Versatile Genetic Algorithm-Bayesian Optimization(GA-BO) Bi-Level Optimization for Decoupling Capacitor Placement

Hyunah Park, Haeyeon Kim, Hyunwoo Kim, Joonsang Park, Seonguk Choi, Jihun Kim, Keeyoung Son, Haeseok Suh, Taesoo Kim, Jungmin Ahn and Joungho Kim
School of Electrical Engineering (EE), Korea Advanced Institute of Science and Technology (KAIST)
hyunah.park@kaist.ac.kr

***Abstract*—This paper proposes a versatile genetic algorithm-Bayesian optimization(GA-BO) bi-level optimization method, in which BO determines the optimal hyperparameters for GA that optimizes the decoupling capacitor (decap) placement. Through optimizing the GA hyperparameters, the proposed method ensures effective optimization that leads to an optimal PDN design that meets the target impedance with the minimum number of decaps. The proposed method was applied to the hierarchical power distribution network (PDN) of high bandwidth memory (HBM) and verified the performance of two objective functions for GA and BO, respectively, and its stability. Furthermore, to verify its versatility, the proposed method was also applied to a different type of PDN and outperformed the random search method by successfully placing 18 decaps that satisfy the target impedance.**

***Index Terms*—Power distribution network, decoupling capacitor, genetic algorithm, Bayesian optimization, hyperparameter optimization, optimal PDN.**

I. Introduction

As the demand for high-bandwidth computing systems has grown with the rise of large artificial intelligence (AI) models, high bandwidth memory (HBM) modules have emerged as a solution, offering up to 1 TB/s data bandwidth between memory and processors. However, the simultaneous switching of HBM's 1024 I/O drivers generates high simultaneous switching current (SSC). This SSC flows through the power distribution network (PDN), resulting in simultaneous switching noise (SSN) that causes significant voltage fluctuations and unreliable power supply. To reduce the amount of SSN, the impedance curve of the PDN should be optimized.

Placing decoupling capacitors (decaps) on the PDN mitigates impedance, leading to maintain SSN within the acceptable noise margin. While increasing the number of decaps improves performance of power integrity (PI), it also raises fabrication costs. Therefore, finding the optimal decap placement that minimizes number of decaps is crucial. However, optimizing the decap placement is challenging due to the complex solution space and involving extensive simulation times that is related to computation budget.

Recently, there have been several AI based methods proposed to address the challenge of optimizing decap placement. The existing reinforcement learning methods [1], [2] are only reusable in terms of probing port. Hence, if the target PDN changes, they cannot be instantly employed and they have to be re-trained, involving huge iterations. Genetic algorithm (GA) is a widely used optimization method known for its speed, reusability, and flexibility [3], [4]. However, the performance of GA relies heavily on hyperparameters such as population size (P), number of generations (G), and the utilization of specific operators like the percentage of elite population (P_{elite}). Finding optimal hyperparameter values requires extensive iterations as different combinations of P and G with the same number of samples yield varying performance. However, none of the previous GA-based decap placement works include a discussion of the specific hyperparameter values used, despite their significance.

In this paper, we proposed a bi-level optimization method, denoted as GA-BO, which integrates the GA and Bayesian optimization (BO). The GA-BO bi-level optimization method offers optimal values of GA hyperparameters with the minimum number of decaps that satisfies the target impedance and an optimal decap placement solution, while eliminating the need for manual hyperparameter tuning when the target PDN changes.

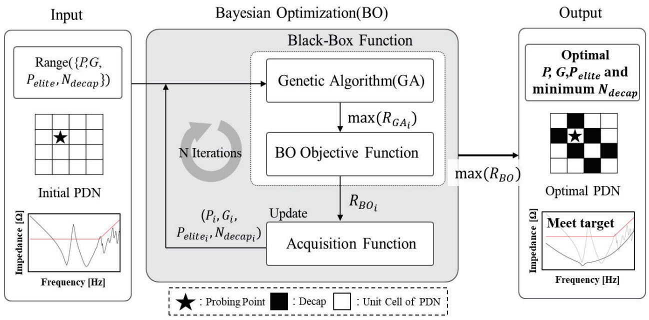


Fig. 1: Overview of the proposed GA-BO bi-level optimization method for optimizing GA hyperparameters and PDN design.

