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SURVEY

Monitoring Powerlines and Vegetation Risks: From Conventional Methods to Digital Twin

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ABSTRACT Traditional distribution lines inspection and asset management methods have evolved significantly by integrating advanced technologies such as 3D sensors, satellite imagery, and drone technology. However, persistent environmental risks, including vegetation encroachment, snow and ice loading, and wind-borne debris, continue to cause power outages, especially during adverse weather conditions, revealing the limitations of these conventional methods. Concurrently, advancements in machine learning (ML) and deep learning (DL) have facilitated a more comprehensive analysis of inspection data. Still, current approaches often struggle to evaluate and mitigate multi-factor risks adequately. In this context, we propose leveraging Digital Twin (DT) technology as a transformative platform for real-time monitoring, predictive analytics, and proactive risk management of distribution powerlines. DT models can simulate various scenarios, predict potential issues, and provide actionable insights, thus enhancing the power systems' reliability and safety. Despite the significant potential of DTs, their application specifically for overhead distribution powerline monitoring remains underexplored. Therefore, this survey reviews DT applications for distribution network monitoring, highlighting how they address vegetation and other environmental hazards while complementing existing inspection technologies. Specifically, we explore the current state of DT technology, its integration with existing powerline inspection systems, and its advantages in terms of predictive analytics and maintenance. Moreover, we introduce a conceptual framework designed to integrate powerline monitoring with vegetation management practices, leveraging the capabilities of DT to optimize infrastructure resilience. Finally, we discuss technical challenges and research directions toward the practical, large-scale deployment of DT-enabled monitoring in distribution networks.

INDEX TERMS Digital twin, powerline monitoring, vegetation management.

I. INTRODUCTION

A. BACKGROUND

Electricity is the backbone of modern society, powering everything from essential services and industries to homes and communication networks. As our dependence on electricity grows, the reliability and safety of power systems have become increasingly critical. A single power outage can have far-reaching consequences, disrupting healthcare facilities, transportation systems, and economic activities, causing significant inconvenience to the public [1], [2], [3]. Consequently, utilities must prioritize the continuous monitoring and maintenance of power systems to prevent outages and ensure uninterrupted service. Historically, power systems inspection and maintenance have relied on traditional, labor-intensive methods to identify outage risks for the distribution network, including manual inspections and on-site visual assessments of equipment's health [4]. Although effective to some extent, these methods are often time-consuming, costly, and prone to human errors. In developing regions, such practices still dominate due to limited resources and infrastructure. However, a practical transition pathway is emerging. Indeed, utilities could first introduce semi-automated processes, such as UAV-based inspections

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combined with manual analysis, before gradually advancing toward fully digital and automated monitoring workflows. This staged evolution lowers initial investment barriers while building local expertise in digital asset management.

In recent years, the integration of advanced sensing technologies, such as 3D scanning, satellite and uncrewed aerial vehicles (UAV) imagery, has reshaped powerline infrastructure management [4], [5]. These techniques enhance data collection, efficiency of inspection, and ultimately precision in identifying potential risks. One of the most significant challenges in powerline management is vegetation encroachment. During adverse weather conditions such as heavy rainfall, strong winds, snowstorms, and hurricanes, trees and branches that come into contact with powerlines can cause short circuits, fires, etc. [6], [7]. As climate change leads to more frequent and severe weather events, the threat posed by vegetation is likely to increase. Addressing this challenge has become a top priority for utilities, leading to the adoption of advanced machine learning (ML) and deep learning (DL) approaches that facilitate the efficient processing and analysis of large volumes of inspection data. The latter enables classifying and segmenting 3D point clouds of Light Detection and Ranging (LiDAR) data, processing UAV imagery, and mapping vegetation using satellite data [8], [9], [10]. Nonetheless, the true value of these sensing technologies is realized when they are interoperable within unified monitoring platforms. Despite these advancements, current methodologies in vegetation management are largely reactive. Utilities often respond to identified risks after their emergence rather than anticipating and proactively mitigating them. Reactive approaches can leave power systems vulnerable to unexpected disruptions, undermining their reliability and resilience.

Amidst these challenges, Digital Twin (DT) technology has emerged as a promising solution to transform powerline outage monitoring and vegetation risk management [11]. A DT is a virtual model of a physical asset that integrates real-time data, simulations, and decision-making tools [12]. By continuously interacting with its physical counterpart, a DT can provide a dynamic and accurate representation of the asset's current state and predict its future behavior/performance. This technology has already made significant strides in various industries, offering unparalleled insights into performance optimization, predictive maintenance, and operational efficiency across complex systems [13]. In the context of powerline monitoring, DT could enable utilities to simulate different scenarios, predict potential risks, and optimize maintenance strategies in real-time. However, efforts to develop this DT application remain nascent and limited.

To the best of our knowledge, this is the first survey that explores the potential of DT technology in the context of distribution power networks with a focus on vegetation risk management. By reviewing the current state of DT technology, examining its application in different parts of power systems, and proposing a conceptual framework for its integration with powerline monitoring and vegetation management, our survey seeks to contribute to the growing body of knowledge on this emerging paradigm. Ultimately, adopting DT technology would optimize power infrastructure resilience and support the transition to a sustainable energy future.

B. MOTIVATION AND CONTRIBUTIONS

Existing surveys cover DT evolution and applications in various industries, but research in energy distribution systems is limited.

For instance, authors in [14] conducted a systematic literature review on the application of energy digital twins (EDTs) across the entire power system, including energy generation, storage, transmission, and consumption. They presented the modeling techniques to create DTs and noted that the transmission subsystem is the least covered in DT applications. In [15], the authors examined the concepts of DTs within electric grid systems. They analyzed the development trend of the grid, transitioning from traditional models to DT-based systems. Their study identified the challenges and opportunities of the next-generation electric grid from various perspectives, including electrical, communication, security, optimization, management, and business. Moreover, they proposed a conceptual DT framework for the electric grid. Kumari et al. conducted in [16] a comprehensive review on DT applications in microgrid components, including energy sources such as wind, biogas, and battery, as well as electric vehicles (EVs) and power converters. They briefly introduced concepts and enabling technologies and examined potential uses of DTs to enhance control, security, and resilience in microgrid operations. The systematic review conducted by Ismail et al. in [17] explored various applications of DT across different energy operations, covering power generation, transmission, and distribution. This review presented some DT implementation solutions developed by leading enterprises. In addition, in [18], Jafari et al. reviewed studies on DT applications in smart cities, focusing on transportation systems, power grids, and microgrids as key components of power systems and energy management. For microgrids, the main applications include forecasting, management and monitoring, fault detection, and infrastructure security. For power grids, the applications involve restoration protection, uncertainty management, and energy hubs. Amin et al. reviewed in [19] the state-of-the-art applications of DT in energy systems, focusing on smart asset management for wind farms, solar power plants, and transformers. They highlighted the growing use of hybrid DT models combining physics-based simulations with AI-driven analytics to enable predictive maintenance and real-time monitoring. Industrial platforms like GE's WindSCADA and DNV's WindGEMINI show tangible gains in reliability and cost savings. However, challenges such as data integration, model updating, and large-scale deployment persist. Song et al. conducted in [20] a comprehensive review on DT applications in power systems, covering the definitions of DT concepts and the requirements for DT implementation in future power systems. The authors proposed a modular and multi-level DT framework and presented several use case scenarios, including economic dispatch, wind farm control, and fault-tolerant control. Similarly, Yassin et al. overviewed DT with a focus on power systems, Internet-of-Things (IoT), and ML. Alternatively, Ghenai et al. presented a comprehensive review focused on decarbonizing and digitalizing the energy sector to reduce carbon dioxide emissions from traditional power sources while transitioning to renewable energies [21]. The review highlighted DT as a key enabling component, covering studies and applications across the energy value chain. Finally, in [22], different methods for image-based 3D reconstruction and its application in creating 3D models of electrical equipment were surveyed, while Djebali et al. reviewed DT application in smart grids from a design perspective [23].

