Digital-Twin-6G Empowered Future Smart Grid Applications

Abdelhak Kharbouch, Farid Hamzeh Aghdam, Narges Gholipoor, and Mehdi Rasti

Abstract

In the era of digitalization, industries are experiencing transformative advancements driven by technology and data utilization. The energy sector, in particular, is leveraging digital solutions to enhance efficiency, sustainability, and resilience. A key innovation in this context is the digital twin (DT), a virtual representation of physical systems that enables real-time monitoring, simulation, and optimization. This article explores the integration of DTs with 6G technology, highlighting the framework and connectivity requirements essential for this synergy. We present two use cases: DT for home energy management and DT for open radio access network (O-RAN), demonstrating the potential benefits and outcomes of such integration. Furthermore, we discuss the challenges and future directions, emphasizing the need for artificial generative intelligence, the Internet of DTs (IoDTs), and sustainable practices in the deployment of 6G and DTs in energy systems. This evolution not only promises improved operational performance but also supports global efforts toward achieving energy sustainability and resilience.

Introduction

In the age of digitalization, industries worldwide are entering a new era marked by unprecedented advancements in technology and data utilization. The energy sector, in particular, is undergoing a significant transformation as it embraces digital solutions to enhance efficiency, sustainability, and resilience. One of the most promising innovations in this context is the Digital Twin (DT), a virtual representation of physical systems that allows for real-time monitoring, simulation, and optimization. By integrating data from various sources, DTs facilitate informed decision-making and predictive analysis, ultimately supporting the transition toward more intelligent and responsive energy systems. This evolution not only improves operational performance but also plays a vital role in global efforts to achieve energy sustainability and resilience amidst emerging challenges.

Definitions of DT from Different Standardization Bodies

DT technology lacks a single, universally accepted definition, leading to diverse interpretations across standardization bodies and industry leaders. Some, like 3GPP and Orange, define DTs as digital representations of physical objects, often considered virtual objects within the metaverse. Ericsson emphasizes synchronization, defining DTs as digital replicas of real-world objects synchronized at specific intervals. ISO and IEC focus on purpose-fit and evolving digital profiles of real-world entities and systems, respectively. IBM and NVIDIA highlight the virtual representation and simulation aspects, with IBM noting their role in lifecycle management and decision-making through real-time data and ML, while NVIDIA emphasizes accurate virtual replicas with true-to-reality physics and AI-enabled behavior. The DTC and IIC stress the synchronization and fidelity of virtual representations, while the International Telecommunication Union (ITU) introduces DTs as real-time representations of physical assets in a digital world, including virtual network representations. Domain-specific definitions such as NASA defines DTs as multiphysics, multiscale simulations; the National Institute of Standards and Technology (NIST) refers to them as electronic representations of real-world entities/concepts; ETSI describes them as detailed virtual information constructs for manufactured products; and Nokia sees them as precise digital replicas using IoT and analytics, surpassing static CAD models for asset management and performance improvement.

The comprehensive and synthesized definition of DT based on the previous definitions can be unified as: DT is a digital or virtual representation of physical objects, systems, or processes, synchronized in real time, and leveraging advanced technologies such as AI and IoT to provide comprehensive, dynamic profiles for simulation, analysis, and decision-making across multiple domains.

Importance of DTs in Power Systems

The integration of Information and Communication Technologies (ICT) has facilitated the convergence of IoT, Big Data, AI, and simulation technologies, paving the way for DT adoption in SGs. While IoT enhances connectivity and enables real-time data collection from distributed sensors and actuators, DTs extend these capabilities by combining IoT data with AI and ML for predictive analytics and dynamic system modeling. Unlike traditional IoT frameworks, DTs enable real-time monitoring, advanced simulations, and scenario-based analysis, which improve overall grid operations. This integration elevates the SG

ISSN: 1536-1284
Digital Object Identifier: 10.1109/MWC.001.2400466

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from simple connectivity to a proactive, intelligent system capable of adaptive management and real-time decision-making.

A DT creates a real-time digital replica of a physical power system, enabling dynamic analysis and control. They offer advanced applications in fault detection, load prediction, system behavior analysis, and condition monitoring of power infrastructure. This allows energy operators to manage power systems more efficiently and securely, addressing challenges in optimal operation, control, and security [1, 2].

