Reliability-Oriented Digital Twins for Identifying Critical Components in Energy Systems via Fault Tree Analysis

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***Abstract*—Digital Twins offer significant potential for assessing and enhancing reliability of energy systems by enabling continuously-updated models of reliability-relevant system behavior, which can be used to predict failures and identify critical components. While our previous and ongoing research demonstrates the capability of Digital Twins to discover reliability models from system data, the use of these models to improve system reliability remains underexplored. This paper aims to address this research gap by presenting a methodology and a proof-of-concept use case of a Digital Twin for a compact photovoltaic system, using Fault Trees as underlying models. The Digital Twin is used to identify components' importance with respect to the overall reliability of the system, inform maintenance strategies, and guide decisions to enhance system reliability while considering maintenance expenditures. Using data from system faults and failures, this study builds upon previous work on discovery of reliability models and applying them to a real-world system to make decisions that enhance system reliability.**

Keywords*—*Digital Twins, energy systems, reliability

I. Introduction

Modern energy systems, especially those heavily reliant on renewable energy sources like solar and wind, face significant reliability challenges, including frequency fluctuations, generation variability, and intermittent energy supply [1]. These challenges were highlighted by the Iberian Peninsula blackout on April 28, 2025, when unexpected generation outages in southern Spain, a region dense with solar energy systems, triggered a cascading loss exceeding 30 GW, severely disrupting critical infrastructure [2]. Such events emphasize the need for affordable and effective technological solutions to ensure stable and secure energy supply with growing renewable integration. Further research is necessary to develop innovative, cost-effective solutions that incorporate modern technologies to minimize unplanned downtime and maintain power supply under varying conditions.

Digital Twins (DTs) have emerged as advanced tools for continuously enhancing reliability of the system through continuous monitoring and predictive analytics [3], [4]. A DT features a virtual replica of the physical system that continuously updates using real-time data to enable simulation, forecast failures, and prescribe corrective actions [5]. In energy systems, DTs are virtual entities replicate the behavior of physical assets, such as power plants, grids, and substations, to enable performance optimization and predictive maintenance through a continuous feedback loop [3], [6], [7].

DT technology can transform energy systems by enhancing efficiency and reliability across energy sectors: generation, transmission, distribution, energy storage, and smart cities [4], [8], [9]. A key feature of DTs is their bidirectional connection to physical systems, with data flowing both from the physical system to the DT and vice versa [5], illustrated in Fig. 1. This adaptability enables DTs to proactively respond to emerging issues and provide decision support to support a more stable, responsive, and sustainable energy infrastructures. Unlike traditional control systems, which require engineers to make valid decisions about faults or warnings, DTs offer automatic decision support to guide operational adjustments and enhance system reliability [6].

While existing research demonstrates the capability of DTs to discover reliability models from system data, the use of these models to improve system reliability remains underexplored. This paper addresses this gap by presenting a Photovoltaic (PV) system use case in which a DT uses simulated system data to extract a Fault Trees (FT) model for quantitative analysis of system reliability, identification of critical components and optimization of maintenance decisions. Section II reviews the background and related work. Section III describes the methodologies applied in the case study. Section IV presents and discusses the results of the case study analysis, identifying the most critical components and providing informed maintenance strategies to enhance system reliability at low cost. Finally, Section V summarizes the key findings and outlines future directions.

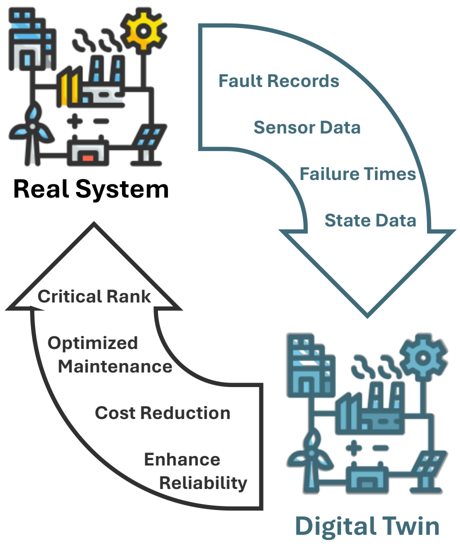

Fig. 1. Bidirectional connection of reliability-oriented Digital Twins of energy systems.

II. Background & Related Work

Reliability of energy systems is typically evaluated using analytical methods based on classical models, such as FTs, Markov models, and Reliability Block Diagrams (RBDs), as well as simulation methods such as Monte Carlo and discrete-event simulation (DES) [10]. In DES, the behavior of a system model is represented as a sequence of discrete, time-ordered events [11]. By generating large numbers of random failure scenarios, DES allows for estimation of system-level reliability indicators such as system downtime, Loss-of-Load Probability (LOLP), and Expected Energy not Supplied (EENS) [12], [13].

Fault Tree Analysis (FTA), a widely used reliability assessment method, systematically identifies potential failure modes and their logical links to system-level failures, offering qualitative insight into critical failure paths and quantitative metrics such as system reliability and failure probabilities [10]. In FTA, a Top Event (TE) is the undesired system failure being analyzed, intermediate events are failures caused by other events, and Basic Events (BEs) are the simplest occurrences that represent component-level faults. While FTA provides valuable qualitative and quantitative analysis, it often relies on expert knowledge for model building rather than operational data, limiting adaptability to evolving systems. Numerous studies have demonstrated the feasibility of using operational data to assess the reliability of energy systems [14], [15], [16]. However, there is limited research on using data generated by energy systems for automatic reliability modelling and analysis to inform decision-making.

Various importance measures have been developed to identify the components that contribute most to system unreliability [17], [18]. Examples of these indices include structural, Birnbaum, criticality and Fussell-Vesely importance [17], [18]. These measures quantify how sensitive system reliability is to individual components, thereby providing guidance on maintenance or design improvement priorities.

