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TOPICAL REVIEW

From Graph Theory to Graph Neural Networks (GNNs): The Opportunities of GNNs in Power Electronics

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ABSTRACT Graph theory within power electronics, developed over a 50-year span, is continually evolving, necessitating ongoing research endeavors. Facing with the never-been-seen explosion of graph-structured data, the state-of-the-art deep learning technique-Graph Neural Networks (GNNs), becomes the leading trend in machine learning within just recent five years and demonstrated surprisingly broad and prominent benefits covering from new drug discovery to better IC design. However, its promising applications in Power Electronics are still rarely discussed and its full potential remains unexplored. Addressing this gap, this review paper is the first to outline GNNs' general workflow in power electronics, laying the groundwork and examining current GNN methodologies within the field. To bridge the gap in the sparse GNN literature within this domain, we also provide extended discussions on leveraging insights from GNN-aided circuit design to enrich power electronics research. Our work includes in-depth GNN-based case studies that demonstrate promising applications from converters to system-level power electronics, showcasing GNNs' unique benefits and untapped possibilities (e.g., accurate component design, voltage predictions on IEEE-13 bus and 118 bus systems). Additionally, we provide a comprehensive survey of GNNs' latest and successful applications, emphasizing their impact on energy-centric sectors, such as transportation electrification, smart grids. Considering the interdisciplinary nature of power electronics in modern energy systems, our review highlights the potential of GNNs emerge as a promising tool to decode the intricate behavior and dynamics of power electronics systems, and we hope such synergies between advanced AI methodologies like GNNs with the ever-evolving graph theory can lead to more powerful tools, novel methodologies, and advancements in the power electronics community.

INDEX TERMS Artificial intelligence, deep learning, energy systems, electronics automation design, graph theory, graph intelligent design, machine learning, neural network, power electronics, power systems, smart grids.

I. INTRODUCTION

As an interdisciplinary research field, Power Electronics involves the use of solid-state electronic devices, communication techniques, digital controllers, etc., for the control, conversion, and conditioning of electrical energy, which plays a crucial role in various applications, such as renewable energy systems, electric vehicles, next-generation smart grid, and so on [1]. Driven by the growing demand for efficient and sustainable energy conversion and management solutions, the field of power electronics has undergone significant advancements in recent years. As power electronics systems become increasingly complex to facilitate modern energy transmission systems, such as renewable energy

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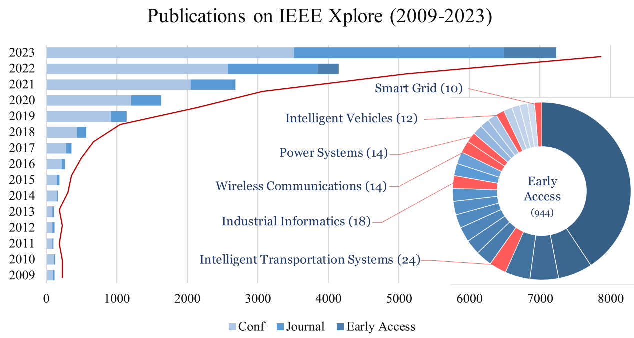


FIGURE 1. Publications of GNN-induced research on IEEE Xplore from 2009 to 2023. The search is done by using keywords "graph neural network" or "deep learning on graph", or "graph convolutional network" and including journal papers, conference papers, and early access papers. The current number of 2023 publication is 7318, which is expected to surpass 7500 at the end of the year. The early access papers (944 papers in total) are further demonstrated at right-side with several highlighted journals: IEEE Transactions on Smart Grid, IEEE Transactions on Power Systems, IEEE Transactions on Industrial Informatics, IEEE Transactions on Intelligent Transportation Systems, etc., showing a rapid growth regarding GNN-related research in Energy/Power domain. (All data is accessed through IEEE Xplore in December 2023.)

resource-based intelligent grids, electrical vehicles, motor drives, uninterruptible power supplies, etc., there is a great need for innovative methods to model, optimize, control, and monitor these systems from both hardware to software.

In this context, Graph Theory has emerged as a promising tool for addressing these challenges, especially in recent years [2]. Serving as a common language among various disciplines, graph theory can be leveraged as a powerful tool to enable systematic modelling and analysis [3], [4], [5], [6], [7], design new converters [8], [9], [10], [11], [12], control their operations [13], [14], estimate and identify potential issues [15], [16], [17], optimize the systems [18], [19], [20], or even facilitate the understanding of the interconnections and interactions between components in power-electronics-based systems [21], [22], [23]. Especially in recent years, innovative research keeps emerging, covering component-level, converter-level and system-level of power electronics [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37]. Leveraging the power of graph, these research works not only feature systematic understanding but also open more possibilities, e.g., integrated with automation and AI. Such progress further inspires us to seek more advanced and flexible techniques that can capture the complex dynamics of these systems (e.g., graph-theory-inspired modeling and operation) and meet composite requirements for practice. This is where Graph Neural Networks (GNNs) come into play.

Unlike the Convolutional Neural Networks (CNNs) which deal with the regular shapes of data (text, image that naturally forms into grids or matrix), GNNs surpass such a limitation and are dedicated to data with irregular shapes or more generally speaking non-Euclidean data. As a specialized category of deep learning models explicitly developed for handling graph-structured data, GNNs tackle the so-called geometric deep learning problem through the automated learning of the network features instead of traditional hand-crafted feature engineering [38], [39]. Therefore, they can overcome the computational bottlenecks of traditional machine learning on graphs and have achieved notable success and attracted significant research interest across various multidisciplinary applications (see the publication trends in Fig. 1). These include social network analysis [40], molecular and drug discovery [41], bioinformatics [42], computer vision [43], language processing [44], materials science, and chemistry [45], as well as more recent advances in internet of things [46], [47], energy systems [48], [49], intelligent transportation systems [50], [51], power systems [52], wireless networks [53], and communication systems [54].

In summary, while GNNs have been extensively explored in various fields, their application in power electronics remains an underexplored territory. The unique graph structures and data inherent to power electronics systems present a fertile ground for GNNs to uncover deep insights into the complex behaviors and interactions within these systems. This untapped potential positions GNNs as a pivotal tool for advancing the efficiency, reliability, and robustness of power electronics. This, in turn, can aid researchers and engineers in the development of more efficient, reliable, and robust solutions that cater to the evolving demands of modern energy systems.

In detail, the benefits brought by GNNs in general can be characterized by the following key aspects:

- **Systematic analysis and design optimization**: GNNs can better process graph-structured data and can effectively capture the complex dependencies and interactions between different components, enabling improved analysis of complex power electronics systems and leading to comprehensive deep-learned models for specific tasks with globally optimal benefits, such as power flow and generation control, load consumption prediction and connection analysis among the whole system, etc.
- **Cross-domain knowledge transformation**: As an interdisciplinary field, power electronics can benefit from the insights and methodologies developed in domains like power systems, transportation, circuit design, etc. This knowledge transfer can lead to innovative solutions and approaches for addressing challenges in power electronics, e.g., through a transferable GNN-based method [55].
- **Fault-tolerance and reliability**: By leveraging GNNs' ability to uncover hidden patterns and dependencies within graph-structured data, researchers can develop a better understanding of potential failure points and devise strategies to increase the lifetime of components and further the overall reliability of power electronics systems.
- **Scalability and adaptability**: GNNs can efficiently process large-scale and dynamic graph-structured data, making them suitable for tackling the growing complexity of modern power electronics systems,

which often involve numerous interconnected components/equipment and rapidly evolving technologies.

- **Ability to handle dynamic graphs**: GNNs can adapt to changes in the graph structure over time, such as the addition or removal of nodes and edges [56]. This makes GNNs well-suited for power electronics systems that may evolve or change during operation [57], allowing them to capture and learn from the dynamic behavior of the system. In contrast, conventional machine learning methods often struggle with handling dynamic graph data, as they generally assume a fixed structure.
- **Relational reasoning**: GNNs can perform relational reasoning by learning to weigh the importance of different relationships and dependencies within the graph [58]. This enables GNNs to identify crucial interactions among components in power electronics systems and make more informed decisions or predictions. Conventional machine learning methods, however, often lack the ability to explicitly model and reason about such relationships, which may lead to overlooking important information.

