Generative AI-assisted Digital Twin for Power Asset Management

Damos Ayobo-Abongo, Wael Jaafar, and Rami Langar

Abstract

Power asset management is a critical public safety service to ensure electrical networks' reliability, efficiency, and resilience. Traditional approaches, relying on periodic inspections and reactive maintenance, often leave the grid vulnerable to failures, costly outages, and operational inefficiencies. Adopting digital twin (DT) technology has introduced a paradigm shift by enabling real-time monitoring, predictive maintenance, and network optimization through virtual replicas of physical assets. However, the effectiveness of DTs is highly dependent on the timely availability of high-quality data, which remains a major challenge. In parallel, recent generative artificial intelligence (GenAI) advancements have demonstrated significant potential in data generation, predictive modeling, and decision support. This article proposes a novel framework integrating GenAI with DT technology to enhance power asset management. By leveraging GenAI techniques, such as generative adversarial networks (GANs) for data augmentation, vision-language models (VLMs) for automated asset analysis, and large language models (LLMs) for decision support, the proposed framework aims to improve asset performance monitoring, failure prediction, and maintenance planning. This integration enables a transition toward a proactive and intelligence-driven approach, thus contributing to a more robust, adaptive, and sustainable power infrastructure.

Introduction

The global power sector is undergoing a transformative shift driven by rising electricity demand and the critical need to enhance network reliability and resilience. These changes are crucial for ensuring public safety and security. Power utilities are responsible not only for delivering electricity to billions of households, businesses, and governmental institutions but also for safeguarding the safety and efficiency of their infrastructure. Effective power asset management is essential to achieving these goals, requiring oversight of the entire lifecycle of critical assets such as power plants, transformers, transmission towers, power lines, and distribution poles [1]. Poor asset management leaves networks vulnerable to failures, resulting in costly economic losses and disruptive service outages, with power interruptions costing billions of dollars annually and jeopardizing essential and public safety services [2]. To mitigate these risks, utilities have increasingly embraced advanced, data-driven technologies that enhance monitoring and maintenance strategies, moving beyond traditional inspection methods. This evolution is crucial as power networks face diverse internal and external threats, ranging from component wear, insulation failure, and mechanical degradation to environmental hazards like extreme weather events, wildfires, and vegetation encroachment near power lines [2, 3]. Climate-induced challenges, including storms, heavy snow, and high winds, further amplify the risks of infrastructure damage, underscoring the urgent need for a more advanced, real-time monitoring paradigm capable of predicting failures and guaranteeing the resilience of modern power grids.

The advent of artificial intelligence (AI), particularly deep learning, has significantly improved asset management by enabling automated defect detection, fault classification, predictive maintenance, and network optimization. For instance, convolutional neural networks (CNNs) have been widely applied to analyze images from vehicular and drone-based inspections, detect power line anomalies, and identify vegetation encroachments [4]. However, despite these advancements, existing AI-driven methods remain largely reactive, where they primarily detect problems after they have already begun, hence affecting the system. Given the dynamic nature of power networks, shifting towards a proactive and predictive approach is essential to mitigate risks before they escalate into failures.

A promising solution that has gained significant traction is digital twin (DT) technology. In essence, DTs create virtual replicas of physical assets, allowing utilities to simulate, monitor, and optimize their performance in real time [5]. Through continuous synchronization with real-world data, DTs provide predictive insights that enable power utilities to anticipate failures, optimize resource allocation, and improve grid resilience. However, implementing DTs at scale presents major challenges, particularly related to data availability and quality. Specifically, the effectiveness of a DT depends on the accuracy and completeness of the data used to train and update it. Yet, in many cases, data is scarce, incomplete, or expensive to acquire, especially for critical infrastructure components that undergo failures infrequently but require extensive monitoring.

To tackle the aforementioned issues, generative AI (GenAI) has emerged as a transformative technology. Unlike traditional AI models that analyze existing data, generative AI is capable of creating new synthetic data, filling gaps in datasets, and enhancing DT accuracy [6, 7]. For instance, gen-

Digital Object Identifier: 10.1109/MCOM.001.2500155

The authors are with the Software and IT Engineering Department of École de Technologie Supérieure (ÉTS), Canada.

erative adversarial networks (GANs) can generate realistic images of power assets under various failure conditions, enabling better training of predictive maintenance models. Moreover, vision-language models (VLMs) can automate image annotation and defect classification, thus accelerating asset monitoring workflows, while large language models (LLMs) can analyze historical data, extract patterns, and provide intelligent decision support by suggesting optimal maintenance actions [6]. Together, these AI-driven capabilities shift power asset management from a data-limited reactive approach to a data-empowered, proactive framework that enhances operational efficiency and grid reliability.

