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Reliability Assessment of an Electrical Network with Digital Twins

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Abstract: Assessing power systems' reliability and condition is a difficult task. This is partly due to the complexity of the many interrelated components that compose these systems. As a result, traditional reliability assessment methods are inadequate. This raises the question of whether digital twins can be used to assess the reliability of power systems. The objective of this paper is to consolidate information on the use of digital twins in the electrical industry and demonstrate how they can be used to assess the reliability of such complex systems. To accomplish this, a literature review is conducted. Then a method for evaluating the reliability of a power system with DTs is proposed.

Keywords: Digital Twin, Reliability, Complex systems, Electrical industry, Asset management.

1. INTRODUCTION

Assessing the reliability of power grid systems, equipment and components is a difficult task for several reasons. First, power networks cover wide geographic areas. Frequent on-site physical inspection is therefore unreasonable, or economically unrealistic (Gitelman, Kozhevnikov, & Kaplin, 2019).

Second, electrical networks are considered large complex systems (Mahmood, Kausar, Sarjoughian, Malik, & Riaz, 2019). Complex systems are characterized by their non-intuitive behaviour and non-linear dynamics. A complex system is also defined not only by the large number of elements that compose it, but, more importantly, by their interrelationships.

Thus, the reliability of electrical networks is assessed based on the interactions between the elements, rather than by the sum of the individual results of each element (Seddari, 2015). Therefore, the probability of failure is difficult to predict, and modelling power system reliability is complex.

As a result, in this context, traditional reliability assessment methods are inadequate, and innovative methods are required. The technologies driven by the fourth Industrial Revolution, or Industry 4.0, can address this issue.

Indeed, the integration of artificial intelligence (AI) in big data processing, as well as modelling, simulation and digital twin (DT) technology can help to overcome this complexity (Biard & Abdul-Nour, 2021). Indeed, when equipment and assets are far away or in a hostile environment, the twin's ability to access the object's health or condition data is particularly useful (Julien & Martin, 2020).

This raises the question of whether DTs can be used to assess the reliability of power systems. The objective of this paper is therefore to document the use of this technology in the power industry and to demonstrate how DTs can be used to assess the reliability of a power system, as a whole.

To accomplish this, the paper is divided as follows: Section 2 defines DT technology and presents the evolution of the literature on this topic. Section 3 details the methodology used in the literature review and sections 4 and 5 present the results. Then, the proposed method for evaluating the reliability of a power system with DTs is discussed in Section 6 and the conclusion is given in Section 7.

2. BACKGROUND

2.1 Digital twin definition

Briefly, a DT is a digital reproduction of an element. The main purpose of a DT is to optimize the performance of the element it represents. However, this digital representation is not limited to the creation of a virtual prototype.

This reproduction can simulate the element's behaviour and predict its reactions, from a digital platform. Thus, the DT is designed to react to external factors in the same way as the real object would and trigger actions on that physical object based on the predictions.

The DT is based on data related to the object it represents. This data can be processed using AI methods and algorithms, including machine learning algorithms. Data acquisition can be done in real time, or not. The process of data transfer is simplified by the use of devices operating with the help of the Internet of Things technology, as well as cloud computing.

Furthermore, Julien and Martin (2020) identified five levels of DT conception. Level distinctions are specified according to DT functionalities and attributes. Table 1 presents a summary of these levels.

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Table 1 DT evolution levels according to their functionalities or attributes

	Levels				
Function or attribute	1: Digital model	2: Digital shadow	3: Digital twin	4: Cognitive twin	5: Autonomous twin
Condition or health assessment	x	x	x	x	x
Real-time automated data collection		x	x	x	x
Simulation		x	x	x	x
Object control			x	x	x
Artificial intelligence			x	x	x
Advanced machine learning algorithms				x	x
Decision support				x	x
Autonomous decision-making					x

2.2 Evolution of literature

DTs have been gaining popularity among researchers for the last five years. Therefore, the literature on this topic is relatively recent. The evolution of the annual number of publications is presented in Figure 1. A distinction is made on keywords targeted by this study and identified by the authors.

Prior to 2011, the term “digital twin” was used to identify digital models or digital shadows, i.e., levels 1 and 2. It was not until 2020 that DTs as described in the previous section emerged (Julien & Martin, 2020). The Digital Shadow is similar to the DT technology, but uses only a unidirectional communication link, from the physical object to its digital representation. As a result, the Digital Shadow can’t trigger actions on the physical object it represents.

