



SHAPING THE NEXT GENERATION OF ELECTRONICS

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Performance-driven Analog Routing via Heterogeneous 3DGNN and Potential Relaxation

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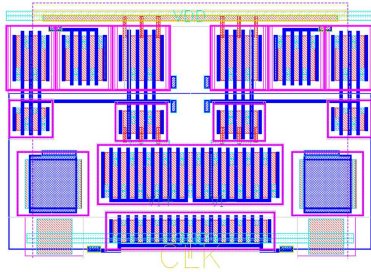
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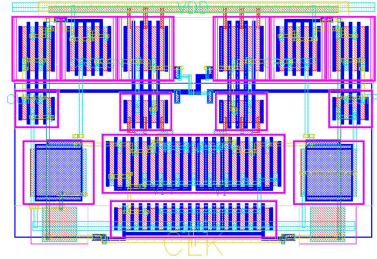
- ① Background
- ② Method
 - 2.1 Performance-Driven Analog Routing
 - 2.2 Non-uniform Routing Guidance
 - 2.3 AnalogFold Framework for Performance Prediction and Relaxation
- ③ Experiments

Background Knowledge

Analog Routing Problem



A result of the placed comparator.

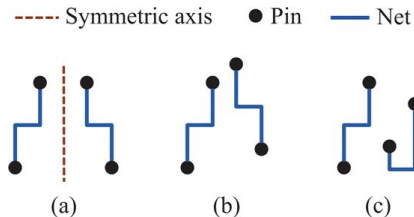


The routing solution.

Analog circuit routing is critical to optimal performance, but obtaining a decent circuit layout requires significant time and expertise.

Existing Methods: Heuristic Constraint-based Methods

Ou et al. propose different levels of geometrical matching constraints¹.

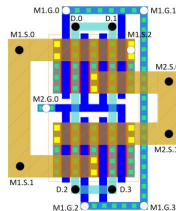


(a) Symmetric constraint. (b) Common-centroid constraint. (c) Topology-matching constraint.

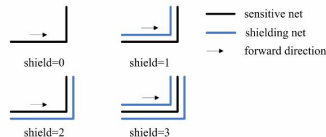
¹H.-C. Ou *et al.*, “Non-uniform multilevel analog routing with matching constraints”, in *Proceedings of the 49th Annual Design Automation Conference*, 2012, pp. 549–554.

Existing Methods: Heuristic Constraint-based Methods

There are other works that optimize power routing² and propose shielding critical nets³.



Optimize power routing.



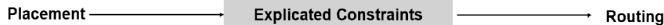
Shielding critical nets.

²R. Martins *et al.*, “Electromigration-aware and ir-drop avoidance routing in analog multiport terminal structures”, in *2014 Design, Automation & Test in Europe Conference & Exhibition (DATE)*, IEEE, 2014, pp. 1–6.

³Q. Gao *et al.*, “Analog circuit shielding routing algorithm based on net classification”, in *Proceedings of the 16th ACM/IEEE international symposium on Low power electronics and design*, 2010, pp. 123–128.

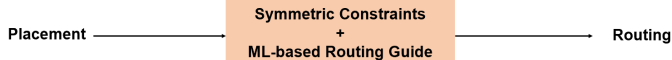
A ML-Guided Analog Routing Problem

Can we automatically summarize the human layout intelligence leveraging ML?⁴



Heuristic constraints

Use a set of detailed heuristics as routing constraints.

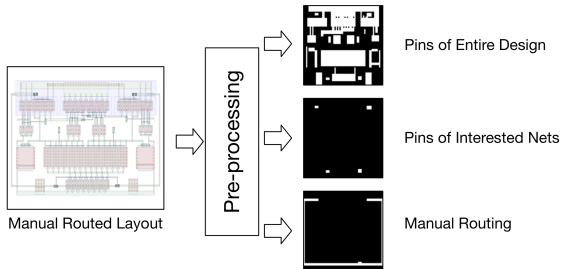


Routing guidance

Routing strategies learned from human

⁴K. Zhu *et al.*, "Geniusroute: A new analog routing paradigm using generative neural network guidance", in *Proc. ICCAD*, 2019.

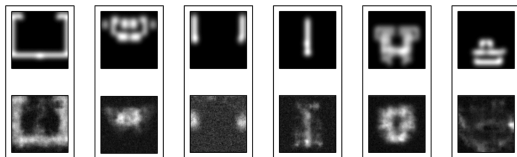
Automatically Learn Guidance from Human Layouts



Human Layout data

- Pre-process the GDS layouts into images
- Extract training data where the human would likely route the nets
- **Problem #1** The human experts' layout data is **pretty scarce**.