In energy systems, DTs play a crucial role in the integration of various sectors, such as transportation, microgrids, Smart Grids (SGs), and smart homes. They support real-time energy infrastructure management. For instance, in smart cities, where Electric Vehicle (EV) charging, traffic management, and energy dispatch systems must be actively monitored. In smart homes, DT also provides real-time monitoring, optimization, and control of energy usage, allowing homeowners to reduce costs and improve efficiency. DTs can also integrate renewable energy sources, such as solar panels, and manage battery storage systems, providing insights for optimizing energy consumption based on real-time conditions. DTs help bridge the gap in information flow by providing accurate digital representations of components such as EVs, charging stations, and power systems. This leads to faster and data-driven decision-making for energy distribution, grid management, and sustainable operations, positioning DTs as a key technology in the modernization of power and energy systems [1].

Paper Structure

In this article, we will delve into the application of 6G-empowered DT in modern energy systems. In the following section we will discuss DT and 6G integration as an enabling technology in energy systems. Then, two use cases will be illustrated for DT smart home energy management system and open radio access network. Following that, the future direction and challenges for DT in SGs will be discussed, and finally, we summarize the findings of the article.

DT and 6G Integration for Smart Grid

DT and 6G are strongly connected. In fact, two concepts coexist: 6G for DT and DT for 6G. 6G provides connectivity and beyond-connectivity capabilities required by DTs, such as Ultra Reliable Low Latency Communication (URLLC), high bandwidth, coverage, reliability, network resilience, and applicable AI and sensing-related capabilities. Similarly, DT can significantly improve the performance and operation of 6G networks by providing a virtual replica of its components, enabling real-time monitoring, simulations, and optimization of network performance.

There are two main deployments of DTs for 6G, one for the underlying infrastructure layer and another for end users or Non-Public Networks (NPNs) [3]. The results of simulations and what-if scenarios run in the DT can be beneficial to optimize the performance and operation of nodes and links in a physical 6G communication environment. The 6G-Infrastructure-layer DT can provide visualization of physical components, from the 6G Core Network (CN) to the edge, facilitating autonomous network management. This comprehensive end-to-end twinning can be achieved by combining multiple DTs of the CN, transport network, and Radio Access Network (RAN). The NPN DT can model coverage areas, predict real-time Quality of Service (QoS) and Quality of Experience (QoE), and prevent network congestion. The work at the standardization level has strongly targeted the DT Network (DTN). For instance, IETF [4] highlighted examples of successful DTN applications, such as DT for 5G Mobile Edge Computing (MEC) and DT-enabled Vehicular Edge Computing (VEC) networks. IETF proposed a reference architecture DTN with three main layers: application layer, DT core layer, and real network layer, enabling network infrastructure management and service provisioning.

As stated by Nokia, 6G research is grounded on the advancement of Beyond 5G (B5G) infrastructure but will bring more accuracy to the dynamic DT worlds and high-resolution representations of the physical world and/or representations of virtual worlds. The key aspects allowing for this transformation are the enhanced and new capabilities mentioned in the IMT-2030 framework agreed upon by the ITU. For instance, enhanced Mobile Broadband (eMBB) and massive Machine-Type Communications (mMTC) are used for immersive, massive, and hyper-reliable low latency communication, and ubiquitous communication, AI, and integrated sensing enable high synchronization of twins with their physical entities, security of communication, and interoperability.

DTs improve various components of the SGs by leveraging real-time data collection, modeling, and analytics through the DT platform's core features, including the data acquisition layer, real-time simulation and modeling, predictive analytics, and cyber-physical security capabilities. In forecasting, DTs rely on real-time data acquisition and predictive analytics to improve load prediction and future energy demand modeling for more accurate resource planning and system efficiency. Reliability and maintenance are reinforced by simulations and condition-based monitoring to forecast potential equipment failures.

For fault detection, the combination of real-time simulation and analytics quickly identifies and isolates faults for faster restoration and reduced downtime. Addressing uncertainties, particularly in renewable sources, is achieved with real-time data acquisition and analysis, which maintain balance amid fluctuating inputs. Lastly, the interoperability layer within DT platforms enhances energy hub functionality, enabling multi-source data integration (electricity, gas, water) to create coordinated, efficient, and resilient energy systems through cross-sector data flow and management. Table 1 provides more details about how DTs could support some of the SG use cases.

The integration of 6G and DT will largely serve the energy vertical. In fact, critical use cases need the best from 6G-DT integration. 6G is not conceived only as a network but as a network of networks. Such an architecture includes a large list of communication protocols from wired and wireless to aerial and non-terrestrial networks. This helps in achieving high coverage for anything and everything to be connected. Connecting the unconnected opens new opportunities for DTs to acquire more contextual data for better predictions