Effective maintenance management balances the trade-offs between preventing failures and minimizing costs. However, it has been reported that more than 30% of maintenance expenditures can result from inadequate or faulty maintenance planning [19]. According to Coandă et al. [19], scheduled maintenance often results in the premature replacement of components that have not yet reached the end of their lifecycle, leading to unnecessary costs. In contrast, predictive maintenance offers significant advantages by continuously monitoring equipment conditions through sensors and other real-time indicators. This approach ensures that maintenance is performed only when necessary, ultimately minimizing downtime and costs.

III. Methodology

In this section, we present a DT methodology for automatically extracting FT models of energy systems using operational data. The methodology combines quantitative reliability analysis, importance measures, and critical component identification within the DT framework. These techniques enable reliability-oriented DTs to support data-driven decisions aimed at improving energy system reliability through targeted maintenance and operational strategies.

A. *Fault Tree Extraction*

The DT approach combines the automated discovery of reliability models, FTs in our context, with reliability analysis to identify critical components in energy systems. We employ the Data-Driven Fault Tree Analysis (DDFTA) algorithm, introduced by Niloofar and Lazarova-Molnar [20], to automatically extract FT models from operational data. This method replaces expert-driven manual modeling with fully automated data-driven modeling of FTs.

The DT uses input data such as time-stamped fault logs, sensor readings from the system (e.g., voltage), and environmental conditions (e.g., solar irradiance). The DDFTA algorithm derives a time-stumped truth table from input data, representing the logical relationships between component-level faults/failures (i.e., BEs) and the overall system reliability (i.e., TE). From these logical relationships, the algorithm derives Minimal Cut Sets (MCSs) representing the minimal combinations of BEs that lead to the TE, typically a system failure. The DT also uses the time-stamped truth table to estimate BEs probability distributions. The accuracy of the extracted FT is validated by generating a truth table from the extracted FT and comparing it with known fault combinations in the original input data.

B. *Quantitative Fault Tree Analysis*

To perform quantitative FTA and simulate system availability, we use the extracted FT model together probability distribution functions or failure rates (if assuming exponential probability distribution) of BEs. The following probability

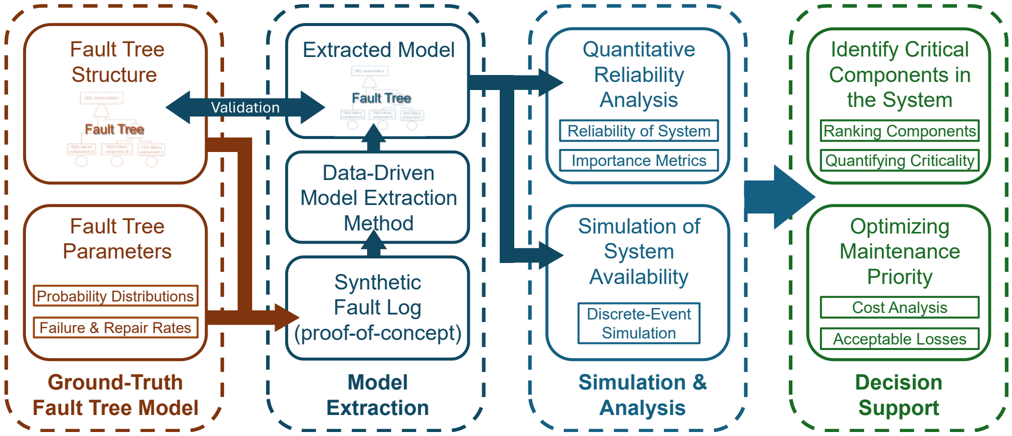

Fig. 2. Workflow of of our proof-of-concept case study for automated reliability assessment of energy systems using synthetic data.

functions are used to calculate system reliability analytically as a function of time and to simulate system availability using DES [10], [11]:

- **Probability of Component Failure (F_{ij}):**

Assuming that component failures follow an exponential probability distribution with a constant failure rate (λ), a common assumption for electronic and electrical equipment [10], the component failure probability as a function of time is given by:

$$F_{ij}(t) = 1 - e^{-\lambda_{ij}t}, \tag{1}$$

where λ_{ij} is the occurrence rate of jth BE within the ith MCS of the FT, i.e., BE_{ij} probability. For example, for MCS_3 which contains BE_3 and BE_4, the probability of BE_3 would be denoted as $F_{31}(t)$ (i.e., probability of the 1st BE within the 3rd MCS).

- **Probability of MCS (F_i):**

Assuming independence among BEs within an MCS, the probability of all BEs in the ith MCS occurring simultaneously (i.e., the probability of MCS_i), where n is the number of components in MCS_i, is given by:

$$F_i(t) = \prod_{j}^{n} F_{ij}(t). \tag{2}$$

- **Probability of System Failure (F_{sys}):**

The probability of the TE (commonly interpreted as the probability of system failure), assuming independence of BEs [21], is given by:

$$F_{sys}(t) = 1 - \prod_{i}^{m} \left(1 - F_i(t)\right), \tag{3}$$

where m is total number of identified MCSs in the FT.

- **Reliability of the System (R_{sys}):**

The reliability of the system as a function of time (i.e., the reliability of TE), is then:

$$R_{sys}(t) = 1 - F_{sys}(t). \tag{4}$$

The DT automates quantitative FTA using the extracted FT model, enabling near-real-time reliability assessment and continuous updating as new operational data becomes available. This approach substantially reduces, and in some cases eliminates, the need for expert intervention.

C. *Importance Measures*

Importance measures quantify the contribution of each component's fault-related behavior to the TE [17], [18]. In the case study, these importance measures are used to identify the components that most significantly affect system reliability. Identifying these critical components allows the DT to guide maintenance strategies and support decision-making. The DT computes four importance measures to rank components according to the criticality of their failures in the extracted FT:

- **Structural Importance (I_Φ):**

Structural importance reflects the influence of a component failure (BE_{ij}) within the logical structure of the FT, independent of actual failure probabilities. The structural importance for BE_{ij} is given by:

$$I_\Phi(BE_{ij}) = 1 - \prod_{i:\, BE_{ij} \in MCS_i} \left[1 - \frac{1}{2^{N_i - 1}}\right], \tag{5}$$

where N_i is the number of BEs in the MCS_i [18]. This provides a topology-based ranking of components solely on the design of the system.