Based on the aforementioned surveys, it is clear that most of them covered general applications of DTs for energy management, particularly smart grids. They also discussed mostly DTs for power generation plant modeling, with few of them addressing DT for transformers, and, according to our knowledge, none for power lines and vegetation management. In this work, we aim to fill this gap by complementing the ongoing efforts of DT for the power sector and providing a comprehensive understanding of its application for power systems. Table 1 below presents a comprehensive summary of the related surveys and compares them to this one.

Motivated by the above, in the present survey, we shed light on diverse methods for powerline monitoring. Specifically, we present a comprehensive study on existing powerline inspection methods. In addition, we present the DT concept and its potential integration for powerline monitoring. Subsequently, we detail our proposed DT framework for powerline monitoring and vegetation risk management, and describe its benefits. Finally, open issues and interesting related research directions are discussed.

C. ORGANIZATION OF OUR SURVEY

The rest of the paper is organized as follows: Section II outlines the need for powerline monitoring, the associated challenges, and provides a brief review of existing methods. Section III defines key DT concepts and reviews their applications in powerline monitoring and vegetation risk management. Section IV presents the proposed DT framework for powerline monitoring and vegetation risk mitigation, and further illustrates its application through representative use case scenarios. Section V discusses the challenges and future directions for implementing DTs in power distribution networks. Finally, Section VI concludes the paper.

II. POWERLINE MONITORING: WHY AND HOW?

A. THE NEED FOR POWERLINE MONITORING

Distribution power networks require significant resources for effective planning and execution. To ensure their reliability and continuous servicing, monitoring powerlines is one of its crucial tasks. The latter involves *component functional operation guarantee* and *external threats management* [4], [8], [25]. For component functionality, regular inspections of infrastructure elements, such as poles, transformers, and conductors, can be made. This includes identifying and addressing issues related to wear and tear, corrosion, or any other form of degradation [26]. Regarding external threat management, it primarily involves risks posed by vegetation and weather conditions. For instance, overgrown trees and plants (helped by an unhealthy state and/or strong winds for instance) can make contact with powerlines and lead to power outages or fires [27], [28]. Moreover, fast-growing invasive species can quickly encroach on powerline corridors, thus requiring frequent and costly maintenance to keep them at bay. Furthermore, monitoring environmental factors, such as temperature and wind, is essential for maintaining the stability and integrity of powerlines [29], [30]. Indeed, extreme weather conditions can exacerbate vegetation-related risks, causing trees and branches to come into contact with the power infrastructure and leading to large-scale disruptions.

B. POWERLINE MONITORING METHODS

To mitigate the above risks, advancements in technology have led to the development of various monitoring techniques to improve the accuracy, efficiency, and scope of powerline inspections. For instance, remote sensing such as 3D scanning using LiDAR, Airborne Laser Scanning (ALS), Mobile Laser Scanning (MLS), and satellite imaging, have emerged as pivotal tools to gather detailed data from hard-to-reach locations [4], [31], [32]. Particularly, drone or UAV-collected aerial images and LiDAR point clouds provide high-resolution views of powerlines and their surroundings, enabling the detection of physical damage, vegetation risks, and infrastructure anomalies with advanced analysis using ML-based algorithms to automate and improve the inspection process.

The data-driven powerline inspection methods involve four key steps: i) *Data collection* includes capturing LiDAR 3D point clouds or aerial 2D images, ii) *Data preprocessing* where collected data is filtered and cleaned to ensure its quality and suitability for modeling, iii) *Modeling* is realized using ML and DL algorithms, along with mathematical approaches to analyze the preprocessed data. This analysis may target tasks such as powerline detection, segmentation, and point classification. Finally, iv) *Postprocessing*, though optional, enhances step 3 results, ensuring accurate and actionable inspection outcomes. The following sections review inspection methods for powerline and pole detection, focusing exclusively on studies related to powerlines and pole, followed by a review of studies addressing vegetation risk for powerlines.

1) POWERLINE AND POLE DETECTION

Several power monitoring methods relied on the use of 2D images collected by UAVs. For instance, Yang et al.

TABLE 1. Summary of related surveys.

Year	Ref.	Summary	Powerline Monitoring	Vegetation Risks	DT Framework	Challenges	Future Directions
2023	[14]	Explored the application of DT in energy generation, storage, transmission, and consumption.	✗	✗	✗	✓✓	✓✓
2023	[15]	Discussed the evolution from traditional grids to electric DT in smart grids, and virtual power plants.	✗	✗	✓	✓✓	✓✓
2023	[16]	Covered DT applications in microgrid systems, focusing on green energy sources.	✗	✗	✗	✓	✗
2024	[17]	The authors reviewed DT system implementations across diverse energy sectors, highlighting leading enterprises and their software solutions.	✗	✗	✗	✓✓	✓✓
2023	[18]	Examined DT applications across various energy sectors, including transportation, microgrids, and power grids focusing on smart cities.	✗	✗	✗	✓	✗
2023	[20]	Discussed DT applications in power systems, covering definitions, concepts and enabling technologies.	✗	✗	✓	✓✓	✗
2023	[24]	Focused on the application of DT in power systems, defining key concepts and enabling technologies.	✗	✗	✗	✓✓	✓✓
2022	[21]	Reviewed DT research studies and applications in the energy sector, covering the entire energy value chain, decarbonization and digitalization.	✗	✗	✗	✓	✗
2023	[22]	Provided an overview of various 3D image reconstruction methods and their application in creating 3D models of electrical equipment.	✓	✗	✗	✓	✓
2024	[23]	The authors introduced a new framework called DTOps for DT applications in smart grids, focusing on system design aspects.	✗	✗	✓	✓✓	✓✓
2025	[19]	The authors reviewed the state-of-the-art applications of DT in energy systems, i.e., smart asset management for wind farms, solar power plants, and transformers	✗	✗	✗	✓✓	✓✓
2025	**Our Work**	This paper reviews powerline inspection methods, explores the application of DT in powerline monitoring, and introduces a framework for monitoring powerlines with a focus on vegetation risks management.	✓	✓	✓	✓✓	✓✓

For the **Powerline Monitoring** and **Vegetation Risks** columns, ✓ indicates that the survey addressed these aspects, while ✗ indicates their absence. In the **DT Framework** column, ✓ signifies that the survey proposed a digital twin framework, while ✗ indicates it did not. For the **Challenges** and **Future Directions** columns, ✓✓ represents a detailed discussion, ✓ indicates partial coverage, and ✗ denotes no coverage.

