IRGNN: A Graph-based Framework Integrating Numerical Solution and Point Cloud for Static IR Drop Prediction

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***Abstract*—With the continued scaling of integrated circuits (ICs), IR drop analysis for on-chip power grids (PGs) is crucial but increasingly computationally demanding. Traditional numerical methods deliver high accuracy but are prohibitively time-intensive, while various machine learning (ML) methods have been introduced to alleviate these computational burdens. However, most CNN-based methods ignore the fine structure and topological information of PGs, and face interpretability or scalability issues. In this work, we propose a novel graph-based framework, IRGNN, leveraging the PG topology with the integration of numerical solutions and point clouds. Our framework applies a numerical solver, AMG-PCG, to generate rough numerical solutions as a reliable interpretability foundation for ML. Then, to capture PG topology, we regard nodes of PG as point clouds and extract point cloud features, and we introduce a novel graph structure, IRGraph. Furthermore, a novel graph-based model IRGNN is designed, incorporating a designed neighbor distance attention (NDA) layer for distance-aware PG features aggregation and graph transformer (GT) layer to capture global information. It should be noted that our framework can analyze the IR drop of each node in PG, which CNN-based methods cannot do. Experimental evaluations demonstrate that our framework achieves significantly higher accuracy than previous CNN-based approaches and numerical solvers while substantially reducing computation time.**

I. Introduction

IR drop occurs as current flows through the on-chip PG from the power pad to each power-consuming cell [1] and affects the quality of power supply [2]. Accurate IR drop analysis is crucial to ensure worst-case IR drop values remain within specified limits, thereby preventing adverse impacts on circuit performance and stability. With the increase in chip integration density, traditional analysis methods become computation-intensive and consume substantial time and memory resources when solving large-scale sparse linear equations [3]. Various numerical methods [4]–[7] are designed to mitigate the computational burden with nearly golden performance. These numerical methods provide almost golden results and are applied to contemporary electronic design automation (EDA) tools. However, numerical methods remain time-consuming and memory-intensive for early and large designs on an industrial scale, limiting their benefits.

In recent years, convolutional neural network (CNN)-based machine learning (ML) methods have been proposed as promising alternatives for accelerating IR drop analysis. These methods regard IR drop prediction as an image regression process. IREDGe [8] presents a designed encoder-decoder architecture with convolution layers for pixel-level prediction. MAVIREC [9] uses a 3D U-Net model for IR drop prediction emphasizing dynamic IR drop problems and is also applicable to static IR drop analysis. PGAU [10] incorporates attention mechanisms to enhance IR drop prediction by focusing on hotspot regions. MAUnet [11] integrates multi-scale convolutional blocks, attention mechanisms, and U-Net architecture to optimize IR drop prediction performance.

Although these methods achieve compelling performance, their notable drawbacks cannot be neglected. Traditional numerical methods [4]–[7] are able to achieve accurate and detailed solutions, obtaining the IR drop at each node in the PG. However, these methods are highly time-consuming. ML-based methods [8]–[11], represented by CNNs, are fast but lack sufficient granularity and can only provide pixel-level predictions, which cannot accurately analyze the IR drop on each node. This limitation makes it challenging to model PG for fine-grained analysis and optimization accurately.

Additionally, due to the lack of transparency in ML and the scarcity of real measured IR drop values at the nodes, ML-based methods [8]–[11] struggle with issues related to model interpretability and generalizability. As a result, these models exhibit unstable performance when faced with different design scenarios and fail to adapt to complex and dynamic design environments. Thus, it is worth exploring whether numerical methods can be combined with ML-based methods for a better trade-off in speed, accuracy, interpretability, and scalability. Numerical methods [4]–[7] solve large-scale linear systems iteratively, where more iterations yield greater accuracy but require longer runtime. By integrating ML, we can perform fewer iterations for a rough solution and use ML to refine it. This fusion enables a better understanding of complex physical or geometric systems, offering more fine-grained and efficient modeling for node-level IR drops.

