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Evolutionary algorithms for the optimal management of coastal groundwater: A comparative study toward future challenges

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SUMMARY

This paper surveys the literature associated with the application of evolutionary algorithms (EAs) in coastal groundwater management problems (CGMPs). This review demonstrates that previous studies were mostly relied on the application of limited and particular EAs, mainly genetic algorithm (GA) and its variants, to a number of specific problems. The exclusive investigation of these problems is often not the representation of the variety of feasible processes may be occurred in coastal aquifers. In this study, eight EAs are evaluated for CGMPs. The considered EAs are: GA, continuous ant colony optimization (CACO), particle swarm optimization (PSO), differential evolution (DE), artificial bee colony optimization (ABC), harmony search (HS), shuffled complex evolution (SCE), and simplex simulated annealing (SIMPSA).

The first application of PSO, ABC, HS, and SCE in CGMPs is reported here. Moreover, the four benchmark problems with different degree of difficulty and variety are considered to address the important issues of groundwater resources in coastal regions. Hence, the wide ranges of popular objective functions and constraints with the number of decision variables ranging from 4 to 15 are included. These benchmark problems are applied in the combined simulation–optimization model to examine the optimization scenarios. Some preliminary experiments are performed to select the most efficient parameters values for EAs to set a fair comparison. The specific capabilities of each EA toward CGMPs in terms of results quality and required computational time are compared. The evaluation of the results highlights EA's applicability in CGMPs, besides the remarkable strengths and weaknesses of them. The comparisons show that SCE, CACO, and PSO yield superior solutions among the EAs according to the quality of solutions whereas ABC presents the poor performance. CACO provides the better solutions (up to 17%) than the worst EA (ABC) for the problem with the highest decision variables and more complexity. In terms of computational time, PSO and SIMPSA are the fastest. SCE needs the highest computational time, even up to four times in comparison to the fastest EAs. CACO and PSO can be recommended for application in CGMPs, in terms of both abovementioned criteria.

1. Introduction

In the recent decades, evolutionary algorithms (EAs) with varying degree of complexities have been used to solve optimization problems in the fields of groundwater resources management (Nicklow et al., 2010; Ataie-Ashtiani and Ketabchi, 2011; Singh, 2012, 2014). Groundwater in coastal aquifers is one of the essential resources of freshwater in coastal regions which are heavily populated or industrialized areas, and have critical ecosystems. Seawater intrusion (SWI) is a widespread environmental concern of coastal aquifers, essentially due to unplanned and over-exploitation of coastal groundwater (Cheng and Ouazar, 2004; Werner et al., 2013). Comprehensive reviews on SWI simulation approaches are given by Bear et al. (1999) and Werner et al. (2013). The SWI status depends on several factors including scale, aquifer properties, groundwater inflow and outflow, upconing due to well pumping, the tidal oscillation of the sea level, and climate change features such as sea-level rise and variations in recharge rate (e.g., Ataie-Ashtiani et al., 1999, 2013b; Ketabchi et al., 2014; Mahmoodzadeh et al., 2014) and there are unreliability or uncertainty in many of these factors, that cause the SWI analysis more complex (Rajabi and Ataie-Ashtiani, 2014; Rajabi et al., 2014).

The combined simulation–optimization techniques can be used to determine optimal management strategies. Various types of

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Nomenclature

EA	Evolutionary algorithm
CGMP	Coastal groundwater management problem
GA	Genetic algorithm
ACO	Ant colony optimization
CACO	Continuous ant colony optimization
PSO	Particle swarm optimization
DE	Differential evolution
ABC	Artificial bee colony optimization
HS	Harmony search
SCE	Shuffled complex evolution
SA	Simulated annealing
SIMPSA	Simplex simulated annealing
MSL	Mean sea level
GWT	Water table
SWI	Seawater intrusion
ANN	Artificial neural network
GP	Genetic programming
x_{best}	best solution found from the previous iteration of optimization procedure
τ	normal distribution
σ	standard deviation in CACO or SIMPSA
Pop	EA's population size
x	decision variable
x^{min}	lower bound of feasible decision variable space
x^{max}	upper bound of feasible decision variable space
D	number of decision variables
f	objective function value
$f_{modified}$	modified objective function value
x_{opt}	best decision variable
f_{opt}	best objective function value
v	velocity
g	generation number index
NG	number of generations
rand	random number
ω	inertia or momentum weight for PSO
b_p	cognitive experience coefficient of PSO
b_g	social interactions coefficient of PSO
C_1	acceleration constant related to local best positions for PSO
C_2	acceleration constant related to global best positions for PSO
F_{DE}	control parameter of differential variations for DE
u	trial vector for DE
j_{rand}	random integer in the range (1,D)
CR	crossover probability of DE
fitness_i	fitness value for ABC
SN	number of food sources
limit	number of trials as an abandonment criteria of scouts and their solutions
Prob_i	probability value for ABC or SCE
HMS	harmony memory size for HS
HMCR	harmony consideration rate for HS
PAR	pitch adjustment rate for HS
b_w	pitch adjustment bandwidth for HS
NC	number of complexes
q_{SCE}	number of simplexes
α_{SCE}	number of consecutive new solutions generated by the same simplexes
β_{SCE}	number of evolution of each complex before complexes are shuffled
m_1	number of successful reflections for SIMPSA
m_2	number of unsuccessful reflections for SIMPSA
A_r	acceptance ratio for SIMPSA
$Temp_{init}$	initial annealing temperature for SIMPSA
Temp	annealing temperature for SIMPSA
K_B	Boltzmann's constant
Δf	difference of objective function values
Δf^+	average increase in objective function values for m_2 reflections for SIMPSA
r_{cool}	cooling rate for SIMPSA
NT	number of successful generations for the current *Temp* of SIMPSA
n	total number of pumping wells
(x_w^i, y_w^i)	coordinates of well i
P_i	pumping from cell or well *i*
$P_{\min}$	minimum pumping from cell or well *i*
$P_{\max}$	maximum pumping from cell or well *i*
Pump	total pumping rate
s_i	hydraulic head level drawdown of well *i*
A	cost dependent constant
MU	monetary unit
T	transmissivity
R_{sw}	radius of influence of the system of wells
r_{ij}	distance between wells *i* and *j*
r_{ij^*}	distance between well *i* and imaginary well j^*
r_w	radius of well
h_f	hydraulic freshwater head
d	aquifer depth from mean sea level
δ	density difference ratio of the seawater and freshwater
ρ	fluid density
ρ_s	seawater density
ρ_f	freshwater density
φ	flow potential
ξ	freshwater depth from mean sea level
K	hydraulic conductivity
q	regional uniform flow per unit length of coastline
X_{toe}^i	distance from the coastline to the toe location according to the pumping well *i*
X_S^i	distance from the coastline to the stagnation points of the pumping well *i*
R	recharge
A_i	cell *i* area
W_i	cell *i* width
T_{ji}	transmissivity and length of the boundary between cell *i* and an adjacent cell *j*
W_{ji}	length of the boundary between cell *i* and an adjacent cell *j*
L_{ji}	distance between centers of the two adjacent cells
L_i	mean seawater intrusion length in the coastal cell *i*
Cost	total cost of pumping
cost_i	cost of pumping and conveyance of water from cell *i*
S_{op}	specific pressure storativity
p	fluid pressure
t	time
c	solute concentration
c^*	solute concentration as a mass fraction of fluid sources
c_{max}	maximum allowable concentration mass fraction for potable water
c_f	freshwater concentration
c_s	seawater concentration
μ	fluid dynamic viscosity
D_{diff}	molecular diffusion
D_{disp}	mechanical dispersion tensor
g_z	gravitational acceleration
ε	aquifer volumetric porosity
k_I	solid matrix intrinsic permeability
Q_p	fluid mass sink or source
α	dispersivity
C_{sc}	penalty coefficient
Pen	penalty function

N_n	the number of generations with no improvement in the objective function value	N_t	the number of total generations from the beginning of computation

models including analytical solutions (e.g., Cheng et al., 2000), numerical models (e.g., Mantoglou and Papantoniou, 2008), and surrogate models such as artificial neural networks (ANNs) and genetic programming (GP) (e.g., Sreekanth and Datta, 2011; Ataie-Ashtiani et al., 2014) can be used as groundwater simulators.

In coastal groundwater management problems (CGMPs), the previous works have obtained optimal solutions at varying degrees of success using traditional (e.g., linear and nonlinear programming techniques) or EA optimization tools in combination with simulation models. Linear programming techniques (e.g., Shamir et al., 1984; Hallaji and Yazicigil, 1996; Nishikawa, 1998; Sethi et al., 2002; Mantoglou et al., 2004; Abarca et al., 2006; Uddameri and Kuchanur, 2007; Karterakis et al., 2007) and nonlinear programming techniques (e.g., Gorelick and Voss, 1984; Willis and Finney, 1988; Finney et al., 1992; Emch and Yeh, 1998; Das and Datta, 1999, 2000; Gordon et al., 2000; Mantoglou et al., 2004; Mantoglou and Papantoniou, 2008) were widely used for CGMPs in the past. Recently, the application of EAs for CGMPs has extensively been developed in order to overcome the shortcomings of traditional optimization techniques (Singh, 2014). A wide range of optimization algorithms are available such as genetic algorithm (GA) (Holland, 1975; Goldberg, 1989), ant colony optimization (ACO) (Dorigo, 1992), evolution strategies (Rechenberg, 1965), particle swarm optimization (PSO) (Kennedy and Eberhart, 1995), differential evolution (DE) (Storn and Price, 1997), artificial bee colony optimization (ABC) (Karaboga, 2005), harmony search (HS) (Geem et al., 2001), bacterial foraging optimization (Passino, 2002), shuffled complex evolution (SCE) (Duan et al., 1992), simulated annealing (SA) (Kirkpatrick et al., 1983), simplex simulated annealing (SIMPSA) (Cardoso et al., 1996), cuckoo search (Yang and Deb, 2010), invasive weed optimization (Mehrabian and Lucas, 2006). Considering the large number of such algorithms and their variants, determining the most appropriate one for the purposes of CGMPs is still an open question. There is no a superior and all-purpose EA for all problems (e.g., Wolpert and Macready, 1997; Pham and Castellani, 2014). The success of each EA on a particular optimization problem depends on how well the algorithm fits to the proposed problem. The precise understanding of an optimization problem is a key factor due to problem-dependent performance of EAs (Pham and Castellani, 2014).

