Effective Multi-Objective Evolutionary Algorithm for Industrial Applications

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ABSTRACT: *Multi-objective evolutionary algorithms (MOEAs) are population based global optimization algorithms and it is said that the performance of the MOEAs depends on the population size. Considering that the recent trends of computer development is in large-scale many-core architectures, and massive parallel computation is getting feasible in more companies and laboratories, the available population size is increasing and the efficiency of MOEA with large population size should be enhanced. This study examines the effect of the population size on MOEAs' performance on a real-world-derived benchmarking optimization problem, with large population size. In this paper, three mate selection schemes with different degree of elitist strategy are adapted to NSGA-II-M2M. The experimental results show that the elitist strategy can efficiently make use of the effect of the large population size, therefore can reduce the turn-around time.*

Keywords: Multi-objective Optimization, Large Population Size, Mate Selection, Real-world Problem

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1. Introduction

Many of industrial design problems involve multiple objectives and constraints and they are so-called constrained multi objective optimization problems. Considering that creating high value-added products in industries is getting more and more important along with the increase of the sophistication and diversity of social needs, it is very important to catch up to the changes in customer demands and so short development time of each product is highly appreciated.

For multi-objective optimization problems, multi-objective evolutionary algorithms (MOEAs) have been regarded as a promising approach. With respect to the application of MOEAs to industrial design problems, the development time of the products corresponds to the turn-around time for MOEAs. The turn-around time of MOEAs corresponds to the number of generations in MOEA, supposing that the runtime for MOEA itself is negligible compared with the runtime for solution evaluations. Here the turn-around time is the time from the beginning of the optimization to the end of the optimization when a desired quality of solution set is obtained.

One of the recent trends of computer development is in large scale many-core architectures [2] and the computational algorithms, say MOEAs, should utilize the large-scale computational resources efficiently. One of the simple yet effective ways of MOEAs for utilizing the large-scale computational resources would be to increase the number of concurrent solution evaluations, i.e., the population size. Note that the increased number of objectives of multi-objective optimization problems also gives a reason to increase the population size: the necessary number of solutions to cover the entire Pareto front exponentially increases as the number of objectives increases [9, 18]. Therefore, the increase in the population size would be the right direction for recent MOEAs.

This study aims to reduce the turn-around time of MOEAs when large population size is used. This paper demonstrates the population size effect on the performance of an MOEA on a real-world-derived benchmarking problem and the reduction of the turn-around time by making use of the population size effect is attempted. This paper is organized as follows. In Section 2, the experimental settings are explained first, and the results demonstrating the impact of the population size on the performance of the MOEAs is presented. Then the method to reduce the turn-around time is described and the experimental results are provided. Section 3 concludes this paper.

2. Reduction of Turn-around Time

2.1 Experimental Setting

Problem: The Mazda CdMOBP problem [11]. This problem has two objectives, 54 constraints, and 222 variables. The problem originates from an actual design optimization of car models and the constraints comprise the requirements for crash worthiness, body torsional stiffness, and low frequency vibration modes. These constraints are evaluated by finite element simulations on a supercomputer in actual design process, however, in the benchmark problem these simulation results are modeled with radial basis functions so as to shorten the evaluation time while retaining the nonlinearity as much as possible. The details are presented in [11] and the problem is available from the website [12].

• **MOEA:** NSGA-II-M2M [15] with the subproblem size of 10. The probability that the parents are chosen from the corresponding subproblem δ is set to 0:9.

• **Constraint Handling Technic:** Multiple constraint ranking (MCR) [5], which generally performs well on constrained optimization benchmarking problems [7]. The constraint handling technic is incorporated into NSGA- II-M2M with the MOEA-CHT incorporation framework [7].

• **Mate Selection Schemes:** Random selection, binary tournament (BT) [1], or Elitist BT (EBT, explained in next subsection) [8]. The random selection scheme is the default mate selection scheme for NSGA-II-M2M [15] and its modified version of Jain et al. [10] is employed so as to handle constraints.

• **Reproduction Operators:** The crossover and mutation operators with the same control parameter values as in [14, 15].

