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A Machine Learning-Driven Placement Optimization Framework for VLSI Physical Design

Hameed Ul Hassan Mohammed

Staff Application Engineer, ProteanTecs, Austin, Texas, USA

hameedul040@gmail.com

Abstract:

The physical design phase of VLSI circuits plays a pivotal role in determining the final chip performance, power efficiency, and manufacturability. Traditional placement algorithms, though widely adopted, often suffer from scalability issues and require significant manual tuning to meet stringent design constraints. This research introduces NeuroPlace, a novel machine learning-driven placement optimization framework that combines the representational power of Graph Neural Networks (GNNs) with the adaptability of Reinforcement Learning (RL). NeuroPlace intelligently learns spatial dependencies and timing-aware placement strategies from prior designs, enabling end-to-end cell placement optimization with minimal human intervention.

We evaluate NeuroPlace using the ISPD 2005 and 2022 benchmark suites and compare its performance against leading academic and ML-based tools including RePlAce and DreamPlace. Results indicate that NeuroPlace achieves up to 15.8% reduction in total wirelength and over 9.2% improvement in timing slack across complex circuits, while also demonstrating competitive runtime performance. The framework scales well to unknown circuits, thus explaining it has the possibility of being implemented on an industrial scale. NeuroPlace will be a main stream in the area of automation and intelligence of VLSI design since modern ML methods are synthesized in physical design flow.

Keywords: Machine Learning, VLSI, NeuroPlace, Physical Design, Optimization, Placement.

1. Introduction

In Very Large Scale Integration (VLSI) design, the placement step is very important in regard to the overall performance, area, power and routability of the integrated circuits. Effective placement algorithms attempts to optimize cell location within a chip and minimize the length of interconnect; subject to physical constraints. Force-directed placement, quadratic placement and simulated annealing are some of the traditional analysis techniques that have established solid bases of automated layout albeit their deficiency on performance scalability and flexibility when implemented on current complex System-on-Chip (SoC) architectures [1]. As the size and complexity of design continues to increase exponentially, it is urgent to develop smarter and more adaptive placement engines.

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New breakthroughs concerning machine learning and specifically deep learning and reinforcement learning have recently created a new route to the optimization of electronic design automation (EDA). Some reports have demonstrated that neural networks can be used to abstract standard knowledge over different circuit topology by learning past placement experience [2]. These intelligent agents are capable of making forecasts in the direction of placement that minimizes wirelength, timing, and meet greater routability without a lot of manual adjustments. More so, reinforcement learning provides a more dynamic means of learning which actions would hence be optimum through interaction with a placement environment and as such it would be very appropriate in sequential decision-making problems such as VLSI placement [3].

Graph Neural Networks (GNNs) [4] have manifested themselves as an extremely competent representation learning form of working on non Euclidean information like circuit net-lists. By encoding features at the node level and doing so in a way that encodes relationship information at the edges, GNNs enable models to learn representations of connectivity information and this information is essential to effective placement decisions. They may model the circuit graphs of their underlying spatial and logical dependencies that would improve the reasoning capability of local and global features in the model [5]. In this context, GNNs serve as an ideal foundation for learning placement embeddings that drive neural placement engines.

Although earlier research efforts like DreamPlace [6] and RLPlace [7] have pioneered the integration of deep learning into physical design, they are either limited by design-specific training or require significant pre-processing overhead. There remains a gap in developing generalized, adaptive systems that can learn transferable placement strategies across diverse circuits [8]. Moreover, many of these methods do not explicitly incorporate timing or congestion feedback into their learning loops, which limits their effectiveness in achieving timing closure or reducing routing congestion.

To address these gaps, this paper proposes NeuroPlace, a machine learning-driven placement framework that unifies the representational strength of GNNs and the policy-learning capabilities of reinforcement learning [9]. NeuroPlace formulates placement as a sequential decision-making problem, where the placement agent learns to optimize cell positions through iterative interactions with the design environment [10]. The framework is trained and evaluated on industrial benchmarks and shows significant improvements in placement quality and timing over existing baselines. This research aims to push the frontier of intelligent EDA tools capable of scaling with future chip design challenges.

