State of the Art for Genetic Algorithms and Beyond in Water Resources Planning and Management

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Abstract: During the last two decades, the water resources planning and management profession has seen a dramatic increase in the development and application of various types of evolutionary algorithms (EAs). This observation is especially true for application of genetic algorithms, arguably the most popular of the several types of EAs. Generally speaking, EAs repeatedly prove to be flexible and powerful tools in solving an array of complex water resources problems. This paper provides a comprehensive review of state-of-the-art methods and their applications in the field of water resources planning and management. A primary goal in this ASCE Task Committee effort is to identify in an organized fashion some of the seminal contributions of EAs in the areas of water distribution systems, urban drainage and sewer systems, water supply and wastewater treatment, hydrologic and fluvial modeling, groundwater systems, and parameter identification. The paper also identifies major challenges and opportunities for the future, including a call to address larger-scale problems that are wrought with uncertainty and an expanded need for cross fertilization and collaboration among our field's subdisciplines. Evolutionary computation will continue to evolve in the future as we encounter increased problem complexities and uncertainty and as the societal pressure for more innovative and efficient solutions rises.

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Introduction

Evolutionary computation (EC), a term devised only in the last two decades, represents a broad spectrum of heuristic approaches for simulating evolution (Back et al. 2000). Primary examples include genetic algorithms (GAs) (Holland 1962; Holland 1975), evolutionary strategies (ES) (Rechenberg 1973; Schwefel 1981), evolutionary programming (Fogel et al. 1966), and genetic programming (Koza 1992). Collectively referred to as evolutionary algorithms (EAs), these methods are comprised of algorithms that operate using a population of alternative solutions or designs, each represented by a potential decision vector. EAs rely on randomized operators that simulate mutation and recombination to create new individuals (i.e., solutions) who then compete to survive via the selection process, which operates according to a problem-specific fitness function (Back et al. 2000). EA popularity is, at least in part, due to their potential to solve nonlinear, nonconvex, multimodal, and discrete problems for which deterministic search techniques incur difficulty or fail completely. The growing complexity and scope of environmental and water resources applications has served to expand EAs' capabilities. The objective of this paper is to critically review recent EC applications and the state-of-the-art, with particular focus on GAs given their dominant use in the historical literature of the water resources planning and management field. Conceptualized by ASCE's Task Committee on Evolutionary Computation in Environmental and Water Resources Engineering, this paper contributes a comprehensive resource for water resources researchers interested in applying EC and seeks to promote cross fertilization between the many areas of water related research where EAs are being applied.

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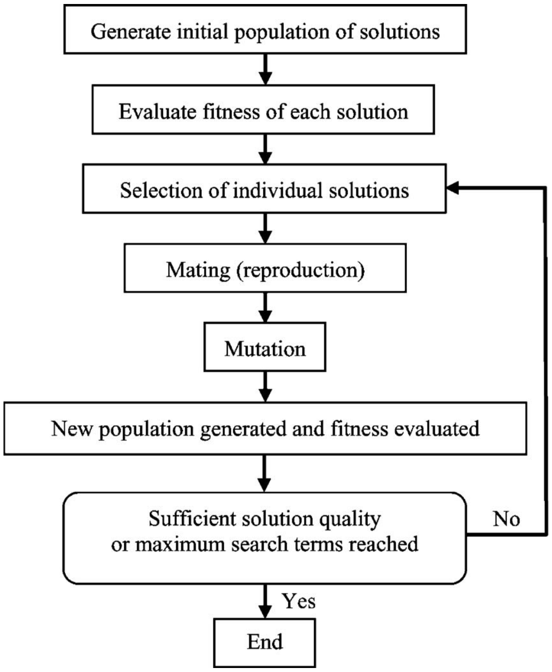

Fig. 1. Generalized framework of a GA

Genetic Algorithm

GAs have been the most commonly applied EA within water resources planning and management literature. Although there is no universal definition, GAs are characterized by the following elements: (1) generation of an initial population of potential solutions, each identified as a chromosome; (2) computation of the objective function value, or fitness metric, of each solution and subsequent ranking of chromosomes according to this metric; (3) some aspect of chromosome ranking and selection of candidate solutions to participate in a mating operator, where information from two or more parent solutions are combined to create offspring solutions; and (4) mutation of each individual offspring to maintain diversity and prevent premature convergence to local optima. These elements are repeated in sequential generations until a suitable solution is obtained. This general framework, illustrated in Fig. 1, lends to the concept that solutions having high fitness values contain specific genes (or characteristics) that are important for optimizing the objective function. By mixing important genes between parent alternatives, it is expected that the GA will produce some offspring that may attain superior characteristics relative to their parent alternatives. In this way, the algorithm simulates survival of the fittest objective function values, without requiring derivative information (Back et al. 2000; Schwefel 1995; Holland 1975; Goldberg 1989). This concept has provided a foundation for development of numerous other single- and multiobjective EAs over the last two decades, many of which will be identified and discussed subsequently herein.

Recent Methodological Advances

Recent methodological advances have served to broaden the scope of environmental and water resources applications where EAs can be effectively applied. The advances emphasized herein focus on EA search innovations that are generally valuable beyond a single water resources application area. The next sections of text are meant to serve two purposes: (1) critically review more traditional EA operators or methods that are commonly employed in the literature and (2) provide guidance on promising methods that have served to increase the size and scope of water resources problems that can be addressed by EAs.

Advances in Representations, Search Operators, and Parameterization

The two broad classes of EA operators consist of (1) selection schemes and (2) variational schemes (e.g., mating and mutation). In combination, these operators serve to generate and explore new candidate solutions that must compete to survive (i.e., attain a population slot) within the evolution analogy. There is a broad array of selection and variational operators available and users should carefully select algorithm operators best suited to the properties and goals of their application. It is important for a user to understand the appropriateness, benefits, and limits of the EA operators they employ.

EA Operators: Bridging Genetic Algorithms and Evolutionary Strategies

To date, the most familiar selection operators available in common GA codes include variants of tournament selection, truncation selection, roulette wheel selection, and Boltzmann selection. In terms of broader EA development, most modern codes implement a form of tournament and/or truncation selection because these selection schemes are scaling invariant and when used in combination, they are implicitly elitist (i.e., the best population members are guaranteed to survive into the next generation). Elitism and scaling invariance (i.e., independence from the fitness function's range) are important properties that have been shown to enhance the effectiveness of EAs in water resources applications (Reed et al. 2000a; Yoon and Shoemaker 2001; Bayer and Finkel 2004). Although roulette wheel selection (or other stochastic proportionate schemes) has been applied in many early water resources applications, this method has significant limitations. Fitness scaling can have severe impacts on roulette wheel selection through two mechanisms: (1) a single supersolution (which often occurs for applications using constraint violation penalties) dominates the probabilities of selection causing premature convergence and (2) late generation solutions with very similar fitness values yield nearly identical selection probabilities that cause search to drift randomly or stall. In general, it is recommended to avoid roulette wheel selection. Boltzmann selection has been used successfully in a variety of water resources applications (Dougherty and Marryott 1991; Karpouzos et al. 2001; Shieh and Peralta 2005) and represents an interesting mixture of concepts from EA literature with the basic sampling scheme used in simulated annealing (SA) (Kirkpatrick et al. 1983). The method has well established theoretical proofs of convergence, but should be implemented carefully to avoid parametric sensitivities (i.e., specifying distribution parameters to sufficiently slow the search to avoid premature convergence).

The discussion of Boltzmann selection is an excellent transition point to provide some historical context on decision variable representations as well as the importance of representation on mating/mutation operator choices. Historically, two algorithm classes—GAs and ES—were developed independently until 1991 when a joint conference between the communities sought to collaborate under the term "Genetic and Evolutionary Computation." The early developments of GAs and ESs were shaped by their respective representations—binary strings for GAs and real-valued continuous variables for ESs. Early work in the water resources area (Wang 1991; McKinney and Lin 1994; Ritzel et al. 1994) focused largely on the binary GA framework as disseminated in large part by the often-cited text by Goldberg (1989). Early applications of real-valued representations of water resources optimization problems were largely associated with SA applications (Dougherty and Marryott 1991) or shuffle-complex evolution (SCE) applications (Duan et al. 1992). These algorithms are conceptually similar to early ESs developed in the 1960s as described by Schwefel (1995). SA is a (1+1)-ES modified to use Boltzmann selection, while SCE is a real-valued ES that modifies the traditional Gaussian noise search step with cluster-based exploration.

Recent water resources applications demonstrating the use and efficiency of ESs demonstrate the importance of real-valued mating/mutation operators in water resources applications when focusing on continuous or mixed integer optimization (Yoon and Shoemaker 2001; Vrugt et al. 2003b; Bayer and Finkel 2004; Reed and Yamaguchi 2004b; Bekele and Nicklow 2005; Kollat and Reed 2006; Tang et al. 2006). Mating and mutation approaches are largely shaped by how decision variables are encoded in an EA: (1) binary vectors; (2) integer vectors; (3) real-coded vectors; or (4) mixed integer/real vectors. The distinction between mating and mutation operators is defined principally on the number of individuals used to generate new solutions. Mutation is a "unary" operator, as defined by Back et al. (2000), where a single solution is perturbed to generate new candidate solutions; whereas, mating involves the transformation of two or more individuals into new candidate solutions. In binary GA applications, jump mutation is the most common local search operator employed, in which bits in a design's binary string are randomly changed from 1 to 0 or vice versa based on a user-specified probability. Alternatively, Schwefel (1995) highlighted that for real-coded ES algorithms, Gaussian mutation is the most common operator that has been employed, in which a single individual composed of a vector of real values is used to generate new solutions by adding normally distributed perturbations to the decision variables.