introduced in [33] DRA-Net, a DL-based method designed for pixel-level extraction of transmission lines in complex backgrounds. Their model combined RCNN and Recursive Residual CNN (RRCNN) in a dual-branch encoder to capture rich semantic information. Also, authors of [34] used SOLOv2 for detecting powerlines in large UAV images with low signal-to-noise ratio and high resolution. Their approach incorporated Path Aggregation Feature Pyramid Network (PaFPN) and MaskIoU branches to enhance data segmentation precision. Alternatively, Abid et al. proposed a deep unsupervised learning method based on Unsupervised Curriculum Learning (UCL) for detecting poles from high-resolution grayscale aerial images [35]. This method used a CNN architecture, K-Means clustering of feature maps, and a selection process to filter out noisy samples. In [36], the authors applied a DL framework to detect transmission towers in UAV images. Specifically, they used the Fuzzy C-Means algorithm for initial segmentation and AlexNet and DenseNet-121 for binary classification. Moreover, authors of [37] addressed powerline recognition as a binary classification problem, using CNN architectures ResNet-50 and VGG-19 pre-trained on the ImageNet dataset. In [38], a method derived from human pose estimation, called kMobileNetV3, was proposed to detect powerlines in aerial images. Finally, hybrid detection techniques have been proposed in [39] and [40] where authors of [39] utilized a combination of Mask-RCNN and domain grouping fitting for powerline extraction, while authors of [40] introduced a method integrating the Hough transform with the Feature Pyramid Network (FPN) structure to improve the precision of transmission line detection.

Advancements in powerline monitoring have not only been propelled by improvements in 2D aerial image analysis but also by significant progress in 3D point cloud data

TABLE 2. Powerline and pole detection methods using 2D images.

Ref.	Category	Methods	Description
[33]	Segmentation	DRA-Net, U-Net, Context Fusion	A dual-branch encoder combining RCNN and Recursive Residual CNN (RRCNN) for capturing rich semantic information to detect powerlines in complex backgrounds.
[34]	Segmentation	SOLOv2, Path Aggregation Feature Pyramid Network (PaFPN), MaskIoU	A method for detecting powerlines in large UAV images, improving segmentation precision in low signal-to-noise ratio and high-resolution images.
[35]	Clustering	Unsupervised Curriculum Learning (UCL), CNN (VGG-16), K-Means	An unsupervised CNN-based architecture with K-Means clustering for detecting poles from high-resolution grayscale aerial images, filtering noisy samples.
[36]	Classification	Fuzzy C-Means, AlexNet, DenseNet-121	A DL framework for detecting transmission towers, enhancing classification accuracy by combining traditional and deep learning approaches.
[37]	Classification	CNNs (ResNet-50, VGG-19), Classifiers	CNN architectures pre-trained on ImageNet for effective powerline detection in UAV images.
[38]	Transformers	kMobileNetV3, Pose Estimation	A novel approach for detecting powerlines in aerial images inspired by human pose estimation.
[39]	Hybrid Detection	Mask-RCNN, Domain Grouping Fitting	A hybrid detection technique for powerline extraction that integrates semantic segmentation and grouping fitting.
[40]	Hybrid Detection	Feature Pyramid Network (FPN), Hough Transform	A hybrid approach to improve precision in transmission line detection using the Hough transform in conjunction with FPN for better feature extraction.

collecting and processing. Indeed, 3D point cloud data, obtained through LiDAR mounted on vehicles, helicopters, or UAVs, offers detailed spatial information about powerlines and their surroundings. This type of data is invaluable for assessing clearance between powerlines and vegetation, creating infrastructure models, and planning maintenance activities. Several methods have been developed to analyze 3D point cloud data in the context of powerline monitoring. For instance, Shen et al. introduced in [41] a method that effectively segments individual wires from bundle conductors using LiDAR point cloud data. Their approach involves voxelizing the points, generating height features to locate pylons, and then applying connected component analysis to separate the powerlines into different bundle conductors. Also, Zhao and Zuo developed in [42] a method combining multi-scale density features with DL-based local features for segmenting powerline towers from LiDAR data. In [43], Kyuroson et al. proposed a 2-stage unsupervised hierarchical clustering that combines DBSCAN and Kd-tree techniques to differentiate various objects within the point cloud, including Linear-likeness (LN) for powerlines and Planar-likeness (PL) for vegetation. Moreover, Wang et al. presented CA-PointNet++, a DL architecture that incorporates the Coordinate Attention module to capture channel relationships and feature space information, enabling precise segmentation of transmission corridor 3D point clouds [44], while Qiao et al. utilized in [45] an improved DeepLabv3+ model to segment overhead conductors from both visible light images and laser point cloud data, integrating 2D and 3D positional relationships for accurate segmentation. Alternatively, Tang et al. proposed a method that enhances classification accuracy for ALS point clouds by combining an enhanced Random Forest (RF) algorithm with multi-scale features [46]. In addition, Askit authors of [47] used RF, trained by geometric-based and eigenvalue-based features, to extract powerline corridors from LiDAR point cloud data. In [48], Li et al. proposed a graph convolutional network (GCN) for powerlines and pylons segmentation through a dual-branch network, capturing local geometry and aggregating neighborhood information effectively. Hybrid methods for powerline and pylon extraction have been presented in [49] and [50] where the former voxelized the point cloud, segmented the pylons, and calculated center coordinates to separate powerlines from pylons, while the latter involved span extraction with the Hough transform and image-based techniques to handle structural characteristics. Finally, advancements in DL architectures further enhanced point cloud semantic segmentation, as demonstrated in [51], where KPConv, PointCNN, and RandLA-Net models have been used for accurate powerline extraction.

Table 2 provides an overview of the methods employed for detecting powerlines and poles using aerial 2D images, while Table 3 focuses on the methods for detection using 3D point clouds.

2) VEGETATION RISK ASSESSMENT FOR POWERLINES

Vegetation encroachment remains a persistent challenge in maintaining the reliability of overhead powerline infrastructure. Uncontrolled tree growth near conductors can lead to short circuits, wildfires, and service interruptions, particularly during adverse weather conditions. Managing these risks requires not only accurate detection but also predictive capabilities to trigger proactive maintenance. Recent research in this domain can be categorized into four main types of modeling approaches: Rule-based models, ML-based models, simulation-based models, and hybrid models.

One of the earliest and most widely adopted approaches involves rule-based models [52]. These rely on predefined

TABLE 3. Powerline and pole detection methods using 3D point cloud.

