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A computer-based simulation methodology of the predetermined maintenance scheme of an irradiation facility

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ABSTRACT

This study presents a computational framework for maintenance modelling aimed at addressing the complexities of the test cell (TC) within the IFMIF DONES, a complex industrial facility in the realm of fusion materials irradiation and testing. The proposed framework, which provides an insight into the maintenance process, is based on high-level Petri nets and captures maintenance tasks, duration, delays, and interactions among components. The proposed method employs global sensitivity analysis (GSA) to gain a better understanding of the influence of the numerous parameters on the system's performance. Three maintenance scenarios are explored, taking into account factors such as workforce assumptions, shift expenses, delays, and task completion timings. Monte Carlo simulations evaluate the probabilistic behaviour of the considered maintenance scenarios to allow for a thorough examination of the impact of uncertainties on maintenance operations. Examination of shift data yields insights into optimizing maintenance strategies minimizing downtime, and enhancing cost effectiveness. The results underscore the significance of implementing a night shift to improve facility availability. Furthermore, the proposed maintenance model is compared against a regression metamodel, which is validated by comparing Sobol indices derived from the Petri net. The novelty of this research is shown through combining shift data analysis, global sensitivity analysis, and innovative hybrid modelling aimed at enhancing maintenance planning within an irradiation facility.

1. Introduction

The question of how to handle climate change and shift to a greener power source has been a matter of debate. Fusion energy looks like an option that could completely transform energy generation and deal with climate change and energy security challenges. Studies in nuclear fusion have come a long way, reaching projects such as the International Thermonuclear Experimental Reactor (ITER), which is evidence of global collaboration and massive investments made towards obtaining fusion energy for a cleaner and sustainable future (Donné, 2019).

The European fusion community has created a comprehensive roadmap called the *European roadmap to the realization of fusion electricity* in order to achieve nuclear power by fusion, which includes key challenges and milestones, such as the development of plasma regimes, heat-exhaust systems, neutron-resistant materials, tritium self-sufficiency and safety concerns among others (Donné, 2019). It emphasizes the roles of ITER, Fusion Demonstration Power Reactor (DEMO) and IFMIF-DONES in driving forward fusion research, qualifying materials for future fusion power plants, and eventually leading to commercialization of fusion energy. Some milestones have already been reached within fusion research, such as the most recent positive net energy gain from laser-driven fusion reactions by US scientists. Additionally, there were several efforts of a similar nature with respect to fusion energy projects (Creely et al., 2020; Rodriguez-Fernandez, Creely, Greenwald, Brunner, Ballinger, Chrobak, Garnier, Granetz, Hartwig, Howard, et al., 2022; Tobita et al., 2019).

At the forefront of research on Fusion Energy is the IFMIF DONES facility, which will be very critical since it will produce crucial data from material irradiation tests applied in design, licensing, construction, operation, and safety-related DEMO (Bernardi et al., 2022). The IFMIF DONES involves intricate components and processes which require effective maintenance strategies due to its industrial application. It comprises interconnected systems such as Accelerator Systems (AS), Lithium Systems (LS) for managing the lithium target, Test Systems

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Table of abbreviations

Abbreviation	Description
AS	Accelerator Systems
APS	Advanced Photon Source
BPM	Beam Position Monitors
CICS	Central Instrumentation and Control Systems
CNN	Convolutional Neural Network
CPES	Cyber-Physical Energy System
DEMO	DEMOnstration Power Plant
DGSM	Derivative-based Global Sensitivity Measures
DRL	Deep Reinforcement Learning
eFAST	Extended Fourier Amplitude Sensitivity Test
EVEDA	Engineering Validation and Engineering Design Activities
FAST	Fourier Amplitude Sensitivity Test
FCN	Fully Convolutional Network
GSA	Global Sensitivity Analysis
HFTM	High Flux Test Module
HLPN	High-level Petri nets
IFMIF DONES	International Fusion Materials Irradiation Facility - DEMO Oriented Neutron Source
IL	Imitation Learning
ITER	International Thermonuclear Experimental Reactor
kNN	K-Nearest Neighbours
LR	Logistic Regression
LS	Lithium Systems
LSP	Lower Shielding Plug
LSTM	Long Short Term Memory networks
NPP	Nuclear Power Plant
OAT	One-at-a-time
OLS	Ordinary Least Squares
O&M	Operations and Maintenance
PCP	Piping and Cabling Plug
PIPE2	Platform Independent Petri net Editor 2
PPO	Proximal Policy Optimization
PS	Plant Systems
RF	Random Forest
SVM	Support Vector Machine
TC	Test Cell
TCCP	Test Cell Cover Plate
TCL	Test Cell Liner
TLIC	Test Systems Lithium Interface Cell
TM	Test Module
TS	Test Systems
UML	Unified Modelling Language
USP	Upper Shielding Plug

(TS) including the Test Cell (TC) and support systems for hosting test specimens, Central Instrumentation and Control Systems (CICS) for plant control and Plant Systems (PS) covering site infrastructure like buildings and supporting facilities such as power supply, cooling systems, ventilation and remote handling. The main subsystems of the DONES facility are illustrated in Fig. 1 with the Test Cell at its core.

The challenges in the simulation of the maintenance of IFMIF DONES are the intrinsic complexities of the swarm of operational activities, which increases with the continuous evolution of the facility's design. Indeed, different works highlight the evolving nature of IFMIF DONES's installations and functionalities, hence making the maintenance even more complex (Dezsi et al., 2019; Królas, Ibarra, Arbeiter, Arranz, Bernardi, Cappelli, Castellanos, Dézsi, Dzitko, Favuzza, et al., 2021; Nomen et al., 2020). On the other hand, the policy and severe governing regulations for such a critical industrial facility, add extra complexities to maintenance. Radiation and safety features preventing contamination of the workers are also part of the maintenance features of the IFMIF DONES (Tian et al., 2018), attaining 70% operational availability by continuous monitoring and predictive maintenance (Arranz et al., 2023), and planning of the maintenance activities by a mix of hands-on and remote handling due to access restrictions resulting from radiation or contamination (Micciché, Ascott, Bakic, Bernardi, Brenosa, Coloma, Crofts, Di Gironimo, Ferre, Fischer, et al., 2019). Hence, advanced computational methods are a need to face the challenges described above.

Furthermore, the complexities of the maintenance of the Test Cell (TC) within the IFMIF DONES facility require advanced methodologies to ensure optimal performance within a radiation environment. The open literature provides very limited studies focusing specifically on nuclear or irradiation infrastructure maintenance. In contrast to other fields like aerospace, automotive and chemical engineering, where there are a lot of research and data resources, the maintenance of critical infrastructures like IFMIF DONES has received less attention. Additionally, there is limited access to nuclear or irradiation fault datasets, hindering the examination and leveraging of data for training maintenance models. The mentioned constraints highlight the significance of the exploration of alternative methodologies and approaches to effectively leverage the existing knowledge and expertise in this field and related ones.

To overcome these obstacles, this research presents a novel adaptive knowledge-based computational technique — an expert system targeting the unique requirements of the IFMIF DONES facility. Petri nets (Petri, 1962) are employed to model the complex maintenance process, taking into account the tasks' duration and interactions among different components, by adding several advanced features enhancing the applicability of traditional models. The present approach dynamically represents the uncertainty and variation of IFMIF DONES' maintenance processes by combining hybrid modelling techniques for higher accuracy and effectiveness. This paper proposes a new maintenance approach for the IFMIF DONES, specifically for the TC and their subsystems, employing high-level Petri nets specially designed to capture the maintenance processes of this type of irradiation facilities. Global sensitivity analysis (GSA) is integrated to study the impact of probabilistic uncertainties of the numerous parameters on system reliability and availability. The integration of all these methods provides an effective way to reduce the facility downtime and costs and to enhance the maintenance policy in such a highly complex and regulated environment.

The explainable architecture provided by the proposed computational model allows exploring the impact of different working shift scenarios on the operational performance. In particular, the model revealed an optimal scheme that increased the average availability from 97.01% to 98.96%, and a average downtime decrease from 253.82 to 83.60 h, respectively. Besides, the computational efficiency was significantly improved by leveraging metamodeling. The implemented approach was approximately twenty times faster in estimating the sobol indices, allowing for a faster and more efficient sensitivity analysis.

The rest of the paper is structured as follows: Section 2 covers maintenance methods used in existing literature for irradiation facilities and nuclear infrastructure, along with discussions on GSA methods. Sections 3 and 4 present the proposed Petri nets architecture GSA methods considered in this study and specific assumptions made. Section 5 showcases results from the TC case study, while Section 6 delves into a discussion of these findings. Concluding remarks are presented in Section 7 followed by an overview of limitations and future directions in Section 8.

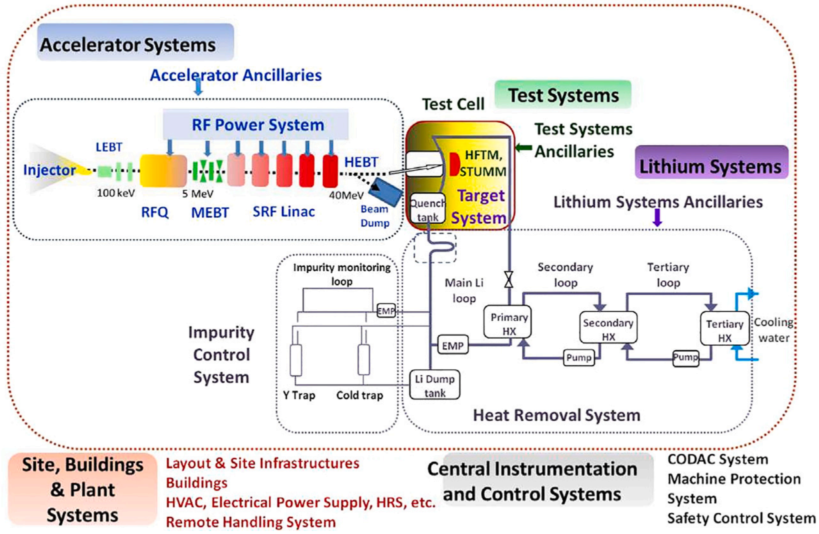


Fig. 1. Main subsystems of the IFMIF DONES (Zsákai, Muñoz, Diez, Román, Marco, García, & Ibarra, 2019).

2. Literature review

2.1. Maintenance in critical infrastructures

Numerous computational strategies for fault prediction and anomaly detection in particle accelerators and nuclear infrastructure have been studied extensively. Martino (2024) proposed techniques for the improvement of the fault detection capabilities of large cyber–physical systems. Anomaly detection in RF cavities by Eichler, Branlard, and Timm (2023) is carried out through a recently proposed novel methodology based on the parity space approach. False positives have minimal effect due to this technique, something that enables it to meet real-time requirements. Similarly, Eichler, Branlard, and Timm (2022) applied autoencoders for detecting anomalies in the APS storage ring, thus recognizing its efficacy in capturing precursor faults. Nonetheless, further validation using diverse data and operating conditions is required to assert these claims.

Regarding fault prognostics for particle accelerators, machine learning models hold great promise. Yucesan et al. (2024) explored the usage of ML algorithms for the detection of faulty beams using beam position monitors (BPM) data. However, in such a context, issues like digital signal processing and data fusion from various sources remain a main concern, especially in terms of data quality. Additionally, such models shall be validated online to allow for application within the context of safety–critical systems like particle accelerators. Felsberger et al. (2020) indicated that deep neural networks were superior to classical machine learning methods with respect to failure prediction after a comparison of different models. Jiqing, Deming, and Haijun (2024) introduced a novel approach for fault diagnosis based on deep learning and multi-sensor feature fusion. The suggested approach incorporates data fusion by combining 1D-CNN and LSTM, achieving superior performance on other ML algorithms (SVM, RF, KNN, CNN, & LSTM), proving its efficiency and generalization capability, and emphasizing the importance of feature fusion and hybrid modelling for fault detection in particle accelerators. The uniqueness of this approach is the extraction of features from multiple sensors while concurrently reducing data length and training time. Nevertheless, despite the numerous advantages of machine learning and deep learning approaches, there is a need for further inspection so as to understand whether these models can be interpreted or not. Also, risk modelling was explored by Wootton et al. (2022) using timed Petri nets on ageing nuclear reactor systems, calling for the inclusion of physical aspects and sensitivity analysis into the model along with emphasizing the importance of uncertainty quantification during the modelling process.

Heinze and Persson (2022) employed deep learning techniques, specifically LSTM, to predict potential errors in an electron accelerator facility, yielding a notable error detection rate. However, there is potential for improvement through the investigation of alternative interpolation methods and systematic optimization of model parameters. Similarly, Rescic, Seviour, and Blokland (2020) presented a method utilizing binary classifiers for predicting machine failures in particle accelerators, achieving a promising 92% accuracy based on beam current measurements. They suggested augmenting the dataset and integrating supplementary metadata for further advancements.

In the context of nuclear infrastructures, Gohel, Upadhyay, Lagos, Cooper, and Sanzetenea (2020) presented a Machine learning-based predictive maintenance architecture which achieved 95% accuracy compared to other algorithms. Hao, Di Maio, and Zio (2024) proposed a deep reinforcement learning (DRL) approach for the optimization of O&M, considering different maintenance strategies (corrective, predictive, & scheduled maintenance) and integrating proximal policy optimization (PPO), imitation learning (IL), and component stochastic failures and ageing of the cyber–physical energy system (CPES) model, applied to an advanced nuclear power plant (NPP). Ran, Zhou, Lin, Wen, and Deng (2019) provided a systematic review of the main predictive maintenance systems' purposes and approaches. This study serves as a valuable resource for understanding fault diagnosis, fault prognosis, and the application of machine learning and deep learning techniques.

Lastly, Serio et al. (2018) introduced an intelligent framework for assessing availability and reliability in particle accelerators. The suggested framework embraced extensive data sources and utilized data analysis, machine learning, and data mining techniques to deduce functional dependencies and fault logic models. This study also suggests the integration of functional dependencies with high-level models and methodologies to account for the chronological sequence of events.

Overall, the reviewed articles show how diverse approaches can be applied, including parity space method, autoencoders, deep learning models, timed Petri nets and binary classifiers for anomaly detection, faults prognosis or risk modelling purposes in particle accelerators or nuclear infrastructures. In addition, these studies highlight the importance of statistical analysis and model parameter optimization, as well as bringing together different information sources to improve diagnostic accuracy and support preventive maintenance activities.

For most applications, data-driven models are fast and cost-effective to develop, but they partly exploit the available information, particularly in machinery Operations and Maintenance (O&M). Hybrid modelling can provide a more reliable analytical foundation through a combination of expert knowledge in machine design, operational characteristics, and degradation mechanisms. The model that accommodates application data at various stages is much stronger than that which depends on just one dataset, thus minimizing its sensitivity to representativity and data quality problems. Kasilingam et al. (2024) conducted a systematic literature review on the challenges, techniques, and application of hybrid modelling within the manufacturing context. This study compared physics-based and data-driven modelling, emphasizing the importance of a physics-informed hybrid machine learning approach for enhancing the accuracy and consistency of model predictions. It sheds light on critical challenges like limited datasets, imbalanced data, benchmark problems, and model selection. Building a more reliable model is possible when expert knowledge is combined with machine learning techniques such as Anomaly Detection Systems, especially if experts have an opportunity to label the datasets before applying any algorithm. A hybrid approach for anomaly detection in particle accelerators was presented by Radaideh, Pappas, Wezensky, et al. (2022). They achieved an accuracy rate of 99% using the CNN Binary Classifier. In their work, Serio (2020) combines model-based approaches with big data analytics using machine learning techniques to extract descriptive models and predictive from data.

