Neural-Network Assistance to Calculate Precise Eigenvalue for Fitness Evaluation of Real Product Design

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ABSTRACT

When applying genetic algorithms (GAs) in the design real products, reducing the computational cost of fitness functions is one of the major challenges. In some cases, the computational cost of calculating specific eigenvalues is a predominant factor and needs to be reduced. We proposed the use of a GA with "neural-network (NN) assistance," which enables this computational cost to be reduced. With this GA, the NN assistance infers the approximate eigenvalues. Then, these approximate eigenvalues are used when starting the convergence calculation to obtain the precise eigenvalues. This procedure is effective in reducing the total computational cost of some of the fitness functions of real products. In addition, the precision of the eigenvalue is retained because the precise eigenvalues are obtained by the convergence calculation. The results of our case study show that the GA using our method achieves a 3x speed-up in fitness computation while maintaining equivalent solution quality.

CCS CONCEPTS

• Theory of computation → Evolutionary algorithms

KEYWORDS

Real-world optimization, genetic algorithms, neural networks

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1 INTRODUCTION

Evolutionary computation techniques such as genetic algorithms (GAs) offer a promising approach to the design of the structures of real products since they enable the exploration and identification of optimal structures by simulation. However, simulations used to evaluate fitness functions are often computationally expensive, which makes GAs difficult to employ in real-world applications. To overcome this problem, there are some reports that neural networks (NNs) are applied as surrogate models of fitness functions. This approach is effective to reduce computational cost [1, 2]. However, some mismatch between the simulation and NN results remains because of surrogation.

Often when designing the structures of real products, it is necessary to analyze specific operating modes and their corresponding eigenvalues using techniques such as the finite-element method (FEM) to evaluate the fitness functions. The convergence calculation to obtain these eigenvalues is a predominant factor in the overall computational cost. In this study, we propose the use of a GA with "neural-network (NN) assistance" to reduce this calculation cost. With this method, approximate eigenvalues are inferred by the NNs, and the convergence calculations used to obtain the precise eigenvalues begin from these approximated eigenvalues. This method is effective in reducing the large computational cost of the convergence calculations. In addition, unlike surrogate models, precision is retained because precise eigenvalues are determined using convergence calculations.

In this study, we applied our GA with the proposed neural-network assistance to an optimization problem involving the surface acoustic wave (SAW) guide structure on an acousto-optic tunable filter (AOTF) [3]. The numerically evaluated results obtained for this case study demonstrate the effectiveness of our proposed method.

2 CASE STUDY AND APPLICATION OF PROPOSED METHOD

AOTFs, which we used in our case study, are filters for optical fiber communications. Given the requirements of a particular application, the optimization objectives of these devices are to increase the AL value, i.e., the SAW power on the optical signal, and to increase the La/Lb value, i.e., the shift length ratio of the SAW power with respect to the wavelength, as shown in Fig. 1 [3]. The optimization of these objectives is realized via the structure of the SiO_2 layer on the surface. Figure 2 shows a flow chart of the GA procedure for this case study. First, we divided the whole device into small 2-μm areas. Then, we encoded each area using either a "1" for layers with SiO_2, or a "0" for those without SiO_2, as shown in Fig. 2(a). This coding enables representation of the structure of the SiO_2 layer by genotype for the GA. Specific operating modes and the corresponding eigenvalues are uniquely determined based on each structure. We solved for these eigenvalues by applying a matrix method, which can be applied to any configuration structure because it is a primitive FEM [4]. By applying this genotype coding and matrix method, we can simultaneously optimize the configuration of the SiO_2 layer and the size parameter using a genotype consisting of 90 codes of either "1" or "0."

This case study required many trials to calculate eigenvalues for each structure because we needed four eigenvalues to evaluate the fitness functions. To address this problem, we applied NNs to infer approximate eigenvalues from the genotypes and rounded each of the inferred eigenvalues into one of 20 kinds of quantized approximate eigenvalues. Then, we determined the precise eigenvalues using these approximated eigenvalues, thereby reducing the total computational cost, as shown in Figs. 2(b) and 2(c).

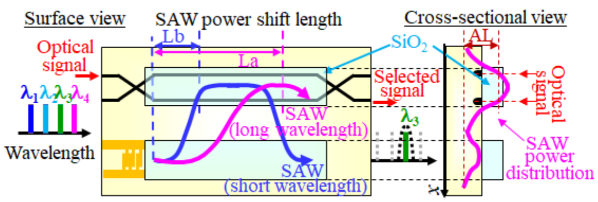

Figure 1: Structure and desired function of AOTFs, with performance optimized by the structure of the SiO2 layer.