Some efforts have been devoted to compare EAs performances for scientific applications. Typically, such comparisons have been based on benchmark mathematical functions (e.g., Pourtakdoust and Nobahari, 2004; Elbeltagi et al., 2005; Afshar et al., 2006; Karaboga and Akay, 2009; Akay and Karaboga, 2012; Civicioglu and Besdok, 2013; Pham and Castellani, 2014). By comparing the performances of EAs in CGMPs, we can have an efficient choice of EAs. However, there has not been any comprehensive comparative study of various EAs and their applicability analyses in CGMPs. Recently, Karpouzos and Katsifarakis (2013) introduced four new benchmark problems in the groundwater resources management field considering the adjustable difficulty through the application of GA and SA. They showed that such set of benchmark problems can be useful for evaluating EAs. Singh (2014) reviewed the different techniques used for the management of CGMPs and highlighted the need to develop appropriate management models for assessing the strategies of SWI protection in coastal aquifers. He investigated the applications of linear and nonlinear programming techniques and GA in CGMPs.

Here, we categorize the applications of EAs in CGMPs to two group of hypothetical problems and real-case applications. Tables 1 and 2 summarize these two categories. The simulation conceptualizations and the variety of features considered in the optimization problems are presented in these Tables. These studies are not conducted as the representative cases of the range of possible processes may be occurred in the coastal aquifers, and sometimes replicate similar cases. The focus of many of these studies is on the application of a particular EA and there is no comparative evaluation of EAs in these studies. Cheng et al. (2000) reported the first application of EAs to investigate the CGMPs, using the structured messy GA in combination with analytical solutions of coastal aquifer problems. Tables 1 and 2 indicate GA and its variants are the most popular of EAs for such problems in comparison with other algorithms and there is a very few applications of CACO (Ataie-Ashtiani and Ketabchi, 2011), DE (Karterakis et al., 2007; Papadopoulou et al., 2010; Elçi and Ayvaz, 2014), SA (Rao et al., 2003, 2004), and SIMPSA (Kourakos and Mantoglou, 2009).

Surveying in the literature demonstrates that other EAs, such as PSO, ABC, HS and SCE, were rarely used in groundwater resources management and there is no report of their application for CGMPs. ACO was considered by Amy and Hilton (2007) to groundwater monitoring design. Gaur et al. (2011) utilized PSO in the Dore river basin, France to solve two groundwater hydraulic management problems. A combined simulation–optimization model using MODFLOW and HS was proposed by Ayvaz (2009) for hypothetical unconfined aquifer while Ayvaz and Elçi (2013) used such model for their investigations on Tahtalı watershed (Izmir-Turkey). It should be noted that it was not found any notable literature, which used ABC, SCE, and other EAs to CGMPs. Although helpful to give more insights on the performances of EAs in CGMPs, aforementioned literatures did not address the need of a systematic and comprehensive evaluation of EAs. Therefore, it is needed to discuss and assess the characteristics of some popular EAs in solving CGMPs.

Tables 1 and 2 also list different objective functions and the sets of constraints that can be considered to define the optimization problems of coastal groundwater resources. Optimal decisions can be related to pumping rate schemes (e.g., Cheng et al., 2000; Mantoglou et al., 2004; Qahman et al., 2009; Ataie-Ashtiani and Ketabchi, 2011), well locations (e.g., Park and Aral, 2004; Elçi and Ayvaz, 2014), the salinity of pumped water from wells (e.g., Abd-Elhamid and Javadi, 2011; Ataie-Ashtiani et al., 2014), water table (GWT) level or drawdown (e.g., Katsifarakis and Tselepidou, 2009), seawater volume into the aquifer (e.g., Finney et al., 1992; Emch and Yeh, 1998), operating cost (e.g., Gordon et al., 2000; Kourakos and Mantoglou, 2009; Abd-Elhamid and Javadi, 2011), net benefit (e.g., Qahman et al., 2005; Ferreira da Silva and Haie, 2007), recharge rate schemes (e.g., Kourakos and Mantoglou, 2011), and also trade-off between environmental and social issues, and interactions between surface and subsurface resources. The review of Singh (2014) also revealed that the management models used in the past mainly considered the abovementioned objectives. Also, constraints which consider limitations and controls, can include pumping limits (e.g., Cheng et al., 2000; Rao et al., 2004; Katsifarakis and Petala, 2006), manage the seawater toe location (e.g., Cheng et al., 2000; Park and Aral, 2004; Ferreira da Silva and Haie, 2007; Mantoglou and Papantoniou,

Table 1
Summary of EA-based literature for hypothetical CGMPs.

References	Simulation[a]	Optimization[b]	Objectives[c]	Consideration[d]	Case[e]
Cheng et al. (2000)	IF, 2D,UNCO, SS, AN	SMGA	PR	PL, TL, SWI, CI	HYP, 22 km^2
Rao et al. (2003)	IF, 2D, T, NU (SHARP), ANN	SO, SA	WL, PR	PL, TL, GWT	HYP, 50 km^2
Park and Aral (2004)	IF, 2D, AN, SS, 2D	MO, MOGA	WL, PR	PL, TL, SWI	HYP, 28 km^2
Rao et al. (2004)	IF, 3D, UNCO, NU (SEAWAT), ANN	SO, SA	PR	PL, SWI, GWT, BW	HYP, 2.64 km^2
Bhattacharjya and Datta (2005)	DD, 3D, NU (FEMWATER), ANN	GA	PR	PL, SWI, BW	HYP, 2.52 km^2
Qahman et al. (2005)	DD, 3D, CO, NU (CODESA3D)	SO, MO, GA	PR, NB, COST	PL, GWT	HYP
Katsifarakis and Petala (2006)	IF, 2D, AN, SS, BEM	SO, GA	WL, PR	PL, SWI	HYP
Ferreira da Silva and Haie (2007)	IF, 2D, AN, NU	SO, EA	WL, NB	PL, TL, SWI, WD, GWT, RES, PS	HYP
Bhattacharjya and Datta (2009)	DD, 3D, NU (FEMWATER), ANN	MO, NSGA-II	PR	PL, SWI, BW	HYP, 2.52 km^2
Dhar and Datta (2009)	DD, 3D, NU (FEMWATER), ANN	MO, NSGA-II	PR	PL, SWI	HYP, 2.52 km^2
Sreekanth and Datta (2010)	DD,3D, UNCO, NU (FEMWATER), GP, MNN	MO, NSGA-II	PR	PL, SWI, BW	HYP, 2.52 km^2
Abd-Elhamid and Javadi (2011)	DD, 2D, CO, T, NU	MO, GA	ADR, COST, WC	PL, SWI, GWT	Henry problem
Ataie-Ashtiani and Ketabchi (2011)	IF, 2D, UNCO, SS, AN, NU	SO, CACO	PR	PL, TL, SWI	HYP, 28 km^2
Kourakos and Mantoglou (2011)	DD, 2D, T, NU (SEAWAT)	MO, NSGA-II	WL, PR, RR, COST	PL, WD, DI	HYP
Sreekanth and Datta (2011)	DD, 3D, UNCO, NU (FEMWATER), GP, ANN	SO, GA	PR	PL, SWI, BW	HYP, 2.52 km^2
Javadi et al. (2012)	DD, 2D, CO, T, NU	MO, GA	ADR, WC, COST	PL, SWI, GWT	Henry problem

[a] IF: sharp-interface flow; DD: density-dependent flow; D: dimension; UNCO: unconfined; CO: confined; SS: steady-state; T: transient; AN: analytical; NU: numerical; ANN, artificial neural network; BEM: boundary element method, artificial neural network MNN: modular neural network.
[b] SO: Single-objective; MO: multi-objective; SMGA: structured messy GA; MOGA: multi-objective GA; NSGA-II: non-dominated sorting GA-II.
[c] PR: pumping rate; WL: Well locations; NB: net benefit; COST: operating cost; RR: recharge rate; WC: Well concentration.
[d] PL: pumping limits, TL: toe location, CI: canal impact; WD: water demand; GWT: GWT level (drawdown); RES: reservoir; PS: pumping station; BW: barrier wells.
[e] HYP: hypothetical aquifer.

Table 2
Summary of EA-based literature for real-case CGMPs.

References	Simulation[a]	Optimization[b]	Objectives[c]	Consideration[d]	Case
Mantoglou et al. (2004)	IF, 2D, UNCO, SS, AN, NU (MODFLOW)	SO, EA	PR	PL, TL, SWI	Greek island of Kalymnos, ~21 km^2
Karterakis et al. (2007)	IF, 2D, UNCO, SS, AN	SO, DE	PR	PL, GWT	Coastal karstic aquifer, Crere, Greece, 17.9 km^2
Guan et al. (2008)	NU (MODFLOW)	IGA	PR	PL, SWI, GWT	Savannah region
Mantoglou and Papantoniou (2008)	IF, 2D, UNCO, SS, AN, NU (MODFLOW)	SO, GA	WL, PR	PL, TL, SWI	Greek island of Kalymnos, ~21 km^2
Kourakos and Mantoglou (2009)	DD, 3D, NU (SEAWAT), MNN	SIMPSA	PR	PL, SWI, GWT	Greek island of Santorini, ~66 km^2
Qahman et al. (2009)	DD, 3D, NU (CODESA3D)	MO, GA	PR	SWI, GWT	Gaza Coastal Aquifer, 4 km^2
Liu et al. (2010)	ANN	GA	WA, COST, SSAT	SWI, WD, JORR	Pearl River Delta, China, 28,079 km^2
Papadopoulou et al. (2010)	AN, RBANN	DE	WA	PL, GWT	Heraklion, Crete, Greece
Abd-Elhamid and Javadi (2011)	DD, 2D, CO, T, NU	MO, GA	ADR, COST, WC	PL, SWI, GWT	Biscayne, Florida, USA, 300 m length
Sedki and Ouazar (2011)	IF, 2D, UNCO, SS, T, NU (MODFLOW)	SO, GA	PR, AER	PL, SWI, WD, GWT, WLOG	Rhis-Nekor plain, Morocco, 100 km^2
Kourakos and Mantoglou (2013)	DD, 3D, NU (SEAWAT), MNN	SO, MO, NSGA-II	PR, COST, ADR	PL, SWI, WD	Greek island of Santorini, ~66 km^2
Ataie-Ashtiani et al. (2014)	DD, 3D,UNCO, NU (SUTRA), ANN	MO, GA	CCC, WC	PL, SWI, LU, MZA	Kish island, Persian Gulf, Iran, ~90 km^2
Elçi and Ayvaz (2014)	IF, 2D, UNCO, SS, NU (MODFLOW)	DE	WL, PR, COST	PL, SWI, GWT, TWL, LU	Coastal aquifer in Tahtalı watershed in Izmir, Turkey

[a] IF: sharp-interface flow; DD: density-dependent flow; D: dimension; UNCO: unconfined; CO: confined; SS: steady-state; T: transient; AN: analytical; NU: numerical; ANN, artificial neural network; RBANN: radial basis function ANN.
[b] SO: Single-objective; MO: multi-objective; NSGA-II: non-dominated sorting GA-II; IGA: Improved GA.
[c] PR: pumping rate; WL: Well locations; COST: operating cost; WC: Well concentration; WA: water allocation; SSAT: social satisfaction, ADR: Abstraction, desalination and recharge; AER: Adverse environmental risks; CCC: Change in concentrations change.
[d] PL: pumping limits, TL: toe location, CI: canal impact; WD: water demand; GWT: GWT level (drawdown); JORR: joint operation of river and reservoirs; TWL: total well length, WLOG: water-logging; LU: land-use; MZA: management zone application.