2.2. Comparison between different maintenance approaches

Table 1 below shows a comparison of different approaches used for the maintenance of particle accelerators and critical infrastructures. The comparison reveals that although deep learning approaches offer high accuracy and ease of implementation, they also come with a high computational burden and need large datasets for training and validation. Besides, these models are considered black-box approaches, making it difficult to understand and to adapt to new modelling conditions. In the context of maintenance of critical infrastructures such as IFMIF DONES, where regulations and policies have great significance, models that can be interpreted and understood are necessary to satisfy this demand. However, other techniques like Petri nets have shown their effectiveness in representing complex infrastructures, systems and processes. Such methods are frequently applied in many domains within which safety issues are paramount, among others. Moreover, Petri nets can deal well with real-time requirements. Nonetheless, optimization and statistical analysis methods must be employed to improve reliability and monitor model performance.

2.3. GSA methods

In terms of performance metrics analysis, there has been an increasing interest in statistical analysis and, in particular, GSA techniques. The advantage of these techniques is that they are able to efficiently extract the influence of the input parameters on the model output, assess the performance of the model, and quantify the interactions and non-linearities. A comprehensive review of these techniques can be found in Saltelli et al. (2008).

GSA methods can be categorized into three main groups: screening techniques, quantitative techniques, and exploration techniques, as illustrated by Iooss and Lemaître (2015). The screening methods rank inputs based on levels of discretization, allowing for rapid exploration of the behaviour of code. The One-at-a-time (OAT) method is a well-known screening method which consists in varying the input one at a time by fixing the others. As a result, OAT methods have high computational cost. The Morris method is a more efficient screening technique (Iooss & Lemaître, 2015).

Quantitative techniques aim to assess the importance of input variables and quantify their influence on the model output. When the relationship between the input variables and the output parameter is linear, the correlation and regression statistical analysis methods are used. These methods are unsuitable for non-linear and non-monotonic relationships between input and output variables, and variance-based methods are preferred.Saltelli, Tarantola, Campolongo, Ratto, et al. (2004) demonstrated that variance-based approaches, such as Sobol indices, are more effective than OAT methods especially when the relationship between input parameters and model output is non-linear. The Fourier Amplitude Sensitivity Test (FAST) (McRae, Tilden, & Seinfeld, 1982) and extended FAST (eFAST) methods are based on Fourier or exponential expansions to reduce computational cost. Saltelli et al. expanded these methods to calculate Sobol indices. However, when the number of input parameters goes beyond ten, stability becomes a problem for FAST methods (Iooss & Lemaître, 2015).

Exploration techniques, as opposed to quantitative methods, investigate the effect of the variation of input on the output by looking at the behaviour of the model over its range of variation. Graphical, non-parametric (smoothing) and metamodels are the three categories of such techniques. Graphical techniques, such as scatter plots, capture the main effects of the input variables (but not the interactions). Smoothing techniques, such as moving averages, kernels, and local polynomials, provide a method of estimating the conditional moments of the output variables under different input configurations. Metamodels, such as regression trees, approximate the mean of the output given the input. More highly sophisticated algorithms for statistical learning, including deep learning models, offer the investigator a more accurate way to represent complex, non-linear systems in their model as opposed to the traditional metamodels (Storlie, Swiler, Helton, & Sallaberry, 2009).

Some studies propose calculating sensitivity indices directly from metamodels, such as polynomial chaos decomposition, as a byproduct (Santner, Williams, Notz, & Williams, 2003). Other approaches, like the Kriging model, use analytical formulas for estimating Sobol indices with confidence intervals derived from the Kriging error (Kleijnen, 2009). However, it is essential to note that the variance proportion of the estimation of Sobol indices by applying intensive sampling techniques on metamodels may not be explainable (Iooss & Ribatet, 2009).

In this paper, we have highlighted the potential of data-driven approaches, machine learning techniques and hybrid modelling in fault detection, predictive maintenance and risk modelling in the domain of particle accelerators and critical infrastructures. From the reviewed studies, the following major findings can be drawn. Firstly, the use of statistical analysis and optimization of model parameters and architecture are needed to accurately perform diagnostics and predictive maintenance from data collected from particle accelerators and critical infrastructures. Secondly, GSA methods have emerged as effective methodologies to quantify the influence of the input parameters on the model output and to diagnose the reliability and behaviour of the model. The use of different categories of GSA methods as screening techniques, quantitative techniques and exploration techniques can reveal a complex and exhaustive diagnostic analysis and assessment of model performance. Finally, hybrid modelling and the inclusion of expert knowledge from different disciplines is crucial to build and assess models that can perform accurately and consistently on real-world applications.

3. Methodology

Petri nets are a mathematical and computational modelling tool used to represent and analyse the behaviours of dynamical systems. At its core, Petri nets are directed graphs composed of places and transitions. Places depict states or conditions, while transitions symbolize events or activities. The connections between places and transitions are indicated by the directed arcs that denote the control flow or tokens movement (Murata, 1989).

One type of Petri nets in this study is the stochastic Petri net which makes it possible for traditional ordinary Petri nets to have probabilistic behaviour in their transitions. Through this approach, we can model and analyse complex systems with uncertainty and variability such as IFMIF DONES Facility TC's predetermined maintenance process. Likewise, two scenarios were investigated; one involved all timed transitions, while the other did not consider delay transitions.

Table 1
Comparison between maintenance methods.

Method	Benefits	Limitations	Refs
Deep Learning (CNN, Ensemble Learning, LSTM, Autoencoders)	Highest accuracy achieved (99%) Learns complex patterns	Complexity of the methods Requires a sufficient dataset	Eichler et al. (2023), Felsberger et al. (2020), Heinze and Persson (2022), Radaideh, Pappas, Ramuhalli, et al. (2022), Radaideh, Pappas, Wezensky, et al. (2022), Serio (2020), Wu and Zhao (2020)
Machine Learning (Binary Classifiers, SVM, LR)	Easy to implement	Accuracy can be improved	Antonello et al. (2019), Gohel et al. (2020), Humble et al. (2022), Rescic et al. (2020), Reščič, Seviour, and Blokland (2022), Tennant et al. (2020)
Knowledge-Based (Parity Space Method, Timed Petri Nets)	Capable of handling real-time requirements Easy representation of complex systems and mechanisms	Parameter optimization required for better reliability Statistical analysis needed for performance metrics Augmentation of physical models or sensitivity analysis needed for improved reliability and performance	Eichler et al. (2023), Wootton et al. (2022)

3.1. Modelling maintenance with high-level Petri nets

As detailed in Section 2, this study employs Petri nets to capture the complex and interconnected activities within the predetermined maintenance process of the TC of the IFMIF DONES. The model accommodates sequential and parallel operations, incorporating time delays associated with each maintenance activity. It depicts the chronological maintenance operations and integrates the required time delays between them.

A Petri Net (PN) is a an directed bipartite graph consisting of places and transition. Transitions, denoted by boxes, drive the dynamic behaviour, allowing the system to change its state. Places, denoted by circles, represent system states, and their token distribution is used to represent the state of the PN. Mathematically, a PN is defined as $N = \langle \mathbf{P}, \mathbf{T}, \mathbf{F}, \mathbf{W}, \mathbf{M}_0 \rangle$, where $\mathbf{P}$ and $\mathbf{T}$ denote places and transitions sets, $\mathbf{F}$ represents connections, $\mathbf{W}$ is a weight function, and $\mathbf{M}_0$ is the initial marking. The dynamics of a Petri net are influenced by the firing of transitions, determined by the marking of places and the network's structure. A marking signifies the distribution of tokens among places, reflecting the system's state. For a transition t_i to fire, the marking of each input place p_j must exceed or equal the weight of the corresponding input arc, defined by the firing rule:

$$M(p_j) \geqslant a^-_{ij} \;\; \forall p_j \in {}^{\bullet}\mathbf{P}_{t_i} \tag{1}$$

where ${}^{\bullet}\mathbf{P}_{t_i}$ is the set of input places of transition t_i, also referred to as the *pre-set* of t_i, and a^-_{ij} are the elements of the backward incidence matrix. The incidence matrix, denoted by $\mathbf{A}$ represents the difference between input and output weights of the arcs that connect places to transitions,*i.e.*:

$$\mathbf{A} = \mathbf{A}^+ - \mathbf{A}^- \tag{2}$$

where $\mathbf{A}^+ = \left[a^+_{ij}\right]$, $\mathbf{A}^- = \left[a^-_{ij}\right]$, $i = 1, \dots, n_t$, $j = 1, \dots, n_p$. The element a^+_{ij} is the weight of the arc from transition $t_i \in \mathbf{T}$ to output place $p_j \in \mathbf{P}$, whereas a^-_{ij} is the weight of the arc to transition t_i from input place p_j. Once the delay time $\tau_i \in \mathbf{D}$ has passed, transition t_i is activated at time k, then $u_{i,k} \in \mathbf{u}_k$ is modified according to the PN firing rule, expressed as follows:

$$u_{i,k} = \begin{cases} 1, & \text{if Eq. (1) is True} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where $M(j) \in \mathbb{N}$ is the marking for place p_j.

Finally, we note that Petri nets models suffer from the state explosion problem, which limits their abilities with large-scale systems. High-level Petri nets (HLPN) have extended modelling power, making them more applicable to complex systems (Gerogiannis, Kameas, & Pintelas, 1998). In the HLPN model studied in this work, inhibitor arcs, represented with a small circle, model the opposite effect of the firing rule, preventing a transition from being enabled once its pre-set places are marked. Also, this work introduces the use of probabilistic weights in some of the arcs to model the consumption of working resources under uncertainty. The specific Petri modelling aspects of the IFMIF DONES inspection and maintenance activities are given in Section 4.

3.2. GSA methods

3.2.1. Challenges related to the application of GSA methods in particle accelerators

There are several major challenges in applying GSA to complex systems such as particle accelerators. One of the main problems is identifying all the factors influencing the uncertainty in the outcome. Particle accelerators represent many aspects ranging from material properties to beam dynamics; therefore, involving all the combined and individual effects is hard. Also, the interaction among these uncertainties cannot be considered linear in general; hence, the contribution of each parameter to the final uncertainty is even more difficult to quantify. This non-linearity, combined with the inherent complexity of particle accelerators, makes the accurate modelling of the latter very demanding. Furthermore, problems involving particle accelerators usually include many input parameters; thus, due to the high dimensionality of the problems, GSA methods are computationally expensive and less effective. Despite the importance of GSA for particle accelerator design, problems like uncertainty quantification, handling nonlinear interactions, and treating high-dimensional data make the application challenging for this methodology (Adelmann, 2019; Corno et al., 2020; Kazemi, Mostajeran, & Romanov, 2024; Putek, Zadeh, Wenskat, Hillert, & van Rienen, 2019; Terrab & Pankavich, 2024).

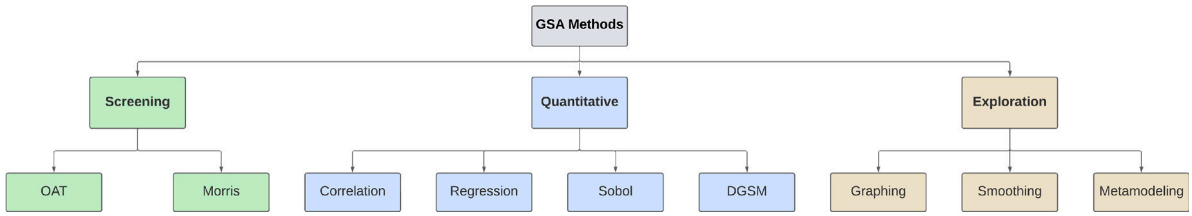


Fig. 2. Classification of GSA methods.
Source: Adapted from Iooss and Lemaître (2015).

3.2.2. Comparison between GSA methods

This section presents the methodological framework for a comprehensive GSA applied to the Petri nets model representing the predetermined maintenance process in the IFMIF DONES Facility TC. Our primary goal is to evaluate the sensitivity of the model's output variables to variations in timed transitions, including availability, uptime, and downtime (Morris, 1991; Saltelli et al., 2008; Sobol̃, 1993).

A thorough GSA was conducted to understand the relative importance of timed transitions and gain insight into the Petri nets model's sensitivity for the predetermined maintenance process. The analysis aims to illustrate the contributions and interactions of each timed transition with the output variables and to identify the critical factors that affect the TC's performance in the IFMIF DONES Facility. This section outlines three different sensitivity analysis techniques that were used in this work, which are Sobol indices, Morris indices, and DGSM indices. The variety of implemented GSA techniques offers a holistic understanding of the system's behaviour and identifies key drivers of relevant output variables.

In the study of particle accelerators and in the field of infrastructure maintenance, researchers deploy GSA methods to assess model performance and evaluate the contribution of input parameters to model output. These methods are well suited to model assessment by capturing the effects of input parameters and their interactions.

There are three primary categories of GSA methods: screening techniques, quantitative techniques and exploration techniques. Screening techniques are designed to rank inputs, particularly on the basis of discretization levels, in order to enable rapid exploration of code behaviour. Quantitative techniques gauge the extent to which input variables are important or have an effect on output by using statistical techniques such as correlation and regression and variance-based techniques such as Sobol indices. Exploration techniques are intended to evaluate the impact of input variation on output and to analyse model behaviour across the range of variation. They comprise three subcategories: graphical, smoothing, and metamodels.

Fig. 2 shows the main classification of the GSA methods, adapted from the work by Iooss and Lemaître (2015). It showcases the three main types of GSA methods used in this work: DGSM indices, Morris indices, and Sobol indices. The GSA classification aligns with the terminology introduced in the earlier discussion in the introduction. This figure provides a visual representation of the categorization of GSA methods, aiding in understanding their classification and relevance to the study. Table 2 shows a comparison between the main GSA methods.

3.2.3. Sobol sensitivity indices

The Sobol indices measure the sensitivity of the output variables with respect to the input variables, capturing both individual and interaction effects. They provide a comprehensive evaluation of the input variables' importance and interactions in explaining the output variability.