II. Proposal of GA-BO Bi-level Optimization

Fig. 1 demonstrates the overview of the proposed GA-BO bi-level optimization method that has a BO encapsulated GA structure. The purpose of the BO phase is to optimize the GA hyperparameters within the specified range, while the GA

979-8-3503-1798-5/23/$31.00 ©2023 IEEE

phase aims to find the optimal decap placement that effectively suppresses impedance below the target impedance with the BO-determined number of decaps and its hyperparameters. The inputs for this method include the range of GA hyperparameters (P, G, P_{elite}), the range of the number of decaps (N_{decap}), and the initial impedance parameters of the target PDN with its target impedance.

The BO provides specific values of P, G, P_{elite} and N_{decap} to the GA. Then, the GA outputs the decap placement solution that maximizes the value of R_{GA}, indicating the most effective impedance suppression out of the generated decap placements. This maximum value of R_{GA} is inputted into the BO objective function, which results in R_{BO} as the output of the black-box function. Influenced by the provided R_{BO}, the acquisition function is updated to generate optimal input values to the GA that overall maximizes R_{BO} as well as R_{GA}.

Through N iterations of the process described above, the decap placement solution and GA hyperparameters with the maximum value of R_{BO} is derived as the final output of the GA-BO bi-level optimization method. Ultimately, this method enables the simultaneous optimization of decap placement and GA hyperparameters with the minimum number of decaps that satisfies the target impedance.

A. Objective function of Genetic Algorithm

The GA computes the objective score for choosing optimal decap placement among total generated decap placements. Subsequently, the maximum objective score of GA is conveyed to the BO, enabling the overall optimization process. The formulation of the GA's objective function is as follows:

$$R(f) = (Z_{target}(f) - Z_{final}(f)) \cdot \frac{\text{1GHz}}{f} \cdot w \quad (1)$$

$$w = \begin{cases} \alpha, & \text{if } Z_{final}(f) < Z_{target}(f). \\ \beta, & \text{otherwise.} \end{cases} \quad (2)$$

To evaluate the PI performance of decap placement, the frequency-dependent impedances at the probing port after decap placement, Z_{final}, are simulated. Then, the frequency-dependent objective scores, $R(f)$, are calculated at each frequency, f, in the set F through Eq. (1) to ensure the impedance suppression below the target impedance, Z_{target}. The weight w is determined by Eq. (2) and α is always greater than β to impose a higher penalty when the impedance fails to meet the target.

$$R_{GA} = \sum_{f \in F} R(f) \quad (3)$$

$$R_{GA} = -100 \cdot R_{GA}, \text{if } \exists Z_{final}(f) > Z_{target}(f). \quad (4)$$

To obtain the final objective score of GA, the objective scores computed for each frequency are aggregated as Eq. (3) and penalty is assigned once again if the impedance at any frequency fails to meet the target as Eq. (4).

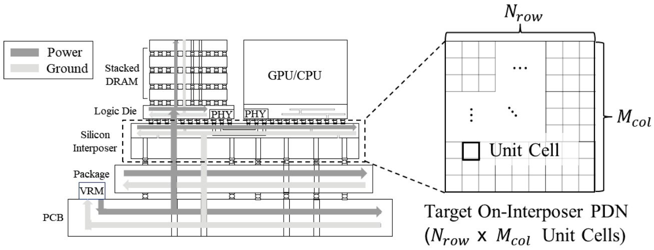


Fig. 2: The target on-interposer PDN of HBM for verification.

