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A Discrete Event Simulator to Support Maintenance Decision-Making considering Economic and Environmental Sustainability

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Abstract:
Maintenance plays a crucial role in sustainability by influencing sustainable practices both through its own actions, which entail inherent flows and consequences, and through its impact on the performance of maintained assets across the triple bottom line. To manage maintenance from a sustainable perspective, appropriate indices able to represent environmental assessment results in an aggregated and synthetic way are necessary, along with rational decision-making tools able to simulate different maintenance alternatives considering various sustainability dimensions. This work builds upon a methodology that integrates Sustainability Indices and RAM Analysis to evaluate the environmental and economic impacts of maintenance activities. Specifically, a Discrete Event Simulator is developed, combining Petri Nets modeling with a design pattern to generate Monte Carlo simulations in Python. Through the application of the proposed methodology to a proof of concept, we demonstrate the simulator's capability to evaluate both the environmental and economic impacts of various maintenance activities. The obtained results highlight the potential applicability of the approach to industrial systems, emphasizing its contribution to the advancement of sustainable maintenance practices.

Keywords: Maintenance Management, Sustainability, Sustainable Maintenance, Environmental Sustainability, Sustainability Indices, RAM Analysis, Reliability Block Diagram, Petri Net, Decision-Making.

1. INTRODUCTION

Sustainability is a critical consideration in contemporary industrial practices, particularly in the context of maintenance and asset management (Ajukumar and Gandhi, 2013). With growing environmental concerns and societal expectations, organizations are increasingly recognizing the importance of integrating sustainable principles into their operations.

Franciosi et al. (2020) define *sustainable maintenance* as 'a set of interconnected processes that, from one hand, has to sustain asset/equipment during their operation to guarantee the compliance of the production process, of the manufactured products and to reduce their industrial impacts on the economy, society, and surrounding environment. On the other hand, itself has to be a sustainable business function to limit its flaws and impacts generated during maintenance activities'. Our work focuses specifically on decision-making related to the economic and environmental sustainability of maintenance activities and does not address their impact on the performance of the maintained assets.

While the correlation between maintenance and sustainability is recognized, numerous scholars have underscored the scarcity of research linking sustainability concepts to maintenance impacts, hindering effective *Maintenance Decision-Making*. Scholars have highlighted that traditional research in maintenance management has mostly focused on economic and technical facets, overlooking the consequential effects on various sustainability dimensions (Karevan and Vasili, 2018; Franciosi et al., 2018; Van Horenbeek et al., 2010). Achieving the full integration of sustainability considerations into maintenance management requires vigilant monitoring and measurement of maintenance impact through the use of (Saihi et al., 2022): (i) appropriate indices capable of presenting assessment results in a consolidated and synthetic manner and (ii) rational decision-making tools (e.g., mathematical models, simulation, etc.) that take into account diverse sustainability dimensions.

In response to this challenge, Barbieri and Hernandez (2024) propose a methodology rooted in *Sustainability Indices* (SIs) and *RAM Analysis* to support decision-making with respect to sustainable maintenance practices. The approach enables the evaluation of both the environmental

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and economic impacts of different maintenance activities. It facilitates the identification of specific environmental dimensions requiring improvement, as well as discerning the distinct contributions of individual components to environmental and economic impacts at the system level. The obtained insights provide valuable information to support informed decision-making. However, these insights are derived from the utilization of different software, as traditional RAM simulators do not assess environmental sustainability.

Building upon the aforementioned considerations, this research introduces a *Discrete Event Simulator* (DES) designed to evaluate the environmental and economic impacts of various maintenance activities. The simulated system is modeled using Petri Nets (PN) (Murata, 1989), with a proposed design pattern – a collection of reusable best practices for software design (Barbieri et al., 2015; Barbieri and Gutierrez, 2021) – employed to transform the model into executable Python code. The paper is organized as follows: Section 2 analyzes the state of the art, while Section 3 presents the proposed DES. The application of the simulator to a proof of concept for validation is illustrated in Section 4. Section 5 discusses the obtained results, followed by the presentation of conclusions and identification of future directions in Section 6.

2. STATE OF THE ART

RAM analysis based on Monte Carlo simulation has been applied in different domains to convert component-level indicators to system-level indicators in order to support maintenance decision-making (e.g., railways (Muhammed et al., 2022), manufacturing (Soltanali et al., 2019), data centers (Ahmed et al., 2021), and electromechanical systems (Wang et al., 2022), amongst others). In RAM analysis, the reliability and maintainability of components are utilized to assess the system availability (Crespo Marquez and Iung, 2007). This method is adopted to quantitatively define the impacts of subsystems and components, redundancy, stock policy, maintenance policy, and logistics on system availability (Calixto, 2016). This information is then utilized to simulate different scenarios and identify strategies to improve system availability.

