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IR-Fusion: A Fusion Framework for Static IR Drop Analysis Combining Numerical Solution and Machine Learning

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Introduction

Background: Power Grid and 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**

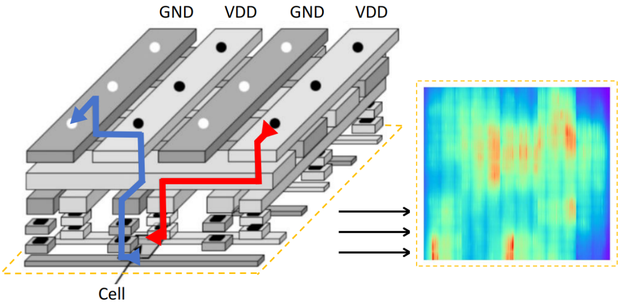

Fig. 1 The multiple-layer structure of PG.

Background: Conventional Numerical Method for PG 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:

$$\boldsymbol{Gx} = \boldsymbol{I} \tag{1}$$

- 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.
- Consequently, the necessity for ML methods becomes evident.

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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.

Background: Machine Learning for IR Drop Analysis

- To address inefficiencies, machine learning (ML)-based methods have been proposed as a promising alternative for accelerating IR drop analysis:
  1. IREDGe[5].
  2. MAVREC[6]
  3. PGAU[7]
  4. MAUnet[8]
- They still face the problem of **insufficiently fine modeling granularity**.
- They struggle with issues related to model **interpretability and generalizability**, which can limit their adoption in practical design environments.

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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. (2022). "MAUnet: Multiscale attention U-Net for effective IR drop prediction," in *Proc. DAC*, pp. 1–6.

Key Point: Integrating Numerical and ML Methods

- **Can numerical and ML methods be combined for a better trade-off in speed, accuracy, and scalability? Yes!**
- Most numerical methods solve large-scale linear systems iteratively, where more iterations yield greater accuracy but require longer runtime.
- By integrating ML, we can perform fewer iterations to **obtain a rough solution and refine it using ML**.
- This fusion enables a better understanding of complex physical or geometric systems, while offering more fine-grained and efficient modeling.

Traditional Solver+ML > > Traditional Solver/ML

Methodologies

Overall Framework: IR-Fusion

- IR-Fusion consists of several components:
  1. An efficient AMG-PCG solver
  2. Hierarchical numerical-structural fusion
  3. Inception Attention U-Net model
  4. Augmented curriculum learning

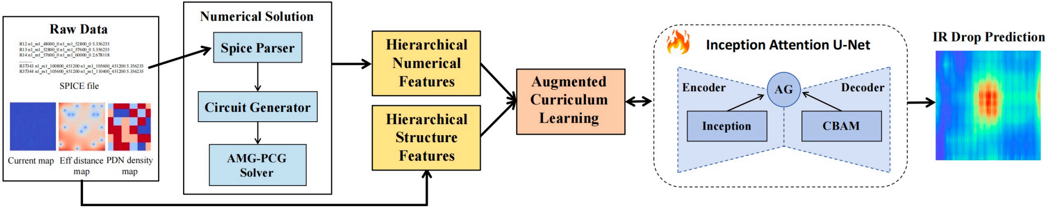


Fig. 2 The overview of IR-Fusion, a fusion framework for static IR drop analysis combining numerical solution and ML.

Numerical Solution using AMG-PCG[9]

- 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

- Using **fewer iterations to obtain fast and rough solutions and construct numerical features** for ML.
- This rough solution provides the IR drop values for each node and constructs detailed hierarchical numerical features, greatly benefiting ML in understanding and learning PG systems.

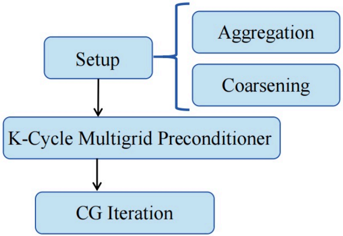


Fig. 3 The illustration of AMG-PCG solver.

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

Hierarchical Numerical-Structural Information Fusion

- Based on the row w and height l from Library Exchange Format (LEF), a design's layer of size $W_c \times L_c$ translates to an image of $W\,(= W_c//w) \times L\,(= L_c//l)$ pixels.
- Each metal layer corresponds to a generated feature map, **allowing the PG to produce feature maps that align with the same number of grid layers in total**.

Features

Given the limited representation of designs, our method extracts more hierarchical structure features using the PG spice file and cell layer features:

1. **The current map** for each layer, representing the current distribution, is allocated proportionally based on the contribution from each layer, which is tied to resistance.
2. **The effective distance**, calculated as the reciprocal of the sum of the reciprocals of Euclidean distances, measures proximity to voltage sources.
3. **The PDN density map** is derived from the average PDN pitch within each grid as detailed in the spice file.
4. **The resistance** and **shortest path resistance maps** are also computed based on their physical significance.