• **Direction Vector Generation Method:** Das and Dennis's systematic approach [4].

• **Stopping Criterion:** The number of generations of 300. The number of fitness evaluations differs according to the population size at a given generation, but the focus is in this study is on the reduction of the required generations, and so the differences in the number of fitness evaluations is not considered in this study. Independent runs: Each case run for 31 times independently.

• **The Population Size** N: N is set to be the numbers in a geometric progression with a scale factor of 100, and a common ratio of $\sqrt{10}$ is used to see the population size effect. Specifically, the population sizes of 100, 316, 1000, and 3162 are used, especially for drawing Figure 3.

2.2 Performance Metric

The hyper volume (HV) indicator [20] is used as the performance indicator. In this study, the solution set used for the calculation of the HV value is the solutions not only in the final population but also in the external unbounded archive [13], considering that the designers in actual industries use MOEAs as design support tools for decision making and so use of the unbounded external archive is more practical than use of the solutions obtained only at the final generation. For calculating the HV value for a generation, non-dominated solutions are extracted from all the feasible solutions obtained by the generation and are used to calculate the HV value. For the details of the formulation for the HV calculation, please refer to [11]. The larger the HV value, the better the approximation to the Pareto front.

2.3 Impact of the Population size on the Performance

Figure 1 presents the convergence history of the mean HV values with various population sizes for NSGA-II-M2M with random selection. It is observed that the cases with higher population size show generally higher mean and smaller standard deviation values. This result supports the motivation for increasing the population size, however, the effect of the increased population size is not clearly observed until around the number of generations of 200, between the cases with the population size of 1000 and 3162.

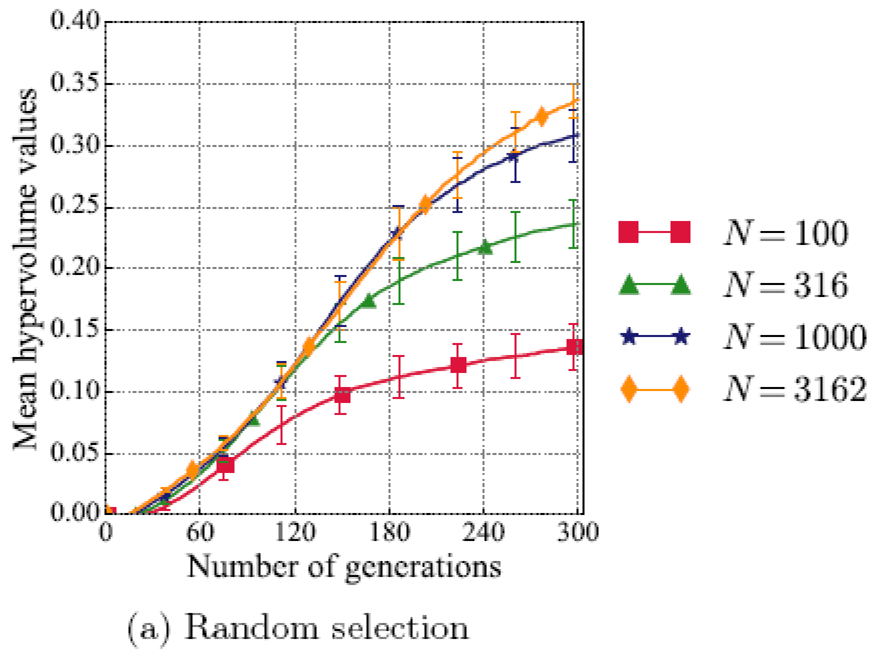


Figure 1. Convergence history of the HV values with various population sizes for the case with random se- lection. The mean and the standard deviation values are plotted