This paper aims to address this underexplored area by providing a comprehensive and timely review of GNNs and their potential applications in power electronics. To reflect the rapid development of GNN-induced applications, a large quantity of recent published surveys/reviews are cited as our major supporting materials. In general, this paper is written as a guide for those interested in harnessing the merits of GNNs in power electronics research. By delving into the fundamentals of GNNs, exploring their promising applications in power electronics, and highlighting their advantages over traditional AI techniques, this paper shed the light on the future integration of GNNs into power electronics, ultimately driving innovation and advancements in this critical domain.

This paper is organized as follows: it begins with a broad introduction (Section I) and is followed by an overview of recent progress of graph theory research in power electronics (Section II); the thorough overview of how GNNs are and will be implemented in power electronics is given in Section III, then, it delves into the fundamentals of GNNs (Section IV); following that, selected scenarios with GNN for filter design and power electronics-enabled microgrid systems are further demonstrated with their unique benefits and potentials (Section V); then we go beyond the power electronics and discuss what GNNs have been done in energy-related systems (Section VI). This paper ends with our outlooks in Section VII and the conclusions in Section VIII.

II. GRAPH THEORY IN POWER ELECTRONICS

A. BASICS

Graph Theory has been applied in electrical engineering since the very beginning of Circuit Theory and its everlasting applications in power electronics can be traced back to the 1950s-1960s and is still under development. In power electronics, graph theory can be employed covering electrical components, power conversion topologies and even converter systems as demonstrated in Fig. 2. By employing fundamental graph theory concepts in different levels of research, such as vertices (representing components), edges (representing connections), and graph properties (like planarity, connectivity and centrality), researchers can gain a deeper understanding of the system's structure and behavior. This enables the study of across a broad scope of power electronics, e.g., modeling, analysis, topology derivation, operation design, etc. In [2], a thorough general picture is given and interesting readers are encouraged to refer to this review paper for detailed and explicit investigations on both historical achievements and emerging developments of graph theory in power converter research.

B. RECENT DEVELOPMENTS

Recent years witnessed some interesting graph-theory-based methods in Power Electronics research covers from component-, converter- as well as system-level research.

(i) Component-level: In [20], a graph model is constructed to represent the complex, heterogeneous layouts of multichip silicon carbide power modules, capturing interconnectivity and design constraints, and using this model in conjunction with integer programming and genetic algorithms for systematic and efficient optimization of module layouts. In the latest framework of design automation technique PowerSynth 2 [59], constraint graphs are constructed to enable bottom-up constraint propagation for synthesizing layouts that respond to various design constraints, such as minimum width, enclosure, and spacing between components, leading to optimized and constraint-aware solutions. In addition, various graph-theory-induced algorithms are also implemented, such as longest path algorithm, path-finding algorithm, etc. In recent circuit synthesis research, graph learning is proposed in [30] to enable superior approximate synthesis, design diagnosis, reverse engineering, etc.

(ii) Converter-level: Leverage the explicit expression power, graph-theory-based modeling and analysis has got some considerable attention, including equivalent circuit identification [3], multilevel converter topologies with parallel connectivity [5], open-circuit fault diagnosis for T-type inverter [15], operation analysis of DC-DC converters considering uncertain states of diodes [33], sneak circuit analysis of semi-DAB [34], fault diagnosis of modular power supply [35], etc. In terms of converter relationship research, isomorphic converter derivation and operation design is proposed in [21], revealing some unique yet broadly existing interconnections between voltage-source and current-source converters. In [60], duality method is exploited to facilitate the systematic analysis and operation design of new multiport converters for renewable generation integration. The work got further extend by proposing the generalized duality method for cognate multiport converters to cover a wider scope of related multiport topologies which feature different circuit appearance but come from the same dual topology [23].

On the other hand, considerable research works deal with the topology derivation challenges covering from DC-DC

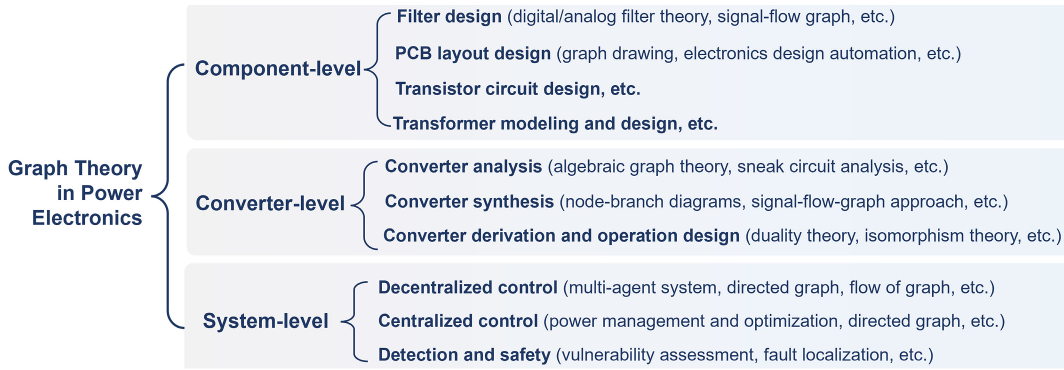


FIGURE 2. A brief summary of different levels of Power Electronics research associated with Graph Theory approaches.

converters [9], [10], DC-AC inverters [37], multiport converters [10], [61], switched-capacitor converters [8], as well as works towards power converters in general [11], [12]. In particular, The topology automatic generation and search is a challenging and trending theme, where works focused on non-resonant dc-dc converters [25], single-inductor multi-input multi-output converters [32], multi-port hybrid circuit breakers [28] and vertex prime degree-based DC–DC converters with two switches [31] representing some most interesting recent progress.

In addition, graph-based operation design and control can also be found recently, such as battery balancing [14], [24], voltage regulation in DC microgrids [36], partitioning of modular multilevel control system [62], etc. In particular, [63] introduces a universal framework for finite-control-set model predictive control design with unified model for isomorphic and dual power converters, which shows a significant simplification compared to the conventional design process.

(iii) System-level: Optimization of distribution systems can benefit from graph theory, such as the work on multiple-output DC distribution system [18], and automatic generation and visualization of optimal network [19]. Smart transformer, as another system-level example, got improved through graph-theory-based control as proposed in [7] and [13]. The implementation of graph theory also spread out to wireless power transfer (WPT) system, where graph sets method is proposed for simplified modeling with comprehensive analysis of multicoil WPT systems [4], [64]. Topology identification in [27], shows some promising benefits bringing unsupervised learning with graph theory for applications in low-voltage distribution systems.

In summary, graph theory applications for power electronics have witnessed rapid progress and development. The recent years innovations on this theme show their great potential on facilitating systematic research of all the major critical aspects of power electronics. As a universal mathematical language, it is also demonstrating interesting opportunities to bring graph and state-of-the-art algorithms altogether, emerging as GNNs as intersection of both graph and AI. In the next section, a bibliometric study will be given to further illustrate such trends in graph theory induced research and solidify the visions on power electronics research evolutions from graph theory to GNNs.

C. BIBLIOMETRIC STUDY

Over the 15-year period from 2009 to 2023, the growing importance and application of graph theory illustrates a consistent upward trend in the number of publications, including computer science, electrical engineering, and many others, indicating a high level of ongoing research activity.

To give a holistic view, the research topics of graph theory-induced research on IEEE Xplore is shown with profound evolution from 2018 to 2023 (see Fig. 3), covering from purely theoretical research to various applications, e.g., learning, semantic networks, pattern clustering, social networks, recommender systems, multi-agent systems, image classifications, object detection, etc.

In general, graph theory is a fundamental mathematical discipline used in many areas of computer science, including network design, data structures, and algorithm theory. It's also crucial in modern AI and machine learning, particularly in the design and implementation of graph neural networks, which can model complex systems and relationships. It's worth noting that the ''Graph Neural Networks'' topic also shows a similar trend as ''Graph Theory'' ''Learning (Artificial Intelligence)'' and ''Deep Learning (AI)'' in the figure, which suggests a relationship between the two topics. This is expected, as Graph Neural Networks are an application of Graph Theory.