2008; Ataie-Ashtiani and Ketabchi, 2011), GWT level (e.g., Uddameri and Kuchanur, 2007; Katsifarakis and Tselepidou, 2009), salt concentration (e.g., Kourakos and Mantoglou, 2011; Ataie-Ashtiani et al., 2014), strategic nature of the aquifer, existing infrastructures, and historical rights rates (e.g., Abarca et al., 2006). The considered benchmark problems in this study cover the range of popular objective functions and constraints such as pumping rate schemes and proposed limits, well locations, operating cost, drawdown, toe location, and salt concentration.

The objective of this paper is to provide a comparative study of eight EAs for CGMPs. Here, we examine the application of PSO, ABC, HS, and SCE for the first time to solve CGMPs. CACO, DE, and SIMPSA which were rarely applied in this field, are also tested besides the wide-use EA of GA. The applicability and efficiency of these eight EAs are investigated using the four benchmark problems to cover variety of features that occur in coastal regions. The comparative investigation describes the efficiency and robustness of an extensive number of EAs.

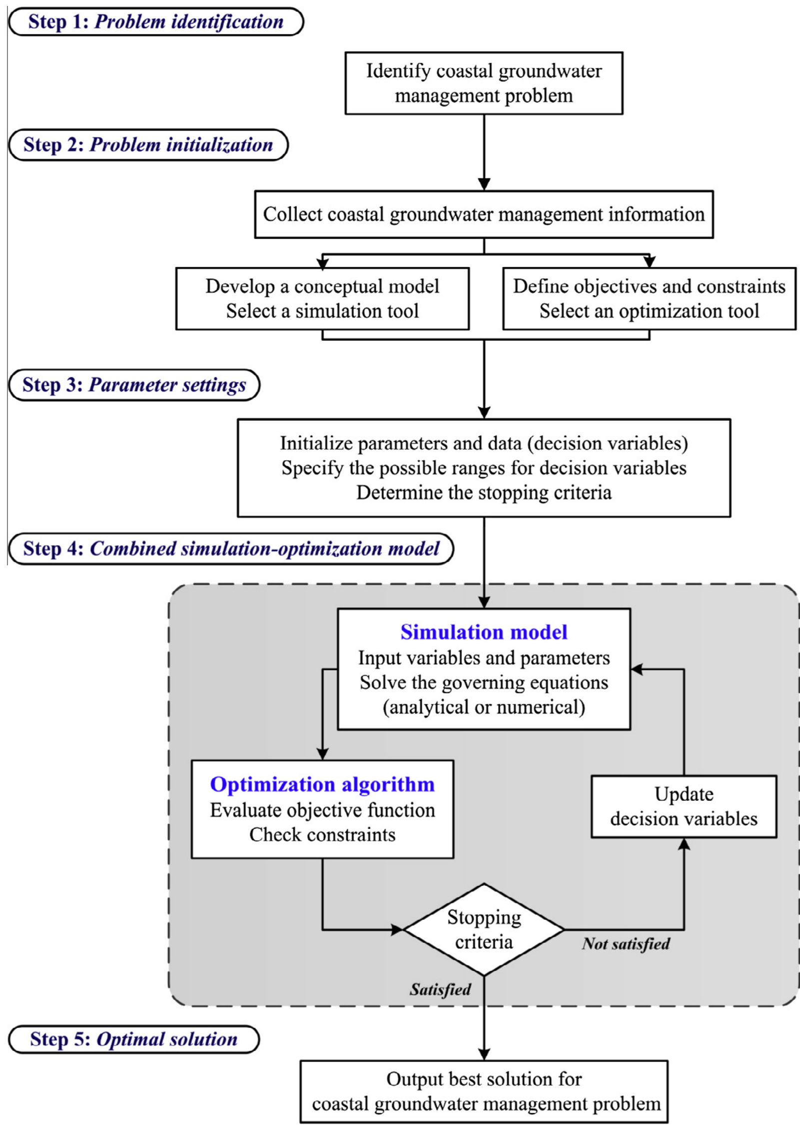

Fig. 1. Flowchart of the combined simulation–optimization approach for CGMP.

2. Methods and tools

A combined simulation–optimization approach is considered as given in the presented through a schematic flowchart in Fig. 1. Following problem identification, initialization, and parameter settings, a combined simulation–optimization methodology is used. Such methodology was suggested by e.g., Dhar and Datta (2009), Abd-Elhamid and Javadi (2011), Ataie-Ashtiani and Ketabchi (2011), and Ataie-Ashtiani et al. (2014) due to key advantages in comparison with other methodologies such as embedding approach applied by e.g., Shamir et al. (1984), and Das and Datta (1999). The two main components of this approach are optimization algorithm and simulation model. EA as an optimization tool calls the simulation model iteratively to evaluate the objective function values and then update decision variables. This process is repeated until the stopping criteria are satisfied and accordingly best solution is obtained. These components are described in the following sections.

2.1. Evolutionary algorithms

EAs are meta-heuristic search methods that are inspired by evolution of biological natures and social behaviors to arrive at a near-optimum solution (Fogel et al., 1966). EAs are based on the collective learning process within a population of potential solutions applying the principle of survival of the fittest in order to refine a set of solution candidates iteratively (Fogel et al., 1966; Holland, 1975). Their potential as global optimization methods in real-world and large-scale applications causes to relax shortcomings imposed by traditional optimization techniques. Traditional techniques are commonly unable to handle large-number of decision variables, nonlinear non-convex problems, and difficulty or fail in providing the global optimum without being trapped in local optimums (Dhar and Datta, 2009; Singh, 2012; Ma et al., 2013; Pham and Castellani, 2014). In this study, we compare the GA, CACO, PSO, DE, ABC, HS, SCE, and SIMPSA. There are other EAs which can be included in such comparison. We have considered these EAs as the most popular because they were applied in many widespread scientific fields. A brief description of the aforementioned algorithms is presented in the following. It should be noted that in this study, the basic variants of the proposed set of EAs are opted.

2.1.1. Genetic algorithm

GA is a search method that mimics the natural biological evolution of species (Holland, 1975; Goldberg, 1989). GA involves several basic mechanisms including initialization, selection, and reproduction (mating) to produce stronger individuals (The algorithm is provided in Supplementary material A: Algorithm A.1). In this method, NG is the number of generations and Pop is the size of chromosome populations. GA starts with a population of chromosome-encoded random potential solutions of the problem. From the initial population, the fittest strings, as measured by objective function, are selected to pass genetic information to the next generation. A new set of solutions is produced from the selected members of the previous population through the application of identified selection, crossover, and mutation operators. These processes are repeated until the user-specified stopping criteria are met.

2.1.2. Continuous ant colony optimization

ACO as a part of swarm intelligence is inspired by the foraging behavior of ant colonies that was first introduced by Dorigo (1992). Ants deposit a pheromone on their path to mark some shorter paths between food sources and their nest. It is followed by other ants, when choosing their way. Accordingly, ants tend to choose paths mark by strong pheromone concentrations. This indirect communication among ants by forming pheromone trails can give rise to the emergence of shortest paths (Dorigo and Stützle, 2004). A similar system for solving optimization problems can be adopted (Socha and Dorigo, 2008).

ACO was originally proposed for discrete optimization problems and extended to continuous decision space by Bilchev and Parmee (1995), namely CACO, and after that improved by some other researchers (e.g., Pourtakdoust and Nobahari, 2004; Afshar et al., 2006; Socha and Dorigo, 2008; Madadgar and Afshar, 2009). In this study, CACO is chosen due to the continuous search space of the considered optimization problems. This algorithm was developed by Pourtakdoust and Nobahari (2004) and improved by Afshar et al. (2006) using elitist strategy (The outline is provided in Supplementary material A: Algorithm A.2). Also, it is closest to the spirit of ACO for discrete problems. The fundamental idea in CACO is the solution construction based on the pheromone-based probabilistic choice of solutions (Socha and Dorigo, 2008). Hence, the probability density function is generally used for determining pheromone information and its update rule considering the best solution of each generation (Pourtakdoust and Nobahari, 2004; Afshar et al., 2006). The normal distribution for calculating pheromone information is:

$$\tau(x) = \frac{1}{2\sigma\sqrt{\pi}} e^{-\frac{(x-x_{best})^2}{2\sigma^2}} \tag{1}$$

where x_{best} is the best solution in the previous generation and σ is the weighted standard deviation of the normal probability density function. σ is used for the modification of the probability distribution at any generation toward the choices leading to optimal solutions and forgetting other ones. The σ is defined as follows (Pourtakdoust and Nobahari, 2004):

$$\sigma = \sqrt{\frac{\sum_{i=1}^{Pop} \frac{1}{f_i - f_{opt}} (x_i - x_{opt})^2}{\sum_{i=1}^{Pop} \frac{1}{f_i - f_{opt}}}} \tag{2}$$

where Pop is the number of ants, x_i is the decision variable selected by ant i (solution), f_i is the value of objective function for solution i, x_{opt} is the best decision variable, and f_{opt} is the best objective function value from the previous generation.

2.1.3. Particle swarm optimization

PSO is a swarm intelligence-based optimization technique inspired by social behavior and dynamic movement of a flock of insects, birds, and fish, which was developed by Kennedy and Eberhart (1995) (The outline is provided in Supplementary material A: Algorithm A.3). A PSO is initialized with a population (swarm) of random candidate solutions (particles) within the proposed boundaries. The particles fly throughout the search space following the current optimum particles. The movements of particles are guided by the best known position of each particle in the search space using its own memory as well as knowledge learned from the entire swarm's best known position. The movement of each particle for better positions in the search space is determined by the particle's velocity. Each generation, the velocities and positions of the particles are updated until the user-specified stopping criteria are satisfied (Kennedy and Eberhart, 2001). Each particle position is updated to the new position, $x(g+1)$, according to its current position, $x(g)$, as follows:

$$x(g+1) = x(g) + v(g+1) \tag{3}$$

where g is a generation number index, and $v(g+1)$ is the new velocity of the particle, updated by the following rule:

$$v(g+1) = \omega v(g) + C_1\ rand_1\ (b_p(g) - x(g)) + C_2\ rand_2\ (b_g(g) - x(g)) \tag{4}$$

where $v(g)$ is the current velocity of particle. $rand_1$ and $rand_2$ are two independent random numbers uniformly distributed in the range of $(0, 1)$. $v(g+1)$ includes three elements that represent the persistence of current condition (controlled by ω as an inertia or momentum weight), cognitive experience (tendency to return to previously found local best position, $b_p(g)$, visited by each particle), and social interactions (tendency to move toward the $b_g(g)$ as the global best position encountered so far with the social neighbors of the particle). Also, C_1 and C_2 are two acceleration constants which control the relative effect of the local and global best positions (Shi and Eberhart, 1998; Kennedy and Eberhart, 2001).

