis. The wavelet analysis was applied to enhance sensitivity to localized changes in the signal and to extract time–frequency features relevant for early degradation detection. The extracted features were subsequently used as inputs to the neural network.

The dataset was divided into training and validation subsets. Network training was conducted using the backpropagation algorithm. The available diagnostic dataset was partitioned into a training subset used for parameter adaptation and a validation subset used for monitoring generalization performance during learning. Model training was performed using an iterative gradient-based optimization procedure implemented in the MATLAB environment, minimizing a classification error-based loss function. The learning process was terminated based on stabilization of validation performance, i.e., when further iterations did not yield a measurable improvement in classification consistency. The purpose of the neural network module was not to achieve optimal predictive performance in

the machine learning sense, but to provide a robust and consistent classification input for the subsequent prescriptive decision-making stage.

In the neural network module, the dataset split was 70% for training and 30% for validation. The network used a learning rate of 0.01, momentum of 0.9, and mean squared error as the loss function. Training proceeded for a maximum of 500 epochs with early stopping triggered when validation loss did not improve for 20 consecutive epochs. Performance metrics during training included classification accuracy per class and confusion matrix evaluation to verify stability across machine-condition categories. Wavelet decomposition applied a Daubechies-4 mother wavelet, level 3 decomposition, capturing time–frequency features relevant for early fault detection.

These parameter ensure the methodology can be independently reproduced while remaining consistent with industrial confidentiality constraints.

The loss function was defined as classification error, and the learning process was continued until convergence of the error was observed. Training was terminated when further iterations no longer resulted in performance improvement on the validation subset.

Model performance was evaluated by comparing network outputs with known machine condition states.

The fuzzy logic module provided a continuous assessment of failure risk, while the neural network delivered a discrete classification of machine condition. Both outputs were integrated within the prescriptive maintenance algorithm and served as inputs to the FAHP-based scenario evaluation module. This integration enabled the generation and prioritization of maintenance scenarios while accounting for technical, organizational, and economic constraints.

To validate the proposed assumptions and test the algorithm's functionality, a software tool – MDPPur – was developed in the MATLAB environment (Figure 6).

As part of the study, interviews and diagnostic assessments were conducted in selected manufacturing companies located in the south-western region of Poland. The objective was to evaluate the current state of maintenance practices, their organizational context, and the demand for decision-support tools.

The analysis focused exclusively on machines that were similar in function, complexity, operating costs, and reliability. The selected group consisted of equipment of the same type, located within a single production cell. These machines exhibited a medium level of operational wear, as confirmed by historical data on inspections, failures, and annual maintenance costs.

Based on the findings from this diagnostic phase, a dataset was compiled and used as input for algorithm testing. It included both process-related data (e.g., routing information, operation times, availability of resources and tools, performance metrics) and external contextual data (e.g., machine costs, estimated task completion times, availability of maintenance staff and spare parts, average repair times, and logistical constraints).

Ultimately, the developed algorithm – together with the MDPPur software – was validated in real production conditions. The tests confirmed its effectiveness in detecting pre-failure states and supporting decision-makers in selecting the most optimal production path.

4. Algorithm validation and research findings

Decision accuracy was defined as the percentage of cases in which the maintenance scenario recommended by the algorithm was consistent with the reference decision (ground truth). The reference decision was established based on the scenario actually implemented in the production system and subsequently validated by maintenance and production experts as the most appropriate under given technical and organizational constraints.

For the validation dataset consisting of 72 machine-month decision instances (six machines observed over a 12-month period), the proposed prescriptive maintenance algorithm achieved a decision accuracy ranging from 94% to 99%. This corresponds to 68–71 correct recommendations out of 72 evaluated cases, where correctness was defined as agreement between the top-ranked algorithm-generated scenario and the expert-validated reference decision.

To verify the performance of the developed algorithm, a validation process was carried out under real industrial conditions. The study was conducted in selected manufacturing companies located in the south-western region of Poland. The analysis focused on machines of the same class, situated within a single production cell – similar in terms of function, age, and operating costs.