Along with the technical dimension, RAM analysis has been largely applied to study the *economic sustainability* of maintenance decision-making throughout the different phases of the asset life cycle (Al-Douri et al., 2021; Regattieri et al., 2015; Setia et al., 2022; Roda et al., 2019).

To the best of our knowledge, and aside from (Barbieri and Hernandez, 2024), the only existing work in the sustainable maintenance field that demonstrates the evaluation of an *overall sustainability score* (akin to SIs) is that discussed in (Ghaleb and Taghipour, 2022). The proposed methodology relies on establishing correlations between sustainability-related indicators and maintenance efficiency, employing the best-worst method to aggregate the indicators of the triple bottom line (TBL). However, assessing maintenance efficiency is a challenging task, involving the assignment of a percentage score to maintenance actions, where 0% corresponds to minimal repair (restoring the system to its state before the maintenance action) and 100% signifies perfect maintenance (restoring a system to an 'as-good-as-new' state) (Wang and Pham, 2006). Given the reliance on a challenging-to-estimate parameter (maintenance efficiency), an alternative method is employed in this paper.

Given the above considerations, this work builds upon the methodology proposed in (Barbieri and Hernandez, 2024) since it supports sustainable maintenance decision-making through (i) RAM analysis and (ii) SIs that can be customized based on the considered case study.

3. DISCRETE EVENT SIMULATOR

In this section, we introduce the DES simulator and its components. First, in Section 3.1, we detail the modeling process using PN. Next, we present the design pattern utilized to generate Monte Carlo simulations in Python. Specifically, the software architecture is discussed in Section 3.2, followed by an explanation of event generation in Section 3.3 and simulation time evolution in Section 3.4. Finally, we describe the assessment of indices and the execution of the Monte Carlo simulation in Section 3.5.

3.1 System Modeling

In this phase, the behavior of the modeled assets is defined. Since this research represents the initial iteration of the approach, only corrective and preventive maintenance are modeled, as illustrated in Figure 1. However, future works may focus on scaling the approach by incorporating additional behaviors.

A timed PN is constructed (Muñoz et al., 2014), where stochastic residence times are assumed in the places. Places (i.e., circles) represent the states of the asset, transitions (i.e., rectangles) are associated with events that trigger changes in state, arcs (i.e., lines) connect places and transitions, defining the system's evolution, and tokens (i.e., points) represent the active state of the asset at a given moment.

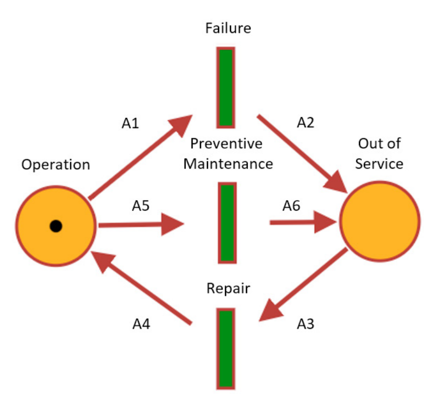

Fig. 1. Timed PN of the modeled asset behaviour using PNets simulator (`https://petri.hp102.ru/index.html`).

3.2 Software Architecture

Software architecture is composed by the basic structure of the software determined by design decisions forming the skeleton of the software (Vogel-Heuser et al., 2022).

These design decisions primarily determine modules' size, interfaces, and interaction.

This work employs object-orientation to translate the timed PN into Python code and adopts a hierarchical coding structure for developing the DES simulator. Each element of the PN, including TOKEN, ARC, TRANSITION, and PLACE, is encapsulated within its own class, along with a class representing the entire network (PETRINET). Additionally, complementary classes, such as CASE and PARAM_DISTRIBUTION, are introduced to facilitate the creation of case studies and the declaration of probability parameters for event occurrence, respectively. Figure 2 illustrates a class diagram featuring the main attributes and methods.

