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

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Introduction

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IR Drop Analysis

• The on-chip **power grid (PG)** transfers voltage and current to each working cell, and IR drop analysis involves obtaining the **IR drop caused by parasitics** between the power pads and cells.

• IR drop analysis becomes very **time-consuming** in industrial-scale designs using **traditional analysis methods.**

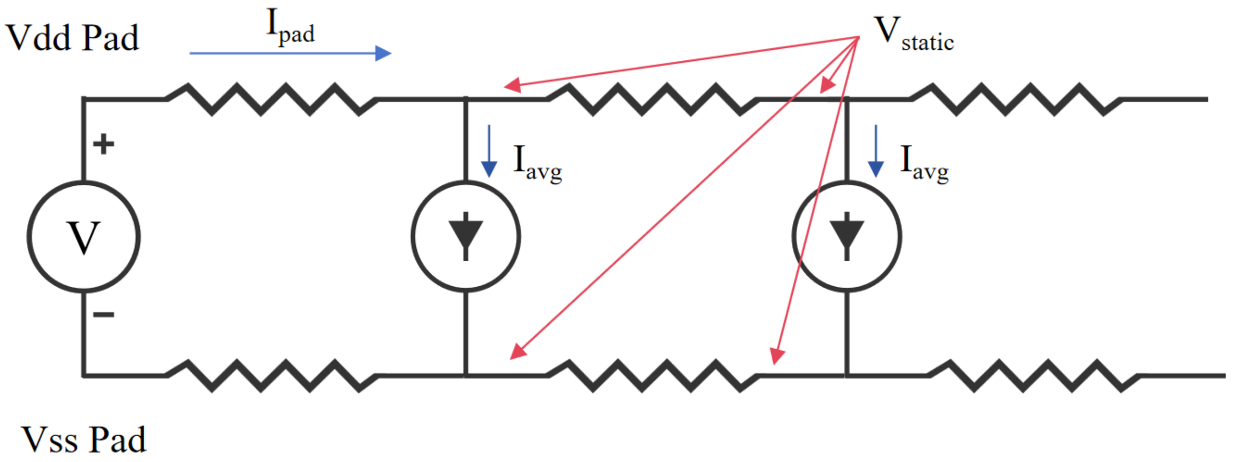

Fig. 1 A simple circuit reflecting IR drop.

IR Drop Analysis

- Many numerical methods have been proposed for this process, including direct solvers [1,2], iterative solvers [3], and other specialized solvers [4].
- The system matrix of a n-node PG network can be formulated as a linear system:

$$\boldsymbol{G}\boldsymbol{V} = \boldsymbol{I} \tag{1}$$

- As the number of nodes in the PG grows exponentially, traditional methods struggle with **longer solution times** or even become infeasible due to high computational demands and memory demands.

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[1] T. A. Davis, et al. (2010). "Algorithm 907: KLU, a direct sparse solver for circuit simulation problems," in *Article TOMS*, pp.1–17.

[2] Y. Chen, et al. (2008). "Algorithm 887: CHOLMOD, supernodal sparse Cholesky factorization and update/downdate," in *Article TOMS*, pp.1–14.

[3] T.-H. Chen, et al. (2001). "Efficient large-scale power grid analysis based on preconditioned Krylov-subspace iterative methods," in *Proc. DAC*, pp.559–562.

[4] Z. Liu, et al. (2024). "PowerRChol: Efficient Power Grid Analysis Based on Fast Randomized Cholesky Factorization," in *Proc. DAC*, pp. 1–6.

Current Work

1. IREDGe[5]
2. MAVREC[6]
3. PGAU[7]
4. MAUnet[8]

- Traditional numerical methods are **highly time-consuming**.
- Current ML-based (mainly CNN-based) methods are fast but **lack sufficient granularity and can only provide pixel-level predictions**, which cannot accurately analyze the IR drop on each node. ML-based methods struggle with issues related to **model interpretability and generalizability**.

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[5] V. A. Chhabria, et al. (2021). "Thermal and IR drop analysis using convolutional encoder-decoder networks," in *Proc. ASP-DAC*, pp.690–696.

[6] V. A. Chhabria, et al. (2021). "MAVIREC: ML-aided vectored IR-drop estimation and classification," in *Proc. DATE*, pp.1825–1828.