The first-order Sobol sensitivity index (S_i) represents the contribution of the individual input variable X_i to the output variance $\mathrm{Var}(Y)$, as follows (Sobol̃, 1993):

$$S_i = \frac{\mathrm{Var}(X_i|X_{\sim i})}{\mathrm{Var}(Y)} \tag{4}$$

where $X_{\sim i}$ represents the rest of input variables other than X_i. The second-order Sobol sensitivity index (S_{ij}) quantifies the contribution of the joint variations of input variables X_i and X_j, in addition to their individual effects, to the output variance (Sobol̃, 1993):

$$S_{ij} = \frac{\mathrm{Var}(X_i X_j|X_{\sim i,j})}{\mathrm{Var}(Y)} \tag{5}$$

The total Sobol sensitivity index (S_{Ti}) represents the total contribution of the input variable X_i, including both its individual and joint effects with other variables, to the output variance (Sobol̃, 1993):

$$S_{Ti} = \frac{\mathrm{Var}(X_i|X_{\sim i}) + \sum_{j\neq i}\mathrm{Var}(X_i X_j|X_{\sim i,j})}{\mathrm{Var}(Y)} \tag{6}$$

Here, $\mathrm{Var}(X_i|X_{\sim i})$ denotes the conditional variance of X_i given all other input variables, $\mathrm{Var}(X_i X_j|X_{\sim i,j})$ represents the conditional variance of the joint variations of X_i and X_j given all other input variables, and $\mathrm{Var}(Y)$ is the total output variance.

3.2.4. Morris elementary effects

The Morris method quantifies the impact of each input variable on the output by calculating elementary effects. It provides insights into the main effects and interactions of the input variables.

The elementary effect for variable X_i is defined as the average absolute difference in the output caused by varying X_i over a small range while keeping the other variables fixed (Morris, 1991), as follows:

$$mu_i = \frac{Y(x_i^+) - Y(x_i^-)}{2\delta} \tag{7}$$

In this equation, $Y(x_i^+)$ and $Y(x_i^-)$ represent the outputs obtained by varying the value of input variable X_i in positive and negative directions, respectively, and δ is the step size of the variation.

3.2.5. Derivative-based global sensitivity measures

DGSM computes sensitivity measures based on derivative information to estimate the impact of input variables on the output. The first-order DGSM ($DGSM_i$) represents the derivative of the output variable Y with respect to the input variable X_i (Kucherenko & Iooss, 2014), and can be expressed mathematically as:

$$DGSM_i = \frac{dY}{dX_i} \tag{8}$$

The total-order DGSM ($DGSM_{Ti}$) considers the standard deviation of both the input variable X_i and the output variable Y to account for their variability (Saltelli et al., 2008), as follows:

$$DGSM_{Ti} = \left(\frac{dY}{dX_i}\right)\left(\frac{\sigma(X_i)}{\sigma(Y)}\right) \tag{9}$$

Table 2
Comparison between GSA methods (inspired by Iooss and Lemaître (2015)).

Method	Class	Benefits	Limitations
OAT	Screening	Good for identification of non-influential variables when the number of inputs is large	Requires a priori knowledge Not suitable for higher than one order terms
Morris	Screening	Captures nonlinearities & interactions Suitable for monotonic discontinuous relations	High computational cost Not useful when the number of experiments is smaller than the number of inputs Requires a priori knoweldge
Correlation	Quantitative	Fast sensitivity estimation method Interpretable results Incorporation of local changes in relationships (Storlie & Helton, 2008)	Not suitable for nonlinear or nonmonotonic relations Limited to low-dimensional models
Regression	Quantitative	Fast sensitivity estimation method Explanatory equations Incorporation of local changes in relationships (Storlie & Helton, 2008)	Not suitable for nonlinear or nonmonotonic relations Limited to low-dimensional models
Sobol	Quantitative	Suitable for high number of inputs Suitable for monotonic discontinuous relations	High computational Cost
DGSM	Quantitative	Suitable for nonlinear and nonmonotonic relations Precise methods	Limited to low-dimensional models High computational cost
FAST, eFAST	Quantitative	Reduced computational cost Suitable for nonmonotonic continuous relations	Limited to low-dimensional models (number of inputs <10) Costly, unstable, and biased for a big number of inputs (>10)
Graphing	Exploration	Ease of interpretation Detection of trends in functional relations	Interactions between input and output variables are not captured
Smoothing	Exploration	Estimation of conditional moments at greater order than one	Lack of intuitive appeal of quantitative methods (Storlie & Helton, 2008)
Metamodels	Exploration	Negligible Computational Cost Suitable for nonmonotonic continuous relations Good prediction capabilities Direct computation of sensitivity indices	Not suitable for highly nonlinear relations and complex simulations

Here, $\frac{dY}{dX_i}$ denotes the partial derivative of the output variable Y with respect to the input variable X_i, and $\sigma(X_i)$ and $\sigma(Y)$ represent the standard deviations of X_i and Y, respectively.

These sensitivity analysis methods provide valuable insights into the relative importance and interactions of the timed transitions, contributing to a comprehensive understanding of the system's behaviour (Saltelli et al., 2004).

4. Maintenance modelling of the TC

4.1. Introduction to the IFMIF-DONES Test Cell (TC)

This section outlines the IFMIF-DONES Test Cell (TC) design, a central component of the facility. It contains the end section of the accelerator, high flux test module (HFTM), target assembly (TA), and some lithium systems (LS) components (Tian, Arbeiter, Gordeev, Gröschel, & Qiu, 2017). Table 3 shows the description and function of the TC critical components. The TC follows the design principles of the IFMIF/EVEDA TC (Tian et al., 2014) with some modifications like a more stable irradiation environment, reduced nuclear power, radiation shielding, and component accommodation. Also, the design of the TC allows for easy access and maintenance with remote handling equipment.

4.2. Basic functions of the IFMIF-DONES TC

The main function of the TC is to host the specimens that would be irradiated for testing in a controlled environment while providing confinement and shielding against irradiation (TC Neutron & Gamma) to the surrounding rooms and allowing the interaction with other subsystems of the IFMIF-DONES (Tian et al., 2018). For the steady-state operation of the facility, two beam stops occur per year. There

Table 3
Description and function of the critical components of the test cell.

Component	Description and function
TCCP	The Test Cell Cover Plate (TCCP) is composed of a stainless-steel plate and a rubber-based sealing gasket. It is used to securely fasten the Test Cell (TC) to create a controlled atmosphere inside the TC.
TCL	The TC liner is constructed with heavy concrete and serves as the primary barrier for neutron irradiation protection. It is exposed to intense neutron irradiation and undergoes significant activation.
USP	The Upper Shielding Plate (USP) is primarily composed of concrete and provides shielding against neutrons and gamma radiation.
LSP	The Lower Shielding Plate (LSP) is made of concrete and is specifically designed to shield the TC during the irradiation period. Its main function is to protect the Access Cell (AC), which is located directly above the TC.
PCPs	Removable Piping and Cabling Plugs (PCPs) are predominantly made of concrete and consist of replaceable parts. They are designed to accommodate cable and pipe penetrations, including those for cooling and cabling connections between the High Flux Test Module (HFTM) and the external components of the TC. The PCPs also provide shielding against gamma and neutron radiation.
HFTM	The High Flux Test Module (HFTM) is a crucial component of the Test Systems (TS). During normal operation, it is positioned within the Test Cell and affixed to the backplate behind the Target Assembly. The HFTM enables irradiation and temperature control of the specimens.

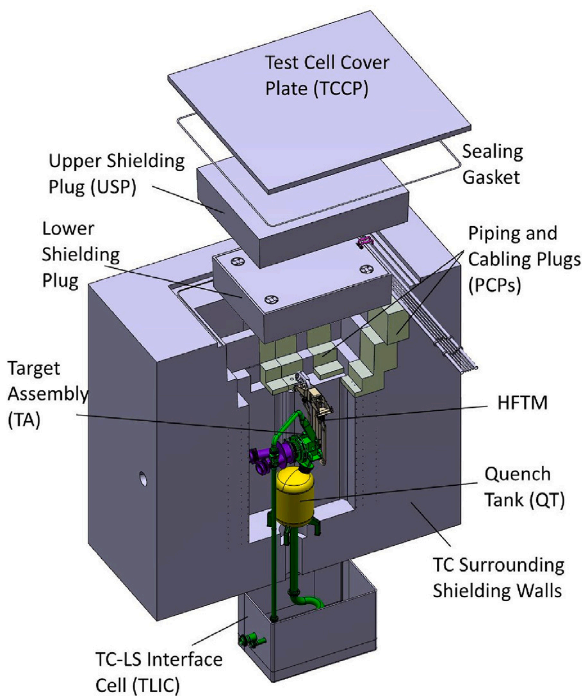


Fig. 3. Sketch of the TC (Tian et al., 2018).

is one that will take three days and another that lasts twenty days. Target Assembly replacement is done annually, a critical maintenance activity requiring careful planning and coordination for safe handling and installation of components in the presence of radiation (Arranz et al., 2023). The TC includes other crucial processes that necessitate proficient maintenance to ensure optimum availability (Tian et al., 2018), as will be shown next.

4.3. Maintenance of the IFMIF-DONES TC

Maintenance work on the TC involves various specialized pieces of equipment such as TCCP, USP, LSP etc (Table 3). Fig. 3 from Ibarra et al. (2019) offers an overview of the TC equipment while Fig. 4 provides an overview of the main components in it. These figures give a good idea about how the TC was designed so that effective planning and execution of maintenance tasks can be carried out.

The maintenance of the TC is modelled using an HLPN of 17 places and 17 transitions, as depicted in Fig. 6. Note that places P_2, P_3, and P_{15}, model the states related to the inspection, the completion of the inspection, and the reinstallation of the TCCP, respectively. Similar representations are adopted for other components, such as the TCCP sealing gasket, USP, LSP, PCPs, TCL, TM supporting structure, TLIC removable pates, and HFTM, using the places P_3 to P_{15}, respectively. For instance, places like P_4 signify the state of replacement for the TCCP sealing gasket, where transition T_2 reflects the time required for the removal and inspection of the TCCP sealing gasket and T_3 signifies the time needed for the replacement and completion of the maintenance task of the corresponding component. Similarly, places P_5 and P_6 refer to the inspection of USP and LSP with the corresponding delay-timed transitions of T_4 and T_5. On the contrary, P_9 and P_{10} correspond to the reinstallation of USP and LSP represented by the transitions T_{12} and T_{13}, respectively. The transitions T_2 and T_{14} represent the time required for the removal and inspection of TCCP and the reinstallation of TCCP, respectively. These activities include sequential and parallel operations and time delays associated with specific timed transitions. Among the timed transitions, T_1 and T_{16} expressly represent timed transitions with delays of 72 and 96 h, respectively, considerably longer than the typical maintenance activities with periods ranging from 1 to 24 h. A detailed representation of the Petri nets model states and transitions is presented in Table 4.

Key performance metrics for maintenance operations are calculated using uptime, downtime, and availability indicators. Uptime represents cumulative time spent on P_0, while downtime represents cumulative time spent on P_1 state. Availability is the ratio of uptime to the sum of uptime and downtime.

4.4. Modelling assumptions

While modelling the TC's predetermined maintenance, several assumptions and estimates were made to ensure a realistic representation of the process. These assumptions include the facility's operational hours, duration of maintenance tasks, delay times after and before the beam stops, number of workers involved, and the sequence of operations. The following assumptions and estimates were considered:

1. Operational hours: The facility operates for 345 days each year, 24 h a day, and seven days a week, resulting in 8280 operational hours before maintenance, modelled through the delay of timed transition T_0.

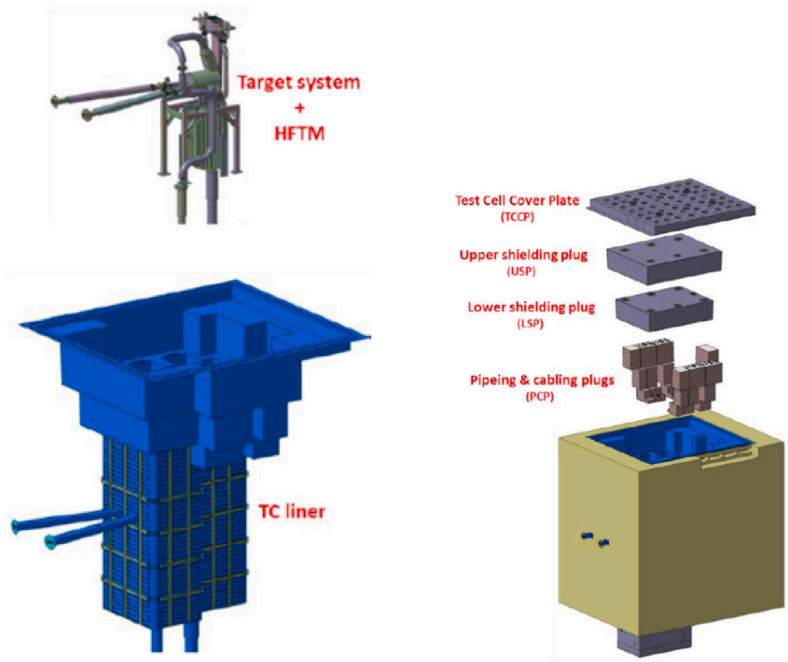


Fig. 4. Exploded view of the TC.

Table 4
Description of the nodes from the PN model shown in Fig. 6.

Petri net	nodes	description
Fig. 6	P_0, P_1	system operational, scheduled maintenance
	T_0	time of operation before the yearly scheduled maintenance of the System
	T_1	delay time after shutdown of the facility and before the start of yearly scheduled maintenance
	P_2, P_3, P_{15}	TCCP is under inspection, TCCP is inspected, TCCP is reinstalled
	T_2, T_{14}	time required for removal and inspection of TCCP, time required for reinstallation of TCCP
	P_4 TCCP sealing gasket is replaced	
	T_3	time required for replacement of TCCP sealing gasket
	P_5, P_{14}	USP is inspected, USP is reinstalled
	T_4, T_{13}	time required for removal and inspection of USP, time required for reinstallation of USP
	P_6, P_{13}	LSP is inspected, LSP is reinstalled
	T_5, T_{12}	time required for removal and inspection of LSP, time required for reinstallation of LSP
	P_7	PCPs are inspected
	T_6	time required for inspection of PCPs
	P_8	TCL is inspected
	T_7	time required for inspection of PCPs
	P_9	TM Supporting Structure is inspected
	T_8	time required for inspection of TM supporting structure
	P_{10}	TLIC plates are inspected
	T_9	time required for inspection of TM supporting structure
	P_{11}, P_{12}	HFTM is under inspection, HFTM PCP bridges are replaced
	T_{10}, T_{11}	time required for removal and inspection of HFTM, time required for replacement of HFTM PCP bridges
	P_{16}	finish of maintenance activities of the Test Cell
	T_{16}	delay time after finish of maintenance of the Test Cell and before the resume of operations

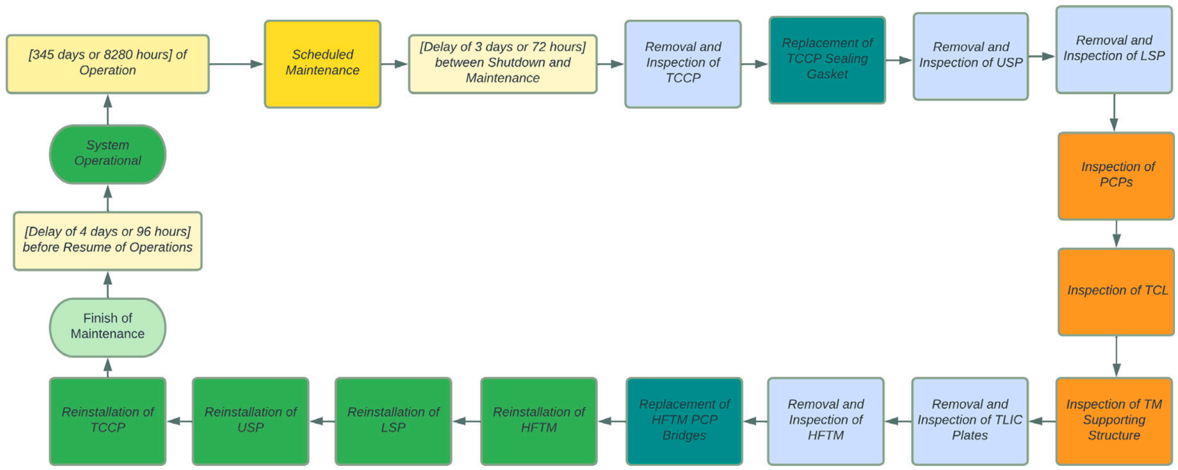


Fig. 5. UML activity diagram of the predetermined maintenance process.