B. Objective function of Bayesian Optimization

The BO receives the maximum objective score of GA and computes its own objective score, R_{BO}. The formulation of the BO's objective function is as follows:

$$R_{BO'} = \begin{cases} 100 \cdot \max(R_{GA}), & if \ \max(R_{GA}) < 0. \\ \max(R_{GA}), & otherwise. \end{cases} \quad (5)$$

$$R_{BO} = R_{BO'} + (\frac{\gamma}{N_{decap}}) \quad (6)$$

where γ refers to the problem-specific weight term. The objective function of BO initially penalizes solutions that do not meet the target impedance by Eq. (5). Then, it assigns a higher score to solutions with the smaller number of decaps through Eq. (6). This approach ensures that the resulting objective score of BO encompasses both impedance suppression below the target and the minimization of the number of decaps.

III. Verification of the Proposed Method

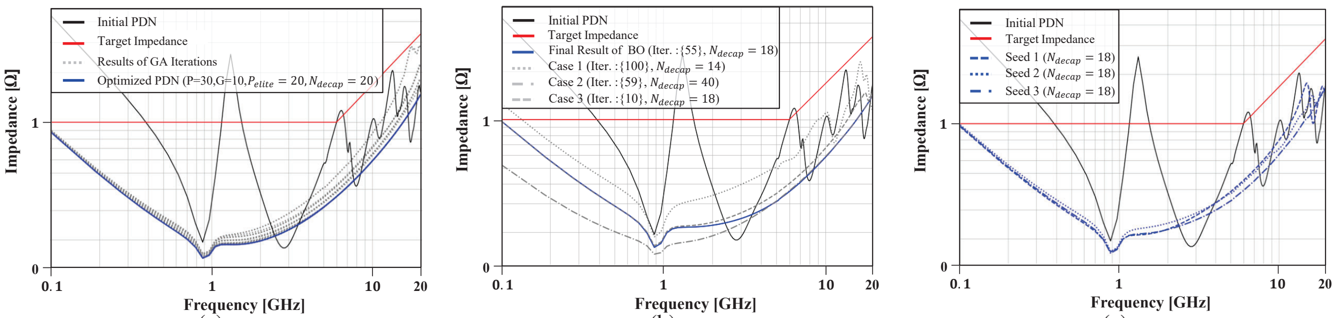
A. Experimental Setup for Verification

The proposed method was verified on the hierarchical PDN of HBM, consisting of package PDN, on-interposer PDN and on-chip PDN. On-interposer PDN and on-chip PDN were modeled through unit-cell segmentation method, and package, which demension is $30mm \times 30mm$, was modeled by 3D simulation tool. Fig. 2 illustrates target on-interposer PDN where decap placement was implemented. This target PDN is composed of $N_{row} \times M_{col}$ $(= 17 \times 8)$ unit cells. High-k metal-insulator-metal (MIM) capacitors were employed as decaps for the target PDN, and their electrical parameters are based on [5]. The frequency range is set from 100 MHz to 20 GHz, and a total of 231 frequency points, denoted as F in Eq. (1), were selected for evaluation.

B. Performance Verification of GA-BO Bi-Level Optimization

Genetic Algorithm. Fig. 3(a) demonstrates the clear objective function behavior of the GA. For this particular case, the GA hyperparameters were configured with P of 30, G of 10, P_{elite} of 20, and N_{decap} set to 20. Throughout the GA iterations, the decap placement exhibiting the highest impedance suppression with the GA objective score (R_{GA}) of 70.7, was identified as the optimal solution, the impedance of which is depicted by the blue plot in Fig. 3(a).

Bayesian Optimization. Fig. 3(b) illustrates the effective construction of the BO objective function. The P was generated within the range of 8 to 30, while ensuring that the



(a) (b) (c)

Fig. 3: (a) Impedance suppression over the process of the GA according to GA objective function. (b) Impedance suppression over the process of the BO with 100 iterations for achieving target impedance with minimum number of decaps. (c) Stability verification of the GA-BO bi-level optimization using three different seeds in terms of impedance suppression.

product of P and G did not exceed 100, and the P_{elite} was bounded between 10 and 50. The BO process was carried out for 100 iterations, resulting in the minimum value of N_{decap} within the range of 14 to 50.