Consequently, we briefly review current power asset management systems in this article and identify the related challenges. Then, we discuss how DT and GenAI can be leveraged in power systems. Afterward, we propose a novel GenAI-assisted DT framework for power asset management to enhance data availability, asset representation, and predictive maintenance in power systems. To illustrate the framework's potential, we discuss key use cases, including data generation to mitigate data scarcity, visual asset analysis for defect detection, automated anomaly identification, and scenario-based risk assessment. Finally, we present the limitations and open challenges of incorporating GenAI into DT and outline future research directions to advance sustainable and resilient power asset management.

Background on Power Asset Management and Current Challenges

Background

Power asset management encompasses the processes and technologies used to monitor, maintain, and optimize the lifecycle of the power infrastructure, including generation facilities, transmission networks, and distribution systems. Effective management ensures grid reliability, cost efficiency, and risk mitigation while balancing operational demands with long-term infrastructure sustainability. Conventionally, utilities relied on fixed maintenance schedules, which often led to inefficiencies, such as unnecessary servicing or unexpected failures [1]. To address these limitations, modern asset management strategies incorporate real-time monitoring, predictive analytics, and AI-driven decision-making. A key component in asset management is the supervisory control and data acquisition (SCADA) system, which enables utilities to monitor and control power networks through sensor-based data collection. Although SCADA provides structured real-time data, it lacks comprehensive situational awareness of external infrastructure conditions. To fill this gap, utilities have adopted vehicular and/or drone-based inspections where the latter are equipped with infrared cameras and LiDAR, hence improving the detection of defects in power lines, transformers, and substations. Moreover, mobile laser scanning (MLS) and satellite-based monitoring further enhance structural assessments and vegetation management by offering high-resolution spatial mapping of transmission line corridors [8]. Also, condition-based maintenance (CBM) utilizes Internet-of-things (IoT) sensors to monitor asset health in real time, while reliability-centered maintenance (RCM) systematically determines the most effective maintenance strategy for each asset based on its function, failure risk, and criticality level.

Challenges

Despite these advancements, power asset management still faces several key challenges. First, the massive adoption of IoT, remote sensing, and AI analytics generates vast volumes of heterogeneous data. Still, fragmented data sources and interoperability issues hinder their seamless integration and limit the effectiveness of predictive analytics. Due to the impact of climate change, power assets are increasingly vulnerable to extreme weather events, vegetation encroachment, and fluctuating load demands. Traditional monitoring methods often fall short in promptly predicting and mitigating climate-induced failures. Third, despite the use of sophisticated technologies such as satellite imaging, UAV inspections, and sensor networks to collect valuable information, the latter's accuracy depends on several factors, including imaging resolution, environmental conditions, sensor calibration, temporal resolution, data integration, geospatial precision, presence of occlusions, and efficacy level of data processing algorithms. As asset management becomes more data-driven, the risk of cyberattacks targeting SCADA systems, IoT sensors, and cloud-based analytics platforms increases, making secure data transmission and real-time threat detection critical for preventing system disruptions. Finally, many utilities still operate reactively, i.e., responding to failures after they occur rather than preventing them. The challenge lies in integrating AI-powered risk assessment, automated anomaly detection, and scenario-based simulations to shift toward proactive and adaptive maintenance strategies.

A key component in asset management is the supervisory control and data acquisition (SCADA) system, which enables utilities to monitor and control power networks through sensor-based data collection.

Integration of DT and Generative AI in Power Systems

Integration of DT in Power Systems

DT has emerged as a transformative approach to asset life cycle management. Typically, a DT is a virtual representation of a physical asset continuously updated with real-time data to simulate, analyze, and optimize asset performance [5]. Originally conceptualized by Dr. Michael Grieves, DT has gained traction across industries, including aerospace, manufacturing, and healthcare [5].

In the context of power systems, DT can simulate different operational scenarios to enhance asset performance and reliability [9]. For instance, DT enables real-time simulations in power plants to assess efficiency, degradation, and heat rate variations, allowing operators to optimize power generation strategies and anticipate maintenance needs. Beyond power generation, DT provides critical insights into transmission and distribution infrastructure by analyzing grid stability, load fluctuations, and equipment performance under diverse operating conditions. By incorporating weather data, DTs can predict how extreme conditions, such as storms, high winds, heat waves, or snow accumulation, affect power assets, helping utilities implement preventive measures to mitigate potential failures. Given that vegetation management, as part of power asset management, is a critical utility task, DT can be leveraged by integrating satellite imagery, LiDAR scans, and historical vegetation growth

Indeed, instead of constructing a monolithic DT encompassing the entire power grid, we advocate for a more scalable and flexible approach by developing instance-specific DTs.

models to monitor and predict encroachment risks in the vicinity of power lines, thus minimizing the likelihood of outages caused by contact with trees or other vegetation. Finally, DTs assist in structural integrity analysis of power lines, transformers, and substations by simulating mechanical stress under various conditions, hence achieving proactive and efficient infrastructure maintenance and resilience.

