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f-MOPSO: An alternative multi-objective PSO algorithm for conjunctive water use management

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ABSTRACT

In recent years, evolutionary techniques have been widely used to search for the global optimum of combinatorial non-linear non-convex problems. In this paper, we present a new algorithm, named fuzzy Multi-Objective Particle Swarm Optimization (f-MOPSO) to improve conjunctive surface water and groundwater management. The f-MOPSO algorithm is simple in concept, easy to implement, and computationally efficient. It is based on the role of weighting method to define partial performance of each point (solution) in the objective space. The proposed algorithm employs a fuzzy inference system to consider all the partial performances for each point when optimizing the objective function values. The f-MOPSO algorithm was compared with two other well-known MOPSOs through a case study of conjunctive use of surface and groundwater in Najafabad Plain in Iran considering two management models, including a typical 12-month operation period and a 10-year planning horizon. Overall, the f-MOPSO outperformed the other MOPSO algorithms with reference to performance criteria and Pareto-front analysis while nearly fully satisfying water demands with least monthly and cumulative groundwater level (GWL) variation. The proposed algorithm is capable of finding the unique optimal solution on the Pareto-front to facilitate decisions to address large-scale optimization problems.

1. Introduction

Conjunctive use of surface water and groundwater resources is commonly practiced in arid and semi-arid regions of the world to meet the growing water demand of urban, agricultural, and industrial users, while reducing climate change related water scarcity (Peralta et al., 1995; Marino, 2001; Schoups et al., 2006; Medellin-Azuara et al., 2008; Safavi et al., 2010; Connell-Buck et al., 2011; Mirchi et al., 2013). While surface water often has lower extraction cost as compared with groundwater withdrawal, it has higher probability of supply failure due to hydrologic variability, justifying the extensive use of more costly but reliable groundwater resources (Burt, 1964; O'Mara, 1988; Fisher et al., 1995; Yang et al., 2009), especially in arid areas of the world. Using both resources conjunctively can increase system reliability by decreasing water supply fluctuations that may disrupt day-to-day activities of users and cause economic loss (Montazar et al., 2010).

Different approaches and techniques have been applied to optimize the conjunctive use of surface water and groundwater (Vedula et al., 2005), including linear programming, dynamic programming, hierarchical optimization, non-linear programming and evolutionary algorithms. Classical optimization methods are typically based on gradient search techniques. The numerical estimation of the gradients is computationally intensive and can be applied only when the objective functions are differentiable and continuous in domain. Furthermore, these conventional methods are not applicable when searching for the global optimum of combinatorial non-linear non-convex problems. To address these drawbacks, population-based evolutionary techniques have been employed along with simulation models in the last four decades to develop efficient conjunctive management models (Maddock, 1974; Peralta et al., 1988; Willis et al., 1989; Ibanez-Castillo et al., 1997; Karamouz et al., 2004; Safavi et al., 2010; Singh and Panda 2013; Safavi and Esmikhani, 2013).

Bazargan-Lari et al. (2009) developed a conflict resolution methodology for conjunctive use of water resources by first generating trade-off curves using a multi-objective genetic algorithm, and then selecting the best non-dominated solution using the

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Young conflict resolution theory (Young, 1993). Marques et al. (2010) applied a two-stage quadratic programming model to maximize economic benefits of conjunctive use from crops, irrigation technology, the areas under permanent and annual crops, and surface water supply. They assumed groundwater withdrawal is constrained by artificial recharge of the aquifer, while also limiting the surface water supply in each year to a "sustainable" annual amount. A set of hydrologic stochastic events with respective probability of occurrence were also considered to address uncertain climate change conditions. Rezapour Tabari and Soltani (2013) developed a multi-objective model for maximizing the reliability of an irrigation system's water supply, while minimizing the cost, using non-dominated sorting genetic algorithm (NSGA-II) to provide optimal compromising objectives. Peralta et al. (2014) used a simulation-optimization conjunctive use model. They applied an artificial neural network model to simulate various flow interactions, as well as an NSGA model to optimize water allocations by maximizing water supply, and hydropower production, while minimizing the operation costs of surface water transfer and groundwater extraction.

Due to multi-objective nature of most real-world water management problems with conflicting and/or incommensurable objectives (Madani and Lund, 2011), developing efficient and robust multi-objective water resources system optimization techniques remains an active research area. Traditional multi-objective optimization approaches such as weighting and ε-constraint methods can produce non-dominated solutions by transforming the multi-objective problems to single-objective ones based on bottom-up information flow. By contrast, in an evolutionary optimization model, the top-down information flow through implementation of preference methods is also needed to detect a unique optimum solution (Abido, 2010; Fallah-Mehdipour et al., 2011).