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Smart Grid Applications	Communication requirement				DT support
	Latency		Data rate		
	Required	6G	Required	6G	
Primary frequency control	~ 50 ms	25 ms – 1 ms	–	UL and DL 1–100 Gb/s	Predicts energy demand, load, and system response using real-time data. –AI: LSTM for time-series forecasting, CNNs for anomaly detection, and DNN multi-layer deep neural networks for short-term (STLF), mid-term (MTLF), and long-term (LTLF) load predictions.
Distributed voltage control	~ 100 ms		–		Simulates grid voltage dynamics and optimizes voltage regulation. –AI: Reinforcement Learning Algorithms such as Deep Q-Learning and Proximal Policy Optimization (PPO) are used for continuous optimization of voltage regulation strategies.
High-speed current differential protection	5 ms		2.5 Mb/s		Simulates current protection mechanisms and predicts faults based on current flow analysis. –AI: Gradient Boosting for identifying abnormal patterns in current. –Predictive Models: Time-series ARIMA for analyzing historical current data to anticipate possible faults.
Millisecond-level precise load control	50 ms		28 kb/s		Simulates distributed load balancing at millisecond granularity. –AI: RNNs for dynamically predicting load changes based on historical data. –Optimization Algorithms: Genetic Algorithms and Particle Swarm Optimization (PSO) for load allocation.
Distributed energy storage	DL: 10 ms UL: 10 ms		UL: 0.6–5 Gb/s DL: 100 kb/s		Monitors charging/discharging cycles, optimizes storage utilization, and predicts energy availability. –AI: LSTM for energy storage forecasting and ARIMA for short-term utilization. –Predictive Maintenance: Predict battery health and degradation using Gradient Boosting and Random Forest.
Advanced metering	100 ms		UL: 2 Mb/s DL: 1 Mb/s		Models consumer energy usage and forecasts demand patterns. –AI: K-Means Clustering to segment consumer profiles and Principal Component Analysis (PCA) for dimensionality reduction. –Predictive models: Regression models to estimate consumption trends.
Distributed energy resources and micro-grids	3 ms		5.4 Mb/s		Models DER performance and simulates micro-grid energy flows. –AI: Multi-Agent Reinforcement Learning for distributed decision-making and optimal load sharing. –Forecasting: Hybrid ARIMA-LSTM models to predict energy production from renewable resources.
Fault isolation and system restoration (FISR)	5 ms		10 Mb/s		Predicts fault propagation and restoration actions. –AI: CNNs for fault localization and Bayesian Networks for probabilistic fault cause analysis.
Identification of fault location	140 ms		100 Mb/s		Pinpoints the exact location of faults in the grid. –AI: Time-of-Flight (ToF) analysis and CNNs for real-time localization.
Fault management for distributed generation	30 ms		1 Mb/s		Predicts fault scenarios in distributed generation systems. –AI: RNNs for sequence prediction of fault events and Autoencoders for unsupervised anomaly detection.

TABLE 1. Smart Grid general use cases and DT support (Based on 3GPP).

and simulations for the benefit of SG's communication networks and operations. The paradigm shift of 6G toward AI-Native and edge computing makes it possible for new processing and analytics approaches to appear as new applications seeking optimization of data exchange and bringing intelligence closer to energy systems. This shift reduces latency and allows on-site analytics, making it feasible to manage SGs with real-time intelligence. By distributing computational resources at the network edge, 6G allows DTs to perform localized energy-efficient computations, facilitating near-instant decision-making for fault detection, predictive maintenance, and energy demand forecasting. In addition, enhanced security and privacy frameworks embedded within 6G provide a critical foundation to protect sensitive data processed by SG DTs, ensuring that data integrity is maintained across all transmission and storage points.

DT Based 6G Framework for Energy

Figure 1 illustrates a suggested layered architecture for the integration of DTs into energy systems, adhering to the NIST framework. The physical layer includes the core energy domains: generation, transmission, distribution, and customers (prosumers), which are interconnected by the electrical grid. Transmission and distribution, as integral components of the grid, inherently provide local measurements without requiring additional communication networks. However, the integration of sensors and actuators within 5G/6G networks enhances real-time data exchange and enables URLLC as an added benefit. Embedded