Integration of GenAI in Power Systems

GenAI, as a recent breakthrough in the AI field, specializes in learning underlying data distributions to extract patterns from large-scale data and produce realistic outputs that mimic real-world patterns [6]. These capabilities make GenAI a powerful tool for various applications, including decision-making support, data generation, risk assessment, anomaly detection, and predictive analytics for power asset management [10]. Power networks produce vast amounts of operational data, including historical outage records, weather patterns, maintenance logs, and sensor readings. Traditional analytics often struggle with processing such high-dimensional and diverse data. In contrast, transformer-based architectures and deep sequence learning techniques of GenAI can uncover hidden correlations between environmental conditions, asset health, and failure events. By analyzing past outages alongside weather information, these GenAI models can predict asset vulnerabilities and implement proactive reinforcement measures before failures occur.

Beyond asset health monitoring, GenAI can simulate grid reliability and assess dynamic risk factors. These models can generate realistic failure scenarios and optimize contingency planning through continuous analysis of sensor readings, real-time energy demand, and climate forecasts. For instance, by identifying correlations between humidity levels, insulation degradation, and transformer failures, utilities can reinforce the infrastructure in high-risk areas. Moreover, document analysis and operational intelligence extraction can be streamlined with GenAI. Specifically, LLMs trained on power system documentation, including maintenance reports, regulatory guidelines, and equipment logs, can extract valuable insights, identify recurring issues, and recommend optimized maintenance or investment strategies. This approach reduces the manual workload and ensures that decision-makers have access to comprehensive, data-driven recommendations. Finally, VLMs can be leveraged to improve the analysis and interpretation of collected image data, improve their quality, and even model the future evolution of components, such as the growth of tree branches.

Proposed Generative AI-Assisted DT Framework for Power Asset Management

Details of Proposed DT Framework

The proposed GenAI-assisted DT framework for power asset management, illustrated in Fig. 1, aims to harness DT and GenAI to enhance asset monitoring and decision-making across the power network, from generation to distribution. Unlike existing approaches focusing on specific components, this framework provides a holistic perspective, integrating AI-driven capabilities to address various challenges in power asset management.

The key components of our DT framework and their roles are as follows:

Physical System: It serves as the foundation for constructing the DT by representing the entire power asset infrastructure, from generation to distribution. This includes power plants, transformers, transmission lines, and other critical components. Data is continuously collected through various methods, such as sensor deployments on equipment, SCADA system, vehicular and drone-based inspections, and advanced scanning technologies like LiDAR or Mobile Laser Scanning (MLS) to enable an accurate virtual counterpart.

Virtual System: It is responsible for replicating the behavior and performance of physical power assets, enabling real-time monitoring, analysis, and optimization. Leveraging the data collected from the physical system, received through the communication layer, creates a dynamic, data-driven digital representation of power infrastructure components. Inspired by the network-based DT approach proposed in [11], which applies DTs to various layers of wireless networks, such as radio access network (RAN), core network, and communication links, we propose a similar modular design for power systems. Indeed, instead of constructing a monolithic DT encompassing the entire power grid, we advocate for a more scalable and flexible approach by developing instance-specific DTs. These include “Power Generation DT,” “Power Transmission DT,” and “Power Distribution DT,” where each DT focuses on a specific segment of the network. This modular design enhances adaptability, facilitates independent upgrades, and enables efficient data management while ensuring seamless integration across the different stages of the power network. Each virtual system DT is composed of a data layer, a generative AI layer, and an application layer. They are described as follows:

- *Data Layer:* This layer is the foundation for integrating, storing, and preprocessing the massive amount of heterogeneous data collected from the physical system. It aggregates diverse data types, including sensor measurements, high-resolution images, LiDAR point clouds, and telemetry data, in a way that raw information is structured and optimized for downstream AI-driven analysis. Given the high volume, velocity, and variety of data generated in power systems, integrating big data analytics techniques is crucial [12]. In fact, techniques such as distributed computing, parallel processing, and advanced data indexing can significantly enhance preprocessing, allowing for real-time data fusion and analysis. Scalable storage solutions should also be leveraged. Traditional databases like MongoDB can handle structured and semi-structured data, while cloud-based platforms provide elastic storage, high-performance computing, and AI model training capabilities. Data processing can be distributed between edge computing and cloud computing environments for reduced latency and enhanced security. Specifically, edge computing allows for low-latency data preprocessing and immediate response, i.e., anomaly detection at the source, while the cloud-based infrastructure supports advanced AI-driven simulations, long-term