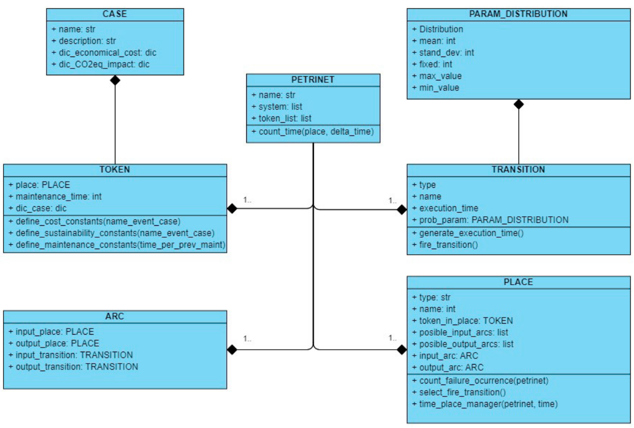

Fig. 2. Class Diagram Depicting Main Attributes and Methods of the DES Simulator.

3.3 Event Generation

The event generation process relies on the 'prob_param' attribute and the 'generate_execution_time()' method of TRANSITION objects. These components work together to create new occurrence times for events. Specifically, the 'generate_execution_time()' method utilizes the 'distribution_manager' function, which directs the data to a specific distribution function implemented using the scipy.stats library. This function then returns an occurrence time based on the provided distribution and probability parameters. Figure 3 illustrates an overview of this process.

To clarify, the execution time associated with each transition represents the duration for which the token will reside in the arrival place following the occurrence of the corresponding event. For instance, the execution time of the 'failure' transition determines the duration the token will remain in the 'operation' place upon the event's occurrence.

To update token placement and generate a new token, the simulator evaluates the current place of the token and the impending event. Subsequently, it assigns a null value to the 'token_in_place' attribute of the current place and transfers the previously removed token element to the 'token_in_place' attribute of the destination place.

3.4 Simulation Time Evolution

The simulation necessitates a time variable representing the asset's operational hours and a 'petrinet' object representing the network. It is conducted using the 'execute_simulation' function. Within this function, the simulator initializes a time variable, starting at zero, which is incremented as events occur. Once this variable surpasses the specified operational time, the simulation terminates. At time zero, the 'execute_simulation' function iterates through the list of network elements, generating occurrence times for each 'transition' element.

Fig. 3. Overview of the event generation process in the DES simulator.

After generating an occurrence time for each transition, the simulator iterates through the list of elements once more to locate the place holding the token. This task is facilitated by the 'looking_for_place' function. Upon locating the token, the simulator updates both the time variable and the time attributes of the 'petrinet' element based on the token's location using the 'time_place_manager' method present in the place elements. Subsequently, the simulator identifies the event closest to occurring, triggers the associated transition, and moves the token to another place.

If the token is in the 'operation' place, the selection of the next event is determined by comparing the execution time reported in the 'failure' transition with the preventive maintenance time reported in the 'token' element. If the execution time of the 'failure' transition is less than the preventive maintenance time, the 'failure' event is selected. Otherwise, preventive maintenance is chosen as the next event, and a new occurrence time for the 'failure' event is generated. Subsequently, the simulator evaluates whether the time variable, after the last update, is less than the operation time. If so, the simulation restarts from the 'looking_for_place' function.

3.5 Indices and Monte Carlo Simulation

To ensure unbiased generation of indicators, the simulator employs a Monte Carlo simulation approach. This involves passing parameters such as the 'petrinet' element, the number of iterations, and the asset's operational time to the 'CPN_Monte_Carlo' function. Within this function, the simulation iterates through the 'execute_simulation' function, saving the generated indicators after each simulation. The loop continues until the number of iterations matches the requested number of simulations. A visual representation of this iterative process is depicted in Figure 4.

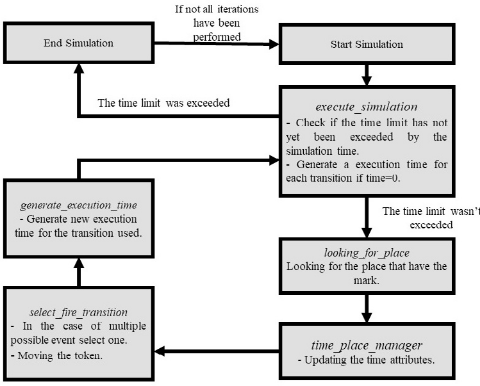

Fig. 4. Schematic representation of the iterative process followed by the developed program to simulate the evolution of the network using a Monte Carlo simulation approach.