In the context of mating operators, there are a wide range of alternatives available depending on the representation used in an algorithm. In binary GA applications, theoretical work (Geiringer 1944; Thierens et al. 1998; Back et al. 2000) has highlighted that uniform crossover is often preferred because it exerts more "search pressure" to explore new regions of an application's decision space. Uniform crossover combines the strings of two binary parent strings, whereby the parents swap bits at each binary digit (or gene) with a user-specified probability. In the case of real-coded representations, there are two classes of mating operators that are common: (1) crossover and (2) intermediate recombination. Crossover is analogous to binary string mating schemes where parent variables are swapped with a user-specified probability (e.g., see Storn and Price 1997). Intermediate recombination is far more commonly employed for real-valued or mixed integer formulations due to its historical origin in the ES literature (Schwefel 1995). Intermediate recombination blends multiple real-valued parent vectors using a variety of statistical averaging and decision variable perturbation schemes. Current state-of-the-art for real-valued intermediate recombination strategies include simulated-binary crossover (SBX, Deb and Agrawal 1995), parentcentric crossover (PCX, Deb et al. 2002), and self-adaptive weighted recombination (Hansen and Ostermeier 2001; Hansen et al. 2003). Although it is beyond the scope of this paper to provide a detailed discussion of these operators, emerging applications of these tools in water resources applications show that they potentially outperform binary-coded crossover and can enhance search efficiency even for binary decisions (Yoon and Shoemaker 2001; Bayer and Finkel 2004; Kollat and Reed 2006).

Parameterization and Evaluation

The preceding text highlights the first and potentially most challenging decision users must face when using EAs: what operators are appropriate and effective? Once operators have been selected, another important challenge lies in specifying the parameters that control an EA's search (e.g., population size, run length, probability of mating, probability of mutation, etc.). Within the water resources literature, Aly and Peralta (1999a,b) clearly demonstrated the importance and challenge posed by identifying robust search operator parameters given the constraints of computationally intensive applications. Reed et al. (2000a) proposed a three-step methodology for parameterizing binary-coded GAs assuming the use of tournament selection, uniform crossover, and jump mutation. Although the parameterization methodology proposed focuses on theoretical population-sizing equations that are difficult to translate to water resources contexts, the study does highlight several important issues EA users need to consider regardless of the type of EC algorithm used: (1) EAs are stochastic and users need to design applications to minimize random seed variability (i.e., attain similar results regardless of the randomly generated initial search population); (2) frequent increases in population size can improve the reliability of search for a single random seed; (3) run duration should grow proportionally to the number of decision variables being searched; and (4) the average computational time for design evaluations should guide population size and run duration decisions.

More recent studies have used, improved, or presented alternatives to the methodology proposed by Reed et al. (2000a) for real or binary-coded EAs in single and multiobjective contexts (Reed et al. 2003; Gibbs et al. 2008; Bayer and Finkel 2004; Reed and Yamaguchi 2004b; Bekele and Nicklow 2005; Espinoza et al. 2005; Kollat and Reed 2006). Overall these studies present useful suggestions for parameterizing a variety of real or binary-coded mating and mutation operators. Several of the studies show that preconditioning search (i.e., injecting known good solutions) yields a significant benefit to search efficiency and reliability. These studies use a series of connected runs where initial small population sizes are exploited with small computational costs to generate initial search results. The initial search results are then injected into larger populations until the best solution's quality does not improve significantly or a user-specified computational limit is reached. When computational limits are small, there have been studies in the EC literature that have shown that using an initially large population size and reducing the population with search progress can also be beneficial (e.g., see Pelikan 2002). It should, however, be noted that there is a trade-off between the time for evolution and size of the population. When a problem has nontrivial evaluation times, a very limited number of search generations evolved at a large population size can consume significant computational time. Overall, it is important when using EAs to have a carefully designed computational experiment with a clear rationale for the representation, operators, and parameters being used as well as a clear framework for assessing search performance.

Computational Search Enhancements

The growing range of water resources problems where EAs are being applied has necessitated advances in the algorithms' search capabilities as well as techniques for reducing their computational demands. The water resources domain requires EAs to navigate highly nonlinear problem spaces that are often constrained and may require a suite of performance objectives. Evaluation of water resources objectives is often done using conceptual, physical, or statistical simulation frameworks with significant computational costs, as well as forecasting uncertainties.

Constrained Optimization and Global-Local Hybrid Search

Constraints highly complicate the topology of search spaces, making it more challenging for EAs to reliably identify near-optimal or optimal solutions. Constrained decision spaces are commonly poorly scaled (typified by a very high fitness variance), multimodal, and potentially discontinuous (Chan Hilton and Culver 2000; Cai et al. 2001; Yu and Harrell 2004; Espinoza et al. 2005; Espinoza and Minsker 2006a). These challenges often motivate the use of EAs by themselves or in combination with some form of local search (i.e., hybrid algorithmic implementations). There are a range of approaches for constraint handling in modern EAs including (1) penalty functions; (2) repair or local search operators; (3) modified mating/mutation operators that preserve constraints; and (4) multiobjective formulations where constraints are reformulated as objectives (Back et al. 2000). Note that these methods can be implemented independently or jointly.

Penalty functions are the most common approach used in water resources applications to account for constraints. Penalty functions typically increase a design's objective function value (assuming minimization) either by an additive or multiplicative factor that varies with the degree with which constraints have been violated. In general, the best methods are often those that do not severely impact the scaling of a decision space (this can be quantified through the variance of the population's fitness), promote competition between infeasible solutions, and limit the amount of trial-and-error analysis required in implementation (Goldberg 1989; Chan Hilton and Culver 2000; Yu and Harrell 2004).

Repair or local search operators are often termed hybrid algorithms in the water resources literature where EAs are combined with other optimization techniques that can rapidly improve solution quality in a localized region of a problem's decision space or "repair" infeasible solutions by identifying the nearest feasible point (Cai et al. 2001; Huang et al. 2002; Kapelan et al. 2003a; van Zyl et al. 2004; Espinoza et al. 2005; Mahinthakumar and Sayeed 2005; Shieh and Peralta 2005; Espinoza and Minsker 2006a). Often in these studies, hybrid search is motivated in the context of improving the probability of identifying solutions that are globally optimal. It is important to consider the benefits of hybrid search for multimodal spaces (or spaces with multiple optima), which commonly result from the enforcement of nonlinear constraints using techniques such as penalty functions.

A special type of hybrid algorithms in water resources applications has been reported by Jourdan et al. (2006), where evolutionary search was integrated with machine learning techniques to limit the number of expensive function evaluations. The methodology uses the learnable evolution model (LEM) (Michalski 2000), which integrates a symbolic learning component within the EA framework. As the search progresses, the symbolic learning component exploits either all of the solutions previously found or a selection of them to classify them as good or bad samples. A set of induction rules is then obtained from the classifier and are used to modify the child solutions generated by the evolutionary search. Jourdan et al. (2006) developed leornable evolution model-multiobjective (LEMMO), a multiobjective version of LEM, and applied it to a benchmark water distribution design problem, while di Pierro et al. (2009) compared its performance on a number of real water distribution networks. They concluded that LEMMO represents a promising way forward to solve complex network design problems when time or financial considerations allow for a limited number of function evaluations to be performed.

In the EA literature, there is a large array of applications that have very strict feasibility constraints on solution representations where the mating and/or mating operators are modified such that each child produced is guaranteed to be feasible. In fact, outside of the water resources domain, the development of specialized mating/mutation operators is one of the most commonly employed constraint management techniques (Back et al. 2000). A classic example is the traveling salesman problem where each potential trip is encoded as a unique series of integers. Although the current water resources literature does not have a significant number of EA applications where heavily restricted combinatorial representations are required, problem classes such as the traveling salesman are important for scheduling or dynamic management strategies that could be helpful in a range of water resources applications (reservoirs, distribution systems, water supply, water security, etc.). For example, work by Savic and Walters (1995a) that focused on pressure regulation in water distribution networks used special chromosome representation to ensure that only connected network layouts are used in the search. This was an important element of the work since only one in 10,000 randomly generated layouts resulted in a connected network. The last constraint handling technique commonly employed is the reformulation of constraints as objectives and the use of EAs in a multiobjective optimization context as described in the next section.

Multiobjective Optimization Developments

One of the fastest growing areas in the EA literature focuses on the extension of the algorithms to evolutionary multiobjective optimization (Deb 2001; Coello Coello et al. 2007). Although it is beyond the scope of this paper to give a detailed overview of the advanced operators required by multiobjective EAs, the algorithms use the same primary selection, mating, and mutation operators as previously discussed. The goal of multiobjective optimization is to approximate the Pareto-optimal trade-offs between an application's conflicting objectives. These trade-offs are composed of the set of solutions that are better than all other solutions in at least one objective and are termed nondominated or Pareto-optimal solutions (Pareto 1896). The Pareto-optimal front is obtained by plotting these solutions according to their objective values, yielding an M dimensional surface where M is equal to the total number of objectives. Multiobjective EA's population-based search enables them to evolve entire trade-off (or Pareto) surfaces within a single run for problems with huge decision spaces. Recent studies have highlighted several very efficient and effective algorithms for water resources applications (Bekele and Nicklow 2005; Farmani et al. 2005a; Kollat and Reed 2006, 2007b; Tang et al. 2006, 2007).

Water resources is, interestingly, one of the first application domains (Cieniawski et al. 1995) to test multiobjective EAs in the early 1990s and the algorithms have been used successfully in a wide array of environmental applications (Ritzel et al. 1994; Cieniawski et al. 1995; Halhal et al. 1997; Loughlin et al. 2000; Reed et al. 2001; Erickson et al. 2002; Reed and Minsker 2004; Farmani et al. 2005a). Recent multiobjective EA applications demonstrate that a growing body of researchers in both the water resources and broader systems analysis communities are seeking to use multiobjective EAs in "*many-objective*" applications where three or more objectives are optimized simultaneously (Deb 2001; Coello Coello et al. 2007; Farina and Amato 2002; Kumar and Ranjithan 2002; Deb et al. 2003; Reed and Minsker 2004; Fleming et al. 2005; Kollat and Reed 2007b). Moreover, many recent multiobjective optimization applications within the water resources literature are applying multiobjective EAs successfully to highly dimensional continuous, integer, and binary decisions (Labadie 2004; McPhee and Yeh 2004; Farmani et al. 2005b; Muleta and Nicklow 2005; Ren and Minsker 2005; Dandy and Engelhardt 2006). For example, multiobjective EA applications in hydrologic model calibration (Vrugt et al. 2003a), nonpoint source pollution management (Muleta and Nicklow 2005), groundwater management (Ren and Minsker 2005), and distribution systems (Farmani et al. 2005b) consider complex integer, continuous, or mixed decisions.

