Evolutionary Algorithm Using Surrogate Assisted Model for Simultaneous Design Optimization Benchmark Problem of Multiple Car Structures

Hiro Ohtsuka
Ritsumeikan University
Kusatsu, Shiga, Japan
is0250fi@ed.ritsumei.ac.jp

Misaki Kaidan
Ritsumeikan University
Kusatsu, Shiga, Japan
is0160xk@ed.ritsumei.ac.jp

Tomohiro Harada
Ritsumeikan University
Kusatsu, Shiga, Japan
harada@ci.ritsumei.ac.jp

Ruck Thawonmas
Ritsumeikan University
Kusatsu, Shiga, Japan
ruck@ci.ritsumei.ac.jp

ABSTRACT

This paper proposes a surrogate-assisted evolutionary algorithm for solving optimization problems with high calculation cost for constraint determination. The proposed method consists of CMOEA/D that extends the ability of MOEA/D to deal with constrained optimization problems and a surrogate evaluation model constructed by a machine learning, extreme learning machine (ELM). To investigate the effectiveness of the proposed method, we conduct an experiment on simultaneous design optimization benchmark problem of multiple car structures developed by Mazda Motor Corporation et al.. The experimental result revealed that the proposed method can obtain optimal solutions faster than CMOEA/D without a surrogate model.

CCS CONCEPTS

• **Mathematics of computing → Evolutionary algorithms**; **Bio-inspired optimization**; • **Computing methodologies → Continuous space search**; *Parallel algorithms*; Neural networks;

KEYWORDS

Surrogate assisted model, Extreme learning machine, Multi-objective optimization, Constraint handling, MOEA/D

ACM Reference Format:
Hiro Ohtsuka, Misaki Kaidan, Tomohiro Harada, and Ruck Thawonmas. 2018. Evolutionary Algorithm Using Surrogate Assisted Model for Simultaneous Design Optimization Benchmark Problem of Multiple Car Structures. In *GECCO '18 Companion: Genetic and Evolutionary Computation Conference Companion, July 15–19, 2018, Kyoto, Japan*, Jennifer B. Sartor, Theo D'Hondt, and Wolfgang De Meuter (Eds.). ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3205651.3208771

GECCO '18 Companion, July 15–19, 2018, Kyoto, Japan

ACM ISBN 978-1-4503-5764-7/18/07.
https://doi.org/10.1145/3205651.3208771

1 INTRODUCTION

In these days of industry, multi-objective evolutionary algorithms (MOEAs) that are robust and high exploration efficiency for multi-objective optimization problems (MOOPs) with many constraints have been studied. Mazda Motor Corporation, Japan Aerospace Exploration Agency (JAXA) and Tokyo University of Science proposed simultaneous design optimization benchmark problem of multiple car structures with characteristics of a real-world problem [3]. Hereafter we call this benchmark problem as the Mazda benchmark problem. The Mazda benchmark problem has 222 design variables, two objectives and 54 constraints, and it takes high calculation cost to evaluate constraint values.

In this research, we propose an evolutionary algorithm with a surrogate evaluation of constraints to solve optimization problems with high calculation cost for constraints by reducing the number of actual constraint evaluations. A surrogate model is constructed by a machine learning technique, in particular extreme learning machine (ELM) [2], and it is applied to CMOEA/D [1]. To investigate the effectiveness of the proposed method, this paper compares the proposed method with CMOEA/D without a surrogate model on the Mazda benchmark problem.

2 SIMULTANEOUS DESIGN OPTIMIZATION BENCHMARK PROBLEM OF MULTIPLE CAR STRUCTURES

Simultaneous design optimization benchmark problem of multiple car structures (Mazda benchmark problem) is constrained MOOP proposed by Mazda Motor Corporation, Japan Aerospace Exploration Agency (JAXA) and Tokyo University of Science. It has thickness of three kind of cars (SUV, CDW, C5H) structures with 222 design variables (74 variables per model) and two objectives that aims at minimizing the total mass of the car structures of three models and maximizing the number of common parts between three models. In addition, this benchmark problem has 54 constraints (18 constraints per model) that are formulated by the magnitude relation between the variables determined by the vehicle body rigidity, low frequency vibration, collision performance and design requirements.

3 PROPOSED METHOD

CMOEA/D was proposed as an extended method of MOEA/D, which is a decomposition based MOEA, for solving MOOPs with constraints. CMOEA/D, however, requires enormous calculation time for optimization in the case where the evaluation cost of constraints is high. This research proposes a new MOEA that estimates the constraint function values using the surrogate evaluation model constructed by ELM in CMOEA/D. The proposed method introduces a procedure to repeat the genetic operation until finding a solution with small estimated constraint function values than a certain threshold τ. The threshold τ is the worst constraint function value among the population in the current generation. This procedure contributes to reduce the proportion of actual evaluations of infeasible solutions with high calculation cost, and improves search performance of CMOEA/D.