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processing and intelligence capabilities play a key role in advancing an autonomous and intelligent internet of distributed intelligent things, where energy systems, sensors, and actuators can efficiently process and analyze data to optimize operations. This will improve the resiliency of energy systems so that they can recover quickly in response to faults. Moreover, other technologies encompassed in the physical layer are meant to help reduce reliance on cloud computing and shift an important processing and analytics load to the edge. Different scenarios are possible to improve communication, such as AI at the edge of the network and AI at the edge of the energy system. The DT layer plays a crucial role in simulating, monitoring, and optimizing the entire system. Through digital replicas of energy systems, it runs what-if scenarios and forecasts energy demand patterns, predicts potential faults based on real-time collected data, and schedules maintenance and optimizing operations for efficient energy services. From a holistic perspective, DTs shall communicate using the twin-to-twin interfaces that ensure interoperability, synchronization, and data exchange to create a comprehensive model that describes the actual context of the energy topology. DTs, combined with 5G/6G networks at the communication layer, significantly enhance the capabilities of SGs, and several types of deployment have been suggested in literature such as edge-based twins, cloud-based-twins, and edge-cloud-based twins. Each of them influences the adopted architecture. Open RAN (O-RAN) plays a transformative role in the communication infrastructure of DTs and SGs by providing a flexible, open, and intelligent RAN environment capable of supporting complex, distributed, and data-intensive needs. O-RAN also aligns with the growing trend of deploying edge computing within SGs. It supports distributed intelligence at the edge, reduces the load on centralized systems, and enhances local processing and decision-making. The Application Layer covers platforms for storage, centralized cloud processing, and AI/ML analytics, enabling operations at the market and service provider levels.

Connectivity Requirements for DT-Empowered SG

According to the 3GPP and Next Generation Mobile Networks Alliance (NGMN), each SG use case demands specific Key Performance Indicators (KPIs) to meet its unique operational requirements. The use cases illustrated in [5], outline the foundational requirements that standardization bodies have leveraged to determine the necessary KPI values.

DT relies extensively on a robust communication, and while integrated together with 6G for SGs, both should be optimized to first fulfill the communication requirements of SGs and then provide enhanced services and features.

Proposed Use Cases of DT and 6G Integration

DT for Home Energy Management

This subsection explores a grid-connected smart home with real-time energy optimization via two-way communication. The smart home encompasses power generation resources, such as the utility grid, photovoltaic (PV) panels, wind turbines, energy storage systems (ESS), and EVs, which collectively power smart appliances that can be inflexible such as televisions and/or flexible like heating, ventilation, and air conditioning systems (HVAC). A home energy management system (HEMS) in Fig. 2, collects data as follows:

- User preferences (load usage, EV schedules, comfort levels), occupancy, and thermal discomfort
- Generation information (PV output, wind speed, energy transactions)
- ESS and EV status/constraints
- Pricing/grid constraints.

This data is securely transmitted for HEMS optimization, aiming to reduce costs and maximize benefits through market participation (e.g., frequency regulation). Integrating DT technology into the HEMS creates a real-time, dynamic simulation of the home's energy profile, enhancing monitoring, control, and optimization. The DT mirrors physical components, enabling adaptive control based on user habits, weather, and grid conditions. The DT-empowered HEMS updates the home's DT, improving uncertainty prediction and optimizing schedules. This synchronization enables optimized load scheduling, renewable energy prioritization, and grid power transaction management, improving efficiency and comfort (e.g., DT-optimized HVAC based on occupancy and weather).

Also, in managing ESS and EV, the DT-powered HEMS takes advantage of the EV's charging flex-