A key strength of multiobjective EAs is their ability to rapidly approximate the true Pareto surface even if it is not exactly quantified, which can often be sufficient in the presence of computational constraints. It should be noted that elitism, population sizing, and solution archiving are all critical issues for successfully applying multiobjective EAs (Bekele and Nicklow 2005; Kollat and Reed 2006). In particular, Kollat and Reed (2007b) have recently shown that these algorithms potentially have a quadratic computational complexity when solving water resources applications. A quadratic complexity implies that a twofold increase in the number of decision variables will yield an eightfold increase in the number of function evaluations required to solve an application. Kollat and Reed (2007b) also demonstrated how solution archiving can be used to reduce multiobjective EAs computational complexities to be approximately linear. There is a clear need and opportunity for water resources researchers to advance the field by developing computational strategies to enhance the efficiency, effectiveness, and reliability of multiobjective EAs (see di Pierro et al. 2007).

Optimization for Unmodeled Objectives

Water resources management and design problems often involve political, societal, and other subjective goals that cannot be represented mathematically. By coupling a simulation model with an EA-based optimization approach, a mathematically optimal solution may be identified, but this solution may be infeasible when considering subjective preferences. Singh et al. (2008) recently developed a methodology for model calibration with interactive evolution to incorporate unmodeled objectives in the search procedure. Interactive evolution (Takagi 2001) is a fast-growing field within EC that aims to utilize subjective responses from human users to drive the evolutionary search. Since GAs are not dependent on derivative information they are ideal for this approach. Human responses are elicited as numerical ranks and these are then used as fitness function for the GA. Singh et al. (2008) extended the interactive paradigm to multiobjective optimization by considering the human response as one of multiple criteria for the fitness calculation. This is especially important for areas such as parameter identification, where quantitative performance metrics are at least as important as the subjective preferences of the modeler. Singh et al. (2008) used nondominated sorted genetic algorithm (NSGA II) as the underlying multiobjective optimizer but used a novel "image-based machine learning" approach to reduce the number of solutions that need to be shown to the expert (thus dealing with the problem of "user fatigue").

A second approach to address unmodeled objectives in the decision-making process is to generate alternative solutions that perform similarly well for the modeled objectives. A set of alternative solutions should provide insight and options for the final stages of decision making. Niching is an EA-based technique that identifies solutions that are distributed throughout the decision space, through operators that favor a diverse population. The modeling to generate alternatives approach, as developed by Brill (1979), is a systemic approach that has been used for identifying maximally different solutions within some target performance for the originally modeled objectives. In the context of this approach, Harrell and Ranjithan (2003) applied a sequential GA (SGA)-based model to identify a set of alternative watershed-scale detention pond designs. Zechman and Ranjithan (2007b) later developed a broader EA-based methodology for explicitly generating a set of alternative solutions. This new algorithm uses multiple populations to identify maximally different alternative solutions.

Exploiting Parallel Computing

Since EA's population-based search makes them amenable to being implemented on distributed or shared memory parallel computing architectures, parallelization is an important way of enhancing search efficiency, effectiveness, and reliability. The "ease-of-parallelization" for evolutionary optimization methods is a widely quoted methodological benefit in the past literature (Goldberg 1989; Cantu-Paz 2000). There are three primary benefits to parallelizing of EAs: (1) reducing application run times; (2) increasing the size and difficulty of water resources applications that can be solved; and (3) reducing random seed effects so search results are attained with high reliability. Despite the frequent characterization of EAs as being easily parallelized, there have been a relatively limited number of water resources applications that have explored parallel implementations (Karpouzos et al. 2001; Babbar and Minsker 2002; Cui and Kuczera 2003, 2005; Reed and Yamaguchi 2004a; Mahinthakumar and Sayeed 2005; Tang et al. 2007).

The most common parallelization approaches that have been applied in the water resources literature are the master-slave and multiple population schemes. The easiest of these approaches is the master-slave implementation where a single master processor controls the evolution operators and the slaves simply evaluate population members. The search dynamics of the master-slave scheme are the same as the base serial EA; the primary difference is that more searches are available per unit of wall-clock time. The prior master-slave implementations in the water literature demonstrate that the ratio of design evaluation times and processor communication costs control the value of adding additional processors. Mahinthakumar and Sayeed (2005) provided an excellent example of using large-scale computing architectures to distribute global and local search in a hybrid search application. Tang et al. (2007) demonstrated that "time continuation" (i.e., periodic injection of random solutions into the search population to maintain diversity; see Goldberg 2002) can dramatically enhance the performance of master-slave search for problems that can be solved with reasonable success using the serial version of an algorithm.

In cases where problem difficulty and not search duration causes an EA to fail in identifying optimal solutions, the master-slave paradigm will not enhance the search (Tang et al. 2007). In these instances, users can consider the value of using either the multiple population or diffusion parallelization schemes. As noted by Back et al. (2000), the multiple population (also termed the island model) scheme fundamentally changes EA search dynamics relative to the serial versions of algorithms. Cantu-Paz (2000) highlighted that it is much more challenging to design and assess multiple population parallelization schemes. In the multiple population model, each processor has a fully functional version of an EA and users must decide on how to design interactions (e.g., see Karpouzos et al. 2001; Tang et al. 2007). Tang et al. (2007) explicitly showed that the multiple population schemes when designed well can be used to solve very difficult problems for which the serial version of an EA performs poorly regardless of search duration. The study also highlights that when judging the effectiveness of parallelization schemes, users should consider both solution quality and speedup jointly. Cantu-Paz (2000) provided a more detailed treatment of the issues EA users should consider when assessing parallel performance; he highlighted that monitoring solution quality will ensure that prematurely converged results with small clock times and poor solution quality do not bias speedup assessments. Ideally, the goal of parallelization is to attain "linear speedups" which means that when P processors are used to solve an application, the parallel computing time will be equal to $1/P$ of the serial computing time (i.e., speedup is equal P or the number of processors used). There is a strong potential for more research to characterize how different hardware architectures and parallel EA configurations can be used to overcome computational limits in water resources and environmental applications.

Optimization under Uncertainty and Fitness Approximation

Uncertainties in objective functions, constraints, and system predictions are very important in water resources planning and management when considering issues such as reliability, system resiliency, or solution robustness to measurement errors. For a groundwater remediation problem, Smalley et al. (2000) demonstrated that the natural selection analogy and population dynamics of EAs can be exploited to efficiently evolve solutions that perform well in the presence of uncertainty. This work applies the recommendations of Miller and Goldberg (1996), which show that very small Monte Carlo samples of uncertain problem parameters can be used to evolve such solutions. The basic premise is that a modest number of Monte Carlo draws ($\sim 5-20$) per population member can be used to compute their average fitness. The selection operator will increase the number of highly fit individuals and implicitly increase the number of Monte Carlo realizations used in their evaluation (assuming new samples are taken at each generation). Subsequent extensions of this work for single and multiobjective applications have introduced age operators that track the survival of fit members and minimize the number of Monte Carlo draws used in their evaluation (Chan Hilton and Culver 2005; Kapelan et al. 2005; Wu et al. 2006). Challenges with respect to these efforts include the inability to exactly specify the reliability or robustness level in the problem formulation prior to running the EA and the increased computational burden posed by added design evaluations.

In context of uncertainty and generally when using of EAs, fitness evaluation using some form of statistical, conceptual or physical simulation is the most computationally intensive and limiting component of water resources applications. The computational limits posed by fitness evaluations have motivated the development of approximation frameworks, whereby a computationally intensive model is replaced with an approximate model such as a artificial neural network (ANN), kriging, or support vector machine. There has been a significant number of applications across several water resources domains that show the potential benefits of fitness approximation (neural network methods—Aly and Peralta 1999b; Muleta and Nicklow 2004; Broad et al. 2005; Yan and Minsker 2006; Behzadian et al. 2009; kriging approaches—Baú and Mayer 2006; and radial basis function-based schemes—Mugunthan and Shoemaker 2005. As highlighted by Jin et al. (2002), the key challenge in fitness approximation is balancing the quality of the approximate model relative to the true model such that evaluation errors do not negatively impact EA search. Yan and Minsker (2006) presented a promising approach that strongly couples evolution and the online training of a neural network (i.e., during an optimization) to adaptively classify the trustworthiness of the approximation model and enhance its performance using the true model. Fitness approximation has broad value for enhancing the complexity of water resources applications that can be solved using EAs and more generally as a means of enhancing global sensitivity or uncertainty analysis for complex models (Mugunthan and Shoemaker 2005).

Application-Specific Research and Innovations

Over the last three decades, documented applications of EAs have grown significantly. There is a strong bias in the literature toward GAs, but a broader range of EAs are rapidly gaining popularity. Applications can be categorically separated into several key areas: water distribution systems design and operation, urban drainage and sewer systems, water supply and wastewater treatment applications, hydrologic and fluvial systems, and groundwater systems design. Note that methods used in model parameter identification are discussed separately herein given that (1) the topic is relevant in every water resources modeling area; (2) there is an extremely rich body of EA literature focusing on this topic alone; and (3) there is distinct applicability and commonality of challenges across multiple subdisciplines.