[7] F. Guo, et al. (2024). "PGAU: Static IR Drop Analysis for Power Grid using Attention U-Net Architecture and Label Distribution Smoothin," in *Proc. GLSVLSI*, pp.452–458.

[8] M. Wang, et al. (2024). "MAUnet: Multiscale attention U-Net for effective IR drop prediction," in *Proc. DAC*, pp.1–6.

Main Idea

Our Contribution

- Propose a novel and comprehensive **graph-based framework, IRGNN** , tailored for node-level **static IR drop analysis** and incorporated numerical solutions and point clouds, achieves a unique **balance between computational accuracy and efficiency**.
- Design **IRGraph, an innovative graph** effectively encoded the PG topology while enriching information at each node.
- 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.

Preliminary

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Graph Neural Network

- **Graph neural network (GNN)** is specifically designed for tasks on graph-structured data by modeling graph structures and aggregating node information.
- Considering the topology of the circuit, many **GNN-based** approaches[9,10] have emerged in the field of EDA.

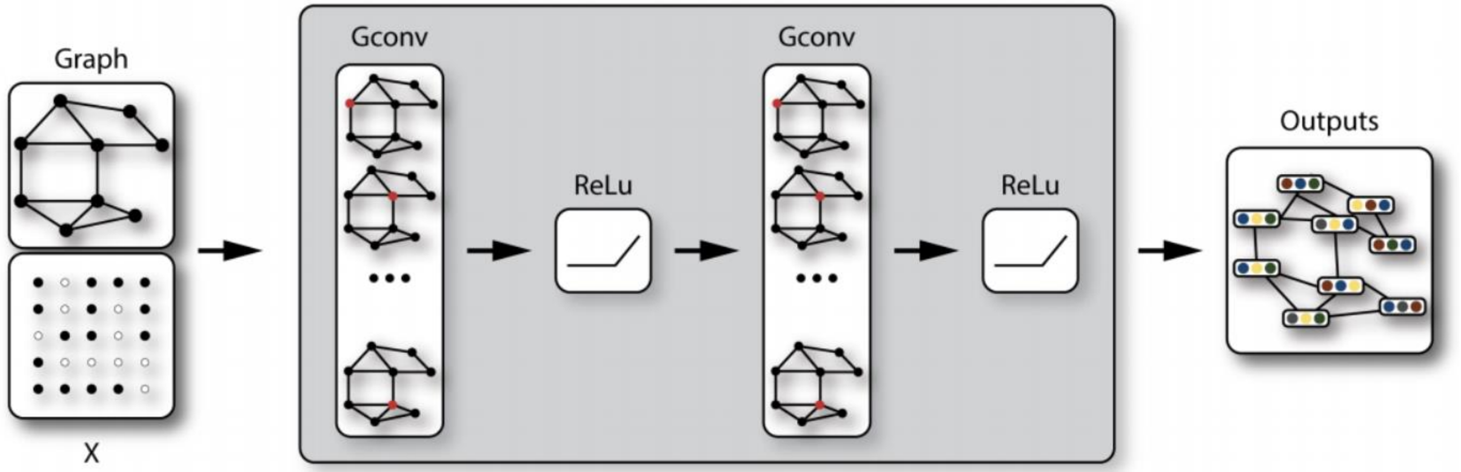

Fig. 2 A Schematic diagram of GNN.

[9]M. Li, et al. (2021) "Deepgate: Learning Neural Representations of Logic Gates," in *Proc. DAC*, pp. 452–458.
[10]J. Liu, et al. (2024) "PolarGate: Breaking the Functionality Representation Bottleneck of And-Inverter Graph Neural Network," in *Proc. ICCAD*, pp. 1–9.

Point Cloud

- 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.

- Zou et al.[11] treats **circuit layouts as point clouds**, applying transformer-based techniques to enhance feature extraction, yielding strong results in congestion prediction and design rule verification.