The selected group was characterized by a medium level of wear and failure frequency, as determined by equipment age and usage indicators (see Table 2). This approach allowed the identification of a representative enterprise, whose equipment shared the highest number of common features, thereby enabling effective validation of the proposed model.

The selection of this specific machine group was necessitated by the overall heterogeneity of the machinery stock, which precluded the application of a uniform methodology across all assets.

The test dataset comprised operational data from six machines (M31–M36) of the same type within a single production cell over a 12-month period ($n = 72$ machine-months). Data included diagnostic signals (vibration, temperature, operating time) and contextual information (maintenance costs, resource availability, production schedules, and estimated repair times).

An operational analysis of the test group of machines (Table 2) confirms the representativeness of the selected equipment in terms of age, complexity, operating costs, and reliability.

Table 2. Fault values of analysed equipment over 12 months

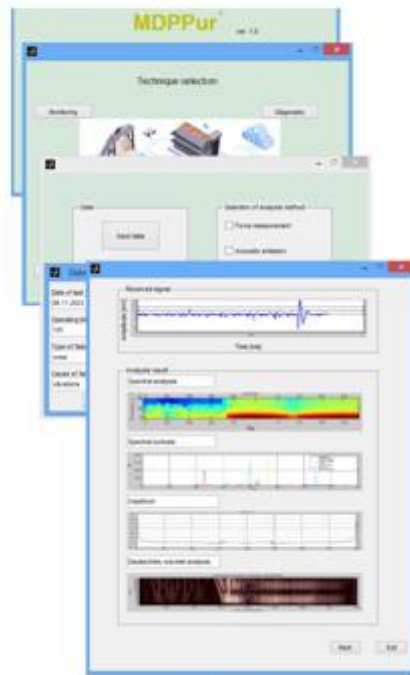
		Eq uip me nt age	Annual number of inspections planned	Annual num- ber of failures	Annual failure cost [EUR]	Failure duration [h per year]
Machines	M31	5	2	4	4000	52
	M32	4	2	5	3800	28
	M33	5	2	2	400	49
	M34	6	3	6	6700	80
	M35	5	2	3	400	8
	M36	5	2	4	700	15
	Average	5	2,17	4	2666,7	38,7

The average number of failures over a 12-month period was four per machine, with an average failure-related cost of approximately €2666,7 and an average downtime of 38,7 hours. This level of utilization provides a suitable basis for algorithm validation and supports the practical applicability of the developed model.

One issue that could not be determined during the analysis was the specific impact of individual equipment failures on the overall production process – such as delays or additional project costs – due to a lack of corresponding data within the surveyed organizations.

To test the algorithm, an input dataset was prepared to reflect real-world operating conditions of the selected resource group. The use of realistic input allowed for a comprehensive system-level analysis and optimization of maintenance-related decisions.

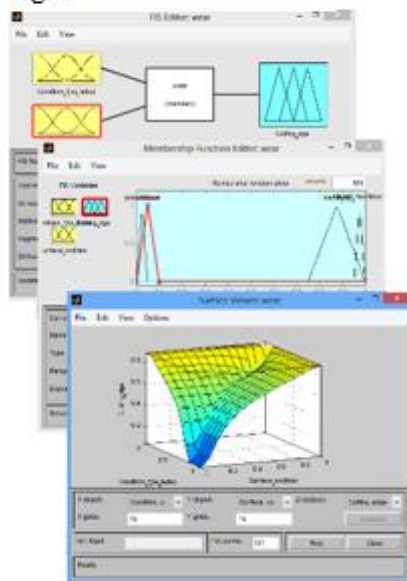
Program MDPPur



Signal analysis using a neural network



Signal analysis using fuzzy logic



Signal analysis using AHP and FAHP

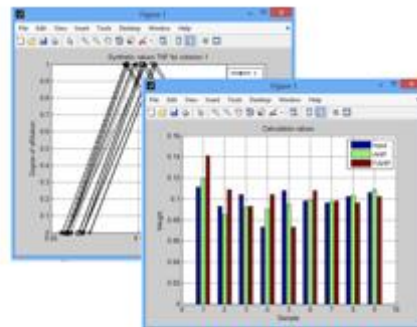


Fig. 6. Example of the operation of the decision-maker's supporting algorithm in MDPPur

The validation of the developed algorithm was carried out both under simulation conditions and directly in an industrial production environment. In the initial testing phase, the algorithm was executed without implementing any corrective actions – resulting in a failure of the machine's support bearing on the table drive. This event validated the algorithm's ability to accurately predict pre-failure conditions.