TABLE I: Objective Scores of BO over Iterations

Case	Meet Target	GA Hyperparameters P	G	P_{elite}	N_{decap}	R_{BO}
1	X	30	3	46	14	-514683
2	O	8	12	10	40	132.1
3	O	25	4	44	18	178.5
Final	**O**	**17**	**5**	**10**	**18**	**181.4**

According to the Table I, the proposed GA-BO bi-level optimization method successfully identifies the optimal decap placement that meets the target impedance with the minimum number of decaps by effectively determining the optimal combinations of GA hyperparameters. Also, we employed the random search method on the same PDN, but despite over 50,000 iterations, it could not outperform the proposed method.

C. Stability Verification of GA-BO Bi-Level Optimization

Furthermore, we carried out the stability analysis of the proposed method by ablating random seeds. Fig. 3(c) demonstrates the resulting impedance of optimal solutions derived from each trial and Table II shows the optimized hyperparameters and their corresponding objective scores.

TABLE II: Stability Verification with Three Different Seeds

Seed	GA Hyperparameters P	G	P_{elite}	N_{decap}	R_{BO}
seed 1	10	10	44	**18**	180
seed 2	8	12	17	**18**	179.7
seed 3	21	4	48	**18**	180.1

As shown in Table II, each trial yields the same number of decaps and similar objective score for the PDN. Notably, BO consistently identified 18 decaps as the optimal number, thus confirming the efficacy of the proposed method in achieving the optimal PDN design with the minimum number of decaps.

D. Versatility Verification of GA-BO Bi-Level Optimization

To verify the versatility, we applied the proposed method to different PDN [2], which consists of package PDN and chip PDN. Metal oxide semiconductor (MOS) capacitors were employed as decaps on the chip PDN, which is composed of 10×10 chip unit cells. The proposed method successfully placed 18 decaps with the objective score of 333.4 that meet the target impedance within 100 BO iterations while the random search method achieved 323.7 with 10,000 iterations, proving that the proposed method is versatile and guarantees better performance than the random search method.

IV. Conclusion

The proposed GA-BO bi-level optimization method tackles the versatile and cost-effective optimization of decap placement problem. By finding the optimal GA hyperparameter values using BO, the proposed method achieved optimal decap placement on the hierarchical PDN of HBM that meets the target impedance with minimum number of decaps within the predefined computation budget.

Acknowledgment

We would like to acknowledge the technical support from ANSYS Korea. This research was supported by National RD Program through the National Research Foundation of Korea (NRF) funded by Ministry of Science and ICT (NRF-2022M3I7A4072293). This work was supported by Samsung Electronics Co., Ltd (IO201207-07813-01)

References

[1] H. Park *et al.*, "Transformer network-based reinforcement learning method for power distribution network (pdn) optimization of high bandwidth memory (hbm)," *IEEE Transactions on Microwave Theory and Techniques*, vol. 70, no. 11, pp. 4772–4786, 2022.
[2] H. Kim, M. Kim, F. Berto, J. Kim, and J. Park, "Devformer: A symmetric transformer for context-aware device placement," 2023.
[3] I. Erdin and R. Achar, "Multi-objective optimization of decoupling capacitors for placement and component value," *IEEE Transactions on Components, Packaging and Manufacturing Technology*, vol. 9, no. 10, pp. 1976–1983, 2019.
[4] Z. Xu, Z. Wang, Y. Sun, C. Hwang, H. Delingette, and J. Fan, "Jitter-aware economic pdn optimization with a genetic algorithm," *IEEE Transactions on Microwave Theory and Techniques*, vol. 69, no. 8, pp. 3715–3725, 2021.
[5] H. Park *et al.*, "Deep reinforcement learning-based optimal decoupling capacitor design method for silicon interposer-based 2.5-d/3-d ics," *IEEE Transactions on Components, Packaging and Manufacturing Technology*, vol. 10, no. 3, pp. 467–478, 2020.