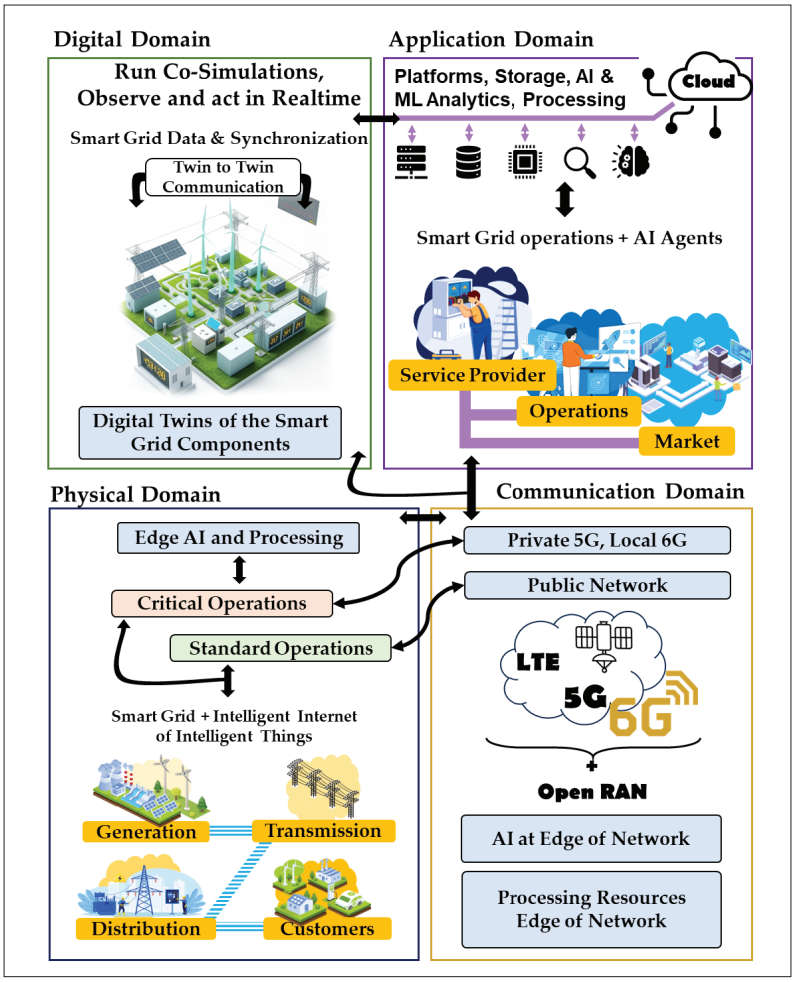

FIGURE 1. Architecture of enabling technologies for Smart Grid.

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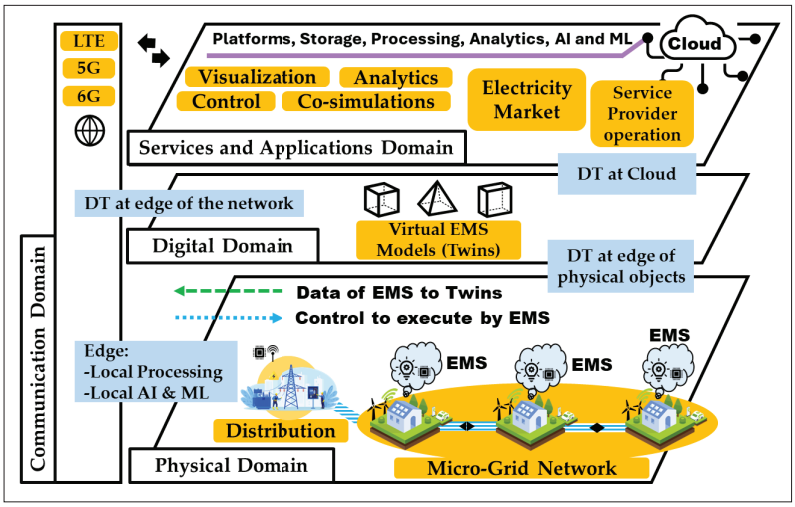

FIGURE 2. A holistic architectural view of the digital twin empowered home energy management system.

ibility and the vehicle-to-grid (V2G) capability. By assessing real-time data on the EV's state of charge, arrival/departure times, and user preferences, HEMS can dynamically adjust charging schedules and discharge energy back to the grid during peak hours. This provides an added layer of flexibility to the home's energy management, balancing peak loads and contributing to grid stability while reducing energy expenses. This V2G capability is particularly beneficial during peak demand, as it allows homes to both consume and supply energy, optimizing grid support.

Furthermore, the DT-enabled HEMS can actively participate in demand response programs, making the home a responsive player in a broader SG ecosystem. By processing real-time energy generation data from solar panels, small-scale wind turbines, and load forecasts, the DT can align household energy use with grid needs and pricing fluctuations. This bi-directional interaction reduces energy costs while maximizing renewable energy utilization, supporting both household sustainability and grid resilience. Essentially, DT-enabled HEMS provides a scalable, intelligent framework for integrating smart homes into a smart energy ecosystem.

DT-Enabled HEMS Simulation: As stated, integrating DTs into HEMS significantly enhances operational efficiency by reducing decision-making times to sub-minute intervals. By forecasting demand and optimizing control actions at 1-minute and 5-minute resolutions, the system ensures energy is allocated intelligently across household appliances, storage, and EVs. Such granular optimization—impossible for a human operator—maximizes renewable energy utilization, minimizes costs, and enhances grid stability. With the aid of an AI assistant empowered via DT, real-time energy management can be performed.

The DT is modeled by leveraging a long short-term memory (LSTM) as an ML algorithm using MATLAB software under Windows 11, core i5 CPU, and 16 GB of RAM. The HEMS is performed via a linkage between GAMS and MATLAB software, and the results of prediction with DT in 1-minute and 15-minute time scales are shown in Fig. 3. The energy management objective function is minimizing the operational costs of the smart home, which includes PV, EV, and smart appliances. The DT-assisted HEMS, specifically in lower time scales (1 minute), can dynamically adjust energy consumption patterns in real time, adapting to fluctuating renewable generation and user behavior. It can be seen in the simulations that 1-min resolution leads to much more precision in the prediction. The ability to make optimal decisions within seconds, rather than relying on static schedules, represents a fundamental shift in home energy management. This advancement is a step toward fully autonomous energy systems, where AI-driven HEMS act as virtual energy managers, transforming households into active participants in the sustainable energy transition.