Water Distribution Systems and Closely Related Applications

Water distribution systems are comprised of interconnected sources, pipes, and hydraulic control elements (e.g., pumps, valves, regulators, and tanks). They are designed to deliver sufficient quantity of water to consumers at required pressure, with required quality (i.e., safe), and in a reliable (i.e., continuous), cost-effective, and sustainable manner. Over the past two decades, considerable investment has been made in developing and applying EAs to improve the design and performance of water distribution systems. Interestingly, one of the first water engineering applications of GAs was the optimization of pump schedules for a serial liquid pipeline (Goldberg and Kuo 1987). Since then, there has been increasing interest in the application of EAs to a wide variety of water distribution system problems, ranging from calibration of water distribution models, through optimal system design, to optimal operation.

Historically, although models for least-cost design of water distribution systems have existed for nearly four decades (e.g., decomposition and nonlinear programming techniques), the capability to provide design solutions has improved dramatically through use of EAs. Simpson et al. (1994) were the first to use GAs for water distribution systems. They applied and compared a GA solution to enumeration and to nonlinear optimization using the network of Gessler (1985). Savic and Walters (1997) used GAs to solve and compare results of the one-loading gravity systems of the two loop network (Alperovits and Shamir 1977), the Hanoi network (Fujiwara and Khang 1990), and the New York Tunnels system (Schaake and Lai 1969). Vairavamoorthy and Ali (2005) presented a GA framework for the least-cost pipe network design problem that excludes regions of the search space where impractical or infeasible solutions are likely to exist, and, thus, improves search efficiency. Wu and Walski (2005) introduced a self-adaptive penalty approach to handle the transformation from a constrained into a nonconstrained framework for least-cost design and rehabilitation problems of a water distribution system, as applied in a GA scheme. Keedwell and Khu (2005) developed a hybrid methodology involving a cellular automata approach to provide a good initial population for GA runs. They demonstrate that the solutions found consistently outperform the nonhybridized GA on three different case studies.

Water distribution systems gradually deteriorate over time, with internal corrosion and depositions causing loss of carrying capacity in pipes and a consequent increase in pumping pressures and energy costs, pressure fluctuations, inadequate pressure at customers' premises, and water quality problems. As the deterioration of water distribution systems and the change in their structural, hydraulic, and water quality performance are a gradual and continuous process, a rehabilitation strategy is unlikely to involve a "one-off" capital expenditure on a system. Rehabilitation is, therefore, more likely to involve a schedule of works phased over a number of years. Halhal et al. (1999) developed a multiobjective optimization method to find the optimal planning of the rehabilitation, upgrading and/or expansion of a water distribution subject to limited funding. The method uses a structured messy GA (Halhal et al. 1997) to define the different alternatives to be undertaken in the network pipes, and their scheduling in the planning period, which yields the maximum benefit with respect to invested money. The method takes into account the different time-varying factors internal and external to the system under consideration. Dandy and Engelhardt (2001) also demonstrated the use of a GA to find a near-optimal schedule for the replacement of pipes in order to minimize the present value of capital, repair, and damage costs. The methodology was applied to a case study in Adelaide, Australia. Both of these studies demonstrated the effects on the optimal solutions of varying parameters such as interest and inflation rates. Engelhardt et al. (2003) introduced whole-life cost principles to water distribution system management. A whole-life cost approach aims to achieve the lowest network provision and operating cost when all costs (direct and indirect, private, and societal) are considered to achieve standards enforced by regulation. The links established between the network management activities and their costs then allowed a GA-based search technique to be applied to identify the least operating or maintenance regime for a given scenario.

In addition to design and construction costs, pumping and energy costs form an important part of the operational expenditure of water distribution systems. As a result, pump scheduling has been increasingly considered as a means of reducing energy costs by taking advantage of off-peak electricity tariff periods and reservoir storage available in a water distribution system. In line with other optimization applications in the water engineering area, the attempts to use classical techniques for pump scheduling were later followed by application of EA approaches. Mackle et al. (1995) were among the first to apply a binary GA to pump scheduling problems, by minimizing energy costs, subject to reservoir filling and emptying constraints. This was followed up by Savic et al. (1997) who developed a multiobjective GA (MOGA) approach capable of minimizing the energy cost while minimizing the number of pump switches, used as a surrogate measure for the maintenance cost due to wear-and-tear caused by frequent switching of pumps. The first industrial application of EAs to the pump scheduling problem was reported by Atkinson et al. (2000) who applied their GA to a water distribution system in the U.K. and were able to reduce the annual operational cost by almost 20% through better utilization of the off-peak electricity tariff periods for pumping. To reduce the excessive run times required by the GA of Atkinson et al. (2000) and van Zyl et al. (2004) developed a hybrid optimization approach, by combining a steady-state GA with the Hooke and Jeeves hill-climbing method. They found that the hybrid method performed significantly better than the pure GA, both in convergence speed and in the quality of the solutions found. Further computational efficiency gains required for near-real-time application of GAs to pump scheduling in water distribution systems have been achieved by Rao and Salomons (2007). They developed a process based on the combined use of an ANN for predicting the consequences of different pump and valve control settings and a GA for selecting the best combination of those settings. The methodology has successfully been demonstrated on the distribution systems of Valencia (Spain) and Haifa (Israel).

Chlorine is commonly used in drinking water treatment as a disinfectant to carry a residual into the distribution system. Compared to conventional methods that apply disinfectant only at the treatment plant or at the reservoir, booster disinfection can reduce the total disinfection dose and still maintain the required level of the residual in the system. Munavalli and Mohan-Kumar (2003) presented a study on the use of a GA to estimate the optimal disinfection dosage for multiple locations in three real systems. Different chlorine dosage models were studied and the three problems varied in network complexity. Prasad et al. (2004) formulated the booster facility location and injection scheduling problem as a multiobjective problem and solved it using the NSGA II approach. The objectives considered are the minimization of the total disinfectant dose and maximization of the volume of water supplied with residuals within specified limits Both studies found that EAs are well suited for optimal scheduling of multiple chlorine sources.

Over the past 5 years, a number of additional applications of multiobjective EAs have appeared in the water distribution systems literature. Prasad and Park (2004) presented a MOGA approach to the optimal design of a water distribution network by minimizing the network cost versus maximizing the network resilience, where the network resilience is defined as a reliability surrogate measure taking into consideration excess pressure heads at the network nodes and loops with practicable pipe diameters. Farmani et al. (2005a) compared three evolutionary multiobjective optimization algorithms for water distribution system design through visualizing the resulting nondominated fronts of each of the methods and by using two performance indicators. Vamvakeridou-Lyroudia et al. (2005) employed a MOGA to evaluate trade-offs between the least cost and maximum benefits of a water distribution system design problem, with the benefits evaluated using fuzzy logic reasoning. Ostfeld and Salomons (2006) introduced a multiobjective algorithm for water distribution systems security, trading off the detection likelihood with the expected time of detection, the expected population affected prior to detection, and the expected demand of contaminated water prior to detection.

Urban Drainage and Sewer System Applications

In the face of increasing budget constraints and more stringent environmental regulation, sewer management practitioners are confronted with a significant challenges, which in turn has encouraged the pursuit of cost-effective strategies for storm sewer system management. However, the presence of combined sewers, as opposed to separate sanitary and storm sewer systems (i.e., where household wastewater and storm-water runoff are not transported through the same pipes), makes the problem even more difficult. A large number of structural and nonstructural solutions exist among methods for optimizing storm sewer management practices. At the design stage, the problem is to seek optimal scenarios for a system's configuration. At the management stage, the problem is to develop optimal alternatives for operation and maintenance, such as real-time control and whole-life-cost management. Over the past 20 years, due to increased consideration of water quality, sustainability, and integrated management, the scope of sewer system design has been greatly expanded (Guo et al. 2008) to involve a wider spectrum of environmental, ecological, climate change, control, and maintenance challenges.

The optimal design of a sewer network aims to minimize construction costs while ensuring adequate system performance under specified design criteria. Since Cembrowicz and Krauter (1987) made an attempt to use EAs for sewer optimization, EC approaches, particularly GAs, have been the most popular and successful optimization techniques for this task (Walters and Lohbeck 1993; Cembrowicz 1994; Walters and Smith 1995; Parker et al. 2000; Liang et al. 2004; Afshar et al. 2006; Barreto et al. 2006; Farmani et al. 2006). GAs, when coupled with appropriate hydraulic simulation software, significantly reduce the need for simplification of system representation and holistically considers internetwork effects (e.g., surcharge and backwater). Hybrid methods and multiobjective techniques are becoming attractive in this field of study as well. Farmani et al. (2006) and Guo et al. (2006) employed local search techniques to seed a MOGA (NSGA II) in the design of sewer networks.

Water Supply and Wastewater Treatment Applications

EAs have been successfully applied in design and operation of water and wastewater treatment plants and to other water quality management problems. They have been applied to identify membrane and operational characteristics for reverse osmosis systems in desalination (water treatment) plants (Murthy and Vengal 2006; Guria et al. 2005) and for designing industrial wastewater applications to identify wastewater treatment configurations within production plants to incorporate water reuse, regeneration, and treatment to minimize wastewater discharge (Tsai and Chang 2001; Li et al. 2003; Lavric et al. 2005). Additionally, a GA was applied to identify process parameters to cost-effectively remove organics from wastewater to meet pollutant removal standards (Suggala and Bhattacharya 2003). For operation of a domestic wastewater treatment plant, Chen et al. (2003) (see also Chang et al. 2001) investigated the use of a GA to identify real-time control strategies, such as pH and nutrient levels, electricity consumption, and effluent flow rates, for meeting cost goals and effluent standards.

As operation of a treatment plant is driven by the conditions of the influent into the plant from the sewer system, and the performance of the treatment plant directly impacts the quality of the receiving water body, wastewater treatment plants have been designed more holistically through integrated modeling and optimization of the treatment plant as part of a larger system. Several studies use GAs to design urban wastewater systems by simultaneously identifying both characteristics of the sewer system and operational settings of the treatment plant to meet quality constraints in the receiving water body (Schutze et al. 1999; Rauch and Harremoes 1999; Langeveld et al. 2002). Alternatively, a wastewater treatment plant may be designed as part of a regional wastewater treatment network. Management strategies for a regional system have been investigated to set the treatment levels at a set of facilities and the conveyance of wastewater between plants to minimize the collective impact on the receiving water quality (Cho et al. 2004; Wang and Jamieson 2002; Vasquez et al. 2000).