2. Delay time: The time delay between the stopping of the particle beam and the lithium flow and the start of the predetermined maintenance process (modelled by T_1) is assumed to be three days, equivalent to 72 h based on 24 h per day.
3. Sequence of operations: The sequence of maintenance operations follows a chronological order from the TC to the access cell. A reduced UML activity diagram that represents the predetermined maintenance process is provided in Fig. 5.

4.4.1. *Description of maintenance operations*

The first maintenance operation is stopping irradiation, during which the particle beam and the lithium flow undergo a complete stop, requiring 72 h of work based on 24 h per day (delay of T_1). The next operation involves removing and inspecting the TCCP (modelled by T_2), which takes about 5 h to complete by two workers. Subsequently goes the replacement of the TCCP sealing gasket (modelled by T_3), which takes 8 h to complete by two workers

Next maintenance tasks include the removal and inspection of USP (4 h, T_4), removal and inspection of LSP (4 h, T_5), an inspection of PCPs (14 h, T_6), an inspection of TCL (8 h, T_7), an inspection of TM supporting structure (4 h, T_8), removal and inspection of TLIC removable plates (8 h, T_9), removal and inspection of HFTM (24 h, T_{10}), replacement of HFTM PCP bridges and reinstallation of HFTM (16 h, T_{11}), reinstallation of LSP (1 h, T_{12}), reinstallation of USP (1 h, T_{13}), reinstallation of TCCP (1 h, T_{14}). Finally, there is a delay time of 4 days (modelled by T_{16}), equivalent to 96 h based on 24 h per day, between the completion of the maintenance process and re-operation, accounting for the resumption of lithium flow and beam-on.

A UML activity diagram illustrating the sequence of maintenance operations is provided in Fig. 5.

4.4.2. *Assumptions made for the GSA*

In addition to the above assumptions, the following assumptions were made specifically for the GSA:

1. Uptime before predetermined maintenance is assumed to be 8232 to 8280 h before the specified maintenance time. This is based on the expectation that a predetermined maintenance will take place after an operational period of 345 days (8280 h). This gives a maximum safety margin. Moreover, two days (48 h) prior to predetermined maintenance have been left as the minimum margin for uncertainties related to administrative work for preventive maintenance.
2. Delay time between stopping the particle beam and lithium flow starts and beginning of maintenance: it was assumed as a Gaussian distribution with a mean value of 3 days (72 h) and deviation that equals to 25% of delay mean value. It accounts for variations in transition time from stoppage through to the end of scheduled repairs.
3. Inspection and maintenance tasks: This is considered as normal distribution where its mean is the actual inspection or downtime for each task while its standard deviation is taken as 25% of its mean so as to accommodate any variation in time spent during these tasks that includes uncertainties about duration when it comes to inspection and maintenance.
4. The duration between the end of maintenance activities and the resume of facility operations is a case in point: It is believed to be a Gaussian distribution with a mean of 4 days (96 h) and a standard deviation of 25% of the mean delay time. This assumption accounts for variability in the time needed to restart the lithium flow and start up the beam for particles moving through the accelerator.

In addition, maintenance tasks within this facility were grouped together according to their radiation exposures under TC. These tasks also fit into two categories; they were either hands-on or remote handling, as explained in 5 below.

Such assumptions are incorporated during each simulation iteration's sample phase, thereby allowing sensitivity analysis to account for uncertainties and variabilities that exist in such a system. Improved knowledge of these assumptions helped in a better understanding of the effect uncertainties and variabilities have on the predetermined maintenance.

5. Results and analysis

5.1. *Petri nets simulation results*

The response of the Petri net model of Fig. 6, evaluated by using the state equation, was simulated by making use of the Monte Carlo method, which is suitable for representing possible uncertainties and variabilities both in the initial conditions and process dynamics. To achieve this, the initial marking has been chosen to consist of one token in P_0 and zero in the rest. The downtime, uptime and availability results are depicted in Fig. 7. This time-dependent dynamic property, availability, has an oscillating nature that tells about the occurrence of some operational situations, maintenance activities, logistic delays or time for preparation for operation. The oscillation means

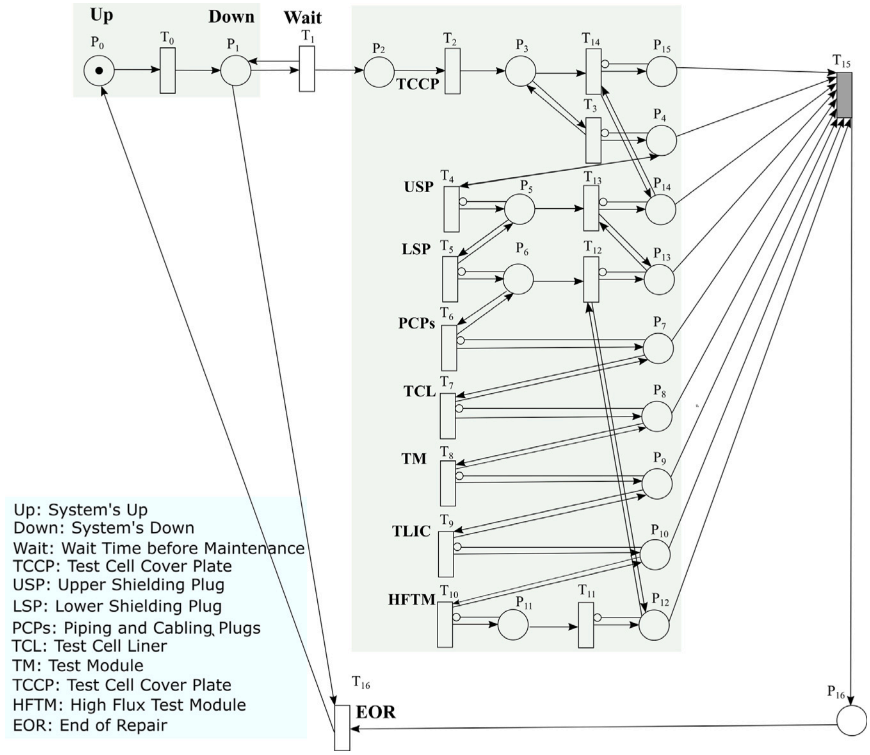


Fig. 6. Petri net architecture used to model the maintenance of the TC of IFMIF DONES.

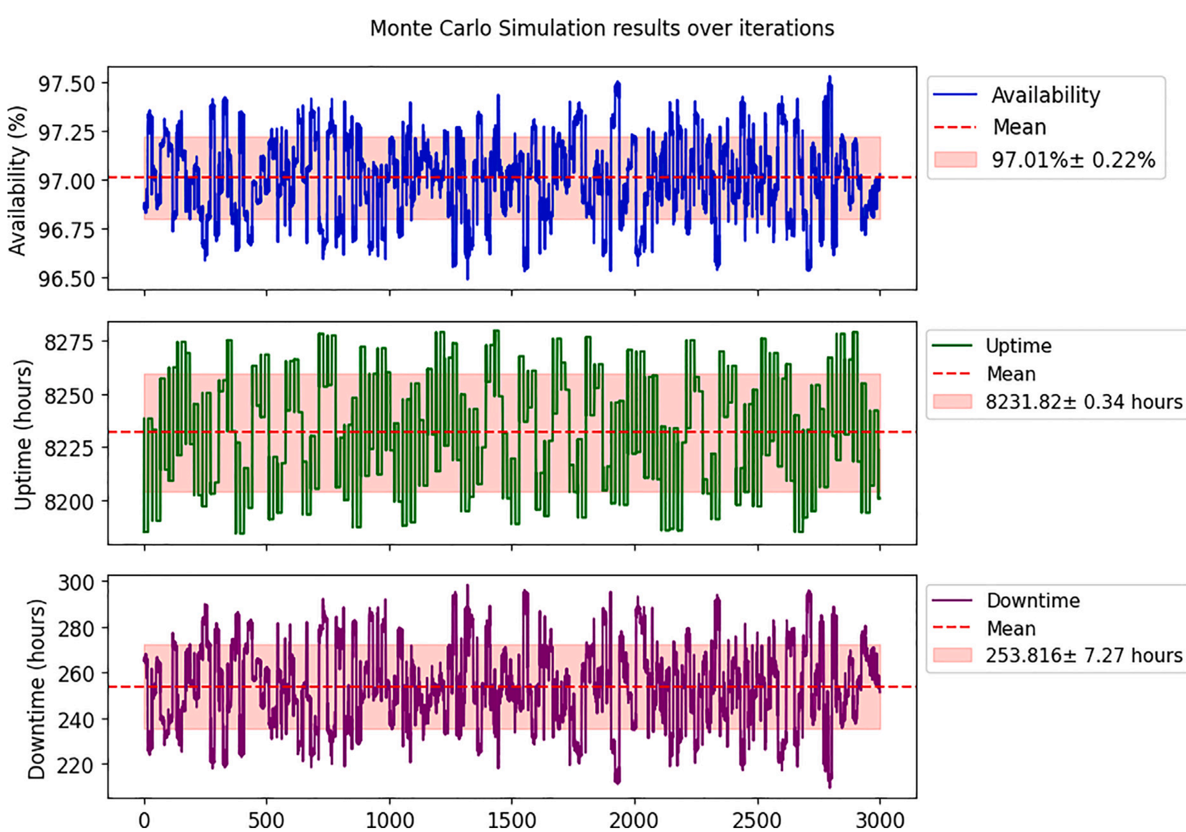


Fig. 7. Variation of availability, uptime, and downtime with respect to the time expressed in hours.

Table 5
Maintenance data for the critical components of the Test Cell considered in the case study.

Subsystem	Component	Maintenance type	Action	Frequency
Test Cell	TCCP	Hands-on	Removal and inspection	Once every year
	TCCP sealing gasket	Hands-on	Replacement	Once every year
	USP	Remote handling	Removal and inspection	Once every year
	LSP	Remote handling	Removal and inspection	Once every year
	PCPs	Remote handling	Inspection	Once every year
	TCL	Remote handling	Inspection	Once every year
	TM supporting structure	Remote handling	Inspection	Once every year
	TLIC removable plates	Remote handling	Removal and inspection	Once every year
HFTM	HFTM	Remote handling	Removal and inspection	Once every year
	HFTM PCP bridges	Remote handling	Replacement	Once every year
	HFTM	Remote handling	Replacement	Once every two years

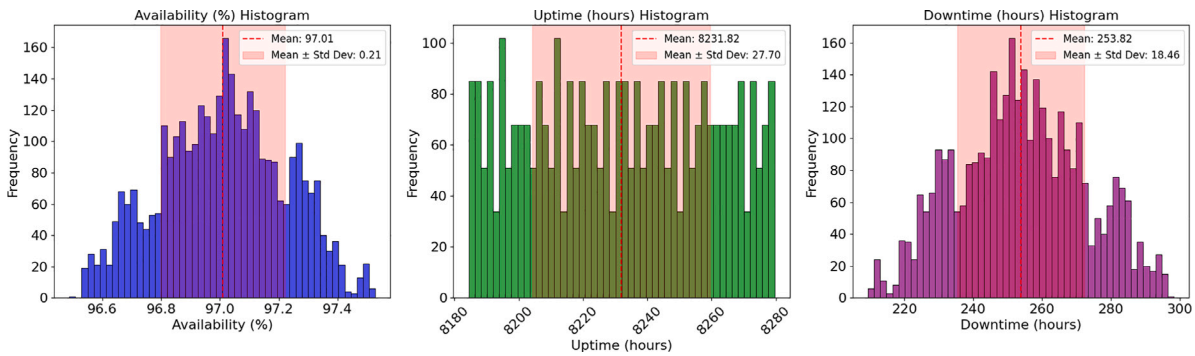


Fig. 8. Histograms of availability, uptime, and downtime.

the system's availability is generally high but subject to fluctuations due to scheduled and unscheduled events reflecting real operational variability. On the other hand, the average uptime of 8231.82 h with a standard deviation of 0.34 h indicates minimal system interruption, which demonstrates the effectiveness of the maintenance scheduling in ensuring its reliable performance. Finally, downtime has an average of 253.815 h and a standard deviation of 7.27 h, which allows calculating periods of unavailability due to planned maintenance and temporary disruptions, reflecting how scheduled maintenance and specific disrupted periods may influence the system's performance. These results give visual insights into the reliability of a system, the effectiveness of a maintenance strategy, and the modes of operation interruption.

The histograms in Fig. 8 present availability, uptime, and downtime, with mean and standard deviation annotations, enabling insight into the variability of the results and the distribution of the simulation outcomes. On the other hand, the impact of fixing timed transitions T_1 and T_{16} on the system's performance is shown in Fig. 9. As availability improves, from 97.01% ±0.21 to 98.96% ±0.06, system stability and predictability improve, reflecting a more reliable operational environment due to reduced variability of critical delays. Uptime, which increases slightly from 8231.82 ±27.70 h to 8232.1 ±0.34 h, results from the depiction of controlled and consistent operation of the system, suggesting that maintenance activities have been effectively scheduled and executed. Downtime decreases significantly from 253.82 ±18.46 h to 86.299 ±5.34 h, highlighting the efficiency of a controlled and predetermined maintenance approach. These improvements underscore the impact of specific timed transitions, T_1 and T_{16}, which model critical delays in the maintenance process, as detailed in the assumptions section. The assumptions include the operational hours, duration of maintenance tasks, the delay times associated with stopping the particle beam and lithium flow, and the sequence of operations. The histograms in Fig. 10 further illustrate the distribution and variability of availability, uptime, and downtime under the influence of fixing these timed transitions, providing comprehensive operational insights into the system's performance and maintenance efficiency.

The results provided insights into the operational performance under different scenarios. The global sensitivity analysis (GSA) identified the influence of parameters on the system's performance, which allowed for targeted optimizations and informed decision-making. The integration of these methods facilitates the development of maintenance strategies that prioritize downtime minimization, optimization of resource allocation, and, in turn, enhancement of the system's operational availability.

