Two-Stream Neural Network for Post-Layout Waveform Prediction

1st Sanghwi Kim
DRAM Design Team
SK Hynix
Icheon, Korea
sanghwi1.kim@sk.com

2nd Hyejin Shin
DRAM Data Science
SK Hynix
Icheon, Korea
hyejin2.shin@sk.com

3rd Hyunkyu Kim
DRAM Data Science
SK Hynix
Icheon, Korea
hyunkyu2.kim@sk.com

***Abstract*—The gap between pre- and post-simulation, as well as the considerable layout time, increases the significance of the post-layout waveform prediction in dynamic random access memory (DRAM) design. This study develops a post-layout prediction model using the following two-stream neural network: (1) a multi-layer perceptron neural network to calculate the coupling noise by using the physical properties of global interconnects, and (2) a convolutional neural network to compute the time series trends of the waveforms by referencing adjacent signals. The proposed model trains two types of heterogeneous data such that accuracy of 95.5% is achieved on the 1b DRAM process 16Gb DDR5 composed of hundreds of millions of transistors. The model significantly improves the design completeness by pre-detecting the deterioration in the signal quality via post-layout waveform prediction. Generally, although a few weeks are required to obtain post-layout waveforms after the circuit design process, waveforms can be instantly predicted using our proposed model.**

***Index Terms*—DRAM, layout, post-layout waveform, prediction**

I. Introduction

Dynamic random access memory (DRAM) requires extremely complex net connections despite the aggressive scaling used presently. Consequently, the capacitive coupling noise between nets creates unexpected glitches in the post-layout simulation. Noise degrades the signal quality and even causes defects that require much time to redesign. However, an accurate evaluation of noise can only be achieved with post-layout waveforms [1]. Furthermore, circuit designers generally estimate coupling noise from previous experiences, resulting in design variabilities and inaccuracies [2]. In DRAM layout design flow, considerable time is required to obtain post-layout waveforms, owing to the complex nature of the layout design. Therefore, post-layout waveforms should be estimated in early layout designs to prevent defects and decrease the total design time. Accordingly, this study proposes a deep learning-based technique to calculate coupling noise and predict the post-layout waveform. Previous studies used the information contained in the schematics to predict interconnect parasitic RC for pre-layout circuits [3]. This study effectively estimates the delay, rise/fall time, and duty cycle; however, the coupling noise cannot be easily predicted owing to the lack of information regarding adjacent signals. In the DRAM layout design flow, global interconnects are generally placed earlier; thus, information on adjacent signals can be obtained through the global interconnects. The section where the glitch occurs can be specified using the patterns of the target and adjacent signals. The proposed technique can assist designers in quickly exploring the waveforms of critical signals.

II. Methodology

A. Data Description

The pre-layout waveform and the layout data are required as input data to predict the post-layout waveform. The pre-layout waveform data type is a time series data. As shown in Fig. 1, the original waveform data is too sparse; therefore, empty points should be interpolated between points. The victim signal is a target signal to be predicted. Further, among the adjacent signals of the victim signal, two major adjacent signals with the largest coupling capacitance are aggressor signals.

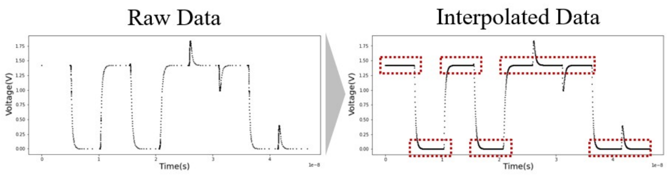

Fig. 1. Data preprocessing: interpolation

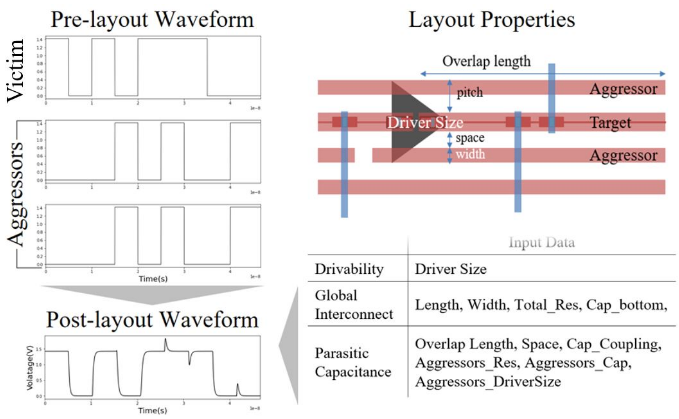

Fig. 2. Input and output data. The logical waveforms of the target signal (victim) and the two most influential adjacent signals (aggressors). Physical properties of the target and relation between signals. Post-simulation analog waveform of the target signal.