- **Marginal Importance (I_B):**

Marginal importance, otherwise known as Birnbaum importance, measures the change in system failure probability when a component failure (BE_{ij}) state changes from not-occurring ($F_{ij} = 0$) to occurring ($F_{ij} = 1$) [17], [18]. Marginal importance at time t for BE_{ij} can be calculated by:

$$I_B(t, BE_{ij}) = F_{sys}(t \mid F_{ij} = 1) - F_{sys}(t \mid F_{ij} = 0), \tag{6}$$

where $F_{sys}(t \mid F_{ij} = 1)$ and $F_{sys}(t \mid F_{ij} = 0)$ denote system failure probabilities at time t given the occurrence ($F_{ij} = 1$) or absence ($F_{ij} = 0$) of BE_{ij}, respectively. The DT can use marginal importance to rank components based on the largest increase in the probability of system failure they can cause.

- **Criticality Importance (I_{Cr}):**

Marginal importance only considers whether the probability of system failure has changed based on whether a component failure (BE_{ij}) has occurred or not. However, marginal importance does not consider the probability of component failure (F_{ij}). This can result in high importance values for events that are very unlikely to occur. Therefore, criticality importance considers component failure probability (F_{ij}) relative to system failure probability (F_{sys}). Criticality importance at time t for BE_{ij} can be calculated by:

$$I_{Cr}(t, BE_{ij}) = I_B(t, BE_{ij}) \frac{F_{ij}(t)}{F_{sys}(t)}, \tag{7}$$

which is the conditional probability that BE_{ij} contributes to the probability of system failure, given the TE has occurred. The DT can use this measure to rank the component failures by how likely they are to be the root cause of system failure.

- **Fussell-Vesely Importance (I_{FV}):**

The Fussell-Vesely (FV) importance accounts for any BEs that exist in multiple MCSs from the FT, and is calculated by:

$$I_{FV}\left(t, BE_{ij}\right) = \frac{\sum_{i:\, BE_{ij} \in MCS_i} F_i(t)}{F_{sys}(t)}, \tag{8}$$

which is the conditional probability that BE_{ij} contributes to the probability of system failure, considering probability of all MCSs containing BE_{ij}, at a given time t. DT can use the FV importance to rank highly sensitive failure events that cause system failure and are involved in multiple MCSs.

The DT continuously updates all importance measures using streaming operational data. This automated, dynamic evaluation represents a key methodological advancement, enabling the DT to autonomously and continuously identify critical components and guide maintenance strategies that adapt to changing system behavior.

D. Reliability-Enhancing Decision Support by Digital Twins

Our methodology integrates FT extraction, quantitative reliability analysis, importance measures, and availability simulation into a single framework that enables DTs to support reliability-oriented decision-making. FTs capture the logical relationships among component failures (typically represented by BEs), while quantitative FTA quantifies system and component reliability. Importance measures, such as Birnbaum, criticality, and FV, rank component failures by their contribution to system unreliability. The DT identifies critical components based on the importance rank of their corresponding failures. DES uses input parameters (i.e., component failure and repair rates) to calculate transient availability of the system.

DTs leverage these outputs to identify intervention points that can most effectively improve system performance at minimal cost. Components with highly critical failures but manageable maintenance costs can be prioritized for inspection or replacement, while high-cost components with limited impact on overall reliability may be maintained less frequently. In this way, DTs not only evaluate reliability but also provide actionable decision support for system reliability improvement and cost-effective maintenance planning. Fig. 2 illustrates the workflow implemented in our proof-of-concept case study for automated reliability assessment of energy systems using synthetic data, demonstrating a reliability-oriented DT use case in energy systems.

Unlike conventional reliability studies that rely on static or expert-defined models, DTs continuously update their underlying reliability models using operational data, recalculating reliability indicators and importance measures in near-real-time. This enables automated identification of critical components and adaptive, cost-efficient maintenance strategies.

IV. Proof-of-Concept Case Study: Model of a Photovoltaic Energy System

In the following, we present a case study that demonstrates the automatic assessment of system reliability, ranking components based on criticality, and simulation of system availability through the DT. Our case study system is a PV System, which we will elaborate on next.

A. Case Study Setup

Our case study examines a small-scale solar power system consisting of a PV module, a diode, Miniature Circuit Breakers (MCBs), a fuse, and a direct current (DC) load. The PV module converts solar energy into electric current; the diode ensures unidirectional current flow to the load; and the fuse protects the system against overcurrent originating in the PV module. Fig. 3(a) and Fig. 3(b) show the system layout and the corresponding ground-truth FT model of the studied PV system, respectively. The underlying model of the reliability-oriented DT, in this case an FT, is automatically constructed from system data using the DDFTA algorithm, as described in Section III.A and our previous works [20], [22].

In this case study, the DT uses two main data inputs: (i) fault logs from the PV system and (ii) occurrence rates for all components faults/failures (BEs). Table 1 shows all component faults/failures, their corresponding BEs and occurrence rates sourced from literature [23]. Table 1 also shows the ith and jth indices corresponding to each BE, as introduced in Section III.B and III.C. To emulate real-world operation, synthetic fault logs were generated using DES based on BE occurrence rates and the ground-truth FT model. Table 2 shows an excerpt from the generated fault logs that were used to extract the FT model. These logs record fault and failure events occurring throughout the system's operational time. The DT converts these fault logs into a truth table representing the PV system's observed fault–failure relationships. Combined with the BE occurrence rates, this truth table constitutes the complete DT input dataset.