To address the aforementioned issues, we propose a novel graph-based framework, IRGNN, with the integration of numerical solutions and point clouds to solve static IR drop analysis. Currently, GNNs have been widely applied to capture circuit topology and address challenges in EDA, demonstrating good performance and generalizability [12]–[17]. For higher generalization and granularity, we utilize graph-based methods to achieve full-chip IR drop analysis. To increase the interpretability and reliability of ML methods, we use the AMG-PCG solver to obtain rough numerical solutions. Furthermore, to better utilize the PG topology, we regard the nodes as point cloud nodes and extract features to display the relationships between nodes. To better capture the multi-

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dimensional PG topology, we model PG as a novel graph structure, IRGraph, integrating numerical solutions and point cloud features representing the PG topology comprehensively. In order to leverage the information provided by IRGraph, we propose a novel graph-based network, IRGNN, specializing designed for static IR drop prediction, combining neighbor and global information. The designed NDA layer aggregates information of neighbor nodes and wires with specialized distance weight, while GT layer focuses on the global information. The main contributions are:

- We present IRGNN, a novel and comprehensive graph-based framework tailored for node-level static IR drop analysis. Incorporating numerical solutions and point clouds, our framework achieves a unique balance between computational accuracy and efficiency, making it highly scalable for complex PG networks.
- We design IRGraph, an innovative graph representation that integrates numerical solutions and point cloud features. This structure effectively encodes the PG topology while enriching information at each node.
- We introduce a specialized graph-based network, integrating the designed NDA layer with distance-aware weight and the GT layer, to simultaneously capture local and global features, thereby improving the performance.

II. Preliminaries

A. Power Grid and IR Drop Analysis

The design of PGs requires thorough evaluation and optimization to ensure reliable performance while minimizing resource consumption. Generally, PG is a complex system with numerous nodes and interconnections, while the current flow is the key to this system. Therefore, consideration of PG topology is essential. As shown in Fig. 1, the intricate structure of PG can be effectively captured by modeling it as a graph, where nodes represent physical nodes (e.g., power sources, sinks, and interconnect junctions), and edges denote the electrical connections between them. This graph-based abstraction allows for a detailed analysis of the PG topology, facilitating the study of current distribution, voltage drops, and potential bottlenecks in the network.

Parasitic effects in PGs lead to IR drops as current flows from power pads to cells, potentially impairing chip performance and even directly affecting its functionality. Consequently, precise IR drop analysis is crucial for evaluating power delivery performance. Traditional IR drop analysis relies on solving linear equations governed by Kirchhoff's Current Law, formulated as $\boldsymbol{GV} = \boldsymbol{I}$, where $\boldsymbol{G}$ is the conductance matrix of PG, $\boldsymbol{I}$ is the current vector, and $\boldsymbol{V}$ is the unknown voltage vector of nodes. With the number of nodes in the PG increasing exponentially, it presents significant challenges to the efficiency of conventional techniques and limits their applicability in large-scale problems, thereby highlighting the need for ML approaches.

B. Graph Neural Network

Graph neural network (GNN) is specifically designed for tasks on graph-structured data, like node classification and graph

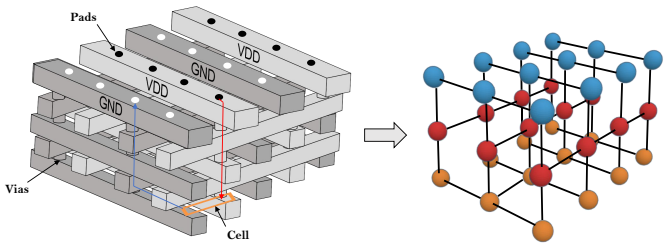

Fig. 1 The illustration of topological structure of PG.

regression, by modeling graph structures and aggregating node information via message-passing. Recently, considering the topology of the circuit, many graph-based approaches have emerged in the field of EDA. The framework in [12] leverages graph attention network (GAT) to model node and edge information in interconnect circuits jointly. GCN [13] effectively predicts chip temperature distribution by modeling thermal resistance networks under varying operating conditions. DeepGate [14] and PolarGate [15] apply GNNs to represent logic gates and Boolean networks, enhancing circuit analysis and design efficiency. EdgeGAT [16] and GNNTrans [17] improve the accuracy and speed of timing estimation from graph-based analysis using GNN. The adaptability of GNNs in modeling relationships among diverse design objectives enhances representation transferability, offering significant utility in EDA through improved task generalization.