In the electrical industry, we notice that the use of DTs is not widespread. Publications about the use of this technology in power grids are also very recent, i.e., dating from 2019

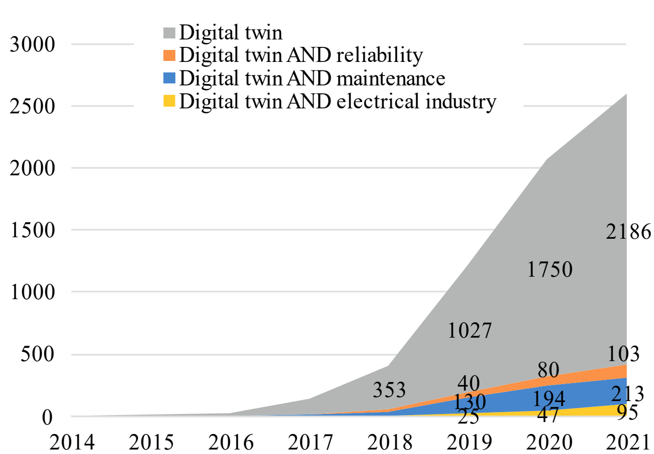

Figure 1. Number of publications by year by keywords since 2014 in the Scopus database

onwards. Moreover, very few publications deal with the use of one or more DT to represent the entire network, including energy production, transmission, and distribution.

The use of DT to assess the reliability of a complex system is also an unusual topic. However, it is recognized that reliability assessment is close to that of predictive maintenance. Indeed, it refers to the evaluation of the probability of failure of an element. Predictive maintenance is based on this same evaluation, as well as on the prediction of defects, in order to take action at the right time to avoid failure. This field of application is more popularized.

2.3 Related work

Some authors have conducted a study similar to the one in this article. First, Liu et al. (2021) and Pan et al. (2020) introduce the research on and application of DT in electrical networks. They provide application ideas and the main fields of application. Then, Jiang, Lv, Li, and Guo (2021) provide a detailed DT architecture applicable to complex systems. The architecture is based on the principle of DT aggregation. Their paper proposes an application case. However, it does not provide a detailed literature review.

Zolin and Ryzhkova (2020) explain two frequently cited examples from the electrical industry. The DT developed by Fingrid within the framework of the ELVIS project for transmission networks is one of them. The second is developed by Slovakia’s VSE Group for a distribution network. However, these authors do not include an aggregation of multiple DTs in order to analyze the complex system as a whole.

Thus, the contribution of this article is a literature review on the use of DT for the assessment of overall power system reliability.

3. METHODOLOGY

The methodology is based on a literature review and comprises several steps. First, publications related to the use of DTs in the electrical industry were analyzed (171 articles). The keywords “Digital Twin”, combined with terms related to the electrical industry (“Power network”, “Distribution grid”, “Transmission network”, “Power plant”, etc.) were used to target the relevant literature in the Scopus database. The objective of this first step is to document the use of this technology in the electrical industry, by application areas.

Then, publications related to the reliability assessment of at least one interrelated piece of equipment (e.g., a plant or a substation) were selected for an in-depth analysis (45 publications). Of the 45 publications, only 20 were retained since they were relevant to the objective of this article.

Table 2 details the selected references, as well as the associated systems. Publications 1 to 12 refer to a specific system or piece of equipment. Publications 13 through 20 refer to a DT of a system of systems.

Table 2. Publications selected and associated systems

	Ref.	System	Use case
1	(Yan, 2021)	Coal-fired generating unit	
2	(Xu et al., 2019)	Coal-fired thermal power-plant unit	X
3	(Oluwasegun & Jung, 2020)	Control Element Drive Mechanism	X
4	(Lim et al., 2021)	Gas turbine	X
5	(Tsoutsanis, Hamadache, & Dixon, 2020)	Gas turbine	X
6	(Nikolaev, Belov, Gusev, & Uzhinsky, 2019)	Gas-turbine flame tubes	X
7	(Gao & Wu, 2021)	Intelligent instrument	X
8	(Dreyer et al., 2021)	Penstocks	X
9	(Huang, Liang, Huang, & Zhou, 2021)	Substation equipment	X
10	(Tang et al., 2021)	Substation equipment	X
11	(Junior, Villanueva, Medeiros, & Almeida, 2021)	Water cooling system	X
12	(Olatunji, Adedeji, Madushele, & Jen, 2021)	Wind turbine	
13	(Cui et al., 2020)	Entire grid	X
14	(Liang, Mulatibieke, Shi, Lv, & Zhou, 2021)	Substation	X
15	(Malozemov, Solomonenko, & Malozemov, 2019)	Power plant with reciprocating engines	X
16	(Pileggi et al., 2019)	Entire Energy System	X
17	(Righetto, Martins, Carvalho, Hattori, & Francisci, 2021)	General	
18	(Semenkov, Promyslov, Poletykin, & Mengazetdinov, 2021)	Instrumentation and control system	X
19	(Song et al., 2020)	Inverter-based power grid	X
20	(Tzanis et al., 2020)	Distribution grid	X