2.1.4. Differential evolution

DE was developed by Storn and Price (1997). DE includes three important operations: mutation, crossover and selection to evolve from a randomly generated initial trial population to the fittest solution (The procedure is presented in Supplementary material A: Algorithm A.4). The mutation operator is used to generate perturbed individual, $x_{perturbed}(g+1)$ as:

$$x_{perturbed}(g+1) = x_{rand_1}(g) + F_{DE} \times (x_{rand_2}(g) - x_{rand_3}(g)) \tag{5}$$

where x_{rand_1}, x_{rand_2}, and x_{rand_3} are randomly selected individuals among the candidate solutions of the current population and must be different from each other. The scaling parameter, F_{DE}, is a control parameter of differential variations. After mutation, a crossover operator forms the trial vector, $u(g+1)$ according to $x_{perturbed}(g+1)$ and the corresponding $x(g)$. Following a discrete recombination approach, this trial vector is produced by:

$$u_j(g+1) = \begin{cases} x^j_{perturbed}(g+1) & \text{if } rand_j \leqslant CR \text{ or } j = j_{rand} \\ x_j(g) & \text{otherwise} \end{cases} \tag{6}$$

where $rand_j$ is a uniformly distributed random number in the range of $(0, 1)$. $rand_j$ regenerates for each decision variable j, where $1 \leqslant j \leqslant D$ and D is the number of decision variables. Also, in Eq. (6), j_{rand} is a random integer in the range $(1,D)$ to ensure that $u(g+1) \neq x(g)$. CR is the crossover probability that varies between 0 and 1 and is specified by user. Selection is then used to determine whether the new generated trial vectors can survive the next generation, $x(g+1)$. Therefore, a candidate solution replaces the parent only if it has better objective function value. Abovementioned operations continue until the stopping criteria are reached.

2.1.5. Artificial bee colony optimization

ABC, introduced by Karaboga (2005), imitates the intelligent foraging behavior of honey bee colonies on finding food sources and sharing the information to other bees in the nest (The detailed process is provided in Supplementary material A: Algorithm A.5). ABC simulates three kinds of bees: employed, onlooker, and scout bees. Half of the colony consists of employed bees, and the other half includes onlooker bees. The employed bees stay on a food source and provide the neighborhood of the source in their memory. The onlooker bees wait in the nest and decide on the food source that is taken based on the information given by the employed bees. The employed bee whose food source has been exhausted becomes a scout bee. Scout bees randomly explore the environment for finding new food sources (Seeley, 1995; Karaboga and Akay, 2009).

The food sources representing a possible solution to the optimization problem are randomly generated in the first step by scout bees within the range of proposed boundaries. Each food source is represented by x_i. x_i has D variables, where D is the number of decision variables. The number of food sources is SN. After initialization, the solutions are subject to repeated generations of the search processes of bees (Karaboga and Akay, 2009; Karaboga et al., 2014). In ABC, finding a neighboring food source is defined by:

$$x_{ij}^{new} = x_{ij} + rand_{ij}(x_{ij} - x_{kj}) \tag{7}$$

Within the neighborhood of x_i, a food source x_{ij}^{new} is determined by changing one parameter of x_i. In Eq. (7), j is a random integer in the range $(1, D)$ and k, where $1 \leqslant k \leqslant SN$ is a randomly chosen index that must be different from i. $rand_{ij}$ is a uniformly distributed real random number in the range $(-1, 1)$. After creating x_i^{new} within the proposed boundaries, a fitness value for an optimization problem (e.g., minimization) can be assigned to the solution x_i^{new} by:

$$fitness_i = \begin{cases} \frac{1}{1+f_i} & \text{if } f_i \geq 0 \\ 1 + |f_i| & \text{if } f_i < 0 \end{cases} \tag{8}$$

where f_i is the objective function value of the solution x_i^{new}. The better one between x_i and x_i^{new} is selected depending on fitness values representing the nectar amount of the food sources at x_i and x_i^{new}. If the source at x_i^{new} is superior to that of x_i, the employed bee memorizes the new position and forgets the old one. If not, the previous position is remained in memory. After completing the searches of all employed bees, each onlooker bee evaluates the nectar information taken from all employed bees and selects the food sources with a probability depending on the fitness values (Karaboga and Akay, 2009; Karaboga et al., 2014). This probability value, Prob_i, can be defined as:

$$\text{Prob}_i = \frac{fitness_i}{\sum_{j=1}^{SN} fitness_j} \tag{9}$$

Following the probabilistically selection of a food source for an onlooker bee, a neighborhood source is determined by Eq. (7), and its fitness value is computed by Eq. (8). Therefore, the best solutions are selected. If a solution obtained by employed bees cannot be improved through a predetermined parameter, namely limit, then that solution is abandoned by scout bees (Karaboga and Akay, 2009; Karaboga et al., 2014). Considering the abandoned solution x_i, the scout bees determine a new solution to be replaced with x_i using the following operation:

$$x_{ij} = x_j^{min} + rand_j \times (x_j^{max} - x_j^{min}) \tag{10}$$

where $rand_j$ is a random number in the range of $(0, 1)$; and x_j^{min} and x_j^{max} are the lower and upper bound of solution space, respectively. The aforementioned steps are repeated until stopping criteria defined for ABC are satisfied.

2.1.6. Harmony search

HS is a meta-heuristic optimization technique developed first by Geem et al. (2001). It conceptually mimics the improvisation process of musicians to obtain better harmony (The algorithm is proposed in Supplementary material A: Algorithm A.6). In this process, each decision variable (musician) generates a value (note) for finding a global optimum (best harmony). HS consists of a harmony memory size (HMS) as a data structure based on previously remembered improvisations. Harmony memory vector stores the candidate solutions including D decision variables, all of which are initialized randomly within the search space. The harmony consideration rate (HMCR) is in the range of $(0, 1)$, pitch adjustment rate (PAR), and the pitch adjustment bandwidth (b_w) are parameters specified by user for controlling the improvisation process (Lee et al., 2005; Moh'd Alia and Mandava, 2011).

In each generation, *HMCR* is the probability of choosing a value from the historic values stored in the harmony memory, and $(1 - HMCR)$ is the probability of randomly choosing a feasible value not limited to those stored in the harmony memory. The solution vector from memory consideration is further adjusted by pitch adjusting process according to the probability of PAR. If the decision is updating the solution, x_j is updated as follows:

$$x_j = x_j + rand_j \times b_w \tag{11}$$

where $rand_j$ is a random number in the range $(-1, 1)$. The probability of $(1 - \text{PAR})$ sets the rate of doing nothing. When the obtained solution vector is better than the worst harmony in the memory, the worst harmony is replaced by with the solution vector. This procedure is repeated until the stopping criteria are reached (Yang, 2009; Lee et al., 2005). The considered HS exploits changeable PAR and b_w in the improvisation process. These parameters change with g and are defined as follows (Mahdavi et al., 2007):

$$\text{PAR}(g) = \text{PAR}_{min} + g \times \frac{\text{PAR}_{max} - \text{PAR}_{min}}{\text{NG}} \tag{12}$$

$$b_w(g) = b_{w_{max}} e^{\frac{\ln(b_{w_{min}}/b_{w_{max}})}{\text{NG}} \times g} \tag{13}$$

where PAR_{max} and PAR_{min} are maximum and minimum pitch adjusting rates, respectively, and $b_{w_{max}}$ and $b_{w_{min}}$ are maximum and minimum bandwidths, respectively.

2.1.7. Shuffled complex evolution

SCE was proposed by Duan et al. (1992) is a population-based optimization method. It combines competitive complex evolution, complex shuffling, and downhill simplex procedure to obtain a global optimal solution (The algorithm is provided in Supplementary material A: Algorithm A.7). Complex shuffling makes the information of each complex shared at the process of searching, therefore avoid trapping the local optimal solution. The search ability of downhill simplex can make the SCE get every local optimal solution rapidly (Duan et al., 1994).

In SCE method, the number of complexes (NC) and the number of points in each complex (NP) where $\text{NC} \geqslant 1$ and $\text{NP} \geqslant D + 1$, are identified by user and the population size is computed as $\text{Pop} = \text{NC} \times \text{NP}$. Pop points in the search space are generated randomly and evaluated according to the objective function value. Then, they are sorted in the order of increasing superiority (for minimization problem) and partitioned into NC complexes. Each complex is evolved by competitive complex evolution algorithm, based on Nelder and Mead (1965) simplex downhill search procedure (local search), and followed by combining the points of the evolved complexes into a single population and sorting them in the order of increasing superiority (complex shuffling). Again, the population partitioned into NP complexes. The local search and shuffling steps are repeated until the stopping criteria are satisfied (Duan et al., 1993, 1994).

In competitive complex evolution algorithm, q, α, and β, where $2 \leqslant q \leqslant \text{NP}$, $\alpha \geqslant 1$, and $\beta \geqslant 1$ are selected by user. Based on triangular probability distribution (Eq. (14)), the weights for points are assigned and q distinct points (simplexes) from each complex are selected according to Prob_i as parents. α and β are the number of consecutive new solutions generated by the same simplexes and the number of evolution of each complex before complexes are shuffled, respectively.

$$\text{Prob}_i = \frac{2 \times (\text{NP} + 1 - i)}{\text{NP} \times (\text{NP} + 1)} \quad i = 1, \ldots, \text{NP} \tag{14}$$

Further details regarding the competitive complex evolution algorithm are available in Nelder and Mead (1965) and Duan et al. (1993).

2.1.8. Simplex simulated annealing

SIMPSA was developed for global continuous optimization problems (Cardoso et al., 1996). It is based on the original SA (Kirkpatrick et al., 1983) that was proposed for discrete optimization problems. SIMPSA combines the Metropolis algorithm (Metropolis et al., 1953) with the Nelder and Mead (1965) simplex downhill search (Press and Teukolsky, 1991) (The outline is provided in Supplementary material A: Algorithm A.8).