5.1.1. Monte Carlo simulation and optimization

Results of model simulation over 3000 Monte Carlo iterations identified the most cost-effective maintenance strategy for critical infrastructure scenarios. This simulation systematically explored variations in mean values for key parameters, *i.e.* the number of workers, shift costs, and downtime. For these parameters, mean values were calculated as 50% over the mean value, and both lower and upper bounds were defined (see Figs. 11 and 12). The simulation was based on the following specific assumptions:

1. **Shift cost:** A day shift costs one unit; a night shift costs two units.
2. **Number of workers:** Two workers are required for each maintenance task.
3. **Shift delays:** It is assumed that there is a 30-minute delay while one worker replaces another. If two shifts are considered, the delay is subtracted from the second shift's duration.
4. **Task completion time:** If two workers take one hour or less to complete a task (remaining time ≤ 1), the shift is extended by the remaining time to finish the task.

The subsequent optimization analysis evaluated three distinct maintenance scenarios:

(a) **One shift (7 h):** Cost is calculated based on the number of workers, shift cost, and downtime.
(b) **Two shifts (7 h each):** The impact of shift transitions are assessed. The delay, cost and downtime are added to the total maintenance cost.

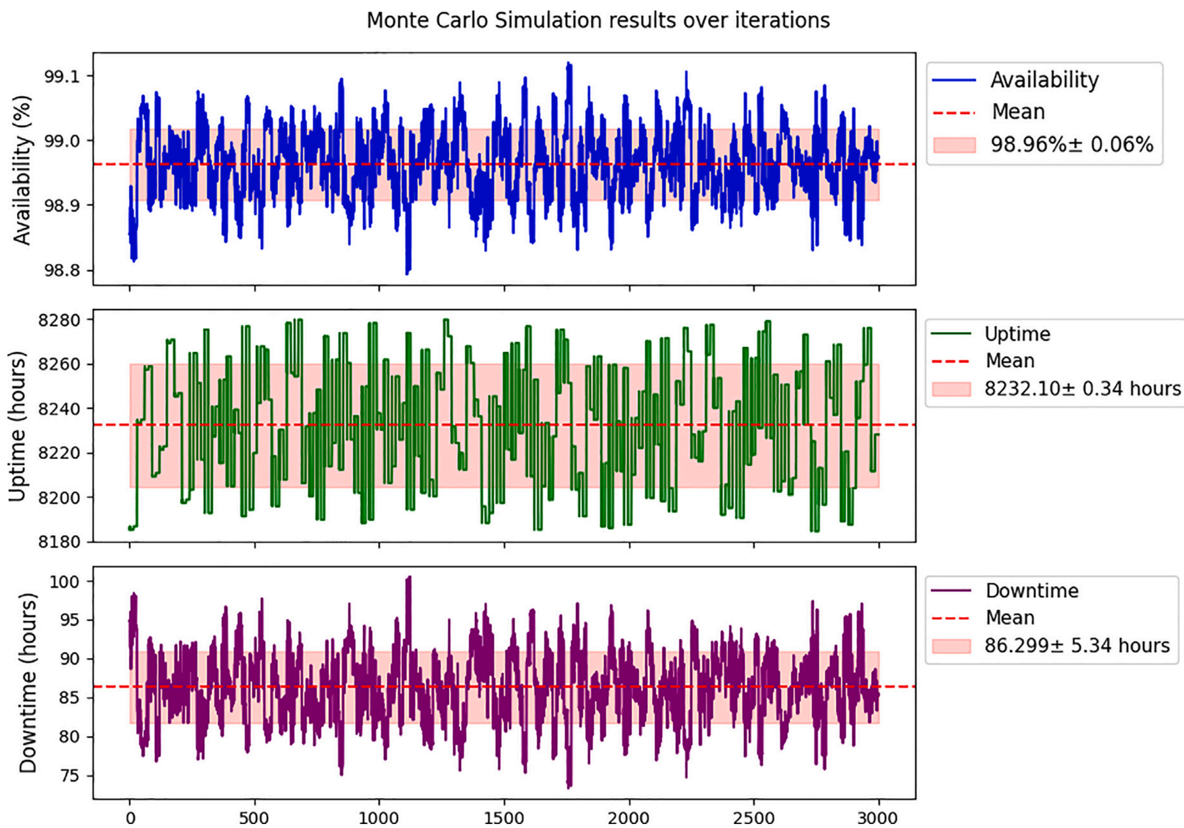


Fig. 9. Temporal variations of availability, uptime, and downtime (with T_1 and T_{16} fixed).

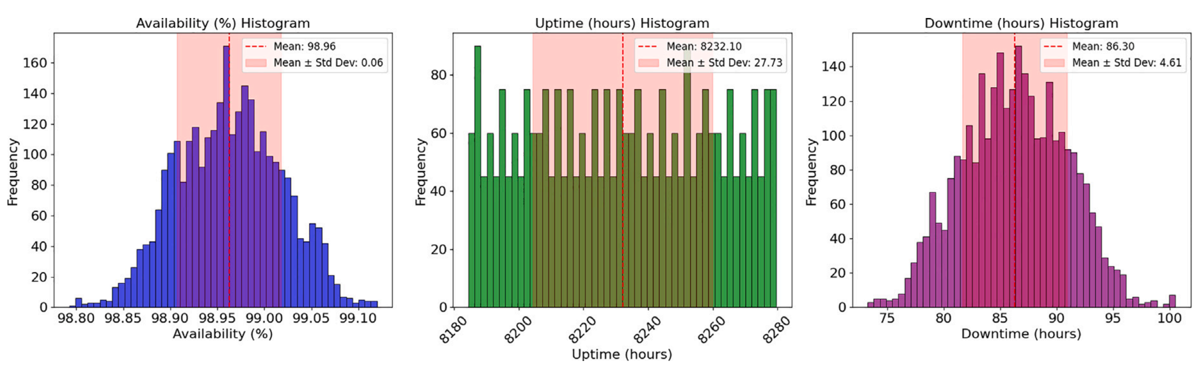


Fig. 10. Histograms of availability, uptime, and downtime (with T_1 and T_{16} fixed).

(c) **Three shifts (7 h each, with the third considered a night shift):** The cost and implication of introducing a night shift are investigated.

Determining the most optimal maintenance strategy depended on minimizing the total cost, optimizing the number of employees, reducing facility downtime, and ensuring that all maintenance tasks were performed as quickly as possible in a minimum number of days. The Monte Carlo simulation results helped to understand the variability in costs for each scenario. This analysis aimed to justify the introduction of night shifts and quantify potential savings, thus enabling decisions to be made regarding the best and least costly maintenance strategy. Figs. 13 and 14 present a graphic representation of shift data analysis. These figures outline downtime, availability, cost, and Shift days related to different maintenance strategies.

For instance, while there was little difference between the hours when comparing them with one another in terms of downtime across all cases, one shift had the lowest unit cost. On the other hand, a critical tradeoff arose since carrying out maintenance activities took approximately four times longer compared to three-shift cases (operations spread over a 24-hour period or more) than two-shift cases, meaning it took more than twice as long. Even though two-shift and three-shift cases are costlier than each other, three-shift was chosen because it finished quicker in terms of duration to carry out maintenance tasks. This decrease minimizes facility downtime by minimizing the number

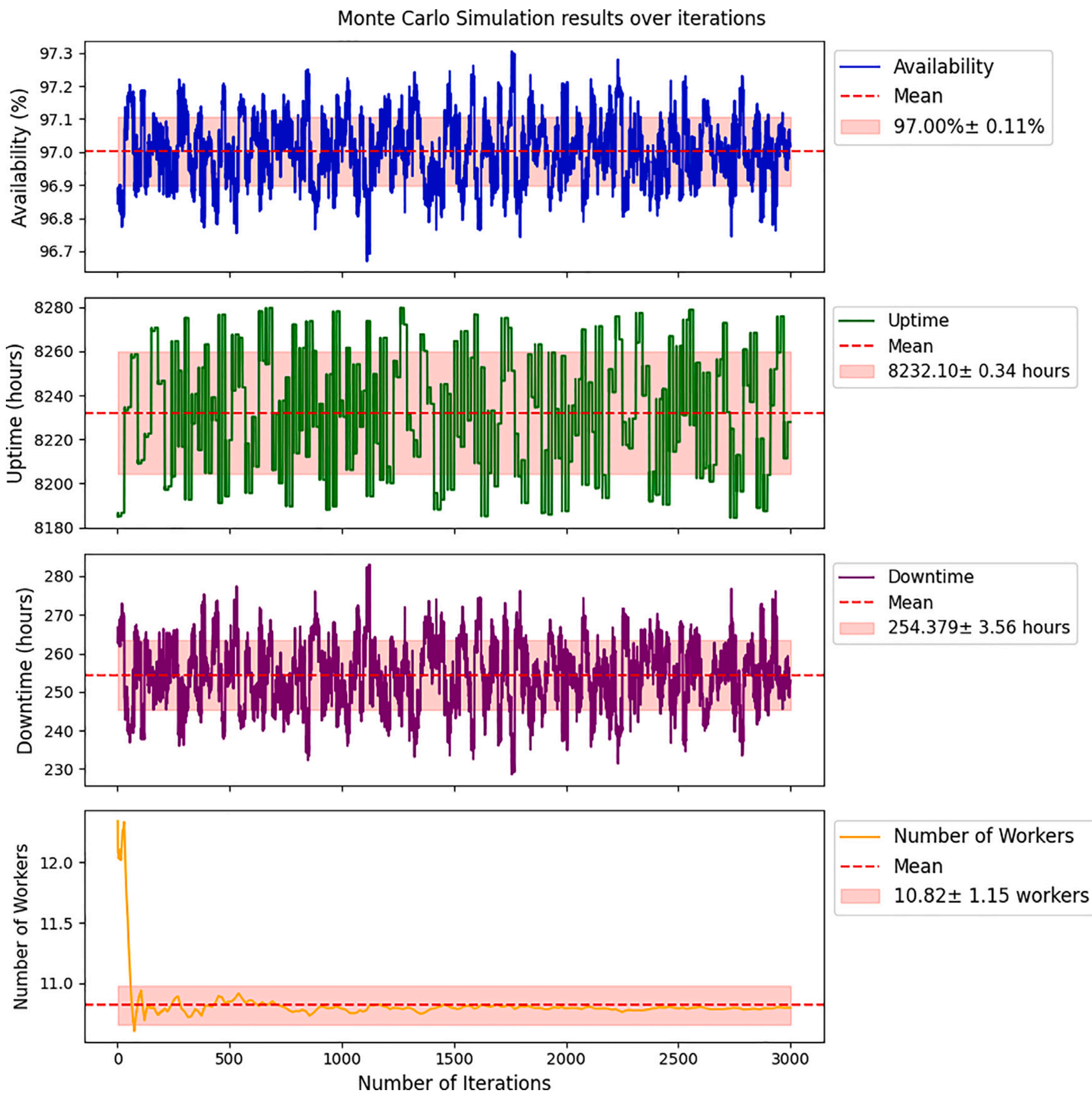


Fig. 11. Monte Carlo simulation results (50% uncertainty).

of days, which results in increased availability – a key performance metric, especially in irradiation facilities. The emphasis on optimizing availability underlies the choice of three shifts' maintenance strategy and strikes a balance between costs and the need to prevent downtime, thus improving overall operational efficiency. The following crucial factors lead to this conclusion:

- **Downtime:** Among these considerations, the three-shift scenario has the least downtime among the considered maintenance strategies, making it important in scenarios where minimizing downtime is essential for uninterrupted operations.
- **Cost:** At the same time as considering cost, the three-shift scenario effectively weighs expenses, considering shift costs and the number of workers needed.
- **Shift days:** In total, among all maintenance scenarios, the three-shift scenario requires the least number of days to complete all maintenance tasks, contributing to swift and efficient execution.

Therefore, the simulation results strongly support implementing the three-shift maintenance strategy for optimizing system reliability and minimizing downtime in critical infrastructure scenarios.

5.2. Correlation results

5.2.1. Correlation results without fixing T_1 and T_{16}

Correlation analysis was conducted to investigate the relationships between the input and output parameters (availability, uptime, and downtime). In this analysis, the delays of timed transitions T_0 to T_{16} serve as input parameters. The correlation coefficients are computed using Pearson's correlation coefficient and analysed using Cohen's convention for interpretation.

Tables 6 and 7 illustrate correlation coefficients between input parameters (T_0-T_{16}) and output parameters, which indicate the nature of relationships, their strength and direction. For instance, input parameter T_{16} has a strong negative correlation(−0.766839) with availability, while input parameter T_0 has a weak positive correlation (0.066031). These results suggest that T_{16} may have possible negative effects on availability, although T_0 might have small positive impacts.

Bar graphs were created for each output parameter to visualize correlations. Fig. 15(a) gives the bar graph of Fig. 15(b) shows the bar graph for uptime, while Fig. 15(c) suggests the bar graph for downtime. By representing these bar graphs, it is easier to understand how both

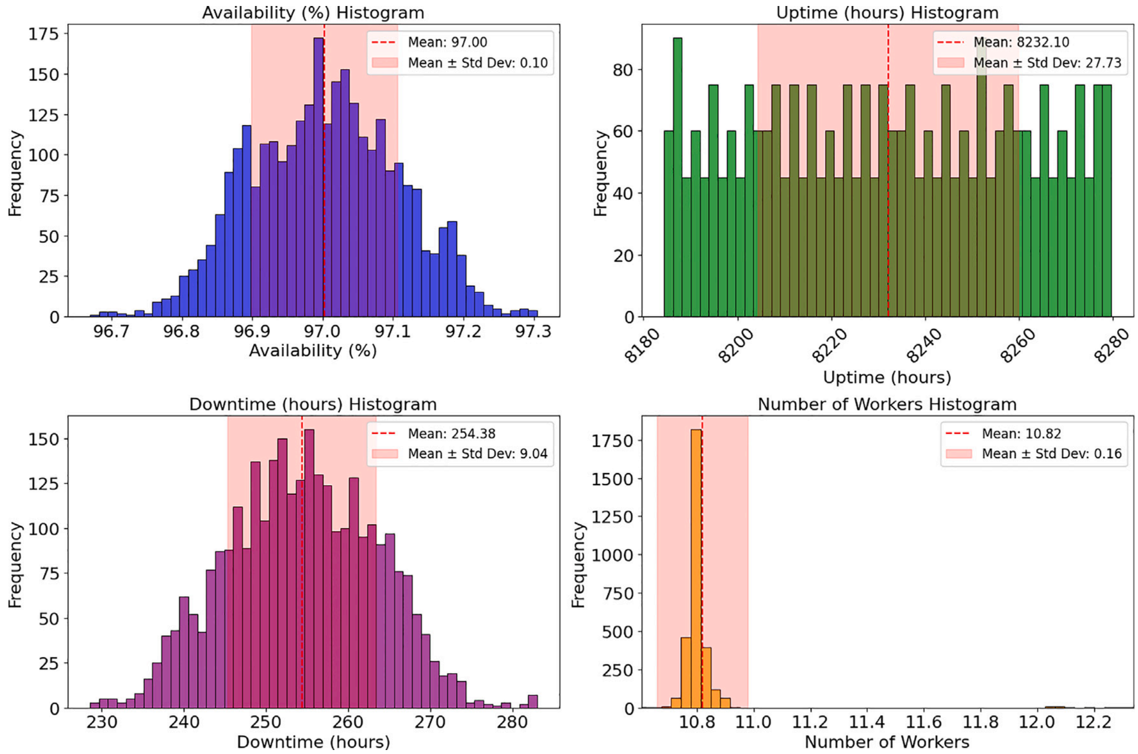


Fig. 12. Monte Carlo simulation results histograms (50% uncertainty).