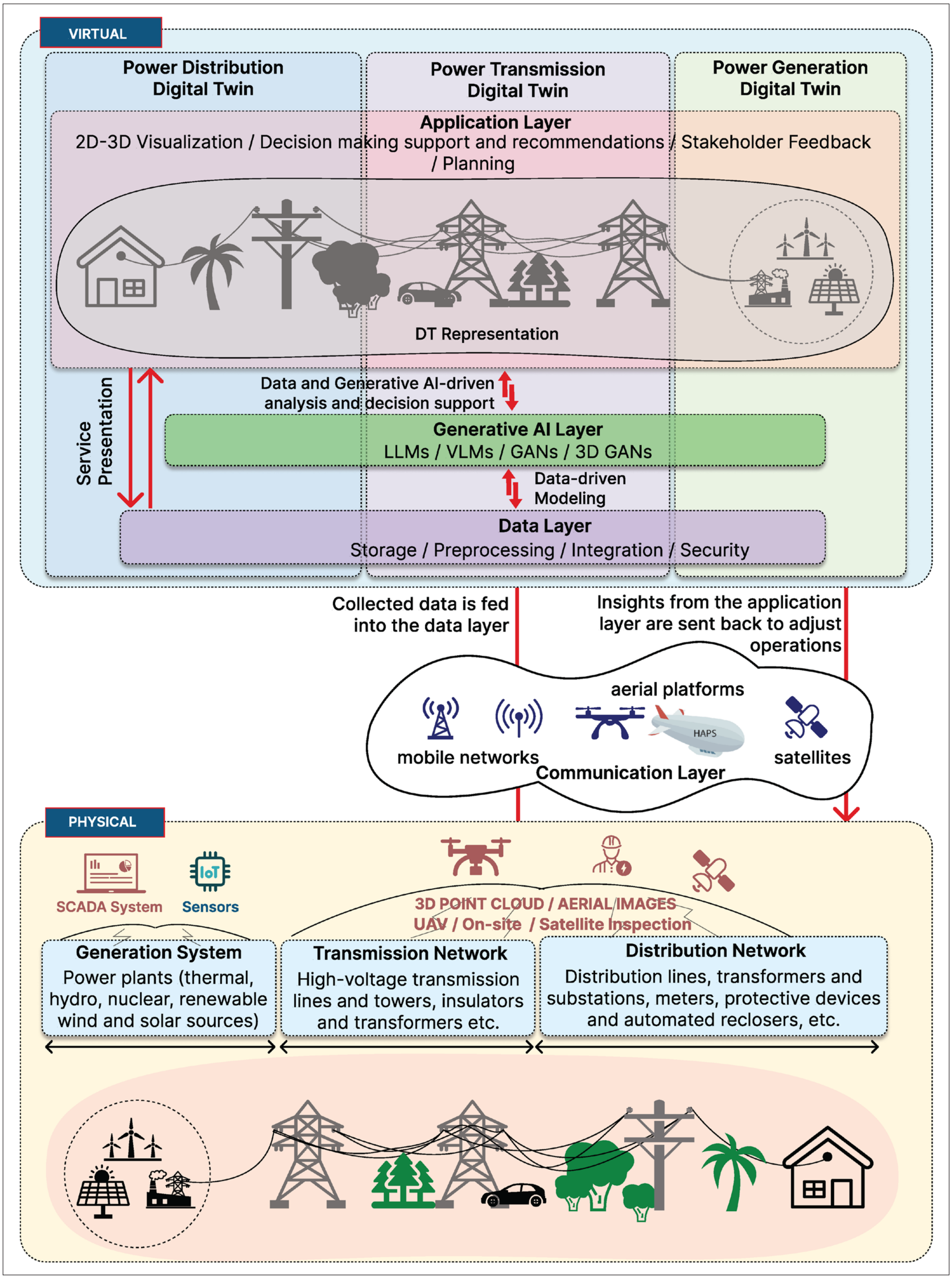

FIGURE 1. Proposed GenAI-assisted DT framework for power asset management.

Traditional databases like MongoDB can handle structured and semi-structured data, while cloud-based platforms provide elastic storage, high-performance computing, and AI model training capabilities.

data retention, and remote accessibility, hence improving the DT's predictive and prescriptive capabilities. To clearly emphasize the operation of the data layer, let ($x \in \mathcal{X}$) denote the collected data from physical assets. Data is transmitted through the "communication layer" (described in subsection IV-A.3) to the virtual environment for further processing. The virtual environment preprocesses, integrates, and stores the incoming data. This transformation can be modeled as a function (f_D: $\mathcal{X} \rightarrow \mathcal{X}'$), such that $x' = f_D(x)$, where ($x' \in \mathcal{X}'$) is the cleaned and integrated representation suitable for AI modeling.