C. Point Cloud

In this work, we employ point cloud methodologies to comprehensively model the complex topology in PGs and to improve the performance of full-chip IR drop prediction. Point cloud is a data format that represents 3D shapes or structures using a large number of spatial points, allowing for a better representation of complex three-dimensional layouts. Point cloud perception methods are divided into voxel-based and point-based. Voxel-based method discretizes continuous three-dimensional space into a finite number of voxels, making data processing and analysis simpler and more intuitive [18]. However, this method often resulted in the loss of multi-dimensional geometric details. In contrast, the point-based approach processes raw point cloud data directly, preserving its structural integrity and enabling end-to-end training without transformation requirements. Zou et al. [19] treat circuit layouts as point clouds, applying transformer-based techniques to enhance feature extraction, yielding strong results in congestion prediction and design rule verification.

D. Problem Formulation

This work aims to analyze the static IR drop at each node in PGs and get better performance. We represent each node in the PG as a vertex in a directed graph, facilitating the representation and prediction of IR drop at every node, including both cell-level and internal nodes. The edges of the graph are modeled to reflect the topological connections between nodes in the PG, whose direction corresponds to the direction of the current in the interconnecting wires. Therefore, the PG is treated as a directed graph, denoted as $G = (V, E)$, where $V = \{v_1, \ldots, v_n\}$ represents the set of n vertices

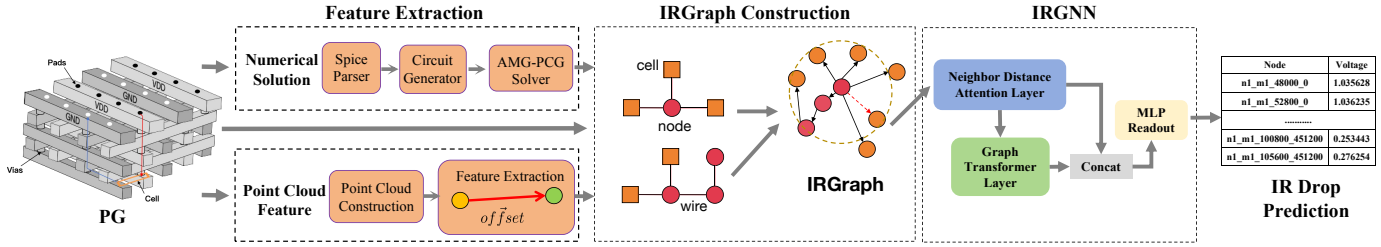

Fig. 2 Illustration of IRGNN framework for static IR drop prediction.

corresponding to both internal nodes and cells in the PG, and $E \subset V \times V$ represents the set of directed edges corresponding to the current-carrying wires. Our object is to design an algorithm F^* to intake the PG-based graph G to give the closest node-level IR drop prediction F, formulated as:

$$F^* = \arg\min_{F} \text{Loss}\left(F\left(G = (V, E)\right), y\right). \tag{1}$$

III. IRGNN Framework

A. Overall Flow

We focus on developing our graph-based framework, IRGNN, specializing in node-level static IR drop prediction, as shown in Fig. 2. The numerical solution provides a strong basis for understanding complex PG systems, while its integration with efficiency-promising GNN contributes to the development of more accurate and efficient analysis. In our framework, an efficient AMG-PCG solver is applied to obtain rough numerical solutions quickly and reliably. Besides, to better capture the extremely high geometric position characteristics of PG nodes, we model PG nodes as point cloud nodes with 3D coordinates and features. Then, we extract point cloud features to represent the relative positional relationships and current flow directions between nodes. Subsequently, to better utilize the topological information of PG, we propose a novel graph structure, IRGraph, with feature extraction that comprehensively represents the fine-grained PG structure. Finally, we introduce a new network, IRGNN, incorporating an NDA layer that aggregates information from nodes and edges using a distance attention mechanism, and a GT layer to capture both local neighbor and global information. More details of several key designs of our framework are elaborated in the following sub-sections.