Due to the application of the simplex downhill search, a simplex with $D + 1$ vertices for D decision variable is used. Starting from a randomly selected solution in the search space, a new candidate solution is chosen according to the Metropolis algorithm and the objective function values are calculated for both solutions. If the new solution is better than the previous one, thus the new solution is accepted and becomes the starting point for the next generation, otherwise the new point is accepted with the probability of $\Delta f/(K_B.Temp)$, where Δf is the difference of objective function values, K_B is Boltzmann's constant, and $Temp$ is the annealing temperature (Cardoso et al., 1996). For assumed acceptance ratio, A_r, the initial annealing temperature $Temp_{init}$ is estimated by:

$$A_r = \frac{m_1 + m_2 e^{\frac{-\Delta f^+}{Temp_{init}}}}{m_1 + m_2} \tag{15}$$

where m_1 and m_2 are the number of successful and unsuccessful reflections, respectively. They are identified in the sufficient preliminary number of generations. In Eq. (15), Δf^+ is the average increase in objective function values for m_2. In the preliminary generations, the temperature value is remained high, but it is decreased during next generations in order to reduce the acceptance probability (Cardoso et al., 1996). The cooling schedule will then continue with estimated $Temp_{init}$ by Eq. (15) as (Aarst and van Laarhoven, 1985):

$$Temp(g+1) = \frac{Temp(g)}{1 + \frac{Temp(g) \times \ln(1 + r_{cool})}{3\sigma}} \tag{16}$$

where r_{cool} is the cooling rate and σ is the standard deviation of all solutions at $Temp(g)$ (current temperature). The simplex downhill search method to generate possible solutions is used and a positive logarithmic distributed variable to the objective function value is added associated with every vertex of the simplex (Press and Teukolsky, 1991). Then, a similar random variable from the function value at every reflected point is presented as:

$$(f_{perturbed})_i = f_i - Temp \times \ln(rand_f) \quad i = 1, \ldots, D + 1 \tag{17}$$

$$(f_{perturbed})_{reflected} = f_{reflected} + Temp \times \ln(rand_f) \tag{18}$$

where f_i is the objective function value of vertex i, $f_{reflected}$ is the objective function value at the replacement point and $f_{perturbed}$ is the perturbed objective function value. $rand_f$ is a random number between 0 and 1.

The abovementioned steps are repeated, and the process is continued with a sufficient number of successful generations (NT) for the current $Temp$. The temperature is then gradually reduced using Eq. (16) and the entire process is repeated for the new temperature. The iterative process is continued until the stopping criteria are met.

2.2. The benchmark problems description

The performances of all aforementioned EAs are investigated using four-type benchmark problems in groundwater resources management field. These problems are selected to examine a variety of objective functions and constraints. The first benchmark problem introduced by Karpouzos and Katsifarakis (2013) is based on the common aspects of groundwater pumping cost problems. The developed EAs are verified by the application of this problem, and then applied to find the optimal solutions of four CGMPs. A brief description is given in the following.

2.2.1. Problem 1: minimization of total pumping cost from a heterogeneous aquifer

An infinite heterogeneous aquifer with two zones of different transmissivities (zones 1 and 2) is considered as shown in Fig. 2. The goal is to minimize the pumping cost of a system of wells. Four pre-existing and two unknown new wells will be pumped for exploitation purposes. The wells 1–4 are located at the fixed coordinates while the coordinates of new wells 5 and 6 are unknown which should be constructed inside the assumed square area. The optimal location of these two wells will be determined via the optimization procedure. Therefore, this problem has ten decision variables including the pumping rate from each of six wells and four coordinates of wells 5 and 6 (Karpouzos and Katsifarakis, 2013).

The management model can be stated as follows:

$$\text{Minimize Cost} = A \times \sum_{i=1}^{n} P_i \times s_i \quad \text{MU/year} \tag{19}$$

where n is the total number of pumping wells, P_i and s_i are the pumping and drawdown of well i located in (x_w^i, y_w^i) coordinates, respectively, A is the cost dependent constant, and MU is monetary unit.

s_i can be calculated analytically, based on the method of imaginary wells and superposition principle (Bear, 1979). Hence, s_i for wells 1 to k, which located in zone 1 is evaluated as follows:

$$s_i = -\frac{1}{2\pi T_1} \sum_{j=1}^{k} P_j \times \ln\left(\frac{r_{ij}}{R_{sw}}\right) - \frac{T_1 - T_2}{2\pi T_1 \times (T_1 + T_2)} \sum_{j=1}^{k} P_j \times \ln\left(\frac{r_{ij}^*}{R_{sw}}\right) - \frac{1}{\pi(T_1 + T_2)} \sum_{j=k+1}^{n} P_j \times \ln\left(\frac{r_{ij}}{R_{sw}}\right) \tag{20}$$

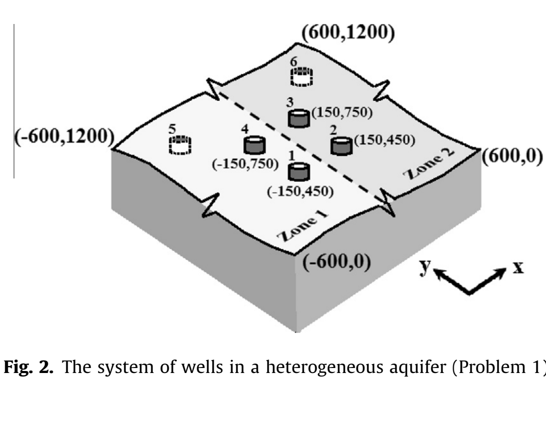

Fig. 2. The system of wells in a heterogeneous aquifer (Problem 1).

while s_i for wells $k+1$ to n, located in zone 2 is expressed as:

$$s_i = -\frac{1}{2\pi T_2}\sum_{j=k+1}^{n} P_j \times \ln\left(\frac{r_{ij}}{R_{sw}}\right) - \frac{T_2 - T_1}{2\pi T_2 \times (T_1 + T_2)}\sum_{j=k+1}^{n} P_j \times \ln\left(\frac{r_{ij^*}}{R_{sw}}\right) - \frac{1}{\pi(T_1+T_2)}\sum_{j=1}^{k} P_j \times \ln\left(\frac{r_{ij}}{R_{sw}}\right) \quad (21)$$

where T_1 and T_2 denote the transmissivities of zones 1 and 2, respectively. R_{sw} is the radius of influence of the system of wells, r_{ij} is the distance between wells i and j, and r_{ij^*} is the distance between well i and imaginary well j^*. The value of r_{ii} is taken equal to the radius of well i as r_w.

By replacing Eqs. (20) and (21) in Eq. (19), the cost of pumping from the system of wells is obtained (Katsifarakis and Tselepidou, 2009) and considered as the objective function. The following constraints also should be satisfied in this problem:

$$\begin{aligned} &\sum_{i=1}^{n} P_i = 6.3 \times 10^6 \quad \mathrm{m^3/year} \\ &0 \le P_i \le 0.127\ \mathrm{m^3/s} \quad 1 \le i \le n \\ &-600 \le x_w^i \le 600\ \mathrm{m} \quad i = 6 \text{ and } 5 \\ &0 \le y_w^i \le 1200\ \mathrm{m} \quad i = 6 \text{ and } 5 \end{aligned} \quad (22)$$

If the coordinates of all pumping wells are known, this optimization problem can be solved analytically (Katsifarakis and Tselepidou, 2009; Karpouzos and Katsifarakis, 2013). Table 3 summarized the values of parameters for this problem based on Karpouzos and Katsifarakis (2013).

Table 3
Problem 1 parameters.

Parameter	Value
T_1 ($\mathrm{m^2/day}$)	172.8
T_2 ($\mathrm{m^2/day}$)	86.4
R_{sw} (m)	2000
r_w (m)	0.25
A (–)	1000

2.2.2. Problem 2: maximization of total pumping from an unconfined aquifer

The objective of this problem is to maximize total pumping from pre-selected wells in an unconfined coastal aquifer while protecting from SWI. The analytical solution of the steady-state sharp-interface SWI model is used in this problem (Cheng et al., 2000; Park and Aral, 2004; Mantoglou and Papantoniou, 2008; Ataie-Ashtiani and Ketabchi, 2011). This solution is based on the single potential mathematical formulation of Strack (1976) and also Dupuit hydraulic assumption.

Fig. 3 presents the system of wells and the cross-section of a coastal aquifer. X_S indicates the stagnation point representing the radius of influence of a pumping well. Badon-Ghyben–Herzberg principle links the hydraulic freshwater head, h_f, to freshwater depth from mean sea level (MSL), ξ, as follows (Bear, 1979):

$$h_f - d = \delta\xi \quad (23)$$

where d is the aquifer depth from MSL and δ represents the density difference ratio of the seawater and freshwater as:

$$\delta = \frac{\rho_s - \rho_f}{\rho_f} \quad (24)$$

where ρ_s and ρ_f are the seawater and freshwater densities, respectively. Following Strack (1976) formulation, the flow potential φ is defined as follows (Ataie-Ashtiani and Ketabchi, 2011):

$$\varphi = \begin{cases} 0.5 \times \left(h_f^2 - (1+\delta)d^2\right) & \text{Zone 1} \\ \frac{1+\delta}{2\delta} \times (h_f - d)^2 & \text{Zone 2} \end{cases} \quad (25)$$

For a homogenous and isotropic aquifer, the φ satisfies the Laplace equation, $\nabla^2\varphi = 0$, in the horizontal plane (Strack, 1976). The interface location ξ can be expressed as (Ataie-Ashtiani and Ketabchi, 2011):

$$\xi = \sqrt{\frac{2\varphi}{\delta(1+\delta)}} \quad (26)$$

From Fig. 3, the toe of seawater can be calculated at $\xi = d$ as:

$$\varphi_{\mathrm{toe}} = 0.5 \times \delta(1+\delta) \times d^2 \quad (27)$$

The freshwater potential for the system of wells, in an unconfined aquifer with regional uniform flow per unit length of coastline, q, can analytically be evaluated using superposition method, (Cheng et al., 2000; Ataie-Ashtiani and Ketabchi, 2011):

$$\varphi = \frac{q}{K}X + \sum_{i=1}^{n}\frac{P_i}{4\pi K}\ln\left(\frac{(X - x_w^i)^2 + (Y - y_w^i)^2}{(X + x_w^i)^2 + (Y - y_w^i)^2}\right) \quad (28)$$

where K is the hydraulic conductivity. Using either Eq. (27) in Eq. (28), the toe location for the system of wells can be obtained. Moreover, the location of stagnation points can be evaluated from (Strack, 1976; Ataie-Ashtiani and Ketabchi, 2011):

$$\frac{\partial\varphi}{\partial X} = \frac{\partial\varphi}{\partial Y} = 0 \quad (29)$$

Groundwater pumping rates are defined as decision variables and exploited from pre-selected known pumping wells. The maximization of pumping in this problem may be formulated as follows:

$$\text{Maximize Pump} = \sum_{i=1}^{n} P_i \quad \mathrm{m^3/day} \quad (30)$$

subject to:

$$\begin{aligned} &P_{min} \leqslant P_i \leqslant P_{max} \quad \mathrm{m^3/day} \quad 1 \leqslant i \leqslant n \\ &X_{toe}^i < X_S^i \quad \mathrm{m} \quad 1 \leqslant i \leqslant n \end{aligned} \quad (31)$$

where P_{min} and P_{max} are the minimum and maximum allowable pumping rates, respectively. X_{toe}^i and X_S^i are the distance from the coastline to the toe and stagnation points of the pumping well i, respectively. These constraints keep the wells located near the coast from SWI risk by not permitting the toe of the interface to contact the stagnation points of the wells. X_{toe}^i and X_S^i are calculated using Eqs. (27)–(29) in the optimization procedure.

