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# Parasitic-Aware Analog Circuit Sizing with Graph Neural Networks and Bayesian Optimization

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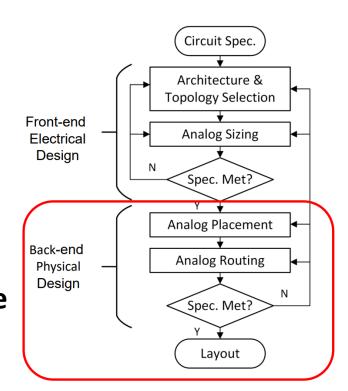


- Background and Prior Work
- Parasitic Prediction with Machine Learning
- Parasitic-Aware Sizing with Bayesian Optimization
  - Improved Surrogate Modeling
  - Uncertainty Estimates with Dropouts
- Experimental Results
- Conclusions

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### **Background and Prior Work**

- Analog design still heavily manual
  - Large degree of freedom
  - Design specific performance
- Iterative optimization between schematic sizing and layout
  - Estimate parasitic to avoid "surprises"
  - Critical parasitic effect performance
- Parasitic becomes difficult to estimate



#### **Background and Prior Work**

- Numerous methods for automated sizing
  - Model first, then optimize
  - Model free black-box optimization
  - Sample efficient black-box optimization
- Parasitic-aware sizing
  - Generate layout in optimization loop
  - Estimate parasitic after placement

Rajan et al. DATE'04, Habel et al. TCAD'11 Hakhamaneshi et al ICCAD'19, Settaluri et al. DATE'20

Lourenco et al. DATE'15

Require some-level of layout generation



### **Background and Prior Work**

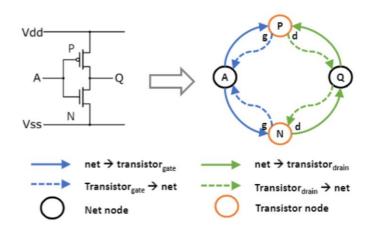
#### • In this work:

- Parasitic-aware sizing framework based on Bayesian optimization
- Replace in-the-loop layout generation with Graph Neural Network (GNN) based parasitic prediction
- Better performance surrogate model with parasitic features
- Leverage dropout as an efficient uncertainty prediction
- Improved runtime and optimization convergence

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### Parasitic Prediction with Machine Learning

- Predicting layout parasitic directly from schematic
  - Graph neural networks (ParaGraph)
  - Random forests (MLParest)



Circuit Input, x Output, y Prelay Net, n Post-Lay Net, n Reff Hierarchy # Mos Random Forest # Source Models # Drain Prelay Net, 1 Ceff Post-Lav Net. 1 Circuit m Prelay Net, n Post-Lav Net. n

Prelay Net, 1 Post-Lay Net,

ParaGraph: Ren et al. DAC'20

MLParest: Shook et al. DAC'20

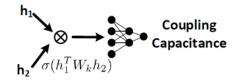
### Parasitic Prediction with Machine Learning

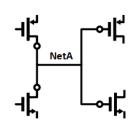
- Our work extend ParaGraph: Ren et al. DAC'20
  - C only → R+C+CC
- R+C+CC data labeling
  - Effective resistance from DC simulations
  - Lump to C and CC

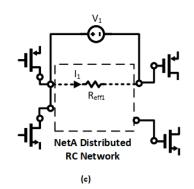
C prediction

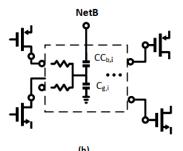
• R/CC prediction

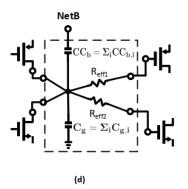






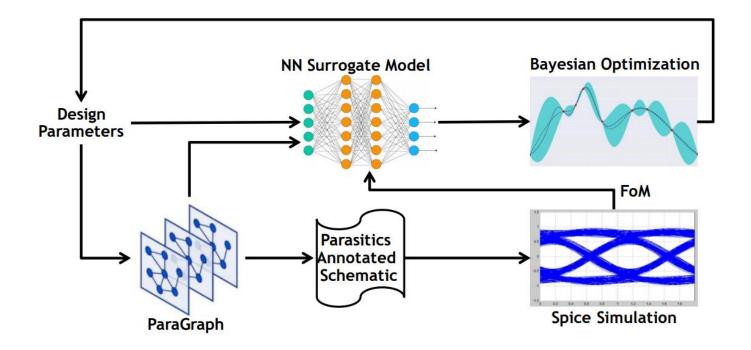






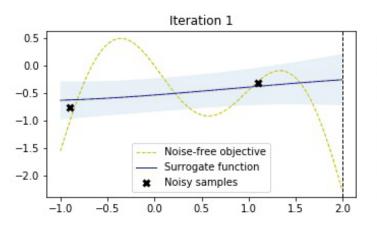
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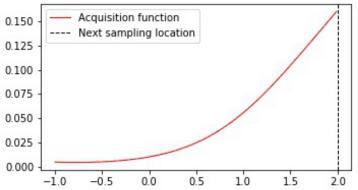
#### Parasitic-Aware Sizing with Bayesian Optimization