TABLE I. BASIC EVENTS AND THEIR OCCURANCE RATES IN THE PV SYSTEM

i	j	Basic Event	Fault / Failure	Occurrence Rate (10^{-3})	i	j	Basic Event	Fault / Failure	Occurrence Rate (10^{-3})
1	1	BE_1	Fuse aging	0.0001	9	1	BE_{10}	PV cell breakage	0.1115
2	1	BE_2	Fuse installation failure	0.0002	10	1	BE_{11}	PV panel solder bond failure	0.1487
3	1	BE_3	Miniature Circuit Breaker 1 failure	0.0008	11	1	BE_{12}	PV panel hot spot	0.0101
	2	BE_4	Miniature Circuit Breaker 2 failure	0.0846	12	1	BE_{13}	PV panel diode failure	0.0021
4	1	BE_5	PV interconnect failure	0.0490	13	1	BE_{14}	Short or open circuit	0.0052
5	1	BE_6	Grounding failure	0.0003	14	1	BE_{15}	Rack structure failure	0.0729
6	1	BE_7	PV glass breakage	0.0013	15	1	BE_{16}	PV panel encapsulant failure	0.0570
7	1	BE_8	PV panel soiling	0.0088	16	1	BE_{17}	Cable insulation failure	0.0001
8	1	BE_9	PV panel shading	0.0001	17	1	BE_{18}	Cable aging	0.0002

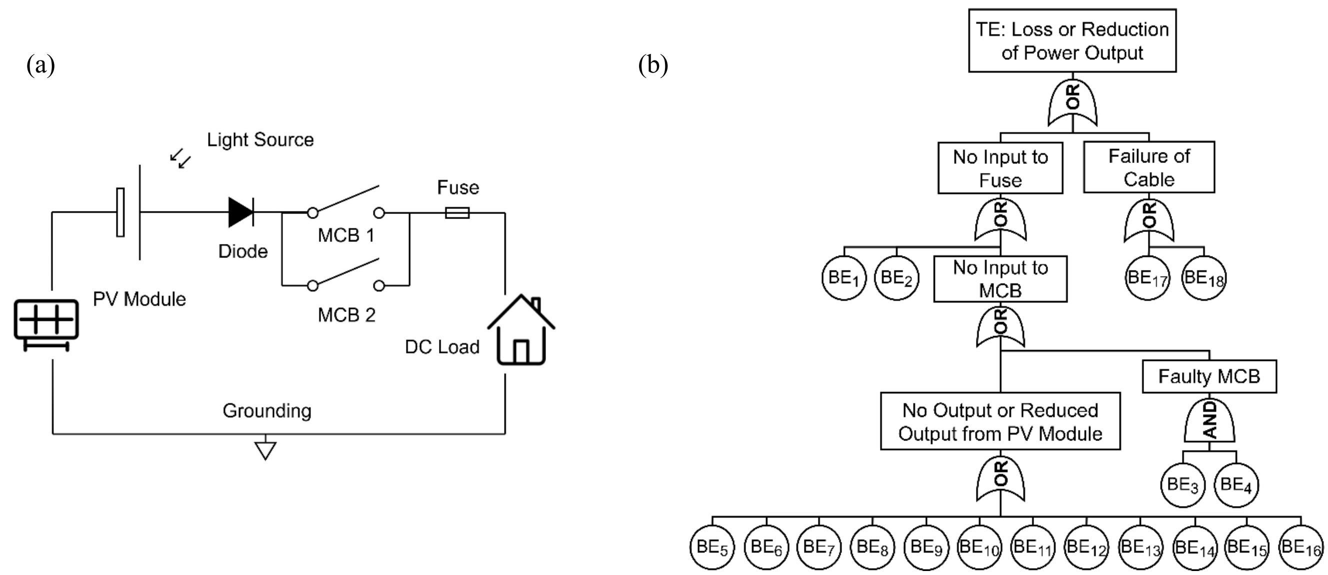

Fig. 3. (a) Photovoltaic (PV) system layout for the case study. (b) Fault Tree (FT) model derived from state data generated by the system model. (BE stands for Basic Event, MCB for Miniature Circuit Breakers)

The DDFTA algorithm identifies MCSs in the truth table to reconstruct the FT model. To construct the truth table from synthetic fault logs, each recorded fault/failure is associated with a BE, which has a binary status (active = 1 or cleared = 0). The TE status is then defined as 1 when the occurrence of one or more BEs causes system failure and 0 otherwise. This establishes a direct mapping between individual component faults/failures and the TE, i.e., the system-level failure. The resulting truth table represents a set of all observed relationships between BEs and the TE. The DDFTA algorithm uses this truth table to automatically extract the FT model of the PV system.

Fig. 3(b) shows the extracted FT obtained using synthetically generated fault logs, which corresponds to the ground-truth FT model, representing component failure logic of the PV system. Using the extracted FT model, the DT performs quantitative reliability analysis and availability simulation to support maintenance planning and optimization. The computation of reliability indicators and informed maintenance strategies is studied in the following subsections.

B. *Quantitative Analysis*

The DT assesses system reliability using two main approaches. The first approach uses analytical methods assuming non-repairable components to evaluate both component- and system-level reliability, as presented in this subsection. The second approach, described in Section IV.C, accounts for component repairs using DES.

The DT performs quantitative FTA using the extracted FT, with the approach from Section III.A, to identify components that most influence overall system reliability, assuming non-repairable components. The resulting importance measures, summarized in Table 3, show that cell breakage and solder bond failure within the PV module, represented by BE_{10} and BE_{11}, respectively, are identified as the most critical events, contributing substantially to system unreliability with criticality importance values of 20.2% and 26.9%, respectively. Other critical components include the interconnect, rack structure and encapsulant of the PV panel (BE_5, BE_{15} and BE_{16}), with corresponding criticality importance of 15.3%, 13.2%, and 10.3%. These findings enable the DT to rank components by their influence on system reliability and to inform maintenance prioritization decisions as outlined by Section III.D.

TABLE II. EXAMPLE OF THE GENERATED PV SYSTEM FAULT LOGS.

Timestamp	Description	Status	Top Event
2025-02-12 10:53:24	Grounding system fault detected.	Active	True
2025-02-12 17:32:11	Grounding system fault detected.	Cleared	True
2025-02-17 11:20:54	PV hot spot detected.	Cleared	False
2025-02-18 13:23:51	Faulty MCB 1 detected.	Active	False
2025-02-18 08:55:02	PV solder bond failure detected.	Active	True

The importance measures calculated by the DT are consistent with the known vulnerability of PV modules [23]. The DT identified PV cell breakage (BE_{10}) and solder bond failure (BE_{11}) as the most critical events, which are consistent with findings of other studies that identified these failure mechanisms as the main cause of unreliability in PV systems [23]. The DT analysis further reveals that the interconnect (BE_5) and encapsulant (BE_{15}) events are highly critical, which is expected given the high rate of their fault occurrence relative to other system faults and their direct relationship to system reliability in the FT. In contrast, components such as the fuse (linked to BE_1 and BE_2) and the Miniature Circuit Breakers (MCBs) (linked to BE_3 and BE_4) demonstrate low levels of importance, indicating their low impact on the overall system reliability despite their prominence in system operation. These DT analysis results emphasize the importance of prioritizing maintenance for components associated with critical events in the system, such as the PV module.