DT-Enabled O-RAN for SG

Each vertical in 6G requires a specific set of communication KPIs, such as latency and data rate, necessitating tailored deployment architecture [5]. For instance, certain HEMS services require low-latency communication; to support these services, all network elements, including base station (BS) and CN components like the User Plane Function (UPF), should be located at the cell sites to minimize latency [6, 7]. Conversely, some HEMS services, such as EV charging scheduling, require centralized processing, where data must be sent to a central processor for analysis and decision-making [7]. O-RAN offers a disaggregated, virtualized, interoperable, and intelligent architecture in which network elements can be deployed across multiple locations, such as cell sites, edge data centers, and regional data centers, based on the specific service requirements [8, 9]. O-RAN disaggregates traditional BSs into three primary components: the Open Centralized Unit (O-CU), Open Distributed Unit (O-DU), and Open Radio Unit (O-RU), each connected by open interfaces. This modular design allows operators to create customized network configurations suited to different QoS requirements. The 3GPP has standardized eight options for splitting O-CU and O-DU functionalities, providing flexibility between distributed and centralized network architectures. Option 2 for the O-CU and O-DU split and Option 7.2x for the O-DU and O-RU split are the most commonly used configurations. Low physical layer (PHY) functions are executed at the O-RU, while high PHY, MAC, and radio link control (RLC) functions are executed at the O-DU. Packet data convergence protocol (PDCP), service data adaptation protocol (SDAP), and radio resource control (RRC) functions are executed by the O-CU. O-Cloud is a commercial off-the-shelf software (COTS) platform with networking, storage, and computing resources, hosting all O-RAN components on virtual machines or containers. The Service Management and Orchestration (SMO) framework orchestrates and manages O-RAN, including O-Cloud and network elements, through open interfaces. RAN Intelligent Controllers (RICs) optimize, monitor, and control O-RAN elements and network resources across various time scales, supporting third-party HEMS applications through ML and AI. O-RAN includes Non-RT RIC, Near-RT RIC, and RT RIC, with response times exceeding one second, between 10 ms and 1 s, and less than 10 ms, respectively. Each RIC hosts functionalities as applications based on network status, traffic

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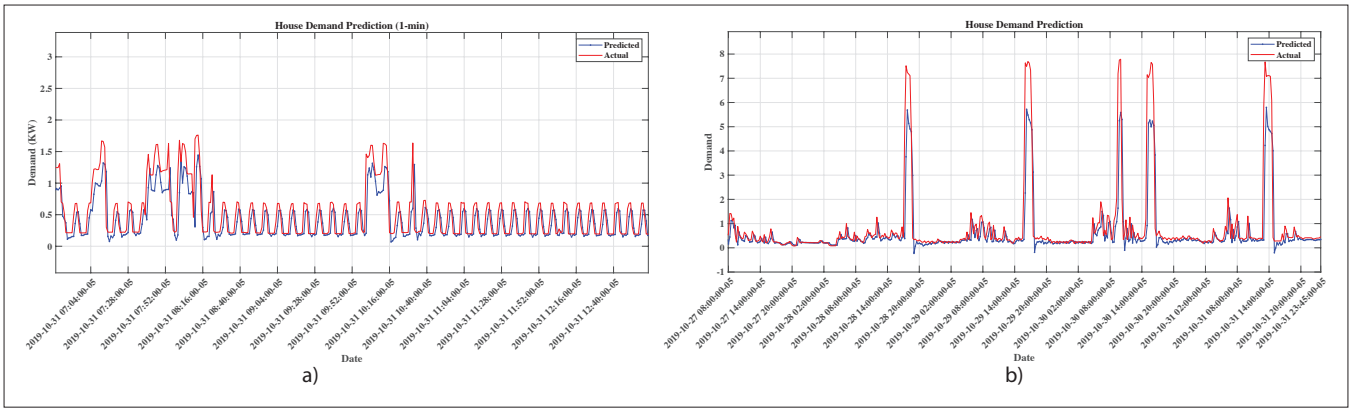

FIGURE 3. Home demand prediction using digital twin with different time resolutions (1-min and 15-min): a) House demand prediction 1-min resolution; b) House demand prediction 15-min resolution.

conditions, and service requirements, hosted on Non-RT RIC as rApps, Near-RT RIC as xApps, and RT RIC as dApps.