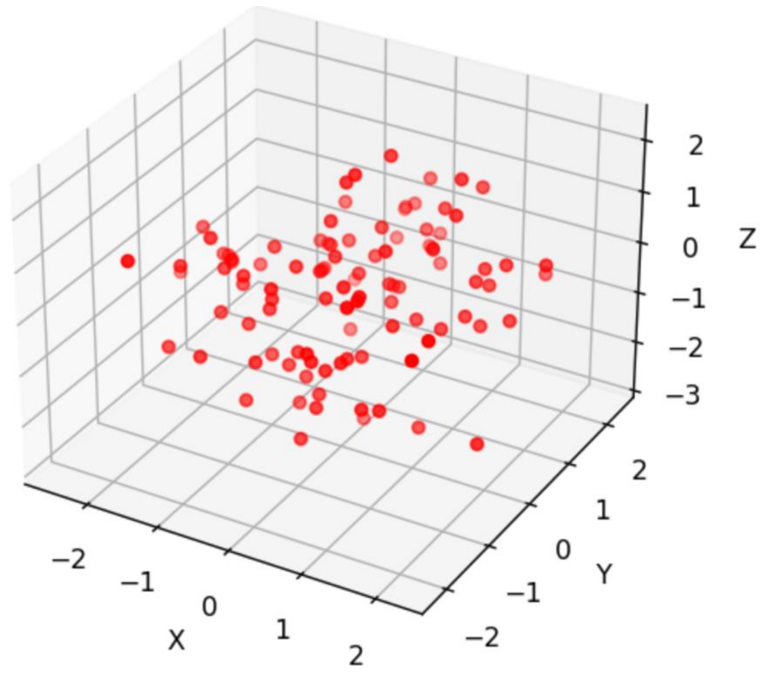

Fig. 3 A Schematic diagram of point cloud data.

[11] J. Zou, et al. (2023) "Circuit as Set of Points," in Proc. NIPS, pp. 32468--32480.

Problem Formulation

- The PG is treated as a directed graph, denoted as $G = (V, E)$, where $V = \{v_1, \dots, v_n\}$ represents the set of n vertices 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:

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

Method

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Overall —— Fusion of Solver and ML

IRGNN consists of several components:

1. An efficient AMG-PCG solver
2. Point Cloud Feature Extraction
3. IRGraph Construction
4. IRGNN model

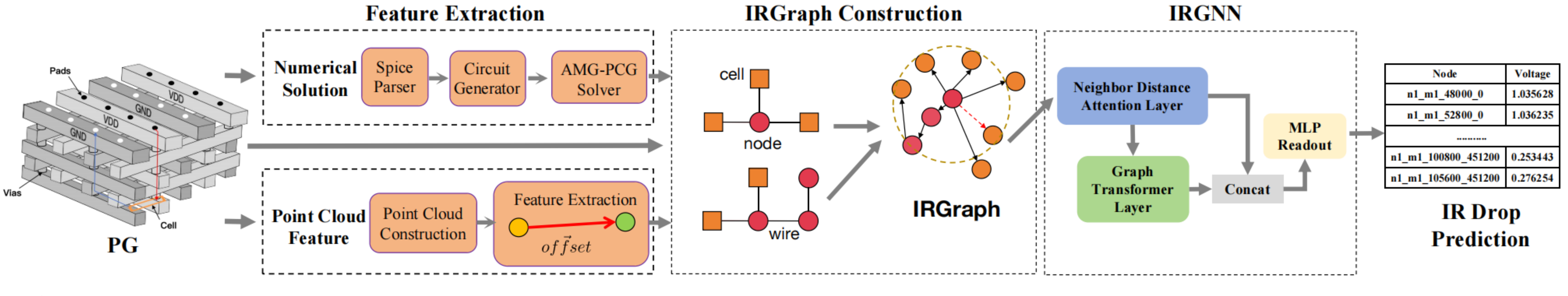

Fig. 4 Illustration of IRGNN framework for static IR drop prediction.

Numerical Solution using AMG-PCG

- In the numerical solution phase
  1. A spice parser
  2. A circuit generator
  3. The algebraic multigrid preconditioned conjugate gradient (AMG-PCG) method in PowerRush[12]
- Using **fewer iterations to obtain fast and rough solutions and construct numerical features** for ML.
- The rough solution effectively provides rough IR drop values at each node, thereby greatly **benefiting ML in understanding and learning PG systems**.