B. Numerical Solution using AMG-PCG

To address the system matrix presented in Section II-A, our goal is to provide as accurate an initial solution as possible in a shorter runtime, laying the foundation for understanding the PG system and subsequent ML phase. The numerical solution, when utilized as a feature, enhances the interpretability of the model and increases the reliability of ML methods, which are often considered black-box approaches. In the numerical solution phase, the PG spice file is loaded with preprocessing involving a SPICE parser and a circuit generator. To achieve rapid and reliable numerical solutions, the algebraic multigrid preconditioned conjugate gradient (AMG-PCG) method proposed in PowerRush [6] is applied.

In AMG-PCG, the conjugate gradient (CG) method is enhanced by using an algebraic multigrid (AMG) preconditioner to improve convergence efficiency. The process begins with the standard CG iteration on the system $\boldsymbol{GV} = \boldsymbol{I}$, where AMG acts as a preconditioner to minimize the high-frequency error components, thus accelerating the solution process. Specifically, AMG constructs a hierarchy of coarser grids with restriction $\boldsymbol{R}^{(l)}$ and prolongation $\boldsymbol{P}^{(l)}$ operators for each level l. The preconditioned system becomes $\boldsymbol{M^{-1}GV} = \boldsymbol{M^{-1}b}$, where $\boldsymbol{M^{-1}}$ represents the AMG preconditioner applied to $\boldsymbol{G}$. By iterating through CG with AMG, the method progressively updates $\boldsymbol{V}$ while minimizing the residual $\boldsymbol{r} = \boldsymbol{I} - \boldsymbol{GV}$ until convergence, getting an accurate final solution efficiently.

Typically, numerical methods require a significant number of iterations to achieve an accurate solution. In our approach, we adopt a reduced iteration strategy to quickly obtain an approximate solution, which serves as a foundational feature for nodes in Graph-based models, as detailed in Section III-D. Despite this solution is not sufficiently accurate, it effectively provides rough IR drop values at each node, thereby greatly benefiting ML in understanding and learning PG systems.

C. Point Cloud Feature

The topology of the PG is just as crucial as the widely recognized and used circuit features, as it governs the path for power transmission directly. However, effectively utilizing the PG topology requires solving challenges related to the relative position of nodes in the PG metal layer and the relative position between nodes. At present, point cloud has proven to be highly effective for 3D object detection. Thus, we treat PG nodes as point cloud nodes, with each node having two attributes: 3D coordinates and features. The 3D coordinates of the nodes in the PG are determined based on the position of the metal layers and the metal rails to which the nodes belong. Specifically, the vertical position z of each node is derived from its corresponding metal layer, while the plane coordinates (x, y) are based on the node's location within the respective metal rail. Since the vertical distance between layers is not proportional to the overall size of PG, we standardize z by normalizing it to the average distance between the rails in the bottom-most layer of the PG. This normalization ensures that the plane coordinates (x, y) remain consistent with the original distribution in the PG, preserving the spatial relationships in the plane while adjusting for the vertical scaling.

Both the wire connections between nodes and the current flow in PG can indirectly affect the IR drop loss, which is critical for IR drop analysis. PointNet++ [20] calculates the distance and positional characteristics between each point and the central point used for feature extraction and weighting

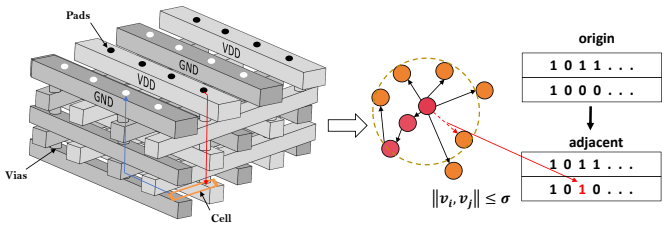

Fig. 3 IRGraph construction with distance-aware edge.