DTs improve the operation, automation, analysis, and intelligence of O-RAN for SG use cases such as HEMS, enabling high-quality, energy-efficient services. DTs serve two main purposes: optimizing RAN for energy use cases and creating an SG model to predict electricity demand profiles, wind and PV generation, temperature, and so on. DTs act as real-time models of network elements within O-RAN, analyzing and simulating various scenarios. They help by adding intelligence, reducing human intervention, and enabling more autonomous network operations. DTs can be integrated into RICs to support AI and ML processes or function outside of O-RAN and connect with RICs as needed. For SG use cases, DTs predict energy demand patterns for accurate energy management. In a DT-enabled O-RAN, non-real-time operations are executed within the Non-RT RIC as rApps, supported by a DT module, while near-real-time operations are executed as xApps within the Near-RT RIC, with DT assistance. This setup creates a comprehensive framework for effective energy management in HEMS. For example, in frequency regulation within SG, DT-enabled O-RAN aggregates electricity profile data and HEMS usage patterns to create digital replicas of the SG and HEMS. This data, analyzed at Non-RT and Near-RT scales, supports informed decision-making. In the Non-RT RIC, the system assesses and controls energy storage units based on long-term demand predictions and SG stability requirements. In the Near-RT RIC, energy utilization across HEMS is dynamically optimized to minimize immediate electricity consumption based on real-time demand. Digital replicas in each RIC assist in decision-making by providing a synchronized view of the system's status, enabling responsive and adaptive SG management.

Finally, the proposed DT-enabled 6G O-RAN framework for SG introduces several unique innovations that distinguish it from prior research. Firstly, the integration of real-time data from diverse sources, including user preferences, occupancy data, and pricing signals, enables the development of a highly adaptive and responsive energy management system that can adjust dynamically to fluctuating conditions. Secondly, the utilization of advanced AI algorithms, such as LSTM networks for demand prediction and optimization, significantly enhances the accuracy and efficiency of the system, surpassing traditional approaches in terms of forecasting precision and operational adaptability. These innovations represent a substantial step forward in paving the way for more intelligent, energy-efficient, and scalable SG solutions in the context of 6G networks.

Challenges and Future Directions

Challenges

Connecting the unconnected not only opens new opportunities for SGs' communication networks and operations but also introduces cybersecurity threats. Traditionally, power systems were designed to operate in isolated environments, and increased connectivity exposes them to potential cyberattacks, where hackers could exploit normal device functionality to cause unprecedented damage. The article [10] discusses the security aspects of DTs and identifies three types of adversaries based on their access: insiders with legitimate access who may perform malicious actions, hackers without access but with harmful intent, and outsiders with limited access, such as application programming interface (API) users who can still pose significant risks. The authors highlight potential 6G-enabled DT threats, including network configuration poisoning, misleading operators about the network state, and causing outages. Building on this, our projection for 6G-powered DTs in SGs introduces additional risks, such as synchronization data tampering and desynchronization attacks, which disrupt real-time data flow and lead to faulty decisions. Data sniffing and tampering at various layers can expose critical process data, while data exfiltration could compromise sensitive grid information. Denial-of-service (DoS) attacks and IP theft threaten DT availability and intellectual property, while visualization tampering misguides operators by altering interfaces. Moreover, the extensive data collection in energy systems presents significant privacy challenges for SG DTs. These systems collect detailed consumption patterns, user behaviors, and device usage data essential for accurate modeling and predictive analysis. However, such data can reveal sensitive personal information, raising privacy concerns. Additionally, regulatory frameworks like the GDPR in Europe and similar data protection laws worldwide restrict how personal and identifiable information can be collected, stored, and processed.

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Integrating diverse DTs requires addressing interoperability (solved through standardized data models like common information model, APIs, and data governance frameworks), data management (requiring robust data governance and secure sharing mechanisms), synchronization (achieved via distributed consensus and real-time communication protocols), security (enhanced by encryption, ACLs, blockchain, and differential privacy), and cross-system coordination (facilitated by distributed control algorithms and shared situational awareness).

These regulations, while essential for protecting user privacy, complicate the data collection processes for DTs in energy systems, often limiting access to the full scope of data needed for detailed modeling [11]. Power systems are critical infrastructure, and the data they generate is highly sensitive, raising significant privacy concerns. Data on grid operations, energy distribution, and substations is crucial for national security and economic stability, making it a prime target for cyberattacks. While access to this data is essential for developing accurate and comprehensive DTs for energy systems, its sensitive nature often restricts data sharing, limiting the scope of simulations and optimizations that could improve system resilience and efficiency [12]. This data sensitivity also creates interoperability issues, as different stakeholders (utilities, grid operators, regulators) may have varying data governance policies and security protocols, making it difficult to share and integrate data across systems. This lack of interoperability further hinders the development and deployment of comprehensive DTs that can provide a holistic view of the power system. Furthermore, the challenge with DTs is maintaining security while interconnecting with other sub-DTs. It is challenged by interconnection needs and ownership complexities. Legal and technical issues arise from differing ownership between physical entities and their DT replicas (e.g., smart home appliance data might be owned by the manufacturer, not the user, impacting control and access).

