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The Role of Digital Twins in Energy Transition

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ABSTRACT

Digital Twin technology, a transformative innovation in the Infrastructure industry, has the potential to drive a sustainable energy transition. By creating interactive virtual representations of physical systems, it boosts operational efficiency, enabling efficient integration of renewable power, interoperable grid components, and long-term decarbonisation planning. It also enables predictive maintenance, reducing energy use and operational costs, thereby democratising energy access. Nonetheless, these important benefits do not come without a price; as digitalisation penetrates the energy grid, it becomes vulnerable to cyberattacks and data interception, while the quality and interpretation of input data bring uncertainty. Critically assessing the holistic impact, underlining the importance of supporting the energy transition, this paper proposes also mitigation strategies to maximise this promising tool's performance. Well-defined cybersecurity regulation, clarity on stakeholder responsibilities, and safe data handling should be prioritised. Furthermore, advanced protection digital tools and a standardised system for intersectoral Digital Twins would unlock additional capabilities.

Keywords: Digital Twins, Renewable Energy, Clean Energy, Energy 4.0

NONMENCLATURE

Abbreviations	
DT	Digital Twins

1. INTRODUCTION

1.1 Digital Twins definition

Digital Twins (DT) are a promising and innovative concepts, first developed by Grieves et al. [1] and the NASA team [2], and now deployed in different fields varying from health to manufacturing and infrastructure systems, such as transportation, energy and water management [3]. Despite the broad spectrum of technologies, functions, and applications, DT can be broadly defined, decoupled from characteristics that apply to specificcases, as a digital representation of a physical, real-world system (element or process) continuously adapted based on an ongoing two-fold exchange of information [3]–[6], which is the alarming difference with simpler simulation models. Beginning from the real-world entity to shape the computerised version and then transferred the other way, it aims at improving the physical twin or obtaining additional input to optimise replication and increase utilisation value [6]. Due to the evolving nature of DT, It can be deduced that it is more a methodology than an actual technology product [3]. DTs are generally used for what-if scenarios simulations, forecasts, diagnostics, optimisations, sensitivity analyses and, ultimately, efficient decision-making [3], [7]. Following the technology leaps in this field, DT's fidelity is constantly enhanced; however, performance restrictions may beimposed due to data storage and computational capacity or cost and decision-making response time requirements [6]. The success and cementation of DT's significantly relies on the underlying telecommunications and data infrastructure, as real-time data collection and transmission speed and capability, data storage volume and security, generate critical interdependencies [8].

1.2 Implementation in energy sector transition

Energy is crucial for economic and social prosperity, with consumption rising globally due to industrial growth, population increase, and, even more lately, a shift towards electricity [9]. However, it is also a major contributor to climate change since the sector accounts for more than 70% of the total CO_2 emissions [10], indicating the vital importance of sustainable practices. In response, stepping towards Energy 4.0 that encapsulates interconnected and sustainable systems, founded on decarbonisation, digitalisation and decentralization, hasinitiated. These pillars are inevitably

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interdependent, with digitalisation possessing a the critical role; decarbonising, demands the integration of multiple decentralised renewable sources, e.g. solar panels, wind turbine farms, geothermal energy facilities supported by storage installations like lithium and hydro batteries, widely geographically distributed – on- and offshore, in remoted or central areas - and managed by various operators under different schemes – public or private, bulk or micro transmission systems [11]. Hence, developing digitalised data-driven systems like DT, supported by the existing advanced digital technologies, such as 5G networks, IoT, AI, are critical to enabling interoperability between the actors, reliability, maximum efficiency of renewable energy production and multi-level managing [12]. Though it is still the infancy of the energy sector DT epoch, there are already several burgeoning success stories illuminating its vast potential. Originally started from the Oil & Gas industry [13], DT implementation swiftly spread into the realm of renewable energy; DT for wind turbine design and predictive maintenance were launched by Siemens in 2015 [14] continuing then throughout the whole spectrum of the industry from manufacturing, operation and grid demand-consumption monitoring to the UK National Digital Twin. As the technology is only just beginning to gain widespread traction in the energy sector, a comprehensive evaluation of its profound benefits, alongside an analysis of the hidden risks and challenges, has not yet been fully realized. Acknowledging the indisputable potential and essential nature of the green energy transition, this paper not only aspires to bridge this knowledge gap, but also aims to propose mitigation strategies that will facilitate the successful adoption of DT.