during convolution operations. Inspired by PointNet++ [20], we introduce an offset vector to describe the positional relationship between nodes and the direction of current flows depending on the nodes' net. For example, the offset between node $v_1 = (x_1, y_1, z_1)$ on the GND net and $v_2 = (x_2, y_2, z_2)$ on the VDD net can be formulated as $offset = (x_2 - x_1, y_2 - y_1, z_2 - z_1)$. With the offset vector, it is possible to describe both the relative positions between nodes in PG and the directivity of the current flow.

D. IRGraph Construction

Existing methods predominantly rely on 2D feature maps derived from current patterns, such as total power or frequency, for IR drop prediction. However, these approaches are limited in that they typically focus on single-layer, grid-based representations, which fail to capture the node-level details of the PG. Moreover, these 2D maps are unable to represent the complex, multidimensional interactions between cells and wires, such as the flow of current and the physical topology of the PG. To overcome these limitations, we model the PG as a graph and propose a novel graph structure, IRGraph, incorporating both the PG topology and current flow information. We enhance the representation of the PG characteristics by extracting additional PG-based features, combining the numerical solution and point cloud data. The IRGraph is constructed depending on the original cell-PG connection and especially virtual edges for local consistency. IRGraph can not only represent the IR drop of the lowest cell granularity but also predict the IR drop of the nodes inside PG, which is impossible to achieve with the previous CNN-based method.

1) Graph Construction

An unweighted directed graph $G = (V, E)$ is constructed to model the practical non-Euclidean topology of the PG network, as shown in Fig. 3. Here, V represents all nodes within the PG network, encompassing both circuit cells and internal nodes. The formation of edges is performed in two stages. First, the original PG connections are treated as edges in the IRGraph to capture voltage propagation through actual current flows. Then, a distance-aware edge construction is applied, incorporating edges based on spatial proximity (Euclidean distance $\|v_i, v_j\|_2 \leq \delta$ for nodes v_i, v_j). These virtual edges facilitate information propagation within the GNN. The extracted features from this process are assigned as features for both V's and E's, detailed in the next part.

2) Feature Extraction

To enhance the accuracy and convergence, we extract more node-level features to improve the representation of nodes.

- **The current** for each node is calculated by the current source and Kirchhoff's current law and voltage law together with the resistance of the wire.
- **The effective distance**, defined as the reciprocal of the sum of the Euclidean distances to all voltage sources, quantifies the node's proximity to these sources.
- **The shortest path resistance** computes the total resistance using the shortest path from node to power sources.
- **The net value** indicates that the node belongs to the VDD or GND network, represented by the binary value 0 or 1.
- **The numerical solution** detailed in Section III-B.
- **The point cloud position** is the 3D coordinate of nodes.

Metal wires in PG also play a crucial role in power delivery since they carry the current flow. To represent the effect of wires in the topologies of PG and current flow, we extract two wire-based features for each edge in IRGraph:

- **The wire resisitance**, extracted from spice file.
- **The wire offset**, calculated as Section III-C.

E. IRGNN Model

In our work, we design a novel graph neural network, IRGNN, specializing in static IR drop prediction, which is a node regression task. The IRGraph is utilized as the input of IRGNN, containing features both on nodes and edges. In IRGNN, to take advantage of both node and edge features, we design an NDA layer, as the node attention aggregator in NDA processes the neighbor node and edge representations simultaneously with attention weight. According to the principle of local consistency, we incorporate the attention weight in this layer based on the neighbor distance between nodes. Then, the global representation of PG is captured by the GT layer, allowing the contact of each node. Finally, the IRGNN representation is exported through an MLP readout.