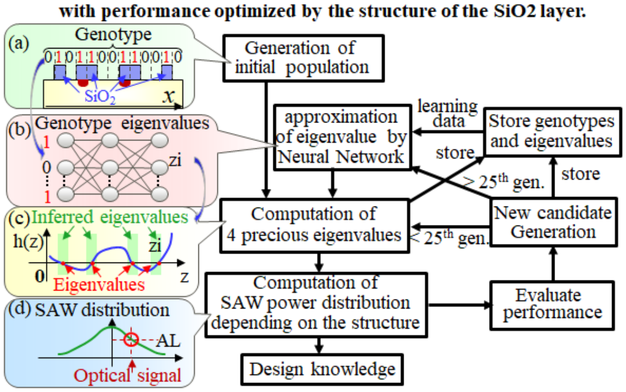

Figure 2: Flow chart of proposed GA with NN assistance.

3 EXPERIMENT

We optimized the configuration structure of the AOTF using a non-dominated sorting GA. We set the population size to 200 and performed the evolution 100 times. To confirm the base performance of the GA on this case study, we did not use the NN assistance at first. As shown in Fig. 3, the Pareto-optimal designs are obtained, and these structures outperforming the known structure [3]. We applied the GA five times, and confirmed that almost the same result was obtained.

Next, we applied the GA with NN assistance, also for five times. The NN inputs are genotypes that indicate the structures and the NN outputs are the approximate eigenvalues. We trained four-layer fully connected NN, 90-90-90-20, and the activation function of the trained NN was sigmoid. Because the structure of this NN is very simple, the computational cost of its training and inference process is sufficiently lower than that of a fitness evaluation. Training data is indispensable for training NNs. Therefore, we solved the initial data for the 1st to 25th generations using the conventional method and used these result as our initial training data. We used the results inferred by the NNs in the computations from the 26th generation onward. Then, we evaluated two methods for training the NNs. In the first method, we used the NNs trained with data from the 1st to 25th generations and applied them to all generations from the 26th onward (Method 1). In the second method, we used the NNs trained with data from the recent 25 generations and continuously updated them with the evolution (Method 2).

Then, we also applied the GA with NN assistance to this case study and evaluated its performance. The Pareto-optimal design is equivalent to that of the GA without NN assistance, as shown in Fig. 3, because the precision of the eigenvalues is not affected. Figure 4 shows the accuracy of the inferred eigenvalue. In this study, we defined top-1 accuracy as an accuracy rate in which the exact eigenvalue is the approximate eigenvalue with the highest probability inferred by the NNs. Top-2 accuracy indicates a rate at which the exact eigenvalue is in either of two highest probabilities. In this study, method 1 achieved a top-1 accuracy of 62–67%, and method 2 achieved 64–78%. The accuracy of method 2 is better, which is because method 2 incorporates recent genetic selections. Because its top-2 accuracy is better than 90%, the precise eigenvalue can be determined at low computational cost using these inferred results. Figure 5 shows the total trial iterations required to calculate the eigenvalues, which represent the average of five trials. With NN assistance, we reduced by a factor of three the amount of computation required to calculate the eigenvalue after the 26th generation. Overall, we reduced the amount of required computation by about half. With method 2, the amount of computation can be reduced further, but the improvement is not significant, so we consider the accuracy of method 1 to be sufficiently high in this case study.

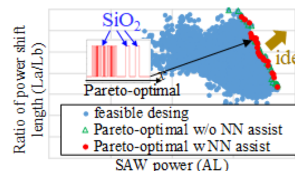

Figure 3: Distribution of Pareto-optimal designs.

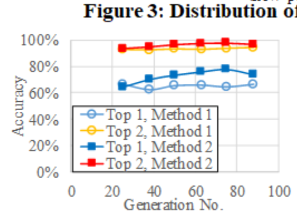

Figure 4: Accuracy depending on the generation No.

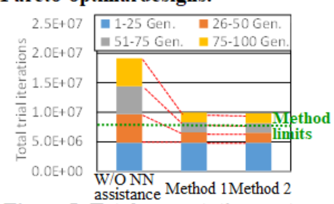

Figure 5: Total computation cost depending on the algorithm

4 CONCLUSIONS

In this paper, we proposed the use of a GA with NN assistance for designing the structures of real products. Some cases require that specific operating modes be solved to evaluate their fitness functions, and the high amount of computation associated with this task is a predominant factor of the total computational cost. To overcome this problem, approximate eigenvalues are inferred by NNs and the convergence calculation begins from these approximated eigenvalues. Using this approach with NN assistance, the amount of computation required to calculate eigenvalues can be reduced by a factor of three. Our case study results, demonstrate the effectiveness of using a GA with NN assistance to suppress computational cost.

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