2. MATERIAL AND METHODS

This study is the result of an extensive literature review, based on international works from different sectors and disciplines, aiming at exploring the role of digital twins in facilitating the energy transition. Preliminary researchon the topic indicated the critical role of digitalization and especially of DT in the complex endeavour of transforming power sector. The initial assortment of articles was organized based on the quantity of citations each received and on the year of publication – research on DT and the energy sector skyrocketed only after 2017 [15], thus studies before were considered outdated and were deprioritized. A reliability check was then conducted on each document to ensure peer-review approval and avoid discernible biases. The selection was further refined based on the following criteria; content relevance, innovative perspectives, practical implications – including case studies, regulation recommendations and technical insights – and geographic and sectoral level diversity to ensure multilateral coverage and smooth out peculiarities; underpinning the broad yet in-depth exploration of the topic.

3. RESULTS AND DISCUSSION

3.1 Benefits - Contribution towards the Energy Transition

3.1.1 Interoperability and supply-demand balance

Interoperability between the parts of the growing energy grid would address the renewables' main drawback: unreliability due to weather conditions [16]. Securing the proper operation of individual energy grid components is insufficient since maximum capacity performance originates from the system's interoperation. A twofold communication between energy and storage installations and accurate supply forecasts based on weather and demand-consumption, all channelled to the same DT model [17]–[18], will lead to timely decision-making apropos the optimal energy and storage mixture. Furthermore, this responsiveness will enable production and energy trading between individuals [16]. Demand-determined production and peak-to-average consumption ratio reduction prevent energy wastage lowering suppliers' operational costs.

3.1.2 Long-term energy infrastructure planning

The massive volume of data and the interconnection between DT could also provide a valuable tool for long term urban planning decisions concerning the capacity, positioning and type of energy supply facility that covers the projected future needs [19]. Articulating predictive scenarios and conducting pertinent cost-benefit analyses is considered challenging since generation, transmission, and distribution functions are usually disintegrated across different entities, demand trends are related with unpredictable technological and economic parameters,and production - particularly from renewable sources - is also unstable [11], [20]. Therefore, optimum energyprojects should be designed based on the transparent process of multiple inputs fulfilling increasing populationdemands, stakeholders' interests and environmental regulations, ensuring maximum renewable energy investment value and eliminating financial and operational risks [17], [21].

3.1.3 Lifetime asset management

Except for this, efficient life-time asset management is a DT feature with significant importance for the energy projects due to high initial investment, long life-span and need for uninterrupted operation. Beginning with theconstruction stage, a virtual project replication before and after the initiation would diminish delays, resources waste and execution risks [22]. Maintenance is usually conducted based on prescheduled checks andreplacements imposed by guidelines that may underestimate components' performance. Especially for wind andsolar farms that need special equipment in remote and inaccessible areas, these unnecessary interventions could burden the operator with considerable costs [11]. An extensive sensor network, collecting information such as voltage level, solar panel temperature, wind blades speed and vibration or leakage detection, and a high-fidelityAI system composing a virtual replication of the grid would enable predictive maintenance strictly when required [16], [23]. Besides end-of-life-time replacement, early damages could cause disruptions or shutdowns with severe repercussions. Advanced pattern recognition algorithms and continuous automated control systems on the digital model provide an early warning, and an intervention can be timely planned. The diagnostic role is similarly essential since data collection after a failure may improve operational systems [17].

3.1.4 Environmental benefits

Boosting renewable's efficiency reduces the operational costs [16], [18], [20] and broadens the profit margin creating a safe investing environment and incentivising private and government funds that will support the research and the execution of these projects [24]. Optimised distribution, storage and interoperability will eliminate energy wastage [7], whereas accurate predictive maintenance will save resources and prevent landfill congestion with non-recyclable wind blades and solar panels [25]. Data extracted from the whole lifetime simulation will provide valuable feedback for efficient sustainability transition regulation updates.

3.1.5 Social benefit

The decrease of energy production costs will be transferred to the retail pricing relieving the pressure on consumers that currently spend up to 1/3 of their income on heavy energy bills [19]. Moreover, access to private energy consumption data, combined with decentralised domestic energy generators, enables citizens to schedule their energy individually needs most efficiently [5]. Insightful energy infrastructure planning will even out energy access inequality and make the grid stable even for remoted underdeveloped areas [26].

