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Enhancing Power Prediction in Digital VLSI Circuits Using Diffusion Models: Synthetic Data Generation and Performance Evaluation

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***Abstract*: Accurate power forecasting plays a crucial role in optimizing the performance of digital VLSI circuits, particularly as design complexities continue to grow. This research delves into the use of diffusion models to create synthetic data aimed at improving the accuracy of power predictions in machine learning frameworks. Running simulations within the HSPICE environment and using advanced CMOS nodes yielded realistic datasets that were employed to train the proposed models. The synthetic data not only resembled real-world data closely but also effectively complemented limited datasets, leading to a significant improvement in power prediction performance metrics. This study underscores the potential of using data augmentation through diffusion models as an innovative strategy in VLSI design.**

***Keywords*: Diffusion models, synthetic data generation, power prediction, digital VLSI circuits, data augmentation.**

1. Introduction

Recently, there has been considerable progress in generative AI thanks to machine learning methods like Generative Adversarial Networks (GANs) [7], Variational Autoencoders (VAEs) [9], and Denoising Diffusion Probabilistic Models (DDPMs) [8]. These models are great at producing high-quality synthetic data, which promotes innovation in areas like image creation, text writing, and speech processing [6]. Diffusion models, in particular, have shown to be a strong approach for generating realistic datasets, especially when there is a lack of available data [3].

In VLSI circuit design, using synthetic data helps overcome issues such as the high costs associated with data collection and limitations in computational power [22]. Diffusion models produce complex datasets that help with tasks like assessing performance, predicting power usage, and testing circuits within electronic design automation (EDA) processes [12], [13]. By mimicking how circuits behave in the real world, these models overcome the challenges of scalability and availability found in conventional data collection techniques, especially in cutting-edge CMOS technologies [20].

This research investigates how DDPMs can be utilized to create synthetic datasets for predicting power in VLSI. By using synthetic data, machine learning models can be improved, particularly in analyzing power dissipation, which is assessed using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) [26], [27]. The results highlight the potential of diffusion models to revolutionize VLSI processes, allowing for machine learning-based design and enhancement while improving EDA techniques for power estimation and evaluation [28].

2. Related Works

The lack of sufficient data presents a serious obstacle in the training of machine learning (ML) models, especially in the field of VLSI design, where having quality datasets is crucial for achieving accuracy [13]. While large datasets of up to 15K or 50K samples are often required [12], [14], the costs, time, and effort involved in acquiring such data limit scalability and efficiency [8], [10]. Generating synthetic data presents a versatile way to create realistic datasets that enhance machine learning performance in various applications [15]–[23], addressing challenges like computation costs and limited dataset availability, especially in VLSI [22]. Generative models like Variational Autoencoders (VAEs) [9], Generative Adversarial Networks (GANs) [7], and Diffusion Models [8] excel in creating high-fidelity synthetic data, with diffusion models particularly suited for high-dimensional VLSI datasets [24], [25]. This study builds on diffusion models to forecast power usage in VLSI circuits by creating synthetic datasets that help improve machine learning-based predictions of power dissipation, thereby enhancing the efficiency of electronic design automation (EDA).

3. The Dataset

This study leverages datasets that include the design, process, and performance features of twelve essential digital cells, as outlined in Table I, to assess the accuracy of power predictions made by machine learning models. Training data is generated with HSPICE, a robust Electronic Design Automation (EDA) tool [26], employing random vectors from Gaussian distributions to represent process parameters, with ±10%

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variations at 3σ in 22nm CMOS High-k metal gate (HKMG) technology. Predictive Technology Models (PTM) help to thoroughly simulate these changes [12]. The dataset includes parameters for PMOS and NMOS process characteristics, temperature changes ranging from −55°C to 125°C, and supply voltage variations of ±10% around 0.8V [8]. The load capacitance is changed in a similar manner to create realistic scenarios. Power dissipation measurements, which are derived from HSPICE Monte-Carlo simulations, account for variations in PVT (Process, Voltage, Temperature) to ensure the dataset accurately represents real-world conditions. Additionally, diffusion models enhance the dataset, increasing its diversity and scalability to boost predictive performance for tasks related to power prediction [12], [22].

