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PROCEEDINGS

Edited by
Simone Arena, University of Cagliari, IT
Irene Roda, Politecnico di Milano, IT
Alexandre Voisin, University of Lorraine, FR
Ajith Kumar Parlikad, University of Cambridge, UK
Christos Emmanouilidis, University of Groningen, NL

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FOREWORD

According to technological and market analyses and forecasts, maintenance and asset lifecycle management have grown in significance and are expected to continue strengthening, driven by their increasing contribution to industry and society. With predictive maintenance acknowledged as among the prime use cases of the accelerating technological change brought by Industry 4.0, and with lifecycle engineering, management, and associated services recognised as key contributors to sustainability and resilience across sectors as diverse as public infrastructure, manufacturing, transportation and logistics, aerospace and defence, energy and utilities, and healthcare, the field receives heightened attention from scientific and industrial communities. Activities across the lifecycle of physical assets, including design, operation, maintenance and end of life management are increasingly seen less as cost contributors but as essential value adding processes. It is within this global context that the 6th IFAC Workshop on Advanced Maintenance Engineering, Services, and Technology (AMEST2024) was held, bringing together international experts from academia and industry to present and debate the latest advances in Maintenance and Asset Lifecycle Management in support of the transition to sustainable, human-centric and resilient industrial systems, aligned with Industry 5.0 aims.

The distinguished role of digitalization and interoperability in the field was highlighted by three inspiring keynotes on “digital transformation in maintenance and asset management”, on “modular and adaptive field – level automation architectures to support predictive maintenance”, and on “ontology-based asset information modelling for predictive maintenance”. The keynotes offered an excellent overarching setting for a series of sessions covering thematically the latest advancement in the field, as follows:

- **Digital Twins for Maintenance Applications**, focused on the application of digital twin concepts and associated technologies across various industries including railway, manufacturing, energy, and steel manufacturing. This theme explored how digital twins can support decision-making covering regulatory compliance, integrated maintenance and energy decision-making, ontology-based decisions, and joint planning for maintenance and production.
- **Artificial Intelligence for Maintenance and Asset and Product Lifecycle Management** highlighted how the rapidly advancing field of AI contributes to improving maintenance and extending the asset lifespan. In particular, contributions presented AI methods applied to quality control, fault diagnosis, and zero-defect manufacturing applications.
- **Maintenance Strategies, Simulation, and Optimization of Complex Systems** included contributions on strategies, methodologies, and solutions for optimizing maintenance processes, such as business intelligence applications for maintenance, lifecycle cost analysis, smart maintenance, and optimizing maintenance strategies post-COVID. It also covered simulation techniques and their applications in various maintenance scenarios.
- **Reliability, Dependability, and Risk-Based Approaches** addressed dependability analysis models, alarm dynamics frameworks, reliability-centered maintenance, risk-based vs. time-based maintenance, and optimization models, targeting and showing benefits for manufacturing and infrastructure sectors.
- **Industry 5.0, Human Factors, Education, and Skills in Maintenance** emphasized new approaches for competencies building in maintenance, the use of augmented reality solutions, decision support systems for Industry 5.0, and integrating machine learning into educational activities. It also discussed sustainability and human factors in maintenance management.
- **Digitalization for Asset and Product Lifecycle Management** explored Internet of Things (IoT) platforms in asset management digitalization, predictive failure modeling, and efficiency improvements in maintenance operations. It also covered the integration of Building Information Modelling (BIM) with digital twins, interoperability testing, and the application of cyber-physical systems for inspection.
- **Prognostics and Health Management, Condition-Based Maintenance, and Condition Monitoring** was another discussed topic**.** This theme covered adaptive learning methods for machine tool prognostics, collaborative frameworks for anomaly detection, data-driven fault detection techniques, and enhanced feature extraction for sensor fault detection.

- **End of Life Management of Complex Systems** addressed strategies for managing the end of life of products and assets. This comprised contributions on decision-making approaches for end-of-life management, impacts of obsolescence and shortages and their management, circular product designs, and resilience strategies to extend the lifespan of complex systems.
- **Product-Service Systems for Maintenance and Asset Management** focused on the design of smart product-service systems, the use of smart devices in remote maintenance, predictive maintenance servitization, and requirements for digital servitization in asset lifecycle management.
- **Resilience and Sustainability** in maintenance covered methodologies for economic and environmental sustainability in maintenance decision-making, resilience in hydrogen terminals, spare parts planning, emerging technologies for sustainability, and broadly Industry 4.0 frameworks for Maintenance (Maintenance 4.0).
- **Maintenance, Product, and Asset Lifecycle Management** targeted the need and introduced methods for investment evaluation in condition monitoring, current and future trends in asset performance management, efficient spare parts management, decision-making frameworks, digitalization in the energy sector, and predictive modelling for for road infrastructure.