3.2 Cost-benefit analysis

The cost of installing DT varies depending on complexity, size and number of facilities included, the sensors coverage area and the level of accuracy required. Noted that the cost is not just limited to the software and hardware components but further includes consulting and integration fees, training costs, and ongoing maintenance [27]. Industry review showcases that the upfront investment for a single high-tech factory, similar to an energy plant, fluctuates between £500K and £650K, whilst the payback period is expected to be six years on average [28]. Since the DT market will surge in the following years, massive application will lower the cost of providing access to smaller companies. Measuring different effects of DT implementation proves the contribution to energy production optimisation, cost and resources efficiency and CO2 emissions decrease (Table 1). It should be noted that the indicators were extracted from studies in different environments and scales, so they can be used more as a proxy than an absolute measurement.

Reference	Indicator description	Change rate	Technology applied
[18]	Energy production	+ 3%-8%	Solar panels maintenance
	Energy cost	- 5-10%	Supply/demand match
[21]	Operating costs	- 63.5%	Day-ahead energy scheduling
[20]	Flattening energy demand	+ 20.9%	Supply-domestic use DT
	Domestic energy cost	- 10%	
[16]	Energy production cost	- 13.2M USD	DT forecasting models
[30]	New investment need	- $270Bn	Smart demand response
	CO2 emissions	- 30M tones	
[illegible]	[illegible]	[illegible]	[illegible]

Fig. 1. Quantified Digital Twins effects in the energy sector based on established literature

3.3 Risks and uncertainties

Implementing digital twins for executing all the management operations renders the energy grid vulnerable to cyberattacks [29]. Malicious software can be installed provoking disruptions in the virtual replication that penetrates automatically to the real system with severe repercussions in the economic activities – in some cases even more than natural disasters [16] - and people's safety, e.g. interrupting hospital's operations [30]. 76% of professionals deem cyber-attack as the number one threat to their operation [31]. Massive interconnection and ongoing data sharing between participants raise concerns regarding data privacy and intellectual property. The flowing sensitive information, like personally identifiable data, bank accounts or confidential energy systems' location and operation, are potentially powerful tools for criminal activities like blackmailing or money embezzlements, as well as targeted insurance and marketing strategies [32].

Additionally, the quality and sufficiency of the accumulated data are questionable. Especially when completely automated data-driven systems, like AI, are deployed, the input origin should be carefully considered. When based on historical data, forecasting might ignore the latest updates or inevitably fails to predict socio-political events like war or pandemic, which will dramatically change energy supply and demand [9]. Moreover, uncritical and oversimplified semantics can generate significant errors in the interpretation [33], while the fact that energy digital twins are still an immature technology makes verification and validation challenging.

Launching a new digital methodology in long-established industries might come across to inexperienced staff unwilling to adaption and innovation [33], a particularly critical factor since human consent is necessary to overcome initial challenges. Energy is also a highly vertical-fragmented sector that lacks standardisation and commonly accepted terminology and framework [18]; substantial obstacles considering that wide interlevel andintersectoral cooperation will be required even from the early designing stage, let alone when the initial investment actions are negotiated. Questions such as who will be responsible for data ownership, hardware installation and maintenance, in which aspect optimisation should focus (e.g., organisation profit or environmental footprint) and whose interests should be prioritised are not rarely a bone of contention [33]. The production of hardware elements like servers and sensors and the constant operation data centres demanda considerable amount of energy and resources [34]. Therefore, whether energy savings caused by digitalisation outweigh, this energy demand rise is still under investigation.

Finally, smart energy transition and the foreshadowed benefits are anticipated to further widen the gap between developed and developing countries. Except for financial deficiency, the chronic shortage of recorded data makes it impossible for weaker economies to keep pace with this surging advancement.