Ref.	Category	Methods	Description
[41]	Segmentation	Voxelization, Connected Component Analysis	A method for segmenting individual wires from bundle conductors by analyzing LiDAR data, generating height feature and applying connected component analysis.
[42]	Segmentation	PointCNN, Density Features, KNN, KDTrees	Segmented powerline towers from LiDAR data by integrating multi-scale and local feature information.
[43]	Segmentation	DBSCAN, Kd-Tree	A method that differentiates objects in LiDAR data, including powerlines and vegetation, using linear and planar likeness features.
[44]	Segmentation	Coordinate Attention (CA)-PointNet++	Precise segmentation of transmission corridor by capturing channel relationships and feature space information.
[45]	Segmentation	DeepLabv3+, MCMLSD, 2D-3D Integration	Integrated 2D and 3D positional relationships to segment overhead conductors accurately from both visible light images and LiDAR point cloud data.
[46]	Classification	Random Forest, Multi-Scale Features	Proposed a method to improve classification accuracy of ALS point clouds for powerline extraction.
[47]	Classification	Random Forest, Geometric Features	Extracted powerline corridors from LiDAR point cloud data using geometric and eigenvalue-based features.
[48]	Graph Convolution	graph convolutional network (GCN), NDI, NGIA	Powerlines and pylons segmentation by capturing local geometry and aggregating neighborhood information.
[49]	Hybrid Methods	Voxelization, Curve Fitting	A hybrid method for powerline and pylon extraction by using voxelization and center coordinate calculation.
[50]	Hybrid Methods	Hough Transform, Image-Based Techniques	Combined span extraction with structural characteristic handling using Hough transform and image techniques for powerline extraction.
[51]	Segmentation	KPConv, PointCNN, RandLA-Net	Advanced segmentation with state-of-the-art architectures

thresholds or domain-specific heuristics, such as minimum clearance distances or trimming schedules, often derived from historical data or utility guidelines. Although rule-based systems are simple to implement and highly interpretable, they are typically reactive and lack the adaptability to respond to dynamic vegetation growth patterns or environmental variability. Nonetheless, they remain useful as foundational decision-support tools and can be embedded into DT environments as operational constraints or safety rules.

As vegetation patterns become more complex and data-rich sensing becomes more common, ML-based models have emerged as powerful alternatives. These approaches can process high-dimensional inputs such as UAV imagery or 3D point clouds to detect and classify vegetation encroachment automatically. For example, Al Najjar et al. introduced in [9] a DL pipeline for point cloud classification followed by proximity-based risk evaluation. Vemula et al. proposed VE-DETR, a transformer-based architecture for image-based detection of vegetation near powerlines [53]. Moreover, Cano-Solis et al. developed in [54] and [55] a dedicated dataset and DL-based segmentation model to support automated risk analysis. In one of our recent works [56], using the 2D aerial imagery dataset provided by [54], we proposed a hybrid ML model combining traditional CNN-based architectures such as U-Net, with transformer-based ones like SegFormer, to detect encroachment between powerlines and vegetation. The complementary strengths of these models significantly improved segmentation accuracy. However, our approach remained limited in terms of accuracy and reliability to identify encroachment areas, due to the lack of explicit spatial information. In [57], Al-Najjar et al. proposed LineShield, a LiDAR-based pipeline for automated vegetation encroachment detection on powerlines. It combined sliding-window traversal, DBSCAN clustering, PCA-based alignment, voxel downsampling, and proximity-based severity classification. Tested on ALS and MLS datasets, e.g., ECLAIR, DALES, and Toronto-3D, their method showed strong detection performance. However, its reliance on manual verification for sparse data reveals the need for improved ground truth benchmarks, an important prerequisite for DT development. Indeed, building reliable DTs for powerline infrastructure depends on access to large-scale, high-quality datasets for training, validation, and continuous updating. Yet, such datasets are rarely publicly available in the power sector, as most remain proprietary, hence limiting reproducibility and slowing research progress.

Complementing the above reactive detection-based strategies, simulation-based models can predict future vegetation growth and its potential interference with the power infrastructure. Often, these models incorporate environmental factors such as rainfall, temperature, and species-specific growth rates to simulate future encroachment scenarios. For instance, Chen et al. proposed a method that combined UAV-based LiDAR data with growth modeling to forecast future high-risk zones [58]. Although biological complexity and variability pose challenges to accuracy, such simulation tools provide DTs with temporal foresight, thus enabling power utilities to assess current conditions and anticipate future threats under different scenarios.

Finally, several studies have proposed hybrid approaches integrating multiple modeling techniques to improve robustness and adaptability. These models combine rule-based methods with data-driven learning or embed simulation-based models within ML pipelines for more context-aware predictions. For instance, authors of [59] combined satellite imagery with DL to estimate vegetation height, which was then evaluated against safety margins. Such hybrid frameworks achieve a trade-off between interpretability and predictive power. Also, they are well-suited for DT architectures, where real-time sensing and scenario analysis are needed.

Although the reviewed approaches offer valuable tools for detecting and assessing vegetation-related risks, most of them are standalone solutions that are not integrated into real-time DT platforms. Current research on vegetation encroachment is largely reactive, relying on satellite/UAV imagery and/or 3D point clouds to identify threats only after they have emerged. This limits the ability of utilities to anticipate and proactively mitigate the risks. For DTs to support continuous vegetation risk management, future research should focus on embedding these detection and modeling pipelines into dynamic virtual environments. In particular, integrating predictive models of vegetation growth, accounting for factors like species characteristics, climatic conditions, and soil variability, would enable more robust simulation of encroachment scenarios. Such integration would transform DTs into proactive decision-support systems, capable of forecasting vegetation threats and optimizing maintenance strategies accordingly. A summary of key vegetation risk assessment methods discussed in this section is presented in Table 4.

III. DT AND ITS APPLICATION FOR POWERLINE MONITORING

A. DEFINITION AND COMPONENTS OF DT

In the literature, many definitions of DT have been proposed that may vary with application and context. Nevertheless, it is agreed that a DT can be defined as a virtual representation of a physical product or process, used to understand and predict the physical counterpart's performance characteristics, and having bidirectional communication between the two entities [61]. Three key components characterize a DT system:

- **Physical Object:** It is the actual physical product or process that exists in the real world. It can be anything from a manufacturing machine, a building, or a whole system. The physical object is equipped with sensors and other data collection tools to gather real-time data about its condition and performance.
- **Virtual Object:** It is the digital counterpart or model of the physical object. The virtual object is created using data collected from the physical object and can include 3D models, simulations, and algorithms that mimic the physical object's behavior and characteristics. The goal of the virtual object is to monitor and analyze the physical/virtual object's behavior and predict its future performance.
- **Communication:** It involves the bidirectional exchange of data between the physical and virtual objects. Sensors on the physical object collect data and send it to the virtual object for processing and analysis. In return, the virtual object can send feedback, control commands, or optimization suggestions to the physical object. This continuous flow of information ensures that the DT is always up-to-date and can accurately reflect and influence the physical object's state.

B. APPLICATION OF DT FOR POWERLINE MONITORING

Recently, novel and efficient solutions are emerging with DT technology standing out as a promising innovation. DTs have been applied across various aspects of powerline monitoring, including transmission lines, transformers, ultra-high voltage systems, and power pole monitoring. Despite their potential, the adoption of DTs in the power industry is still limited. We review here existing research efforts that assess the application of DTs for power system monitoring.