The workshop successfully pursued the cross-fertilisation of ideas in the above areas by bringing together support from highly relevant scientific and industrial communities. Specifically, it was fully supported and sponsored by the IFAC TC 5.1. Manufacturing Plant Control, and co-sponsored by TC 5.2. Management and Control in Manufacturing and Logistics, TC 5.3. Integration and Interoperability of Enterprise Systems (I2ES) and TC 6.4. Fault Detection, Supervision & Safety of Technical Processes – SAFEPROCESS, the workshop was also supported by the International Federation for Information Processing (IFIP) WG5.7 Advances in Production Management Systems, the Prognostics and Health Management (PHM) Society, and the European Safety and Reliability Association (ESRA).

The papers presented at AMEST2024 brought a diverse range of topics that reflect the forefront of research and innovation in maintenance and asset management. Central themes included the transformative role of digital twins and artificial intelligence in optimizing maintenance strategies, enhancing reliability, and integrating advanced predictive models. The focus on digitalization, including IoT platforms and cyber-physical systems, underscores the drive towards smarter and more efficient operations. Human factors and Industry 5.0 highlight the critical importance of skills development and human-centricity in modern maintenance practices. Sustainability and resilience are pivotal, emphasizing the need for environmentally conscious and economically viable solutions. Finally, the integration of product-service systems and effective end-of-life management strategies showcases the holistic approach required for robust asset lifecycle management. Together, these themes illustrate a comprehensive vision for the future of maintenance and asset management, driven by innovation, digitalization, and a commitment to sustainability practices.

The Editors

Simone Arena, University of Cagliari
Irene Roda, Politecnico di Milano
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Christos Emmanouilidis, University of Groningen

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Maintenance lifecycle cost analysis through Agent-Based Simulation

Roberto Sala *, Fabiana Pirola*, Veronica Arioli*, Emanuele Dovere*

*Department of Management, Information and Production Engineering, University of Bergamo, via Marconi 5, 24044 Dalmine (BG), Italy (e-mail: roberto.sala@unibg.it, fabiana.pirola@unibg.it, veronica.arioli@unibg.it, emanuele.dovere@guest.unibg.it)

Abstract: Proper maintenance management allows companies to reduce failures and breakdowns while keeping high asset productivity. Several variables and uncertainties affect the selection of the optimal maintenance policy, and the one that might seem more cost effective in the short-term, might reveal having a total higher cost over the complete asset lifecycle. In this sense, the use of simulation to quantify the maintenance costs over the entire asset lifecycle can be helpful, allowing companies to test different scenarios and compare their result in a dynamic way, looking at long-term effects instead of short-term ones. The paper proposes an agent-based simulation model that allows to quantify the total costs associated with different maintenance policies, as well as computing productivity and important maintenance indexes to help companies in evaluating the most suitable maintenance strategy, being it used internally, or as a selling point for maintenance services towards customers.

Keywords: maintenance; cost; total cost of ownership; TCO; simulation; agent-based simulation; service.

1. INTRODUCTION

Recently, the increased competitiveness of the market forced companies to improve their operations to reduce failures, contain costs, increase safety, effectiveness, and efficiency of the assets, transforming maintenance in a strategic function. Poor maintenance strategies are estimated to reduce a plant's overall production capacity from 5 to 20% (Coleman *et al.*, 2022). Cost is often a decision-making driver for companies, but the risk is, in many cases, to have a myopic view, only focusing on the short-term. Total Cost of Ownership (TCO) should be considered when making investment decisions, since it includes all the costs (e.g., purchase, installation, management, maintenance, and disposal) a user (or a provider) must sustain throughout the asset life cycle. One of the costs impacting the TCO are the maintenance costs that depend on several variables (e.g., adopted policy, asset usage, environmental conditions). Simulation can be used to estimate the maintenance cost, allowing considering the variability and uncertainty of the system behavior over time, and evaluating business problems at different decision-making levels (e.g., strategic, tactical or operational) (Borshchev and Grigoryev, 2020). Previous attempts have been done to do so. For instance, Roda *et al.* (2020) used Monte Carlo Simulation to evaluate the performance of an asset and then feed to the TCO model for decisions on asset configuration or performance. Despite, other typologies of simulation might be used to evaluate the problem from a different perspective and model complex relationships of components influencing each other's.