4. USE OF DIGITAL TWINS IN THE ELECTRICAL INDUSTRY

Figure 2 shows the results of the analysis of 171 publications related to the electrical industry. This analysis presents the distribution of the use of DTs in the literature, according to the function of the network that is the focus of the article. Articles focusing on more than one sector (29% of the publications) are represented individually in each category. Of these :

- 23 refer to Smart Grids, as well as at least one other fields of application.
- 16 refer to transmission and distribution networks or equipment
- 6 refer to production plants and transmission networks

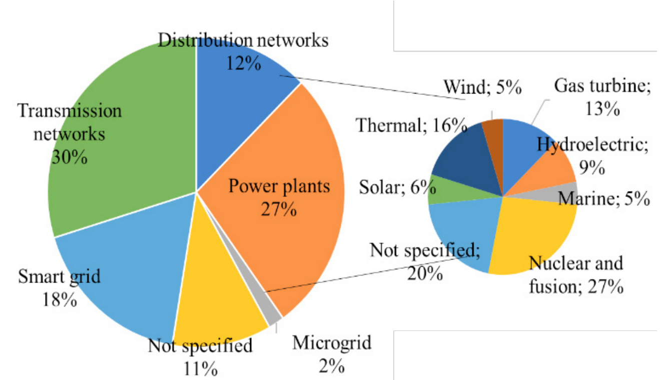

Figure 2. Distribution of articles according to their field of application in the electrical industry

ery few publications deal with the entire electrical network, i.e., generation, transmission and distribution.

5. USE OF DIGITAL TWINS FOR RELIABILITY ASSESSMENT

The following section discusses the 20 publications related to the use of DTs for the calculation of a reliability element. The publications were analyzed to identify the main objective of the digital model. Then, the attributes that establish its level of evolution as presented in Table 1 are identified. Table 3 presents the results.

Table 3. Publication's objectives and DT level attribute identification

Ref.	Main objective							Bidirectional communication	Machine learning algorithms	Autonomous decision-making
	Failure analysis	Failure/anomaly detection	Failure prediction	Monitoring/health evaluation	Performance evaluation	Automated decision support	Control			
1	X		X	X				X	X	
2					X					
3		X		X					X	
4	X	X	X	X	X				X	
5				X	X					
6	X								X	
7	X		X						X	
8				X						
9				X						
10	X			X					X	
11						X			X	
12	X			X					X	
13				X	X			X	X	
14	X	X	X	X	X				X	
15	*Structure only*									
16	X	X								
17			X	X					X	
18				X			X	X	X	
19				X					X	
20		X							X	

None of these publications use the virtual clone to control the real object. Although some models use a bidirectional communication process, this link is not intended to perform actions autonomously on the object. Unidirectional communication is also mostly used in the literature. In this type of structure, the physical element's data are only sent to the DT. The results of the analyses carried out by this digital double therefore do not automatically influence the real system. Thus, most of the literature seems to confirm that one-way communication is sufficient to effectively evaluate elements used to calculate reliability.

On the other hand, AI is present in a large majority of publications, mainly for data processing and the integration of machine learning algorithms. Thus, a combination of the functionalities and attributes of the digital shadow and the cognitive twin are applicable in this context.

Regarding the development of a DT to evaluate the reliability of a system of systems, most of the literature proposes an aggregation of DTs. This structure is based on dividing the complex system into subsystems and equipment, in order to simplify it. We then find one DT per elementary object of the structure. Then, these multiple digital models are combined in order to represent their interrelationships. However, it is currently recognized that the ability to integrate multiple DTs with each other is still weak (Julien & Martin, 2020).

Furthermore, for this to be feasible and to ensure interoperability, the purpose of the twins, their level of detail, as well as their level of accuracy must be similar or integrable. However, the approach proposed by Jiang et al. (2021) demonstrates the applicability of this method.

Liang et al. (2021) propose a similar approach. The proposed methodology is based on dividing the system, without, however, using an aggregation of multiple DT. In their model, the elementary objects of the simplified structure are given a unique identifier, and each calculates its health indicator from its own historical data and machine learning algorithms. This approach offsets the challenge of interoperability among multiple DTs.

Finally, Julien and Martin (2020) also recognize that it is more efficient to concentrate efforts on critical objects or processes. Thus, one should consider the critical elements first, as proposed in Tang et al. (2021).

6. DISCUSSION

Electrical networks are considered large complex systems. Therefore, grid reliability assessments must represent interactions between the elements that constitute the complex system. Considering the literature review, assessing the reliability of an electrical network from a global point of view requires several DTs.

The proposed approach is based on the development of a block diagram composed of multiple interconnected DTs. Thus, to develop a model to assess the reliability level of power networks, the following steps are suggested.