2.4 Reduction of Turn-around Time by Enhancing the Population Size Effect

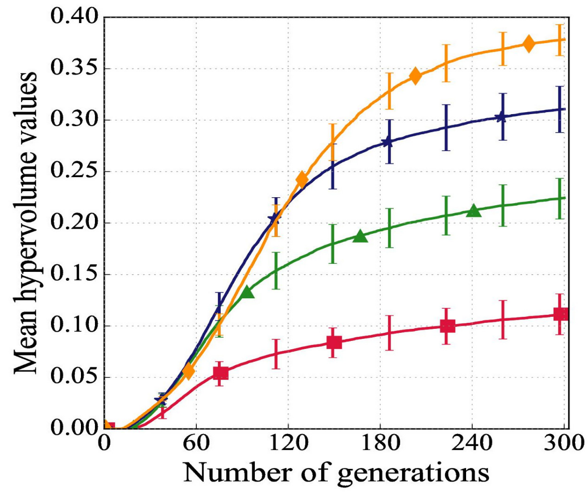
The population size affects the diversity of the solutions and the convergence speed, and now it is commonly accepted that the population size should be large enough to guarantee the diversity of the solutions while the large population size makes the convergence slow [16, 3, 17, 19].

Considering that the phenomenon of the population size effect can be explained by a term \selection pressure" [19], we attempt to mitigate the slow convergence with large population by somehow strengthening the selection pressure. In this study, a standard and popular mate selection of BT and a recently proposed mate selection scheme with a strong elitist strategy named EBT [8], both of which have stronger selection pressure than the random selection, are employed. In EBT, i) the usual BT selection is conducted at first for all the solutions in each subproblem then the indices of the selected solutions are sorted according the number of times the each index is selected. Apart from that, ii) the indices of the solutions are also sorted according the solutions' fitness. Finally, every sorted indices i) is replaced by the index in ii) with the same rank order with i), so that the solution with higher rank is selected more. For further details of EBT, please refer to [8].

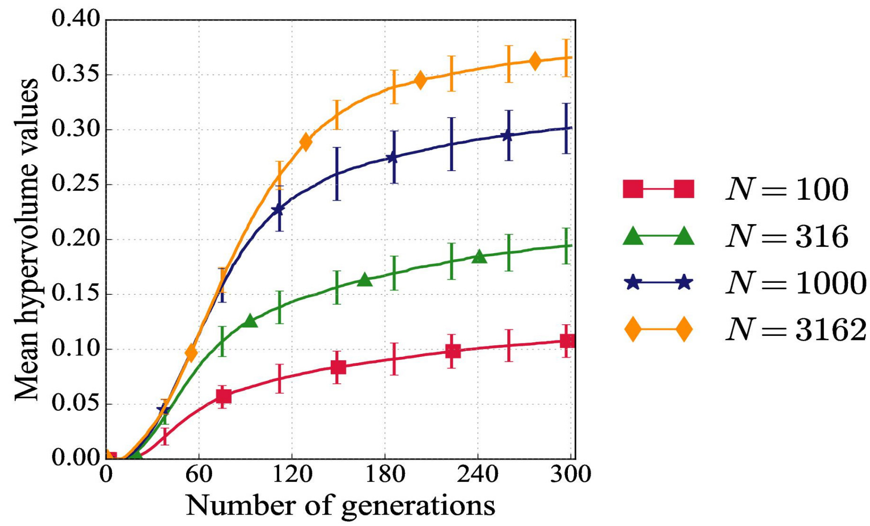
The most elitist is EBT, followed in order by BT and random selection.

It must be noted that the strong elitist strategy tends to deteriorate the diversity of the solutions, and the negative effect of the strong elitist strategy should be compensated by using some diversity-enhancing method. In this study, we enhance the MOEAs' capability of keeping diversity by employing M2M, and this is the reason why the base algorithm in this study is not NSGA-II [6] but NSGA-II-M2M.

Figure 2 shows the convergence history of the mean HV values with various population sizes for NSGA-II-M2M with



(a) BT



(b) EBT

Figure 2. Convergence history of the HV values with various population sizes for the cases with BT and EBT selection. The mean and the standard deviation values are plotted

BT and EBT. Comparing Figure 1 and 2, it can be observed that the strong elitist mate selection enhances the large population size effect and the differences in the mean HV values can be observed more clearly and from earlier generations.

With regard to the reduction of the turn-around time, Figure 3 shows the generation that is required to attain a HV value against the population size. For example, in Figure 3, the HV value of $0{:}2$ can be attained with the number of generations of approximately 300 with the population size of approximately 300, and with the number of generations of approximately 160 with the population size of approximately 1000. The subfigures in Figure 3 show that the required generation to attain a certain HV value is reduced with stronger mate selection scheme.