For each simulation, the following data are saved: the number of failure events, the number of preventive maintenance events, and the downtime measured in hours. Based on this data, the simulator calculates a set of technical, economic and sustainability indicators for each simulation. These data are then saved in a CSV file. Finally, using the data from all iterations, the simulator calculates the mean, standard deviation, maximum value, and minimum value of the economic and sustainability indices.

4. PROOF OF CONCEPT

In this section, we implement and validate the DES simulator described in Section 3 through a proof of concept (PoC). A semi-realistic case study is developed to evaluate its effectiveness. In the PoC, various alternatives for corrective and preventive maintenance are compared in terms of their economic and environmental sustainability. To simulate the behavior, we choose a time frame of 25 years. Simulations are executed with 50 repetitions, which have proven suitable for obtaining consistently convergent results.

4.1 Parameters

An asset presents the maintenance-related parameters (i.e. transition events in PN) listed in Table 1 and is designed for continuous operation, running 24 h a day and 7 days a week.

Table 1. Maintenance-related parameters expressed in hours.

Transition	Distribution	Parameters
Failure	Exponential	$\mu = 35040$, $\sigma = 75$
Repair	Log-Normal	$\mu = 15$, $\sigma = 2$
Preventive Maintenance	Constant	7

In the event of a failure, a local technician is responsible for repairing the asset. However, an inspector must travel 430 km to oversee the repair work. Conversely, during preventive maintenance, the asset is replaced by the local technician, eliminating the need for an inspector. Additionally, when the asset is non-operational, the company incurs penalty costs due to production downtime.

The DES simulator is utilized to explore two travel options for the technician: flight and bus. Table 2 details the environmental and economic parameters for both scenarios.

Table 2. Environmental and economic parameters.

Parameter	Symbol	Flight	Bus
Environmental Parameters			
Inspector travel (kg-CO2-eq/failure)	EI_{IT}	320	23
Spare (kg-CO2-eq/prev. maint.)	EI_S	58	58
Economic Parameters			
Spare (USD)	C_S	500	500
Local Technician (USD/hour)	C_{LT}	15	15
Inspector Travel (USD/failure)	C_{IT}	85	125
Penalization (USD/hour)	C_P	6000	6000

4.2 Sustainability Indices

In the work conducted by (Barbieri and Hernandez, 2024), a series of indices for economic and environmental sustainability are introduced. Environmental Sustainability (ENS) is quantified in kilograms of CO2 equivalent emissions (kg-CO2-eq), reflecting the carbon footprint resulting from each maintenance activity. Economic Sustainability (ECS) is measured in US dollars, representing the financial expenditure associated with each maintenance action. It is important to note that while the study focuses on assessing the economic and environmental sustainability of maintenance activities, the impact of system operation is not taken into account.

Economic sustainability is calculated using the following formula:

$$ECS = DT * (C_{LT} + C_P) + N_F * C_{IT} + N_{PM} * C_S \quad (1)$$

where DT represents downtime, N_F denotes the number of failures, and N_{PM} signifies the number of preventive maintenance actions.

Environmental sustainability is assessed using the following equation:

$$ENS = N_F * EI_{IT} + N_{PM} * EI_S \quad (2)$$

4.3 DES Validation

The DES simulator's results are validated by simulating the same asset in a commercial software, RAPTOR (Murphy et al., 2007). Specifically, two RAM indicators are compared: Mean Time Between Downing Events (MTBDE) and Mean Down Time (MDT), computed as follows:

$$MTBDE = \frac{(TT - DT)}{N_F + N_{PM}} \quad (3)$$

$$MDT = \frac{DT}{N_F + N_{PM}} \quad (4)$$

where TT represents the simulation time.

To assess the significance of the differences between the RAM indicators, we apply the t-Student statistical test. This test determine whether the means of MTBDE and MDT generated by the DES simulator and RAPTOR are statistically different, using a significance level of 5%. The results indicate that for both MTBDE and MDT, the p-values are less than 0.001. This rejection of the null hypothesis suggests that there is no significant difference between the means of MTBDE and MDT produced by RAPTOR and the developed simulator, respectively. Detailed results are provided in Table 3.

Table 3. Statistical test for the validation of the DES simulator. DoF stands for Degrees of Freedom.

Independent Samples T-Test				
Indicator	Probability Test	Statistic	DoF	p
MTBDE	Student's t	−5.47	398	< 0.001
MDT	Student's t	32.3	398	< 0.001

Based on the analysis presented above, we conclude that the data generated by the DES simulator is statistically equivalent to that produced by RAPTOR. Consequently, the developed simulator can be considered validated.