This paper aims at developing a simulation model that can help companies in choosing the optimal maintenance plan for an asset considering the maintenance lifecycle costs while also providing information on the asset productivity. The simulation model was developed and validated with the support of an Italian manufacturing company producing packing and bottling machines. After a short literature background on maintenance and simulation, the paper provides an overview of the main application of agent-based simulation in maintenance (section 2). The simulation model is presented (section 3), and results are presented (section 4), before the paper conclusion (section 5).

2. LITERATURE BACKGROUND

This section aims at introducing the main concepts related to maintenance and simulation, providing also an overview of the main applications of agent-based simulation in maintenance.

2.1 Maintenance typologies and costs

The term maintenance, as reported in the UNI EN 13306 standard, refers to the "*combination of all technical, administrative and managerial actions, during the life cycle of an entity, aimed at maintaining it or bringing it back to a state in which it can perform the required function*" (UNI EN 13306:2018, 2018). The purpose of maintenance is to ensure that the entities are reliable, i.e., as defined by the UNI EN 13306 and UNI 9910 standards, "*capable of performing a required function under given conditions, during a set time interval*". Maintenance can be classified into different policies depending on the approach to fault management (Furlanetto *et al.*, 2007).

2.2 Modelling and simulation

Simulation proved, over the years, to be a reliable instrument to study the behavior of processes or business models. After creating a simplified model of the original system with an adequate level of abstraction, it is possible to analyze and drill down into the structure and behavior of the original system, dynamically examining how it will act in different situations and scenarios (Borshchev and Grigoryev, 2020).

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The three main simulation paradigms are System Dynamics (SD), Discrete Event Simulation (DES), and Agent-Based Simulation (ABS). Table 1 provides an overview of the features that every simulation paradigm offers. When necessary, SD, DES, and ABS can be mixed in hybrid approaches.

Table 1 - Comparison of different simulation paradigms

DES	ABS	SD
Process-oriented: focus is on modeling the system in detail	Individual-oriented: the focus is on modeling the agents and interaction between them	System-oriented: the focus is on modeling the system observable
Based on entity flows through blocks	Based on single agents interacting with each other's	Based on stocks and flows between stocks
Entities are passive	Agents are active	Continuous systems, no entities
Global system behavior	Global behavior results as the interaction of many agents	Global system behavior as several interacting feedback loops
Suited for tactical and/or operational decision-making	Suited for strategic, tactical, and operational decisions	Suited for strategic modelling purposes
Adopted in business process, manufacturing, logistics and service delivery processes	Mainly applied in social sciences including marketing, social processes, and healthcare/epidemic models	Adopted in urban, social, ecological types of systems.

In this paper, agent-based simulation has been selected to evaluate the behavior of an asset over its full lifecycle considering the adoption of different maintenance strategies because of its flexibility and capability of handling complex problems (Kono and Haneda, 2021). Thus, the next section presents applications of ABS in the context of maintenance found in the literature, highlighting the present of cost-related analysis in the papers.

