Environmental Modelling & Software 62 (2014) 271–299

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

Position paper

Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions☆,☆☆

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ARTICLE INFO

Article history:
Received 28 March 2014
Received in revised form
12 September 2014
Accepted 12 September 2014
Available online

Keywords:
Optimisation
Water resources
Evolutionary algorithms
Metaheuristics
Review
Research directions

ABSTRACT

The development and application of evolutionary algorithms (EAs) and other metaheuristics for the optimisation of water resources systems has been an active research field for over two decades. Research to date has emphasized algorithmic improvements and individual applications in specific areas (e.g. model calibration, water distribution systems, groundwater management, river-basin planning and management, etc.). However, there has been limited synthesis between shared problem traits, common EA challenges, and needed advances across major applications. This paper clarifies the current status and future research directions for better solving key water resources problems using EAs. Advances in understanding fitness landscape properties and their effects on algorithm performance are critical. Future EA-based applications to real-world problems require a fundamental shift of focus towards improving problem formulations, understanding general theoretic frameworks for problem decompositions, major advances in EA computational efficiency, and most importantly aiding real decision-making in complex, uncertain application contexts.

☆ Thematic Issue on Evolutionary Algorithms in Water Resources.

☆☆ Position papers aim to synthesise some key aspect of the knowledge platform for environmental modelling and software issues. The review process is twofold – a normal external review process followed by extensive review by EMS Board members. See the Editorial in Volume 21 (2006).

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http://dx.doi.org/10.1016/j.envsoft.2014.09.013
1364-8152/

1. Introduction

1.1. Background

Environmental change, economic and social pressures, and limited resources motivate systems analysis techniques that can help planners determine new management strategies, develop better designs and operational regimes, improve and calibrate simulation models, and resolve conflicts between divergent stakeholders. Metaheuristics are emerging as popular tools to facilitate these tasks, and in the field of water resources, they have been used extensively for a variety of purposes (e.g. model calibration, the planning, design and operation of water resources systems etc.) in many different application areas over the last few decades (Nicklow et al., 2010). Since metaheuristics were first applied in the water resources field (Dougherty and Marryott, 1991; McKinney and Lin, 1994; Ritzel et al., 1994; Gupta et al., 1998), their popularity has increased dramatically, probably facilitated by the simultaneous increase of available computational power (Washington et al., 2009), to the point where they are widely used (Nicklow et al., 2010), even by actual water planning utilities (Basdekas, 2014).

Zufferey (2012) defines a metaheuristic "as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space", as part of which "learning strategies are used to structure information in order to find efficiently near-optimal solutions." Unlike more "traditional" approaches, which use mathematical programming to specify the optimal value of one or more objective functions, metaheuristics incorporate elements of structured randomness for search and follow empirical guidelines, often motivated by observations of natural phenomena (Collette and Siarry, 2003).

Metaheuristics can be divided into two groups, including population-based algorithms (e.g. genetic algorithms, evolutionary strategies, particle swarm optimization, ant colony optimization, etc.) and single point-based methods (e.g. simulated annealing, tabu search, simple (1+1) evolutionary strategies, trajectory or local search methods, etc.). Evolutionary algorithms (EAs) are the most well-established class of metaheuristics for solving water resources problems and are inspired by various mechanisms of biological evolution (e.g. reproduction, mutation, crossover, selection, etc.) (Nicklow et al., 2010). Consequently, the focus of the remainder of this paper is on EAs, although many of the concepts discussed also broadly apply to other metaheuristics. The paper also provides general guidelines and future research directions for the broader class of systems analysis approaches that take any sort of optimisation into account.

When using EAs, the steps in the optimisation process generally include (Fig. 1):

1. Problem formulation (i.e. selection and definition of decision variables, objectives, and constraints).
2. Selection of decision variable values.
3. Evaluation of objectives and constraints for the selected decision variable values, which is generally done using one or more simulation models.
4. Selection of an updated set of decision variable values based on feedback received from the evaluation process using some search methodology.
5. Repetition of points 3 and 4 until the selected stopping criterion has been satisfied.
6. Passing the optimal solutions into an appropriate decision-making process.

As outlined below, compared with more "traditional" optimisation methods, EAs have a number of advantages, which are most likely responsible for their widespread adoption for water resources problems.

1. The basic analogies that inform their optimisation strategies are conceptually easy to understand.
2. As simulation models are generally used to calculate objective function values and check constraints, it is easy to add optimisation to existing simulation approaches. This gives rise to the potential for greater confidence in the results by end users, as the outcomes of the optimisation process are based on the results of simulation tools that are already used for the purposes of decision-making.
3. EAs are capable of solving problems with difficult mathematical properties (Reed et al., 2013). This is because the ability to link with simulation models reduces the need for problem simplification, which is required for many traditional optimisation algorithms that are unable to deal with nonlinearities (e.g. exact finitely terminating algorithms, like linear and nonlinear programming) or discontinuities (e.g. iterative/convergent algorithms, such as first or second order gradient methods). For example, in linear programming applications, there is no ability

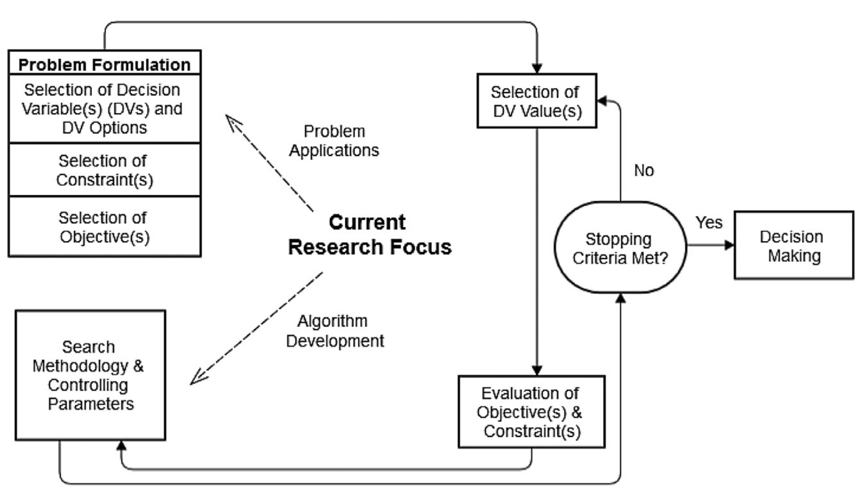

Fig. 1. Steps in EA optimisation process, highlighting areas of current research focus. The square shapes represent the steps in the EA process and the oval shape represents a decision point.