III. GNNS IN POWER ELECTRONICS

Power electronics devices are penetrating different areas in energy systems to significantly promote efficiency and functions; however, such a trend also provokes serious concerns about their cost, safety, reliability, etc., and calls for emerging needs for more advanced modeling, analyzing, deriving, operating the power-electronics-enabled systems [65]. Given the superior graph-structured handling capability over conventional machine learning methods, GNN-based methods can fit well for such tasks, facilitating the research by

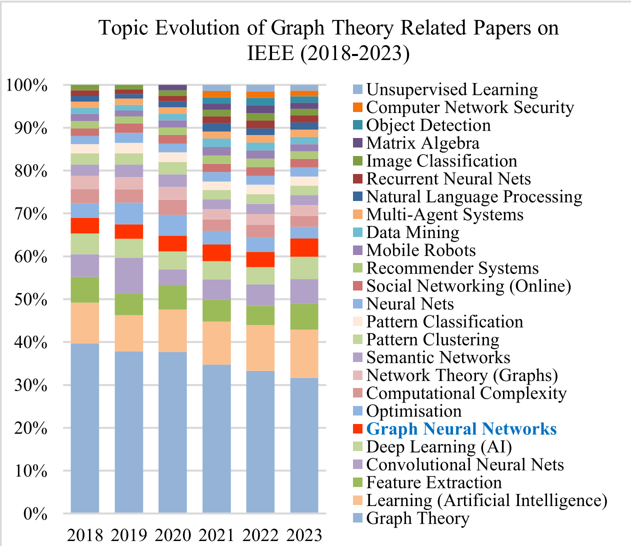


FIGURE 3. The topic evolution of the publications of Graph Theory related research on IEEE Xplore from 2018 to 2023. The search is done by using keywords "graph theory". (All data is accessed through IEEE Xplore in November 2023.)

automatically learning the complex topological relationships and dependencies in power-electronics-enabled applications.

A. WORKFLOW OF GNNS IN POWER ELECTRONICS

The GNN-based methods can follow a similar workflow in [66] for different applications as summarized in Fig. 4.

The *graph identification and characterization* step are to deal with different dataset types of power electronics, and by conducting graph modeling methods, either structured data, or non-structured data can be transformed into the compatible form for GNN algorithms.

The *computational modules and training* will basically follow the philosophy as reviewed in [66] by exploring the diverse design space of GNNs. Similar concept has also been found in converter optimal design [67], e.g., set of selected design- and operating parameters, materials, components, topology, etc.

The *loss function design* step is closely related to how the ground truth of node/edge/graph embeddings are generated, and what are the downstream tasks. In general, it will be recommended to transform the component-level, converter-level, system-level power electronics tasks (more details are listed in Fig. 4) into standard graphical grammar, i.e., node-level, edge-level, graph-level tasks. This is when the domain knowledge plays important roles to make sure such translation aligns well with the engineering requirements.

B. EXISTING APPLICATIONS OF GNNS IN POWER ELECTRONICS

As mentioned before, despite the growing interest in GNNs, their full utility in power electronics is still unexplored. By the time of preparing this review, there has been a limited number of works published regarding this direction, covering specific topics such as GNNs for converter modeling and derivation, rectifier fault diagnosis, and regulation of DC microgrids or clusters of microgrids.

(i) Converter-level research. To better implement machine learning methods for tasks including regression, classification, clustering, and synthesis of power electronic converter circuits, a systematic circuit mapping framework is proposed in [68]. In this work, the bond graph is used for converter modeling to cope with the multi-physics nature of power converters, and GCN with Mean pooling is used for circuit feature encoding, such that, datasets can be generated in a unique graphical format for downstream tasks, e.g., classification of converter types.

In [69], a novel learning-based framework for deriving the topology of power electronics converters is introduced. The framework represents the circuit as a graph, which allows for enhanced flexibility in modeling complex converter topologies. Features of the circuit graph are then extracted using GNNs and fed into a reinforcement learning framework to derive new converter topologies. The proposed framework is effective in deriving new complex topologies such as six-port, eight-port, and even ten-port converters, which were previously difficult to design using traditional approaches.

The GCN-based fault diagnosis would link the data with the associated graph, such that the time-frequency features can be embedded as node features, while the similarity of measurements can be modeled as the edge connections in graph. By introducing the prior knowledge during the association graph constructing process, the authors in [70] greatly improve the diagnostic accuracy regarding a typical traction system rectifier, where special focus is given to IGBT open circuit faults. This work got further improvement by tackling the over-smoothing problems in GCN-based methods [71], where the learnable weight coefficient θ is added into the conventional GCN forward propagation formula.

*(ii) System-level research.*As power converters play a crucial role in modern microgrids, bridging renewable energy sources with load and grid, intelligent control becomes vital to stem the high system efficiency, good power quality and resilient operation [72].

In [73], the authors introduce a novel approach for fault detection and identification in low-voltage DC microgrids with meshed configurations. Their proposed methodology is based on GCN, which effectively leverages the explicit spatial information of the network topology and measurement data to accurately detect faults. Notably, the proposed method is robust to noise and corrupted data, exhibiting a strong feature extraction capability.

In [74], a multi-agent reinforcement learning method featuring an augmented GCN with proximal policy optimization algorithm is proposed for the cost-effective voltage regulation, allowing for the decentralized training with privacy preservation. By extracting the key features from the network topology via the techniques of critical bus and electric distance, it can help convey various system dynamics and uncertainties, including renewable generation, demand,

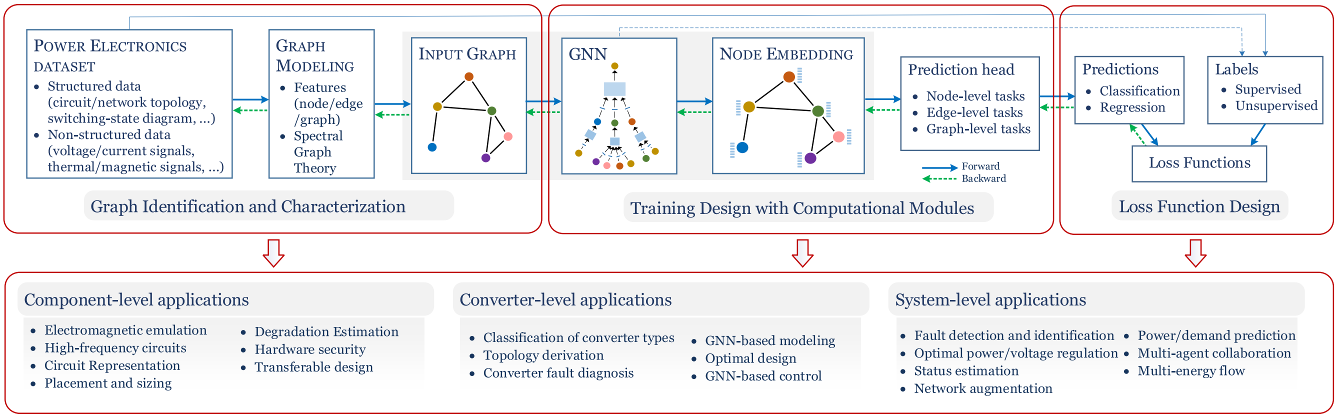


FIGURE 4. The workflow and GNN-based applications for Power Electronics.

and price signals, and integrate them into the optimization process.

In summary, GNNs in power electronics are still in a very early stage, and the research focuses mainly on converter and system-level, and there is still great potential that GNNs could bring to power electronics research. To further explore the implementation of GNNs, in the next section, the applications of GNNs in circuit design will be presented.

C. RELEVANT APPLICATIONS OF GNNS IN CIRCUIT DESIGN

To provide a tangible sense of how GNNs can be implemented in Power Electronics, we will also highlight some papers from the circuit-design domain which are considered closely relevant here, where the topics circle around analog integrated circuit (IC) design, transistor sizing, circuit aging, etc.

(i) Electromagnetic emulation. To tackle the high-frequency circuit design, a specialized GNN method is proposed in [75] to simulate the electromagnetic properties of distributed circuits, e.g., resonator filters in 5G/6G system. By capturing the relationships between circuit components, the electrical and magnetic couples can be learned and then, help solve the inverse design problems, i.e., given desired circuit transfer function and optimize the geometrical floor planning and parameters. Such an application of GNN can be transferred to power electronics component-level design, for instance, automated EMI filter design for high-frequency converters.

*(ii) Radio-frequency circuits.*The work in [76] proposes a unique multimodal policy network consisting of a circuit topology-based GNN (both GCN and GAT are used to learn the embedding of circuit-level physical features) and a fully connected neural network to embed key domain knowledge of circuit design and achieves higher accuracy, efficiency, and optimality. By generalizing the same idea, one can implement GNN-based methods for automated and more intelligent analog circuit design in power conversion where traditional CNNs cannot handle the geometric learning efficiently.