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Therefore, one victim signal should be predicted, and two major adjacent signals should be used as input data. The layout data consist of 11 features related to physical information which are extracted by designers on a regular basis with in-house tools. The features are rigorously selected, based on the values used in conventional calculation methods, such as the ground capacitance, coupling capacitance, and driver size. For accurate noise prediction, time series data are fixed and approximately 1.5 million post-layout waveforms generated according to changes in layout data are used as y data.

B. Two-Stream Neural Network

We used two deep learning architectures for the two data types (layout and waveform) and then combined the two architectures into one model. The structure of the model is shown in Fig. 3. The first stream utilizes a multi-layer perceptron (MLP) model the layout data. Regarding the pre-layout waveform data, we applied a 1-dimensional convolutional neural network(1D CNN), which is mostly used for time series forecasting. Because time series data have waveforms of one victim signal and two aggressors, the 1D CNN converts three stacked vectors into a single vector. Finally, the features from the two separate streams are concatenated into a single vector, and we obtain the output through three perceptron layers.

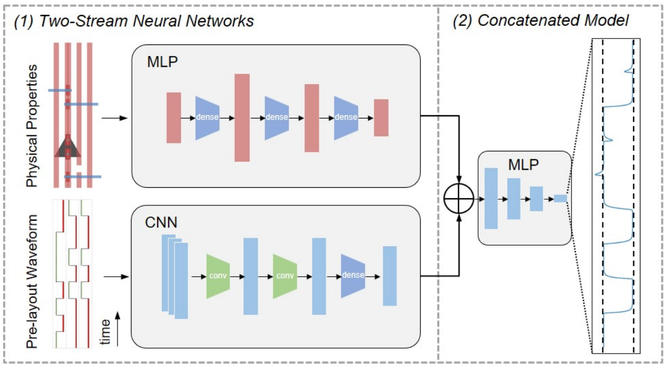

Fig. 3. The structure of the model

III. EXPERIMENTAL RESULTS

We evaluated the proposed method using the mean absolute percentage error (MAPE) to measure the model's accuracy. We applied the model to 15nm DRAM process 16Gb DDR5 and achieved an accuracy of 95.5%. The predicted and actual (post-layout) waveforms of the test samples are shown in Fig. 4. The predicted waveform is almost identical to the actual waveform when the points of the glitches are accurately predicted.

Compared with other models, the two-stream neural network model shows a higher performance of approximately 10%. Furthermore, when CNN and MLP are trained simultaneously for 20 epochs, the highest performance and shortest training time are recorded as shown in Table. I. The lower performance for complex models such as inception/FCN suggests that simple models are more suitable for this study.

Our experiment was performed on a cloud-based platform with GeForce GT 730 GPU and 16GB memory.

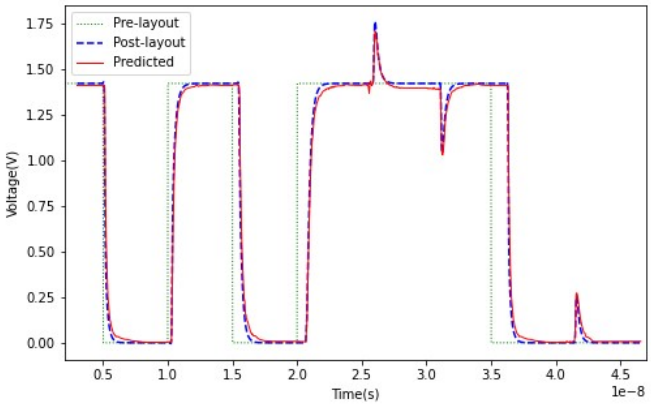

Fig. 4. The predicted, pre-layout, and post-layout waveforms of the 1b DRAM process 16Gb DDR5

TABLE I
COMPARISON OF POST-LAYOUT WAVEFORM PREDICTION USING DEEP LEARNING MODELS AND PRE-LAYOUT WAVEFORMS

	Model performance		
	Model	***MAPE(%)***	***Training time(s)***
1	Two-stream (CNN + MLP)	95.5	340
2	Two-stream (CNN + CNN)	92.9	410
3	Inception / FCN	83.3	4500
4	Pre-layout Waveform	82.1	-

[a]Trained for 20 epochs

IV. CONCLUSION

This study built a two-stream neural network model for post-layout waveform prediction. The CNN model accurately analyzed the time series of patterns, and the MLP model accurately calculated the amount of noise. The model is advantageous in that post-layout waveforms can be computed in a short time without previous knowledge, although they are computation-intensive and time-consuming. Based on several examples, the predicted results provided waveforms that were close to the actual waveforms. The accurate prediction can guarantee signal quality. Further, the deep learning algorithm increased the value of the model, adapting to increasingly complex noise calculations with continuous learning. Therefore, this study is elaborate and will evidently contribute to the automation of layout designs in the future.

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