2.3 Applications of ABS for maintenance decision-making

Licup and Materum (2023), created an ABS model predicting the impact of technology adoption in the implementation of maintenance activities to ensure high availability of broadband internet service letting out cost analysis. Sun, Han and Zhang (2023), optimize resource allocation to maximize the resilience of the infrastructure network. Again, no cost analysis is reported. Allal *et al.* (2021) use ABS to optimize maintenance route planning in an offshore wind farm to minimize travel costs. Nordal and El-Thalji (2021) simulate individual physical components and their failure modes, preventive maintenance plans, and opportunistic maintenance intervals to exploit these intervals in terms of intelligent maintenance. While the model simulates the lifecycle of the asset, it does not take into consideration costs. Kono and Haneda (2021) model support maintenance design, by comparing different scenarios, making it possible to predict the associated KPIs, but does not consider costs. Meissner, Meyer and Wicke (2021) optimize maintenance planning estimating their operational impact. Maintenance activities are ranked according to their cost. Liu *et al.* (2021) simulate the aircraft maintenance process and produce large amounts of reliability data while performing fault classification through an ad-hoc algorithm. The model allows, among other things, to quantify the costs associated with a certain maintenance strategy. Abdelkhalek and Zayed (2020) used hybrid modeling (DES + ABS) to plan inspections of the scaffolding of a concrete bridge. The model quantifies the duration and cost of the inspection in different scenarios to identify the best ones. Lee and Mitici (2020) propose a simulation model to evaluate the safety and efficiency of aircraft maintenance strategies using ABS in combination with Petri Nets and Monte Carlo Simulation. The model allows the evaluation of new maintenance strategies before their practical implementation. Liu *et al.* (2019) use historical and real-time data to optimize maintenance plans according to service level, reliability, and cost. Wang *et al.* (2017) use ABS to model the availability of a complex multi-unit system, but costs are not considered in the simulation. Alsina, Cabri and Regattieri (2014) use ABS to simulate the behavior of a production line and the effect of maintenance on its performance. Cost analysis is not considered in the model. Lynch *et al.* (2013) integrate a genetic algorithm with an ABS model to optimize spare parts inventory and maintenance operations. Cost analysis is used as a driver of comparison. Kaegi, Mock and Kröger (2009) developed a model that evaluates the performance of the system concerning different maintenance strategies through a cost-benefit analysis. Hilletofth *et al.* (2009) compare different maintenance scenario based on multiple inputs. Costs are not considered in the model. From this brief overview, it emerges that the application of ABS in maintenance can contribute to decision-making at different levels but, at the same time, it also emerges that the cost perspective is not always considered.

3. SIMULATION MODEL

This section presents the developed model and the validation process, carried out with the support of an Italian manufacturing company producing packaging and bottling machines. For privacy purposes, data reported in this paper are realistic, but not the real one. The machine used for developing and validating the simulation model is a shrink wrapper. First, the Failure Modes and Effect Analysis (FMECA) was used to understand the functional structure of the asset and create a counterpart in the simulation model, as well as understand effects of components' failure. Based on the FMECA shared by the company, the analyzed machine is composed of around 70 components, each one belonging to a specific functional group and contributing to the machine's functioning.

The model is created with AnyLogic 8.8.6 Personal Learning Edition software and is built upon two agents: System agent (describes the behavior of the system as an ensemble of components, thus representing the asset), and Component agent (that represents the operations of the individual components). The functioning of System agent type depends on the Component agent type as described in the following.

3.1 Input and Output

Table 2 summarizes the input used to run the model. The data is read by AnyLogic from an Excel file, in which each row represents an asset component, at the beginning of the simulation. The output is represented by the calculation of relevant indexes at both the system level (i.e., for the asset) and at component level. In particular, a list of maintenance indexes (computed for each component and the system) was defined. Time Between Failures (TBF) – i.e., the time interval between the end of the repair of the previous failure and the occurrence of the next failure – and Mean Time Between Failures (MTBF) – i.e., average of the TBF – were used for repairable entities. For non-repairable entities, Time To Failure (TTF) and Mean Time To Failure (MTTF) were used. To measure maintenance time, Time Between Maintenance (TBM) – i.e., the time interval between two consecutive maintenance interventions, corrective or preventive – as well as Mean Time Between Maintenance (MTBM) were selected. Then, Time To Repair (TTR) – i.e., the time required to execute a maintenance intervention – and Mean Time To Repair (MTTR). In addition, indexes related to costs and production time (nominal, slow, and downtime) were used. Depending on the data availability, the model may include direct (e.g., maintenance personnel, materials, spare parts, and third-party costs due to outsourcing) and indirect costs (cost of other personnel, cost required for maintenance structure to work, financial costs for spare parts in the warehouse, auxiliary maintenance costs), as well as hidden costs (costs due to downtime, contribution margin, to not using the production personnel, scraps and reworks, inefficiency, safety). For space constraints, only cost-related indexes will be presented in the results section.

3.2 "Component" agent

A population of agents "Component", as well as their characteristics, is created based on the number of rows (one for each component) in the input file. During the simulation, each agent (Figure 1) can enter in one of the states listed in Table 3. The *PM* (Preventive Maintenance) state puts the machine in a stoppage state. When a failure happens to the component, the *Fault* state is activated and, depending on the component, the production is stopped or slowed down. The component goes into *MachineStopped* state when the system is stopped due to a failure or maintenance operation on a different component. In ABS, transitions (Table 4) are used to allow an agent to move from one state to another.

