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Annotating Slack Directly on Your Verilog: Fine-Grained RTL Timing Evaluation for Early Optimization

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Background: Timing Evaluation in Design Flow



- Timing in the design flow
 - Performance sign-off criterion
 - Turnaround optimization for timing closure

- Existing timing evaluation methods
 - 1. Traditional: STA
 - 2. ML-based: early-stage prediction



Prior Works: ML for Early-Stage Timing Evaluation

- Netlist & Layout Stage
 - Existing explorations most target these stages ([DAC'22¹, DAC'23², etc.])
 - Predict later-stage register slack with timing-related physical features
 - Customize ML models based on STA mechanism
 - Only available after logic synthesis
- RTL Stage
 - More challenging (vs. netlist & layout): no physical information in RTL code!

¹Guo et al. A timing engine inspired graph neural network model for pre-routing slack prediction. In DAC'22. ²Wang et al. Restructure-Tolerant Timing Prediction via Multimodal Fusion. In DAC'23.



Prior Works: ML for Early-Stage Timing Evaluation

- RTL Stage
 - Only coarse-grained overall WNS/TNS or combinational delay
 - No prior work evaluates fine-grained timing slack at the RTL stage
 - No prior work applies early timing optimization at the RTL stage

Mathada	Fine-	Genera	l Solution	Applied in
	Grained	Sequential	Cross-Design	Optimization
Lopera (ICCAD'22)			\checkmark	
Xu (ISCA'22)				
Sengupta (ICCAD'22)				
Fang (ICCAD'23)		\checkmark		
Ouyang (MLCAD'23)				
Lopera (MLCAD'23)				
Sengupta (MLCAD'23)				✓★
RTL-Timer	\checkmark	\checkmark	\checkmark	\checkmark



Motivation: RTL-Stage Timing Slack Evaluation



Can we evaluate fine-grained timing slack earlier at the RTL stage?

- RTL describes functional behaviors with HDL code
- Annotate slack directly on HDL
- Earlier stage with higher optimization flexibility for designers/EDA tools vs. post-syn



Challenges in RTL-Stage Prediction

- Design RTL is originally in HDL code format
 - Cannot be directly processed by either ML or traditional STA tools
- No direct mapping between most RTL signals and post-syn cells/nets
 - Cannot annotate delay labels





Our Solution: RTL-Timer in Design Flow



- RTL-stage fine-grained timing slack evaluation
 - Arrival time value prediction
 - Arrival time critical ranking

- Enable predictive optimizations
 - Annotate slack on HDL → RTL designer
 - Opt in commercial logic synthesis tool



Existing RTL Representations

- Logic transformation
 - Logic synthesis & verification
 - Binary Decision Diagrams (BDD)
 - Conjunctive Normal Form (CNF)
 - And-Inverter Graphs (AIGER)
 - Btor2
 - Not optimized for ML-based solutions
 - Without the correlation between RTL and netlist

- ML-based modeling
 - Design quality prediction
 - Abstract syntax tree (AST) ([SNS])
 - Simple operator graph (SOG) ([MasterRTL])
 - And-Inverter Graphs (AIGER)
 - Ad-hoc solutions
 - Without systematically exploring better candidates



Universal ML-friendly RTL Representation



- Proposed representation: Boolean Operator Graph (BOG)
 - Universal **bit-level** RTL representation
 - Specialized into different variants (SOG, AIG, XAG, etc.) → multi-view for each design



Boolean Operator Graph



- One-to-one mapping of registers
 - Sequential RTL signal bits ⇔ bit-wise netlist registers
 - Annotate slack label on each bit-wise RTL register for fine-grained ML training
- Treat BOG as a pseudo netlist We can directly perform STA on it!
 - Registers and operators: standard cells from the liberty file



Workflow of RTL-Timer



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1. Register-Oriented RTL Processing Workflow

- Inspired by STA propagation
 - Endpoint accumulates arrival time AT from all its driving registers (cone)
- Capture timing-related information from register cone
 - STA on BOG \rightarrow slowest path $S^{C}_{* \rightarrow i}$ (not real critical path)
 - K random sampled paths $L_{*\to i}^{C(k)}$
 - Customized max AT loss

•
$$AT_{i}^{pred} = max(F_{AT}(S_{*\rightarrow i}^{C}), \{F_{AT}(L_{*\rightarrow i}^{C(k)})\})$$





2. ML Modeling in RTL-Timer

- Feature exploration
 - Design-level
 - Global features
 - Compare endpoints across designs
 - Cone-level
 - Size of the cone
 - Path-level
 - Physical-related features on timing paths

Туре	Feature	Avg. <i>R</i>	
	Rank level		
	% of the endpoint rank		
Design	# of sequential cells	/	
	# of combinational cells		
	# of total cells		
Cone	# driving reg of input cone	0.45	
	Arrival time by STA on ${\cal R}$	0.43	
	# of level of the timing path	0.51	
Dath	# of operators	0.56	
Path	Fanout	0.40	
	Load capacitance	0.38	
Slew		0.38	



