A New Multi-Objective Driving-Training-Based Optimization Algorithm

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ABSTRACT

This paper presents a driving-training-based optimization algorithm for multi-objective problems. In this first multi-objective variant, each learner driver participates in two phases. A set of driving instructors is adaptively selected based on the size of the population and the rate of progress in the optimization process. In the first phase, the learner driver is trained by a driving instructor. The learner driver then has the option of modeling the driving instructor's skills or improving its performances through personal practice in the second phase. The proposed algorithm is compared to well-known and state-of-the-art algorithms. It has demonstrated promising results in multi-objective problems.

Keywords: Driving-training, Multi-objective optimization, Population-based algorithms

1 Introduction

Multi-objective optimization is defined as minimizing or maximizing a vector of Mobjective functions $F(X) = (F_1(X), F_2(X), \dots F_M(X))$ by finding the best compromise vectors composed of D decision variables, $X = (X_1, X_2, \dots X_D)$. The set of compromise solutions is called the Pareto-optimal set (PS), and its projection in the objective space is known as the Pareto-optimal front (PF). Metaheuristic optimization algorithms, categorized into evolutionary, swarm, physics, plant, human, and quantum-based approaches, have emerged as a solution to the inefficiency of deterministic methods in handling complex multi-objective problems, including nonlinear and complex ones [1]. In 2022, Dehghani *et al.* [2] proposed a driving-training-based optimization (DTBO) algorithm for mono-objective optimization problems, which mimics the process of acquiring driving skills. The algorithm consists of three phases: instructor training, instructor skill patterning, and personal practice. This paper proposes a DTBO variant for multi-objective optimization problems (MOPs), based on two main phases.

2 The proposed Multi-Objective Driving-Training-Based Optimization (MODTBO)

The proposed MODTBO algorithm involves two phases: instructor training and patterning and personal practice. It uses non-dominated sorting and crowding distance mechanisms to sort individuals and select driving instructors.

In ***the phase of training by the driving instructor***, the decision vector X_i of each individual in the population is updated using equation (1). Where, R and I are two random numbers and DI_k is a driving instructor selected randomly among a list of driving instructors. The new population $P1$ is evaluated and merged with the current population P. Then, all individuals are sorted based on their rank and crowding distance. The N best individuals are selected to participate in the second phase.

$$X_i^{P1} = X_i + R * (DI_k - I * X_i) \tag{2}$$

In ***the phase of patterning and personal practice***, the learner driver decides to imitate the instructor's skills using equation (2) or to practice individually, by modifying one decision variable j, using equation (3). Among the merged population $P = P \cup P2$, the N best individuals are selected to participate in the next iteration based on rank and crowding distance.

DOI: 10.21467/abstracts.163 ISBN: 978-81-965621-5-1 (eBook)

$$X_i^{P2} = \begin{cases} X_i + PI * X_i - (1 - PI) * DI_k & if\ rand < 0.5 \\ X_i + (1 - PI) * X_i - PI * DI_k & otherwise \end{cases} \quad (3)$$

Where, DI_k is a randomly selected driving instructor and PI is patterning index calculated by $PI = 0.01 + 0.9 * (1 - FE/MaxFE)$.

$$X_i^{P2} = X_i\ ,\ X_{i,j}^{P2} = X_{i,j} + (1 - 2rand) * PI * (U_j - L_j) \quad (4)$$

Where, $rand \in [0,1]$, $U_j\ and\ L_j$ are, respectively, the decision variable's upper and lower bounds.

3 Results and Discussion

The proposed MODTBO algorithm was compared to other state-of-the-art algorithms using ZDT and DTLZ benchmarks. The experiments were conducted on the PlatEMO platform [3] using an Intel Core i5 3337 1.80 GHz CPU and 4 Go of RAM. Figure 1 displays the true Pareto front (PF) and median of 30 runs generated by the three best algorithms in each benchmark. As we can see, MODTBO exhibits good intensification and acceptable diversification.

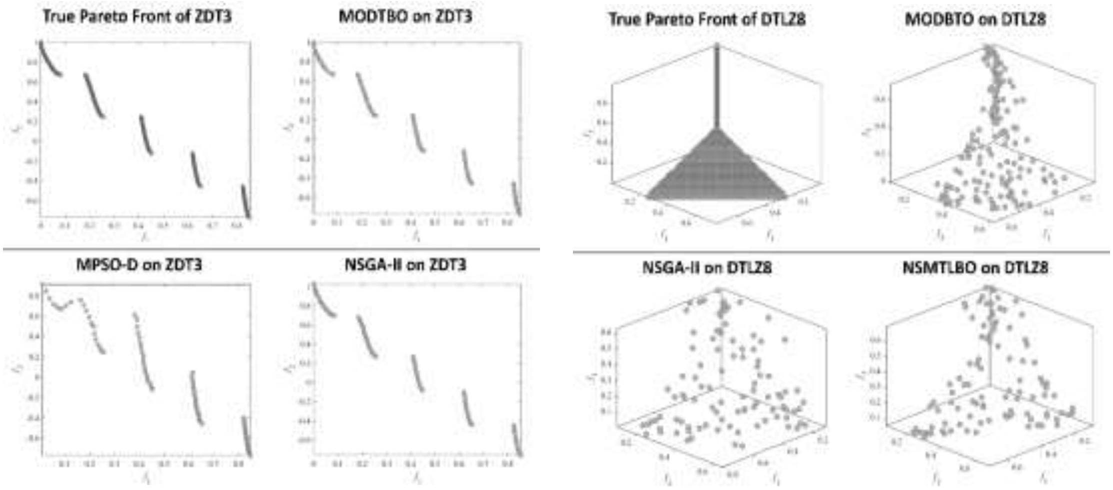

Figure 1: *The Pareto front obtained by compared algorithms on ZDT3 and DTLZ8 benchmarks*

4 Conclusion

The paper proposes a driving-training-based optimization algorithm for solving multi-objective problems. The proposed algorithm, MODTBO, differs from the mono-objective DTBO, which has three phases. The learner driver participates in two phases: training by a randomly chosen instructor and choosing between the instructor's skills and personal practice. The proposed algorithm shows promising performance in convergence, diversity of obtained solutions, and computation time.

5 Competing Interests

The authors declared that no conflict of interest exists in this work

How to Cite

W. Aouadj and R. Seghir, "A New Multi-Objective Driving-Training-Based Optimization Algorithm", *AIJR Abstracts*, pp. 36–38, Feb. 2024.

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ISBN: 978-81-965621-5-1

Series: AIJR Abstracts

DOI: 10.21467/abstracts.163