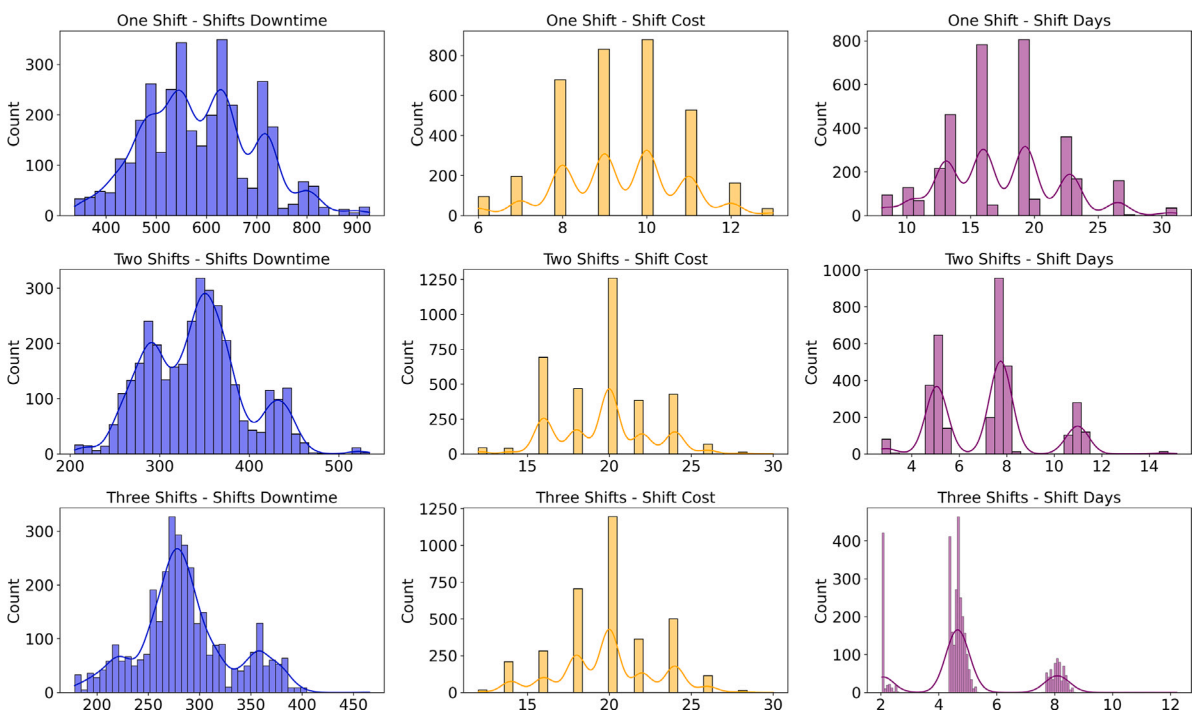


Fig. 13. Analysis of shift data: downtime, cost, and shift days for different maintenance scenarios.

Table 6
Correlation coefficients (Part 1).

	T_0	T_1	T_2	T_3	T_4	T_5	T_6	T_7
Availability	0.066031	−0.567598	−0.041323	−0.063797	−0.031066	−0.031871	−0.109470	−0.061599
Uptime	1.000000	−0.000288	0.000153	−0.000762	0.000008	0.000000	0.000013	−0.000035
Downtime	−0.018001	0.568673	0.041521	0.063776	0.031502	0.031922	0.109732	0.061785

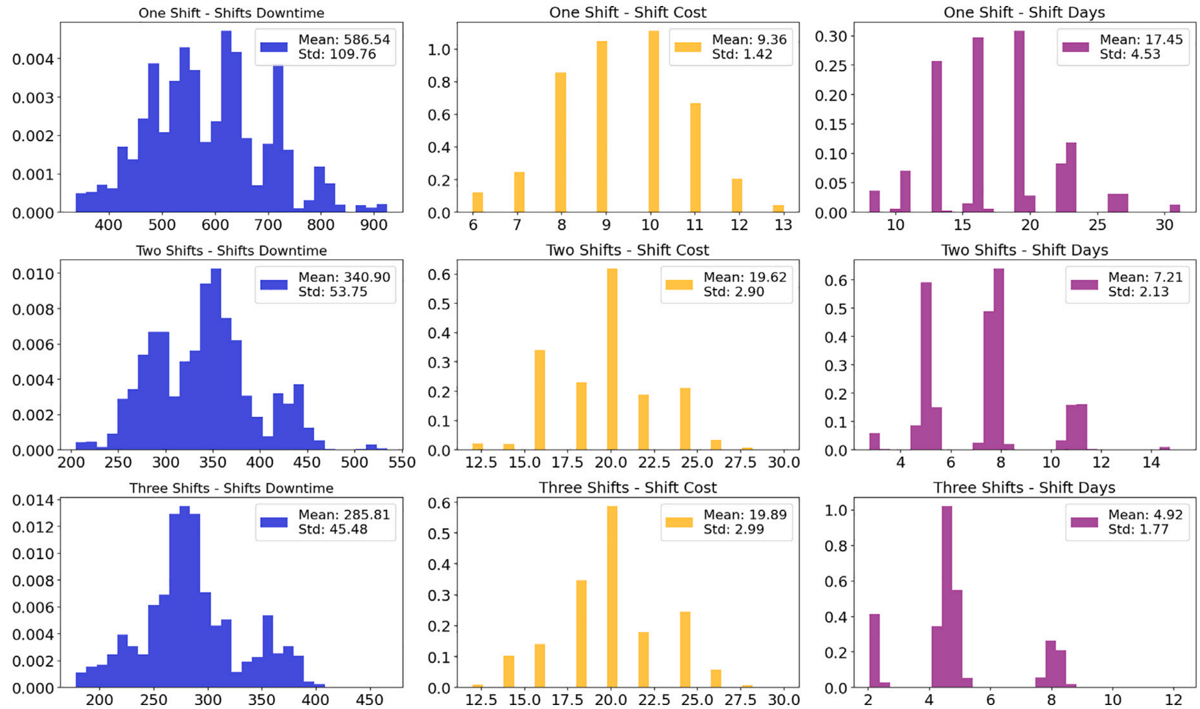


Fig. 14. Continuation of the shift data analysis: downtime, cost, and shift days for different maintenance scenarios.

Table 7
Correlation coefficients (Part 2).

	T_8	T_9	T_{10}	T_{11}	T_{12}	T_{13}	T_{14}	T_{16}
Availability	−0.028929	−0.065044	−0.193824	−0.030304	−0.006275	−0.004383	−0.012014	−0.766839
Uptime	0.000751	0.000288	−0.011030	−0.000022	0.000057	0.002677	−0.000323	−0.020123
Downtime	0.029075	0.065207	0.193807	0.030302	0.006463	0.004723	0.007509	0.767421

inputs are related to outputs since these are graphic illustrations of correlation coefficients.

Correlation analysis helps in understanding what input parameters associate negatively or positively with outputs. It indicates which specific input parameters can affect system performance adversely or conversely benefit it. These findings help in understanding the relationships and implications on the system adequately hence facilitating further examination and decision making processes as well.

Upon analysing the availability output variable, a range of correlation coefficients between the input parameters (T_0-T_{16}) and availability was observed, spanning from −0.766839 to 0.066031. Most of these coefficients indicated weak to very weak relationships, with two exceptions: T_1 and T_{16} exhibited strong negative correlations of −0.567598 and −0.766839, respectively. These findings suggest that variations in T_1 and T_{16} might significantly affect availability. Conversely, the input parameter T_0 showed a weak positive correlation (0.066031), indicating a minimal positive influence on availability.

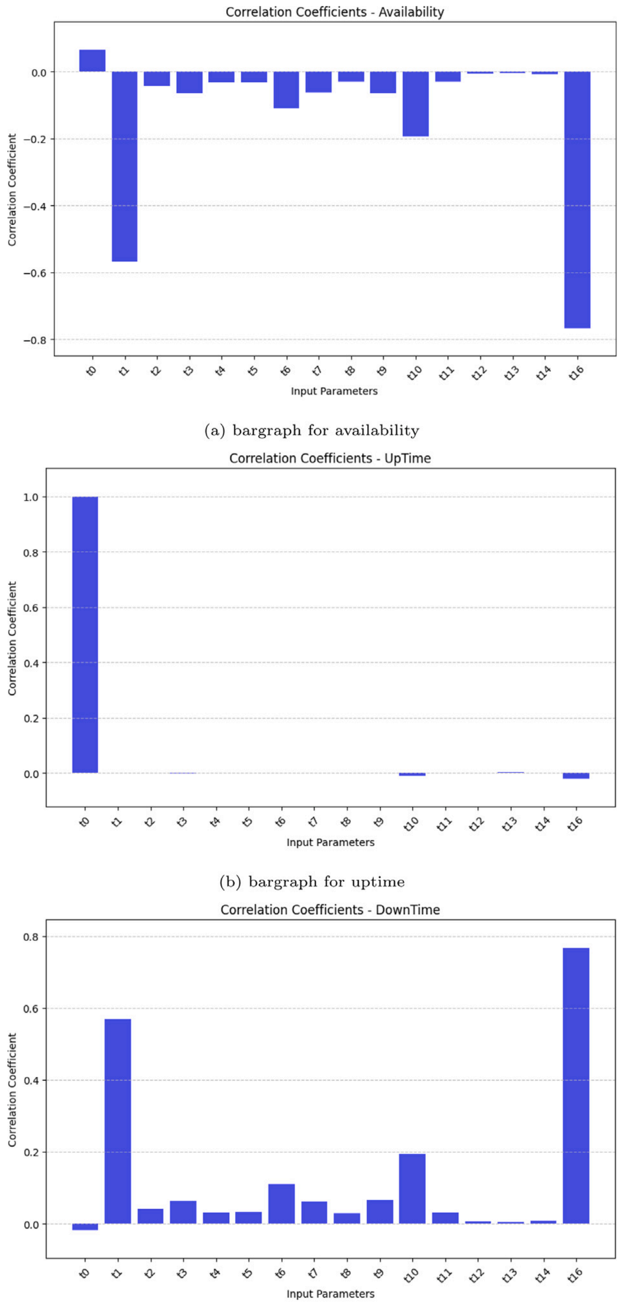
Uptime correlated from −0.020123 to 1.000000 with the input parameters that encompassed the lowest values and highest values, respectively, in correlation coefficients. Most of these correlation coefficients indicated very weak to weak relationships, except for T_0, which had a perfect positive correlation (1.000000) with uptime. Similarly, input parameter T_{16} had a very weak negative correlation (−0.020123) with uptime, thus having no significant effect.

Correlation coefficients for the downtime output variable ranged from 0.004723 to 0.767421. There were several strong correlations; however, most correlations were weak or moderate, two notable exceptions being T_1 and T_{16}, which showed strong positive correlations of 0.568673 and 0.767421 respectively. Thus, this means that changes in either T_1 or T_{16} could considerably affect how long the system remains off or its downtime durations. On the other hand, Downtime was seen to have a weak positive relationship (0.004723) with input parameter T_{13}.

The correlation analysis results reveal strong correlations between T_1 and T_{16} with the availability and downtime output variables, respectively. Additionally, T_0 showed a perfect positive correlation with the Uptime output variable. However, most of the other input parameters have weak relationships with availability. Moreover, the uptime and downtime output variables do not exhibit significant correlations with the input parameters.

The sensitivity analysis was able to show how individual inputs impact outputs, while the correlation analysis only identified those inputs having negative or positive associations alongside their outputs. It enabled to find out which parameters can have adverse effects or promote performance variations in the system. These results enable additional analysis and decision-making processes by providing a thorough grasp of the relationships and potential effects on the system.

Extensive simulations have been carried out, and it was found that the other input parameters' correlation coefficients had little or no values compared to the delay times of T_1 and T_{16}, which had much greater ones than all the other timed transitions. The above finding implies that most of the systems' performance scenarios are caused by time delays represented by only two transitions, namely T1 and T16. Consequently, a decision was made to fix T_1 and T_{16} in one scenario of the Petri nets model, thereby enabling an understanding of how other input parameters affect each other. In doing this, it aimed to isolate the effect from other input parameters with regard to maintenance and determine their relative importance during the evaluation process. A better comprehension of underlying dynamics in maintenance processes formed the basis for choosing such a scenario where T_1 as well as T_{16} run with constant times on the Petri nets model during simulation studies. This could help allocate resources more



(a) bargraph for availability

(b) bargraph for uptime

(c) bargraph for downtime

Fig. 15. Correlation bar graphs for the output parameters.

effectively and optimize decision-making about system performance based on prioritization of problems among all different potential options while increasing overall efficiency and reliability level in the IFMIF DONES Facility TC Maintenance Scheme. These assumptions apply for correlation and GSA outcomes elaborated in Section 5.2, 5.3, and 6.

5.2.2. Correlation results with fixed T_1 and T_{16}

Table 8 presents the correlation coefficients between the input parameters (T_0 to T_{14}) and the output variables (availability, uptime, and downtime) with fixed T_1 and T_{16}

.

For the availability output variable, T_0 showed a positive correlation coefficient of 0.151686, indicating a weak positive linear relationship. On the other hand, T_6 (−0.415454) and T_{10} (−0.715177) demonstrated negative correlations, suggesting a moderate and strong negative relationship with availability, respectively. The remaining correlation coefficients ranged from −0.236865 to 0.151686, indicating weak correlations.

Regarding the Uptime output variable, a significant positive correlation was observed only with T_0, exhibiting a perfect correlation coefficient 1. However, no significant correlation was found with the other input parameters, as their correlation coefficients ranged from −0.082637 to 0.001971, indicating very weak or no linear relationships.

Similarly, for the downtime output variable, T_6 (0.418614) and T_{10} (0.720610) demonstrated significant positive correlations, suggesting a moderate and strong relationship with downtime, respectively. In contrast, no significant correlation was observed with the other input parameters, as their correlation coefficients ranged from −0.090966 to 0.238708, showing weak to no correlation.

Overall, the correlation analysis results indicate that T_0 exhibits a perfect positive correlation with the uptime and a weak positive correlation with the availability output variable. On the other hand, T_6 and T_{10} show significant positive correlations with the downtime and strong negative correlations with the availability output variable, respectively. However, the other input parameters have weak relationships with the availability and downtime output variables. Additionally, the uptime does not show significant correlations with the other input parameters.

Bar graph images have been created to visualize the correlation coefficients for each output variable: bar graph of availability (Fig. 16(a)), bar graph of uptime (Fig. 16(b)), and bar graph of downtime (Fig. 16(c)). These bar graphs provide a visual representation of the correlation coefficients. Bars above the axis represent positive correlation coefficients, indicating a positive relationship between the corresponding input parameter and the output variable. Conversely, the bar graphs below the axis represent negative correlation coefficients, indicating a negative relationship. The length of each bar indicates the strength of the correlation, with longer bars representing stronger correlations and shorter bars representing weaker correlations.