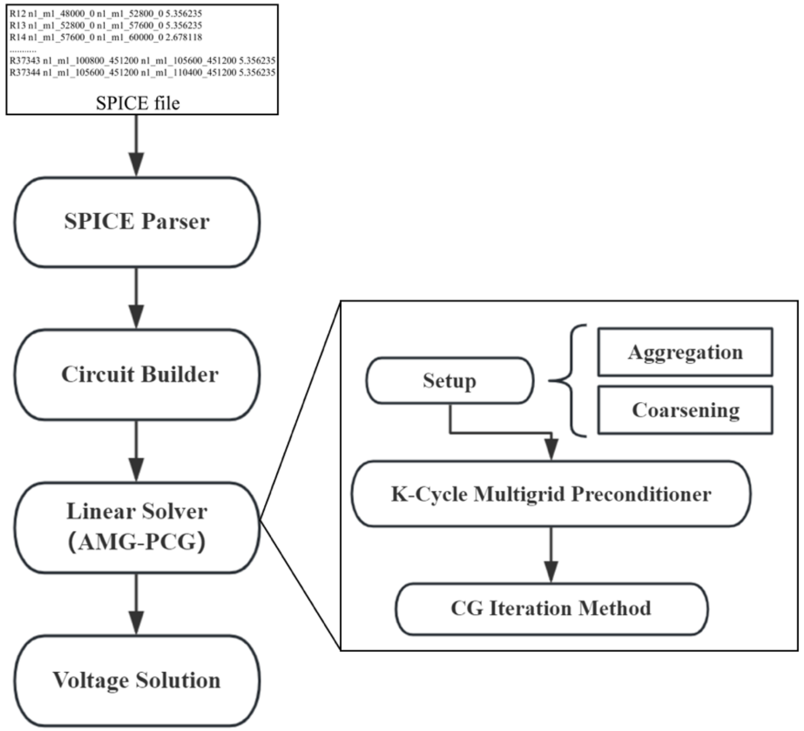

Fig. 5 The illustration of AMG-PCG solver.

[12]J. Yang, et al. (2013). “PowerRush: An efficient simulator for static power grid analysis”, in *Article. TLVSI*, pp. 2103–2116.

Point Cloud Representation

- 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.
- Inspired by PointNet++[11], 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 $offset = (x_2 - x_1, y_2 - y_1, z_2 - z_1)$.

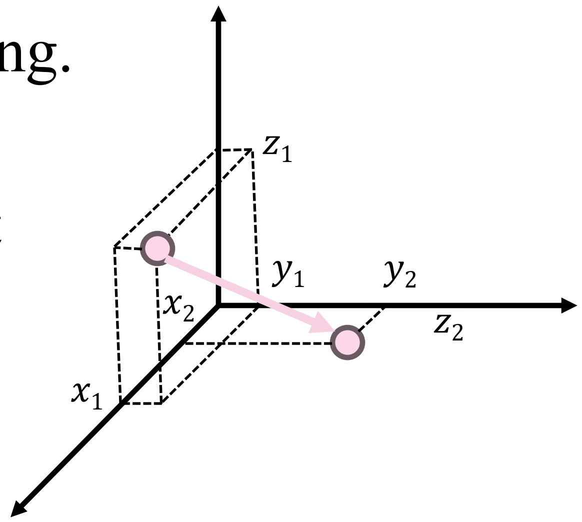

Fig. 6 The illustration of point cloud representation.

[13]G. Qian, et al. (2022). "Pointnext: Revisiting Pointnet++ with Improved Training and Scaling Strategies," in *Proc.* NIPS, pp. 23192–23204.

IRGraph

An unweighted directed graph $G = (V, E)$ is constructed to model the practical non-Euclidean topology of the PG network.

A distance-aware edge construction is applied, incorporating edges based on spatial proximity (Euclidean distance $||vi\ , vj||2\ \leq\ \delta$ for nodes $v_i\ , vj$).