The reliability as a function of time was calculated for the system and its components by the DT using the equations from Section III.B, and exhibit behavior consistent with that of other systems featuring comparable FT models [24]. Fig. 4 and Fig. 5 show the resulting system reliability as a function of time compared with the most and least critical components. Fig. 5 shows that the most critical components (e.g., the PV module component linked to BE_{11} and BE_{10}) exhibit a decline in

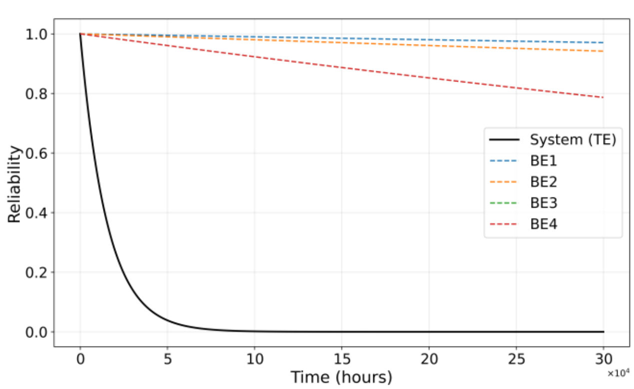

Fig. 4. The reliability of the system and probability of the least critical basic events determined by the Digital Twin using the extracted Fault Tree model and event occurrence rates.

TABLE III. IMPORTANCE FACTORS SORTED FROM THE MOST CRITICAL EVENT TO THE LEAST CRITICAL EVENT

Basic Event	Structural Importance (I_Φ)	Marginal Importance (I_B) at 1000 hours	Criticality Importance (I_{Cr}) at 1000 hours	Fussell-Vesely Importance (I_{FV}) at 1000 hours
BE_{11}	1	1	0.269335	0.269335
BE_{10}	1	1	0.201956	0.201956
BE_5	1	1	0.153233	0.153233
BE_{15}	1	1	0.132041	0.132041
BE_{16}	1	1	0.103242	0.103242
BE_6	1	1	0.088752	0.088752
BE_{12}	1	1	0.018294	0.018294
BE_9	1	1	0.015939	0.015939
BE_{14}	1	1	0.009419	0.009419
BE_{13}	1	1	0.003804	0.003804
BE_8	1	1	0.002355	0.002355
BE_7	1	1	0.000543	0.000543
BE_2	1	1	0.000362	0.000362
BE_{18}	1	1	0.000362	0.000362
BE_1	1	1	0.000181	0.000181
BE_{17}	1	1	0.000181	0.000181
BE_3	0.5	0.008	0.000001	0.000001
BE_4	0.5	0.008	0.000001	0.000001

reliability that closely mirrors that of the overall system reliability, suggesting their potential impact on system reliability curve. Conversely, Fig. 4 shows that the least critical components (e.g., the fuse component linked to BE_1 and BE_2) exhibit high reliability with minimal impact on the system reliability curve. The alignment of the system reliability curve with the curves of high-importance component failures shows the extent to which these components influence system reliability and contribute to the probability of the TE, thereby identifying critical components.

C. Simulation of System Availability

Although quantitative reliability analysis provides useful insights into the reliability of the system, it does not consider repairs and is limited by the probability distribution of time for component failures. Simulation, on the other hand, can easily

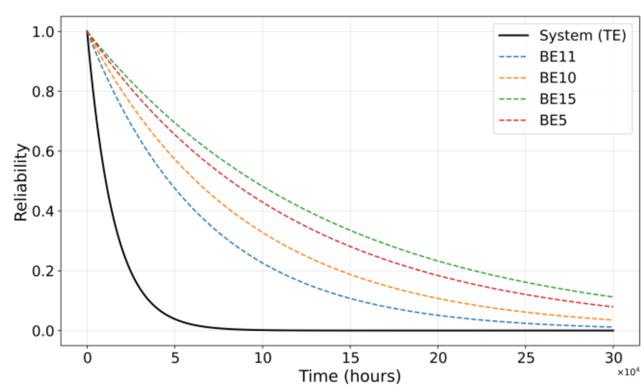

Fig. 5. The reliability of the system and the probability of the most critical basic events determined by the Digital Twin using the extracted Fault Tree model and event occurrence rates.

consider repairs after failures and is not limited by probability distributions for either failures or repairs. Simulation can also incorporate stochastic failure and repair behavior to test different maintenance strategies and recommend those that reduce maintenance costs. Although simulations are more computationally expensive and time-consuming than reliability analysis, a comprehensive reliability-oriented DT of energy systems requires both approaches.

Our case study DT employs DES to mimic the availability behavior of components and the overall system and evaluate unavailability. In each simulation cycle, failure times for BEs are modeled using random sampling from an exponential failure distribution, which is defined by BE occurrence rate. Using exponential distribution is not a limitation to our approach, as it was selected for its applicability in modeling electronic and electrical component failures. Mean Time to Repair (MTTR) for components are assumed based on typical preventive maintenance durations of PV energy systems [25].

The simulation was run for a total duration of 10,000 hours with 3,000 independent replications. When a BE occurs, the corresponding component enters a failure state that lasts until the assumed repair time. The influence of the change in BE states is propagated through the FT logic to generate the timeline of system (and components) downtime. The DT uses the Boolean timelines generated by DES to compute the cumulative mean unavailability, Mean Time to Failure (MTTF) and MTTR of the system and its components. Cumulative mean unavailability (i.e., the downtime fraction) as the total downtime per run divided by the total run time and then averaged across all simulation runs [12]. Fig. 6 shows the unavailability of the system and Fig. 6. shows MTTF and MTTR for each component, calculated by the DT. Table 4 shows the MTTF and MTTR results for the system and its components, where Table 5 shows the unavailability results for the system and its components at the end of the simulation experiment. The Python code of this DT experiment is publicly available and automatically performs the entire data-driven analysis and simulation in this case study [26].