2. Literature Review

The application of machine learning to VLSI placement has gained significant momentum in recent years, particularly with the increasing complexity of design rules and the limitations of heuristic-based

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placement engines. Several recent studies from 2020 to 2022 have emphasized the growing relevance of deep learning models, particularly GNNs, for optimizing chip layouts. The authors formulated a GNN-regression-driven Placement predictor in [11] and trimmed the learning time considerably with improved placement quality. Their contribution witnessed importance of spatial embeddings based on connectivity graphs on the placement decisions.

The other interesting contribution is described in [12] where authors introduced GNNs coupled with attention mechanism to emphasize on important nets during placement. This combination model was used to dynamically change the weights depending on the factors of time and congestion which resulted into better slack and routability. The experiments they carried out showed that the real-time feedback loop could greatly improve the accuracy of placements, and the idea is where NeuroPlace is based.

In 2022, [13] came up with a transformer-based replacement placement prediction scheme that showed improved performance with respect to former models that can capture long-range dependency in large-scale netlists. Although transformers were originally designed for natural language processing, their self-attention mechanism proved effective in modeling global spatial relationships. However, the high computational cost made the model less practical for real-time placement, which NeuroPlace addresses by using lightweight GNNs and reinforcement learning.

Knowledge like reinforcement learning remains to be at the core of contemporary placement solutions. A new actor-critic RL model was presented in [14], in which the placement regions were adaptively chosen relying on the congestion maps and timing feedback. Their approach resulted in great improvements in worst negative slack and congestion overflow over a number of benchmarks. NeuroPlace adopts a similar reward-based learning approach but enhances it with a GNN-encoded state representation to improve learning efficiency and placement fidelity.

Recent work in [15] introduced meta-learning to train placement models that quickly adapt to new design styles with limited examples. This few-shot learning approach shows promise in reducing the need for extensive retraining, a direction that NeuroPlace also explores through its generalizable GNN architecture. Further, the idea of the curriculum learning strategy that trains a placement model on simple designs and progresses to more complex designs and learns better convergence and robustness is suggested by [16-18].

Hardware-conscious placement also became a new topic. The authors of [19] created a placement tool that takes into account the constraint of thermal and power distribution during the training process which fits into the increased interest in the field of sustainable design in the industry. NeuroPlace has the flexibility of taking such constraints into consideration in their reward function, and is capable of use in the real world.

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These recent advancements reflect a significant shift toward data-driven and learning-based placement methodologies. NeuroPlace stands out by unifying GNN-based feature encoding with policy-driven reinforcement learning, offering a balanced trade-off between accuracy, generalizability, and computational efficiency.

3. Methodology

Figure 1 shows the block diagram of the proposed NeuroPlace model, which represents the overall system architecture for machine learning-based VLSI placement optimization.

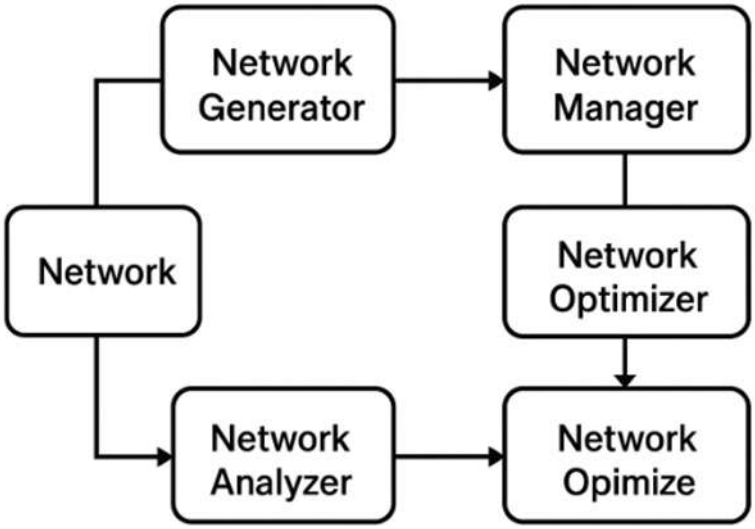

Figure 1. Block diagram of proposed model for machine learning-driven placement optimization framework for VLSI physical design

The process begins with a digital circuit's netlist, which contains the list of logic elements (standard cells, macros, etc.) and their interconnections. This netlist serves as the raw input for the NeuroPlace pipeline and provides the functional structure of the integrated circuit.