The system of seven-wells (wells 8 and 9 are inactive) and eight wells (well 3 is inactive) are considered in this problem (Fig. 3). The parameters of model are given in Table 4, which was adopted from Cheng et al. (2000), Park and Aral (2004), and Ataie-Ashtiani and Ketabchi (2011).

2.2.3. Problem 3: Allocation of pumping in an unconfined aquifer

This problem was first proposed by Bear (1979) and solved by applying the linear programming technique. A 10 km × 10 km unconfined coastal aquifer is considered in this problem as shown in Fig. 4. No-flow boundaries at three impermeable sides and bottom of aquifer are assumed while the remaining lateral side is a sea boundary. The recharge from precipitation at a rate of 100 mm/year is entered into the groundwater system from top boundary. Under no-pumping condition, the hydraulic gradient is toward the sea. The aquifer is homogenous and isotropic with transmissivity of 1000 $\mathrm{m^2/day}$.

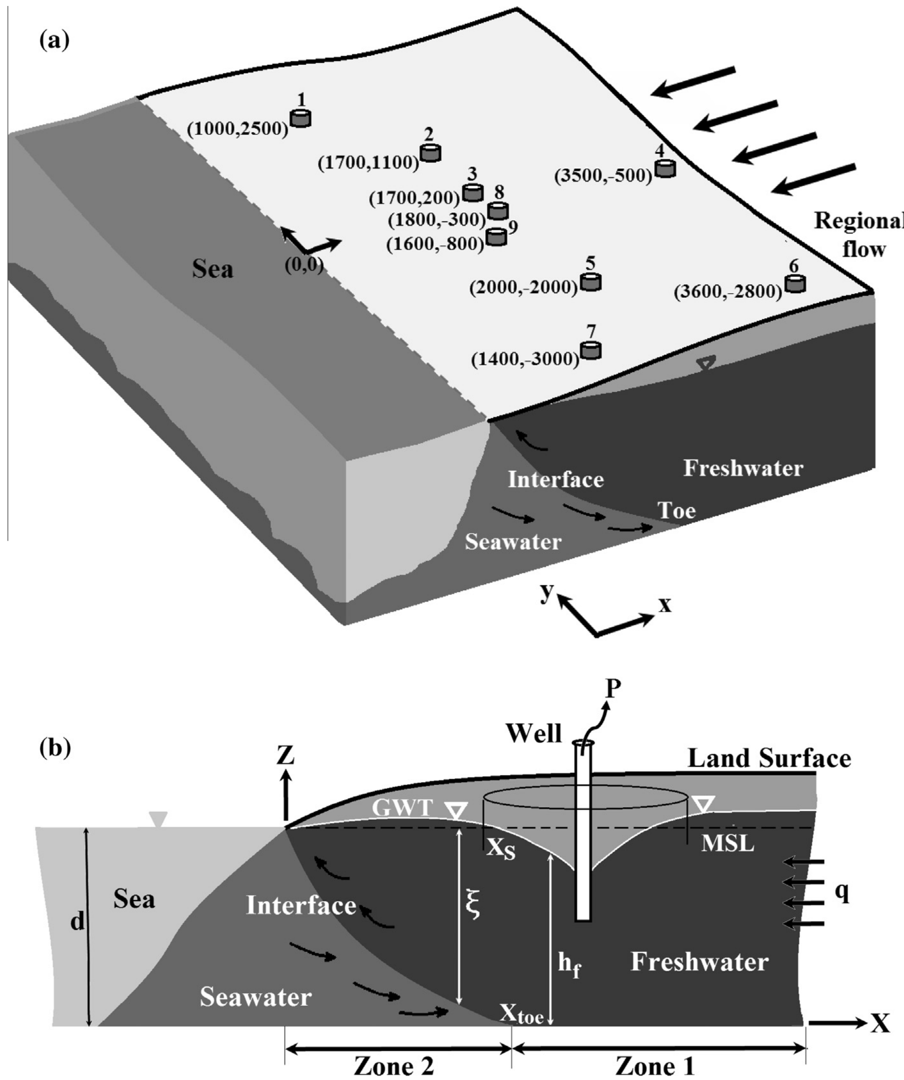

Fig. 3. An unconfined coastal aquifer (a) the system of wells and (b) the cross-section (Problem 2).

Table 4
Problem 2 parameters.

Parameter	Value
ρ_s (kg/m^3)	1025
ρ_f (kg/m^3)	1000
d (m)	15
K (m/day)	40
q (m^3/day/m)	0.4015
P_{min} (m^3/day)	150
P_{max} (m^3/day)	1500

The finite difference discretization using 25 cells of 2 km × 2 km is selected (Bear, 1979). Each cell is considered as a single pumping point. The steady-state water balance equation for the cell i can be given as (Bear, 1979; Shamir et al., 1984; Ataie-Ashtiani and Ketabchi, 2011):

$$R_i - \frac{P_i}{A_i} - \frac{q \times W_i}{A_i} = \frac{1}{A_i} \times \sum_j \left(\frac{T_{ji} \times W_{ji}}{L_{ji}} \times (h_i - h_j) \right) \quad (32)$$

where R_i is the recharge rate into cell i, P_i is the pumping from cell i, A_i and W_i are cell i area and width, respectively. T_{ji} and W_{ji} representing the transmissivity and length of the boundary between cell i and an adjacent cell j, L_{ji} is the distance between centers of the two

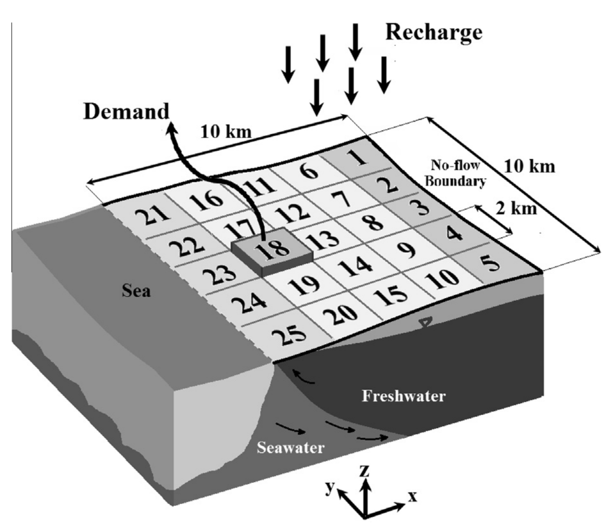

Fig. 4. A coastal aquifer and modeling domain (Problem 3).

adjacent cells, h_i and h_j are the groundwater level in cells i and j above MSL, respectively. q is 0 for cells of 1–20, while for the coastal cells i, where $21 \leqslant i \leqslant 25$, can be formulated as (Bear, 1979; Shamir et al., 1984):

$$q = \frac{2T_i \times h_i}{L_i} \tag{33}$$

where T_i and L_i are mean transmissivity and mean SWI length in the coastal cell i, respectively.

Pumping is planned in 15 cells of 6–20. The total water demand of 7 Mm^3/year is identified in cell 18. The cost of pumping and conveyance of water from cell 18 is 1.0 MU/m^3. Also, the cost increases with distance from the other pumping cell to the demand location at a rate of 0.5 MU/m^3 for per 1 km distance.

The objective function is to minimize the total cost of supplying the required demand:

$$\text{Minimize Cost} = \sum_{i=6}^{20} \text{cost}_i \times P_i \quad \text{MU/year} \tag{34}$$

where cost$_i$ is the cost of pumping and conveyance of water from cell i. The pumping rates are subjected to the following constraints:

$$\begin{aligned}
&\sum_{i=6}^{20} P_i = 7\ \text{Mm}^3/\text{year} \\
&0 \leqslant P_i \leqslant 3\ \text{Mm}^3/\text{year} \quad 6 \leqslant i \leq 20 \\
&h_i \geqslant \begin{cases} 0.95\ \text{m} & 16 \leqslant i \leqslant 20 \\ 0.64\ \text{m} & 21 \leqslant i \leqslant 25 \end{cases}
\end{aligned} \tag{35}$$

GWT levels in the aquifer along the sea should have certain minimum level to avoid SWI into the aquifer. These GWT levels are decided to be +0.64 m and +0.95 m above MSL at distances of 1 km and 3 km from the sea, respectively. This formulation as the objective function (Eq. (34)) along with the constraints (Eq. (35)) constitutes a nonlinear optimization problem. Although it can be converted to a linear optimization problem as described in detail by Bear (1979).

2.2.4. Problem 4: maximization of total pumping from an island's groundwater lens

Fig. 5 shows the modeling domain and the system of four wells in a two-dimensional island aquifer which has a length of 6000 m, a depth of 200 m, and a width of 200 m. The pumping from these wells is carried out at 50 m below MSL.

Numerical modeling is selected for the simulation of this problem which is conducted using SUTRA model (Voss and Provost, 2010) to determine the hydraulic heads and concentration of groundwater. The fluid mass balance equation (Eq. (36)) representing the single-phase flow in saturated porous media and the solute mass balance equation (Eq. (37)) characterizing the solute transport including advection and dispersion mechanisms, are solved simultaneously to characterize density-dependent flow associated with SWI (Ataie-Ashtiani et al., 1999; Voss and Provost, 2010).

$$\rho S_{op}\frac{\partial p}{\partial t} + \varepsilon\frac{\partial \rho}{\partial c}\frac{\partial c}{\partial t} - \nabla.\left(\frac{k_I \rho}{\mu}(\nabla.p - \rho g_z)\right) = Q_p \tag{36}$$

$$\frac{\partial(\varepsilon\rho c)}{\partial t} + \nabla.(\varepsilon\rho v c) - \nabla.(\varepsilon\rho(D_{\text{diff}} I + D_{\text{disp}}).\nabla c) = Q_p c^* \tag{37}$$

where ρ (M L^{-3}) is fluid density, S_{op} (L T^2 M^{-1}) is specific pressure storativity, p (M L^{-1} T^{-2}) is fluid pressure, t (T) is time, ε [–] is aquifer volumetric porosity, c (M$_s$ M^{-1}) is solute concentration, k_I (L^2) is solid matrix intrinsic permeability, μ (M L^{-1} T^{-1}) is fluid dynamic viscosity, g_z (L^2 T^{-1}) is gravitational acceleration, Q_p (M L^{-3} T^{-1}) is fluid mass sink or source, v (L T^{-1}) is average fluid velocity, D_{diff} (L^2 T^{-1}) is molecular diffusion, I is identity tensor, D_{disp} (L^2 T^{-1}) is mechanical dispersion tensor, and c^* (M$_s$ M^{-1}) is the solute concentration as a mass fraction of fluid sources. The parameters considered in this problem (Table 5) here are chosen to be similar to the Kourakos and Mantoglou (2011) case.

