Chapter VII
Evolutionary Population Dynamics and Multi-Objective Optimisation Problems

Andrew Lewis
Griffith University, Australia

Sanaz Mostaghim
University of Karlsruhe, Germany

Marcus Randall
Bond University, Australia

ABSTRACT

Problems for which many objective functions are to be simultaneously optimised are widely encountered in science and industry. These multi-objective problems have also been the subject of intensive investigation and development recently for metaheuristic search algorithms such as ant colony optimisation, particle swarm optimisation and extremal optimisation. In this chapter, a unifying framework called evolutionary programming dynamics (EPD) is examined. Using underlying concepts of self organised criticality and evolutionary programming, it can be applied to many optimisation algorithms as a controlling metaheuristic, to improve performance and results. We show this to be effective for both continuous and combinatorial problems.

INTRODUCTION

Due to the large number of applications in science and industry, multi-objective optimisation using evolutionary algorithms (MOEAs) have been increasingly studied during the last decade (Coello Coello, Van Veldhuizen, & Lamont, 2002; Deb, 2001; Zitzler, 1999). There are many issues to be resolved for effective use of MOEAs, such as developing new algorithms to obtain solutions with good diversity and convergence, designing metrics for measuring the quality of the achieved solutions, producing test functions in static and dynamic environments. Any new development in these areas is valuable for scientific and industrial applications. However, solving large-scale problems with a large number of objectives is still a major challenge (Deb, 2001; Purshouse & Flemming, 2003).

In this chapter, we outline the development and use of evolutionary population dynamics (EPD) as a metaheuristic for population based optimisation algorithms. These include, but are not limited to, ant colony optimisation (ACO) (Dorigo, 1999), Extremal Optimisation (EO) (Boettcher & Percus, 2000) and Particle Swarm Optimisation (PSO) (Eberhart & Kennedy, 1995). This approach can be applied to both continuous and combinatorial problems for single-valued and multi-objective problems.

MULTI-OBJECTIVE ORIENTED METAHEURISTICS

As preliminary background, we describe three well-known metaheuristics: particle swarm optimisation, ant colony optimisation and extremal optimisation. The general mechanics of each method is briefly outlined along with how they have been applied to multi-objective optimisation.

Particle Swarm Optimisation

PSO is motivated from the simulation of social behaviour of animals (Eberhart & Kennedy, 1995; Englebrecht, 2005; Kennedy & Eberhart, 1995). PSO is a population-based technique, similar in some respects to evolutionary algorithms, except that potential solutions (called particles) move, rather than evolve, through the search space. The rules or particle dynamics, which govern this movement, are inspired by models of swarming and flocking. Each particle has a position and a velocity, and experiences linear spring-like attractions towards two guides:

1. The best position attained by that particle so far (local guide), and
2. The best position found by the swarm as a whole (global guide),

where "best" is in relation to evaluation of an objective function at that position. The global guide therefore enables information sharing between particles, whilst the local guides serve as individual particle memories.

The optimisation process is iterative. At each iteration the acceleration vectors of all the particles are calculated based on the positions of the corresponding guides. Then this acceleration is added to the velocity vector. The updated velocity is constricted so that the particles progressively slow down, and this new velocity is used to move the individual from the current to the new position.

Due to the success of particle swarm optimisation in single objective optimisation, in recent years more attempts have been made to extend PSO to the domain of multi-objective problems (Alvarez-Benitez, Everson & Fieldsend, 2005; Mostaghim, 2005; Mostaghim & Teich, 2003; Parsopoulos & Vrahatis, 2002). The main challenge in multi-objective particle swarm optimisation (MOPSO) is to select the global and local guides such that the swarm is guided towards the Pareto optimal front and maintains sufficient diversity. In MOPSO, the set of nondominated solutions must be used to determine the global guide for each particle. Selecting, or constructing, the guide from this set for each particle of the population is a very difficult yet important problem for attaining convergence and diversity of solutions. Several methodologies in MOPSO for selecting the global guide and their influences on the convergence and diversity of solutions are being explored (Alvarez-Benitez et al., 2005; Fieldsend & Singh, 2002; Ireland, Lewis, Mostaghim & Lu,