3.4 Recommendations for mitigation of challenges

Considering the prospective spectacular advancement of DT implementation in the energy sector, it is profound that the adoption process is now irreversible. Hence, these alarming risks should be better seen as valuable toolsfor further improvement rather than deterring reasons. First of all, appropriate elaboration of the legislative framework for data protection is of paramount importance. A clear and considerable regulation update should be established to define ambiguities regarding data intellectual ownership [7]. Partial access permission should be provided to different actors depending on their role in the digital process sequence [3]. Data interception should be deemed a severe crime and penalised accordingly. Determining clearly the responsibilities of each stakeholder in the funding, operating and maintenance stage will make procedures more transparent and functional and, digital twins project more credible, speeding up investment and business plans approval [32], [35].

Pertaining to the cyber-security threat, as DT become widely used, the accumulated experience and the technological evolution will enable more sophisticated tools to identify cyber threats, diagnose the weaknesses or activate timely recovery practices [32]. The majority of cyberattacks is initiated by internal users; therefore, monitoring and recognising human behaviour motives might counteract this threat [36]. Algorithms trained to discern attacks and system failures and respond accordingly preserving functionality in any case will be decisive for critical energy infrastructure [26]. DTs themselves also hold a decisive role. The personnel can be safely trained by simulating potential attack scenarios, and more robust, multi-agent response strategies can be configured [29].

Digital twins' usefulness can be further maximised if intersectoral virtual infrastructure models are deployed [5], especially for achieving ambitious objectives like sustainability, where so many different actors are inseparably interdependent. A case in point would be merging electrical transportation and energy models or electricity and telecommunications in a shared digital twin. This would enable deeper comprehension of the indirect consequences of a disruption; e.g., in case of a natural disaster a fault in energy transition would immediately affect railways systems or telecommunication operations. This interdependency cannot be overlooked in a realistic digital replication. This holistic view contributes to more accurate predictions and planning. To make this interconnection feasible and overcome internal fragmentation, a standardized metric, terminology and regulation system is necessary to monitor the digitalisation progress, the data quality and the benefits, especially those that are hard to monetise, like social and environmental advantages [14], [18]. This framework has to be agile and adaptive to the continuously evolving society and needs, and the technological leaps; otherwise, it can be counterproductive, leading to bureaucratic dead ends.

4. CONCLUSIONS

The present study discusses the deployment of Digital Twins in sustainable energy transition, aiming to assess the prominent benefits and level of uncertainty, articulate the perceived risk and challenges, and propose mitigation strategies. Their crucial role in achieving the fundamental goals of decarbonisation and decentralisation has been identified. In particular, interconnecting all the energy grid components in a shared virtual model maximise interoperability efficiency, exhausting renewables capacity and regularising supply and demand. Long-term energy infrastructure planning is improved, whereas the existing assets are managed based on predictive maintenance. From an environmental and social perspective, energy and resource saving and lower energy production costs are also substantial.

Nonetheless, the risks and uncertainties of this technology should not be disregarded. Cyber-security and data privacy are major concerns, while quality and considerate data interpretation are necessary to ensure the results' credibility and usefulness. The possibilities of consuming more energy than saving and exacerbating social inequalities are still under investigation. Remarkable progress has been made apropos the mitigation of these challenges; appropriate, carefully elaborated regulations and policies should be instituted to protect data ownership and configure a standardised collaborative environment to accomplish wider intersectoral Digital Twins. More sophisticated digital tools should be deployed to prevent disruptions caused by cyberattacks.

Limitations of the present study include: Firstly, that a digital twin is not a specifically defined technology product, but an emerging concept. Therefore, explicit boundaries cannot be delineated to assess anticipated costs and quantify benefits with certainty. The data provided in the cost-benefit analysis section are rough estimations from research campaigns concerning digital twins of varying sizes and qualifications. Secondly, digital twin actual installation and deployment is recent while the research around this topic has escalated in the last years, so it is reasonable that case studies results are quite premature. More comprehensive implementation and observation of the physical and virtual models' interaction throughout the whole lifetime of energy operations would be more reliable, since further data collection and algorithms' training result in models' better performance.

Further research should be conducted about the long-term economic, social and environmental implications of Digital Twins in the energy sector to decrease uncertainty. The golden thread should be detected between data privacy and safety while achieving optimum performance and predictability since this is strongly related to the amount and quality of information inserted into the model. Authorities and policymakers should seriously consider the investigation results to cultivate a safe environment for users and companies and provide an impetus for future investments that will boost Digital Twin development.

DECLARATION OF INTEREST STATEMENT

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. All authors read and approved the final manuscript.

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