6.1 Define the problem to be addressed

The first step involves the definition of the objective and scope of the analysis. According to the objective, the relevant indicators are identified (ex: availability, number of failures, customer minutes lost). Then, the required level of detail and the accuracy threshold can be identified. The different twins must have a consistent and sufficient level of detail and accuracy. This step aims to reduce the complexity of DT conception but can be challenging. It is recognized that one of the main challenges in DT conception is adequately defining the required level of detail for the model and determining the most significant parameters and data (Julien & Martin, 2020).

6.2 Identify Assets to be Modelled

As electrical networks are large complex systems, the decomposition of the system into several subsystems with a structural model allows simplifying the complexity. The block diagram is based on this structural model. The block diagram must be built in order to represent interrelations between blocks, according, among others, to the network topology. Each block represents a critical element and is modelled by a distinct DT. In a reliability assessment context, critical elements are those that significantly influence the identified performance indicator.

6.3 Collect Data Related to the Elements

For each critical element, all related existing data and their relevance according to the objective and scope must be identified. Simultaneously, the list of required data is developed and compared to available data. A unidirectional communication link between the physical element or the information system and the DT must be automated in order to retrieve in real time, or periodically, the required data. Internet of Things technology can be used to facilitate data acquisition or to obtain unavailable data.

6.4 Analyze Data and Evaluate Reliability

Depending on the objective and data availability, various models and algorithms can be used. For example, equipment condition data can feed a neural network and/or evaluate the condition in real time and historical data can provide the inputs needed to calculate reliability laws and metrics such as MTBF.

Once the appropriate and relevant models are established, data analysis models are embedded in each of the DT (each block). Relevant AI algorithms should be integrated in this step. The results of the targeted indicators are obtained for each block. Then, to evaluate the overall power system reliability, the interrelationships between each block must be considered.

6.5 Continuous Improvement

This final step ensures the continuous improvement of the model. It can include, among others:

- Data quality, quantity or availability improvement
- Output precision enhancement from AI algorithms improvement
- Scope and detail level increase
- Performance indicators addition

6.6 Challenges of Using DTs to Assess the Reliability of Power Systems

One of the main issues in the development of DTs for power system reliability assessment is the first step i.e., the problem definition. The scope and the level of detail required influence the overall implementation. Too much detail makes the analysis more complex and increases uncertainty. This can lead to high variability in outputs and unusable results. Restricting the scope and level of detail to an acceptable limit is an essential step for successful model development. Once the model is proven, the scope can be expanded.

There are also issues related to the quality and quantity of available data. Electrical industries have been working for decades and electrical networks are composed of assets with lifetimes extending over several decades. Since then, information systems, as well as data collection methods have undergone several evolutions. Thus, the multiplicity of databases or different data sources present in these industries represent an obstacle to information consolidation. Also, DT implementation must also consider the following issues:

- Significant investments in human and financial resources.
- The quality of internet connectivity, due to the need for real-time interaction and communication between the virtual environment and the physical system (Ingenium, 2019).
- The obsolescence of the software by which the digital model is made (Ingenium, 2019).
- Cybersecurity vulnerabilities related to hosting DT in the cloud and to data transmission (Institute, 2021).

Moreover, as complex systems involve multiple DTs that interact with each other, more data sharing takes place between physical objects. This therefore increases the risks and confirms the need to develop an effective cybersecurity system (Institute, 2021).

7. CONCLUSION

The objective of this paper is to document the use of DTs in the electrical industry and demonstrate how they can be used to assess the reliability of an entire electrical network.

To do so, a literature review was conducted. The application of this technology in different sectors of the electrical industry was estimated. Next, the use of DTs to evaluate reliability elements was studied. From this specific analysis, we can see that these digital representations mostly have a one-way communication link between the physical object and its digital clone. DTs also mainly integrate machine learning algorithms. These algorithms aim to evaluate the health index, to diagnose or to predict the failures of the object.

Then, a global methodology to evaluate the reliability of an electrical network using this technology is proposed. The next step is to develop a case study to demonstrate the applicability of the proposed method. The case study to evaluate the applicability could aim at prioritizing the most critical assets according to their impact on the availability of the overall network. This case study also requires analyses to identify the optimal software and tools for developing this type of application. Machine learning algorithms and data analysis models applicable to this context could also be studied. Then, a second case study could evaluate various maintenance and investment scenarios, based on the aging of the assets and the impact on the continuity of service to customers.

These subsequent studies would then allow a better knowledge of the assets, minimization of the risks related to their reliability and an optimization of the investments. However, in order to reduce the scope and help the success of the model, the study should focus on one section of the network only. Then, an extension of the scope can be considered. In addition, the impact of climate change and weather events on system reliability could also be modelled using this method.

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