Please refer to Table 8 for the detailed correlation coefficients and Figs. 16(a), 16(b), and 16(c) for the corresponding bar graphs.

5.3. GSA results

Below is a presentation of the obtained results and findings from GSA techniques applied to the Petri nets model of scheduled maintenance process in IFMIF DONES Facility TC. By using GSA, it helps to evaluate the significance of timed transitions in relation to output variables. Sobol indices were used to assess how important timed transitions were in terms of availability, uptime and downtime for TC. The results revealed that each timed transition contributes differently into output variability and its own interaction with other times.

This section presents the results and findings from the GSA techniques applied to the Petri nets model for the predetermined maintenance process in the IFMIF DONES Facility TC. GSA allows us to assess the relative importance of timed transitions and gain insights into their sensitivity concerning the output variables.

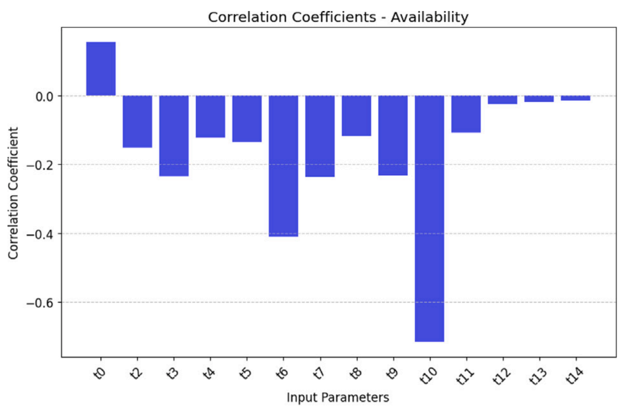
5.3.1. Sobol indices

Sobol indices offer important insights into the sensitivity of the Petri nets model towards critical factors that influence system performance. The obtained results highlight the contribution of input variables and their interaction with respect to the output parameter variations. Findings provide a better understanding of the factors affecting the system's performance. Figs. 17 illustrate the outcomes for sobol indices.

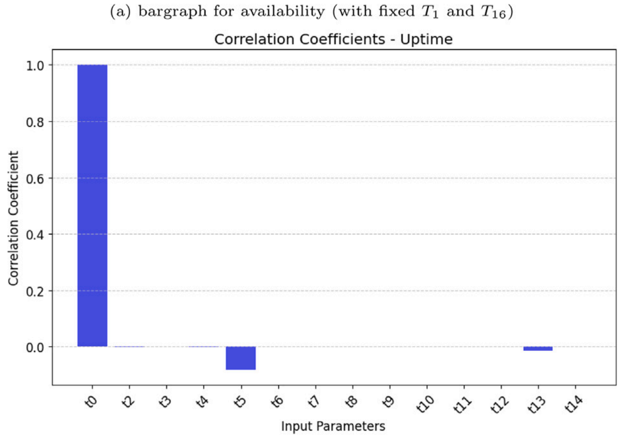
Table 8
Correlation coefficients.

	T_0	T_2	T_3	T_4	T_5	T_6	T_7
Availability	0.151686	−0.150954	−0.236865	−0.124415	−0.129184	−0.415454	−0.232869
Uptime	1.000000	−0.003046	−0.000128	−0.001019	−0.082637	−0.000067	−0.000018
Downtime	−0.090966	0.152052	0.238708	0.125364	0.125146	0.418614	0.234629

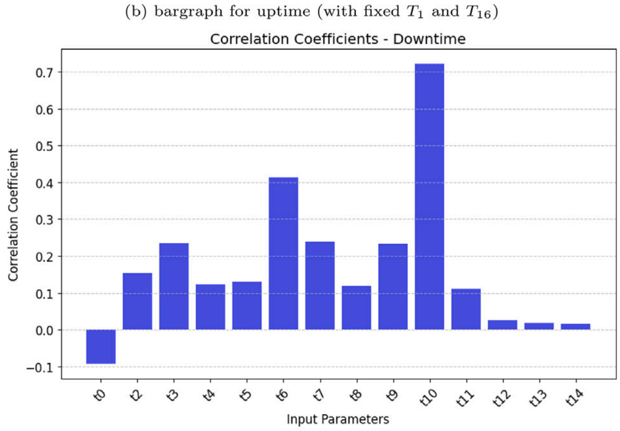
	T_8	T_9	T_{10}	T_{11}	T_{12}	T_{13}	T_{14}
Availability	−0.116817	−0.234491	−0.715177	−0.108810	−0.025397	−0.021404	−0.013836
Uptime	−0.000040	−0.000220	0.000009	0.000021	−0.000204	−0.013748	0.001971
Downtime	0.117771	0.236309	0.720610	0.109635	0.025577	0.020715	0.014086



(a) bargraph for availability (with fixed T_1 and T_{16})



(b) bargraph for uptime (with fixed T_1 and T_{16})



(c) bargraph for downtime (with fixed T_1 and T_{16})

Fig. 16. Correlation bar graphs for the output parameters (With fixed T_1 and T_{16}).

5.3.2. *Morris indices*

Morris indices were also calculated to determine the sensitivity of the Petri nets Model due to changes in timed transitions. It provides insights into the quantitative effect and interaction between timed transitions with regard to output variables. Morris indices assist in identifying the influence of timed transition variability on availability, uptime, downtime, as well as other relevant outputs. Figs. 19, 20, 21, 22, 23, and 24, show the Morris indices results.

5.3.3. *DGSM indices*

The DGSM indices were used to ascertain the global sensitivity of the Petri nets model. These consider derivatives of the model's response function with respect to each timed transition, enabling a better apprehension of how important timed transitions are and what their joint influence on output variables is. The DGSM analysis helps understand system behaviour and identify such timed transitions that significantly contribute to its variability. The DGSM indices results are shown in Fig. 18.

5.3.4. *Comparison with metamodel*

Metamodels provide a more accurate representation of the effect of inputs variation on outputs, especially for complex and nonlinear systems, than traditional GSA methods. This study employed a new hybrid modelling method for GSA. Sobol indices were calculated using metamodels and the Petri nets model for comparative analysis, which reveals the sensitivity and importance of input parameters on the output variables. Fig. 25 shows the Sobol indices for availability and downtime without fixing T_1 and T_{16}, while Fig. 26 shows the Sobol indices for availability and downtime with T_1 and T_{16} fixed.

6. Discussion of results

Our study placed a significant emphasis on shift data analysis to reveal complex relationships between workforce allocation and operational performance of the IFMIF DONES Facility TC; Monte Carlo simulation aimed at defining optimal maintenance strategy for critical infrastructure scenarios. The goal of the analysis was reducing total costs, optimizing number of workers, minimizing downtime and delivering efficient completion of tasks. Such results showed that one-shift scenario had the lowest unit cost but took significantly more days than two or three. Three-shift scenario however, as it reduced downtime and allowed for efficient execution emerged as optimal strategy emphasizing critical balancing in terms of cost consideration against mitigation of downtime. This conclusion is aligned with the wider objective of improving overall operational efficiency in maintaining this critical infrastructure.

Correlation analysis was also conducted to examine the relationship between the input parameters and the output variables. Pearson's correlation coefficients were computed and analysed using Cohen's convention. The correlation analysis, conducted without fixing T_1 and T_{16} in the Petri nets model, aimed to uncover relationships between input parameters (delays of timed transitions T_0 to T_{16}) and output parameters (availability, uptime, and downtime). Notable correlations were observed, with T_{16} (time required for preparation of operation) displaying a strong negative correlation with availability, T_1 (delay time between the beam stop and the yearly predetermined maintenance) exhibiting a strong negative correlation with availability and downtime, and T_0 (operational time before the annual predetermined maintenance) showing a weak positive correlation with availability. The correlation analysis indicated that T_1 and T_{16} significantly influenced availability and downtime. Following the decision to fix these transitions in the Petri nets model, a second correlation analysis was conducted. In this selected scenario, T_0 exhibited a weak positive correlation with availability. At the same time, T_6 (time required for inspection of PCPs) and T_{10} (time needed for removal and inspection of HFTM) displayed a strong positive correlations with downtime. The other input parameters demonstrated weak relationships with the output variables.

Equally important, we also carried out an extensive GSA with three different methods that pointed out the relative significance of timed transitions in terms of availability, uptime and downtime. The results obtained from this analysis were fundamental in determining the sensitivity of the Petri nets model. Sobol indices showed that among all transitions (except T_1 and T_{16}), T_0 was the most significant factor affecting uptime. Nevertheless, they were found to be essential for system availability and downtime. Conversely, under fixed T_1 and T_{16} conditions, T_6 then chiefly influenced downtime, while for availability, it was T_{10} which stood out as key. Morris and DGSM indices lent some weight to these findings, also reinforcing the fact that not all changes in inputs have an influence on the system in equal measure. It is worth noting that the Sobol indices calculated from the linear regression metamodel and the Petri nets model were found to be similar, thus confirming the accuracy of the metamodel for complex interactions between time transitions and output variables.

These findings show how hybrid modelling improves efficient computation without compromising the accuracy of sensitivity analysis. Metamodeling was leveraged to enhance computational efficiency more compared to the Petri nets model. When data analytics were integrated with expert knowledge, the global sensitivity analysis was done much faster, and it provided important insights into system behaviour for better real-world applications. To support faster sensitivity analysis, the implemented approach needed twenty times less time to estimate Sobol indices. By doing so, this increased efficiency will help researchers and practitioners better understand the relative significance of input variables and make informed decisions towards optimizing or improving systems.

7. Conclusions

This study utilized a novel approach for maintenance modelling, incorporating the impact of shifts on the predetermined maintenance process in the TC of the IFMIF DONES Facility. GSA was carried out in this study using hybrid modelling for the predetermined maintenance procedures within the TC. Unlike traditional approaches that require running computationally expensive Petri nets simulations, the hybrid modelling approach considerably speeded sensitivity analysis process and improved its efficiency and practicality. Complexities of the maintenance process are addressed by enhancing system reliability and operational availability. Findings highlighted the importance of the implementation of the three-shift strategy to minimize downtime and improve operational availability. These results are important for decision-making in complex industrial facilities like IFMIF DONES as they take into account the expected real-life scenarios and considering real irradiation policies.

Furthermore, a holistic understanding of the complete outcome space is necessary for industry practitioners. In this sense, the results emerged that GSA allows engineers to identify the most performance-sensitive uncertainties, prioritize efforts in the optimization stage, focus on the most essential aspects, and bring improved benefits like efficient design and enhanced uncertainty quantification, which ensures fewer unexpected behaviours from particle accelerators. The GSA outputs can be chained in a sequence of optimizations for design iterations so that continuous design optimization is enabled as uncertainty is successively reduced.

Such improvements have their appropriate application in providing the means for better predictions, targeted data collection choices, and appropriate quantification of the uncertainties within the context of particle accelerators. Practitioners can focus on the possible modelling outcomes, collect data based on GSA outcomes, and iteratively design the maintenance strategy to deal with those uncertainties that provide the most significant impact.

8. Future work

Future work should, therefore, include refining the Petri nets model by validating data, incorporating more external factors as well as dependencies that may have an impact on system performance (*e.g.* more realistic timing and duration of maintenance activities), and addressing uncertainties arising from assumptions in order to overcome limitations and constraints identified in this study. Therefore, exploring other alternatives for conducting sensitivity analysis can supplement insight into system behaviour and probity. As a result, the accuracy and applicability of sensitivity and correlation analyses will be increased through the collection and validation of additional data, which will be helpful for improving reliability models.

Moreover, incorporating real-world data and verifying the model through empirical observations can help to improve the accuracy and applicability of sensitivity and correlation analysis results. This empirical validation will provide a stronger foundation for decision-making and optimization strategies and increase belief in the findings of the study. These future research directions shall be addressed to provide a better understanding to accurately predict failure patterns for the planned maintenance process in the TC of IFMIF DONES Facility and similar contexts.

CRediT authorship contribution statement

Mohammad Hisham Ismail: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis. **Manuel Chiachío:** Writing – review & editing, Methodology, Conceptualization. **Juan Chiachío:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Fernando Arranz:** Writing – review & editing, Validation, Supervision, Conceptualization. **Ali Saleh:** Writing – review & editing, Software, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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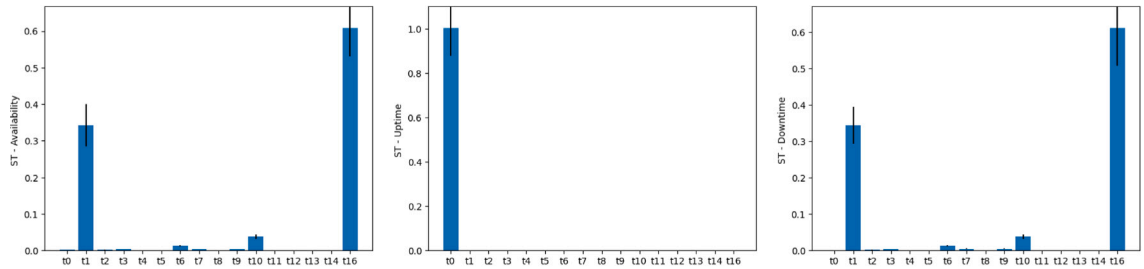
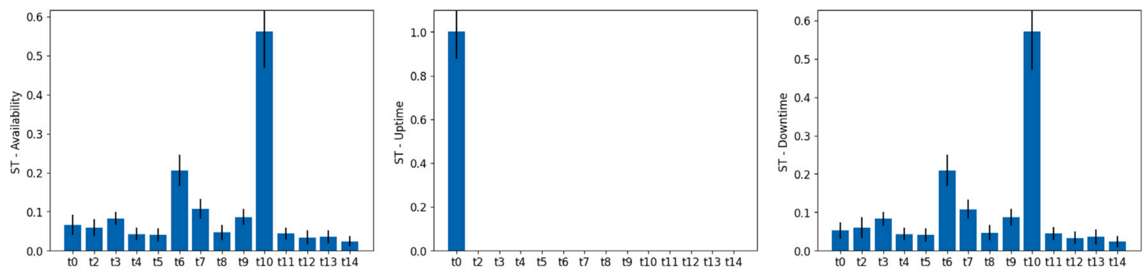
Appendix

See Figs. 17–26.

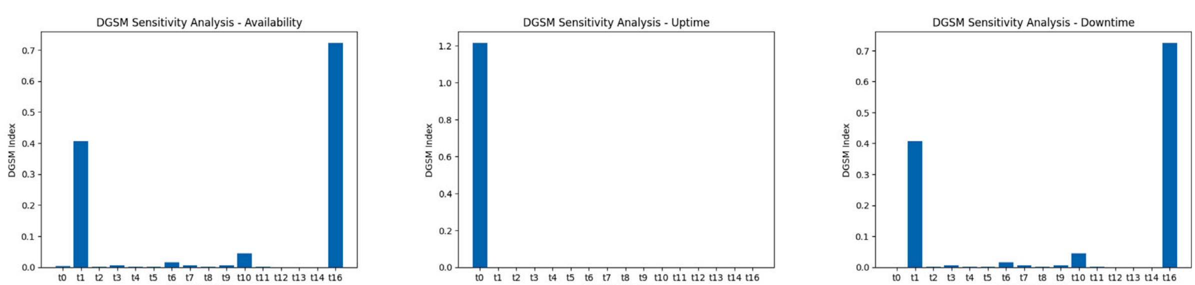


(a) Availability. (b) Uptime. (c) Downtime.

