

# Chapter 6

## Parallel Single and Multiple Objectives Genetic Algorithms: A Survey

**B. S. P. Mishra**  
KIIT University, India

**R. Mall**  
Indian Institute of Technology Kharagpur, India

**S. Dehuri**  
Fakir Mohan University, India

**A. Ghosh**  
Indian Statistical Institute, India

### ABSTRACT

*This paper critically reviews the reported research on parallel single and multi-objective genetic algorithms. Many early efforts on single and multi-objective genetic algorithms were introduced to reduce the processing time needed to reach an acceptable solution. However, some parallel single and multi-objective genetic algorithms converged to better solutions as compared to comparable sequential single and multiple objective genetic algorithms. The authors review several representative models for parallelizing single and multi-objective genetic algorithms. Further, some of the issues that have not yet been studied systematically are identified in the context of parallel single and parallel multi-objective genetic algorithms. Finally, some of the potential applications of parallel multi-objective GAs are discussed.*

### 1. INTRODUCTION

Genetic algorithms (GAs) are a class of powerful search techniques that are popularly being used to solve problems in many different disciplines such as business, engineering, and science (Aguirre & Coello, 2002; Al-Somani, 2000; Alander, 1994). Researchers have found GAs to be especially useful for solving problems with large number

of parameters whose effects on the problems are not well understood. For many complex problems, GAs find good solutions in reasonable amounts of time. However, GAs usually require large number of expensive function evaluations to be made. Based on the cost of each evaluation GAs may take days, months or even years to find an acceptable solution. Therefore, parallelization of GAs is an attractive proposition in such situation.

Parallel GAs (PGAs) have been found to be particularly easy to implement and at the same

DOI: 10.4018/978-1-4666-3628-6.ch006

time yield substantial gains in performance (Grama, Gupta, & Kumar, 1993). For example, adoption of sequential GA based solution to problems such as classification and association rule mining tasks with very large population sizes and long chromosomal representations may take considerable amount of time. Parallel GAs can provide effective solutions to these problems. PGAs have been observed to yield good results for different classes of problems. However, there are many problems that are highly dominated by computational costs and also many open questions arise in designing appropriate PGAs for these (Alba & Tomasdini, 2002). In particular, the design of PGAs involves making choices like single or multiple population, size of the population in either case, and for multiple population one must decide how many to use. Furthermore the population may remain isolated or they may communicate by exchanging individual or some other information. Communication involves extra cost and additional decision making depending on the pattern of communication, on the number of individuals participating in the communication, and on the frequency of communication. This paper reviews the state-of-the-art models of the PGAs and identifies their pros and cons. Additionally, some of the emerging issues (Cantu-Paz, 1998; Alba & Troya, 2002) are discussed.

So far, we have confined our discussions to the single objective genetic algorithms and its parallelization. However, most real world search and optimization problems do involve multiple objectives (Coello et al., 2002). A suitable solution may require making trade-offs (conflicting scenario) among different objectives. A solution that is optimum with respect to one objective may require compromising other objectives. Hence, simultaneous optimization of various objectives considering Pareto- optimal solutions (Coello, 1999) is required.

The ability of GAs to find multiple Pareto optimal solutions in one run makes it a preferred technique for solving multi-objective optimiza-

tion problems. Over the years a large number of multi-objective evolutionary algorithms (MOEAs) have been proposed (Coello, 2000, 2001; Knowles & Corne, 2000; Deb, 2001; Fonseca & Fleming, 1993; Zitzler et al., 2003). MOEAs like Vector Evaluated Genetic Algorithm (VEGA), Multi-Objective Genetic Algorithm (specifically Fonseca MOGA), Niched-Pareto Genetic Algorithm (NPGA), Non-Dominated Sorting Genetic Algorithm-II (NSGA II), Strength Pareto Evolutionary Algorithm (SPEA), Pareto-Archived Evolution Strategy (PAES), etc, are computationally very expensive, because instead of searching for single optimal solution, one generally needs to find the whole front of Pareto optimal solution. For that reason, parallelizing MOGAs (in general) has caught the attention of interest of many researchers.

In the context of parallelization, the main difference between single and multi-objective genetic algorithms seems to be that in the multi-objective case a set of non-dominated solutions is sought rather than a single optimum solution (Soh & Kirley, 2006). This opens up the possibility of having the different processors search for different solutions, rather than each to cooperate to find the overall solution. We discuss several models in parallel multi-objective genetic algorithm including parallel GAs (Alba & Troya, 2001). There are also several specialized parallel multi-objective genetic algorithms (PMOGAs) such as divide range multi-objective genetic algorithms, Parallel NSGA-II, Clustering based parallel MOGAs, etc, which are also addressed in this paper.

The remainder of this paper is organized as follows. In Section 2 a short review of state-of-the-art GAs is presented. Section 3 discusses the PGAs. Section 4 discusses present research issues in PGAs. Section 5 discusses multi-objective genetic algorithms. Section 6 presents the parallel multi-objective genetic algorithms and Section 7 provides few of the applications areas. Finally, we conclude the paper in Section 8.

36 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:  
[www.igi-global.com/chapter/parallel-single-multiple-objectives-genetic/74924](http://www.igi-global.com/chapter/parallel-single-multiple-objectives-genetic/74924)

## Related Content

---

### Optimization Methods for Estimation of Missing Data

Tshilidzi Marwala (2009). *Computational Intelligence for Missing Data Imputation, Estimation, and Management: Knowledge Optimization Techniques* (pp. 210-232).

[www.irma-international.org/chapter/optimization-methods-estimation-missing-data/6802](http://www.irma-international.org/chapter/optimization-methods-estimation-missing-data/6802)

### Development Support of Learning Agent on Repository-based Agent Framework

Syo Itazuro, Takahiro Uchiya, Tetsuo Kinoshita and Ichi Takumi (2012). *International Journal of Software Science and Computational Intelligence* (pp. 62-79).

[www.irma-international.org/article/development-support-learning-agent-repository/76270](http://www.irma-international.org/article/development-support-learning-agent-repository/76270)

### Test Suite Optimization Using Firefly and Genetic Algorithm

Abhishek Pandey and Soumya Banerjee (2019). *International Journal of Software Science and Computational Intelligence* (pp. 31-46).

[www.irma-international.org/article/test-suite-optimization-using-firefly-and-genetic-algorithm/227735](http://www.irma-international.org/article/test-suite-optimization-using-firefly-and-genetic-algorithm/227735)

### Artificial Intelligence and Rubble-Mound Breakwater Stability

Gregorio Iglesias Rodriguez, Alberte Castro Ponte, Rodrigo Carballo Sanchez and Miguel Ángel Losada Rodriguez (2012). *Machine Learning: Concepts, Methodologies, Tools and Applications* (pp. 1499-1506).

[www.irma-international.org/chapter/artificial-intelligence-rubble-mound-breakwater/56209](http://www.irma-international.org/chapter/artificial-intelligence-rubble-mound-breakwater/56209)

### Construction of Normal Fuzzy Numbers using the Mathematics of Partial Presence

Hemanta K. Baruah (2014). *Mathematics of Uncertainty Modeling in the Analysis of Engineering and Science Problems* (pp. 109-126).

[www.irma-international.org/chapter/construction-of-normal-fuzzy-numbers-using-the-mathematics-of-partial-presence/94509](http://www.irma-international.org/chapter/construction-of-normal-fuzzy-numbers-using-the-mathematics-of-partial-presence/94509)