

# Performance Measures and Particle Swarm Methods for Dynamic Multiobjective Optimization Problems

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## 1. INTRODUCTION

Multiobjective optimization represents an important class of optimization techniques which have a direct implication for solving many real-world problems. In recent years, using evolutionary algorithms to solve multiobjective optimization problems, commonly known as EMO (Evolutionary Multiobjective Optimization), has gained rapid popularity. Since Evolutionary Algorithms (EAs) make use of a population of candidate solutions, a diverse set of optimal solutions so called Pareto-optimal solutions can be found within a single run. EAs offer a distinct advantage over many traditional optimization methods where multiple solutions must be found in multiple separate runs.

Many EMO algorithms, most prominently NSGA II, SPEA, PAES, have shown to be very successful in solving multiobjective optimization problems. However, literature review shows that current EMO algorithms are largely focused on solving static multiobjective optimization problems. Very few studies have been devoted to solving dynamic multiobjective optimization problems where the approximate Pareto-front changes over the course of optimization [?]. As many real-world multiobjective optimization problems do show time-varying behaviour [?], it is important to measure how well an optimization algorithm adapts to a changing environment. Although there have been studies of performance measures on static MO problems, research questions remain on performance measures for EMO algorithms in a dynamic environment. This paper attempts to answer some of these questions.

This research describes two performance measures, one being the  $rGD(t)$  (reversed Generational Distance) and the second being the  $HVR(t)$  (Hyper Volume Ratio), for measuring an EMO algorithm's ability to track a time-varying Pareto-front in a dynamic environment. These measures

extend similar ones defined for multiobjective optimization in a static environment. The proposed measures are evaluated using a simple dynamic multiobjective test function and a dynamic multiobjective PSO, *maximinPSOD*, which is capable of handling dynamic multiobjective optimization problems. *maximinPSOD* is an extension from a previously proposed multiobjective PSO, *maximinPSO*. Our results suggest that these performance measures can be used to provide useful information about how well a dynamic EMO algorithm performs in tracking a time-varying Pareto-front. The results also show that *maximinPSOD* can be made self-adaptive, tracking effectively the dynamically changing Pareto-front.

*maximinPSO* makes use of a maximin fitness function to evaluate the fitness of an individual in a swarm population in terms of non-dominance and as well as diversity [?]. *maximinPSO* has shown to have a rapid convergence with good solution distribution [?]. This motivated us to develop *maximinPSOD* (*maximinPSO* for Dynamic environment) which seems to be suitable for tracking a time-varying  $\mathcal{P}^*(t)$  in a dynamic environment.

## 2. SUMMARY

This research investigates performance measures for measuring an EMO's performance in a dynamic environment. Our preliminary results suggest that the two performance measures described are useful performance indicators for measuring EMO algorithms in their ability to track a time-varying Pareto-optimal front  $\mathcal{P}^*(t)$ , although there are drawbacks such as the assumption of a known  $\mathcal{P}^*(t)$ . Our results also show that by resetting  $\mathbf{p}_i$  to its  $\mathbf{x}_i$  at each iteration, *maximinPSOD* can be made self-adaptive to the changing  $\mathcal{P}^*(t)$ . One advantage of this PSO model is the avoidance of explicit detection methods, which are often required by an optimization algorithm in dynamic environments.

## 3. REFERENCES

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