(iii) Circuit Representation. To preserve the important topological and geometrical information, the circuits are modeled as heterogeneous graphs in [77]. By utilizing circuit GNN algorithms, the information can be distinctively propagated on both topological and geometrical edges and then fuse the messages to update cells and nets representations. Therefore, the design framework can work well in both logic synthesis stage and placement stage. This is indeed a good hint for power electronics circuit design, since both the topology features (which are related to the operation behaviors like switching states of a converter) and the geometrical features (which are related to the physical realization like device package, heat dissipation, EMI, etc.) need to be considered organically during the design process.

(iv) Placement and sizing. To improve the analog IC placement, authors in [78] incorporate GAT and DiffPool, outperform the recent CNN-based model and achieve performance similar to manual designs. To consider the layout parasitic (e.g., parasitic resistance and coupling capacitance) in transistor sizing problem, the work in [79] utilizes parasitic graph embeddings from GNN-based pre-trained prediction networks and achieves optimization convergence by 3.7 times and 2.1 times compared to conventional Gaussian process regression and neural network based Bayesian linear regression, respectively. Such layout parasitic problems are also emerged in wide-bandgap power module design, thus, could benefit from a similar treatment in IC design philosophy.

(v) Degradation Estimation. To make a fast estimation of aging-induced transistor degradation, the authors in [80] propose a heterogeneous GCN to characterize the multi-typed devices and connection pins. By further extending the proposed algorithm, information from multi-hop devices can be extracted without an over-smoothing issue and enables significant performance improvement compared to traditional graph learning methods and the static aging reliability simulations. Aging and its diagnosis in modern power electronics devices is drawing increasing attention in recent years [81] and GNN-based methods could be a potential solution for more-integrated power generations, e.g., power-on-chip, ultra-low voltage/power applications.

(vi) Hardware security of ICs. To tackle the circuit-related tasks related to hardware security, a generic end-to-end

GNN-based pipeline is suggested in [82]. Concerns like implantation hardware Trojans, piracy of design intellectual property, and reverse-engineering are highlighted. GNN-based methods have been used to address some of them, such as hardware Trojans detection, piracy detection, functional reverse engineering, and attacks on design-for-trust (including predictions of key leakage, link formation, structural leakage, etc.). Security problems also received considerable research efforts in power electronics, while mostly focused on cyber security [83]. Given the recent development regarding hardware security research in IC design, this topic could also inspire some works in the power domain and similar GNNs could be implemented.

(vii) Knowledge transfer design. To reduce the re-design from one circuit to another, authors in [55] combine both the GCN and the reinforcement learning to transfer the knowledge between different technology nodes (180nm, 65nm, etc.) and topologies. GCN is built to help open the black box during optimization and improve the circuit performance with learned domain knowledge. In [84], a similar idea of hybrid GNNs, i.e., GIN with transfer learning, is adopted to transfer learned device sizing knowledge to predict the performance of new topologies.

Such applications can also be expected in power converter topology design to capture the domain knowledge from conventional dataset and help to design different converters where different semiconductors and topologies are used.

In summary, GNNs have been applied in circuit design covering from circuit analysis to synthesis, from Multiphysics considerations to different circuit scales, which shows great potential of their extension to power electronics.

D. SPECIFIC DIRECTIONS OF GNNS IN POWER ELECTRONICS

The integration of graph theory and deep learning through GNNs offers exciting opportunities for the field of power electronics. By leveraging the interdisciplinary nature of power electronics and the powerful capabilities of GNNs, researchers and practitioners can develop more efficient and reliable solutions, driving further advancements in this critical domain. In this section, merits, future potential as well as challenges are presented.

Based on the previous overview, there are several interesting topics that we believe could receive further development in power electronics research based on GNN-aided techniques.

- **Enhancing power converter modeling and analysis.**When designing or analyzing power converters (and their systems), both the topological and geometrical information such as the circuit networks and positions of the components (converters) play important roles. In this direction, identity-/position- aware GNNs [85], [86] can be trained with the holistic datasets to accurately model the converter (and/or its system). Thanks to the Universal Approximation Theorem, embedding MLPs in GNN layer could further improve the algorithm expressiveness, capturing different graph structures of the power electronics systems [87].
- **Expanding the power of neural network controls.** Neural-network-based controls (e.g., MLP, fuzzy neural network, recurrent neural network, etc.) have been applied during the past two decades for different problems of power electronics [88], such as space vector PWM of voltage-fed inverter, speed sensorless operation, delayless filtering and waveform processing, and so on. As a natural extension, GNNs can be seamlessly substituted in wherever conventional neural-network-based controls can fit, plus, achieve more accurate and/or more computation-efficient predictions for other scenarios when non-Euclidean data are needed to be handled, such as multi-agent-based vehicle systems [89].
- **Advanced power electronics design and automation.** With the semiconductor industry approaching the limitation of Moore's law's, advanced power electronics topology like multilevel converters also get implemented in ICs [90]. But still, the difference between ICs and power electronics circuits could remain to be prominent [91]: (1) circuitry nonlinearity, (2) high degree of accuracy with switching actions, (3) the wide variation of circuit node impedances and time constants, (4) high sensitivity of the layout parasitic elements. Following a similar path in EDA, the power electronics design can utilize GNN-based methods to facilitate the automation of the whole process. In particular, advanced GNN methods can be redesigned with the integration of domain knowledge to handle the above heterogeneous features.
- **Developing advanced fault diagnosis and tolerant operation.** The recent work of GCN-based fault diagnosis of single-phase rectifier opens some more opportunities that other advanced spectral GNN algorithms can also be utilized for different power converters and their systems. As summarized in [92], spectral GNNs learn node or graph representations from spectral information (e.g., multivariate time-series fault signals), and possess different expressiveness and interpretability from spatial methods, resulting in diverse groups of methods that have been still unexplored.

In summary, even though GNNs are generally underdeveloped in power electronics, but their great implementation in relevant domain like electrical design automation has already show convincing promises that they can serve as tools for enhancing power converter modeling and analysis, expanding the power of neural network controls, advanced power electronics design and automation and developing advanced fault diagnosis and tolerant operation.

IV. FUNDAMENTALS OF GNNS

GNNs are under the broader umbrella of graph representation learning, which emerged from the need of learning tasks from graph data and follow a similar yet different structure of other learning algorithms.

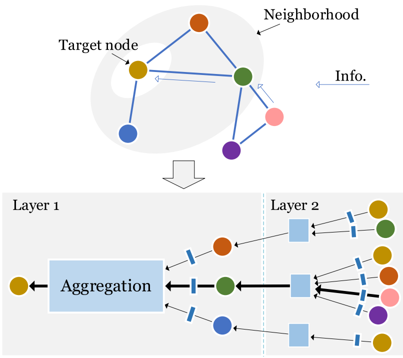


FIGURE 5. **The visualization of message passing (information propagation) process from the adjacent nodes to the target node. The integration of neighborhood is normally realized by aggregation function, e.g., MEAN, MAX, SUM, etc.**

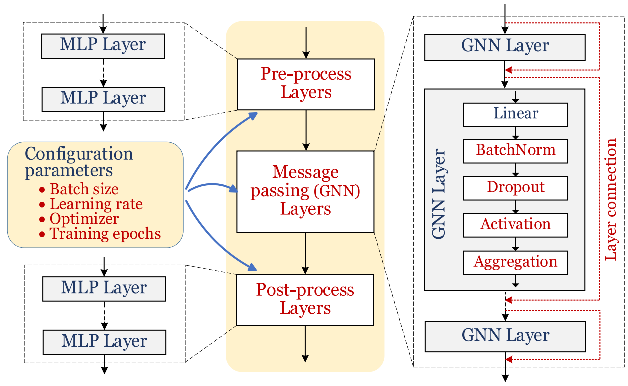


FIGURE 6. **Design space of GNNs. (MLP denotes the Multi-layer Perceptron which possess a combination of multiple linear functions and non-linear functions.)**

Founded on an information diffusion mechanism, the core difference of GNNs over conventional graph representation learning lies in how topological information is encoded during the learning process [93], [94]. This not only sets them apart from conventional machine learning methodologies, but also brings various unique features:

- Local and global context awareness [45].
- Invariance to permutations [95]. [96].
- Powerful expressivities [87].
- Optimal approximation [97].