4. Synthetic Circuit-Data Generation Using Diffusion Models

The design and optimization of VLSI circuits significantly depend on parametric information that includes design specifications, process details, and performance metrics, which are crucial for machine learning tasks such as predicting power usage and validating designs. To address the issues of limited data and high acquisition costs, this study utilizes denoising diffusion probabilistic models (DDPMs) to create synthetic datasets specifically devised for VLSI applications. By concentrating on 22nm CMOS technology, this method improves the accuracy of ML models in situations where data is scarce, while also providing scalability and adaptability for a wider range of uses.

A. Development of a Denoising Diffusion Probabilistic Model for VLSI Circuit Information

Diffusion models serve as generative frameworks that aim to understand the fundamental data distribution by gradually introducing random noise into the input data and subsequently reversing this process to recreate the original data. This two-step approach consists of the following processes:

Forward Process: In the forward diffusion process, the original data gradually receives Gaussian noise at multiple time intervals. This procedure is mathematically formulated as:

$$z_t = \sqrt{\bar{\alpha}_t} z_0 + \sqrt{1 - \bar{\alpha}_t}\epsilon, \quad \epsilon \sim \mathcal{N}(0, I)$$

Here, z_t represents the data at time step t, with z_0 denoting the original (real) data. The term $\bar{\alpha}_t$ signifies the cumulative noise scaling factors, and ϵ is sampled from a standard normal distribution. The forward process shifts the data into a state primarily influenced by noise, yet it maintains crucial structural details needed for recovery.

Reverse Process: The reverse process seeks to recreate the original data from the noisy version produced in the forward process. A neural network, which has been trained on the forward diffusion process, estimates the noise added at every step. The denoising process is expressed as:

$$z_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left(z_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}} f_\theta(z_t)\right)$$

where f_θ represents the learned denoising function parameterized by the network, and β_t controls the amount of variance added at each step. By applying this process repeatedly, we can accurately restore the original distribution of data, which makes this framework particularly suitable for high-dimensional datasets, such as those involving VLSI circuit parameters, where having noise-resistant representations is essential. Generation of New Data: After being trained, diffusion models create artificial datasets by executing the reverse procedure on random noise samples from $N(0, I)$. This feature enhances their effectiveness in improving datasets when data is limited. To keep things straightforward, this study employs an encoder-decoder structure for the reversing process rather than opting for more intricate designs such as UNET [27].

B. Qualitative Assessment of Generated Synthetic Data

Evaluating synthetic datasets generated by diffusion models for circuit design requires metrics that focus on performance. Unlike conventional metrics used for image generation, like inception scores or Frechet inception distances, circuit-related tasks emphasize accuracy metrics such as Mean Absolute Percentage Error (MAPE) in accordance with VLSI design standards [28]. The outputs of synthetic data are juxtaposed with actual HSPICE-simulated data, with MAPE serving as the primary benchmark. A diffusion model that has been trained on 500 authentic samples creates synthetic data after reaching convergence. Continuous tuning of hyperparameters ensures compatibility with real-world distributions, facilitating dependable performance assessment. Utilizing synthetic datasets helps to mitigate data shortages in VLSI tasks, such as power forecasting, thus enhancing precision and scalability for electronic design automation (EDA) purposes.

5. Experimental Setup and Model Architecture

The training of Denoising Diffusion Probabilistic Models (DDPMs) used *Python-3.8.16* in VS Code with libraries like *Pandas*, *NumPy*, *TensorFlow-Keras* from *TensorFlow-2.0*, *Matplotlib*, and *Scikit-learn*. Using mixed precision training with an NVIDIA RTX GPU and CUDA enables efficient management of large datasets, which leads to reduced memory usage and faster convergence. As noted in [8], the forward process gradually varies β_t from 0.001 to 0.02, introducing noise while preserving the integrity of the data. The reverse process employs an encoder-decoder framework [27] that incorporates batch normalization and Leaky ReLU activations to reconstruct the data distribution.

6. Results

To assess how well the proposed diffusion model performs, we compared the synthetic data it generated with actual data. This was done using various metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE), as mentioned in Section IV-B. These metrics help us measure how closely the synthetic data resembles the real data, highlighting the diffusion model's ability to accurately represent the underlying data distributions

Table 1
A comparison of the statistics for real and synthetic data utilized in this study (Input parameters for assessment: supply voltage, temperature, load capacitance; output parameters for assessment: power dissipation)

Dataset	Parameters	Dataset	Parameters
NOT gate power	17	Three input AND-OR circuit power	21
Two input NAND gate power	19	Full adder power	21
Two input AND gate power	19	2:1 Multiplexer power	21
Two input NOR gate power	19	Three input NAND gate power	21
Two input OR gate power	19	Three input AND gate power	21
Two input XOR gate power	19	Three input NOR gate power	21