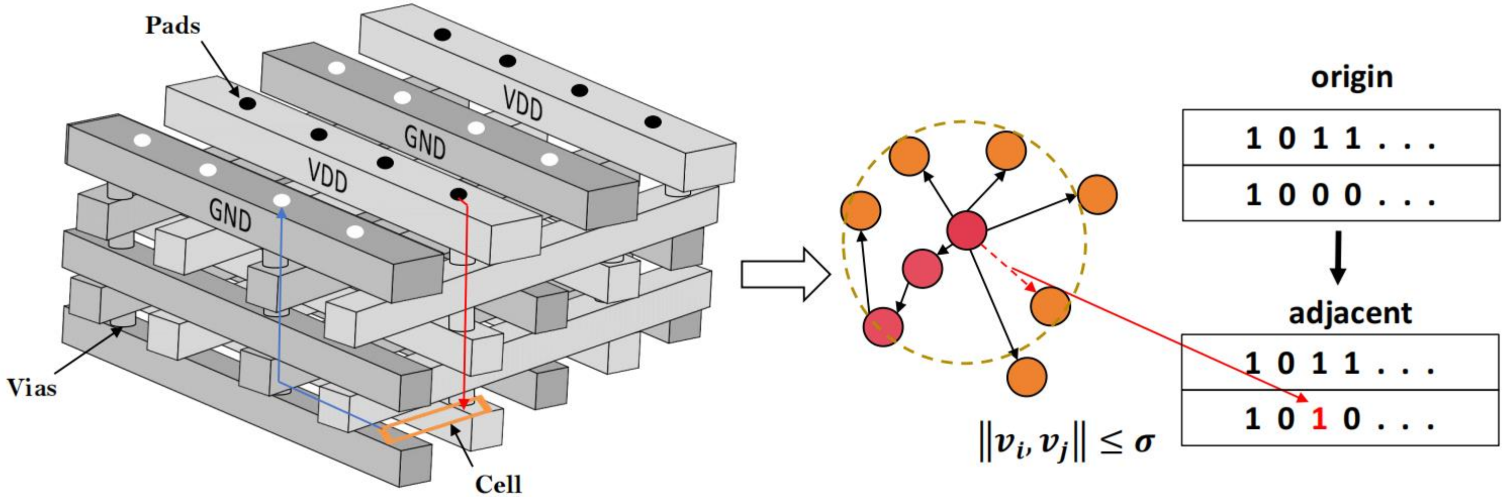

Fig. 7 IRGraph construction with distance-aware edge.

IRGraph

Node Features

- **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** (AMG-PCG).
- **The point cloud position** is the 3D coordinate of nodes.

Edge Features

- **The wire resisitance**, extracted from spice file.
- **The wire offset**, $offset = (x_2 - x_1, y_2 - y_1, z_2 - z_1)$

IRGNN

Neighbor Distance Attention Layer

- We design an NDA layer, as the node attention aggregator in NDA **processes the neighbor node and edge representations simultaneously** with attention weight.
- 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.

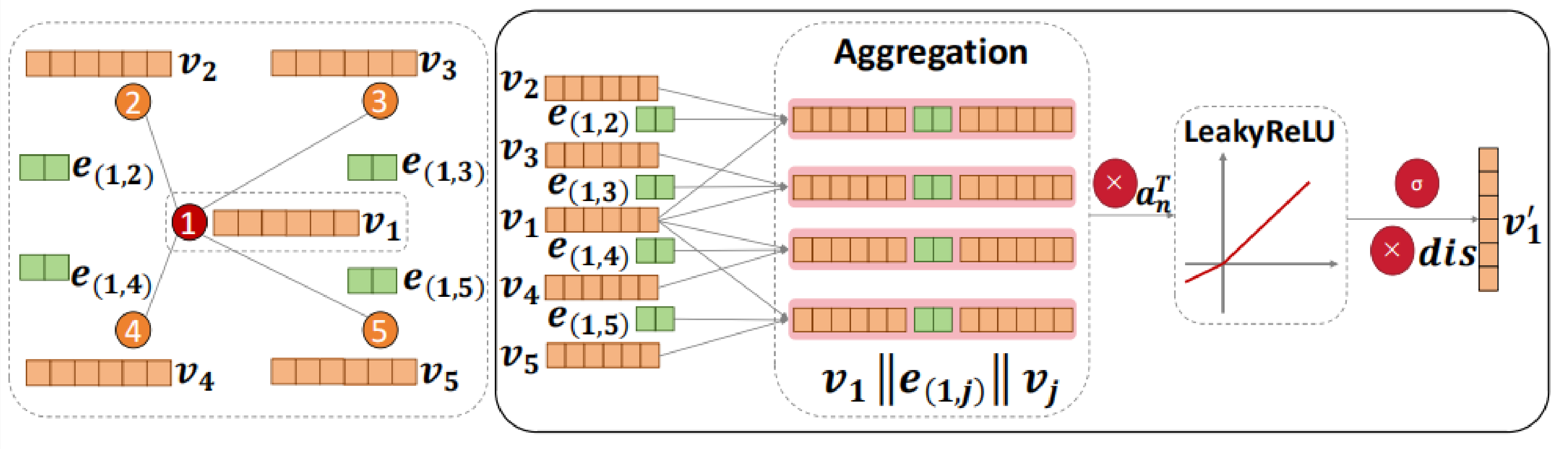

Fig. 8 The architecture of our designed NDA layer.