In each layer of GNNs, the information propagation is designed to be conducted around the neighborhood (the adjacent nodes) of each targeted node (see the conceptual visualization of this process in Fig. 5 which is adapted from [98]). Compared to convolutional neural networks (CNNs), the most distinctive part in computation module is the aggregation function (as indicated in Fig. 5), which takes the information of the adjacent nodes and generates a "message" and updates the target node. The topological features will be embedded in this process by default, while such information is normally overlooked by CNNs or other Euclidean data-handling methods.

Next, we will discuss the concept of design space of GNNs, which sets the grounds for the design possibilities of GNN algorithms in theory. This will provide a general picture as well as guidance of GNN design tasks from a software-engineering perspective. (For readers who are interested in more details, please refer to books like [94], [98].) Fig. 6 shows the detailed GNN learning algorithm structures with function modules and descriptions based on the work in [99], which demonstrates a hierarchical design philosophy including three major design categories: (1) intra-layer design, (2) inter-layer design, (3) learning configuration.

Intra-layer configurations define the core function of a single GNN layer, and directly influence the general features and performance of GNN algorithms. A typical GNN layer consists of several message-passing sub-layers (as shown in the right-hand side of Fig. 6), where consecutive sub-layers can be treated as specialized functions that take the input from the previous sub-layer and generate the output as input for the next sub-layer. The complete pipeline features five modules, i.e., a linear layer, batch normalization, dropout, non-linear activation function and aggregation function (please refer to deep learning fundamentals textbooks like [100] and [101] for their basic definitions). By altering these modules, various GNN layers can be obtained, resulting in different GNN algorithms, such as GCN, GraphSAGE, GIN, etc.

Inter-layer design is categorized based on how multiple GNN layers are connected together, e.g., direct stacking, adding skip connections, etc. By different concatenation methods, GNN layers can be organized in various ways, and demonstrate different merits, further expanding the design space.

Same as other learning algorithms, different training settings and optimization methods could be implemented for pre-/post- process and message-passing layers, leading to distinctive performance, and thus, their fine-tuning and optimal selection would be important for GNNs to fit the desired applications. To provide a more holistic view of GNN, interested researchers are recommended to refer to various GNN algorithms listed in Appendix Table 2 and various datasets for learning on graphs listed in Appendix Table 3.

V. CASE STUDIES

To demonstrate the practical opportunities of introducing GNNs into Power Electronics, here we choose three examples to further illustrate: (1) case study 1 is focused on the converter-level applications, where GNN algorithm is trained for optimal design of a high-frequency filter; (1) case study 2 is focused on the converter-system-level applications, where data from power-electronics-enabled systems like microgrids can be collected; (2)case study 3 is extended from the first one, by implementing the similar GNN algorithms for larger system, e.g., local distribution system. Case 1 was running on the local computer with Intel i9-11980HK @ 2.60GHz 3.30 GHz and NVIDIA GeForce RTX3080 Laptop GPU.

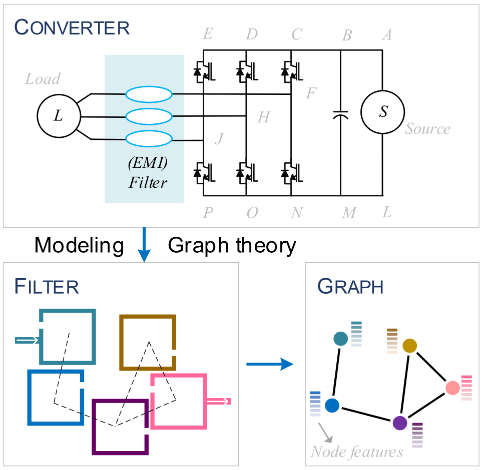


FIGURE 7. Graph modeling of distributed parameter filters.

Both cases 2 and 3 have been running with Google Colab environment.

A. CASE STUDY 1: HIGH-FREQUENCY FILTER DESIGN

This case study follows the workflow proposed in [102] and is focused on high-frequency filter design problem (from MHz to GHz), which gains increasing attention in power electronics miniature applications [103], e.g., power-on-chip systems, gallium nitride (GaN)-based power amplifiers, etc. The basic idea is illustrated as in Fig.7, by adopting the graph theory model of converter, the filter design can be transferred into a layout planning which can be learned and designed through the GNN-based methods.

Due to the ultra-high frequency range the problem dealt with, the lumped parameter modeling can no longer be valid, and traditional manual design methodologies are increasingly proving to be insufficient for these complex systems. In detail, we've adopted a supervised GNN algorithm in [75] to address the inverse design of distributed-parameter filter design in GHz range. The algorithm is specifically configured to ingest a pre-defined circuit transfer function and subsequently optimize both the geometrical floor planning and the circuit parameters.

As for the algorithmic settings, the GNN model operates with a batch size of 128 and a learning rate of 2e-4, with 117 epochs for training. The architecture comprises three GNN layers, with edge and node attributes dimensioned at 20 and 11, respectively. The hidden layer is robust, featuring 400 neurons and employing a leaky ReLU activation function. These parameters were chosen to maintain a balance between computational efficiency and predictive accuracy, thereby fortifying the model's robustness in addressing high-frequency filter design complexities.

Fig. 8 shows the loss of the training and validation of the algorithm, where the performance tends to maintain steady after 60 epochs. The average error of training is around 1.1dB for 4-resonator topology (~1.7dB for validation/testing), and around 1.3dB for 5-resonator topology (~2.2dB for validation /testing). Fig. 9 presents the prediction results for a filter with 3 resonators, demonstrating that the GNN-based prediction error closely aligns with the theoretically calculated frequency response. The Fig. 10 further demonstrate another example for bandpass filter design within the frequency range of 260-290 GHz, where the delivered band is 255-293 GHz which considered quite close to target. Please note that, within the GNN-based workflow, such a distributed circuit design task only requires several minutes, while the same task would take an expert multiple orders of time, like days if not weeks to reach the same level of optimality. It is anticipated that the same methodology can be further developed for other parts of the power converters, especially considering application within radio frequency range or even beyond.

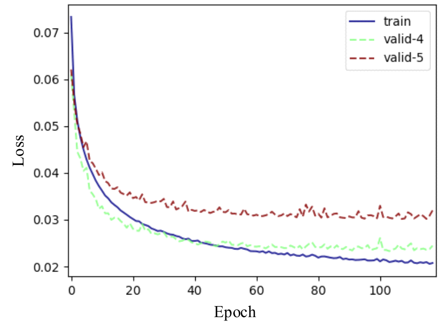


FIGURE 8. Loss of GNN-based filter design training/valid results.

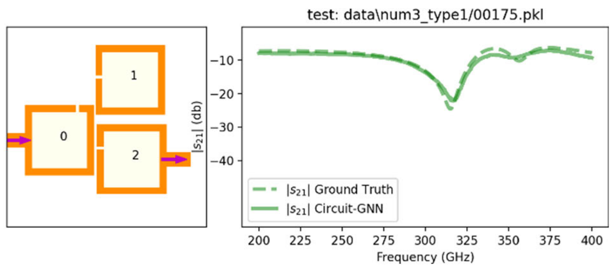


FIGURE 9. S-function prediction example of filter with 3 resonators.

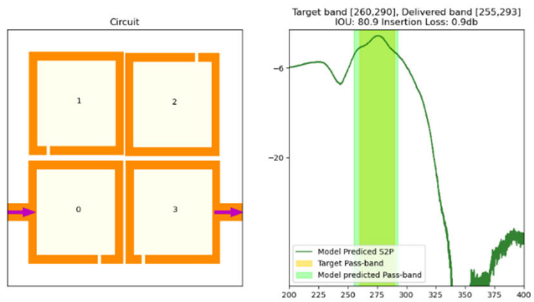


FIGURE 10. Bandpass filter design results target band 260-290 GHz.