Table 4
A comparison of statistics from actual and generated data with associated error metrics (Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE))

Feature	Real Mean	Synthetic Mean	Real Std	Synthetic Std	MAE	MSE	MAPE
Supply Voltage	0.5598	0.3070	0.2548	0.3791	0.4480	0.2656	0.8682
Temperature	0.5409	0.1846	0.2614	0.2629	0.4460	0.2678	0.8387
Load Capacitance	0.5537	0.2062	0.2569	0.2906	0.4617	0.2789	0.8316
Power Static	0.5664	0.3628	0.2636	0.4096	0.4721	0.2919	1.0437
Power Dynamic	0.5540	0.1864	0.2651	0.2654	0.4554	0.2775	0.7928

for important parameters, including *load capacitance*, *power dynamic*, *power static*, *supply voltage*, and *temperature*. Density plots provide a clearer view of the strong correlation between the two datasets, confirming that the synthetic data is of high quality for subsequent tasks such as power prediction. When we compare different methods, it's scarcity. The model demonstrated stability across different training data sizes, showing only slight decreases in MAPE and MAE, which underlines its usefulness in VLSI applications where labelled data might be scarce.

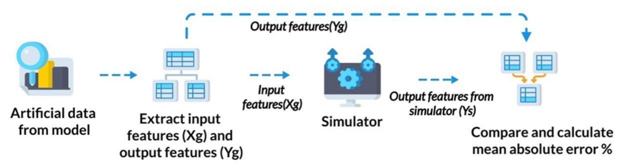

Fig. 1. Assessment methodology for data produced artificially

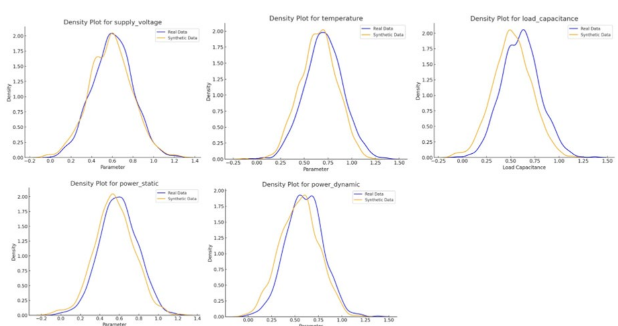

Fig. 2. Density plots comparing real and synthetic data distributions for supply voltage, temperature, load capacitance, power

Through optimization studies and hyper-parameter adjustments, the model's performance was significantly improved. A five-layer architecture proved to be the best fit for datasets containing 17 to 19 attributes, while a six-layer setup excelled with 21 attributes, striking a good balance between complexity and accuracy. Using a learning rate of 0.001 effectively minimized MAPE and allowed for smooth convergence. These findings underscore the diffusion model's capability to produce high-quality synthetic data and support power prediction tasks in VLSI design, effectively tackling issues related to data scarcity.

Table 2
Performance comparison of models with varying layers across all features

No. of layers	Avg. of MAPE (%)
4 hidden layers	14.5
5 hidden layers	23.51

Clear that the diffusion-based approach consistently delivers better accuracy and scalability, especially in scenarios of data.

Table 3
Comparison of metrics evaluated across different learning rates for model training

Metrics	Learning Rate
MAE	0.01
MSE	0.005
MAPE	0.001

7. Conclusion

This research presents a customized diffusion model designed to create synthetic datasets for VLSI circuit design, tackling the difficult issue of obtaining high-quality real world training data, which is both costly and scarce. Through simulations conducted in the HSPICE environment, the model has been validated and effectively generates synthetic data with a low mean absolute percentage error (MAPE) when compared to real-world results, while maintaining the statistical characteristics of the original dataset. Tests conducted on twelve essential digital circuit designs confirm the dependability of the synthetic data in improving the accuracy of machine learning models, thereby minimizing the dependence on large volumes of real-world data. By incorporating synthetic data into existing workflows, this method provides a scalable and cost-efficient strategy for data augmentation, proving especially beneficial for complex VLSI design tasks like fault detection, performance enhancement, and thermal management. The study underscores the promise of diffusion models in solving wider challenges within electronic design automation (EDA) and the semiconductor sector, setting the stage for future advancements.

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