1) Neighbor Distance Attention Layer

Traditional GAT is designed primarily for node classification tasks and has achieved significant success. We design the NDA layer, displayed in Fig. 4, to adapt it to IR drop prediction. This layer accepts the transformed node and edge representations generated through the linear transformer as inputs, $\{\boldsymbol{v}_i^l, \forall i \in N_v\}$ and $\{\boldsymbol{e}_{ij}^l, \forall (i,j) \in N_e\}$, and produces attention based aggregated node representations $\{\boldsymbol{v}_i^{l+1}, \forall i \in N_v\}$, where l is number of layers of network.

To utilize features from nodes and edges, we execute a convolution operation to aggregate information from a node's neighboring nodes and connected edge data in the update process of the node. In this way, the information provided by the topology of the PG system and current load patterns is unified, enabling a cohesive representation that leverages both spatial and geometric insights. The node attention coefficient $\boldsymbol{h}_{ij}^l$ indicates the importance of neighborhood information to the target node and is computed as:

$$\boldsymbol{h}_{ij}^l = \left(\boldsymbol{a}^l\right)^\top \left[\boldsymbol{v}_i^l \| \boldsymbol{e}_{ij}^l \| \boldsymbol{v}_j^l\right] \boldsymbol{d}_{ij}, \tag{2}$$

where i denotes the target node, and j is its neighboring node within the neighborhood set N_i. The attention mechanism, represented by the shared vector $\boldsymbol{a}$, allows for consistent attention across all nodes. To capture edge directionality, we

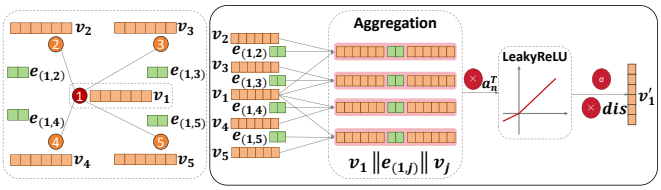

Fig. 4 The architecture of our designed NDA layer.

introduce $\boldsymbol{d}_{ij}$, where a value of 1 indicates the direction from node i to j, and -1 indicates the opposite direction.

The cell connection edges cause complex interactive relationships owning to discriminative node distances. To adaptively rescale and aggregate more significant information from complex edge connections of different-distance regions, the distance attention weight is designed as:

$$\boldsymbol{dis}_{ij} = \left(\frac{\|\boldsymbol{v}_i, \boldsymbol{v}_j\|_2}{h} \right)^{-\beta}, \tag{3}$$

where h denotes the distance threshold, and β controls the decay rate. $\|\boldsymbol{v}_i, \boldsymbol{v}_j\|_2$ is their Euclidean distance.

To make coefficients easily comparable across different nodes, all node attention coefficients of node i are normalized using the softmax function with distance attention weight, like:

$$\alpha_{ij}^l = \frac{\exp\left(\text{LeakyReLU}\left(\boldsymbol{h}_{ij}^l\right)\right)}{\sum_{k \in N_i} \exp\left(\text{LeakyReLU}\left(\boldsymbol{h}_{ik}^l\right)\right)} \boldsymbol{dis}_{ij}. \tag{4}$$

With the activate function σ, the node representation is updated with neighbor distance and other features' aggregation:

$$\boldsymbol{v}_i^{l+1} = \sigma\left(\sum_{j \in N_i} \alpha_{ij}^l \boldsymbol{v}_j^l \right), \quad \forall i \in N_v. \tag{5}$$

2) Graph Transformer Layer

Different from the CNN-based method, which focuses on exploring the local information of IR drop, the GNN-based method uses the way of message passing, which leads to too much local information and ignores the global information easily. In IRGNN, we leverage the GT layer [21] to capture global information across the graph structure, which is essential for improving the performance in IR drop prediction. The GT layer allows each node to attend to all other nodes in the graph, enabling global interactions without the limitation of local neighborhoods. Through a self-attention mechanism, each node's representation is updated by aggregating features from all nodes, weighted by learned relevance scores, which embeds global context into individual node features. This global attention mechanism effectively captures complex dependencies between distant nodes, leading to a more holistic node representation. Additionally, the GT layer incorporates position encodings to enhance focus on critical regions, injecting more structural information into the model.