2. ML Modeling in RTL-Timer

- Capture max slack on each register endpoint
 - Customized loss function
- Ensemble learning with four BOG variants
 - Multi-view for each design
- Timing evaluation
 - Bit-wise endpoint slack
 - Signal-wise endpoint
 - Signal max slack
 - Signal critical ranking
 - Design overall WNS/TNS





3. Optimization Enabled by RTL-Timer

Path

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- Enhancing logic synthesis process
 - Constraints for commercial tools
 - Path grouping: group all endpoints based on ranking
 - **Register retiming:** only top-10% critical endpoints
- Automatic slack annotation on HDL
 - Benefit RTL designers
 - Find and optimize timing-critical components





Experiment Setup

- Dataset
 - 21 open-source RTL designs
- Label collection

Bonchmarks*	#Designs	Design	HDI Type		
Dencimarks	#Designs	#K Gates	#K Endpoints		
ITC'99	6	9 - 45	0.4 - 1.3	VHDL	
OpenCores	4	6 - 56	0.2 - 3.8	Verilog	
Chipyard	3	20 - 32	2.5 - 4.1	Chisel	
VexRiscv	8	7 - 510	1.2 - 146	SpinalHDL	

* Small designs (<5K Gates) and those dominated by huge memory modules are excluded from the original benchmarks.

- Synopsys Design Compiler / Prime Time + NanGate 45nm PDK
- Slack on each endpoint register

Evaluation metrics

- Regression
 - Correlation/Determination coefficient (R/R²)
 - Mean absolute percentage error (MAPE)

MAPE =
$$\frac{1}{n} \sum_{i=1}^{n} \frac{|y_i - \hat{y_i}|}{y_i} \times 100\%$$

- Ranking
 - Critical level ranking coverage (COVR)

COVR =
$$\frac{1}{m} \sum_{g=1}^{m} \frac{\#(S_g \cap \hat{S_g})}{\#S_g} \times 100\%$$



Modeling Performance

- Fine-grained modeling (slack)
 - Accurate prediction on each reg bit/signal bus
 - Regression: XGBoost w. cus. loss performs best (R=0.89)
 - Ranking: L2R outperforms all regression models (COVR=80%)
- Design overall timing modeling (WNS/TNS)
 - Calibration based on fine-grained modeling
 - RTL-Timer outperforms all baselines

_	Fine-Grained	Method	R	MAPE (%)	COVR (%)
-		Tree-based w/o sample	0.80	26	59
		MLP	A R MAPE (%) COVR (%) sed w/o sample 0.80 26 59 0.71 35 56 'o sample 0.65 38 54 rmer 0.73 35 57 ized GNN 0.25 53 46 ner 0.88 12 66 ion w/o bit-wise 0.56 28 56 g w/o bit-wise / / 39 ner (regression) 0.89 15 71 ner (ranking) / / 80	56	
	Dit wise	MLP w/o sample			
	Dit-wise	Transformer	0.73	35	57
		Transformer0.733557Customized GNN0.255340PTL Timer0.8812	46		
		RTL-Timer	R MAPE (%) COVI 0.80 26 59 0.71 35 56 0.65 38 54 0.73 35 57 0.25 53 44 0.88 12 66 0.56 28 56 / / 39 0.89 15 77 / / 80	66	
_		Regression w/o bit-wise	0.56	28	56
	Signal wise	Ranking w/o bit-wise	/	/	39
	Signal-wise	RTL-Timer (regression)	0.89	15	71
		RTL-Timer (ranking)	ample 0.80 26 59 0.71 35 56 0.65 38 54 0.73 35 57 0.25 53 46 0.88 12 66 it-wise 0.56 28 56 wise / / 39 ssion) 0.89 15 7 ing) / / 86	80	

Overall	Method	R	R^2	MAPE (%)
	SNS [17]	0.73	0.58	33
WNS	MasterRTL [4]	knod R R ² MAR 5 [17] 0.73 0.58 3 sterRTL [4] 0.89 0.74 1 L-Timer 0.91 0.86 1 CAD'22 [13] 0.65 0.32 4 sterRTL [4] 0.96 0.94 3	15	
	RTL-Timer	0.91	0.86	12
	ICCAD'22 [13]	0.65	0.32	42
TNS	MasterRTL [4]	R R ² MA 0.73 0.58 0.89 0.74 0.91 0.86 0.65 0.32 0.96 0.94 0.98 0.97	34	
	RTL-Timer	0.98	0.97	18



Modeling Performance

- BOG variants ensemble learning
 - Each variant contributes to the prediction
 - Robustness across benchmarks and tasks
- Visualization of prediction
 - RTL-STA is not accurate enough
 - Bit-wise calibrates RTL-STA
 - Signal-wise calibrates bit-wise