Particle Swarm Optimization (PSO) algorithm (Kennedy and Eberhart, 1995) is the most commonly used stochastic population-based evolutionary computation technique inspired by the evolution of nature (Kennedy and Eberhart, 1995). Compared to other meta-heuristic techniques (e.g., genetic algorithm), PSO has a more flexible and well-balanced mechanism to enhance and adapt the global and local exploration, needing fewer particles (solutions) to provide the required diversity and faster convergence rate (Abido, 2010). A Vector Evaluated PSO (VEPSO) was developed by Parsopoulos and Vrahatis (2002) based on the concept of Vector Evaluated Genetic Algorithm (VEGA) to perform multi-objective optimization. VEPSO uses one swarm for each objective and the best particle of each swarm is used as the global best particle to determine particle velocities and positions. Hu and Eberhart (2002) presented a multi-objective PSO (MOPSO) with a dynamic neighborhood strategy to obtain the global best for each particle in bi-objective problems. In this method, the global best particle in each stage is the local optimum among all neighbors selected in the previous stage with respect to the other objective value. However, this process poses limits to algorithm performance due to multi-objectivity of the problem, increasing the convergence rate without finding the global best particle (Abido, 2010).

A suite of MOPSO methods have been introduced in the past two decades. Coello and Lechuga (2002) proposed a MOPSO method based on investigation of externally archived non-dominated solutions. In this MOPSO, the best solution in the archive with the smallest density value is assigned the maximum probability to be found as the global best by imposing a selection operator similar to the roulette-wheel selection operator. To find the personal best particle in this MOPSO, the new position is selected only if it dominates the old position and in case of non-dominance of either position, one of them is randomly selected as the personal best position. Performance-wise, the main drawback of these MOPSOs results from neglecting the fitness among the non-dominated solutions, the dominance criteria, and the way to consider density of solutions. Mostaghim and Teich (2003a) proposed a sigma method in which the sigma vector for each particle is the gradient of a line drawn between that particle and the origin. The algorithm selects the guide (global best) particle by finding the nearest non-dominated member in terms of Euclidian distance between that member's sigma value and that of the swarm member, assigning each particle a particular global best. This process may cause premature convergence in some cases such as multi-frontal problems (Abido, 2010). Furthermore, Mostaghim and Teich (2003b) proposed using ε-dominance in MOPSO. This method limits the number of non-dominated solutions in the archive which is very influential in the algorithm running time, rate of convergence and diversity (Abido, 2010). They also introduced a new method which uses the property of moving particles in MOPSO to divide the population into sub-swarms (Mostaghim and Teich, 2004), trying to cover the gaps between the non-dominated solutions found in the initial run.

Wei and Wang (2006) proposed a novel MOPSO algorithm in which a three-parent crossover operator was suggested in order to move the solutions toward the feasible region, and a dynamically changing inertia weight was designed to keep the diversity of the swarm and escape from local optima. Ireland et al. (2006) introduced a centroid method to construct the guide particle based upon a distance-weighted average of the archive members. They concluded that the centroid method generates more diversity in the Pareto-front with slow convergence as compared with the sigma method which has a tendency to converge too rapidly with very little diversity. Thus, they developed a hybrid centroid/sigma algorithm as a more efficient and robust MOPSO algorithm. Reddy and Kumar (2007a) proposed an efficient multi-objective PSO algorithm, in which a variable size external repository is employed to store non-dominated solutions. They also applied a crowding distance operator to measure the amount of diversity of the stored solutions whenever the size of the repository exceeds desired size while doing mutation on the solutions using a strategy called elitist-mutation whenever needed. Reddy and Kumar (2007b) employed their proposed EM-MOPSO algorithm to solve a multi-objective reservoir operation problem. Thereafter, they reduced the obtained non-dominated solutions to a few representative ones, applying a clustering technique to ease handling the solutions. Finally for facilitating the decision-making, a pseudo-weight vector was calculated for each objective over Pareto-front points and the desired weight combination was extracted. Cabrera and Coello (2010) proposed Micro-MOPSO to handle very small population sizes using an auxiliary archive for storing non-dominated solutions found throughout the search, and a final archive for storing final non-dominated solutions. In this algorithm, the global best particle (called the leader) is selected from a sub-set of the final archive members with the best crowding distances. The neighborhood for creating the swarm is then selected based on the smallest Euclidian distance to the leader particle, while implementing a reinitialization process and a mutation operator to avoid stagnation.

Abido (2010) introduced an approach using two sets of non-dominated solutions, i.e., a non-dominated local set to store the non-dominated solutions obtained by the jth particle to the current time (i.e., $S_j^*(t)$) and a non-dominated global set to store the non-dominated solutions obtained by all particles up to the current time (i.e., $S^{**}(t)$). Then the individual distances between members in $S_j^*(t)$ and members in $S^{**}(t)$ are measured in the objective space. If $X_j^*(t)$ and $X_j^{**}(t)$ are, respectively, members of $S_j^*(t)$ and $S^{**}(t)$ that give the minimum distance, they are selected as the personal best and the global best of the jth particle. Liu and Zhao (2011) pro-