Fast IR Drop Estimation with Machine Learning

Zhiyao Xie*, Hai Li*, Xiaoqing Xu[‡], Jiang Hu[§], Yiran Chen*

*Duke University, [‡]ARM Inc, [§]Texas A&M University

Outline

- Background
- An overview of ML-based IR drop estimators
- Static IR drop estimators
- Dynamic IR drop estimators
- General challenges and possible solutions

Challenge: Faster IR Drop Estimator Desired

- To optimize PPA & meet constraint, IR drop mitigation may takes many iterations
- Accurate IR drop simulation by commercial tools is very time consuming
- Fast IR drop estimation with machine learning (ML) !



[*] Cadence, Voltus User Guide. ³

Background: IR Drop Types

- Static IR drop
 - Usually measures the average current
 - Identify the weakness of PDN
- Dynamic IR drop
 - Captures the peak transient current
 - Whether toggling vectors required:
 - Yes: Vector-based IR drop
 - No: Vectorless IR drop
- Power Supply Noise (PSN)
 - Comprises both IR drop & L * di/dt



Static and dynamic analysis. [*]

Methods	Type of IR Drop	Time	ML Model	Cross- Design	Features	Objective
IncPIRD	Statia ID	2019	XGBoost	Yes	I_g, R_g, PDN, G	IR mitigation
XGBIR	Static IR	2020	XGBoost	-	I_g, R_g, PDN	PDN design
Yamato <i>et al</i> .	Vector-based IR	2012	Linear Regression	No	P _c	IR-aware timing
Dhotre <i>et al</i> .		2017	Clustering	Yes	r_{tog}, c	IR prediction
Lin <i>et al</i> .		2018	ANN	No	$P_c, R_c, t_c, r_{tog}, c$	IR mitigation
Fang <i>et al</i> .		2018	CNN, XGBoost	No	$P_c, I_c, R_c, t_c, r_{tog}, c$	IR mitigation
PowerNet	Vectorless IR	2020	CNN	Yes	P_c, t_c, r_{tog}	IR mitigation
Mozaffari <i>et al</i> .	Sillicon PSN	2019	ANN, CNN, NLP	Yes	r_{tog}, G	PSN prediction

The existing ML estimators cover different types of IR drop:

- Static IR drop
- Dynamic IR drop
- Power Supply Noise (PSN)

Methods	Type of IR Drop	Time	ML Model	Cross- Design	Features	Objective
IncPIRD	Statia ID	2019	XGBoost	Yes	I_g, R_g, PDN, G	IR mitigation
XGBIR	Static IK	2020	XGBoost	-	I_g, R_g, PDN	PDN design
Yamato <i>et al.</i>	Vector-based IR	2012	Linear Regression	No	P _c	IR-aware timing
Dhotre <i>et al</i> .		2017	Clustering	Yes	r _{tog} , c	IR prediction
Lin <i>et al</i> .		2018	ANN	No	$P_c, R_c, t_c, r_{tog}, c$	IR mitigation
Fang <i>et al</i> .		2018	CNN, XGBoost	No	$P_c, I_c, R_c, t_c, r_{tog}, c$	IR mitigation
PowerNet	Vectorless IR	2020	CNN	Yes	P_c, t_c, r_{tog}	IR mitigation
Mozaffari <i>et al.</i>	Sillicon PSN	2019	ANN, CNN, NLP	Yes	r_{tog}, G	PSN prediction

The existing ML estimators cover different ML models:

- One-dimensional input: Linear Regression, ANN, XGBoost,
- Two-dimensional input: CNN, NLP...

Methods	Type of IR Drop	Time	ML Model	Cross- Design	Features	Objective
IncPIRD	Statia ID	2019	XGBoost	Yes	I_g, R_g, PDN, G	IR mitigation
XGBIR	Static IR	2020	XGBoost	-	I_g, R_g, PDN	PDN design
Yamato <i>et al</i> .	Vector-based IR	2012	Linear Regression	No	P _c	IR-aware timing
Dhotre <i>et al</i> .		2017	Clustering	Yes	r _{tog} , c	IR prediction
Lin <i>et al.</i>		2018	ANN	No	$P_c, R_c, t_c, r_{tog}, c$	IR mitigation
Fang <i>et al.</i>		2018	CNN, XGBoost	No	$P_c, I_c, R_c, t_c, r_{tog}, c$	IR mitigation
PowerNet	Vectorless IR	2020	CNN	Yes	P_c, t_c, r_{tog}	IR mitigation
Mozaffari <i>et al.</i>	Sillicon PSN	2019	ANN, CNN, NLP	Yes	r_{tog}, G	PSN prediction
	-					

Cross-design:

- Model applies to new designs that are not in the training set
- Test and training design differ at least at netlist level