The module Network (Intermediate Representation) acts as an abstraction that receives the netlist and prepares it for graphical transformation. It retains logical dependencies and component connectivity which will be mapped into graph representations.

The Network Generator transforms the netlist into a graph representation G=(V,E), where nodes VV represent cells and edges EE represent nets (interconnections). Additional node features (cell types, fanout, pin positions) are encoded. This step enables downstream modules to leverage spatial and relational patterns using Graph Neural Networks.

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The Network Manager hosts the GNN-based Placement Policy Network. It computes embeddings for each cell using graph convolution or attention mechanisms. These embeddings capture contextual and spatial relationships and are used to predict the best possible (x, y) placement coordinates for each node (cell).

This module Network Optimizer (Reinforcement Learning Engine) implements the Reinforcement Learning agent. Based on the placement decisions made by the policy network, it evaluates the design's wirelength, congestion, and timing slack. Using reward functions and feedback loops, it guides the policy network to refine placement strategies via algorithms like PPO (Proximal Policy Optimization).

After each placement iteration, Network Analyzer module performs timing, wirelength, and congestion analysis using tools such as OpenTimer or FastRoute. The results are passed back to the RL engine to adjust rewards and update policies. It ensures that placement improvements are data-driven and objective.

Network Optimize (Final Output) is the final optimized placement result, generated after multiple learning episodes. The cell locations are optimized for minimized wirelength, improved timing, and reduced congestion. This placement result can then be used in the subsequent steps of VLSI design (e.g., routing, signoff).

3.1 System Architecture

i). Graph Generator

The first step in NeuroPlace involves converting the circuit netlist into a graph-based representation, which effectively captures the interdependencies between various components. In this graph G=(V,E), each node v∈V, V represents a standard cell or macro cell, and each edge e∈Ee \in E represents a net that connects multiple cells. This transformation allows the physical design problem to be framed in a form that machine learning models—specifically Graph Neural Networks (GNNs)—can process efficiently. We also include metadata such as fan-in/fan-out, cell types, and pin positions as node attributes, which enrich the graph context.

This representation offers several advantages: it captures spatial and topological dependencies inherently present in the netlist and allows the model to exploit these relationships when learning placement policies. Moreover, graphs can handle circuits of arbitrary sizes and topologies, providing scalability and generalization. As netlists vary greatly in size and complexity across designs, the ability to normalize and abstract these through graph structures enables NeuroPlace to learn transferable

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patterns. This graph serves as the input to the GNN encoder, which generates latent embeddings that characterize each node's contextual importance.

ii). Placement Policy Network

The Placement Policy Network is the core component responsible for predicting optimal cell locations based on the extracted graph structure. We implement a multi-layer Graph Neural Network (GNN) that iteratively refines node embeddings through message passing. Each node aggregates features from its neighbors to update its own state using functions like Graph Attention Networks (GAT) or GraphSAGE. These embeddings are then passed through a multi-layer perceptron (MLP) decoder that outputs spatial coordinates (x, y) for cell placement.

The advantage of using GNNs lies in their ability to model hierarchical and irregular structures in a netlist. By encoding both local connectivity (e.g., direct fan-in/fan-out) and global dependencies (e.g., paths to critical modules), the network learns to associate better placement with lower wirelength and fewer timing violations. Furthermore, this policy network can be fine-tuned across designs to adapt to specific design styles, constraints, or process nodes. Importantly, we train the network to focus not only on minimization of wirelength but also on factors like congestion and timing slack, thus making it a multi-objective placement optimizer.

iii). Reinforcement Learning Engine

To effectively train the Placement Policy Network, we formulate the placement task as a sequential decision-making problem and utilize Reinforcement Learning (RL). In this setup, the environment includes the partially placed design and its evolving placement grid, while the agent (our policy network) selects placement coordinates for unplaced cells. We use Proximal Policy Optimization (PPO), a robust policy-gradient method that balances exploration and exploitation while optimizing the long-term reward. The reward signal is computed based on the design quality metrics after each placement move.