For electrical infrastructure modeling, the authors of [62] proposed a DT framework representing the electrical structure under hurricane conditions, in which physics-based models are combined with data-driven methods, using a Dynamic Bayesian Network (DBN) for real-time decision support. The framework included detailed data collection and preprocessing, transforming raw data into directed graph formats and clustering building information. Risk analysis is conducted using Advanced Circulation (ADCIRC) and Simulating Waves Nearshore (SWAN) models, while fragility analysis estimates the conditional probability of physical failures for various components, based on parameters such as wind speed, water velocity, and structural attributes. Similarly, a method that utilizes 3D Geographic Information System (3D GIS) and Grid Information Model (GIM) is proposed in [63] to construct a 3D scene of powerlines. The approach begins with data collection using airborne imagery in visible light and capturing point clouds. A photogrammetric model is then generated from these images. Subsequently, points corresponding to transmission lines and pylons are extracted from the overall point cloud data. Utilizing GIM, a transmission line model is developed. Finally, spatial locations of transmission line routes are mapped within the 3D scene. Authors of [64] presented a novel DT-based framework to accurately estimate the maximum leaning angle of electrical poles in UAV-captured images. Moreover, Chen et al. proposed a dynamic modeling method for the deicing system of transmission lines based on DT [65]. The deicing process is formulated through differential equations, integrating analytical solutions with data-driven approaches, while dynamic geometric models of the transmission lines

TABLE 4. Vegetation risk assessment methods.

Ref.	Category	Methods	Description
[58]	Simulation-based model	Elevation filtering, growth modeling (Richards growth models)	Combined UAV-based LiDAR with predictive tree growth models to identify future vegetation encroachment zones.
[9]	ML-based model	RandLA-Net, P-BED (Point-Based Encroachment Detection)	Applied DL for point cloud classification followed by a proximity-based encroachment detection algorithm.
[60]	Rule-based model	Point filtering, handcrafted features, traditional classifiers	Used geometric and spectral features extracted from LiDAR point clouds for vegetation classification and risk detection.
[59]	Hybrid model	NDVI, Res-UNet, satellite imagery analysis	Fused satellite data with DL-based segmentation to estimate vegetation height and assess risk near powerlines.
[53]	ML-based model	VE-DETR, Mask R-CNN, ResNet backbone	Proposed a transformer-based model for detecting vegetation encroachment from UAV imagery using instance segmentation.
[54], [55]	ML-based model	U-Net, VGG, DeepLabV3	Developed a dataset and DL pipeline for semantic segmentation of vegetation encroachment along distribution lines.
[56]	ML-based model	U-Net, SegFormer, and meta-learning	Combined CNN (U-Net) and Transformer (SegFormer) models for vegetation encroachment segmentation in 2D aerial images.
[57]	ML-based model	DBSCAN clustering, PCA, and voxel downsampling	Proposed a generalized LiDAR-based pipeline for automated vegetation-powerline encroachment detection.

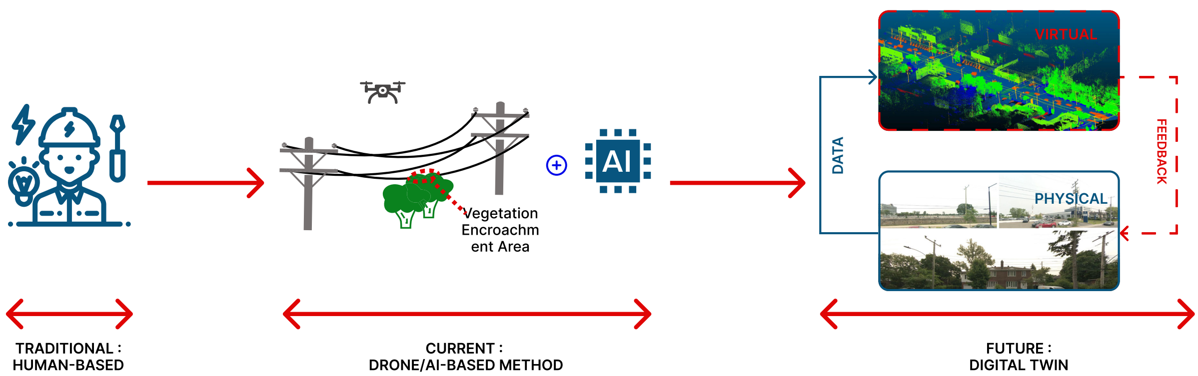

FIGURE 1. Evolution of powerline monitoring systems towards digital twin.

are created using both static and dynamic data. Furthermore, authors of [66] proposed a DT-based system for monitoring the safety of live workers on high voltage transmission lines. It combines sensor data of worker movements with Solidworks skeleton drawings to create geometric models of postures. Electrostatic field numerical modeling is used to calculate the electric field distribution around the worker, enabling real-time mapping from the real scene to a digital virtual scene. Safety risk assessment is performed by evaluating the complex gap length, worker's working boundary, and electric field distribution on the human body during live operations. Also, authors in [67] introduced a simulation method for detecting powerline safety distances using LiDAR point cloud data. This method considers variations in transmission line tension due to environmental factors such as weather dynamics. Utilizing a parabolic catenary equation combined with the tension, the simulation accurately models the sag curve of transmission lines under various weather conditions.

In the context of distribution networks, Chai and Ma combined DT and hologram technology to assess distribution network reliability through an interface model and conversion algorithm that considers network topology, switch states, equipment parameters, and user load states [68]. The framework calculates power supply reliability indices such as SAIFI, SAIDI, ASAI to assess the reliability of the distribution network. Similarly, Gaucers et al. applied in [69] DT for inspecting medium-voltage overhead networks. Their method involved creating 3D models of physical entities from point cloud data. They analyzed the integration of various inspection use cases, including geometrical parameter measurement, visual defect identification, vegetation management, and unplanned network infrastructure management during emergencies. In [70], the authors discussed best

TABLE 5. Summary of works on DT application for powerline monitoring.

Ref.	Component.s	Description	Methods	Vege. Risk
[62]	Transmission Lines	Proposed a digital twin framework for electrical infrastructure under hurricane conditions using a Dynamic Bayesian Network for real-time decision support.	Dynamic Bayesian Network (DBN), ADCIRC, SWAN, data preprocessing, risk analysis, fragility analysis.	✗
[63]	Transmission Lines	Utilized 3D GIS and GIM to create a 3D scene of transmission lines, improving accuracy with photogrammetric models and point cloud data.	3D Geographic Information System (3D GIS), Grid Information Model (GIM), photogrammetry, point cloud data.	✗
[64]	Electrical Poles	Developed a digital twin framework to estimate the maximum leaning angle of electrical poles using UAV-captured images and 3D geometric information.	UAV-captured images, pinhole camera model, back-projection, Keyhole Markup Language (KML), 3D geometric information.	✗
[65]	Transmission Lines	Proposed a dynamic modeling method for the deicing system of transmission lines, integrating analytical solutions with data-driven approaches.	Differential equations, time-series segmentation algorithm, Unity3D, real-time visualization, simulation.	✗
[66]	High Voltage Transmission Lines	Proposed a digital twin system for monitoring the safety of live workers on high voltage transmission lines using sensor data and electrostatic field modeling.	Sensor data, Solidworks skeleton drawings, electrostatic field numerical modeling, real-time mapping, safety risk assessment.	✗
[67]	Transmission Lines	Introduced a simulation method for detecting power line safety distances using lidar point cloud data, modeling sag curves under various conditions.	Lidar point cloud data, parabolic catenary equation, environmental factor modeling, sag curve simulation.	✗
[68]	Distribution Network	Combined digital twin and hologram technology to assess distribution network reliability through an interface model and conversion algorithm.	Hologram technology, interface model, conversion algorithm, geographic data, power supply reliability indices.	✗
[69]	Medium-Voltage Networks	Applied digital twin technology for inspecting medium-voltage overhead networks using 3D models created from aerial methods.	3D models, aerial methods, point clouds, photogrammetry, defect identification, vegetation management.	✓
[70]	Distribution Networks	Discussed best practices for developing digital twins for distribution networks, featuring foundational, intelligence, and human interface layers.	LiDAR, georadar, drones, GNSS, artificial intelligence, predictive maintenance, VR/AR technologies.	✗
[71]	UHVDC Systems	Constructed a digital model using CNNs to measure losses in UHVDC systems, involving physical, data interaction, and digital layers.	Convolutional Neural Networks (CNN), sensors, loss analysis algorithms, simulation models, optimization algorithms.	✗

