

Pre-Routing Path Delay Estimation Based on Transformer and Residual Framework

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OUTLINE



- Background
- Related Work
- Pre-Routing Path Delay Framework
- Results
- Conclusion

Background





Problems: As the design flow gets closer to tape-out, the updated circuit timing faces nonnegligible mismatch between each stage of design flow, posing severe challenges for circuit optimization.

Background





> This work: pre- and post-routing timing correlation

[DAC'19]E. C. Barboza, N. Shukla, Y. Chen, J. Hu, "Machine learning-based pre-routing timing prediction with reduced pessimism," in 2019 56th ACM/IEEE Design Automation Conference (DAC), pp. 1-6, IEEE, 2019.

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Fast pre-routing timing estimation based on traditional mathematical model

Timing analysis based on machine learning method



Fast pre-routing timing estimation based on traditional mathematical model

Ref.	Affiliation	Title	Focus
10'SLIP	Synopsys, Brown University	Fast, accurate a priori routing delay estimation	Post-routing delay estimation
04'DAC	University of California	Pre-layout wire length and congestion estimation	Wire length and congestion estimation
06'ICECC	Syracuse University	Pre-layout estimation of interconnect lengths for digital integrated circuits	Pre-layout interconnect lengths estimation
00'SLIP	University of Toronto	Pre-layout estimation of individual wire lengths	Individual wire lengths estimating during the technology mapping phase of logic synthesis
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Focus: wire length or wire delay estimation



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Average increase ratio of net delays between routing and placement stages for all types of cells

The impact of routing to the cell delay is much more significant than that of wire delay.



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Average increase ratio of net delays between routing and placement stages for all types of cells

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Focus: wire length or wire delay estimation

Pre-routing timing estimation requirement: (1)fast and accurate (2)pay more attention to cell delay or path delay





In recent years, the learning-based methods have been extended in the application of timing analysis

- Application: A fast and accurate timing estimator which can highly correlate with a sign-off timer to shorten turn-around time
- ◆ ML models: RF, Lasso, XGBoost



[DAC'20, H. H. Cheng, Fast and accurate wire timing estimation on tree and non-tree net structures]

- Application: Wire delay/slew models for internal incremental STA to delay the deviation in endpoint slack from a STA tool.
- ML models: Least squares regression



[SLIP'13, A. B. Kahng, Learning-based approximation of interconnect delay and slew in signoff timing tools]

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In recent years, the learning-based methods have been extended in the application of timing analysis

- Application: Predict path-based slack from graphbased timing analysis
- ♦ ML models: RF

GBA Timing Re	ports	PBA Timir	ng Reports
	Feature Ex Model Ti	traction raining	Training
GBA Timing Re unseen	Predictive	Model	Testing
	Predicted PE	BA Timing	

[ICCD'18, A. B. Kahng, Using machine learning to predict pathbased slack from graph-based timing analysis]

- Application: MLParest provides an accurate estimate of expected post-layout interconnect parasitics in the pre-layout design phase
- ◆ ML models: RF



[[]DAC'20, B. Shook, MLParest: Machine learning based parasitic estimation for custom circuit design]



Problems:

- Neglect of the delay correlation along the path
- Prediction error accumulation and computational complexity increase

An efficient and accurate pre-routing path delay prediction framework is proposed in this work by employing transformer network and residual model.

- Sequence features at placement stage
- Transformer network: exploits the correlations through circuit path
- Residual model: calibrate the mismatch between the pre- and post-routing path delay
- Without additional computation

Pre-Routing Path Delay Framework





Overview of the prediction

Framework: feature selection





Overview of the prediction

Feature selection and data pre-process

Features	Continuous variable	Discrete variable
Physical sequence	Pin cap, pin location	Cell type
Timing sequence	Input/output transition time, cell delay	Signal polarity
Timing scalar	Pre-routing path delay	

Sequence:

the representation of path characteristics

Framework: data pre-process





Overview of the prediction

Feature selection and data pre-process

Features	Continuous variable	Discrete variable
Physical sequence	Pin cap, pin location	Cell type
Timing sequence	Input/output transition time, cell delay	Signal polarity
data pre-process	Bin +padding	Tokenizer +padding

Framework: "pre-routing path delay"





Framework: transformer encoder





Framework: attention mechanism





Overview of the prediction

Framework: data dimension reduction





- Dimension reduction and data concatenation
- Predict the residual value and add it to the pre-routing path delay



Experiment setup:

- Framework implementation: Python, keras
- TSMC 28nm technology
- Circuits: 5 circuits

3 seen circuits, randomly divide training and test sets2 unseen circuits, all of them are test sets

Circuit Statistics

Circuits	# Train	# Test	#cell	#net	category
ckt #1	40791	17483	10154	18892	seen
ckt #2	93786	40194	234391	340004	seen
ckt #3	16099	6900	37958	51175	seen
ckt #4	0	16998	6667	9072	unseen
ckt #5	0	23785	11830	15170	unseen
Total	150676	105360	301000	434312	



Accuracy Comparison:



Error distribution of different models on seen and unseen designs.

	Seen ckt	Unseen ckt
rRMSE	<1.68%	<3.12%
Compared with RF, reduced by	2.3X~5X	2.4X~2.7X
Compared with CNN, reduced by	1.7X~2.9X	1.1X~1.5X
Residual model benefits	>30%	>10%

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Accuracy Comparison:





Runtime Comparison:

			Predicti	rediction Runtime (s)			
Model		ckt #1	ckt #2	ckt #3	ckt #4	ckt #5	
	CTS	1378	31896	109	193	620	
Traditional	Routing	1818	411968	143	254	816	
IC flow	STA (PT)	655	1608	276	680	951	
	Total	3851	445472	528	1127	2387	
RF		11.2	26.5	10.6	15.7	28.4	
CNN		1.28	2.68	0.57	1.22	1.66	
This work		1.02 (3775X)	2.16 (206237X)	0.40 (1320X)	1.02 (1105X)	1.38 (1730X)	

Runtime analysis

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An efficient and accurate pre-routing path delay prediction framework is proposed in this work by employing transformer network and residual model.

- Transformer network: exploits the correlations of the timing and physical information through circuit path by its multi-head self-attention mechanism
- Residual model: calibrate the mismatch between the pre- and post-routing path delay
- More accurate and less runtime



THANKS Q&A

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