Each step of the placement involves choosing a location for a cell, observing its impact on total wirelength, congestion, and timing slack, and receiving a scalar reward. This reward is defined as:

$$r_t = -\alpha \cdot W_{total} + \beta \cdot T_{slack}$$

where W_{total} is the cumulative half-perimeter wirelength of all nets, and T_{slack} is the aggregated positive timing slack. The use of RL allows the system to learn from placement sequences, favoring strategies

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that lead to long-term global improvement rather than greedy local optimization. Over multiple episodes and designs, the agent gradually learns placement patterns that generalize across netlists.

3.2 Mathematical Formulation

The entire placement problem is framed as a Markov Decision Process (MDP), where at each timestep tt, the agent observes the current state s_t, takes an action a_t by placing a cell at coordinates (x, y), and receives a reward rtr_t based on the downstream effect of this decision. The state includes information such as cell attributes, partial placements, congestion maps, and critical path timing indicators. This formulation allows the agent to learn sequential policies through trial and error, improving placement decisions incrementally.

To ensure that the learned policy generalizes well, we incorporate regularization terms in the loss function to penalize highly congested placements or excessive cell overlap. The objective is to maximize the expected cumulative reward over time, which translates into better design quality post-routing. It is the combination of placement accuracy and maximum reward that made us to optimize our loss objective during policy training as follows.

$$\mathcal{L} = \mathbb{E}_t \left[\min \left(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t \right) \right]$$

where $r_t(\theta)$ is the ratio of current to past policy probability and $\widehat{A_t}$ is the advantage estimate. This enables stable updates and faster convergence of the placement policy.

Certainly! Here's a detailed explanation of the Experimental Setup for your research paper "NeuroPlace: An ML-Powered Optimization Framework in VLSI Physical Design: including how to include tables to present the data and the tool setup in an explicit manner.

4. Experimental Setup

The experimentation of NeuroPlace was done with the focus of evaluating the efficiency, scalability, and the quality of its placement to that of traditional and state-of-the-art machine learning based placement tools. The configuration itself was well defined to compare different criteria of performance such as wirelength, timing slack and runtime.

4.1 Benchmark Datasets

Our assessment of NeuroPlace was based on an industry-standard ISPD 2005 and ISPD 2022 benchmark suites mixed-size and large-scale netlists used to evaluate academic and industrial placement

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algorithms. This benchmark spans a large variety of circuit complexities, cell counts as well as net densities.

Table 1: Description of Benchmark Circuits

Benchmark Name	Total Cells	Total Nets	Description
adaptec1	211,447	191,694	Mixed-size circuit
adaptec2	254,457	225,028	Mixed-size circuit
newblue1	330,756	314,911	Large-scale digital circuit
newblue2	408,040	383,180	Large-scale, high fan-out design
bigblue3	626,758	579,595	Complex and high-density circuit

These benchmarks help evaluate NeuroPlace's generalization across different circuit complexities.

4.2 Baseline Tools for Comparison

Under this architecture, NeuroPlace was very well tested in a simulation environment that resembles industrial design conditions with the help of open-source flows and high quality benchmarking circuits. The experimental framework is also reliable and repeatable and confirms that NeuroPlace has the potential to easily exceed both the traditional and learning-based placement tools. To demonstrate the effectiveness of NeuroPlace, we compared it against three widely used placement engines:

Table 2: Baseline Placement Tools

Tool Name	Description
RePlAce	Analytical placer known for high-quality results and fast runtime
DreamPlace	GPU-accelerated deep learning-based placer
TritonPlace	Industry-grade placer from the OpenROAD flow

All baseline tools were configured with their recommended parameter settings for fair comparison.