Inception Attention U-Net Model

- Based on PGAU, we design our Inception Attention Unet.
- **The inception module** is applied to enhance the network's ability to capture both local details and broader context.
- **The convolutional block attention module (CBAM)** is incorporated to focus on various scales and directions in subsequent decoder stages.

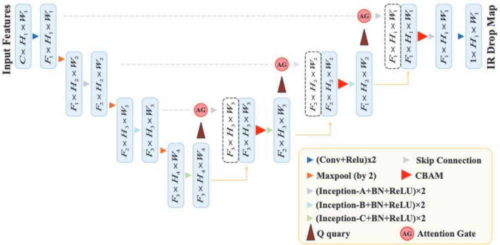


Fig. 4 The architecture of Inception Attention U-Net.

Evaluation

Datasets

- The ICCAD2023 dataset[10], 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[11], named fake designs, close to realistic PGs. We perform the following setup on the dataset:

1. We follow the contest setup, using 10 real designs for testing and the rest for training.
2. Data augmentation increases the dataset size fourfold, with oversampling applied: fake designs are doubled, and real ones are quintupled.
3. Following a curriculum learning strategy, fake designs are categorized as "easier," while real designs are classified as "harder."

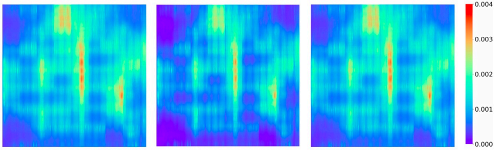
[10] Winners at ICCAD 2023 Contest. [Online]. Available: https://www.iccad-contest.org/2023/Winners.html.
[11] V. A. Chhabria, et al. (2021). "BeGAN: Power grid benchmark generation using a process-portable GAN-based methodology," in *Proc. ICCAD*, pp. 1–8.

Experiment 1: Main Experiment with Baselines

- IR-Fusion achieves better performance with the improvement of **28.3% on MAE, 14.5% on F1, and 27.6% on MIRDE, with no significant time cost increase** compared to the SOTA baseline, i.e., MAUnet.
- IR-Fusion still outperforms all baselines in MIRDE, representing more accuracy in the worst-case region.
- Our proposed fusion framework achieves more outstanding and robust performance within an acceptable runtime.

TABLE I Main results. The unit of MAE and MIRDE is $\times 10^{-4}V$ and runtime is s.

Methods	MAE↓	F1↑	Runtime↓	MIRDE↓
IREDGe [17]	3.75	0.49	1.55	7.52
MAVIREC [18]	2.78	0.46	1.97	5.88
IRPnet [19]	1.66	0.61	2.22	5.25
PGAU [20]	1.72	0.60	2.07	5.02
MAUnet [21]	1.06	0.62	2.31	4.38
Contest Winner [31]	1.08	0.57	2.24	4.33
IR-Fusion (Ours)	**0.72**	**0.71**	6.98	**3.05**

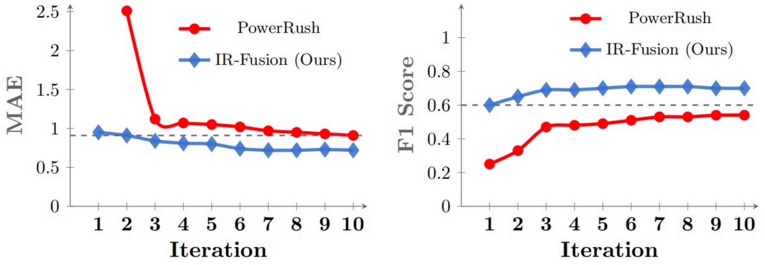


(a) Golden (b) MAUnet (c) IR-Fusion (Ours)

Fig. 6 Visualization of IR Drop distribution of a PG.

Experiment 2: Trade-off Study

- IR-Fusion surpasses PowerRush in all evaluated metrics.
- A key advantage of IR-Fusion is its ability to achieve the same MAE in just 2 iterations, while PowerRush requires 10 iterations to reach the same level.
- IR-Fusion consistently achieves a higher F1 score— a performance level PowerRush cannot reach at any iteration.
- Thanks to the fusion of numerical and ML methods, **IR-Fusion achieves a better trade-off between accuracy and efficiency**.



(a) MAE (b) F1 Score

Fig. 7 The analysis results of IR-Fusion and PowerRush [15].

THANK YOU!