5. RESULTS AND DISCUSSION

In this section, the obtained results are presented and discussed. The PoC is first analyzed (Section 5.1), followed by the proposed DES simulator (Section 5.2).

5.1 Proof of Concept

The maintenance scenarios evaluated through the DES simulator include:

- *Transportation means*: in the event of a failure, the inspector can travel either by bus or plane.
- *Preventive maintenance period*: different periods are tested to identify the effects of this parameter on environmental and economic sustainability.

The results obtained for bus transportation are represented in Figure 5, while those for flight transportation are shown in Figure 6. Each point corresponds to a different preventive maintenance period, with error bars representing three standard deviations.

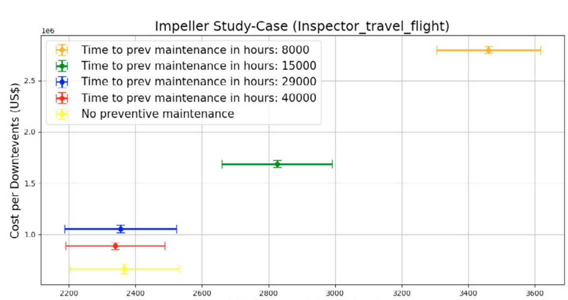

Fig. 5. Economic and environmental indicators for the flight transportation scenario.

Comparison between Figure 5 and Figure 6 highlights that bus transportation yields fewer kg-CO2-eq emissions compared to flight transportation, despite similar costs. Surprisingly, in this PoC, the absence of preventive maintenance emerges as the most advantageous strategy for the company, entailing minimal economic losses and the lowest carbon emissions.

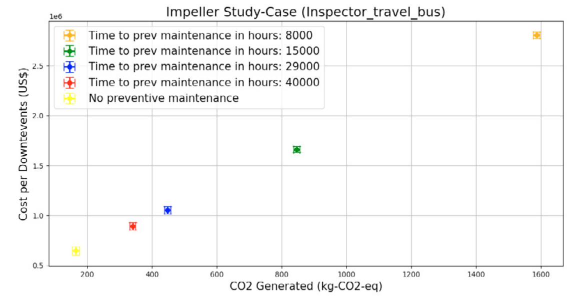

Fig. 6. Economic and environmental indicators for the bus transportation scenario

5.2 DES Simulator

The PoC demonstrates how the developed DES simulator supports decision-making for maintenance activities, considering not only technical and economic aspects but also environmental factors. Furthermore, since the simulator operates using Python code, different scenarios can be easily parameterized and executed with just one click. This stands in contrast to traditional RAM software, where a simulation must be run for each parameter value separately.

As an initial iteration, the simulation only includes an asset undergoing corrective and preventive maintenance, along with one index each for economic and environmental sustainability. However, future iterations should expand the modeled behaviors to include more indices and other assets and their interactions, such as standby modes, etc.

The pipeline, which involves modeling behavior in PN and generating code through a design pattern, has proven to be robust. While validation is essential for identifying and fixing errors during implementation, automating this process through model-driven engineering could further reduce errors.

6. CONCLUSION AND FUTURE WORK

This study builds upon an approach for maintenance decision-making that incorporates economic and environmental sustainability considerations. By developing a *DES simulator*, the research introduces a structured framework for conducting comprehensive evaluations of maintenance activities' impacts on both economic and environmental dimensions. Through the integration of Sustainability Indices and RAM Analysis, the simulator effectively assesses various maintenance scenarios. For instance, in a proof of concept, it examined transportation means for technicians and different preventive maintenance periods.

This tool holds significant promise for practitioners in the context of *sustainable maintenance* by offering a systematic and data-driven approach to decision-making. By integrating economic and environmental sustainability considerations into maintenance evaluations, the DES simulator provides practitioners with valuable insights into the trade-offs between different maintenance strategies. With the ability to assess various scenarios, practitioners can make informed decisions that optimize both economic efficiency and environmental impact.

Notably, the proposed methodology constitutes a preliminary concept that, in the future, should be further validated and improved. Some identified areas are summarized as follows:

- *Simulator functionality*: the modeled behaviors should be expanded to encompass additional indices and other assets, including their interactions such as standby modes.
- *Model-driven engineering*: automating the proposed design pattern could reduce errors in generating Python code.
- *Sustainable Maintenance*: while this work focuses solely on maintenance activities, future iterations should incorporate their broader effect on sustaining assets/equipment and reducing their industrial impacts on the economy, society, and surrounding environment.

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