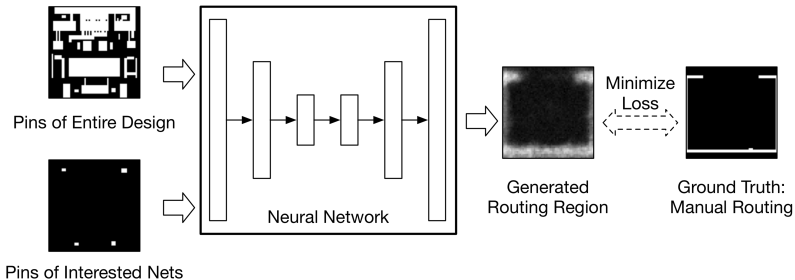
2D Uniform Routing Guidance



2D Uniform Routing Guidance

- Predict a 2D probability map of the routing likelihoods in each region.
- The 2D uniform routing guidance is honored via penalties in the cost function.
- **Problem #2** Fail to deal with **designs of different sizes or aspect ratios** and **resource competition** between different pins close to each other.

VAE-based Generation

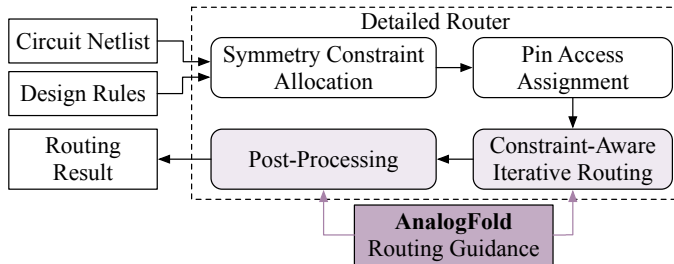


VAE-based Generation

- Leveraging variational autoencoder (VAE) to reconstruct the routing solutions.
- Minimize the distance between ground truth and inferred output.
- **Problem #3** The generative model makes it hard to guarantee a **performance boost**.

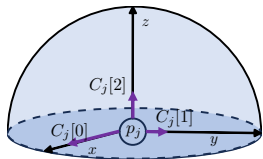
Proposed Method: PARoute

Problem #1: Performance-Driven Analog Routing

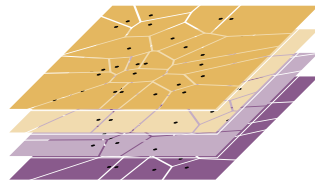
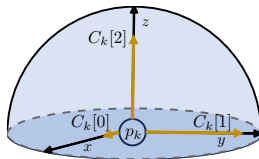


- We introduce a performance-driven analog routing approach.
- Learn from the **automatically generated routing patterns** and their **simulation results** without **human labeling effort**.

Problem #2: Non-uniform Routing Guidance



(a)

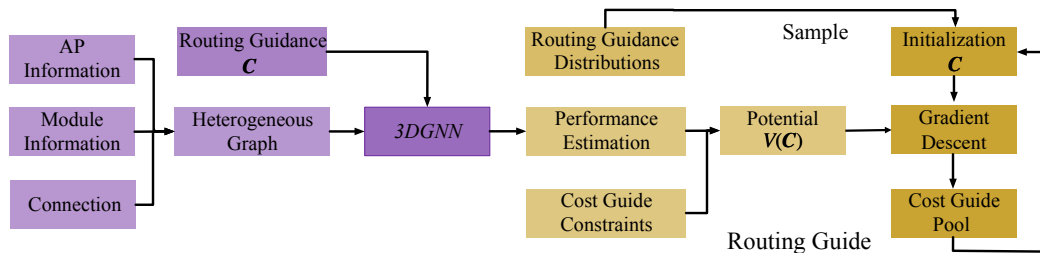


(b)

(a) Two examples of non-uniform routing guidance; (b) The 3D visualization.

- We propose a non-uniform and adaptive routing guidance, which assigns different routing guidance c_i along different directions for each net n_i .
- Adapt the route guide distribution to areas with different densities and support a 3D cost map.

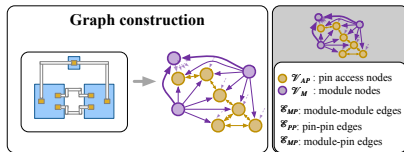
Problem #3: AnalogFold Framework for Performance Relaxation



- We proposed a customized AnalogFold framework to enable accurate modeling of the performance potential of routing guidance.
- AnalogFold contains a heterogeneous routing graph, a protein-inspired 3DGNN network, and a pool-aided potential relaxation process.

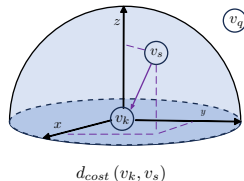
Heterogeneous Graph for Analog Routing

We design a heterogeneous graph $\mathcal{G}_H = \langle \mathcal{V}_{AP}, \mathcal{V}_M, \mathcal{E}_{PP}, \mathcal{E}_{PM}, \mathcal{E}_{MM} \rangle$ to represent the interactions between pin access points and modules.



- The vertex sets \mathcal{V}_{AP} and \mathcal{V}_M correspond to the pin access points and modules.
- \mathcal{E}_{PP} is designed to reflect the interactions between different pin access points.
- \mathcal{E}_{MM} contains the edges that connect the modules according to the netlist.
- We add the edge \mathcal{E}_{PM} to model the relationship between the pin access points and the modules.