Subsequent testing phases involved deploying the algorithm in actual production settings. Measurement data were collected indirectly via vibration sensors mounted on the table

drive's support bearing, identified as a critical component responsible for the highest failure rates.

Using the prescriptive analysis module, the algorithm generated five alternative production scenarios (Figure 7). The pre-failure condition was identified based on the onset of degradation, determined through historical test data. The scenario marked in green demonstrated the smallest deviation from the target project parameters – only a 10% cost deviation and 4% deviation in execution time. In contrast, the red scenario showed significant deviations, with 32% and 19% variances

in cost and time, respectively. The remaining three scenarios, marked in light green, purple, and yellow, represented intermediate values – offering decision-makers flexibility in selecting an optimal strategy that matches the current production context and resource availability.

A comparison of the generated scenarios with the original production routing (Table 3) revealed that Scenario S1 (marked in green) exhibited the smallest deviation from the designed workflow. This finding was further confirmed during its implementation in real industrial conditions. Execution of this scenario resulted in an 11.3% increase in order completion time and a 3.8% rise in production costs.

Table 3. Overview of scenarios with a designed manufacturing pathway

		Workstation										
		W 1	W 2	W 3	W 4	W 5	W 6	W 7	W 8	W 9	W 10	W 11
Designed production path	SZ	2	3	4	3	2	5	5	2	2	1	2
	Scenario	2	3	5	3	3	5	6	3	3	1	2
Scenario	S1	2	3	6	6	3	5	2	2	3	1	1
	S2	2	3	3	2	4	5	6	3	2	1	2
	S3	2	3	2	4	4	3	5	3	1	1	1
	S4	2	3	1	3	2	3	1	2	1	1	1
	S5	2	3	1	3	2	3	1	2	1	1	1

The reported deviations in cost and execution time refer to two different evaluation stages and are therefore not directly comparable. The values of 10% cost deviation and 4% time deviation correspond to the scenario-based prescriptive analysis illustrated in Fig. 7 and represent relative deviations of alternative scenarios with respect to the designed production parameters, calculated at the scenario evaluation stage. In contrast, the values of 3.8% cost increase and 11.3% time increase refer specifically to Scenario S1 after its implementation in real industrial conditions, as reported in Table 3. These values represent observed relative differences between the executed scenario and the originally designed production path (SZ). In all cases, deviations were calculated as relative percentage differences with respect to the designed production path, which served as the reference baseline. No averaging across scenarios was applied. The reported values correspond to individual simulated scenarios generated by the prescriptive algorithm (Fig. 7) or to a single implemented scenario (S1) evaluated under real production conditions.

These deviations fall within an acceptable range, attributable to factors such as approximations in the input data and inherent variability in production environments. Under the given circumstances, the observed values are considered satisfactory and validate the practical relevance of the algorithm's recommendations. Running the algorithm in the MATLAB environment enabled the generation of corrective action scenarios for the analyzed domain. The results were presented as a set of recommended production scenarios that accounted not only for the technical condition of the equipment, but also for relevant organizational and economic constraints. Based on these outputs, decision-makers were able to select the most optimal maintenance strategy.



Fig. 7. Production scenarios generated via prescriptive analysis

The validation results confirmed both the logical consistency and practical applicability of the algorithm. Due to the specificity of the dataset and the operational context, direct comparison with other prescriptive maintenance methods was not feasible. The study focused on validating the algorithm under real industrial conditions, ensuring practical relevance and demonstrating the improvement in decision accuracy through integration of technical and organizational data. The generated scenarios aligned closely with real-world conditions observed in the studied enterprises and effectively incorporated critical constraints related to resource availability and the organizational-technical environment.

