

Comparison of Two Versions of Surrogate Model Assisted Optimization

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Performances of two different surrogate model assisted optimizations are compared. While genetic algorithm based optimization is powerful, it requires a significant amount of finite element analysis (FEA) calculations. To reduce the heavy calculation, the surrogate model assisted optimization in which the FEA calculations are replaced with surrogate models is drawing attention. There are several options for incorporating surrogate models in the optimization process. Two typical configurations are taken up. One is the configuration in which surrogate model generations are substituted between FEA generations. The other configuration uses surrogate models to expand the exploration scope of each FEA generation. The results show that both configurations have higher FEA calculation cost performance than the original FEA optimization, and the acceleration effects of the two different configurations are at the same level despite the different intentions.

Index Terms—Optimization, Surrogate model, Finite element analysis, Electromagnetic analysis

I. INTRODUCTION

EVOLUTION ALGORITHM (EA) optimization is powerful and robust for multi-objective optimization problems which are inevitable for designs of advanced electrical machines such as traction motors for electric vehicles and is becoming indispensable for those applications[1]. At the same time, those problems are becoming complex, and the size of the optimization is increasing so that the amount of required FEA is reaching a practical limit.

The machine learning based surrogate model is expected to reduce the amount of FEA, and the surrogate model assisted optimizations are composed[2], [3]. There are multiple ways of incorporating surrogate models into the GA optimization process. Although they must have different characteristics and performances, the differences have not been well known.

We examined two typical configurations and compared their performance. One configuration involves sequentially performing multiple surrogate generations between FEA generations, aiming to advance the Pareto front through surrogate model evolution. In the other configuration, surrogate models are used in parallel within each FEA generation to expand the population, with the goal of improving the prediction for the next generation and accelerating the optimization process.

The comparison results showed that both configurations have the same level of acceleration effect.

This paper describes the optimization behavior of each configuration and discusses the reasons for the similarity in the performance.

II. “SERIES” AND “PARALLEL” CONFIGURATIONS.

Two configurations, Series and Parallel, are defined as follows. In Series, the surrogate model generations are substituted between FEA generations, and the surrogate and FEA generations are performed in series. The surrogate models are trained based on the results of the FEA generations. The additional surrogate model generations are expected to push the Pareto front forward without paying additional FEA costs. While Series has such a preferable aspect, it also has a

misleading effect, which misleads the optimization due to the inaccuracy of the surrogate models[2].

The cycle of the appearance of FEA generation in the sequence is a key parameter of Series, which is noted as N_c . For example, the $N_c=3$ means an FEA generation appears after two consecutive surrogate model generations.

On the other hand, in Parallel, the surrogate models are used to increase the number of trials of each FEA generation. It is known that a larger population size provides better convergence in GA optimization. Parallel is expected to make the same effect.

In Parallel, firstly, the individuals are examined by the surrogate models and superior solutions are selected. Secondly, the resulting superior solutions are re-examined by FEA to generate the next generation’s individuals.

The number of individuals N_s to be examined by the surrogate models is determined with a parameter N_e and the population size N_p as N_e multiplied by N_p . For example, when $N_e=3$ and $N_p=10$, $N_s=30$. The size of the superior solution to be examined by FEA is the population size.

In the same way as the series, the surrogate models are trained based on the FEA results of each generation.

The role of the surrogate model in Parallel is not to push Pareto front but to improve individuals for the FEA examination, so it does not have the misleading effect which Series has.

Note that the same numbers of N_c and N_e make the same number of trials in each Series and Parallel.

III. COMPARISON

Series and Parallel are compared on an interior permanent magnet synchronous machine model which has 8 poles I-type magnets and 48 slots, and design objects are to maximize average torque and minimize torque ripple. The number of design variables is 6.

Optimizations are conducted by changing parameters which are the population $N_p=(12, 60)$, $N_c=(3, 10)$ in Series, and $N_e=(3, 10)$ in Parallel. NSGA-II is used as a GA optimization.

As the results, the differential hypervolume (DHV), which is the hypervolume difference between the observed optimization

and the FEA optimization with $N_p=60$, is plotted versus FEA generation which is the main cost of the optimizations in Fig.1. Acceleration effects are found in both Serial and Parallel. Larger parameters make more acceleration. This can be explained as follows. The acceleration effect is determined by the area of the surrogate model exploration and the number of trials. The exploration area and the number of trials increase in proportion to N_c in Series and to N_e in Parallel. Fig.2 shows the distribution of the trials of each method. It can be observed that the area of the FEA optimization is significantly smaller than that of the surrogate model assisted optimizations.

It can also be found in Fig.1 that Series and Parallel show the same level of acceleration effect when the number of trials is the same. Despite the difference in how the surrogate model trials are added, the areas are close to each other under the given conditions as shown in Fig.2. The similarity of the accuracy of the surrogate models supports this similarity of exploration. As for accuracy, the coefficient of determination (CoD) is shown in Fig.3, where the graphs show the history of CoD in the case of $N_p=12$. It can be confirmed that both lines trace the same trajectory in all cases.