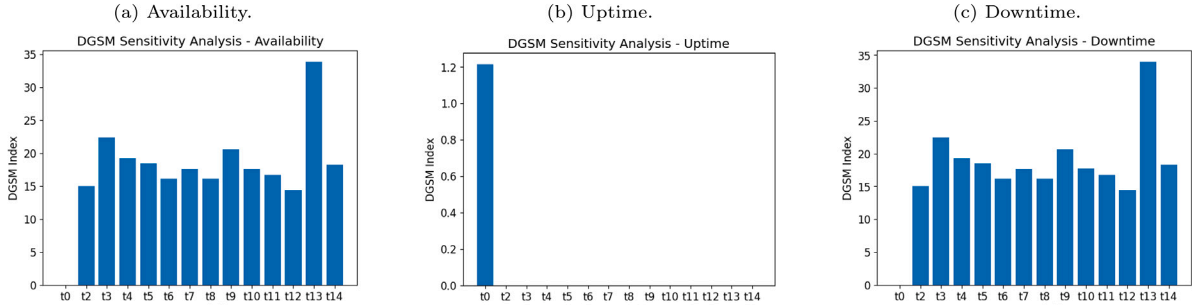


(d) Availability with fixed T_1 and T_{16}. (e) Uptime with fixed T_1 and T_{16}. (f) Downtime with fixed T_1 and T_{16}.

Fig. 17. Sobol sensitivity indices.



(a) Availability. (b) Uptime. (c) Downtime.



(d) Availability with fixed T_1 and T_{16}. (e) Uptime with fixed T_1 and T_{16}. (f) Downtime with fixed T_1 and T_{16}.

Fig. 18. DGSM sensitivity indices.

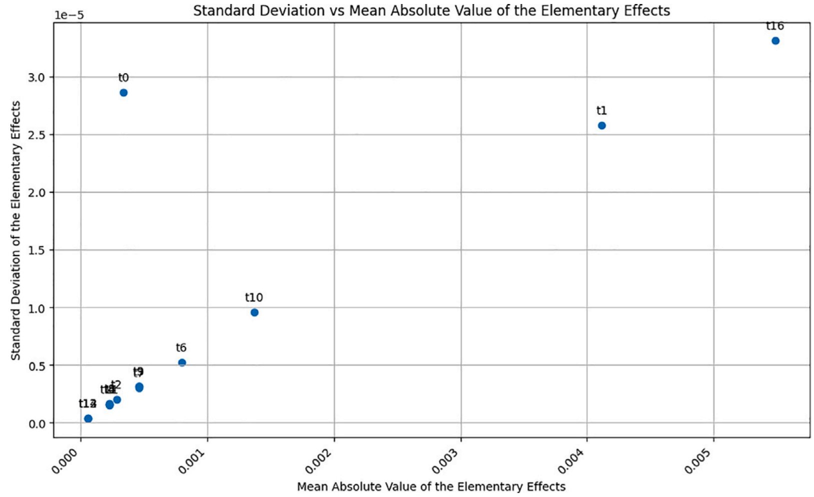


Fig. 19. Morris sensitivity indices without fixing transitions T_1 and T_{16} for availability.

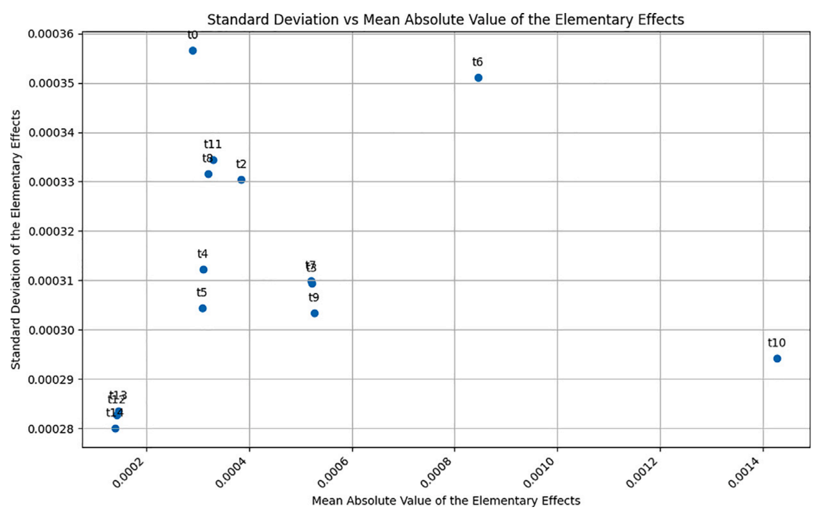


Fig. 20. Morris sensitivity indices with fixed transitions T_1 and T_{16} for availability.

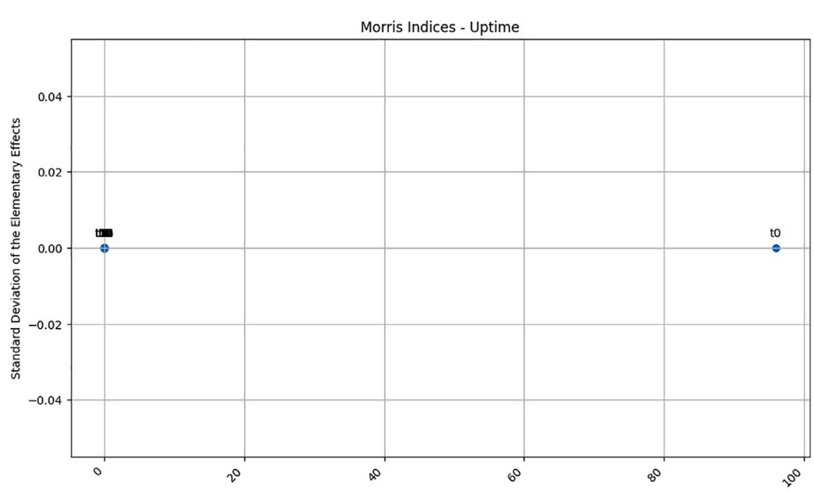


Fig. 21. Morris sensitivity indices without fixing transitions T_1 and T_{16} for uptime.

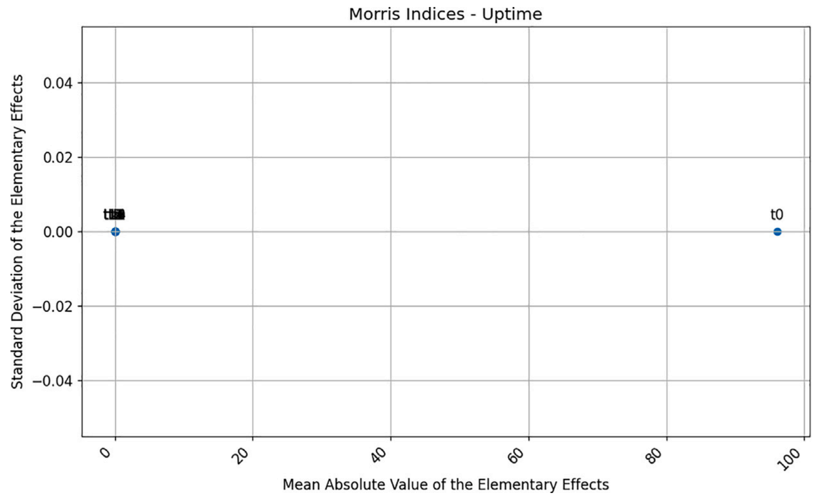


Fig. 22. Morris sensitivity indices with fixed transitions T_1 and T_{16} for uptime.

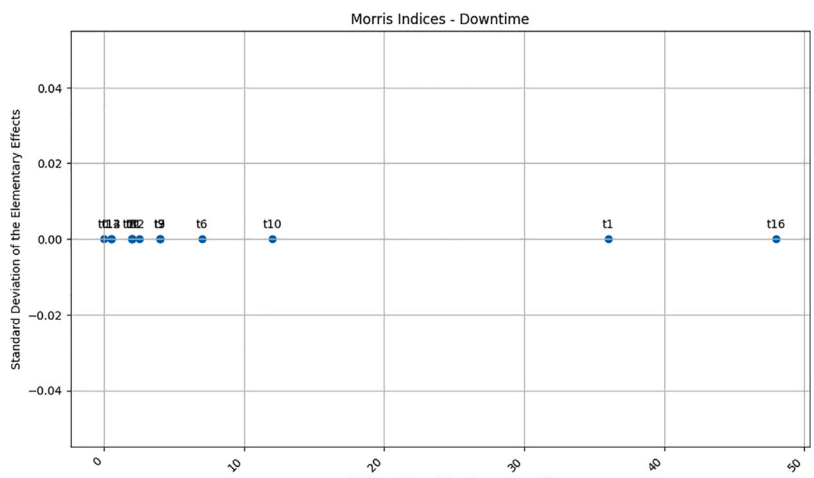


Fig. 23. Sobol sensitivity indices without fixing transitions T_1 and T_{16} for downtime.

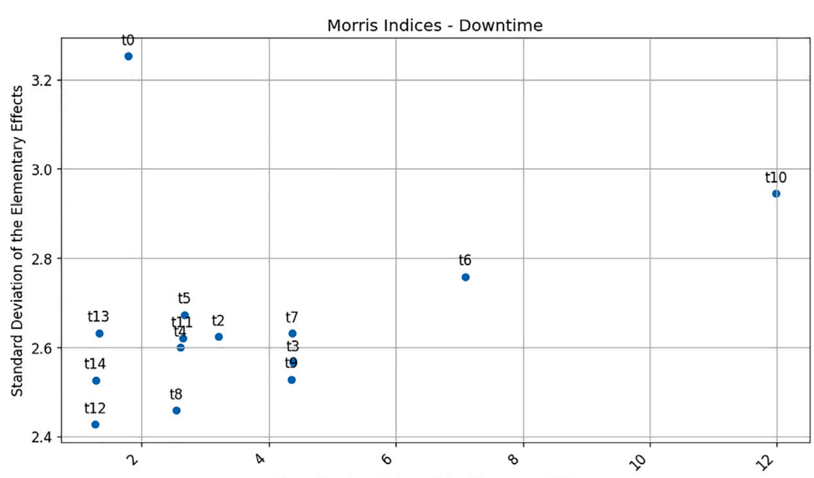


Fig. 24. Sobol sensitivity indices with fixed transitions T_1 and T_{16} for downtime.

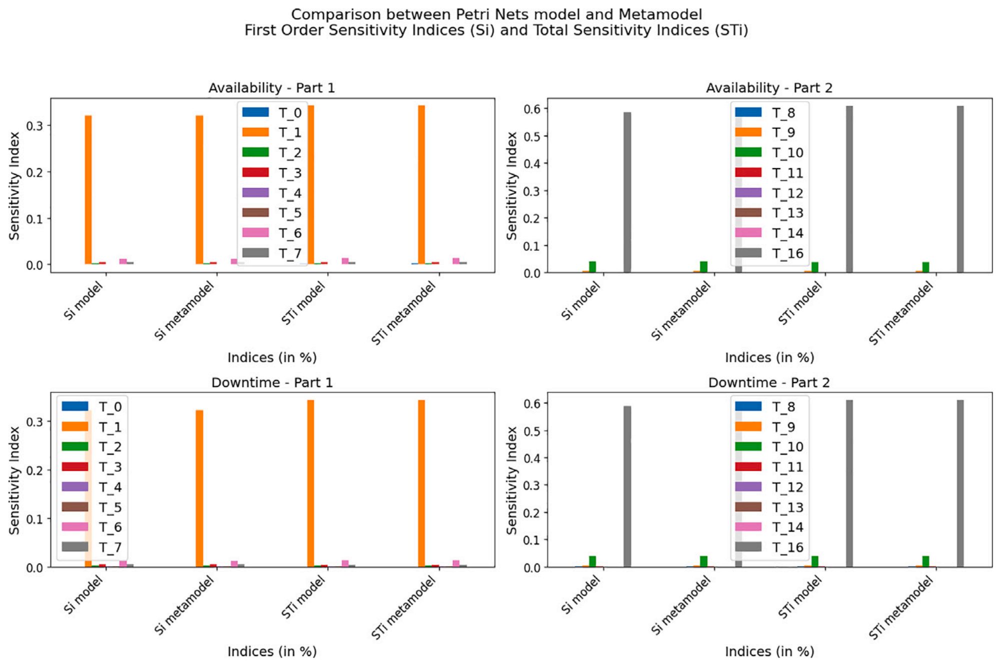


Fig. 25. Comparison between Sobol indices calculated from Petri nets model and metamodel.

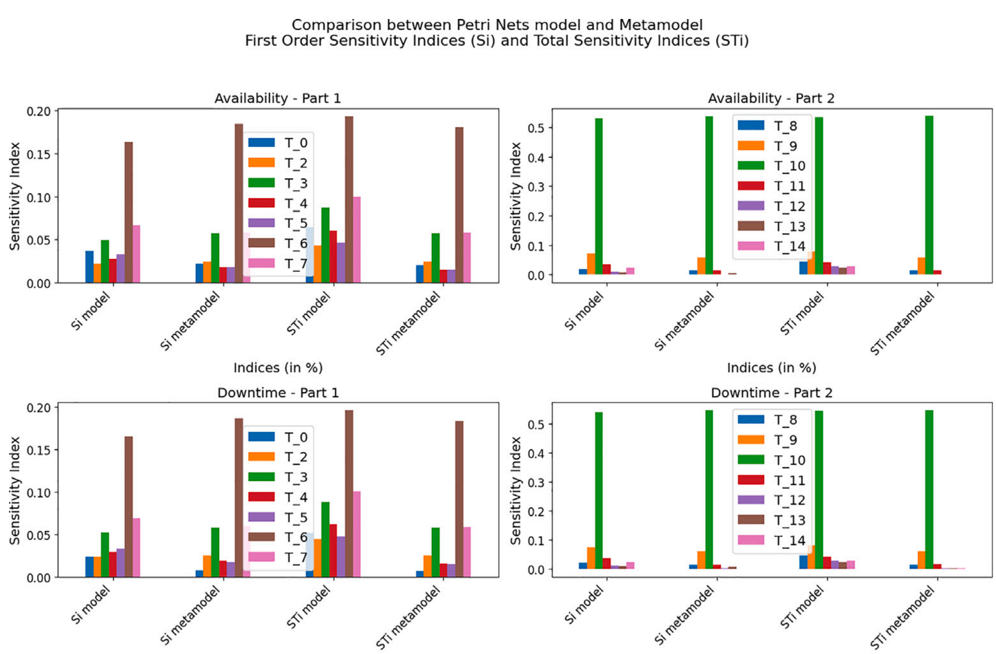


Fig. 26. Comparison between Sobol indices calculated from Petri nets model and metamodel (with fixed timed transitions T_1 and T_{16}).

Data availability

No data was used for the research described in the article.

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