- *Generative AI Layer:* This novel layer, proposed in our framework, enhances the DT system by generating, augmenting, and analyzing data tailored to the specific needs of power generation, transmission, and distribution. By leveraging generative models such as LLMs, GANs, 3DGANs, and VLMs, this layer interacts with the data layer to address key challenges like data scarcity, predictive analysis, and asset representation. For instance, GenAI can synthesize operational power generation data under varying environmental and load conditions to support predictive maintenance and performance

To address this gap, future research should prioritize the creation of open, domain-specific benchmarking frameworks that reflect real operational conditions and provide a common basis for comparative evaluation and reproducibility.

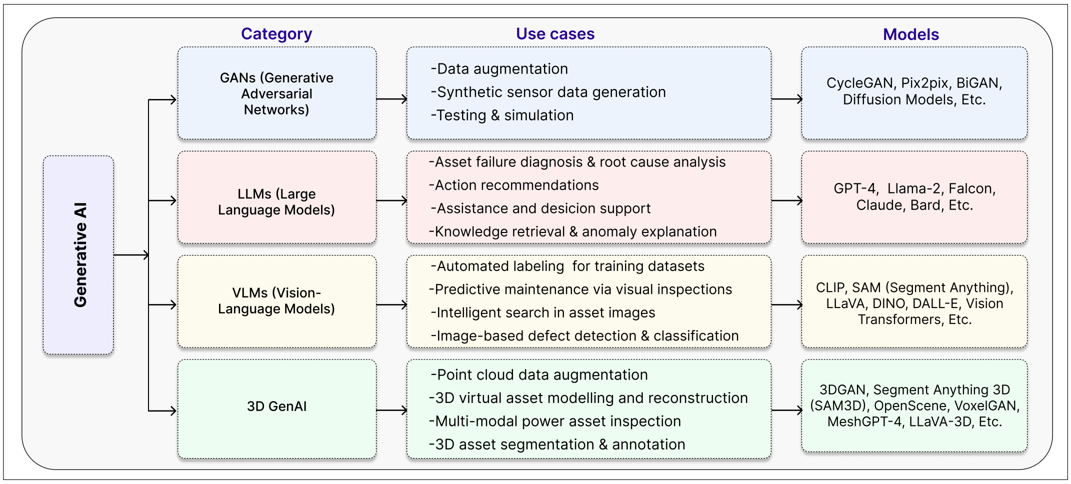

FIGURE 2. How GenAI integrates into the DT framework for power asset management.

optimization of power plants. In power transmission and distribution, GenAI can support image and LiDAR data analysis automation for defect detection, encroachment assessment, and failure anticipation. Also, it improves the structural modeling of network assets, refining predictive maintenance and fault detection strategies. Finally, it may interact with the application layer (described below) to provide data-driven and explainable guidance for maintenance planning, risk assessment, and operational optimization. Mathematically, Generative AI and predictive models operate on the preprocessed data (x'), producing insights or augmented data. Formally, this can be defined with function (f_G: $\mathcal{X}' \rightarrow \mathcal{Y}$) such that $y = f_G(x')$, where ($y \in \mathcal{Y}$) contains model outputs like synthetic data, predictions, or extracted features.

- *Application Layer:* It serves as the interface between the DT systems and end users, facilitating real-time monitoring, decision-making, and strategic planning. It integrates advanced visualization tools, including 2D dashboards, interactive 3D models, and immersive virtual/augmented reality (VR/AR) technologies, which provide an intuitive and detailed representation of power assets. This layer uses data from the data layer to serve these presentations, ensuring accurate and up-to-date visualizations. Moreover, AI-driven decision-support mechanisms are integrated to offer predictive maintenance insights, risk assessments, and automated anomaly detection alerts. This layer supports proactive asset management strategies by enabling customized analytics dashboards, simulation tools, and scenario-based modeling. This layer consumes the AI outputs (y) to support visualization, decision-making, and maintenance planning through a function (f_A: $\mathcal{Y} \rightarrow \mathcal{Z}$) such that $z = f_A(y)$, where ($z \in \mathcal{Z}$) represents actionable recommendations, alerts, or reports presented to operators. Hence, the full processing pipeline is $z = f_A(f_G(f_D(x)))$, indicating a sequential data transformation from physical collection to actionable outputs.