Methods	Type of IR Drop	Time	ML Model	Cross- Design	Features	Objective
IncPIRD	Statio ID	2019	XGBoost	Yes	I_g, R_g, PDN, G	IR mitigation
XGBIR	Static IR	2020	XGBoost	-	I_g, R_g, PDN	PDN design
Yamato <i>et al.</i>		2012	Linear Regression	No	P _c	IR-aware timing
Dhotre <i>et al</i> .	Vector-based IR	2017	Clustering	Yes	r_{tog}, c	IR prediction
Lin <i>et al</i> .		2018	ANN	No	$P_c, R_c, t_c, r_{tog}, c$	IR mitigation
Fang <i>et al.</i>		2018	CNN, XGBoost	No	$P_c, I_c, R_c, t_c, r_{tog}, c$	IR mitigation
PowerNet	Vectorless IR	2020	CNN	Yes	P_c, t_c, r_{tog}	IR mitigation
Mozaffari <i>et al.</i>	Sillicon PSN	2019	ANN, CNN, NLP	Yes	r_{tog}, G	PSN prediction

 $\{I_c, I_g\}$ Current:

- *I_c* : Average or peak current measured on each <u>c</u>ell instance
- I_g : Current loads or the total current on power **g**rids
- $\{R_c, R_g\}$ Resistance:
 - R_c : resistance on the path from power pad to each <u>c</u>ell instance
 - R_g : resistance measured on power <u>g</u>rids and power nodes

c IR	2019	XGBoost	Voc		TD '(' ('
	0000	nemer neuroparene contra sono sono sono sono sono sono sono son	165	I_g, K_g, PDN, G	IR mitigation
	2020	XGBoost	-	I_g, R_g, PDN	PDN design
	2012	Linear Regression	No	P _c	IR-aware timing
Vector-based IR	2017	Clustering	Yes	r_{tog}, c	IR prediction
	2018	ANN	No	$P_c, R_c, t_c, r_{tog}, c$	IR mitigation
	2018	CNN, XGBoost	No	$P_c, I_c, R_c, t_c, r_{tog}, c$	IR mitigation
orless IR	2020	CNN	Yes	P_c, t_c, r_{tog}	IR mitigation
on PSN	2019	ANN, CNN, NLP	Yes	r_{tog}, G	PSN prediction
	or-based IR orless IR on PSN	or-based IR 2012 2017 2018 2018 2018 2018 orless IR 2020 on PSN 2019	or-based IR 2012 Linear Regression 2017 Clustering 2018 ANN 2018 CNN, XGBoost orless IR 2020 CNN on PSN 2019 ANN, CNN, NLP	or-based IR 2012 Linear Regression No 2017 Clustering Yes 2018 ANN No 2018 CNN, XGBoost No orless IR 2020 CNN Yes on PSN 2019 ANN, CNN, NLP Yes	or-based IR2012Linear RegressionNo P_c 2017ClusteringYes r_{tog} , c2018ANNNo P_c , R_c , t_c , r_{tog} , c2018CNN, XGBoostNo P_c , I_c , R_c , t_c , r_{tog} , corless IR2020CNNYes P_c , t_c , r_{tog} on PSN2019ANN, CNN, NLPYes r_{tog} , G

{PDN}: The information about PDN

 $\{P_c\}$ Power: Power dissipation of each <u>c</u>ell instance (internal, switching, leakage)

{G} Global information: process, voltage, temperature, frequency, layout size

{*c*} Cell information: cell area, cell load, cell type

Methods	Type of IR Drop	Time	ML Model	Cross- Design	Features	Objective
IncPIRD	Statia ID	2019	XGBoost	Yes	I_g, R_g, PDN, G	IR mitigation
XGBIR	Static IR	2020	XGBoost	-	I_g, R_g, PDN	PDN design
Yamato <i>et al</i> .	Vector-based IR	2012	Linear Regression	No	P_c	IR-aware timing
Dhotre <i>et al</i> .		2017	Clustering	Yes	r_{tog}, c	IR prediction
Lin et al.		2018	ANN	No	$P_c, R_c, t_c, r_{tog}, c$	IR mitigation
Fang <i>et al.</i>		2018	CNN, XGBoost	No	$P_c, I_c, R_c, t_c, r_{tog}, c$	IR mitigation
PowerNet	Vectorless IR	2020	CNN	Yes	P_c, t_c, r_{tog}	IR mitigation
Mozaffari <i>et al.</i>	Sillicon PSN	2019	ANN, CNN, NLP	Yes	r_{tog}, G	PSN prediction

$\{r_{tog}\}$ Toggling activity

• Switching activity of each cell. Usually measured by toggle rate.