B. CASE STUDY 2: MICROGRIDS VOLTAGE PREDICTION

As mentioned in [1], a key component in a modern microgrid is the Power-Electronics-based smart interfacing

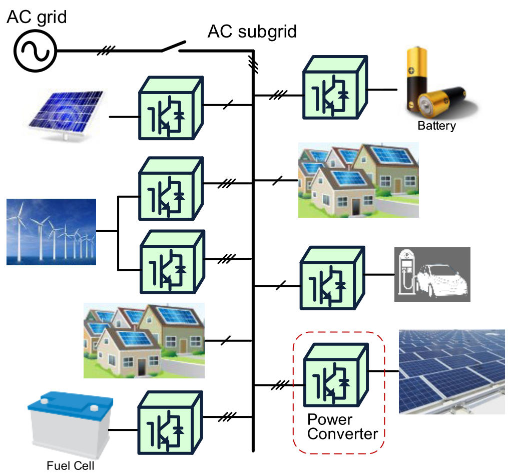


FIGURE 11. **Power-Electronics-enabled AC-coupled microgrid system.**

converter (IFC), which enables flexible power flow control and is the actuator of smart functions. Those IFCs connect renewable/non-renewable energy generation/storage systems and loads to the AC and DC subgrids of microgrids as shown in Fig. 11. However, the intermittent of renewable energy (wind and/or PV power generations) as well as low inertia of power converters in microgrid systems, could lead to power fluctuations, or even stability problems, especially in high penetration levels. In this case study, we will leverage GNN-based algorithm to help predict the voltage fluctuations inside a microgrid.

To emulate the networks of a microgrid system, we choose the IEEE 14-bus system as our benchmark [104], [105]. The IEEE 14-bus diagram is adopted from [106] and the original graph-structured dataset is available from [107]. The detailed workflow is shown in Fig. 12.

First, the network data needs to be converted into graph as demonstrated in the graph modeling Fig. 13. Then, the graph can be further represented by utilizing adjacent matrix $\boldsymbol{A}$:

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \tag{1}$$

where the value of element a_{ij} in $\boldsymbol{A}$ is assigned as "1" when the corresponding ith node is connected to the jth node through an edge, Otherwise, assigned as "0". In practice, sparse matrix will be converted into standard edge_index form and both the connection information and node attributes can be stored efficiently and processed by the GNN algorithms. Then, the GNN algorithm is built for a node label prediction task. To accommodate our specific needs, i.e., a voltage fluctuation prediction, the graph node attribute is also embedded by a data pre-process with first, a Mean function, and then, a Classifier to indicate if the binary classifications of voltage magnitude higher or lower the threshold.

In this demo, we implemented supervised learning as our training settings, and chose GCN as the GNN layer, utilizing three convolutional layers. For the node classification task, we applied mean pooling followed by two fully connected layers. Since our focus was on binary classification, we utilized a binary-cross entropy loss function. To determine the optimal set of hyperparameters, we employed a grid-search method and fine-tune them through trial and error. The graph features and detailed hyperparameter setups are summarized in Table 1.

The training process is to use a certain amount of graph data samples as training set, while a randomly chosen graph is our testing set. Fig. 14 shows the prediction results are getting more accurate with a higher number of epochs. Fig. 15 shows the loss function value changes with epoch numbers, as well as the confusion matrix of the classification prediction. The final achieved accuracy is around 92.85%. It is worth noting that the epoch number cannot go too high due to an overfitting problem, which will cause performance degradation. Another thing worth noting is our selected dataset contains 10000 samples for the IEEE 14-bus system and contains various voltage patterns. Therefore, during each time training, the GCN algorithm needs to tune the parameters and capture the patterns of those node voltage labels from different data graphs without knowing the possible patterns of the testing case. Due to the non-regular form of the data, such a task cannot be directly handled with conventional CNNs, unless hand-crafted features are provided.

C. CASE STUDY 3: A LARGER SYSTEM VOLTAGE PREDICTION

To show the scalability of GNN-based methods on an even larger Power-Electronics-based system, we choose the IEEE 118-bus network as our benchmark as shown in the Fig. 16(a) [108]. The original graph-structured dataset is available from [107]. And in this case, we implement the same pre-processing of the data, and the same GCN algorithm for the voltage fluctuation prediction with considerations of the network topological information (as opposed to conventional methods where this graphical information is normally overlooked and cannot achieve straightforward generalization). Its graph representation with the labeled node is shown in Fig. 16(b). The graph features and detailed hyper parameters can be found in Table 1.

To increase the robustness for such a large network, different from the case 2, the training is done by using each graph data sample with some masked nodes (meaning that some of the nodes' labels are hidden) and the task is to predict the nodes' labels in a completely new graph.

Fig. 17(a)-(d) shows the prediction results with different epoch numbers. It can be observed that the exact same GCN algorithm can predict most of the node voltage labels correctly with a large enough epoch number which shows an impressive scalability of the GNN-based method. Since the dataset gets more complicated, it took more iterations to forward and backpropagation and modify the parameters inside the GCN model to learn the patterns. Fig. 18 shows the loss function value changes with epoch numbers, as well as

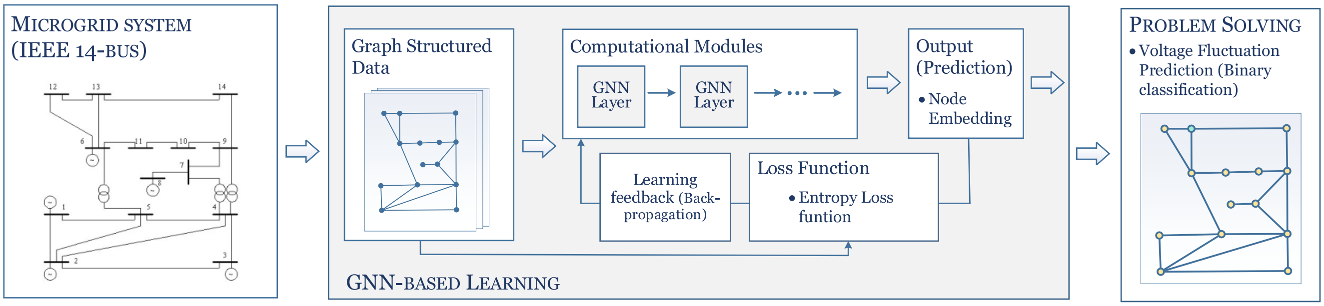


FIGURE 12. The workflow of GNN-based applications for voltage fluctuation prediction for a microgrid/distribution system with IEEE 14-bus network.

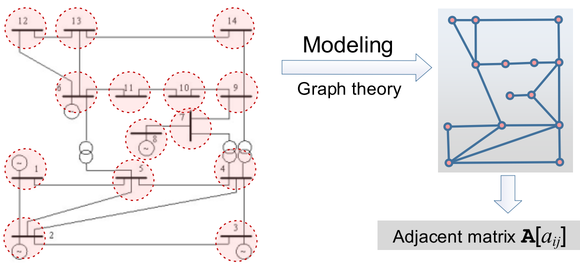


FIGURE 13. Graph modeling of IEEE 14-bus configuration-based microgrid.

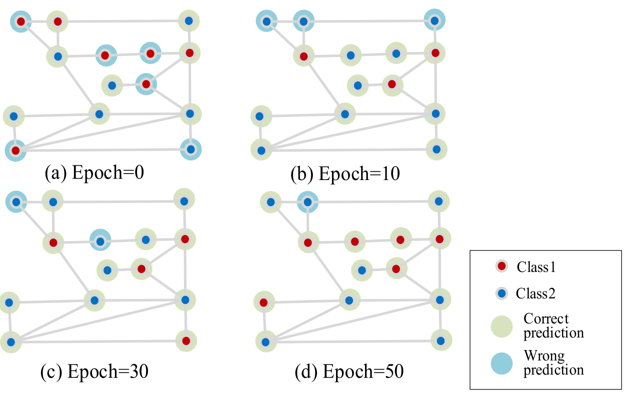


FIGURE 14. The prediction results for voltage fluctuation (Case 1, Microgrid with IEEE 14-BUS): (a) epoch 0, (b) epoch 10, (c) epoch 30, (d) epoch 50.

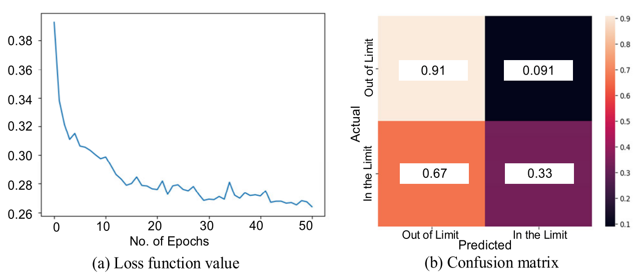


FIGURE 15. The learning results for IEEE 14-bus case. (a) The loss function value changes with epoch numbers. (b) The confusion matrix of the voltage label prediction results.

the confusion matrix of the classification prediction. The final achieved accuracy is around 90.67%. Typically, conventional methods will overlook the topological information of the network and cannot handle such a task well [109].