Chen and Chang (1998) introduced a GA to solve a nonlinear fuzzy multiobjective programming model, but they only considered biochemical oxygen demand and dissolved oxygen (DO) as water quality parameters, and the water quality calculation was based on the Streeter-Phelps equation. Bobbin and Recknagel (2001) established inducing explanatory rules for the prediction of algal blooms by GA. Burn and Yulianti (2001) explored waste-load allocation problems using GAs. Three optimization model formulations were developed, each meant to be examples of the types of waste-load allocation problems that can be addressed using the techniques developed. The formulations of two of these models address problems arising in the planning context, while the third model addresses waste-load allocation decisions of use when developing an operational strategy for a river basin. Yandamuri et al. (2006) similarly proposed optimal waste load allocation models for rivers. A multiobjective optimization framework (NSGA II) was used, considering (1) the total treatment cost; (2) the equity among the waste dischargers; and (3) a comprehensive performance measure that reflects the DO violation characteristics. Kerachian and Karamouz (2005) extended some of the classical waste load allocation models for river water quality management for determining the monthly treatment or removal fraction to evaporation ponds. The high dimensionality of the problem (large number of decision variables) is handled using a sequential dynamic GA.

Applications in Hydrologic and Fluvial Modeling

In surface-water hydrology, applications of EAs can be broadly categorized as those that focus on watershed planning and management and those that center on instream management of flows. Major complicating issues in both cases are the unique characteristics of surface-water flow and its interaction with climate, topography, and local soils.

The application of GAs for watershed planning was introduced by Yeh and Labadie (1997), who presented a multiobjective watershed-level planning of storm-water detention systems. A MOGA was applied to generate nondominated solutions for system cost and detention effect for a watershed-level detention system. Harrell and Ranjithan (2003) applied a GA-based methodology to identify detention pond designs and landuse allocations within subbasins to manage water quality at a watershed scale. Muleta and Nicklow (2005) linked a GA with USDA's Soil and Water Assessment Tool (SWAT) to identify land use patterns to meet water quality and cost objectives. The strength Pareto EA is integrated with SWAT for multiobjective optimization. To reduce the computational burden of SWAT, an ANN is trained to mimic SWAT and ultimately replace it during the search process. Perez-Pedini et al. (2005) developed a distributed hydrologic model of an urban watershed in the northeast of the United States and combined it with a GA to determine the optimal location of infiltration-based best management practices (BMPs) for storm-water management. The results indicate that the optimal location and number of BMPs are complex functions of watershed network connectivity, flow travel time, land use, distance to channel, and contributing area. A Pareto frontier describing the trade-off between the project cost and extent of watershed flooding was developed.

A closely related problem deals with reservoir system operation for water supply and/or other objectives, often a major concern for municipalities and regional development activities. Single reservoir operating policies are usually defined by rules that specify either reservoir desired (target) storage volumes or desired (target) releases based on the time of year and the existing storage volume of the reservoir. Storage is typically computed via the continuity equation, representing a straightforward balance of reservoir inflow and outflows. Multiple-operating policies must also take into account the existing total storage volume in all reservoirs. Oliveira and Loucks (1997) were one of the first to use a GA to derive these multireservoir operating policies. Real-valued representation, elitism, arithmetic crossover, mutation, and "en bloc" replacement were used in the algorithms to generate successive sets of possible operating policies. Wardlaw and Sharif (1999) investigated several alternative GA formulations for reservoir system optimization. They concluded that the most promising GA approach for a four-reservoir problem consists of real-value coding, tournament selection, uniform crossover, and modified uniform mutation. Nixon et al. (2001) used a GA-based model to identify water allocation schedules for off-farm irrigation systems. The aggregated objective function focused on maximizing the number of water orders that are delivered at a particular time, limiting variations in supply channel flow rates, and minimizing the exceedance of channel capacity. Merabtene et al. (2002) assessed the susceptibility of water supply systems to droughts and determined optimal supply strategies through linking a real-time rainfall-runoff forecasting model, a water demand forecast model, and a reservoir operation model with a GA. New GA-based operators were introduced to minimize the risks of drought damage and improve the convergence of the model toward practical solutions. Dessalegne et al. (2004) integrated the National Weather Service's unsteady hydraulic simulation model, FLDWAV, with both binary and real-coded GA to develop optimal operation of locks and dams in the Illinois river for ecosystem and navigational requirements. Kerachian and Karamouz (2006, 2007) combined a water quality simulation model and a stochastic conflict resolution GA-based optimization technique for determining optimal reservoir operation rules. This GA-based stochastic optimization model accounted for inherent uncertainty of reservoir inflows. Ganji et al. (2007) and Kerachian and Karamouz (2006) developed a modified version of the simple GA, called SGA, for application to a reservoir operation problem. The SGA reduces the overall run time as compared to the simple GA through dynamically updating the length of chromosomes. The SGA model was applied to the Zayandeh-Rud river basin located in the central part of Iran to derive operating rules for water allocation. Karamouz et al. (2007) solved a similar problem using a GA-K nearest neighborhood (GA-KNN)-based optimization model. In this methodology, the lengths of chromosomes are increased based on the results of a KNN forecasting model. Finally, Kuo et al. (2006) used a hybrid neural GA for water quality management of the Feitsui Reservoir in Taiwan, and Kerachian et al. (2006) developed a model that combined a numerical water quality simulation model and a GA for determining optimal reservoir operating rules. Nagesh Kumar et al. (2006) similarly developed a GA model for obtaining an optimal reservoir operating policy, but focusing on optimal crop water allocations from an irrigation reservoir in Karnataka state, India. The objective in that study was to maximize relative yield from a specified cropping pattern.

Kerachian and Karamouz (2006, 2007) used an algorithm combining a water quality simulation model and a stochastic conflict resolution GA-based optimization technique for determining optimal reservoir operation rules. This GA-based stochastic optimization model accounted for inherent uncertainty of reservoir inflows in a general framework. To reduce the computational burden of the GAs, the concept of SGA is used to develop a new approach called varying chromosome length GA (VLGA). The method was used to maximize utility functions of different water users within the overall reservoir operation problem. Utility functions related to allocated water demand, end-of-month storage, and the concentration of a selected water quality variable within allocated water. A traditional GA is first used to solve for near-optimal operating policies for a small time horizon (e.g., 1 year). The planning period and corresponding chromosome length is then increased (e.g., 2 years) in subsequent evaluations, and the initial value for each new gene is considered to be equal to the optimal values obtained in the previous sequence. The process is continued until the full time horizon is realized, thus allowing the GA to efficiently solve the entire problem.

Zahraie et al. (2008) solved a similar problem using a GA-KNN-based optimization model. The KNN method is a nonparametric regression methodology that uses the similarity between observations of predictors and K similar sets of historical observations to obtain the best estimate for a dependent variable. K vectors of the past observations are obtained based on the minimum Euclidean norm from the present condition among all candidates. For the application to reservoir operation, near-optimal monthly water allocation is evaluated for a short period (e.g., 1 year). The second year is then forecasted by the KNN method and added to the first year to create an enlarged chromosome length. It is different from VLGA, primarily, in that with VLGA, mean values are used for genes in sequential years.

Groundwater System Applications

A variety of EA approaches have been proposed and applied to solve groundwater system problems. Researchers explored the use of EAs in part because of the challenges faced by traditional gradient-based methods: the complex and highly nonlinear nature of groundwater problems, the discrete and/or discontinuous decision variables and cost functions included in many groundwater optimization formulations, and the significant computational requirements when numerical simulation models are used. Groundwater optimization problems include remediation design, monitoring network design, groundwater and coastal aquifer management, and parameter estimation and source identification. The first published works that describe EAs developed and applied to groundwater remediation and monitoring network design problems include Dougherty and Marryott (1991), which demonstrated SA as a potential flexible approach; McKinney and Lin (1994), which demonstrated the use of a simple GA to two fairly simple groundwater supply hypothetical problems and a nonlinear groundwater remediation hypothetical problem; and Ritzel et al. (1994), which tested two MOGAs (vector-evaluated GA and a Pareto GA) for solving a remediation optimization in which the objectives were reliability and cost and compared the GAs to mixed integer chance constrained programming. Mayer et al. (2002) and Cunha (2002) presented reviews of design optimization problems that apply traditional and heuristic solution approaches to solve groundwater flow and contaminant transport processes and remediation problems, while Qin et al. (2009) also reviewed both groundwater simulation and optimization approaches.

Within groundwater applications of EAs, the level of complexity and sophistication of the EA techniques developed has evolved as the literature demonstrates that these techniques continue to be promising and effective and in response to the nature of groundwater problems developed. Earlier works focused on the applicability of EAs on groundwater problems and the solution quality and computation requirements of the EA approaches. More recent works have proposed methods that address issues such as multiobjective optimization, reducing computational time associated with field-scale problems and parameter uncertainty.

Groundwater Remediation

Groundwater remediation design optimization has been the focus of the majority of the literature in which EAs have been applied to groundwater problems. Many works have explored the application of GAs for pump-and-treat, in situ remediation, or soil vapor extraction design optimization (e.g., Huang and Mayer 1997; Wang and Zheng 1997; Aly and Peralta 1999a,b; Guan and Aral 1999; Katsifarakis et al. 1999; Sun and Zheng 1999; Aksoy and Culver 2000, 2004; Chan Hilton and Culver 2000, 2001, 2005; Gumrah et al. 2000a,b; Liu et al. 2000; Yoon and Shoemaker 2001; Hsiao and Chang 2005; Ko et al. 2005; Kalwij and Peralta 2006; Chang et al. 2007; Park et al. 2007; Sidiropoulos and Tolikas 2008). SA or GA-SA hybrid approaches have also been applied to similar groundwater remediation problems (e.g., Rizzo and Dougherty 1996; Wu et al. 1999; Skaggs et al. 2001; Shieh and Peralta 2005).