The transition from *Working* to *PM* status is unlocked upon condition. This occurs when a specific timer, counting the hours elapsed since the last maintenance intervention, reaches the number of hours scheduled for preventive maintenance. At the end of any maintenance work, the timer is reset, to consider the preventive maintenance policy (at a constant age) adopted.

Table 2. Input data for the simulation model

Variable	Unit of measure
Name, sub-zone, group, ID (from FMECA)	/
SparePartCost	€/piece
PMInterval	h
PMLenght	h/intervention
CMLenght	h/intervention
PercentageReplaced	%
Alpha	h
LogisticTime	h
TechnicianCost	€/h

Table 3. States of the "Component" agent

State	Description
Working	The entity is working normally
PM	Component is under PM
Fault	Component suffered a failure
Replacement	Component is replaced
Repair	Component is repaired
MachineStopped	The component is not working because the machine is stopped for some reason

Table 4. Transitions used in the model

Transition	Trigger
Timeout	The agent has spent a certain amount of time in a certain state.
Rate	Same logic used in the "timeout" but the time is given by an exponential distribution of which the average value is known.
Condition	A condition is satisfied.
Message	A certain message arrives from other agents.

The agent returns to the status of a working component upon a timeout transition which is dictated by the *PreventiveDuration* parameter indicated in the input Excel file. Transitions between the *Working* and *MachineStopped* states are defined by an exchange of messages with the System agent. When an agent "Component" causes the stoppage, either due to the occurrence of the failure or the execution of PM, a message is sent to the system agent, which causes the System stoppage. As a result, the System agent communicates, via message to the other components, that the plant is inactive, causing it to switch to the *MachineStopped* state. At the end of maintenance intervention, a message is sent for the return of the machine to the *Working* state. In turn, again via message, this will activate the operating state of the other components. The transition from *Working* to *Fault* is modeled by applying the definition of reliability through a Weibull distribution (Hossain and Zimmer, 2003). Like for *PM*, the timer is reset after every intervention. As the working time increases, the reliability will decrease following the negative exponential trend of the reliability distribution. The occurrence of failure events is simulated by comparing the reliability parameter with a variable that simulates the probability of a random failure. A *FaultRandomness* variable is therefore defined for each component, and calculated after each intervention that the component undergoes, assuming a random value between zero and one. As soon as the reliability value falls below the *FaultRandomness* value, the transition to the fault state is activated (lasting until the maintenance intervention is completed). In this way, the probability of failure – that increases as the machine's working time increases – was simulated. After the fault, the status of the component can change to *Repair* or *Replacement*, depending on the activity for the broken component. The *PercentageReplaced*, uniquely defined for each component, is used to determine whether a component is replaced or repaired. The duration of the corrective interventions is established by the *CMLenght* parameter, through a timeout transition that returns the component to the *Working* state. At the level of individual components, for diagnostic purposes, it was considered useful to collect some simulation data. This is why whenever the state of a component changes to *PM*, *Fault* or *Replacement*, a counter keeping track of the total number of PM, breakdowns or replacements is added. Multiplying the number of replacements made by the cost of the individual component (input from Excel) allows to calculate the total cost due to the purchase of spare parts. In the *Working*, *PM*, *Replacement* and *Repair* states, there are internal *Timeout* transitions that, every hour, update the values of the parameters used to collect data on the operational status of the component.

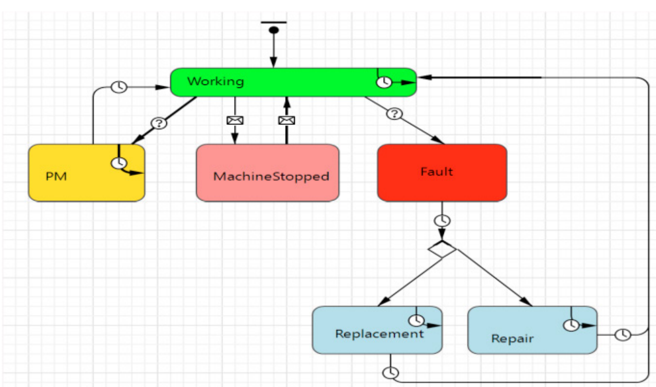

Figure 1. "Component" agent

At the end of the simulation, reliability and maintainability parameters, useful for evaluating and improving the maintenance management, are calculated. Subsequently, all the data collected are reported on a database where the history of the results of the various simulations is stored, allowing them to be tracked. In this way, by varying the input data, it is possible to compare various preventive maintenance plans to define the most beneficial.