	Metrics	SOG	AIG	AIMG	XAG	Ensemble
Dit wice	Avg. R	0.85	0.75	0.76	0.77	0.88
Dit-wise	Std. R	0.18	0.25	0.26 0.21 0.08 0.84 0.8 0.8	0.08	
Signal wise	Avg. R	0.82	0.81	0.84	0.8	0.89
	Std. R	0.15	0.22	0.1	0.1	0.06
Signal-wise	Avg. COVR	65	71	72	71	80
	Std. COVR	18	19	21	21	8





Optimization Performance

- Guiding commercial synthesis tool
 - Improve WNS(3.1%)/ TNS(9%) for most designs
 - Maintain or even decrease area/power
 - Reduce time-consuming iterations:

Concurrently run default and opt flows

- Impact after placement
 - Still remains significant after place (w. place opt)
 - WNS(3.1%)/ TNS(6.8%)

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Design	Singal-wise Pred.			Op	Opt. w. Pred. (%)				Opt. w. Real (%)			
Design	R	MAPE	COVR	WNS	TNS	Pwr	Area	WNS	TNS	Pwr	Area	
syscdes	0.94	26%	94%	-1.3	-17	-0.8	1.8	-1.8	-17.3	0	2.6	
syscaes	0.86	23%	77%	-1.3	-13.7	2.1	3.2	-0.1	-14.4	2.1	3.5	
Vex_1	0.87	24%	86%	6.9	7	-3.1	-2.8	-0.3	-1.1	0.5	-0.8	
b20*	0.91	7%	86%	5.6	-4.3	26.2	25	0.2	-6.6	26.2	23.4	
Vex_2	0.86	16%	83%	-0.2	-1.6	-0.9	0	-0.7	-1.8	-0.6	0.3	
Vex_3	0.93	30%	86%	-2.8	-4.8	3.9	1.2	-0.1	-2.2	1.9	1	
b22*	0.74	18%	83%	0.7	-4.8	23.4	23.3	2.9	0.4	22.7	20.2	
b17	0.93	8%	75%	1.9	-5.2	2.2	0	-0.9	-5.6	0.2	1	
b17_1	0.94	5%	79%	5.8	-3.2	1.7	2.1	0.9	-5.8	-0.6	0.4	
Rocket1	0.89	11%	63%	-7.1	-21.4	2.8	1.7	-3.7	-25.4	-66	2.9	
Rocket2	0.92	18%	64%	-7	-23.1	-69.4	-0.6	-4.1	-23.1	1.6	-0.8	
Rocket3	0.88	12%	69%	-7.2	-17.4	-69.4	-0.6	-6.2	-18.3	-69.7	0.8	
conmax	0.91	12%	83%	-1.9	-3	3.4	2.7	-0.9	-0.6	3	2.1	
b18	0.82	13%	84%	-16.4	-33.5	3.8	3.9	-17.9	-35.5	3.6	3.4	
b18_1	0.88	10%	86%	-3.9	-26	0.5	-0.4	-9.8	-27	1.8	0.2	
FPU	0.89	31%	85%	6.2	0.2	0.5	1	4.3	-1.7	-86.6	0.6	
Marax	0.88	16%	78%	-1.7	-3	-0.1	-0.1	2.4	-2.2	0	-0.5	
Vex_4	0.79	16%	67%	-4.8	-18.6	0	-0.7	-7.2	-21.9	0.4	-1	
Vex5	0.92	4%	81%	-1.8	-4.6	0.2	-1.3	-3.6	-10.7	0.3	-0.6	
Vex6	0.94	6%	82%	-1.5	-12.8	0.4	-0.5	-3	-5.3	0.3	-1.3	
Vex7	0.87	6%	81%	-5.7	-7.2	0.5	-0.8	-3	-12.3	0.5	-0.2	
Avg1	0.00	15	90	-1.9	-10.4	-3.4	2.8	-2.5	-11.2	-7.5	2.7	
Avg2	0.89	13	00	-3.1	-9.9	-5.9	0.5	-3	-10.6	-5.7	0.6	

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Optimization Performance

- Optimization impact on slack distribution
 - Path grouping: single high peak \rightarrow two lower peaks (better TNS)
 - Register retiming: improved WNS





Runtime Analysis

- Prediction
 - 4% of default logic synthesis runtime
 - Two key parts:
 - RTL processing
 - HDL to BOG (parallel): 3.2%
 - Register-oriented processing: 0.8%
 - Model inference: <0.1s

Optimization

- Logic synthesis w/ optimization
- Runtime extends by an average of 45% vs. default synthesis flow



Conclusion

- RTL-Timer: estimate slack on each register at the RTL stage
 - Ensemble four ML-friendly RTL representations
 - Capture max slack with register-oriented RTL processing and customized ML model
- Enable early timing optimization
 - Annotate slack on HDL code for RTL designers
 - Predictive timing optimization for logic synthesis process



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Available at: <u>https://github.com/hkust-zhiyao/RTL-Timer</u>