Communication Layer: This layer ensures real-time data exchange between the physical assets and the virtual DTs, leveraging advanced communication technologies such as terrestrial mobile networks, aerial networks supported by unmanned aerial vehicles (UAVs) [13], high-altitude platform stations (HAPS) [14], and network/routing protocols [15]. Secure communication protocols combining for instance message queuing telemetry transport (MQTT), constrained application protocol (CoAP) and long range wide area network (LoRAWAN) with transport layer security/secure sockets layer (TLS/SSL) and advanced encryption standard (AES) can be used to reliably and securely transmit data between devices in the physical system and the data layer [15]. Moreover, this layer facilitates feedback and insights, e.g., include recommendations, planning, or actions aimed at optimizing network performance, from the application layer. Maintaining synchronization between the physical and virtual systems is crucial for accurate representation and timely decision-making, as any lag or mismatch in data can lead to discrepancies, errors, and obsolete decisions or recommendations.

Boosting DT Framework with GenAI

GenAI can be integrated into our DT framework in many ways, depending on the generative AI category used. This is summarized in Fig. 2, along with the suitable use cases for power asset management and the recommended existing GenAI models. Below, we identify and present key use cases that significantly improve the DT framework operations.

Data Generation and Augmentation: Generative AI can play a pivotal role in data generation and augmentation, particularly in the context of power systems. Indeed, the large-scale deployment of sensors and collection of inspection data across the entire power network can be complex and costly. Generative models, especially GANs, can address this issue by generating high-quality synthetic data that reflects the real-world behavior and performance of system components. Synthetic data can fill gaps in sensor coverage, enhance training datasets for machine learning models, and improve the overall accuracy of DTs.

Automated Image Annotation and Analysis: can be leveraged to streamline the process of image labeling, enabling efficient and accurate analysis. This capability is especially valuable in visual inspections for power system monitoring, where it plays a critical role in identifying defects, detecting anomalies, and addressing similar diagnostic tasks. Indeed, CNNs used in these applications typically require annotated datasets, but manual annotation is time-consuming and resource-intensive. Instead, image-to-text models, e.g., GPT-4, can automate the annotation process by generating descriptive labels or annotations for images. Moreover, VLM models, like the Segment Anything Model (SAM), have demonstrated strong performance in one-shot segmentation predictions, while other models, such as the Contrastive Language-Image Pre-training (CLIP), can be fine-tuned for specific tasks, e.g., failure type classification. Such techniques of image annotation and analysis significantly improve the efficiency and accuracy of visual power assets inspection.

3D Object Modeling and Reconstruction: Modeling power assets in the virtual environment can be a difficult and slow process. GenAI can accelerate this process by leveraging existing 3D generative models, such as LLaVA-3D, which can convert 2D images into detailed 3D models. In addition, models like OpenScene enable advanced scene understanding, particularly for tasks of powerline detection from 3D LiDAR point clouds. The latter can analyze 3D data to identify risk areas, such as encroachments with vegetation, and provide detailed descriptions of the potential hazards. Typically, in the preprocessing of 3D data, important data can be lost in the process. In such a case, 3D GANs can be used to reconstruct missing points, ensuring more complete and accurate results. Also, combined with vegetation growth models, 3D GANs and VLMs, like DALL-E, can predict the vegetation evolution over time.

Decision Support and Action Recommendations: The LLMs' capabilities can be used in power asset management to enhance decision support and risk-based action recommendations and present them in an understandable language to decision-makers. By analyzing historical data, real-time monitoring, maintenance logs, and environmental factors, LLMs can effectively assess risks associated with various power assets and components. These models provide tailored recommendations based on the severity of identified risks, such as prioritizing maintenance for assets at higher risk of failure or in high-risk areas. In summary, the integration of LLMs at the application layer of the DT framework enables dynamic, data-driven risk assessment and presentation, as well as structured recommendations and decisions.

Explainability and AI-Driven Insights: As AI models, particularly deep learning and LLMs, become increasingly integrated into industry processes, ensuring the explainability of their decisions is critical. Explainability fosters trust by enabling stakeholders to understand the reasoning behind AI-driven recommendations and actions. GenAI can enhance this process by generating interpretable outputs, such as visualizations, textual summaries, or counterfactual explanations that clarify the model's decision-making process. Explainability AI techniques, e.g., SHAP and LIME, can provide more accessible explanations of the AI models' decisions by automatically generating detailed explanations of how predictions were derived. Hence, power asset managers can gain deeper insights into the factors influencing the assets' performance, identify failure causes, and transparently assess risk factors.

While the proposed framework suggests a specific model type for each given task/use case, their suitability depends on the deployment requirements, including accuracy, inference latency, model size, and interpretability. The mentioned models serve only as representative examples, but selecting the most appropriate one would require balancing trade-offs (e.g., requirements vs. task vs. complexity) in alignment with the task and operational context.