GAs and other EAs have been evaluated and compared to other gradient and heuristic optimization methods for solving groundwater remediation optimization problems. Maskey et al. (2002) compared four global optimization techniques [GA, multistart and clustering, adaptive cluster covering, and controlled random search (CRS4)] for remediation design of hypothetical and real systems and concluded that there was not one consistently better approach for their examples. Matott et al. (2006) tested five optimization algorithms [SA, particle swarm optimization (PSO), real-coded GA, Fletcher-Reeves conjugate gradient, and a random search algorithm] to solve a pump-and-treat optimization problem in which the hydraulic control was simulated using an analytical element method. They found that PSO had the best performance in terms of solution quality and parallelization. Yoon and Shoemaker (1999) compared three optimization approaches [binary-coded GA, derandomized evolution strategy (DES), and direct search methods] for bioremediation optimization. Their results did not identify one superior method, although DES was efficient and accurate for the three problems solved. Bayer and Finkel (2004) evaluated simple GAs and DESs for optimizing pump-and-treat designs and found that DES in general resulted in better performance. Other works have also demonstrated the use of ES for remediation optimization. Bürger et al. (2007) developed a DES with covariance matrix adaptation (CMA-ES) for funnel-and-gate remediation design optimization. Bayer and Finkel (2007) proposed ES with CMA-ES and rank μ update to solve pump-and-treat design problems.

Over the years, researchers have demonstrated the potential for EAs to be used to address field-scale remediation optimization problems. Even as computational power and the costs of computation have decreased, reducing computational costs for field-scale problems continues to be an important issue. Rogers et al. (1995) was the first to apply a GA to a field-scale remediation problem by using an ANN in place of numerical groundwater flow and contaminant transport simulation model. Yan and Minsker (2006) proposed an adaptive neural network GA that incorporates an ANN as an approximation model that is adaptively and automatically trained within a GA, providing significant reduction in computational cost with no loss in accuracy of the optimal solutions for the hypothetical remediation test case analyzed. Another approach for reducing computational costs is to replace the numerical groundwater simulation model with approximation functions. Rizzo and Dougherty (1996) developed an SA with importance functions and applied it to a time-varying field-scale problem at Lawrence Livermore National Laboratory. Zheng and Wang (2002) applied a GA with response functions to solve a field-scale remediation problem at the Massachusetts Military Reservation that included 500,000 nodes in the simulation model and a 30-year planning horizon. Regis and Shoemaker (2004) evaluated cost function approximation techniques to reduce computational costs within an ES optimization approach. Other researchers proposed extended GAs to speed up the search process and reduce computational costs. Espinoza et al. (2005) proposed the self-adaptive hybrid GA and demonstrated its ability to reduce computation cost for groundwater remediation problems. Espinoza and Minsker (2006a,b) developed two hybrid GAs that include local search to speed up and improve the robustness of the search process; they evaluated the hybrid GAs to eight remediation optimization test cases. Babbar and Minsker (2006) proposed multiscale GAs to overcome solution reliability and computational cost issues when GAs are applied to field-scale problems. Sinha and Minsker (2007) proposed multiscale island injection GAs, which includes multiple population functions at different spatial scales, to reduce the computational time to solve a field-scale pump-and-treat remediation optimization problem. Others have focused on parallelization strategies for reducing computational costs of groundwater optimization problems (He et al. 2007; Tang et al. 2007; Kobayashi et al. 2008).

An inherent attribute of groundwater problems is parameter uncertainty. Ignoring this uncertainty can significantly impact optimal designs and design performance in many cases. In most problems, the uncertainty is the parameter values that describe groundwater flow and contaminant transport processes, either due to limited data and/or heterogeneities in the groundwater systems. A number of works have proposed EA-based approaches to incorporate parameter uncertainty in solving groundwater remediation optimization problems (Aly and Peralta 1999b; Smalley et al. 2000; Guan and Aral 2004, 2005; Chan Hilton and Culver 2005; Amaziane et al. 2005; Kalwij and Peralta 2006; Wu et al. 2006; He et al. 2008; Bayer et al. 2008). Smalley et al. (2000) applied a noisy GA to bioremediation design with health risk included in the formulation. The noisy GA calculates the cost function-based evaluations for multiple realizations of the uncertainty parameter. Guan and Aral (2004, 2005) incorporated fuzzy sets into a GA to account for uncertainty in hydraulic conductivity and dispersion coefficients. Chan Hilton and Culver (2005) proposed the robust GA that introduced the concept of string age and a form of realization sampling into the GA to account for parameter uncertainty. Wu et al. (2006) compared a Monte Carlo simple GA (MCSGA) with a noisy GA to solve a sampling network problem with uncertainty in the hydraulic conductivity. Their results indicate that the more computationally efficient noisy GA produces similar results to the MCSGA. Bayer et al. (2008) proposed a computationally efficient and promising algorithm and introduced the concept of "stack ordering" based on ranking of multiple realizations of uncertain parameters.

Other researchers extended the application of EAs to groundwater remediation problems by exploring MOGAs with or without parameter uncertainty. Erickson et al. (2001, 2002) proposed niched Pareto GAs that used Pareto dominance ranking to solve a multiobjective remediation problem. Hu et al. (2007) presented an application of two-objective optimization (cost and efficiency) of an in situ bioremediation system for a hypothetical site under uncertainty. Mantoglou and Kourakos (2007) proposed a MOGA for remediation optimization under hydraulic conductivity uncertainty in which they developed a simple ranking method to identify critical realizations that affect the optimal solution. Singh and Minsker (2008) developed a probabilistic MOGA (PMOGA), which combines a method similar to the noisy GA with an additional archiving step with the NSGA II, and applied it to two pump-and-treat problems—a hypothetical case study and a field-scale case study at the Umatilla Chemical Depot in Oregon. They compared the solutions identified by the PMOGA to those from an averaging-based multiobjective approach, a stochastic single-objective approach, and a deterministic multiobjective approach and found that the PMOGA found solutions that, by simultaneously considering conductivity uncertainty and multiple remediation objectives, had better objective functions.

Groundwater Monitoring

A number of works have proposed EA approaches to groundwater monitoring network design (Chadalavada and Datta 2008), multiobjective EAs (Cieniawski et al. 1995; Reed et al. 2000b, 2003, 2007; Reed and Minsker 2004; Wu et al. 2005, 2006; Kollat and Reed 2006, 2007a,b; Zhang et al. 2005; Dhar and Datta 2007; Tang et al. 2007; Kollat et al. 2008; Lee and Ellis 1996). In these groundwater monitoring optimization problems, the focus has been on reducing redundant monitoring wells while capturing information about the contaminant plume. Cieniawski et al. (1995) proposed two MOGAs to solve a monitoring network optimization problem under uncertainty and generate trade-off curves for the cost and reliability of the monitoring network. They compared a vector-evaluated GA in which a fraction of the surviving population is selected for each objective and a Pareto GA in which the strings' fitness values are based on the Pareto-optimality ranking. These proposed MOGAs were not able to generate the entire trade-off curve in a single iteration.

Later works demonstrated and developed alternative multiobjective EAs that are more effective in developing a wide range of solutions on the Pareto curve. Reed and Minsker (2004) applied NSGA II (Deb et al. 2002) to a multiobjective long-term monitoring (LTM) network design optimization problem. This was later expanded upon by Kollat and Reed (2006), in which they compared four EC approaches for multiobjective optimization of LTM design: NSGA II, epsilon-dominance NSGA II (ε-NSGA II), epsilon-dominance multiobjective evolutionary algorithm (ε-MOEA), and the strength Pareto evolutionary algorithm 2 (SPEA2). They found that the ε-NSGA II had superior performance compared to the other algorithms when tested on a four-objective formulation problem. Later, Reed et al. (2007) showed that ε-dominance archiving and automatic parameterization techniques can improve the efficiency and ease-of-use of an ε-NSGA II by applying this approach to four-objective LTM problems.

Evolutionary Computation in Hydrologic Parameter Identification

Parameter identification is a critical component of water resources modeling given that all water resources applications, whether surface water, groundwater, water supply or others, depend on well-calibrated models that can be used to make meaningful predictions for decision makers and modelers. It is also important to recognize that there exist subtle distinct differences between the terms *parameter identification*, *calibration*, and *inverse modeling*. Parameter identification is a generalized term that denotes any exercise, including field or experimental work, to identify parameters for a model; calibration is the exercise of reducing the error between a known model and measurements, typically by adjusting the parameters of the model; and inverse modeling refers to the establishment of an explicit model that maps the (reverse) relationship between the data and the model inputs (as opposed to the model, which maps the "forward" relationship between model inputs and data). In cases where inverse modeling is a nonlinear process, nonlinear solvers, including EAs, need to be used to find the optimal inverse relationship. In most cases, this is the same process as finding optimal model parameters or solving the calibration problem. For the sake of simplicity, these terms are treated equivalently in this study and will generally be used interchangeably.

Studies such as Duan et al. (1992), Beven and Binley (1992), Yeh (1986), and McLaughlin and Townley (1996) have shown that the parameter identification problem for most hydrologic applications is ill posed, multimodal, nonlinear, and nonconvex. Furthermore, Duan et al. (1992) performed a comprehensive analysis of the search space for different types of calibration problems and reported the following challenges with the search space:

- Presence of many regions of attraction in the objective surface;
- Presence of multiple local optima within each region of attraction;
- Discontinuities, nonconvexity, and lack of smoothness in objective space;
- High dimensionality of search space; and
- Varying degrees of sensitivity and a large amount of nonlinear interactions between parameter values.

Because of these challenges, EAs have emerged as the method of choice in automated hydrologic model identification.