### **Bayesian Optimization**

- Problem formulation: constrained single-objective
- Bayesian optimization
  - Gaussian process regression: predict both mean and uncertainty
  - Acquisition function: determine where next to evaluate (balance exploration and exploitation)

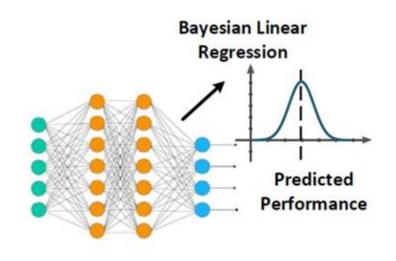




### **Improved Surrogate Modeling**

- Gaussian Process Regression
  - Non-parametric probabilistic model
  - Poor scalability O(N³) training
- Scalable Bayesian Optimization
  - Neural networks as trainable kernel function
  - Replace FC layer with Bayesian linear regression (BLR)
  - Better scalability O(N) training

Snoek et al. PMLR'15, Zhang et al. DATE'19



## **Improved Surrogate Modeling**

- Use neural networks
  - For scalability
  - Additional parasitic features from ParaGraph
- Method:
  - ParaGraph is pre-trained with abundant data
  - Circuit graph is fixed, node input attributes (contains sizing) change
  - Obtain node embedding matrix  $H = \{h_1 \cdot \cdot \cdot h_n\} \in \mathbb{R}^{n \times d}$
  - Get graph embedding
    - Average:

$$g = \frac{1}{n} \sum_{i=1}^{n} h_i$$

Weighted:

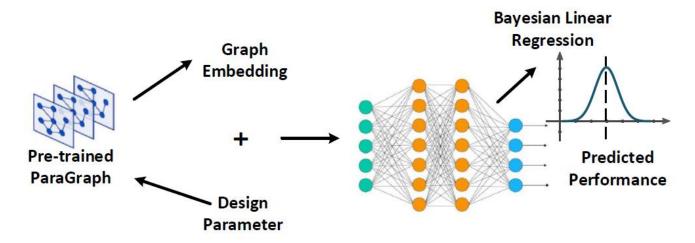
$$z_{i} = \sigma(w^{T} h_{i})$$

$$w_{i} = softmax(z_{i}) = \frac{exp(z_{i})}{\sum_{1}^{n} exp(z_{i})}$$

$$g = \frac{1}{n} \sum_{1}^{n} w_{i} \cdot h_{i},$$

## **Improved Surrogate Modeling**

- Use neural networks
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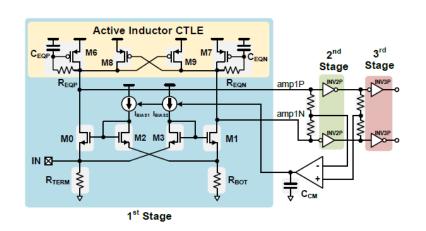


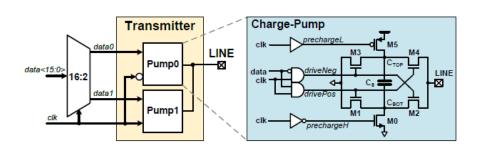
#### **Uncertainty Estimates with Dropout**

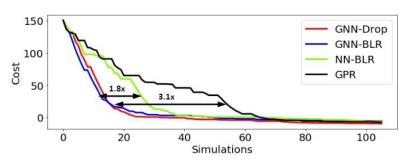
- Replace BLR with dropouts:
  - Train model with dropout
  - Retain model in training mode and batch inference
  - Obtain statistical mean and variance (uncertainty)
- Pros: Easy to implement and works!
- Cons: Difficult to obtain gradients of acquisition function
- Solution: Maximize acquisition function with non-gradient methods (particle swarm optimization)
- More details in paper.

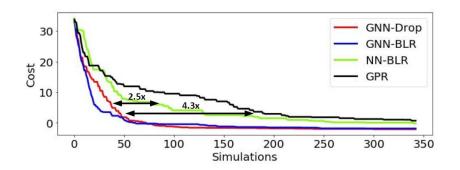
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#### **Experimental Results**









### **Experimental Results**

- Extended C+CC parasitic estimation reduces simulation errors by 41.3% compared with C only model
- Improved surrogate performance model outperforms Gaussian process regression (GPR) by more than 20%
- Our method improves convergence by 2.1x speedup compared with NN-BLR and 3.7x speedup compared with GPR
- More details in the paper

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#### **Conclusions**

#### Conclusions:

- Parasitic-aware sizing without layout generation
- Extend parasitic estimation to R+C+CC
- Improved surrogate model with parasitic graph embedding
- Leverage dropouts for uncertainty prediction with Bayesian optimization

# Thank You