According to the results in Table 4 and Table 5, the simulation experiment resulted in an overall system unavailability of 2.28×10^{-3} h, an estimated system failure rate of $\lambda_{sys} \approx 6 \times 10^{-5}$, MTTF of 4482 h, and MTTR of 36 h. These results are consistent with the analytical system reliability derived from the FT in Section IV.B, which identifies PV module component as a dominant contributor to unreliability, whereas other components (fuse, MCBs, and cable) have a negligible impact. Furthermore, the simulation experiment calculated the time-series mean cumulative availability of the system of 3000 replications for 10,000 hours of mission time shown in Fig. 7.

The unavailability of each component, shown in Fig. 6., further emphasizes that the PV module is the component with the most frequent failures throughout the experiment. Moreover, to study the sensitivity of system unavailability to different BE occurrence rates, DT compared system unavailability with increased occurrence rates for the most and least critical events, shown in Fig. 8. Both results in Fig. 6. and Fig. 8. match with critical component identified by the quantitative analysis in Section IV.B (i.e., the PV Module linked to cell breakage BE_{10} and solder bond failure BE_{11}). Since these events are associated with the PV module component, the results indicate that this component must be prioritized in maintenance schedules.

D. Maintenance Stratigies and Cost Analysis

To demonstrate the DT potential in informing cost-effective maintenance strategies, we have manually performed this analysis based on the DT results. This analysis shows how the change in maintenance frequency for components can influence overall system reliability and maintenance costs. The aim is to identify the components for which increasing maintenance frequency would result in the greatest improvement in system reliability. Additionally, the aim is to identify the components for which increasing maintenance frequency would result in minimal improvement in system reliability.

In this study, the components were assumed to have a predetermined replacement schedule (i.e., scheduled maintenance). Scheduled maintenance typically involves performing maintenance at set intervals, including replacing components regardless of their condition [19]. Although this type of maintenance can be costly due to labor and premature replacement of functional components, it has significant advantages such as preventing unexpected failures and reducing the probability of loss of power (i.e., the TE).

For the cost analysis in this case study, repair costs were assumed based on recent industry data on solar panel repair costs [27]. The average cost of solar panel repair is $507, which varies depending on the type of failure [27].

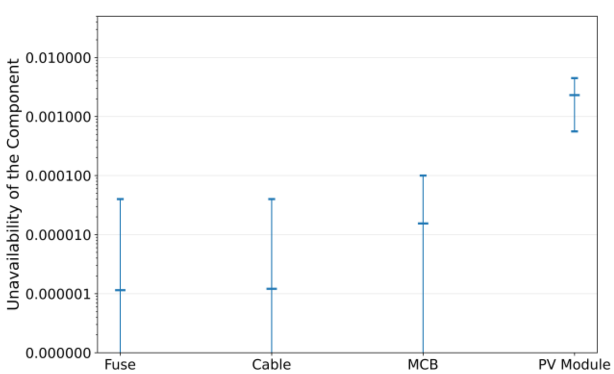

Fig. 6. Unavailability of each component in the system during mission time 100,000 hours with 95% confidence interval (plotted on a logarithmic scale).

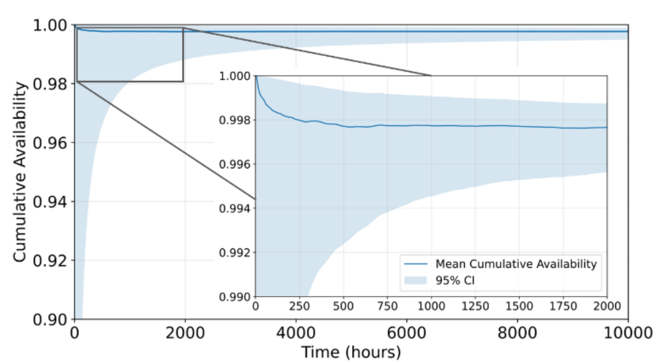

Fig. 7. Cumulative mean availability of the Photovoltaic system during mission time 10,000 hours with 95% confidence interval.

TABLE IV. MEAN TIME TO FAILURE AND REPAIR FOR THE SYSTEM AND ITS COMPONENTS DURING 10,000 HOURS MISSION TIME AND 3,000 REPLICATIONS

Element	Event in FT	MTTF (hrs.)	MTTR (hrs.)
Fuse	BE_1	5477.02	3.98
	BE_2		
MCB	BE_3	5631.17	10.02
	BE_4		
PV Module	BE_5	4502.10	36.31
	BE_6		
	BE_7		
	BE_8		
	BE_9		
	BE_{10}		
	BE_{11}		
	BE_{12}		
	BE_{13}		
	BE_{14}		
	BE_{15}		
	BE_{16}		
Cable	BE_{17}	6963.21	4.03
	BE_{18}		
System	***TE***	**4481.94**	**36.30**

To demonstrate the practical implications of the DT's reliability analysis, importance measures, and availability simulation from an economic perspective, we have manually examined two hypothetical scenarios:

The first scenario examines the broken interconnect failure within the PV module (BE_5), which the DT identified with a high criticality importance of 15.3%. Despite its significant impact on system reliability, average repair cost for this fault is low (~$100) compared to repair costs of other faults in the system [27]. This analysis shows an opportunity to enhance overall system reliability at relatively low additional costs and recommends that investing in higher-quality interconnect materials or increasing the frequency of scheduled inspections and preventive maintenance could effectively reduce the probability of BE_5. Thus, the DT facilitated the identification of a cost-effective solution that can improve system reliability while considering expenditure.