For the **Vegetation** column, ✓ indicates that the paper addressed vegetation-related risks, while ✗ indicates that the aspect was not covered.

practices for developing DTs for distribution network systems based on the Network Digital Twin (NDT) project of the São Paulo grid. The NDT platform featured three essential layers: 1) The foundational layer integrating essential tools for image capturing, processing, and database organization. 2) the twin intelligence layer that involves ML algorithms for predictive maintenance, anomaly detection, and network modeling, and 3) the human interface layer that leverages virtual reality (VR) and augmented reality (AR) for enhanced visualization and interaction with the DT. Finally, Yin et al. constructed in [71] a DT model based on CNNs to measure losses in Ultra-High Voltage Direct Current (UHVDC) systems.

Table 5 provides an overview of DT applications in powerline monitoring, highlighting the components covered, the methods used, and indicating whether vegetation risk is addressed.

C. APPLICATION OF DT FOR VEGETATION MANAGEMENT

Most existing studies that proposed DT for vegetation management addressed broad ecological and environmental contexts, without specific application to powerlines. For instance, Hanqing Qiu et al. built in [72] a DT to model forest ecosystems such as Huangfengqiao and Shanxia forests in China. Their study involved data collection on trees (e.g., tree coordinates, age, Diameter at Breast Height (DBH), height, crown width, under-living branch height, and texture), used with growth models, optimization techniques, and visualization, to assess the forest structure and health. Similarly, authors of [73] developed a DT framework to model forests through spatiotemporal graphs and using reinforcement learning (RL). Their framework integrated real-time data on soil moisture, tree growth patterns, wildlife activity, and atmospheric conditions using SUMO and OMNET++ simulators. In [74], Jiang et al.constructed a DT system using 20 years of historical remote sensing image data from Landsat 7. This framework combined Long Short-Term Memory (LSTM) networks with Generative Adversarial Networks (GANs) to extract temporal features and predict future forest images, thus improving the accuracy of forest simulations. Moreover, Münzinger et al. proposed in [75] a GIS workflow to classify urban forests and reconstruct individual tree crowns from LiDAR point clouds. It included an object-based data fusion approach to combine LiDAR data with multispectral imagery and building 3D models. This process is conducted within a GIS environment and supported by free software libraries in R, such as rLiDAR and lidR to integrate detailed tree data into semantic 3D city models. In [76], the authors presented a novel method to correct time differences in tree height growth estimates on a monthly scale using UAV-collected stereo images and LiDAR point cloud data. The objective is to produce digital elevation models (DEMs) and canopy height models (CHMs). Alternatively, Chen et al. proposed a point cloud-based modeling for large-scale urban trees, extracting tree points using color-based segmentation and DL, and modeling the trees using the space colonization algorithm [77]. In [78], Li et al. modeled a poplar plantation forest using point cloud data to reconstruct tree trunks and branches with the AdTree method and tree leaves with the transition particle flow method. Unity3D was utilized for virtual simulation, mapping the virtual forest to the real one and updating it with data on tree growth trends and physiological indicators. In addition, Kohek et al. proposed a forest growth simulation using 3D topographic LiDAR point clouds [79]. The process classified the point cloud data into vegetation, ground, and buildings, prior to calculating the digital terrain model (DTM). Vegetation points are then segmented into individual trees, and parameters such as height, crown diameter, and species probability are extracted directly from the LiDAR data. The latter are combined with the estimated species composition of the area and input into the forest simulator, BWINPro, for tree growth simulation. In [80], Tarsha Kurdi et al. developed an algorithm to automatically model tree trunk geometry using 3D LiDAR point clouds. Finally, Mitsanis et al. developed in [81] a conceptual framework for 3D plant modeling based on Functional Structural Plant Modeling (FSPM). The latter integrated physiological processes influenced by environmental factors to analyze plant responses and the impact of different traits on plant performance.

Table 6 provides a summary of Digital Twin (DT) applications for vegetation management, outlining the applied methods, their focus, and relevance in powerline monitoring.

IV. PROPOSED DT FRAMEWORK

In this section, we propose a novel DT framework designed for distribution powerline monitoring and vegetation risk management. The framework aims to enhance the overall reliability and safety of the powerline infrastructure, specifically by assessing vegetation risks to prevent widespread power outages. Unlike previous DT frameworks, ours seeks to integrate individual modules such as preprocessing of 2D/3D data, powerline-vegetation detection, tree growth simulation etc. into a unified system, with a particular emphasis on vegetation risk assessment. Inspired by Michael Grieves' conceptualization of DT components and based on the DT construction process proposed in [72], the proposed framework, as depicted in Fig. 2, consists of five key elements: 1) Physical layer, 2) Virtual layer, 3) Data Management layer, 4) Application layer, and 5) Communication layer.

A. DT FRAMEWORK COMPONENTS

1) PHYSICAL LAYER

The *Physical Layer* is the foundational component of our DT framework, representing the real-world power infrastructure. It includes physical assets such as powerlines, poles, towers, vegetation, and surrounding terrain, along with environmental factors like wind and temperature. These physical elements provide essential data and context for accurate and functional virtual models. Accurate data collection using UAVs, 3D LiDAR, and satellite imagery is essential for precise asset modeling. UAVs provide high-resolution 2D images and 3D point clouds, which are key for vegetation and structural risk assessment. Satellite imagery and environmental sensors, along with on-site surveys, further enhance data for comprehensive analysis.

2) VIRTUAL LAYER

The *Virtual Layer* consists of digital representations of physical components, driven by AI to create and train data-driven models to predict, simulate, and enhance the operational efficiency of the power system, focusing on powerline detection, vegetation characterization, and risk assessment. It integrates vegetation management models for tasks like species identification, tree health detection, and growth simulation to predict tree interference with powerlines. Combining tree growth models like L-Systems [82], [83], Richards models [84], [85], and GIS data enhances risk assessment, helping utilities prioritize mitigation. Weather prediction models also support vegetation management and power distribution resilience. In addition, weather models integrated into the virtual layer help simulate the impact of storms, wind, or snow on distribution network performance.

3) DATA MANAGEMENT LAYER

The *Data Management Layer* is responsible for data preprocessing, integration, storage, and security to ensure effective data use in model development. Preprocessing includes optimizing 3D point clouds, extracting tree parameters, and preparing aerial images and weather data for analysis. Data fusion combines various data sources like 2D images, 3D point clouds, IoT, and satellite data for a comprehensive view of the power network. Data storage ensures secure and efficient access to historical data for ongoing model training, using solutions like SQL, cloud, or edge-based systems. Data security is critical for maintaining data integrity, employing encryption, access control, and transparency in model development to ensure trust and accuracy.