Single-Objective Parameter Identification

Early efforts in automated parameter identification concentrated on the single-objective domain, relying upon minimizing aggregate calibration error (such as the root-mean square error or the sum of squared residuals) between model predictions and measurements as the primary objective. Most approaches fall under two broad categories of optimization algorithms: SCE [sometimes referred to as SCE-University of Arizona (SCE-UA)] and GAs. Of these, GAs have been used more in the groundwater community while SCE-UA has been the more popular approach for surface-water models.

In the realm of watershed flow and water quality modeling, Wang (1991) was among the first to apply the "simple" GA to the calibration problem. In addition to using the GA for the global search, Wang (1991) also investigated local search techniques (based on simplex) to "fine tune" the final set of model parameters, though with only modest success. Subsequently, many other studies have applied GAs and their variants to watershed calibration. These include Babovic et al. (1994), Franchini and Galeati (1997), Solomatine (1998), and Zou and Lung (2004) among others. Of these, Zou and Lung (2004), proposed a robust approach to calibrating water quality models for problems with sparse field data. The approach, called "alternating fitness GA" (AFGA) adopted GAs to inversely solve the governing equations, with an "alternating" fitness method to maintain solution diversity and reduce premature convergence. The AFGA gradually changed (alternated) the fitness function by varying the weights for different data points used to compute the weighted sum of square residual objective function). The variation could either be temporal (i.e., subsequent generations of the GA would be evolved under changing fitness functions) or spatial (i.e., different members of the same population would be stochastically evaluated using different variations of the fitness function). Zechman and Ranjithan (2007a) developed a methodology to address the difficulties associated with model parameterization by combining calibration for identification of numeric parameter values with a symbolic search for an error term that would correct structural errors in the model. This methodology was implemented by integrating GA and genetic programming searches.

A number of studies, including Solomatine (1998), Franchini et al. (1998), and Duan et al. (2003), have reported problems with slow and unstable convergence with GAs. Consequently, many researches have "hybrid" approaches that use a GA to search for "globally" promising solutions and local search algorithms to expedite convergence to local basins of attractions; examples include coupling GAs with sequential quadratic programming in the case of Franchini (1996) and GAs with local hill climbing for Ndiritu and Daniell (1999).

Among the earlier applications for GAs for groundwater calibration can be found in Zheng (1997), who developed a modular GA-based simulation-optimization environment (called the modGA) that could be applied to different groundwater optimization problems. A version of the modGA, called modGA_P (the P standing for parameter estimation), was developed specifically for groundwater model calibration. Other subsequent applications of the simple GA to groundwater calibration include Wang and Zheng (1998) and Solomatine et al. (1999). However, the high dimensionality of the search space for groundwater model identification has limited the number of EC applications.

As with parameter identification in watershed modeling, hybrid approaches have also been proposed for the groundwater field. Such hybrid approaches have been used by Tsai et al. (2003) and Mahinthakumar and Sayeed (2005). Tsai et al. (2003), in particular, proposed a hierarchical "global-local" optimization approach to solve what they called the "generalized inverse problem" of not only finding the right values of parameters but also the correct structure for the parameter field. They used the GA to find the approximately optimal "structures" (in their example, zones of hydraulic conductivity) of the parameter field, the local search to fine tune the configurations of these zones, and finally a gradient-based search mechanism [the Broyden-Fletcher-Goldfarb-Shanno algorithm] to find the parameter values for the optimal zones. Mahinthakumar and Sayeed (2005) proposed a similar approach, whereby the GA was used to quickly find promising alternative solutions that were then used as starting points for local (both gradient and nongradient based) optimization approaches. Another interesting variant has been proposed by Ines and Droogers (2002), who used a "microGA" to solve the groundwater calibration problem. A microGA [Krishnakumar 1989; D.L. Carroll, GA Fortran Driver Version 1.7, 1998 (www.cuaerospace.com/carroll/ga.html)] is a GA with a small population size (typically only 5–10) that is repeatedly run for short durations and then restarted (while keeping a few optimal solutions from the previous runs) until convergence is achieved. MicroGAs exploit the random injection of new solutions to maintain search for as long as necessary or feasible (time continuation termed by Goldberg 2002). MicroGAs have been reported to be computationally efficient and robust relative to standard GAs.

The SCE-UA was first introduced by Duan et al. (1992) and has subsequently emerged as arguably the most popular approach for parameter identification in watershed modeling. The motivation for the development of this global optimization algorithm was the work done by Duan et al. (1992) that showed that the problem was an inherent multimodal problem with multiple local optima that could "trap" most gradient-based solvers and may lead to local convergence of even global optimization algorithms, such as simple GAs. SCE-UA was developed as a robust alternative for solving such multimodal problems. In their original work, Duan et al. (1992) acknowledged three optimization approaches as the motivation for SCE-UA-simplex (Nelder and Mead 1965), controlled random search (Price 1983), and evolutionary optimization (Holland 1975). The main idea behind SCE-UA is to partition the search population into several communities or "complexes." Each complex represents different subspace of the global fitness landscape and is evolved independently for a few generations.

Cooper et al. (1997) who compared the performance of SCE, GA, and SA for conceptual rainfall-runoff model calibration reported that the SCE method "was the most robust and accurate results, followed by the GA method, and then SA." They also reported that the GA had problems converging to the exact optimal solution, although it did find solutions in the neighborhood of the global optimum. Following the work by Duan et al. (1992) many studies have used and enhanced the SCE-UA algorithm. These include Sorooshian et al. (1993), Kuczera (1997), Madsen (2000), Wang et al. (2001), and Eckhardt et al. (2005) among others. The most recent development in this regard is the shuffled complex evolution metropolis (SCEM) algorithm proposed by Vrugt et al. (2003a). The SCEM combines the global optimization capabilities of SCE-UA with a Markov chain Monte Carlo (Gamerman 1997) sampler to generate the posterior distributions of uncertain parameters. The distinguishing feature in the SCEM algorithm is the evolution of individual complexes using a stochastic approach called "sequence evolution metropolis" (SEM) (instead of the deterministic approach used in SCE-UA).

SCE-UA (and related algorithms) is most popular within the watershed modeling community. Based on the most current literature review, the aforementioned techniques have rarely been applied to subsurface models. While the reasons for this are open to discussion, the high dimensionality of most groundwater models, which typically have spatially continuous and highly heterogeneous parameters (such as hydraulic conductivities) compared to the lumped-parameter approach that is more popular for surface-water models, may be a possible deterrent to the use of such approaches. The simplex search strategy (used in SCE-UA) is known to suffer from slow convergence in high-dimensional space, while the metropolis sampling technique (used in SCEM) requires the calculation of the covariance of the n dimensional parameter space, an operation that becomes computationally intractable with higher dimensions. However, this trend has been recently reversed by the work of Vrugt et al. (2004), who reported some success applying the SCEM algorithm on a distributed, large-scale, subsurface (vadose zone) model.

Bates (1994), Sumner et al. (1997), and Thyer et al. (1999) were among the first to use SA for watershed model calibration while Zheng and Wang (1996) were among the first to utilize this technique for groundwater system. A number of studies proposed a hybrid version of the SA algorithm, which combined SA with the simplex method (Nelder and Mead 1965). This algorithm (called SA-SX) starts out with pure SA, in turn perturbing (heating) and converging (cooling) the solution set until a prespecified minimum temperature is reached. At this point the simplex method is used to quickly converge to the nearest local optima. The motivation behind this approach is that the initial SA steps would effectively search the parameter space and identify a region around the global optimum. The simplex method then converges to this optimum, thus, significantly reducing the number of iterations required by the typical SA for convergence. While SA-SX linked SA with simplex in a two-step sequential manner, the hybrid SA proposed by Efstratiadis and Koutsoyiannis (2002) combined these two search methodologies within every iteration of the optimization process.

Numerous optimization procedures for identifying parameters for water distribution hydraulic models have been developed since the 1970s (Savic et al. 2009). However, it was not until the mid-1990s that the applications of EAs to this type of problem first appeared (Savic and Walters 1995b; Walters et al. 1998; Lingireddy and Ormsbee 1998, 1999). These first studies used a binary GA to optimize a normalized least-square type objective function subject to implicit (hydraulic) and explicit (bound) system constraints. Savic and Walters (1995b) and Walters et al. (1998) focused on multiple steady-state (i.e., snapshot) models for unknown pipe friction factors (roughness) by minimizing the weighted sum of squared errors of pressure at nodes and flow in pipes. Variables other than pipe roughness could, in principle, be used as, for instance, demands may not be known precisely. Lingireddy and Ormsbee (1998, 1999) calibrated an extended period simulation (EPS) model for pipe friction factors and nodal demands using a binary GA. The turn of the century also saw the appearance of first commercial GA-based software for parameter identification in water distribution hydraulic models, which is now normally provided by all major water distribution software vendors. However, these commercial tools have not embraced all the latest developments provided by the research community, which could be one of the contributing factors as to why they are not being significantly used in practice (Savic et al. 2009).

The focus on the computational efficiency and effectiveness in obtaining optimal parameter values means that little effort has been applied to determine the uncertainties (i.e., errors) associated with these values and related water distribution model predictions during the EA parameter identification process. To remedy this, Kapelan et al. (2007) used the SCEM-UA optimization methodology (Vrugt et al. 2003b) to apply the Bayesian recursive approach to water distribution model calibration. Kapelan et al. (2007) reported that the main advantages of the Bayesian calibration methodology over other approaches are that both parameter values and associated uncertainties are determined in a single optimization run and that the approach enables the specification of prior information on parameters in a flexible probabilistic framework. Jonkergouw et al. (2008) combined calibration for unknown or uncertain demands with water quality model calibration. They used a modified SCE algorithm (Duan et al. 1992) and the derivative-based Levenberg-Marquart algorithm in sequence to determine the demand multipliers and water quality model parameters. The results presented by Jonkergouw et al. (2008) demonstrate that water quality and hydraulic data can be used for hydraulic and water quality models simultaneously.