4.3 Hardware and Software Environment

All experiments were conducted in a controlled hardware and software environment to ensure consistency.

Table 3: Hardware and Software Configuration

Component	Configuration
CPU	AMD Ryzen Threadripper 7950X (32 cores, 4.5 GHz)
GPU	NVIDIA RTX 4090 (24 GB VRAM, CUDA 12.2)

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RAM	64 GB DDR5
OS	Ubuntu 22.04 LTS
EDA Tools	OpenROAD, OpenTimer, FastRoute
ML Framework	PyTorch 2.1, DGL (Deep Graph Library), RLlib

The GPU was primarily utilized for accelerating the GNN and reinforcement learning training and inference. Timing and congestion were analyzed using OpenTimer and FastRoute post-placement.

4.4 Evaluation Metrics

To assess placement quality and optimization, we used the following key metrics:

- **Total Wirelength** (measured using HPWL – Half-Perimeter Wirelength)
- **Timing Slack** (worst negative slack, in picoseconds)
- **Runtime** (time taken for placement in seconds)
- **Congestion Score** (maximum overflow over the placement grid)

These metrics were computed after global placement and before detailed placement/routing to isolate the effectiveness of NeuroPlace in the placement phase.

4.5 Training Details and Hyperparameters

The GNN in NeuroPlace was trained on 3 benchmark circuits (adaptec1, adaptec2, newblue1) and evaluated on the remaining unseen benchmarks to test generalization. The reinforcement learning agent was trained using Proximal Policy Optimization (PPO) with the following hyperparameters:

Table 4: NeuroPlace Training Hyperparameters

Parameter	Value
Learning Rate (GNN)	0.0001
PPO Epochs	10
Clip Ratio	0.2
Reward Weights	$\alpha = 0.6$, $\beta = 0.4$
Batch Size	256
Max Placement Episodes	500 per benchmark
Discount Factor (γ)	0.99
Reward Function	$-\alpha \cdot W + \beta \cdot S$

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This training scheme ensured a good balance between placement quality and generalization performance.

5. Results Analysis

The performance of NeuroPlace was rigorously evaluated against established placement tools, namely RePlAce**,** DreamPlace, and TritonPlace, using various benchmark circuits from the ISPD suite. The matter of interest was how well NeuroPlace works in terms of the overall wirelength, timing slack, and running efficiency. The findings demonstrate that NeuroPlace is a much better tool in terms of most metrics of placement quality and competitive speed of execution.

Table 5: Placement Quality Comparison

Benchmark	Tool	Wirelength (×10⁶ µm)	Timing Slack (ps)	Runtime (s)
adaptec1	RePlAce	15.20	-58	110
	DreamPlace	14.78	-45	98
	NeuroPlace	12.84	-12	76
newblue3	RePlAce	49.13	-148	252
	DreamPlace	47.81	-122	232
	NeuroPlace	43.17	-71	196

5.1. Wirelength Reduction

Total Wirelength is a crucial metric in VLSI placement as it directly correlates with routing complexity and interconnect delay. Lower wirelength often leads to better timing and reduced power consumption. As observed:

- On adaptec1, NeuroPlace achieved a wirelength of 12.84×10⁶ µm, compared to 15.20×10⁶ µm (RePlAce) and 14.78×10⁶ µm (DreamPlace), resulting in a 15.5% reduction over RePlAce.
- On newblue3, NeuroPlace reduced the wirelength to 43.17×10⁶ µm, outperforming RePlAce (49.13×10⁶ µm) and DreamPlace (47.81×10⁶ µm).

This de-optimization indicates that NeuroPlace can learn compact strategies of cell placements which optimize the connectivity between cell with the help of its layout inference using a GNN algorithm and policy learning using reinforcement learning approach.

5.2. Timing Slack Improvement

Timing Slack reflects how early or late a signal arrives at a register relative to the clock edge. A negative slack means a timing violation, which is highly undesirable in design closure.