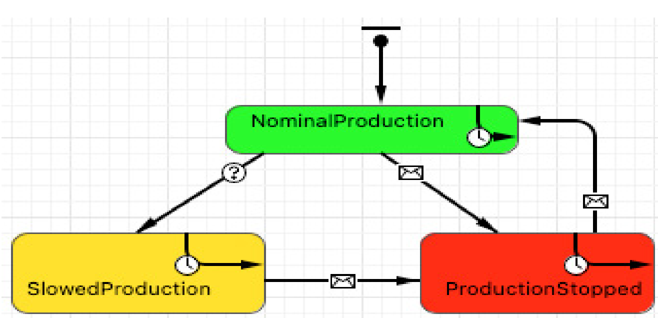

Figure 2. "System" agent

3.2 *"System" agent*

The "System" agent (Figure 2) is also represented through state-chart whose states are summarized in Table 5. The transitions among states are determined by the "Component" agent states.

Table 5. States of the "System" agent

State	Description
NominalProduction	The productivity is within acceptable range
SlowedProduction	In operation, but productivity is below minimum of acceptability
ProductionStopped	One of the components stop the production due to a fault or a maintenance intervention

The transition from *NominalProduction* to *SlowedProduction* is managed through a condition (Table 4) which is unlocked when the machine's productivity falls below the tolerance limit (established through a parameter). According to the knowledge of the company, the productivity of the machine decreases by 0,5% every hundred hours of uninterrupted production. This is accomplished in the simulation model through an event that cyclically changes the value of the productivity parameter. When a maintenance intervention is executed, productivity is restored to its maximum. When the plant produces, regardless of the production rate, it can switch to a stopped state in the event of a breakdown or if preventive maintenance is planned to stop the production of the machine. These switches between *SlowedProduction* and *StoppedProduction* states, as well as between *NominalProduction* and *StoppedProduction* states and vice versa, are managed through messages transitions (Table 4), sent between the "Components" agent and the "System" agent. When a *PM* or a *Fault* state is active in one of the components, signaled through a message, the System goes into the StoppedProduction state. The *NominalProduction* state is restored as soon as maintenance is finished. As for the "Component" agent, there are internal transitions in the system states that are collected in parameters used to monitor the operational status of the system.

4. RESULTS AND DISCUSSION

Due to privacy concerns, the input used for the simulation presented in this paper was realistic ones and not the real data of the company. As above-mentioned, information related to components' failure as well as all the input data reported in Table 2 was derived from the FMECA. The simulation length was set to 20 years, as the company declared it to be the average lifetime of the machine. At the end of the simulation, multiple performance indexes related to maintenance, cost and production time were obtained at the asset level (Figure 3), and at the component level. For instance, the breakdown of the 20 years into nominal and slowed production as well as stoppage hours could be an important proxy to evaluate the impact of the maintenance plan and policies on the machine productivity, also considering the number of produced products. On the cost side, the PM and CM costs can be identified as well as the total maintenance cost. Maintenance indexes (MTBF, MTTR, Availability) can be calculated at asset and components levels to evaluate the effectiveness of the applied policies.

From a deeper analysis of outputs, a problem with the film winding rod component was noticed, being it the one with the higher number of failures and, in turn, the lowest MTBF. Since the company did not have in place any preventive maintenance plan for this component, four preventive maintenance scenarios were simulated and compared to investigate the effect of each maintenance plan on the asset productivity and cost. Table 6 summarizes the results of the simulation, detailing the lifecycle maintenance costs, the number of failures, and the number of PM interventions associated with different PM intervals.

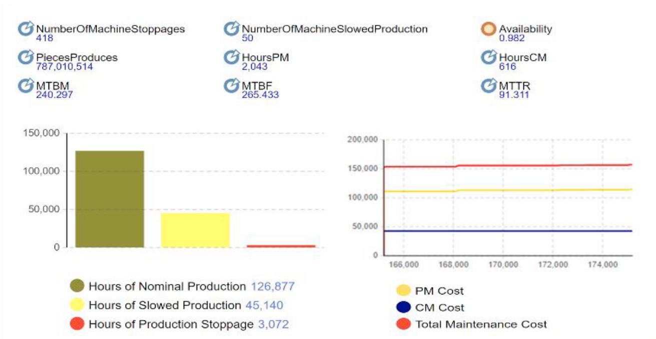

Figure 3. Simulation results

Table 6. Comparison of simulation scenario

PM interval [h]	Total Maintenance costs [€]	Number of failures	PM interventions
-	156.500	15	0
20.000	161.000	15	3
16.000	159.800	11	6
12.000	153.000	8	10
6.000	170.800	6	27