4) APPLICATION LAYER

The *Application Layer* serves as the operational interface of the DT framework by providing key functionalities for decision-making in power distribution networks. It includes

TABLE 6. Summary of works on DT application for vegetation management.

Ref.	Application	Methods	Focus	Relevance to Powerlines
[72]	Forest management	Digital twin, Bayesian methods, Particle Swarm Optimization, Unreal Engine 4	Detailed forest structure analysis, thinning strategies	Methodologies can be adapted for managing vegetation along powerlines
[73]	Forest ecosystems	Spatiotemporal graph modeling, reinforcement learning, SUMO, OMNET++	Real-time synchronization of forest ecosystem data	Can help model vegetation dynamics along powerlines
[74]	Forest simulation	LSTM networks, GAN networks	Predictive modeling of forest images	Predictions of vegetation growth along powerlines
[75]	Urban forests	GIS workflow, LiDAR point clouds, multispectral imagery, 3D building models	Classification of urban forests, reconstruction of tree crowns	Approaches useful for urban vegetation management near powerlines
[76]	Urban forests	UAV technology, stereo imaging, LiDAR, watershed segmentation	Correction of tree height growth estimates, canopy height models	Can improve accuracy of tree height estimates near powerlines
[77]	Urban trees	Point cloud-based modeling, space colonization algorithm, parametric L-system	Large-scale urban tree modeling	Approaches useful for modeling vegetation around powerlines in urban areas
[78]	Poplar plantation forest	Point cloud data, AdTree method, transition particle flow method, Unity3D	Tree trunk and branch reconstruction, growth trend prediction	Techniques can be applied to vegetation modeling near powerlines
[79]	Forest growth simulation	3D topographic LiDAR point clouds, BWINPro simulator	Simulation of tree growth using LiDAR data	Can be adapted for modeling vegetation growth near powerlines
[80]	Tree trunk modeling	3D LiDAR point clouds, cylinder fitting	Automatic modeling of tree trunk geometry	Useful for detailed tree modeling near powerlines
[81]	Agricultural plants	Functional Structural Plant Modeling (FSPM), L-system strings	3D plant modeling, analysis of plant responses	Can inform modeling of plant responses and growth near powerlines

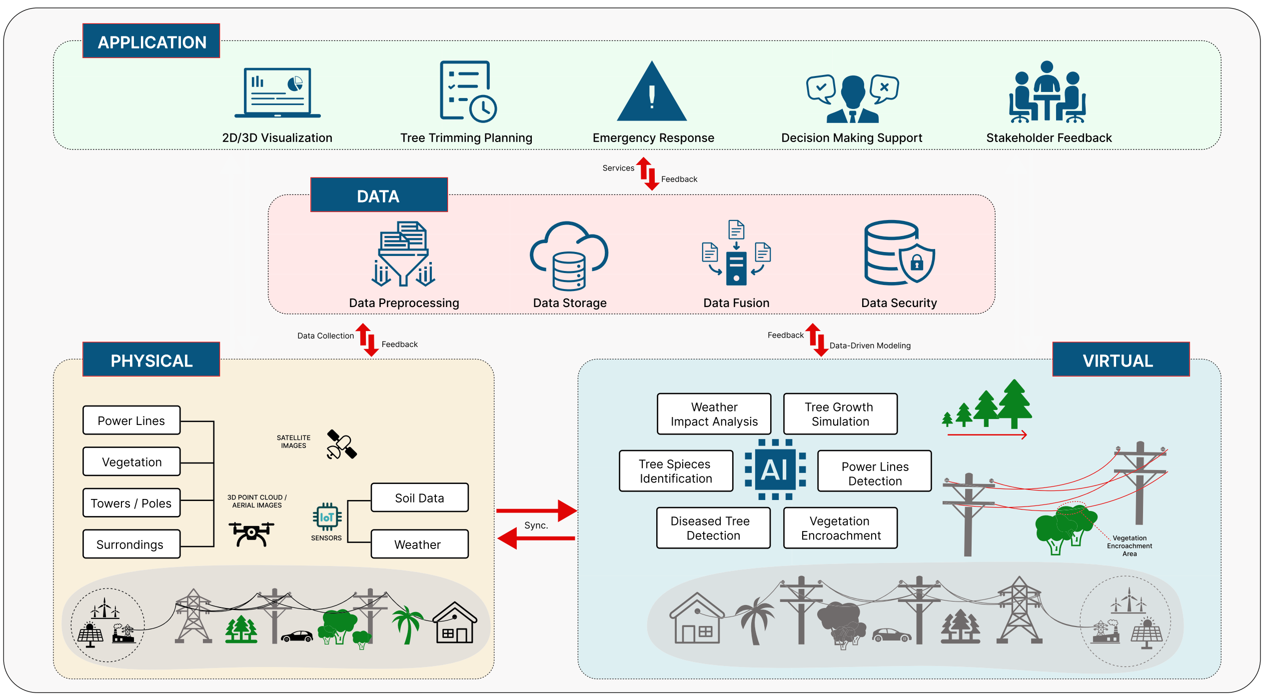

FIGURE 2. Proposed DT framework for distribution power network monitoring and vegetation risk management (Arrows represent data exchanges).

modules for tree trimming planning, emergency response, decision support, and stakeholder feedback. Tree trimming planning optimizes scheduling based on data insights, while emergency response uses real-time data for coordinated actions. Decision support provides actionable recommendations through simulations, and visualization tools like VR and AR enhance data interpretation. The stakeholder feedback module fosters continuous improvement by gathering perspectives from various professionals, ensuring the framework adapts to evolving needs and enhances network resilience.

5) COMMUNICATION LAYER

The *Communication Layer* facilitates the exchange of data between physical objects and their digital representations. It enables real-time, secure transmission of sensor and UAV-captured data using technologies like terrestrial mobile networks, UAV-based aerial networks, and satellite or high-altitude platforms [86]. The physical layer sends data to the data management layer, which is then used by the virtual layer for model development. Communication protocols such as Message Queuing Telemetry Transport (MQTT), Constrained Application Protocol (CoAP), and Long-Range Wide Area Network (LoRaWAN) support efficient data transfer, secured by Transport Layer Security/Secure Sockets Layer (TLS/SSL) and Advanced Encryption Standard (AES) encryption [87], [88]. Also, there is bidirectional communication with the application layer for service operation and feedback. Synchronization between the physical and virtual layers is essential, with event-based and periodic updates to ensure the DT reflects real-world conditions. Event-based updates occur in response to specific triggers, while periodic updates align with vegetation growth and infrastructure changes.