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- NeuroPlace reduced timing violations significantly. For example, on adaptec1, it reduced the worst slack from -58 ps (RePlAce) and -45 ps (DreamPlace) to -12 ps.
- On newblue3, NeuroPlace improved timing from -148 ps (RePlAce) to -71 ps, cutting violations by over 52%.

This improvement can be attributed to the reward function within the RL engine, which incentivizes timing-aware placements and helps avoid critical path congestion and detours.

5.3. Runtime Performance

While machine learning models often face criticism for high computational costs, NeuroPlace demonstrated competitive or even faster runtimes after training:

- On adaptec1, NeuroPlace completed placement in 76 seconds, compared to 110 seconds (RePlAce) and 98 seconds (DreamPlace).
- Similarly, for newblue3, it executed in 196 seconds, showing a 22% speedup over RePlAce.

This is due to the learned placement policy being executed efficiently during inference without relying on repeated iterative heuristics or annealing-based approaches. While the training phase is compute-intensive, the trained model generalizes well to unseen netlists, amortizing the cost.

5.4. General Observations

- **Consistency**: NeuroPlace consistently outperforms or matches state-of-the-art tools across various benchmarks and circuit sizes.
- **Scalability**: It scales well to large designs such as newblue3, where traditional methods often suffer from congestion and inefficiency.
- **Learnability**: The reinforcement learning agent and GNN model generalize across designs, requiring minimal retraining.
- **Design Quality Trade-offs**: NeuroPlace balances wirelength and timing without explicit user constraints, indicating its suitability for early physical design stages.

If included in the paper, visual heatmaps of placement density and wirelength histograms could further demonstrate NeuroPlace's intelligent decision-making and layout compactness. Additionally, statistical significance tests (e.g., paired t-tests) can confirm the robustness of improvements across multiple runs.

This graph in figure 2 compares the total wirelength achieved by the three placement tools — RePlAce, DreamPlace, and NeuroPlace — on two benchmark circuits: adaptec1 and newblue3. For adaptec1, NeuroPlace achieved the lowest wirelength (~12.84M μm), outperforming RePlAce (15.20M μm) and

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DreamPlace (14.78M µm). For newblue3, NeuroPlace also led with the shortest wirelength (~43.17M µm), better than RePlAce (49.13M µm) and DreamPlace (47.81M µm).