The reported prediction error below 0.05% refers to the maximum relative deviation between the predicted and the observed onset of a pre-failure condition, estimated from historical operational data. This value does not represent a classical regression error metric, but a relative deviation used to assess temporal consistency between predicted and observed degradation events.

It was also observed that including additional external data – such as spare parts availability or personnel qualification levels – significantly improved the accuracy of recommendations, compared to traditional approaches that rely solely on technical condition monitoring.

To evaluate the impact of omitting contextual data (e.g., production schedules, resource availability, and personnel qualifications), a subset of the validation dataset was analyzed. This subset comprised 30 distinct production cycles selected from the total 72 machine-month observations, ensuring representation across all machines and operational conditions. Within these 30 cycles, 85% of the maintenance scenarios generated without contextual information did not match the reference decisions validated by experts. Each deviation was quantified in terms of cost and production time, confirming that the absence of contextual inputs led to suboptimal recommendations. This analysis demonstrates that inclusion of organizational and operational context is critical for accurate prescriptive decision-making, and clarifies the relationship between the smaller sample (30 cycles) and the full validation dataset (72 machine-months). The deviations occurred primarily in cases with simultaneous resource constraints or unexpected machine load variations. In emergency situations, production path decisions were often made without considering economic viability or resource availability, resulting in further delays and inefficiencies.

Here, machine-month instance refers to a single decision event for a given machine in a specific production month, while production cycle aggregates all six machines for one month. The 30 cycles correspond to 30 months of combined observations, covering all 72 machine-month instances evaluated.

In this context, the proposed prescriptive maintenance algorithm – together with its implementation in the MDPPur software – can serve as a valuable tool for enhancing maintenance efficiency, reducing production delays, and optimizing both cost and lead time in manufacturing operations.

The objective of the validation was not to evaluate a predictive model, but to verify the correctness of prescriptive decisions generated under real industrial conditions. Therefore, standard classification and regression performance metrics (such as Accuracy, F1-score, AUC, MAE, or RMSE) were not reported, as the algorithm does not output discrete class labels or continuous target variables, but ranked decision scenarios. Each evaluated case corresponded to a single machine-month decision instance, for which exactly one reference scenario was defined, ensuring one-to-one correspondence between algorithm output and expert-validated ground truth.

5. Summary and conclusion

This article presented the concept and practical implementation of a prescriptive maintenance algorithm within the context of Industry 4.0. The primary aim of the study was to develop and validate a decision-making algorithm that integrates both technical and organizational data. The literature review confirmed the relevance and necessity of such data integration in the design of prescriptive systems.

The proposed decision-support algorithm, implemented in the MATLAB environment, directly addresses this identified gap. It was designed not only to detect pre-failure states but also to generate actionable prescriptive maintenance scenarios based on real-world data – both technical and organizational. The use of artificial intelligence methods provided the algorithm with flexibility and adaptability to a variety of operational conditions.

Experimental results validated the algorithm's effectiveness. For the scenario deemed most optimal, the deviation from the planned production time was 11.3%, while the cost deviation was only 3.8%, both within acceptable tolerance levels defined by the host enterprise. It was also found that neglecting organizational factors (e.g., staff qualifications, spare parts availability) led to incorrect decisions in more than 85% of cases. This clearly demonstrates that integrating technical and organizational data significantly improves the accuracy of maintenance decisions. Nevertheless, certain limitations of the proposed approach were identified. The algorithm's effectiveness depends on the availability of up-to-date data and stable technological conditions. Some potential action scenarios were not generated when acceptable deviation thresholds were exceeded, limiting the adaptability of the model.

Future work will focus on expanding the algorithm by incorporating adaptive methods and fractal analysis techniques. Additional external variables will be included in the data model, and the scope of testing will be broadened to cover more assets and maintenance strategies, enhancing the tool's utility across various industrial domains.

Overall, the findings confirm that integrating technical and organizational data improves maintenance decision accuracy and aligns with the guiding principles of Industry 4.0.

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