B. USE CASE SCENARIOS FOR PROPOSED DT FRAMEWORK

To illustrate the practical relevance of the proposed DT framework, we outline several representative use case scenarios that span monitoring, prediction, and decision-making across the power distribution network. These scenarios highlight how real-time data integration, predictive modeling, and simulation capabilities within the DT can improve operational efficiency and risk mitigation, as follows:

- **Real-Time Powerline Condition Monitoring:** The DT continuously synchronizes field data from UAVs and ground sensors to create an up-to-date 3D model of powerline infrastructure. This allows operators to monitor structural conditions, detect anomalies, e.g., cable sag or pole tilt, and respond promptly to physical degradations.
- **Vegetation Encroachment Prediction and Management:** By integrating 2D and 3D imagery-derived vegetation maps with growth models, the DT forecasts potential encroachment areas. This enables proactive vegetation control, helping utilities prevent outages and fire hazards.
- **Weather-Driven Risk Assessment:** The DT ingests meteorological data to simulate environmental stress on network assets. For example, it can model the impact of ice accumulation or high winds on conductor integrity, supporting early warning and mitigation strategies.
- **Predictive Maintenance Planning:** Maintenance decisions are informed by historical inspection records, sensor trends, and degradation models. The DT calculates asset failure probabilities and recommends optimized maintenance operations.
- **Emergency Response Simulation:** In the event of extreme weather or natural disaster, the DT enables real-time simulation of powerline disruptions and response strategies. This improves situational awareness and supports coordination among emergency teams.

These examples illustrate how the proposed DT framework can be operationalized across multiple stages of powerline management, from real-time monitoring to emergency response, demonstrating its adaptability and practical relevance in utility settings. Beyond the aforementioned scenarios, the broader strategic benefits of this framework lie in its ability to unify predictive analytics, simulation, and real-time data into a single decision-support system. Evidence from related domains reinforces this potential. For instance, authors of [89] showed that AI-enhanced DT models achieved up to 35% reduction in unplanned downtime and 8.5% gain in maintenance efficiency. Also, DT adoption for pipeline monitoring has delivered reduced fault-related downtime [90], while DT-based power plant models have improved load balancing and energy efficiency [91].

V. OPEN ISSUES AND FUTURE DIRECTIONS

Despite their benefits, DTs for power monitoring present several issues. Below, we enumerate key challenges.

A. ROOT-CAUSE ANALYSIS

Current powerline monitoring systems face significant limitations in performing effective root-cause analysis, particularly when assessing historical records of power outages. These systems often provide only surface-level data, lacking the capability to uncover the underlying factors that contributed to failures. This situation hinders utilities' ability to implement targeted preventive measures and optimize maintenance strategies. Looking forward, integrating generative and explainable AI models, such as large language models (LLMs), into powerline monitoring frameworks could offer substantial benefits. Indeed, such models can facilitate the analysis of large volumes of historical and real-time data, enabling more advanced diagnostics and richer contextual understanding of outage events. By identifying hidden patterns and inferring causal relationships, such as those involving vegetation encroachment, equipment aging, and weather-related stress, generative AI would improve the decision process and contribute to more explainable, transparent, and resilient grid operations.

B. TREE GROWTH SIMULATIONS

To effectively simulate tree growth, it is necessary to extract various tree parameters, including height, diameter, and canopy structure, and accurately identify tree species. However, obtaining such information from 2D or 3D collected data is complex. Indeed, dense vegetation and occlusions complicate data extraction, making accurate predictions challenging. Collaboration with botanists and ecologists is mandatory to refine models and ensure biological accuracy. Combining traditional vegetation growth models, such as Richards' model, with generative AI capabilities [92], can improve this task by synthesizing plausible future scenarios, filling gaps in incomplete data, and enabling more accurate and proactive vegetation management.

C. DATA FUSION, INTEGRATION, AND MANAGEMENT

The effectiveness of DT systems for powerline infrastructure relies on the integration of heterogeneous data from sources, such as LiDAR, UAV imagery, satellite observations, cameras, SCADA, and GIS databases. Key challenges include data heterogeneity, inconsistencies, scalability constraints, limited interoperability, and security concerns, all of which may compromise simulation fidelity and predictive capabilities. Managing large volumes of multimodal data in real-time further exacerbates these challenges, particularly when sensitive information, such as high-resolution imagery, is involved. Several standards can guide the implementation of robust data fusion and management. For instance, the Common Information Model (CIM) provides a unified ontology for modeling electrical network components and facilitates data exchange across platforms [93], while IEC 61970 [94] and MultiSpeak [95] define standardized interfaces and protocols for utility applications, supporting interoperability among diverse systems. At the DT level, ISO 23247 proposes a layered framework encompassing observation, communication, and simulation layers, providing a structured approach for system integration [96].

D. SCALABLE, FLEXIBLE, EDGE-ENABLED DT FRAMEWORK

DT frameworks for powerline infrastructure must support scalable, flexible, and adaptable operations to accommodate diverse system sizes, varying operational requirements, and evolving technologies. Handling large unstructured data is computationally difficult and complex. Although edge computing could reduce latency and bandwidth requirements for data processing, such tasks at the edge are technically constrained by device memory, processing power, and energy capacity. Hence, a hybrid cloud–edge approach is recommended, where edge nodes perform lightweight tasks, such as data preprocessing, compression, and preliminary anomaly detection, for instance. At the same time, intensive model inference and full-resolution analysis may occur in the cloud. Real-time responsiveness can also be improved through the use of lightweight model architectures, voxelization strategies, and GPU-accelerated ML pipelines. Despite ensemble methods being widely recognized for enhancing detection accuracy and robustness, their computational overhead may limit feasibility in DT platforms, particularly under edge resource constraints. Instead, prioritizing lightweight yet multimodal approaches that can jointly process heterogeneous data, such as 3D LiDAR/Radar and 2D imagery, and outage logs, offers a more practical and energy-efficient approach. To ensure flexibility and extensibility, modular plug-and-play architectures would be leveraged to efficiently integrate emerging sensing technologies and AI models without major redesigns. In addition, incorporating self-configuration, self-optimization, and self-healing management approaches could further enhance the system's resilience over time.

E. DEPLOYMENT CHALLENGES

Large-scale deployment of DT frameworks for powerline monitoring in existing utility systems can be complex due to incompatible equipment, legacy software, and heterogeneous data formats. The availability and coverage of network data are often limited, while data quality issues, including gaps, inconsistencies, and low resolution, can reduce DT framework reliability. Moreover, computational demands for processing high-resolution 3D datasets and real-time monitoring require careful computing infrastructure planning. Given these constraints, implementation should be progressive and modular, starting with pilot segments or selected corridors to validate system performance and integration strategies. Incremental deployment allows utilities to refine data acquisition and preprocessing, and to establish hybrid computation approaches, while minimizing operational disruptions.

VI. CONCLUSION

In this survey, we provided an extensive review of power infrastructure monitoring and vegetation risk assessment techniques. We started by covering the motivation and current tools of powerline monitoring, prior to discussing the DT technology and its recent integration into power network systems. Subsequently, we proposed a novel DT-based framework for powerline monitoring and vegetation risk evaluation, detailed its structure, and identified its benefits. We also exposed use case scenarios to illustrate how DT can enhance distribution powerlines monitoring, decision-making, and proactive maintenance. Finally, we identified open issues and future research directions to stimulate research around DT for powerline monitoring. As DT technologies mature, we anticipate increasing real-world deployments that validate and refine the proposed framework across diverse geographic and operational contexts. Indeed, the future of power grid management will likely depend on successfully integrating DT, thus enhancing resilience and sustainability.

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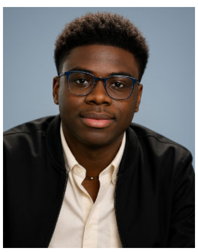

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