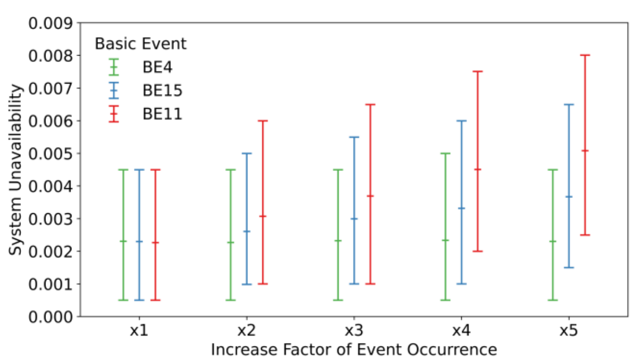

Fig. 8. Sensitivity of system unavailability to basic event occurrence rate: Comparison of the impact of multiplying the occurrence rates of the most and least critical events on system unavailability during a 10,000 hour mission, with a 95% confidence interval.

The second scenario examines the fuse installation fault (BE_2), which the DT identified with a low criticality importance of 0.036%. However, repair costs for this fault might be high (~$150) compared to repair costs of other faults in the system [27]. Since the DT identified the fuse component as non-critical, with a limited impact on system reliability, increasing the frequency of maintenance and scheduling inspections for this component is not recommended given its rare failure rate and high repair costs.

TABLE V. UNAVAILABILITY METRICS FOR THE SYSTEM AND ITS COMPONENTS DURING 10,000 HOURS MISSION TIME AND 3,000 REPLICATIONS

Element	Event in FT	Unavailability (10^{-3} hrs.)	Confidence Interval (95%)	
			Lower bound	Upper bound
Fuse	BE_1	0.000267	0.0000	0.0400
	BE_2			
MCB	BE_3	0.019331	0.0000	0.1000
	BE_4			
PV Module	BE_5	2.283772	0.5600	4.5600
	BE_6			
	BE_7			
	BE_8			
	BE_9			
	BE_{10}			
	BE_{11}			
	BE_{12}			
	BE_{13}			
	BE_{14}			
	BE_{15}			
	BE_{16}			
Cable	BE_{17}	0.000400	0.0000	0.0400
	BE_{18}			
System	***TE***	**2.284440**	**0.55999**	**4.5599**

Through continuous, near-real-time analysis, the DT dynamically calculates reliability indicators from system data. The DT results allow operators to optimize maintenance frequency for cost-effective maintenance decisions, effectively reducing unnecessary expenses while maintaining an acceptable level of reliability.

V. SUMMARY AND OUTLOOK

We present a methodology for developing reliability-oriented Digital Twins of energy systems, demonstrated through a proof-of-concept case study of a solar photovoltaic system. The proposed approach integrates data-driven Fault Tree extraction, quantitative reliability analysis, component importance evaluation, and availability simulation. Overall, the results highlight the capability of Digital Twins to serve as effective tools that support automatic reliability assessment and proactive maintenance planning to improve reliability. By leveraging operational data, the data-driven model extraction enables Digital Twins to support decision-making and quantitatively evaluate system behavior.

Reliability importance measures, such as Criticality and Fussell-Vesely importance, allow Digital Twins to identify the most critical components for system performance. In this photovoltaic system case study, the Digital Twin successfully identified critical components, quantified their impact on overall system reliability, and supported maintenance prioritization decisions. Unlike traditional reliability analyses, which rely on static models made by experts, the Digital Twin continuously updates reliability indicators and importance measures using near-real-time operational data.

Future research could build on this work in several ways. First, while our study assumed constant failure rates and exponential failure distributions, future studies could consider more complex distributions to more accurately capture component degradation. Second, incorporating real-time condition monitoring data and sensor data would improve the accuracy of automatically extracted Fault Trees and enhance the adaptability of Digital Twins. Third, including additional cost-based factors into the analysis would allow for more effective decisions about the trade-off between reliability improvement and maintenance expenses. Finally, applying the proposed methodology to larger, more complex systems, such as microgrids or transmission networks, and exploring alternative reliability models is essential for evaluating scalability. These extensions would further support the development of Digital Twins as standard tools for reliability-oriented decision support in next-generation energy systems.

REFERENCES

[1] S. Kumar, R. K. Saket, D. K. Dheer, J. B. Holm-Nielsen, and P. Sanjeevikumar, "Reliability enhancement of electrical power system including impacts of renewable energy sources: a comprehensive review," *IET Generation, Transmission, and Distribution*, vol. 14, no. 10, pp. 1799–1815, May 2020, doi: 10.1049/iet-gtd.2019.1402.

[2] "2025 Iberian Peninsula blackout," *Wikipedia*. June 29, 2025. Accessed: July 01, 2025. [Online]. Available: https://en.wikipedia.org/w/index.php?title=2025_Iberian_Peninsula_blackout&oldid=1297978224

[3] Z. Song *et al.*, "Digital Twins for the Future Power System: An Overview and a Future Perspective," *Sustainability*, vol. 15, no. 6, Art. no. 6, Jan. 2023, doi: 10.3390/su15065259.

[4] M. Jafari, A. Kavousi-Fard, T. Chen, and M. Karimi, "A Review on Digital Twin Technology in Smart Grid, Transportation System and Smart City: Challenges and Future," *IEEE Access*, vol. 11, pp. 17471–17484, 2023, doi: 10.1109/ACCESS.2023.3241588.

[5] M. Grieves and J. Vickers, "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems," in *Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches*, F.-J. Kahlen, S. Flumerfelt, and A. Alves, Eds., Cham: Springer International Publishing, 2017, pp. 85–113. doi: 10.1007/978-3-319-38756-7_4.

[6] P. Palensky, M. Cvetkovic, D. Gusain, and A. Joseph, "Digital twins and their use in future power systems," *Digital Twin*, vol. 1, p. 4, Aug. 2022, doi: 10.12688/digitaltwin.17435.2.

[7] H. Pan, Z. Dou, Y. Cai, W. Li, X. Lei, and D. Han, "Digital Twin and Its Application in Power System," in *2020 5th International Conference on Power and Renewable Energy (ICPRE)*, Shanghai, China: IEEE, Sept. 2020, pp. 21–26. doi: 10.1109/ICPRE51194.2020.9233278.