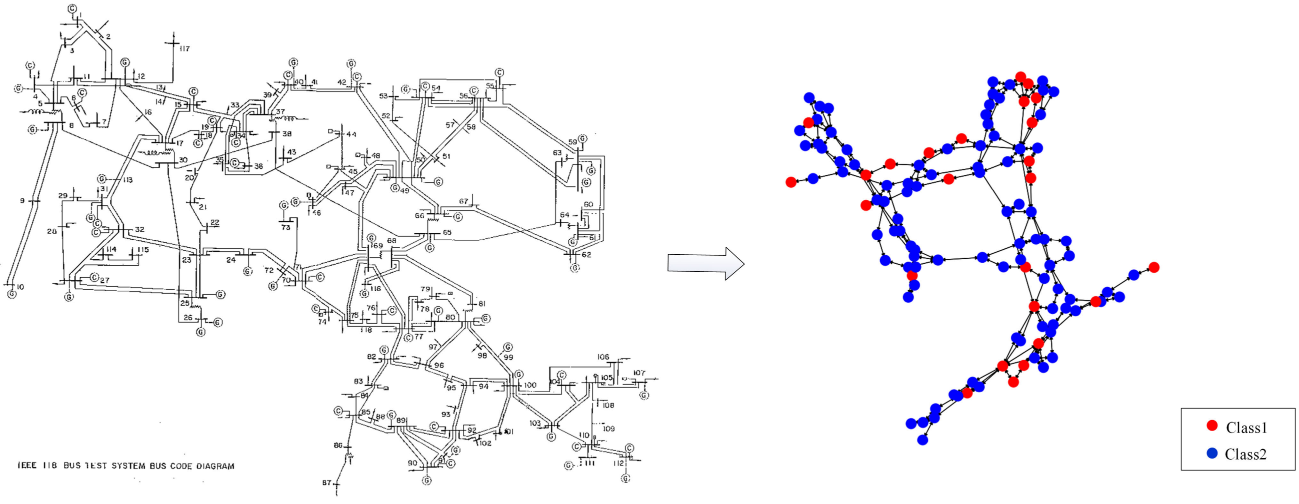
TABLE 1. Graph features and hyper-parameter settings.

Case study	Microgrid with IEEE 14-bus	Microgrid with IEEE 118-bus
Dataset	PGLIB-Case 14 IEEE	PGLIB-Case 118 IEEE
Dataset size (samples)	10000	10000
Graph Type	Undirected graph	Undirected graph
No. Of Nodes/Edges	14 nodes, 20 edges	118 nodes, 186 edges
Graph Diameters	5	14
Max Degree	4	9
Min Degree	1	1
GNN Algorithm	GCN	GCN
No. Of GNN Layers	3	3
Learning Rate	0.01	0.005
Dropout Rate	0.25	0.25
Batch Size	64	64
Epoch No.	~50	~200
Aggregation Function	Mean	Mean
Activation (hidden layer)	ReLU	ReLU
Activation (output layer)	Sigmoid	Sigmoid

The main purpose of the case studies is to demonstrate the opportunity of GNN-based methods in power-electronics-enabled applications; therefore, all algorithms are implemented without further fine-tuning. In practice, the prediction accuracy can be further improved by (1) feeding more data into the model, (2) human-based/auto fine-tuning the parameters of the model, (3) choosing some other advanced GNN-based models. In fact, one major challenge in the implementation of the GNN-based model in practice is the lack of enough open-source datasets embedded with graphical structured data. Parameter tuning and model searching are other challenges that can greatly affect the final performance. There are some promising research works like Graph Neural Architecture Search, which is an automated approach to search for optimal GNN architectures using neural architecture search (NAS) techniques [69].

VI. EMERGING APPLICATIONS OF GNNS BEYOND POWER ELECTRONICS

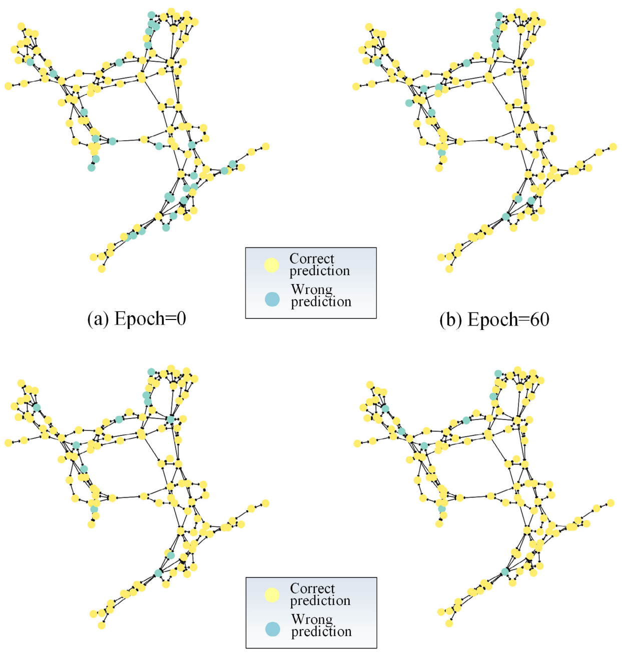
It is well-acknowledged that power electronics is a key technology for enabling the transition to a more sustainable



(a) Diagram of IEEE 118-bus network

(b) The labeled graph of IEEE 118-bus network

FIGURE 16. From diagram to graph: (a) the diagram of IEEE 118-bus network; (b) the labeled graph of the IEEE 118-bus network.



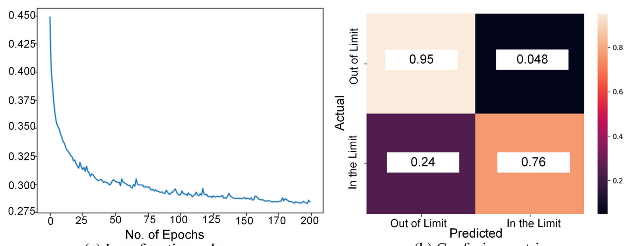
(a) Epoch=0

(b) Epoch=60

(c) Epoch=120

(d) Epoch=200

FIGURE 17. The prediction results for voltage fluctuation of distribution networks based on IEEE 118-bus configuration: (a) epoch 0, (b) epoch 60, (c) epoch 120, (d) epoch 200.



(a) Loss function value

(b) Confusion matrix

FIGURE 18. The learning results for IEEE 14-bus case. (a) The loss function value changes with epoch numbers. (b) The confusion matrix of the voltage label prediction results.

and low-carbon energy system [110], where interdisciplinary fields encompass various aspects such as energy generation, transmission, distribution, storage, and conversion, etc. To envision a broader scope of how GNN can bring benefits for modern power electronics, in this section, the emerging applications of GNNs in energy-related domains are covered in terms of industrial and academic applications.

A. INDUSTRIAL APPLICATIONS

GNNs have emerged as a leading trend in machine learning, offering exceptional capabilities in modeling and analyzing complex relationships and interactions found in graph-structured data. Their widespread adoption can be witnessed in various applications today, including social network analysis, recommendation systems, drug discovery, knowledge graphs, traffic prediction, computer vision, natural language processing, and more. For example, GNNs have been instrumental in ranking thousands of drugs based on their potential efficacy against diseases like SARS-CoV-2, or facilitating the identification of potential treatments for Covid-19 [111]. Furthermore, GNNs are being utilized in materials science research. The Lincoln Laboratory team is developing GNNs capable of learning the relationships between a material's crystalline structure and its properties. This approach accelerates the process of screening materials for specific applications by predicting properties from new crystal structures [41].

In the realm of web mapping services like Google Maps, the accurate estimation of travel time is critical for optimizing commuting experiences. GNNs offer a remarkable opportunity to leverage graphical representations at scale, considering factors such as road conditions and traffic along specific routes. A GNN estimator collaboratively proposed by Google, DeepMind, Facebook AI, and other institutions has been introduced to enhance the precision of estimated travel time predictions [112]. Moreover, to ensure the practicality and scalability of GNNs in growing and global services, a random-walk GCN, i.e., the PinSage was developed in [113], which excels at learning node embeddings within massive web-scale graphs containing billions of objects. Through these representative scenarios, GNNs have revolutionized various fields of study and commercial applications, proving their value in tackling complex problems and leveraging graphical representations effectively. With ongoing research and advancements, GNNs are poised to continue making significant contributions across diverse domains.