The discretization consists of 34 columns in the x direction and 20 layers vertically in the z direction, and one column in the y direction, giving 735 nodes and 680 elements. Therefore all results are investigated as per 200 m width of island. The x direction is discretized with 200 m mesh spacing except around the pumping wells, where they are 100 m wide. In the z direction, elements are 10 m high everywhere. This is a similar discretization to that of Kourakos and Mantoglou (2011).

No flow boundary condition is imposed at the bottom boundary in the deep depth of 200 m below MSL. Specified pressure boundaries are assigned to all nodes below MSL along the sea boundaries and set to hydrostatic seawater pressure. Inflowing fluid at these nodes has a concentration of seawater. The land-surface boundary condition is adopted as a freshwater recharge boundary. The initial groundwater salinity is set to that of seawater, and hydrostatic pressures are adopted as the initial flow conditions. Then the aquifer is simulated for a long-time period without any pumping to reach steady-state equilibrium. Then, this equilibrium condition is considered in the optimization problem with the object of total pumping maximization from an island's groundwater lens for the 10,000 days planning period (Kourakos and Mantoglou, 2011).

The management model is given as follows:

$$\text{Maximize Pump} = \sum_{i=1}^{n} P_i\ \text{m}^3/\text{day} \tag{38}$$

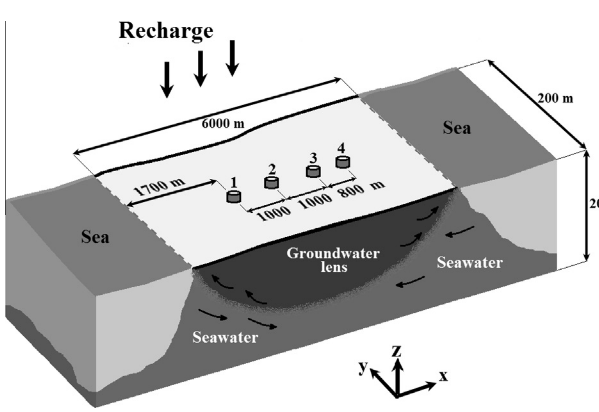

Fig. 5. Modeling domain and the system of wells in an island aquifer (Problem 4).

Table 5
Problem 4 parameters.

Parameter	Value
ρ_s (kg/m^3)	1025
ρ_f (kg/m^3)	1000
c_s (kg/kg)	0
c_f (kg/kg)	0.03415
μ (kg/m s)	0.001
D_{diff} (m^2/s)	1.48×10^{-9}
g_z (m/s^2)	9.81
ε (–)	0.25
K_H (m/day)	10
K_V (m/day)	0.1
R (mm/year)	146
α_L (m)	20
α_T (m)	2
α_V (m)	0.2
P_{min} (m^3/day)	0
P_{max} (m^3/day)	600
c_{max} (kg/kg)	5.0×10^{-4}

subject to:

$$\begin{aligned} &P_{min} \leqslant P_i \leqslant P_{max} \quad \mathrm{m^3/day} \quad 1 \leqslant i \leqslant n \\ &c_i < c_{max} \quad \mathrm{kg/kg} \quad 1 \leqslant i \leqslant n \end{aligned} \tag{39}$$

where c_i is the concentration of pumped water as a mass fraction from well i. c_{max} is the maximum allowable concentration mass fraction for potable water (equivalent to 0.5 kg/m^3 (Kourakos and Mantoglou, 2011)).

3. Application and results

We apply the developed combined simulation–optimization methodology to solve the above benchmark CGMPs after the parameter settings of EAs. The obtained results are also presented and discussed here. All simulation and optimization algorithms and their related combinations are coded via Matlab platform.

3.1. Problem setup for evolutionary algorithms

The proposed EAs find feasible solutions of the constrained problem by penalizing infeasibilities to force the search toward the feasible region. Moreover, some constraints e.g., the search space of decision variables are automatically satisfied by forcing EAs to identify optimal solution in the proper pre-introduced space. The underlying constrained problem is transformed to an unconstrained one, using the penalty function (Pen) and building a single objective function, which in turn is optimized using an unconstrained optimization procedure (Katsifarakis and Petala, 2006; Ataie-Ashtiani and Ketabchi, 2011). The value of Pen, which depends on the exceedance of constraints, is regulated heuristically during the EA process. To ensure all constraints are satisfied, a modified objective function which affected by Pen is assigned to optimization problems as:

$$f_{modified} = f - C_{sc} \times \mathrm{Pen} \tag{40}$$

where C_{sc} is a penalty coefficient. C_{sc} is zero when the constraints are satisfied and gets a large positive value for maximization problems and a large negative values for minimization problems when the respective constraints are violated. It means violate the constraints, significantly increase the modified objective function value in the minimization problems and decrease it in the maximization ones (Katsifarakis et al., 1999; Ataie-Ashtiani and Ketabchi, 2011).

3.2. Parameter settings for evolutionary algorithms

To obtain the most appropriate parameter values of EAs, around 10,000 preliminary experiments are conducted using a variety of values previously reported in the literature. Accordingly, the preferred efficient parameter values set for EAs are given in Table 6. The example references suggested such values are also provided in this Table.

For instance, the experiments of the first parameter setting of each EA which is mentioned in Table 6 (for Problem 3 as an example) are presented in Fig. 6 and the preferred value of this parameter is shown. Similar procedures are performed for other parameters in all problems.

Stopping the computation after the fixed number of simulations is used as the stopping criterion which is identified based on the following analysis. The number of required simulations is obtained and rounded on the basis of some preliminary experiments as two following criteria are satisfied: (1) the exceedance of 10% of the N_n/N_t ratio is reached, where N_n is the number of generations with no improvement in the objective function value and N_t is the number of total generations from the beginning of computation (i.e. the objective function value does not improve in sufficient consecutive generations.) and (2) the convergence rate of the objective function value is less than 0.01% (i.e. an acceptable tolerance of the objective function value variations is reached in two consecutive generations with different values of objective function). Such types of stopping criteria were considered by e.g. Elbeltagi et al. (2005) and Ayvaz (2009).

In the following evaluations, each problem is independently solved 30 times using considered EAs and the average optimal solutions are recorded as same as Karaboga and Akay (2009).

3.3. The combined simulation–optimization results

The developed algorithms and codes are verified using Problem 1. This problem is solved with linear programming technique by setting (−600, 1200) and (−600, 0) to two unknown well coordinates inside the proposed square area (Fig. 2). This setting is based on Karpouzos and Katsifarakis (2013) description because $T_1 > T_2$. Table 7 shows that the minimum total cost is equal to 9486.60 MU/year which is the global optimum for this problem. This agrees with the previous result of Karpouzos and Katsifarakis (2013). Drawdown of all pumping wells is 47.43 m in this condition. In Table 7, the optimal solutions obtained from proposed EAs are presented. The number of required simulations for EAs is also listed in this Table. The results of CACO, SCE, DE, PSO, and HS are similar to linear programming solution. Also, the results of ABC, GA, and SIMPSA are close to exact solution. The difference between the best and the poor results of EAs, obtained by CACO and ABC respectively, is about 3%. Therefore, the applicability of such EAs and also the developed methodology are satisfactory and verified for investigations considered in this study.

Tables 8 and 9 present the optimal solutions of Problems 2a and 2b which consist of the system of seven-wells and eight-wells, respectively. Problem 2 covers the two variants of this type problem. SCE and PSO achieve the best solutions (3906.74 m^3/day and 3698.90 m^3/day) after 50,000 and 10,000 simulations while CACO and SCE (3901.70 m^3/day and 3684.93 m^3/day) are ranked in the second level in terms of solutions quality after 10,000 and 50,000 simulations for Problems 2a and 2b, respectively. The performance of ABC and SIMPSA was poor compared to SCE and PSO. ABC results (3341.74 m^3/day and 3189.82 m^3/day) exhibit 14.5% and 13.8% difference while the results of SIMPSA (3640.27 m^3/day and 3466.7 m^3/day) demonstrate 6.8% and 6.3% difference compared to the best results for Problems 2a and 2b, respectively. It should be noted that while SCE is one of superior EAs in terms of the quality of solutions, but it ranked in the poor place due to need to the most number of simulations. Problems 2a and 2b were also previously solved by Cheng et al. (2000), Park and Aral (2004), and Ataie-Ashtiani and Ketabchi (2011). Elitist CACO was applied in the field of CGMPs for the first time by Ataie-Ashtiani and Ketabchi (2011) and 3901.5 m^3/day and 3669.2 m^3/day were correspondingly estimated for Problems 2a and 2b which were the best solutions of these problems found in the previous studies.

When we compare the obtained results of this study with the best previous solutions given by Ataie-Ashtiani and Ketabchi (2011), SCE and CACO for Problem 2a and PSO, SCE, and CACO for Problem 2b produced slightly better results. Also, the results obtained by the application of Problems 2a and 2b as the variants of this type problem confirm the procedure of our methodology to find the best quality of solutions and the required number of simulations. In the optimal condition, the toe location of SWI and the stagnation points of the system of active and inactive wells are illustrated in Fig. 7 for Problems 2a and 2b, respectively. As shown, the toe location is restricted by the stagnation points of pumping wells generally closer to sea.

The optimal solutions obtained from both linear programming technique as the global optimum and EAs are presented for

Table 6
EA parameters.

EA	Parameters	Selection [a]	Example references
GA	Chromosome size	20–150[b]	Goldberg (1989)
	Selection	Stochastic uniform	Michalewicz (1996)
	Mutation	Gaussian	Bäck and Schwefel (1993)
	Crossover	Scattered	Glover (1994)
	Crossover probability	0.8	Goldberg (1989)
CACO	Ant colony size	30–200[b]	Ataie-Ashtiani and Ketabchi (2011)
PSO	Swarm size	20–150[b]	Kennedy and Eberhart (2001)
	ω	0.2	Clerc and Kennedy (2002)
	C_1	2	Kennedy and Eberhart (2001)
	C_2	2	Kennedy and Eberhart (2001)
DE	Individual size	50–150[b]	Corne et al. (1999)
	F_{DE}	0.9	Corne et al. (1999)
	CR	0.5	Corne et al. (1999)
ABC	Bee colony size	50–300[b]	Karaboga et al. (2014)
	$limit = (0.5P \times D)$	100–2250[b]	Karaboga and Akay (2009)
HS	HMS	20–150[b]	Lee et al. (2005)
	HMCR	0.9	Lee et al. (2005)
	$b_{w_{min}}$	0.0001	Mahdavi et al. (2007)
	$b_{w_{max}}$	1	Mahdavi et al. (2007)
	PAR_{min}	0.1	Lee et al. (2005)
	PAR_{max}	0.5	Lee et al. (2005)
SCE	NC	5–30[b]	Duan et al. (1994)
	$\mathrm{NP} = (2D + 1)$	9–31[b]	Duan et al. (1993)
	$q_{SCE} = D + 1$	5–16[b]	Nelder and Mead (1965)
	α_{SCE}	1	Duan et al. (1993)
	$\beta_{SCE} = (2D + 1)$	9–31[b]	Duan et al. (1993)
SIMPSA	$NT = 10D$	40–150[b]	Cardoso et al. (1996)
	A_r	0.01	Cardoso et al. (1996)
	r_{cool}	0.95	Cardoso et al. (1996)

[a] Based on 1200 preliminary experiments.
[b] The test problems dependent.