$\{t_c\}$ Timing window

• The timing interval of switching for each cell. Min/max signal arrival time.

Methods for Static IR Drop

• Similarities between IncPIRD & XGBIR:

• ML model: both use XGBoost

Category	Description of Feature on node <i>n</i>
Chin / DDN	Pitch of all metal layers
Chip / PDN	Width / height of the chip
	<i>Pullup</i> : The effective resistance at <i>n</i>
Electrical	<i>Pulldown</i> : The symbolic IR drop at <i>n</i>
	Pullup and Pulldown of <i>n</i> 's neighbors

Features in IncPIRD

Features in **XGBIR**

Category	Description of Feature on node n				
	The number of power tracks				
Chip / PDN	Distance between n and boundary				
	Power track segmental resistance				
	<i>Pullup</i> : Voltage sources' impact on <i>n</i>				
Flootminal	<i>Pulldown</i> : Current loads' impact on <i>n</i>				
Electrical	<i>V2I</i> : Resistance between voltage				
	sources and current loads				

• Special property of IncPIRD :

- Model used for iterative PDN design
- Use 'update condition' to decide whether model needs to be retrained

IncPIRD: Ho, *et al.*, ICCAD 19 XGBIR: Pao, *et al.*, DATE 20

11

Dynamic IR Drop with Power Only [*]

- A linear model for each cell instance
 - IR drop = k * power + b
 - Captures correlation between IR drop and power
- Discussion:
 - Impact from neighboring cells not captured.



Power Power vs. IR-drop on cells with high correlation. [*]

[*] Yamato, et al., ITC 12

Dynamic IR Drop with Spatial Info^[*]

- Predict the overall PSN of the whole SOC
- Method:
 - Input (local) features: Togging rate density map + cell density map
 - Use CNN to capture **spatial information** at local region
 - Global information about the whole chip provided in FC layers
- Discussion:



Dynamic IR Drop with Spatial & Timing Info^[*]

- Predict the IR drop of each cell, considering timing info
- Method:
 - Local current & power maps around the target cell as 2D input
 - Timing window & location of each cell directly provided in 1D input
 - Compared with Mozaffari, et al., similar 2D & 1D inputs through CNN



Dynamic IR Drop with Spatial & Timing Info^[*]

- Predict IR drop of each grid. Capture the time instant with peak IR.
- Method (features):
 - Power maps as features $P_{internal}$, $P_{switching}$, P_{total} ,
 - Divide clock cycle into N time instants.
 - For each grid, measure time-decomposed power maps $P_t[1]-P_t[N]$ around it
 - Only the cells that can switch at instant j contribute to $P_t[j]$



[*] Xie, et al., ASPDAC 20

Dynamic IR Drop with Spatial & Timing Info^[*]

- Predict IR drop of each grid. Capture the time instant with peak IR.
- Method (model):
 - Use the same CNN model to process all N input features $P_t[1]-P_t[N]$ in parallel
 - Generate N outputs $o_1 o_N$, corresponding to N transient IR drops
 - Take the $max([o_1: o_N])$ as estimated IR. It measures the highest transient IR



Challenges & Future Works

• Challenge 1: Evaluation & comparison



Challenge 2: Human effort



Challenge 3: Robustness & generalization

Challenges & Possible Solution

• Challenge 1: difficulty in evaluation & comparison among models

- For static IR drop: IncPIRD vs XGBIR?
- For dynamic IR drop: Fang *et al.* vs PowerNet vs ...?
- Similar for other tasks: routability, parameter tuning,
- Possible solution: open-sourced benchmark for ML applications
 - Designs & flows dedicated to ML applications on multiple design objectives
 - Benefit:
 - Enable rapid and clear comparisons
 - Ensure high-quality training & validation data
 - Relieve researchers from data generation

Challenges & Possible Solution

• Challenge 2: model development & maintenance take human effort

- Estimators tuned for both feature selection and model architecture
- Estimators may vary for different dataset & application scenarios
- Tuning heavily rely on human expertise.
- Possible solution: search ML algorithms automatically
 - Search both appropriate features combination and ML model structure
 - Automated machine learning (AutoML)
 - NAS (Neural Architecture Searching)



Challenges & Possible Solution

Challenge 3: model's robustness & generalization not verified

- How model will perform on previously unseen data
- Not likely to perform well on every new cases (designs/technology nodes)
- Risky every time when inferring a new test case.
- Possible solution: measure model's robustness before inference
 - Quantify similarity between training & testing cases
 - Example: the 'update condition' in IncPIRD, deciding whether ML model needs to be retrained [1]





- We summarize the latest progress in ML models for fast IR drop estimation
- We introduce the innovations and technical details of representative methods
- We discuss some general challenges in ML estimators

Thank You! Questions?