The EU's AI Act classifies AI risks from unacceptable to minimal, posing a challenge for DTs in energy systems. Since DTs rely on AI for simulations and scenario modeling, they fall under high-risk applications that require strict compliance. This may limit their deployment and innovation in SG management, making regulatory alignment crucial.

Future Directions and Solutions

Addressing DTs-SGs Threats: Mitigating DT threats in SGs demands a comprehensive, multi-layered security approach [10]. Securing the crucial state synchronization between physical and virtual systems necessitates robust protocols like TLS/SSL and cryptographic hashing to prevent data manipulation. Data and model security relies on trusted repositories with ACLs (access-control list) and version control, coupled with anomaly detection algorithms (ML-based) to identify data tampering, exfiltration (e.g., via unusual network traffic), and poisoning (e.g., adversarial attacks). API security requires strong authentication (e.g., OAuth 2.0), authorization, real-time monitoring (e.g., rate limiting, request pattern analysis), and input validation to prevent injection attacks. Resilience is built through redundancy (e.g., redundant communication channels, backup DTs), fault detection (e.g., heartbeat mechanisms, sensor data validation), and proactive failure management (e.g., predictive maintenance). Emerging technologies like federated learning enable decentralized, privacy-preserving model training on edge devices enhanced by differential privacy. For instance, in the context of residential energy consumption forecasting, individual homes can use federated learning to train predictive models on their local data. These models are then aggregated at the grid level without exposing personal energy usage data, thereby safeguarding consumer privacy while improving the accuracy of demand forecasts. Distributed edge computing minimizes latency and improves synchronization by processing data closer to physical systems. Edge-based intrusion detection systems, using techniques like deep packet inspection or ML-based anomaly detection, can analyze network traffic for malicious activity targeting DT APIs. Homomorphic encryption can further enhance privacy by enabling computations on encrypted data within the DT. Consider a scenario in SGs where distributed edge nodes at substations process local grid conditions (e.g., voltage fluctuations, load variations) in real time. These nodes communicate with each other to synchronize their DT models, allowing for rapid adjustments to grid operations without relying on centralized control, thereby improving both operational efficiency and resilience.

Artificial Generative Intelligence for DT: The rapid advancements in Large Language Models (LLMs) represent a transformative leap in AI, moving far beyond traditional chatbot capabilities. For example, FunSearch recently contributed innovative solutions to the cap set problem [13]. Visionaries like Bill Gates anticipate that LLMs will reshape our daily tasks [14]. This progression also holds significant implications for the energy sector, where specialized AI assistants may facilitate the formation and coordination of local SG communities, potentially assuming leadership roles to drive engagement and sustainable practices.

Advancements in LLMs have boosted the potential of Artificial General Intelligence (AGI), which could surpass human intelligence in complex tasks. However, ethical considerations and competing interests may limit the development of AGI-driven energy systems. These self-reliant systems could revolutionize the energy sector, enabling real-time optimization, predictive maintenance, and adaptive system advancements. AGI can also contribute to the generation of Synthetic Data, addressing data access challenges in the energy vertical.

Internet of DTs: The Internet of Digital Twins (IoDT) offers transformative potential for SG management but faces key challenges. Integrating diverse DTs requires addressing interoperability (solved through standardized data models like common information model, APIs, and data governance frameworks), data management (requiring robust data governance and secure sharing mechanisms), synchronization (achieved via distributed consensus and real-time communication protocols), security (enhanced by encryption, ACLs, blockchain, and differential privacy), and cross-system coordination (facilitated by distributed control algorithms and shared situational awareness). Semantic interoperability, enabled by ontologies and modular, open architectures, further supports IoDT implementation.

Conclusion

The integration of DT technology with emerging 6G networks offers transformative potential for the SG, driving advancements in efficiency, sustainability, and resilience. Through practical examples, including HEMS and DT-enabled O-RAN architectures for SG applications, this article illustrates the substantial benefits DTs bring to SG management. While challenges such as data pri-

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vacy, security, and regulatory constraints remain, the convergence of DTs and 6G promises to optimize energy systems more effectively. As we look forward, advancements in AI and federated DTs are expected to deliver even greater gains, paving the way toward more intelligent, responsive, and sustainable energy infrastructures.

Acknowledgment

This work was supported by Business Finland via the REEVA project under Grant No. 10284/31/2022, the DigiPave project under Grant No. 3992/31/2023, and the research grant of the University of Oulu and the Research Council of Finland (formerly known as the Academy of Finland) Profi6 336449.

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