IRGNN

Graph Transformer (GT) Layer

- We leverage the **GT layer**[14] 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.

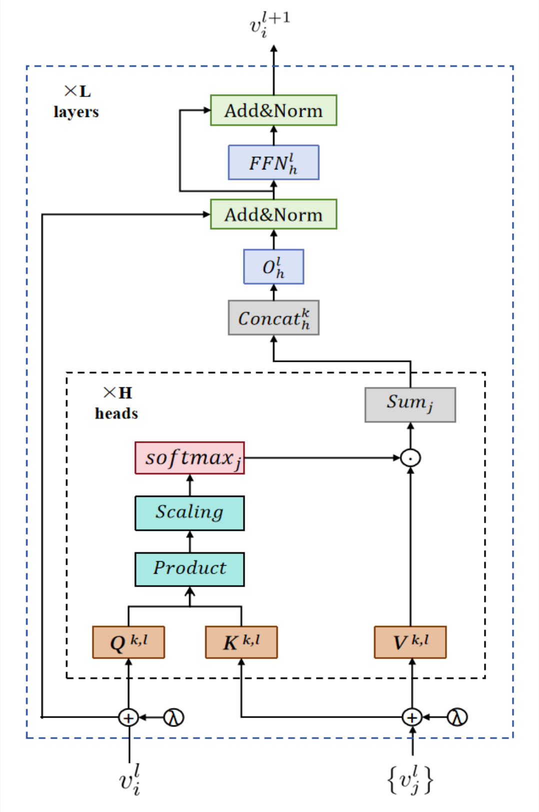

Fig. 9 The architecture of Graph Transformer Layer.

[14] V. P. Dwivedi, et al. (2021). "A Generalization of Transformer Networks to Graphs," in Proc. AAAI.

Evaluation

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Experimental Settings

Baseline

- IREDGe[5]
- MAUnet[8]
- Contest Winner（ICCAD 2023）[12]

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[5] V. A. Chhabria, et al. (2021). "Thermal and IR drop analysis using convolutional encoder-decoder networks," in *Proc. ASP-DAC*, pp. 690–696.

[8] M. Wang, et al. (2024). "MAUnet: Multiscale attention U-Net for effective IR drop prediction," in *Proc. DAC*, pp. 1–6.

[12] Winners at ICCAD 2023 Contest. [Online]. Available: https://www.iccad-contest.org/2023/Winners.html.

Experimental Settings

Datasets

- The ICCAD2023 dataset[12], specialized for the static IR drop prediction task, is used for evaluation. It contains **120 designs, 20 of which are real designs, and the rest were artificially generated** based on BeGAN[13], named fake designs, close to realistic PGs.)

- To increase dataset diversity and assess model generalization, three open-source benchmarks[13] are utilized: Nangate, ASAP, and Skywater, **comprising 1000, 1000, and 418 designs**, respectively.

[12] Winners at ICCAD 2023 Contest. [Online]. Available: https://www.iccad-contest.org/2023/Winners.html.
[13] V. A. Chhabria, et al. (2021). "BeGAN: Power grid benchmark generation using a process-portable GAN-based methodology," in *Proc. ICCAD*, pp. 1–8.

Experimental Settings

Metrics

- **Mean Absolute Error(MAE)**

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

- **F1 score**

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

- **Pearson Correlation Coefficient (CC)**

$$CC = \frac{Cov\ (y, \hat{y})}{\sigma_y \sigma_{\hat{y}}}$$

- **Maximum IR Drop Error (MIRDE)**

$$MIRDE = max_i|y_i - \hat{y}_i|$$

Comparison with ML-based Method

- **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.