IV. CONCLUSION.

As the surrogate model assisted optimization, two different configurations, Series and Parallel, were compared. The comparisons were performed by changing the population and the amount of use of the surrogate models.

It was found that both configurations give the same level of acceleration in terms of the optimization progress per FEA generation despite the differences in the way surrogate models are used. It can be understood that the acceleration effects are determined by the exploration areas expanded by the surrogate models, which are similar when the accuracies are at the same level.

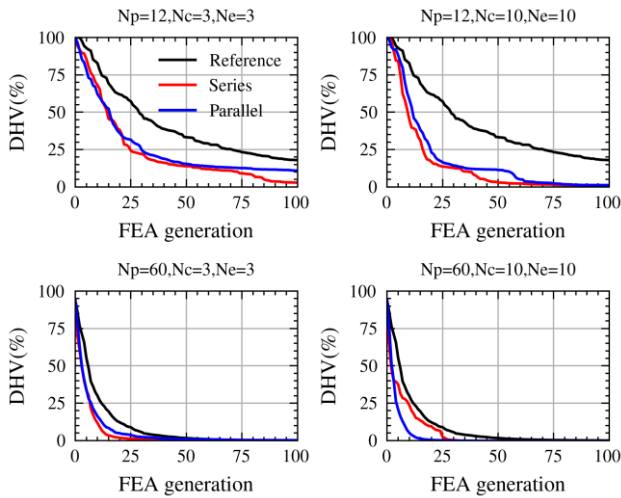


Fig.1 Histories of differential hyper volume
The Pareto progress is accelerated by the use of surrogate models in all cases. The acceleration effects are at the same level in cases that N_c and N_e have the same number.

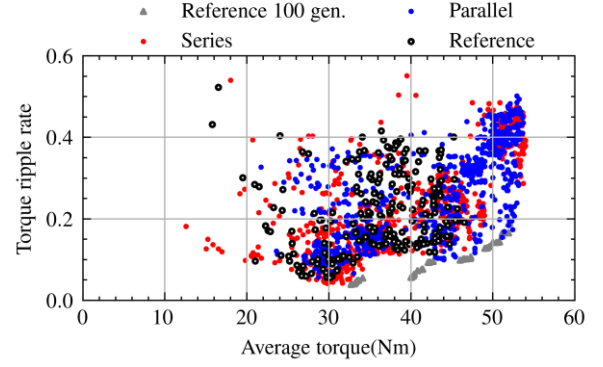


Fig.2 Exploration area with surrogate models
The solution distributions with $N_c=3$, $N_e=3$, and $N_p=12$ at the 22nd generation, when DHV of the surrogate model assisted optimizations reach the final DHV of the reference, are shown. The exploration of both Series and Parallel come close to the final Pareto front of the reference while that of the reference at the 22nd generation stays in a smaller area.

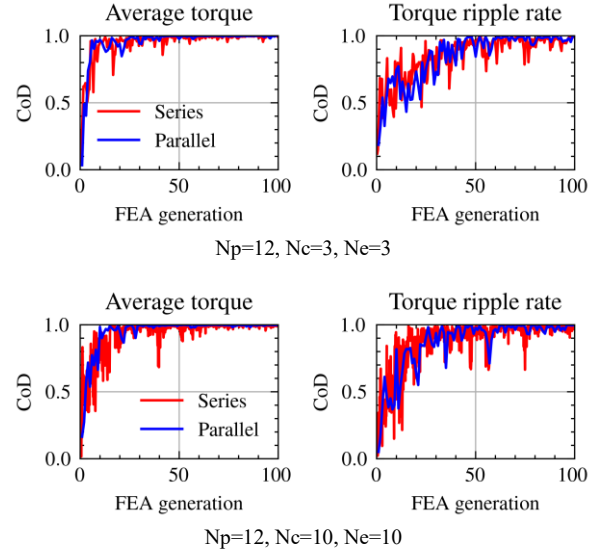


Fig. 3 History of Coefficient of Determination (CoD)
The CoD histories of $(N_c, N_e)=(3,3)$ and $(10,10)$ with $N_p=12$ is shown. Series and Parallel share similar trajectory in each case.

Further investigations are necessary to understand the characteristics of the two versions by applying them to complex problems.

References

- [1] A. Fatemi, N. A. O. Demerdash, T. W. Nehl, and D. M. Ionel, "Large-Scale Design Optimization of PM Machines over a Target Operating Cycle," *IEEE Transactions on Industry Applications*, vol. 52, no. 5, pp. 3772–3782, 2016.
- [2] H. Sano, R. Utsunomiya, T. Senda, K. Tani, and T. Yamada, "Performance Study of Surrogate Models for Large-Scale Optimization," in *2024 International Conference on Electrical Machines (ICEM)*, Sep. 2024, pp. 1–6.
- [3] M. Cheng, X. Zhao, M. Dhimish, W. Qiu, and S. Niu, "A Review of Data-driven Surrogate Models for Design Optimization of Electric Motors," *IEEE Transactions on Transportation Electrification*, pp. 1–1, 2024.