The four scenarios tested and compared against the original one showed interesting insights. First, from an economic standpoint, carrying out too frequent (i.e., every 6000 hours) or too rare (i.e., every 20000 hours) PM actions led to worst results compared to the original scenario. Indeed, when the 20.000 h PM interval was applied, the number of failures suffered by the component, as well as the MTBF, remained unchanged, while the total number of interventions (corrective and preventive) increased since PM was performed 3 times, only causing an increase in the total maintenance cost with respect to the original scenario. Instead, very frequent maintenance (i.e., every 6.000 h), lead to a reduction of failures, but significantly increase the number of PM interventions, having bad effects on the maintenance costs, also having negative effects on the productivity, since the machine is frequently stopped to carry out the interventions. The 16.000 h PM interval provide cost improvements over the 20.000 h scenario but is still worse than the original one. Instead, from a cost-wise perspective, the 12.000 h interval is the most convenient among the ones analyzed. Here, the number of failures is reduced to eight (second lowest), compared to ten PM interventions carried out (second highest). Also, improvements in terms of general index are achieved (e.g., MTBF).

It should be noted that, for long PM intervals (e.g., 20000 h), the reduction in the probability of failure is not sufficient to justify the use of a PM policy. In fact, out of the total, the increase in costs due to scheduled maintenance is greater than the savings obtained thanks to the reduction in the number of failures. Instead, with too frequent maintenance, costs increase significantly due to the high number of replacements of non-failed components. Compared to the original scenario, it is only possible to reduce costs by adopting 12.000 h PM intervals. This strikes a balance between the costly occurrence and the high cost of too many PM interventions.

5. CONCLUSIONS

The paper developed an agent-based simulation model to predict the maintenance costs that occur during the lifecycle of an asset, taking into consideration the variability in its behavior. Through a scenario analysis, the model allows to evaluate the costs and effectiveness of various maintenance policies in terms of reliability, availability, and productivity, and allow to select the most convenient one considering different performance indexes (e.g., cost, productivity). Thanks to the lifecycle perspective, this model could be integrated in the TCO calculation of an asset since it forecasts the total lifecycle maintenance cost that the owner of the asset should sustain, considering the decrease of reliability of the asset during its life and the uncertainty of failures occurrence.

Compared to the literature, the proposed model integrates a strong cost perspective that, added to the computation of the maintenance index, can support companies for improved decision-making, and could be used as a selling point in case of maintenance-based service offering, showing to customers the importance of executing PM during the asset lifecycle and comparing different working scenario. The adoption of ABS and the structure of the model favor generalization and adaptation to other cases since the relationship component/system is easily replicable to other assets.

During the development, it was necessary to make some approximations due to lack of data or modeling necessities. In this sense, possible improvements for future research have been identified, for example through the systematics collection and processing of historical data to be used as input. This would be useful to model the Weibull function and, improve the reliability analysis used during the simulation. Another aspect relates to the assumption that, after maintenance, a component returns to the optimal working state ("as good as new"). This assumption could be removed, and other modeling approaches could be adopted. A more in-depth study of the effects that a component health has on overall productivity could be carried out. Considering the importance of knowing the lifecycle cost for the company to make decisions at a strategic level, the inclusion of additional costs (e.g., spare parts disposal), in a TCO fashion, could support the company in making better decisions. Currently, due to the lack of some data, it is not possible to include all the costs in the TCO analysis. Having more information on the costs incurred by the company would be able to enrich the model for more detailed analyses.

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REFERENCES

Abdelkhalek, S. and Zayed, T. (2020), “Simulation-based planning of concrete bridge deck inspection with non-destructive technologies”, *Automation in Construction*, Elsevier, Vol. 119, p. 103337.

Allal, A., Sahnoun, M., Adjoudj, R., Benslimane, S.M. and Mazar, M. (2021), “Multi-agent based simulation-optimization of maintenance routing in offshore wind farms”, *Computers & Industrial Engineering*, Elsevier, Vol. 157, p. 107342.