Table 1 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**

Comparison with ML-based Method

- Considering the performance potential of **large-scale datasets**, another experiment is conducted.
- 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.**

Table 2 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**

Comparison with Numerical Method

Table 3 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**

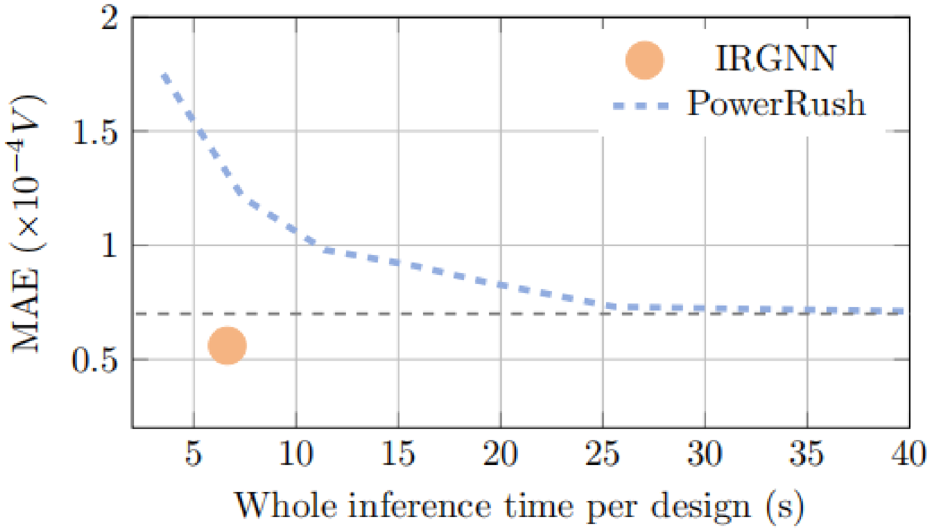

Fig. 10 Comparison of IRGNN and PowerRush.

- **IRGNN surpasses PowerRush in all metrics**, with significantly less time cost, indicating great performance on nodes of both the bottom layer and inner layers.

Transfer Learning

- 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**.

Table 4 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**

Ablation Study

- The results demonstrate that the numerical solution (Num. Solu.) significantly reduces 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.

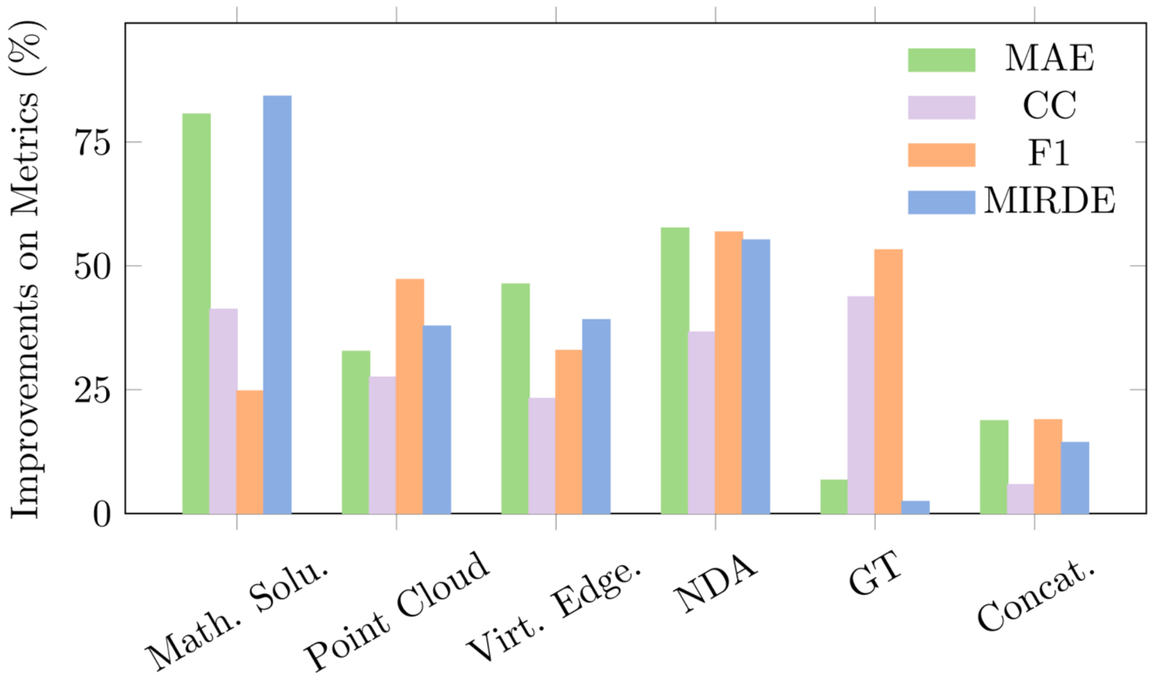

Fig. 11 Results of Ablation Study.

Conclusion

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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.

Traditional Solver+ML ＞ Traditional Solver / ML

Thank You!

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