B. ACADEMIC APPLICATIONS

GNNs in intelligent transportation systems provide a powerful framework for understanding, modeling, and optimizing transportation systems. By exploiting the inherent graph structure of transportation networks, GNNs can capture complex relationships and dynamics, leading to improved traffic management, enhanced user experience, and more efficient and sustainable transportation systems [114], [115], GNNs are well-suited for modeling and analyzing the complex relationships present in wireless networks for tasks such as link prediction, node classification, network optimization, and resource allocation [53], [54], [116], [117], [118]. The Internet of Things (IoT) connects physical devices over wireless networks, and device-to-device (D2D) communication is a promising technology for IoT [119].

As chip design becomes increasingly complex, traditional EDA approaches are struggling to cope with the challenges of very large-scale integration (VLSI). While EDA tools offer scalability, reliability, and time-to-market advantages, they are often computationally demanding and do not always guarantee optimal solutions. To address these limitations, researchers have turned to GNNs as a promising new approach for solving EDA problems directly using graph structures for circuits, intermediate Register Transfer Levels, and netlists [120], [121], [122].

For power system problems recorded as graph-structured data with nodes and edges, GNNs can effectively capture the complex dependencies and interactions between different components in a power system, enabling a range of applications, such as optimal power generation and flow, load forecasting, fault detection and diagnosis, etc. [123]. With GNNs, the features of the power system network can be extracted and utilized to improve overall system performance [72]. GNNs can be applied to solar and wind power prediction tasks by leveraging the spatial and temporal dependencies present in weather data and power generation patterns [124], [125], [126], [127].

Other applications of GNNs can be found in the field of smart grids, e.g., fault detection and identification in low-voltage DC microgrids with meshed configurations [73], fault detection and classification problems in shipboard networks [128].

Based on the graph structure of interconnected components or sensors in a system, the fault detection tasks can be completed by the GNNs-based method [129].

VII. OUTLOOKS

Accompanied by great potentials, bringing GNNs into power electronics research also brings some novel challenges:

Domain knowledge. Power Electronics as a discipline dealing with electrical power handling has a very long history [130], where a large portion of rich legacy of trailblazing inventions is still in the non-digital form, or even hidden in the innumerable literature. This calls for a great need to organically re-organize and systematically digitalize/modernize this valuable knowledge in Power Electronics in the context of contemporary AI technology, like GNNs.

Power Electronics datasets. There is a great absence of GNN-compatible datasets in Power Electronics field and thus, calls for the non-Euclidean data construction in the near future. The datasets can be generated through simulation software (MATLAB, PLEXIM, ANSYS, etc.), hardware-in-the-loop platforms and experimental validations, where their comparative study is also a potential direction for future research. In particular, by leveraging the digital models with Digital Twin-enabled technologies, datasets with different scales and timespans can be synthesized, providing holistic views of the whole system [131].

Graph formulation. Graph-theory-based modeling provides a promising way of formulating power electronics problems and mathematically characterizing the graph features, which is still under development. Problems like dimension reduction, and non-structured data formulation, are still quite challenging and need further investigations.

Computation theory. The efficiency of running an algorithm like GNN for specific tasks can be denoted by computation theory notions and in return, it can help design a better algorithm. However, such a formulization of the power electronics problems is still missing, and several critical problems remain open, such as what are NP-hard (or NP-complete) problems in power electronics?

Knowledge-informed algorithm design. Rule-based operation methods have received major attention in the Power Electronics community. However, how to embed such prior knowledge into GNNs for power electronics problems is still unexplored.

Real-time implementation. Given the sophisticated nature of GNNs, finding the solutions to reduce computation burden to enable real-time learning would be quite challenging, but valuable in practice.

Hyper-parameter tuning. As mentioned before, the design space of GNNs could be extremely huge and poses great challenge to fine-tuning the hyper-parameters.

Goal-directed GNNs. The real-world power electronics problems normally come with practical constraints, and thus, result in great challenges to cope with the learning process of GNNs.

Trustworthy GNNs. Like other deep learning methods, featuring the ''black box'' nature, GNNs may invoke the questioning of the reliability of the results/models/learning outcomes. This is especially important since nowadays, power electronics devices are widely implemented in critical applications. Therefore, it will be essential to develop trustworthy GNNs, with the recent progress of the explainability and interpretability of AI [132].

VIII. CONCLUSION

The research paradigm of Power Electronics is experiencing seminal transience from the classical William E. Newell's triangle (Electronics, Power, and Control) to a deeper multidisciplinary driven, higher requirement motivated, larger research volume anticipated future. We believe combining graph theory knowledge with the leading deep learning techniques, i.e., GNNs can open new opportunities covering major research aspects in our fields.

To support our envisions, this paper is prepared by covering comprehensive overviews with the most recent research works and surveys and in-depth discussions on this rapidly developing topic. In details:

- We reviewed the comprehensive introduction of GNNs' basics to lay the foundations for the following discussions.
- For the first time, the existing GNN-based methods in power electronics are reviewed. To go beyond the very limited existing GNN research works, extended discussions on how we can learn from GNN-aided circuit design for power electronics research is also provided.
- We also conducted several GNN-based case studies covering converter-level to converter-system-level applications in power electronics and provided our outlooks on GNNs in power electronics with further discussions on their unique merits, emerging potentials.
- We provided a holistic and timely survey of the most recent and successful applications of GNNs in various applications, especially highlighting the emerging GNNs' benefits in energy-related fields: intelligent transportation systems, communication systems, power systems, smart grids, EDA, fault detection, etc.
- Several novel challenges are summarized, e.g., digitalization of domain knowledge in power electronics, graph datasets establish, mathematical formulation, reliable and responsible implementations, etc.

We hope this review paper can serve as a starting point, as well as a timely and handy summary for engineers/students who want to enter the field and promote the innovation of power-electronics-enabled applications.

APPENDIX

A. GNN-BASED ALGORITHMS

TABLE 2. Some GNN-based algorithms for different applications.

GNN category	Tasks	Domain	Ref.
MULTIMODAL GNN	Drug rank and identification	Mole, drug discovery and bioinformatics	[111]
METAGRADIENTS TRAINING-BASED GNN	Estimated travel time prediction	Intelligent transportation system	[112]
RANDOM-WALK GCN (PINSAGE)	Learning massive web-scale graphs	Recommender system	[113]
GCN	Molecular structure prediction	Molecular, drug discovery and bioinformatics	[133]
WIDE AND DEEP GNN (WD-GNN)	Distributed online learning mechanisms and non-convex problems handling.	Distributed GNNs architectures	[134]
GRAPH-NAS	Discover architectures well-suited for specific graph-based tasks.	GNN model search	[135]
SPATIAL-TEMPORAL GNN (ST-GNN)	Time series traffic forecasting applications	Intelligent transportation systems (ITS)	[54]
SUPERVISED GNN	D2D resource allocation	IoT networks	[119]
SPATIAL-TEMPORAL GNN	Solar generation forecasting	Generation prediction of solar and wind resource	[124]
GCNS AND LONG SHORT-TERM MEMORY (LSTM)	Short-term wind power forecasting	Generation prediction of solar and wind resource	[126]
DISTANCE-BASED AND MODEL-BASED GCN	Transformer fault diagnosis	Detection of fault attack	[136]

B. GRAPH-STRUCTURED DATASETS

TABLE 3. Some open-source datasets for learning on graphs.

Datasets	Features and applications	Ref.
NETWORK REPOSITORY	The largest network repository with thousands of donations in 30+ domains (from biological to social network data).	[137]
TUDATASETS	A collection of benchmark datasets for graph classification and regression.	[138]
OPEN GRAPH BENCHMARK	A collection of realistic, large-scale, and diverse benchmark datasets for machine learning on graphs.	[139]
OPFLEARNDATA	Dataset for Learning AC Optimal Power Flow	[107]
UCI ML DATA REPOSITORY	A collection of databases, domain theories, and data generators that are used by the machine learning community for the empirical analysis of machine learning algorithms.	[140]
TORCH_GEOMETRIC.DATASETS	A collection of datasets covering homogeneous datasets, heterogeneous datasets, synthetic datasets, graph generators, motif generators	[141]
GRAPH LEARNING INDEXER	A contributor-friendly and metadata-rich platform for various graph learning benchmarks.	[142]
BENCHMARKING GRAPH NEURAL NETWORKS	A diverse collection of mathematical and real-world graphs within an open-source, easy-to-use and reproducible code infrastructure.	[143]

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