IV. Evaluation

A. Experimental Settings

Baselines. IRGNN is evaluated against competitive ML-based IR drop prediction models, including IREDGe [8] and MAUnet [11]. Furthermore, it is also compared to the winner of the ICCAD 2023 contest [22].

Datasets. The ICCAD2023 [22] dataset focuses on static IR drop prediction, featuring 20 real designs and 100 synthetic designs generated based on [23], closely resembling realistic PGs. To increase dataset diversity and assess model generalization, three open-source benchmarks [23] are utilized: Nangate, ASAP, and Skywater, comprising 1000, 1000, and 418 designs, respectively. Experiments with baselines are conducted on ICCAD2023 and Nangate to validate the framework's effectiveness. The trainset and testset are evenly divided according to the number of nodes in PGs, to verify model's generality and improve rationality of experiments. Additionally, large-scale datasets are employed to assess performance scalability. Three benchmarks are used during pretraining, and fine-tuning is performed on fake and real designs from the ICCAD2023.

Metrics. Following the contest [22], the mean absolute error (MAE), F1 score, Pearson correlation coefficient (CC), and runtime are selected as the evaluation metrics. The MAE is the average absolute difference between a prediction and the ground truth. The CC measures the linear correlation between predicted values and ground truth values. The F1 score is a binary classification metric utilized to assess the prediction performance of hotspot regions. Given that designers are particularly concerned with the worst-case IR drop, minimizing modeling maximum error is of utmost importance. The Maximum IR Drop Error (MIRDE) metric is introduced.

B. Main Results

To compare with the ML-based baselines, our experiments first compare the result on the bottom layer, which mainly includes the nodes of the working cells and is most concerned. Considering former CNN-based methods can only predict roughly at the pixel level, our graph-based method can analyze the IR drop of each node in PG. Therefore, the golden result is obtained for all nodes, and we make a comparison with a famous numerical simulator PowerRush [6], including the analysis error and efficiency of all nodes in PGs.

Comparison with ML-based Method. Like the method of dealing with small trainsets problem by pretraining with public training sets which have higher uncertainty, IRGNN is trained first with fake designs, which may not be clean in some maps to get general representations of IR drop. Then, half of the real designs are used to fine-tune. TABLE I shows the IR drop analysis results of different methods. Considering the newly proposed competitive MAUnet [11], our approach achieves better performance on each dataset with no significant time cost increase. IRGNN still outperforms all baselines in MIRDE, representing more accuracy in the worst-case region. Our model is trained from the foundation of numerical solutions, and the topology information utilized by NDA increases the interpretability and robustness of the model.

Considering the performance potential of large-scale datasets, another experiment is conducted. In the pretraining phase, three open-source benchmarks aforementioned are utilized, while the fake designs and real designs in the same setting of the last ICCAD2023 experiment are fine-tuned relatively step by step. The results are summarized in TABLE II.

TABLE I Comparison with ML-based Methods. The Unit of MAE and MIRDE is $\times 10^{-4}V$.

Methods	ICCAD2023 dataset				Nangate dataset			
	MAE↓	F1↑	CC↑	MIRDE↓	MAE↓	F1↑	CC↑	MIRDE↓
IREDGe [8]	3.54	0.48	0.86	6.42	0.83	0.67	0.89	2.26
MAUnet [11]	1.12	0.60	0.95	4.35	0.43	0.77	0.99	1.17
Contest Winner [22]	1.15	0.58	0.94	4.37	0.62	0.75	0.96	1.15
IRGNN (Ours)	**0.83**	**0.72**	**0.97**	**2.89**	**0.26**	**0.80**	**0.99**	**0.96**

TABLE II Results of Large-scale Dataset.

Methods	MAE↓	F1↑	CC↑	MIRDE↓
IREDGe [8]	2.79	0.53	0.89	5.58
MAUnet [11]	0.75	0.71	0.97	3.05
Contest Winner [22]	0.89	0.67	0.97	3.44
IRGNN (Ours)	**0.46**	**0.77**	**0.98**	**2.37**

TABLE III Results of Evaluation on every Node in PG.

