Performance of Dynamic Algorithms on the Dynamic Distance Minimization Problem

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ABSTRACT

In the area of multi-objective optimization, a special challenge is dynamic optimization problems. These problems change their optimal values or optimal configurations of input variables over time, making it harder for metaheuristic algorithms to track these changes and find the new optima. To test the search ability of such dynamic multi-objective algorithms, a dynamic benchmark called the Dynamic Distance Minimization Problem (dDMP) was proposed in the literature. The dDMP implements multiple changes, not only in location and fitness values of the Pareto-optimal sets, but also in the complexity of the problem. This work aims to test the performance of two well-known dynamic multi-objective algorithms on different instances of the dDMP with varying complexity. This involves changes in the number of objectives and changes of the distance metric at runtime, which has not been done before with this problem in the literature. The results show that both algorithms struggled to recover after the number of objectives was reduced and then increased again. When the distance metric was changed over time both algorithms performed reasonable well. However, there were gaps in the found Pareto fronts when switching between the Euclidean and the Manhattan distance metrics.

CCS CONCEPTS

• **Theory of computation → Evolutionary algorithms**; • **Computing methodologies → Genetic algorithms**;

KEYWORDS

Dynamic optimization, Multi-objective optimization, dynamic algorithm, Distance minimization problem

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1 INTRODUCTION

To test the abilities and limitations of optimization algorithms on dynamic problems, benchmarks are commonly used. One such problem, which has been shown to be difficult to solve in the static and dynamic case, is the dynamic Distance Minimisation Problem (dDMP) [6]. The dDMP is scalable in the number of variables and objective functions and implements a variety of dynamic changes. In a previous work [6], it has been shown that due to its varying complexity, classical dynamic approaches like the dynamic non-dominated sorting genetic algorithm II (DNSGA-II), have difficulties to approximate the optimal solutions in the objective space, even when only 2 decision variables are used. The same was observed for different static versions of the problem [7, 8]. This work aims to investigate the performance of a more sophisticated, state-of-art method, the dynamic vector evaluated particle swarm optimisation (DVEPSO) algorithm [5], on this dDMP and analyze its performance for different problem sizes and complexities.

2 DYNAMIC PROBLEM AND ALGORITHMS

The general Distance Minimization Problem (DMP) has been used in its static version in a variety of works in the literature [7, 8]. In the DMP, each objective function corresponds to one point in the n-dimensional decision space (*objective-points*). The goal of the optimization is to find the Pareto-optimal solutions with minimum distances from these predefined points. A key part of this problem is the distance function, and Euclidean as well as Manhattan distances have been used in the literature. The used metric has a large influence on the shape of the Pareto-optimal front and also defines the complexity of the problem. Recently, a dynamic version of the DMP has been proposed [6]. This dDMP allows for various kinds of changes, which influence the problem and its optimal solutions in different ways. The type of change that is easiest to track and analyze would be a rotation and translation of the

Algorithm	Stepsize	acc	$stab$	Wins_{acc}	Losses_{acc}	Diff_{acc}	Wins_{stab}	Losses_{stab}	Diff_{stab}
DVEPSO	12	6.5435 (6.0531)	11.888 (0.1474)	1	23	-22	0	24	-24
DNSGA-II	12	**6.4306** (6.017)	**11.8114** (0.259)	23	1	22	24	0	24
DVEPSO	4	6.5451 (6.052)	6.5451 (6.052)	1	23	-22	1	23	-22
DNSGA-II	4	**6.4368** (6.0192)	**6.4368** (6.01923)	23	1	22	23	1	22