[8] U. Cali *et al.*, "Digital Twins: Shaping the Future of Energy Systems and Smart Cities through Cybersecurity, Efficiency, and Sustainability," in *2023 International Conference on Future Energy Solutions (FES)*, Vaasa, Finland: IEEE, June 2023, pp. 1–6. doi: 10.1109/FES57669.2023.10182868.

[9] N. Mchirgui, N. Quadar, H. Kraiem, and A. Lakhssassi, "The Applications and Challenges of Digital Twin Technology in Smart Grids: A Comprehensive Review," *Applied Sciences*, vol. 14, no. 23, Art. no. 23, Jan. 2024, doi: 10.3390/app142310933.

[10] B. W. Tuinema, J. L. Rueda Torres, A. I. Stefanov, F. M. Gonzalez-Longatt, and M. A. M. M. Van Der Meijden, *Probabilistic Reliability Analysis of Power Systems: A Student's Introduction*. Cham: Springer International Publishing, 2020. doi: 10.1007/978-3-030-43498-4.

[11] J. Banks, D. Nicol, J. Carson, and B. Nelson, *Discrete-Event System Simulation*. Pearson International, 2013. Accessed: Nov. 05, 2025. [Online]. Available: https://elibrary.pearson.de/book/99.150005/9781292037264

[12] G. Kumar, V. Jain, and U. Soni, "Modelling and simulation of repairable mechanical systems reliability and availability," *Int J Syst Assur Eng Manag*, vol. 10, no. 5, pp. 1221–1233, Oct. 2019, doi: 10.1007/s13198-019-00852-3.

[13] K. Hou, P. Tang, Z. Liu, H. Jia, and L. Zhu, "Reliability Assessment of Power Systems with High Renewable Energy Penetration Using Shadow Price and Impact Increment Methods," *Front. Energy Res.*, vol. 9, Mar. 2021, doi: 10.3389/fenrg.2021.635071.

[14] O. Bertozzi, H. R. Chamorro, E. O. Gomez-Diaz, M. S. Chong, and S. Ahmed, "Application of data-driven methods in power systems analysis and control," *IET Energy Systems Integration*, vol. 6, no. 3, pp. 197–212, doi: 10.1049/esi2.12122.

[15] L. Duchesne, E. Karangelos, and L. Wehenkel, "Recent Developments in Machine Learning for Energy Systems Reliability Management," *Proceedings of the IEEE*, vol. 108, no. 9, pp. 1656–1676, Sept. 2020, doi: 10.1109/JPROC.2020.2988715.

[16] A. Bera, A. Chowdhury, J. Mitra, S. Almasabi, and M. Benidris, "Data-driven Assessment of Power System Reliability in Presence of Renewable Energy," in *2020 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, Liege, Belgium: IEEE, Aug. 2020, pp. 1–6. doi: 10.1109/PMAPS47429.2020.9183481.

[17] Y. Dutuit and A. Rauzy, "Efficient algorithms to assess component and gate importance in fault tree analysis," *Reliability Engineering & System Safety*, vol. 72, no. 2, pp. 213–222, May 2001, doi: 10.1016/S0951-8320(01)00004-7.

[18] "Reliability Importance Measures | PTC Inc." Accessed: Aug. 17, 2025. [Online]. Available: https://support.ptc.com/help/wrr/r12.0.0.0/en/index.html#page/wrr/PractitionersGuide/ImportanceMeasures.html#ID0E2KS1C

[19] P. Coandă, M. Avram, and V. Constantin, "A state of the art of predictive maintenance techniques," *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 997, no. 1, p. 012039, Dec. 2020, doi: 10.1088/1757-899X/997/1/012039.

[20] P. Niloofar and S. Lazarova-Molnar, "Data-driven extraction and analysis of repairable fault trees from time series data," *Expert Systems with Applications*, vol. 215, p. 119345, Apr. 2023, doi: 10.1016/j.eswa.2022.119345.

[21] B. Gjorgiev, A. Antenucci, A. Volkanovski, and G. Sansavini, "An FTA Method for the Unavailability of Supply in Gas Networks Supported by Physical Models," *IEEE Transactions on Reliability*, vol. 69, no. 2, pp. 740–753, June 2020, doi: 10.1109/TR.2019.2895396.

[22] S. Lazarova-Molnar, P. Niloofar, and G. K. Barta, "Data-Driven Fault Tree Modeling for Reliability Assessment of Cyber-Physical Systems," in *2020 Winter Simulation Conference (WSC)*, Orlando, FL, USA: IEEE, Dec. 2020, pp. 2719–2730. doi: 10.1109/WSC48552.2020.9383882.

[23] P. R. Sonawane, S. Bhandari, R. B. Patil, and S. Al-Dahidi, "Reliability and Criticality Analysis of a Large-Scale Solar Photovoltaic System Using Fault Tree Analysis Approach," *Sustainability*, vol. 15, no. 5, p. 4609, Mar. 2023, doi: 10.3390/su15054609.

[24] X. Shi and A. M. Bazzi, "Fault tree reliability analysis of a micro-grid using Monte Carlo simulations," in *2015 IEEE Power and Energy Conference at Illinois (PECI)*, Champaign, IL, USA: IEEE, Feb. 2015, pp. 1–5. doi: 10.1109/PECI.2015.7064928.

[25] F. Spertino, A. Amato, G. Casali, A. Ciocia, and G. Malgaroli, "Reliability Analysis and Repair Activity for the Components of 350 kW Inverters in a Large Scale Grid-Connected Photovoltaic System," *Electronics*, vol. 10, no. 5, Art. no. 5, Jan. 2021, doi: 10.3390/electronics10050564.

[26] O. Mostafa, "Python for Fault Tree Extraction (PyFTE) GitHub Repository." [Online]. Available: https://github.com/omarstfa/PyFTE

[27] "How Much Does Solar Panel Repair Cost? [2025 Data]," Angi. Accessed: July 31, 2025. [Online]. Available: https://www.angi.com/articles/how-much-does-it-cost-repair-solar-panels.htm