Methods	MAE↓	F1↑	CC↑	MIRDE↓	Runtime↓
PowerRush [6]	0.71	0.58	0.94	2.89	30.52
IRGNN (Ours)	**0.56**	**0.75**	**0.96**	**2.83**	**6.64**

IRGNN achieves better performance with the improvement of 38.67% on MAE, 8.45% on F1, 1.03% on CC, and 22.29% on MIRDE with no significant time cost increase.

Comparison with Numerical Method. The CNN-based method has the limitation of using pixel as coarse-grained prediction. However, IRGNN breaks this limitation with every node's prediction. To evaluate the IRGNN's ability on node-level prediction, the comparison with PowerRush [6] is conducted and results are shown in TABLE III. Notably, IRGNN surpasses PowerRush in all metrics, with significantly less time cost, indicating great performance on nodes of both the bottom layer and inner layers. From the visual comparison in Fig. 5, it is clear that IRGNN can achieve better MAE at a speed that cannot be matched by PowerRush. Thanks to the fusion of numerical and GNN methods, IRGNN achieves a better trade-off between accuracy and efficiency.

C. Transfer Learning

The transferability is of great significance in IR drop analysis since the amount of dataset is limited and the style of design is diverse. In order to evaluate the transferability and generalizability of our proposed method model, the experiment uses the Nangate as a training set and regards the real designs from ICCAD2023 as test samples. From the results in TABLE IV, our method is much better in generalization ability with better prediction on the corresponding IR drop in the face of very different and never-seen PGs. The numerical solution provides a reliable foundation of IR drop distribution and the ability to deal with topological neighbor information of NDA increases the interpretability of the model's decisions, allowing it to perform robustly under varying conditions.

D. Ablation Study

Ablation experiments are conducted to evaluate the impact of various techniques in our IRGNN. Fig. 6 shows the improved results with a certain technique. The results demonstrate that the numerical solution (Num. Solu.) significantly reduces

TABLE IV Transfer Results on ICCAD2023 Dataset.

Method	MAE↓	F1↑	CC↑	MIRDE↓
IREDGe [8]	4.88	0.39	0.71	8.01
MAUnet [11]	2.07	0.55	0.84	4.78
Contest Winner [22]	1.95	0.55	0.83	4.92
IRGNN (ours)	**1.68**	**0.62**	**0.88**	**3.61**

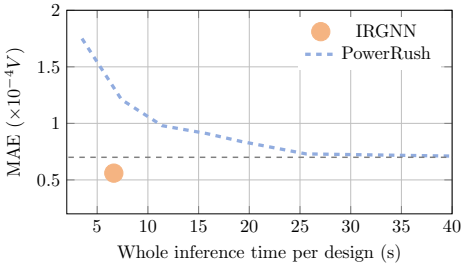

Fig. 5 Comparison of IRGNN and PowerRush [6].

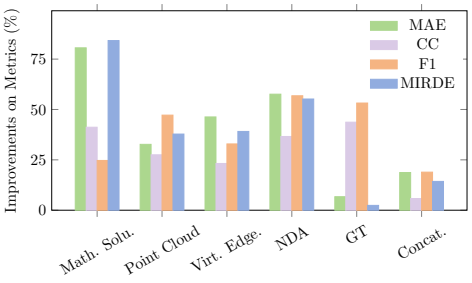

Fig. 6 Results of Ablation Study.

MAE and MIRDE, likely due to its precise initial point for learning. Additionally, our point cloud features also improve performance with better F1. Both the NDA and GT layers also contribute to performance gains, especially in the CC and F1.

V. Conclusion

We propose a novel graph-based framework, IRGNN, combining the numerical solution with ML and utilizing the topological information of PG. IRGNN exploits the advantages of both numerical solution and ML methods, and can strike a good trade-off between efficiency and accuracy. Experiments demonstrate that our framework can achieve the best performance compared to newly proposed methods.

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