Leak detection by inverse analysis of a water distribution model has long been considered unlikely to bring satisfactory results due to very limited observation information. Consequently, a number of researchers investigated the use of transient measured data to provide enough information for a GA-based analysis (Vítkovský and Simpson 1997; Tang et al. (1999); Vítkovský et al. 2000, 2003). More recently, Wu and Sage (2006) reported on a leakage detection model that uses an EPS model and flow emitters to emulate leakage at a node and applied a fast messy GA (Goldberg et al. 1993) to simultaneously optimize the emitter locations and the corresponding emitter coefficients. The approach has been successfully applied to identify the leakage hotspots in a real district metering area in the United Kingdom.

Multiobjective Parameter Identification

Single-objective approaches attempt to approximate the "global" optimum for a single aggregated objective. More often than not, there are multiple sources of information (for example, hydrographs at different locations within the watershed) that can be used to assess different aspects of model performance. Moreover, even with a single source (and type) of data, the information can be multidimensional (for example, in most cases the hydrologic measurements exhibit spatiotemporal variability). Since different sources of information and dimensions of the data are sensitive to different aspects of the model, no one single objective can be used to assess the performance of such a model. For watershed modeling, different objectives can be used to assess different aspects of the hydrographs that need to be matched by the model prediction. Some typical objectives include peak/low flow error (difference between the peak/low flows of the predicted and measured hydrograph), average error (an overall error), overall runoff volume error, Nash-Sutcliffe measure, etc. (see Gupta et al. 1999 and Madsen 2000 for a discussion of different objectives and their roles). For groundwater parameter identification, often the multiple objectives represent different sources of information (such as water levels, direct geological measurement, or contaminant tracer tests). Aggregating such multidimensional criteria into one objective can lead to loss of information (Wagener and Gupta 2005). It has been persuasively argued that this loss of information exacerbates the problem of nonuniqueness and multimodality, by making it difficult to discriminate between different parameters (Yapo et al. 1998; Gupta et al. 1999). Over the last few years, there has been a growing awareness that instead of optimizing a single aggregated objective it is often worthwhile to pose the problem in a multiobjective context, using the multiple sources of information and dimensions of data to formulate different objective measures. Such a multiobjective approach does not suffer from the loss of information inherent in the single-objective approach and provides valuable insights into information content of different data sources and the limitations and uncertainties in the model.

One of the simplest (though not necessarily the most efficient) approaches to solving for multiple objectives is to weigh and aggregate them in a single objective and optimize for this aggregated objective function. By changing the weights used in the aggregation, different parts of the Pareto-optimal surface can be generated, assuming the objectives are conflicting. This approach has been applied in watershed modeling by Madsen (2003) who used the SCE-UA to solve these multiple single-objective formulations with different weightings. While such an approach seems feasible for computationally tractable problems, rerunning a population-based optimization approach (such as SCE-UA) multiple times can impose a formidable burden for most large-scale watershed problems. Another drawback to this methodology is that it has been shown (Das and Dennis 1997) that weighting is only effective in finding Pareto-optimal solutions along the convex portion of the Pareto front, thus, solutions along nonconvex portions of the front could not be found by this method. An alternative (and more efficient) approach to multiobjective optimization is to simultaneously generate multiple solutions each representing a different trade-off level between the objectives.

The goal of Pareto optimization algorithms, then, is to optimize the watershed parameters to find a set of "nondominated" (or Pareto optimal) parameter values (instead of one unique global optimum) that represent the optimal trade-off between all the objectives. Similar to the work on single-objective optimization, the two dominant categories of approaches for multiobjective optimization are GAs and SCE-UA. Liong et al. (2001) were among the first to use a Pareto optimization approach for watershed applications. Liong et al. (2001) also proposed other techniques that made their accelerated convergence GA (ACGA) more efficient and computationally tractable. First, instead of initializing the GA population randomly, they used an experimental design scheme called "fractional factorial design and central composite design" (FFD-CCD) to initialize the GA population. FFD-CCD is based on a polynomial approximation for the system response with respect to the parameters (to be calibrated). FFD-CCD ensures that data from the upper and lower bounds for each parameter as well as values that lead to good coverage over the approximated polynomial surface are included in the initial GA population. The other significant contribution by Liong et al. (2001) was to use the ACGA to identify only a relatively few solutions along the Pareto surface (by using a small population size). The rest of the Pareto surface was "filled in" by an ANN that was trained on the solutions found by the ACGA.

While Liong et al. (2001) based their GA on the Fonseca and Fleming (1993) ranking scheme, most other MOGAs used for watershed calibration have used the Goldberg (1989) Pareto ranking scheme discussed earlier. NSGA II (Deb et al. 2000) and its variants use this ranking scheme and have, in particular, been widely used for multiobjective parameter identification in watershed modeling. Two salient studies using this approach are Khu and Madsen (2005) and Tang et al. (2006). In addition to using NSGA II, Khu and Madsen (2005) introduced a useful postprocessing step called "preference ordering scheme" (POS). As previously discussed, multiobjective optimization can lead to a potentially large set of solutions (the number of Pareto-optimal solutions is known to explode with each additional orthogonal objective), comprising the final converged Pareto front. POS is an approach that can be used to "filter" through all these solutions and identify a subset of high performance solutions, which can then be further analyzed by the decision maker. Khu and Madsen (2005) showed that for a four-objective problem, such an approach can filter a Pareto set with almost 400 solutions to a set of just 10 highly efficient solutions. These gains can grow incrementally as the number of objectives increases for more complex large-scale applications.

While Khu and Madsen (2005) focused on improving the postoptimization analysis for multiobjective optimization, Tang et al. (2006) explored approaches to make multiobjective optimization (specifically the NSGA II algorithm) more user friendly and scalable to different kinds of problems. The salient enhancements proposed by Tang et al. (2006) in their algorithm (ε-NSGA II) were ε-dominance archiving (Laumanns et al. 2002; Deb et al. 2003), adaptive population sizing, and self-termination scheme to reduce the need for parameter specification by the user (Reed et al. 2003). ε-dominance archiving requires the specification of a front-coverage precision threshold (ε) for each objective. Small values of ε lead to dense Pareto fronts, while large values of ε lead to sparser (but well distributed) Pareto fronts (more amenable for problems with multiple objectives and large computational expenses, requiring small population sizes). Thus ε-dominance archiving optimally distributes the given population across the converged Pareto front.

In addition to testing the ε-NSGA II on a watershed calibration problem, Tang et al. (2006) also compared its performance with two other state-of-the-art multiobjective algorithms—the SPEA2 (Zitzler and Thiele 1999; Zitzler et al. 2002) and the multiobjective SCEM algorithm (MOSCEM-UA) (Vrugt et al. 2003a,b). Similar to ε-NSGA II, SPEA2 aims to optimally allocate solutions across the Pareto front. Comparing these three approaches, Tang et al. (2006) found that both SPEA2 and ε-NSGA II performed competitively for problems with a large number of decision variables (high-dimensional search space). In general, SPEA2 had superior coverage across Pareto fronts but its performance depended on the appropriate specification of population size. ε-NSGA II, on the other hand, was advantageous due to its efficient adaptive population-sizing and parameter-setting approach but had worse coverage compared to SPEA2. The performance of MOSCEM-UA was least competitive for high-dimensional problems but improved significantly as the problem size is reduced (indicating that MOSCEM-UA might be better suited for applications with fewer parameters).

A topic closely related to parameter identification is sampling design in water distribution system modeling. The aim of the sampling procedure is to determine optimal sensor locations in the network. Many of the optimization formulations of the sampling design problem were based on the work by Bush and Uber (1998), who proposed sampling design models based on the analysis of the water distribution system sensitivity (Jacobian) matrix, but have not used optimization themselves. Kapelan et al. (2003b) were the first to use a multiobjective EA to solve a sampling design problem by considering simultaneously the sampling design cost and model accuracy. Results from case studies indicate that the optimal set of locations for a number of monitoring points is not always a superset of the optimal set for a smaller number of monitoring points, as is often assumed, and that greedy procedures would not always result in the optimal design.

Summary and Conclusions

The growing body of work in the development and application of EAs to environmental and water resources problems over the past 20 years has shown that these tools can be flexible and powerful when used appropriately. However, several challenges and opportunities for further research remain. There is a growing recognition in water resources management that our methodologies must themselves evolve to address "change" from local to global scale human impacts and climate variability (Milly et al. 2008; Vorosmarty et al. 2000). These issues call for advances in our ability to forecast highly uncertain nonstationary futures and expose the importance of coupling engineering design and water cycle science (National Research Council 2004). Emerging research is showing that the historical disciplinary boundaries in water resources need to be reconsidered and that our future management frameworks will likely have to address strong nonlinearities, system couplings, and a broader range of uncertainties.

These issues pose significant challenges and motivate the need for EC applications to advance adaptive decision making under uncertainty. As a field, it will be important to clarify across our domains of focus (surface water, groundwater, water supply, etc.) what general problem properties are posing computational barriers for large-scale integrated water resources management frameworks. It will be important for future EC-based frameworks to bridge process science and operational engineering management to elucidate the generational and geographical trade-offs implicit to future water resources systems. Quantifying these trade-offs and their associated uncertainties motivates a tremendous need for advances in fitness approximation, parallelization, multiobjective search, interactive optimization, and multialgorithm search frameworks (e.g., see Vrugt and Robinson 2007). Fundamental to the advancement of the use and value of EAs in environmental and water resources: (1) there is an immediate need to formally characterize operational successes and failures of EAs used in water resources engineering practice and (2) the water resources field should begin to explore a broader range of policy/design problem classes that have a history of dealing with highly uncertain nonstationary environments (i.e., robust optimization, combinatorial scheduling, game theory, control theory, etc.). In combination, addressing these two challenges will serve to bridge the existing research summarized in this paper to practice while also providing opportunities for researchers to continue to expand the size and scope of water resources problems that can be addressed using future innovations in EC.

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