Alsina, E.F., Cabri, G. and Regattieri, A. (2014), “An agent-based approach to simulate production, degradation, repair, replacement and preventive maintenance of manufacturing systems”, *2014 IEEE Symposium on Computational Intelligence in Production and Logistics Systems (CIPLS)*, IEEE, pp. 24–31.

Borshchev, A. and Grigoryev, I. (2020), “Modeling and simulation modeling”, *The Big Book of Simulation Modeling: Multimethod Modeling with AnyLogic*, Vol. 8.

Coleman, C., Damodaran, S. and Deuel, E. (2022), *Predictive Maintenance and the Smart Factory*, Deloitte.

Furlanetto, L., Garetti, M. and Macchi, M. (2007), *Ingegneria Della Manutenzione. Strategie e Metodi*, Vol. 677, FrancoAngeli.

Hilletofth, P., Lättilä, L., Ujvari, S. and Hilmola, O.-P. (2009), “Agent-based decision support in maintenance service operations”, *The 16th International Annual EurOMA Conference*.

Hossain, A. and Zimmer, W. (2003), “Comparison of estimation methods for weibull parameters: Complete and censored samples”, *Journal of Statistical Computation and Simulation*, Taylor & Francis Group, doi: 10.1080/00949650215730.

Kaegi, M., Mock, R. and Kröger, W. (2009), “Analyzing maintenance strategies by agent-based simulations: A feasibility study”, *Reliability Engineering & System Safety*, Elsevier, Vol. 94 No. 9, pp. 1416–1421.

Kono, T. and Haneda, K. (2021), “Simulation-supported maintenance design and decision-making using agent-based modeling technology”, *CIRP Annals*, Elsevier, Vol. 70 No. 1, pp. 13–16.

Lee, J. and Mitici, M. (2020), “An integrated assessment of safety and efficiency of aircraft maintenance strategies using agent-based modelling and stochastic Petri nets”, *Reliability Engineering & System Safety*, Elsevier, Vol. 202, p. 107052.

Licup, R.J.M. and Materum, L. (2023), “Technology Adoption: Intelligent Agent-based Model for Philippines FTTH Broadband Service”, *Journal of Communications*, Vol. 18 No. 4.

Liu, Y., Wang, T., Zhang, H. and Cheutet, V. (2021), “Simulation-based fuzzy-rough nearest neighbour fault classification and prediction for aircraft maintenance”, *Journal of Simulation*, Taylor & Francis, Vol. 15 No. 3, pp. 202–216.

Liu, Y., Wang, T., Zhang, H., Cheutet, V. and Shen, G. (2019), “The design and simulation of an autonomous system for aircraft maintenance scheduling”, *Computers & Industrial Engineering*, Elsevier, Vol. 137, p. 106041.

Lynch, P., Adendorff, K., Yadavalli, V.S. and Adetunji, O. (2013), “Optimal spares and preventive maintenance frequencies for constrained industrial systems”, *Computers & Industrial Engineering*, Elsevier, Vol. 65 No. 3, pp. 378–387.

Meissner, R., Meyer, H. and Wicke, K. (2021), “Concept and economic evaluation of prescriptive maintenance strategies for an automated condition monitoring system”, *International Journal of Prognostics and Health Management*, Vol. 12 No. 3.

Nordal, H. and El-Thalji, I. (2021), “Lifetime benefit analysis of intelligent maintenance: Simulation modeling approach and industrial case study”, *Applied Sciences*, MDPI, Vol. 11 No. 8, p. 3487.

Roda, I., Macchi, M. and Albanese, S. (2020), “Building a Total Cost of Ownership model to support manufacturing asset lifecycle management”, *Production Planning and Control*, Taylor and Francis Ltd., Vol. 31 No. 1, pp. 19–37, doi: 10.1080/09537287.2019.1625079.

Sun, J., Han, Z. and Zhang, Z. (2023), “Resource Allocation Framework for Optimizing Long-Term Infrastructure Network Resilience”, *Journal of Infrastructure Systems*, American Society of Civil Engineers, Vol. 29 No. 1, p. 04022048.

UNI EN 13306:2018. (2018), “Manutenzione - Terminologia di manutenzione”.

Wang, L., Xu, H., Wu, J., Chen, X. and Na, W. (2017), “Agent-based modeling of availability for complex multiple units systems”, *Journal of Quality in Maintenance Engineering*, Emerald Publishing Limited, Vol. 23 No. 1, pp. 71–81.