This paper addresses the Mazda benchmark problem, and we propose an ELM model to estimate the sum of constraint function values for each type of car targeting the Mazda benchmark problem. This ELM model consists of a network of 222 inputs and 3 outputs ($3d$ input and 3 outputs) and is formulated by the following equation:

$$\{\hat{CV}_{\mathrm{SUV}}, \hat{CV}_{\mathrm{CDW}}, \hat{CV}_{\mathrm{C5H}}\} = \mathrm{ELM}(\mathbf{x}) \approx \left\{ \sum_{i=1}^{P} g_i(\mathbf{x}), \sum_{i=1+P}^{2P} g_i(\mathbf{x}), \sum_{i=1+2P}^{3P} g_i(\mathbf{x}) \right\} \quad (1)$$

4 EXPERIMENT

To investigate the effectiveness of the proposed method, we compare the proposed method with CMOEA/D without a surrogate model on the Mazda benchmark problem. We employ the evaluation criterion used in the evolutionary computation competition held in the 14th evolutionary computation symposium in Japan[1]. This competition addresses the Mazda benchmark problem, and compares the median HV of the final generation in 21 independent trials. In order to calculate HV, the objective function values are normalized as follows:

$$f_1^{'}(\boldsymbol{x}) = f_1(\boldsymbol{x}) - 2.0 \quad (2)$$

$$f_2^{'}(\boldsymbol{x}) = f_2(\boldsymbol{x})/74 \quad (3)$$

f_1 is the objective function to obtain the total mass, while f_2 is the objective function to find the number of common parts. HV is calculated with the reference point at $(1.1, 0)$.

Figure 1 shows the transition of HV for each generation. The horizontal axis represents the number of generations with actual constraint evaluations, while the vertical axis represents the HV value. Figure 2 shows the obtained solutions in the median HV trial. The horizontal axis represents the number of common parts, while the vertical axis represents the total mass. From Fig. 1 and Fig. 2, it is indicated that the CMOEA/D with ELM can obtain higher HV value and better solutions quicker than CMOEA/D without ELM. In particular, the proposed method can find feasible solutions quicker than the conventional one. From this result, it is revealed that the combination of CMOEA/D with the ELM surrogate model

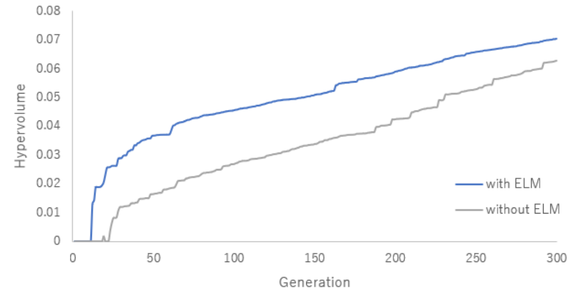

Figure 1: The transition of HV for each generation

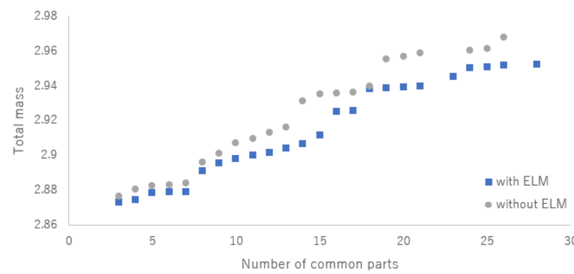

Figure 2: The obtained solutions in the median HV trial

accelerates the convergence speed on the optimization problem with many constraints.

5 CONCLUSIONS

In this research, as a solution to the constrained MOOP with high evaluation cost, we proposed a MOEA with a surrogate evaluation model constructed using ELM. The constructed ELM model estimates constraint function values, and solutions that have low estimated constraint function values are selected for the actual high cost evaluations.

To investigate the effectiveness of the proposed method, the proposed method and the conventional method without a surrogate evaluation model are compared. The experimental result revealed that the proposed method can obtain obtain a solution set with better objective function values faster than the conventional method.

In the future, we plan to apply the proposed method to other MOOPs and attempt other conditions to select solutions for actual evaluation.

REFERENCES

[1] M. Asafuddoula, T. Ray, R. Sarker, and K. Alam. 2012. An adaptive constraint handling approach embedded MOEA/D. In *2012 IEEE Congress on Evolutionary Computation*. 1–8. https://doi.org/10.1109/CEC.2012.6252868

[2] Guang-Bin Huang, Qin-Yu Zhu, and Chee-Kheong Siew. 2004. Extreme learning machine: a new learning scheme of feedforward neural networks. In *2004 IEEE International Joint Conference on Neural Networks (IEEE Cat. No.04CH37541)*, Vol. 2. 985–990 vol.2. https://doi.org/10.1109/IJCNN.2004.1380068

[3] Takehisa Kohira, Hiromasa Kemmotsu, Akira Oyama, and Tomoaki Tatsukawa. 2017. Proposal of Simultaneous Design Optimization Benchmark Problem of Multiple Car Structures Using Response Surface Method. *Transaction of the Japanese Society for Evolutionary Computation* 8, 1 (2017), 11–21. https://doi.org/10.11394/tjpnsec.8.11

[1]Evolutionary computation competition 2017. http://is-csse-muroran.sakura.ne.jp/ec2017/EC2017compe.html (in Japanese).