The mentioned models serve only as representative examples, but selecting the most appropriate one would require balancing trade-offs (e.g., requirements vs. task vs. complexity) in alignment with the task and operational context.

Performance Evaluation Perspectives

Since the proposed framework is currently theoretical and does not yet have an empirical implementation, we discuss here key performance aspects based on the typical characteristics of constituent GenAI models and DT components. Specifically, the efficiency of the framework depends primarily on the computational demands of its core GenAI modules, including VLMs, LLMs, and 3D data processing models. The latter vary significantly in their *complexity* and *resource requirements*. For instance, GANs and VLMs require substantial computational power to produce high-fidelity outputs. In contrast, LLMs range from lightweight models suitable for edge deployment to large-scale ones hosted in the cloud.

Latency and *throughput* requirements are critical parameters to guarantee near real-time responsiveness in power asset management applications. The framework anticipates that latency will be affected by factors including model size, inference optimization techniques, and underlying hardware capabilities. Similarly, throughput depends on the volume of data generated, processed, and analyzed simultaneously. The *accuracy* of the GenAI models depends heavily on the availability of high-quality input data to fine-tune or train the models effectively for tasks such as prediction, detection, and anomaly identification. This is tightly tied to the availability of *high-quality data* and usage of *robust models*. For the DT, evaluating how accurately its virtual layer mirrors the physical one is an important issue due to the lack of standardized performance evaluation frameworks. Typically, utilities rely on expert judgment and operational feedback (from asset managers and end users) to assess the DT's fidelity and practical outcomes. Hence, the human-in-the-loop process is necessary to refine and validate the DT framework.

Challenges & Future Research Directions

Building a GenAI-assisted DT presents several challenges. Below, we highlight the most significant ones.

Data Quality

Integrating different data types from heterogeneous sources, including real-time sensor data, historical records, inspection data, and external environmental data into a unified and consistent framework is a difficult task. Indeed, achieving accurate multimodal data fusion requires robust preprocessing and synchronization pipelines, as well as standardized data interfaces that are compatible with existing utility systems and field equipment. Also, future research should focus on developing advanced AI-driven data harmonization techniques to ensure data consistency, reduce redundancy, and handle missing or incomplete data.

Although GenAI holds great potential in data augmentation and synthetic data generation, fine-tuning these models to generate data that resembles real-world conditions remains difficult, especially when collected training data is sparse, unbalanced, or domain-specific. Indeed, models such as GANs/3D GANs may struggle to produce realistic outputs without extensive training. This is particularly relevant for power systems where 3D models of the power infrastructure can enhance risk assessment, predictive maintenance, and failure detection. In the same vein, integration of multimodal GenAI, such as GPT-4o and ImageBind, holds significant potential for DTs. Indeed, a unified multimodal GenAI model can natively process and generate insights from various data inputs, e.g., images, 3D point clouds, and outage records, enabling a richer contextual understanding and informed decision-making.

Cost and Scalability

GenAI models tend to be resource-greedy, which may hinder their deployment on a large scale. Nevertheless, several efforts are ongoing to bring it to the edge, with methods such as TensorFlow Lite, OpenFlamingo, and DeepSeek R1. Despite these alternatives' potential, practical on-site integration remains a barrier, particularly when real-time inference and low latency are required. Moreover, improving self-supervised learning methods could help DTs autonomously refine their models over time with minimal human intervention, making them more adaptive and scalable.

Human-in-The-Loop and Explainability Integration

A major challenge in the development and deployment of DTs lies in the absence of open and standardized methodologies for assessing their fidelity and performance. This gap complicates the benchmarking and validation of proposed solutions, particularly in safety-critical domains such as power systems. To address this gap, future research should prioritize the creation of open, domain-specific benchmarking frameworks that reflect real operational conditions and provide a common basis for comparative evaluation and reproducibility.

In parallel, the incorporation of human-in-the-loop (HITL) supervision is essential to enhance both reliability and operational trust. HITL enables domain experts to validate AI-generated outputs, verify anomaly detections, and apply domain-specific insights that may be missed by fully automated models. This collaborative approach not only improves model transparency but also provides an additional safeguard in contexts where erroneous decisions could result in substantial operational or safety risks.

Finally, AI explainability and interpretability must be advanced to support both benchmarking and HITL. Interpretable AI models would empower operators to comprehend the rationale underlying AI recommendations, thereby increasing trust and adoption in mission-critical applications. Complementary visualization tools and interactive interfaces can further support this objective by facilitating real-time human–AI collaboration and enabling more effective validation of DT-driven insights. Together, these research directions will be instrumental in bridging the gap between AI-driven automation and expert oversight in next-generation power system DTs.