Cost-aware Distance Augmented Module

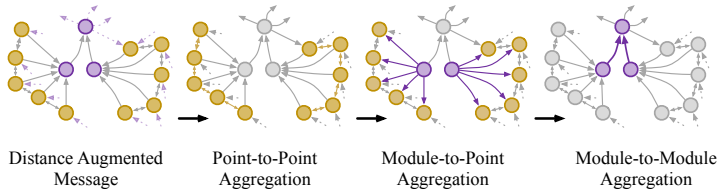


We can define the distance honors routing cost as follows:

$$d_{cost}(v_k, v_s) = \sqrt{(c[0] \cdot h_{ks})^2 + (c[1] \cdot w_{ks})^2 + (c[2] \cdot z_{ks})^2}, \quad (1)$$

where c is the cost guide assigned for each access point, $h_{ks}/w_{ks}/z_{ks}$ is the distance between v_k and v_s along horizontal/vertical/Z-axis direction. **The distance between nodes is embedded to reflect the routing resource competition.**

Protein-inspired 3DGNN for Analog Routing

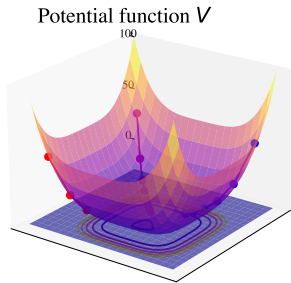


In 3D-GNN, the proposed cost-aware message passing can be defined as:

$$\begin{aligned} \mathbf{e}_k^l &= \phi^e \left(\mathbf{e}_k, v_{r_k}, v_{s_k}, \mathcal{E}_{s_k}, \rho^{p \rightarrow e} \left(\{\mathbf{r}_h\}_{h=r_k \cup s_k} \right) \right), \\ v_i^l &= \phi^v \left(v_i, \rho^{e \rightarrow v} \left(\mathcal{E}_i^l \right) \right), \mathbf{u}^l = \phi^u \left(\mathbf{u}, \rho^{v \rightarrow u} \left(\mathcal{V}^l \right) \right), \end{aligned} \quad (2)$$

where ϕ^e , ϕ^v , and ϕ^u are three information update functions on edges, pin access points/modules, and the whole graph, respectively. **Especially, the 3D information in P is incorporated to update each message e_k .**

Routing Guide Performance Potential Modeling and Relaxation



- We created a differentiable model using the 3DGNN to predict the post-layout performance of the routing guidance.
- We then apply a gradient-based optimization of routing guidance potential **multiple times with different initialization** to derive the top-N routing guidance results.

Experiment Results

Post-layout Performance Comparisons on OTA benchmarks

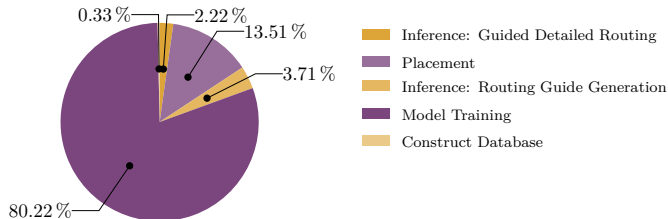
Table: The comparisons between baseline methods and the proposed method.

Circuits		Schematic	MagicalRoute ⁵	GeniusRoute ⁶	PARoute (ours)
Average	Offset Voltage(μV) \downarrow	-	1.000	10.426	0.546
	CMRR(dB) \uparrow	-	1.000	0.998	1.163
	BandWidth(MHz) \uparrow	-	1.000	1.002	1.113
	DC Gain(dB) \uparrow	-	1.000	0.999	2.368
	Noise(μV_{rms}) \downarrow	-	1.000	1.007	0.787
	Runtime(s) \downarrow	-	1.000	17.147	7.480

⁵H. Chen *et al.*, "Toward silicon-proven detailed routing for analog and mixed-signal circuits", in *Proc. ICCAD*, 2020, pp. 1–8.

⁶K. Zhu *et al.*, "Geniusroute: A new analog routing paradigm using generative neural network guidance", in *Proc. ICCAD*, 2019.

Runtime Breakdown



- Although the average runtime of our proposed approach is $7.48\times$ slower than MagicalRoute⁷, it is nearly $2.29\times$ faster than GeniusRoute⁸ due to the simplified 3D graph structure.
- The most consuming part is the model training part, which takes 80.22% of the total runtime and 3.71% of the total time for the routing cost generation.

⁷H. Chen *et al.*, “Toward silicon-proven detailed routing for analog and mixed-signal circuits”, in *Proc. ICCAD*, 2020, pp. 1–8.

⁸K. Zhu *et al.*, “Geniusroute: A new analog routing paradigm using generative neural network guidance”, in *Proc. ICCAD*, 2019.



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