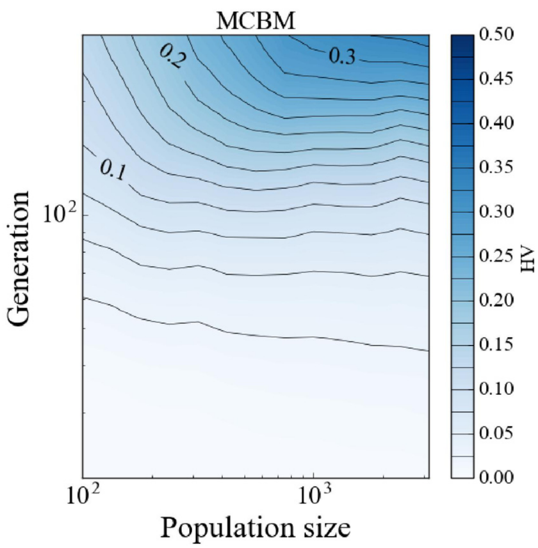
Compared with the case with BT, the results for EBT shows relatively poor performance with small population sizes, and so further development of more robust and more efficient algorithm for reducing the turn-around time will be required.

3. Conclusions

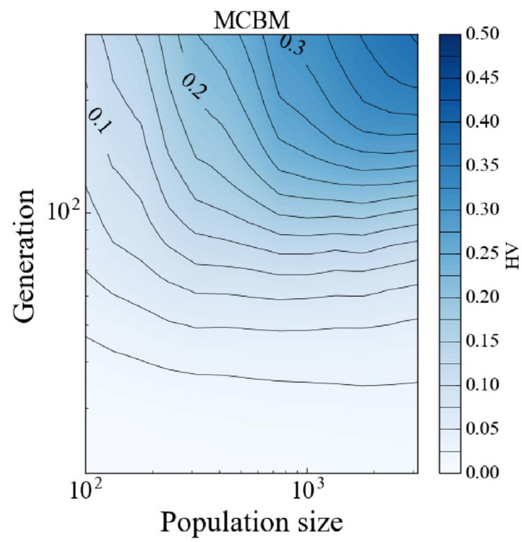
This paper demonstrates the population size effect on the performance of an MOEA on a real-world-derived bench- marking problem (Mazda CdMOBP) and the reduction of the turn-around time by making use of the population size effect is attempted.

By the demonstration of the population size effect, it is shown that the large population size can improve the performance of an MOEA, and it is also shown that the population size effect is not clearly shown until late stage of the evolution with random mate selection scheme.

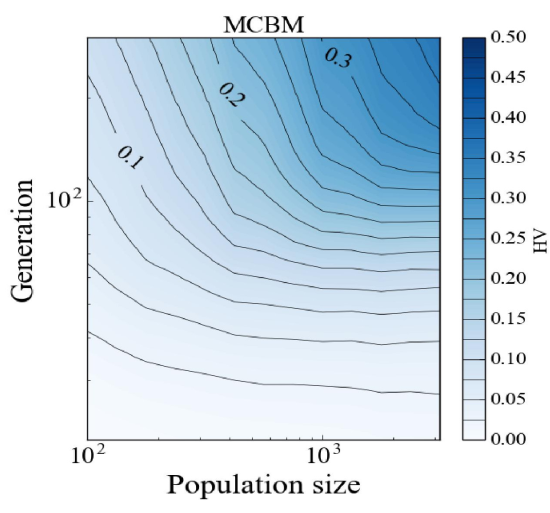
The late-appearing population size effect is then improved by employing two techniques: a strong mate selection scheme and its complementary scheme of M2M. The results show that the case with stronger elitist strategy exhibits relatively faster large



(a) Random selection



(b) BT



(c) EBT

Figure 3. Plot for the generation that is required to attain a HV value against population size

population size effect and the aim of reducing turn-around time is achieved in some degree. Future work will include further improvement of the population size effect, even with much smaller population size.

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