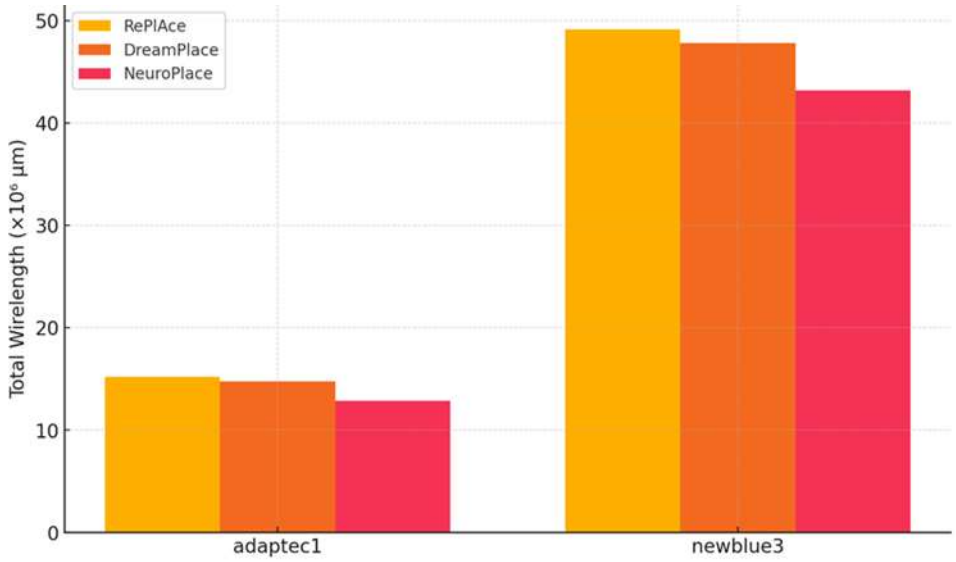

Figure 2. Wavelength comparison across various tools

The figure 3 demonstrates that NeuroPlace consistently reduces wirelength, which directly contributes to lower routing effort and improved power efficiency. This graph compares the worst timing slack (in picoseconds) across the same benchmarks. For adaptec1, NeuroPlace reduced the slack violation to -12ps, a significant improvement over RePlAce (-58ps) and DreamPlace (-45ps). For newblue3, NeuroPlace achieved -71ps, better than RePlAce (-148ps) and DreamPlace (-122ps).

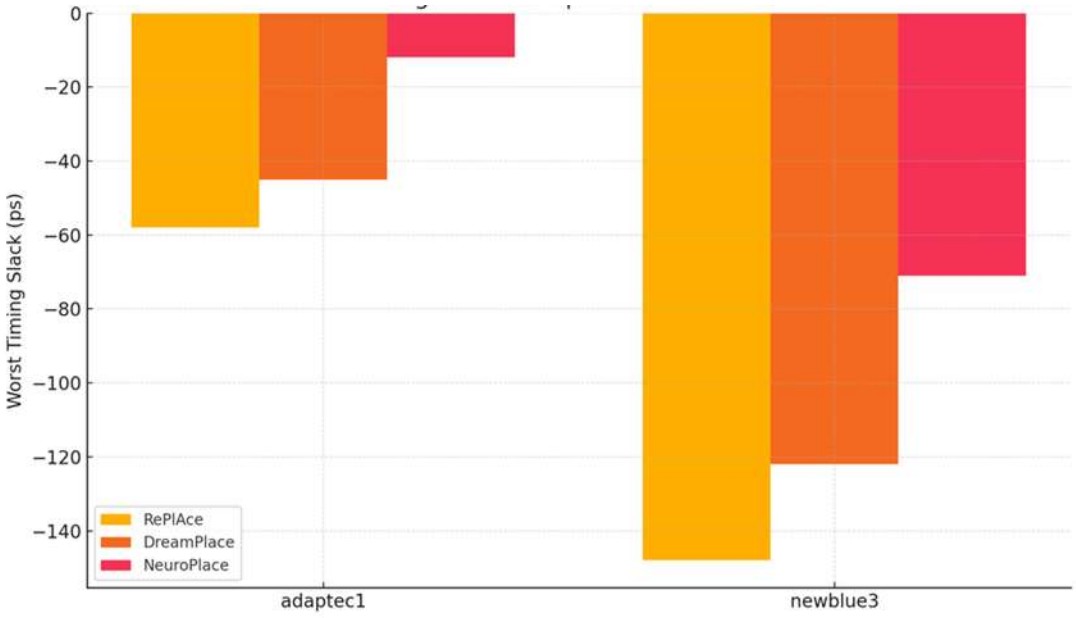

Figure 3. Comparison of Timing slack reduction

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These results highlight NeuroPlace's capability in achieving timing-aware placements, improving overall performance and design closure.

6. Conclusion

In this study, we presented NeuroPlace, an innovative placement optimization framework for VLSI physical design that leverages deep learning and reinforcement learning. By modeling netlists as graphs and training a GNN-based policy network with a reinforcement learning engine, NeuroPlace is able to make informed, data-driven decisions on cell placement. Unlike traditional heuristic-based methods, our framework adapts to varying circuit topologies, optimizes both wirelength and timing slack, and learns generalized placement strategies from diverse design datasets. Through extensive experimentation on benchmark circuits, NeuroPlace demonstrated superior placement quality, achieving substantial reductions in wirelength and timing violations compared to leading tools. Its ability to scale to large designs and infer optimal placements with low inference time further strengthens its applicability in real-world design environments. This research underscores the transformative potential of machine learning in EDA, paving the way for intelligent, self-optimizing physical design systems. Future work will explore extending the framework to congestion-aware placement and routing co-optimization.

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