Chapter 20
Swarm Intelligence for Multiobjective Optimization of Extraction Process

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ABSTRACT

Multi objective (MO) optimization is an emerging field which is increasingly being implemented in many industries globally. In this work, the MO optimization of the extraction process of bioactive compounds from the Gardenia Jasminoides Ellis fruit was solved. Three swarm-based algorithms have been applied in conjunction with normal-boundary intersection (NBI) method to solve this MO problem. The gravitational search algorithm (GSA) and the particle swarm optimization (PSO) technique were implemented in this work. In addition, a novel Hopfield-enhanced particle swarm optimization was developed and applied to the extraction problem. By measuring the levels of dominance, the optimality of the approximate Pareto frontiers produced by all the algorithms were gauged and compared. Besides, by measuring the levels of convergence of the frontier, some understanding regarding the structure of the objective space in terms of its relation to the level of frontier dominance is uncovered. Detail comparative studies were conducted on all the algorithms employed and developed in this work.

INTRODUCTION

Multi-criteria or multi-objective (MO) scenarios have become increasingly prevalent in industrial engineering environments (Statnikov & Matusov, 1995; Zhang and Li, 2007; Li and Zhou, 2011). MO optimization problems are commonly tackled using the concept of Pareto-optimality to trace-out the

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non-dominated solution options at the Pareto curve (Zitzler & Thiele, 1998; Deb *et al.*, 2002). Other methods include the weighted techniques which involve objective function aggregation resulting in a master weighted function. This master weighted function is then solved for various weight values (which are usually fractional) (Fishburn, 1967; Triantaphyllou, 2000; Luyben. & Floudas, 1994; Das & Dennis, 1998). Using these techniques, the weights are used to consign relative importance or priority to the objectives in the master aggregate function. Hence, alternative near-optimal solution options are generated for various values of the scalars. In this chapter, the Normal Boundary Intersection (NBI) scheme (Das & Dennis, 1998) was used as a scalarization tool to construct the Pareto frontier. In Sandgren (1994) and Statnikov & Matusov (1995), detail examples and analyses on MO techniques for problems in engineering optimization are presented.

Many optimization techniques have been implemented for solving the extraction process problem (e.g. Hismath *et al.*, 2011; Jie and Wei, 2008). In addition, evolutionary techniques such as DE have also been employed for extraction process optimization (Ubaidullah *et al*., 2012). The MO problem considered in this work was formulated by Shashi *et al*, (2010). This problem involves the optimization of the yields of certain chemical products which are extracted from the Gardenia *Jasminoides Ellis* fruit. The MO optimization model was developed in Shashi *et al*, (2010) to maximize the extraction yields which are the three bioactive compounds; crocin, geniposide and total phenolic compounds. The optimal extraction parameters which construct the most dominant Pareto frontier are then identified such that the process constraints remain unviolated. In Shashi *et al*., (2010), the MO problem was tackled using the real-coded Genetic Algorithm (GA) approach to obtain a single individual optima and not a Pareto frontier. In that work, measurement metrics were not employed to evaluate the solution quality in detail. In addition, the work done in Shashi *et al*., (2010) focused on modeling the system rather than optimizing it. The authors of that work employed only one optimization technique and did not carry out extensive comparative analysis on the optimization capabilities. Due to this setbacks, these factors are systematically addressed in this chapter to provide some insights on the optimization of the extraction process.

Over the past years, swarm intelligence-based meta-heuristic techniques have been applied with increasing frequency to industrial MO scenarios. Some of the most effective swarm approaches have been devised using ideas from Newtonian gravitational theory (Rashedi *et al*., 2009), dynamics of fish movement (Neshat *et al*., 2012) and birds flocking behaviors (Kennedy & Eberhart, 1995). In this work, three swarm-based techniques; gravitational search algorithm (GSA) (Rashedi *et al*., 2009), particle swarm optimization (PSO) (Kennedy & Eberhart, 1995) and the novel Hopfield-Enhanced PSO (HoPSO) were employed to the extraction problem (Shashi *et al*, 2010). The measurement techniques; the convergence metric (Deb & Jain, 2002) and the Hypervolume Indicator (HVI) (Zitzler & Thiele, 1998) were used to analyze the solution spread produced by these algorithms.

The HVI is a set measure reflecting the volume enclosed by a Pareto front approximation and a reference set (Emmerich *et al*., 2005). The convergence metric on the other hand measures the degree at which the solutions conglomerate towards optimal regions of the objective space. Using the values obtained by the measurement metrics, the correlation between the convergence and the degree of dominance (measured by the HVI) of the solution sets is obtained and discussed. The solutions constructing the Pareto frontier obtained using the developed HoPSO algorithm is also subjected to the analyses mentioned above. In this work, all computational procedures were developed using the Visual C++ Programming Language on a PC with an Intel i5-3470 (3.2 GHz) Processor.

This chapter is organized as follows: Section 2 presents an overview on industrial MO optimization while Section 3 discusses some fundamentals on pareto dominance. Section 4 gives the problem de-