Table 1: Results for dDMP with a changing distance metric

objective-points. For a more detailed explanation of the changes and their implementation, the reader is referred to [6–8]. When solving dynamic multi-objective optimization problems (DMOPs) an algorithm has to be able to detect when a change in the environment occurs and then respond correspondingly to the change. The co-operative particle swarm optimization (PSO)-based vector evaluated PSO (VEPSO) algorithm from the literature was extended for dynamic multi-objective optimization (DMOO) by Greeff and Engelbrecht [3], referred to as DVEPSO. The number of DVEPSO's sub-swarms is equal to the number of the DMOP's objectives that the algorithm is optimizing. Each sub-swarm optimizes only one objective function and knowledge of its best solutions is shared with the other sub-swarms. This shared knowledge is contained in the global guide and is used to update the velocity of the particles. For more details on the functionality of the DVEPSO, the reader is referred to [3]. In addition, we use the dynamic version of the NSGA-II algortihm (DNSGA-II) in this work for comparison [2].

Algorithm	Stepsize	acc	$stab$
DVEPSO	12	427.017 (231.414)	442.6755 (200.9652)
DNSGA-II	12	425.9413 (231.1624)	441.794 (200.4856)
DVEPSO	4	5.9742 (5.688)	5.974219(5.6880)
DNSGA-II	4	6.1828 (5.3855)	6.182826 (5.3855)

Table 2: Results for dDMP with a changing number of objective functions

3 EVALUATION

Each algorithm was executed for 30 independent runs on each benchmark function and for each environment[1]. Each run had 24 environment changes. The following configurations of dDMP were used in the study: (1) Changing the number of objectives by switching between 2 and 3 objectives, while the number of decision variables remained fixed at 2. The Manhatten distance metric was used and the first environment used 2 objectives. (2) Changing the metric by switching between the Euclidean and Manhatten distance, while the number of decision variables and objectives remained fixed at 2. The first environment used the Euclidean distance. For each of these two configurations, the stepsize was set to 4000 and the number of different environments of the problem which occur periodically were set to either 4 or 12. For measuring performance, we apply two performance measures in this study: The alternative accuracy measure (*acc*) [1] (a low *acc* value indicates good performance), and the stability (*stab*) [1], which quantifies the effect that changes in the environment have on *acc* of the dynamic multi-objective algorithm (DMOA). A low *stab* value indicates good performance. For each environment and performance measure, wins and losses were calculated as proposed in [4]. For each time step just before a change in the environment occurred, the average performance measure is calculated. A Mann-Whitney U test (confidence level 95%) is used for each pair of DVEPSO and DNSGA-II. The averages and standard deviations are reported. If the Mann-Whitney U test indicates a statistical significant difference, wins and losses were awarded at each time step as follows: For each environment, the DMOA with the best performance measure value was awarded a win and the other was awarded a loss.

[1]The authors would like to thank CHPC in South Africa for the usage of their resources to obtain the data for this research.

The results for dDMP with a changing number of objective functions are shown in Table 2. Values in bold indicate a statistical significant difference. Values in parenthesis indicate the standard deviation. There were no statistical significant difference between the two algorithms' performance and therefore no wins and losses were calculated. DNSGA-II did slightly outperform DVEPSO when a stepsize of 12 was used. Both algorithms struggled to perform well with a stepsize of 12 and obtained huge *acc* values, but performed much better when a stepsize of 4 was used. DVEPSO outperformed DNSGA-II on both *acc* and *stab* for a stepsize of 4. Both algorithms struggled to find good solutions when the number of objectives changed from 2 to 3 objectives. However, DNSGA-II recovered better than DVEPSO after such a change.

The results for dDMP with a changing distance metric are presented in Table 1. From the results can be seen that DNSGA-II outperformed DVEPSO on this dDMP configuration. There is only a slight difference in performance measure values between these two algorithms. However, there was a statistical significant difference in their performances. From the wins and losses it can be seen that DNSGA-II did obtain much more wins than DVEPSO. DVEPSO outperformed DNSGA-II on the Manhatten metric when a stepsize of 4 is being used. However, with a stepsize of 12 both algorithms' Pareto front (POF) had huge gaps where no solutions were found that were close to the POF. Both algorithms performed better when the Euclidean metric was used. However, DVEPSO did obtain a better spread of solutions for the Euclidean metric than DNSGA-II.

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