Conclusion

In this article, we discuss the potential integration of DT and GenAI technologies for efficient power asset management, aiming to optimize the latter's operations and support data-driven decision-making. First, we present an overview of power asset management and its challenges. Then, we discuss the potential advantages of integrating DT and GenAI in power systems. Subsequently, we propose a novel framework for a GenAI-assisted DT framework tailored for power asset management, where we detail its architecture, components, and functions. Moreover, we highlight how GenAI can be integrated to boost the DT operations. By integrating GenAI, the DT framework enhances data synthesis, 3D modeling, predictive analytics, and automated risk-based recommendations. However, several challenges must be addressed to ensure the seamless integration of DT and GenAI for power asset management. Overcoming them will be key to developing reliable and scalable DTs, ultimately enabling precise asset monitoring, proactive maintenance, and resilient power systems management.

References

[1] S. R. Khuntia *et al.*, "A Literature Survey on Asset Management in Electrical Power [Transmission and Distribution] System," *Int'l. Trans. Elec. Energy Syst.*, vol. 26, 02 2016.

[2] M. Macmillan *et al.*, "Shedding Light on the Economic Costs of Long-Duration Power Outages: A Review of Resilience Assessment Methods and Strategies," *Energy Res. Soc. Sci.*, vol. 99, 2023, p. 103055.

[3] X. Liu *et al.*, "Data Analysis in Visual Power Line Inspection: An In-Depth Review of Deep Learning for Component Detection and Fault Diagnosis," *Ann. Rev. in Contr.*, vol. 50, 2020, pp. 253–77.

[4] S. Akhtar *et al.*, "Deep Learning Methods Utilization in Electric Power Systems," *Energy Rep.*, vol. 10, 2023, pp. 2138–51.

[5] S. Mihai *et al.*, "Digital Twins: A Survey on Enabling Technologies, Challenges, Trends and Future Prospects," *IEEE Commun. Surv. Tuts.*, vol. 24, no. 4, 2022, pp. 2255–91.

[6] R. Gozalo-Brizuela and E. C. Garrido-Merchán, "A Survey of Generative AI Applications," *J. of Comp. Sci.*, no. 8, May 2024, pp. 801–18.

[7] Y. Chang *et al.*, "A Survey on Evaluation of Large Language Models," *ACM Trans. Intell. Syst. Technol.*, vol. 15, no. 3, Mar. 2024.

[8] L. Matikainen *et al.*, "Remote sensing methods for power line corridor surveys," ISPRS J. of Photogram. Remote Sens., vol. 119, pp. 10–31, 2016.

[9] F. B. Ismail *et al.*, "A Comprehensive Review of the Dynamic Applications of the Digital Twin Technology Across Diverse Energy Sectors," *Energy Strat. Rev.*, vol. 52, 2024, p. 101334.

[10] X. Zhang *et al.*, "Deep Generative Models in Energy System Applications: Review, Challenges, and Future Directions," *Appli. Energy*, vol. 380, 2025, p. 125059.

[11] Z. Tao *et al.*, "Wireless Network Digital Twin for 6G: Generative AI as A Key Enabler," *IEEE Wireless Commun.*, vol. 31, no. 4, Aug. 2024 , pp. 24–31.

[12] J. N. Njoku *et al.*, "Leveraging Digital Twin Technology for Battery Management: A Case Study Review," *IEEE Access*, vol. 13, 2025, pp. 21,382–412.

[13] L. Bariah *et al.*, "On the Error Performance of Lora-Enabled Aerial Networks over Shadowed Rician Fading Channels," *IEEE Commun. Lett.*, vol. 26, no. 10, 2022, pp. 2322–26.

[14] S. Alfattani *et al.*, "Multimode High-Altitude Platform Stations for Next-Generation Wireless Networks: Selection Mechanism, Benefits, and Potential Challenges," *IEEE Veh. Tech. Mag.*, vol. 18, no. 3, 2023, pp. 20–28.

[15] R. Giuliano *et al.*, "Security Access Protocols in IoT Capillary Networks," *IEEE IoT J.*, vol. 4, no. 3, 2017, pp. 645–57.

Biographies

Damos Ayobo-Abongo (damos.ayobo-abongo.1@ens.etsmtl.ca) is a Ph.D. student at École de Technologie Supérieure (ÉTS), QC, Canada. He is currently working on Digital Twin systems for power networks.

Wael Jaafar [SM] (wael.jaafar@etsmtl.ca) is an Associate Professor at ÉTS, QC, Canada since 2022. His research interests include aerial networks, 5G and beyond technologies, and machine learning.

Rami Langar [M] (rami.langar@etsmtl.ca) is a Full Professor at ÉTS, QC, Canada since June 2021. His research interests include resource management and network slicing in 5G/6G networks, O-RAN, Network Digital Twin, and green networking.