Problem 3, in Table 10. The obtained results are in agreement with the previously reported results of this problem by Bear (1979) which was resolved by the application of the linear programming technique. Fig. 8 presents the GWT level in the no-pumping steady-state condition and also under optimal pumping condition with the minimum total cost. As shown in Fig. 8a, the hydraulic gradient is toward the sea for the no-pumping condition. The GWT level drops due to pumping (Fig. 8b) but SWI can be controlled by keeping the determined GWT level in the near-sea cells.

The best solution is obtained by CACO with the optimal solution of 14.04 MU/year which shows 2.0% difference in comparison with the global minimum. HS, PSO, and DE are ranked in the next levels in terms of solutions quality with 4.2%, 4.6%, and 6.0% differences comparing to the optimum, respectively. CACO also needs the lowest simulation numbers among EAs. The obtained results indicate the superiority of CACO in this problem with the highest number of decision variables (15 decision variables). In this problem, ABC and SCE with 19.7% and 14.5% extra cost of the optimal value, provide the worst results. The quality of SCE solution is considerably different among this problem and Problems 1 and 2. Also, in this problem similar to the former problems, SCE is ranked in the low rank as it requires a high number of simulations.

Problem 4 also deals with the maximization of total pumping rates from an aquifer system by application of numerical model of SUTRA (Voss and Provost, 2010). This problem represents a class of island aquifer problems and typical of real-case objectives and constraints (Ataie-Ashtiani et al., 2014). The results are summarized in Table 11. The obtained results are compared with that the solution of 764 m^3/day given by Kourakos and Mantoglou (2011) using SEAWAT and non-dominated sorting GA-II. As seen in Table 11, SCE, SIMPSA, and CACO are the best EAs with the maximum total pumping of 777.27 m^3/day, 774.78 m^3/day, and 762.12 m^3/day, respectively. ABC finds the poorest solution equal to 720.11 m^3/day, with 7.4% difference compared to SCE results. HS (730.47 m^3/day), PSO (734.19 m^3/day), and GA (735.17 m^3/day) did not performed well in this problem in comparison with their performances for Problems 1, 2, and 3. The comparison of the number of simulations shows that GA, CACO, PSO, and HS require 1500 simulations whereas SCE requires 5000 simulations.

For Problem 4, Fig. 9a illustrates the no-pumping steady-state salinity distributions as the initial condition while Fig. 9b shows the obtained condition under optimal pumping rates after the 10,000 days planning period. The salinity distributions of 1.5% (equivalent to 5.0×10^{-4} kg/kg, the maximum allowable concentration mass fraction for potable water) approaches the pumping points of wells, however does not enter them. Therefore, the pumping wells are safe from violated salinities. In this condition, the pumped groundwater has an appropriate quality but the island groundwater quality is deteriorated. Consequently, the smaller exploitation from these four pumping wells can be provided in next planning periods. For example, the optimal total pumping of 232.7 m^3/day (41.7, 89.9, 76.4, and 24.7 m^3/day for wells 1–4, respectively) is obtained for next 10,000 days planning period using e.g., CACO which is extremely smaller than the total exploitation of 777.27 m^3/day obtained in the first planning period. The total pumping rate of 197 m^3/day was reported by Kourakos and Mantoglou (2011) for similar condition.

4. Discussions

In this section, we evaluate the performances of EAs and provide comparative assessments. Then, some of the important remaining challenges for future research in this field are provided.

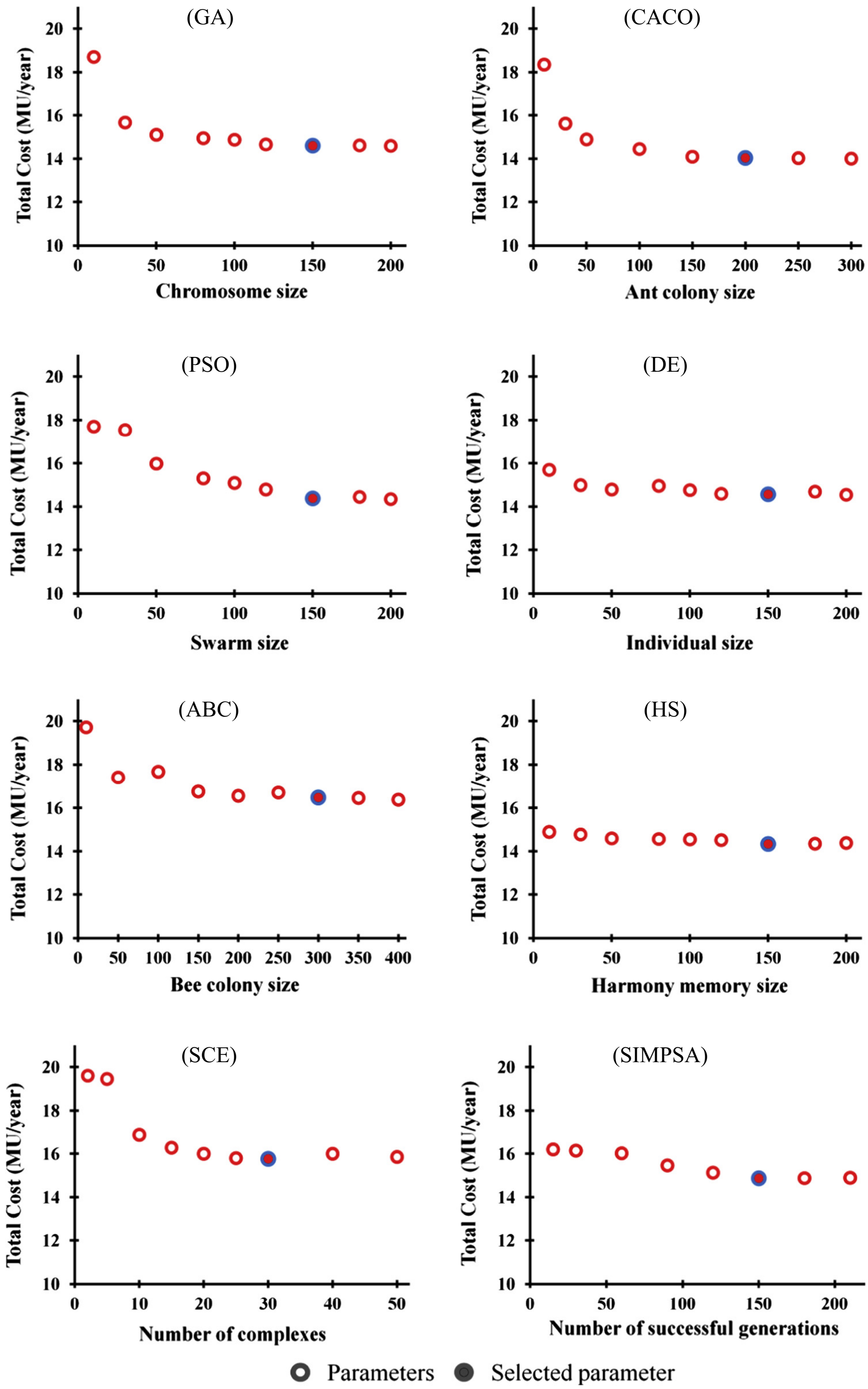

Fig. 6. The first parameter setting examinations of EAs for problem 3.

4.1. Performance evaluations

The mean, maximum, minimum, and standard deviation of optimal solution results have been computed by analyzing the recorded results of 30 independent runs. These results are obtained using nominal 2.20 GHz Intel® Core™ i7 processor with 8.00 GB RAM based on 1,200 experiments (30 times independently runs of eight EAs and five problems). Within the framework of the comparative study, around 60,000,000 numbers of simulations (see Tables 7–11) for abovementioned experiments have been performed.

Table 12 summarizes these statistical results and also indicates the ranking of EAs based on the projected performance (the quality of solution and computational time) in each problem. The processing

Table 7
Problem 1: Comparison of optimal solution results.

Decision variable (m^3/s and m)	Optimal solution results									
	LP[a]	Present Study								
		LP	GA	CACO	PSO	DE	ABC	HS	SCE	SIMPSA
P_1	0.0325	0.0326	0.0340	0.0328	0.0327	0.0325	0.0325	0.0327	0.0326	0.0326
P_2	0.018	0.018	0.0192	0.0179	0.0178	0.0180	0.0187	0.0180	0.0180	0.0185
P_3	0.0325	0.0326	0.0303	0.0326	0.0325	0.0325	0.0291	0.0326	0.0326	0.0326
P_4	0.018	0.018	0.0183	0.0180	0.0182	0.0179	0.0214	0.0179	0.0180	0.0177
P_5	0.0495	0.0495	0.0480	0.0495	0.0496	0.0496	0.0470	0.0494	0.0495	0.0476
P_6	0.0495	0.0495	0.0501	0.0493	0.0492	0.0495	0.0513	0.0495	0.0495	0.0511
x_5	−600	−600	−600	−600	−599.8	−600	−600	−599.7	−600.0	−600
y_5	1200	1200	1,199.2	1200	1,199.8	1200	1200	1,199.4	1200	1200
x_6	−600	−600	−600	−600	−600	−600	−600	−599.6	−600	−600
y_6	0	0	0.1	0	0.1	0	0	0.4	0.0044	0
Total cost (MU/year)	9486.81	9486.60	9517.68	9486.62	9488.22	9486.72	9781.33	9488.65	9486.63	9499.19
Number of simulations	–	–	100,000	10,000	10,000	50,000	20,000	80,000	150,000	80,000

[a] Karpouzos and Katsifarakis (2013).

Table 8
Problem 2a: Comparison of optimal solution results for the system of 7 wells.

Decision variable (m^3/day)	Optimal solution results										
	SMGA[a]	MOGA[b]	CACO[c]	Present study							
				GA	CACO	PSO	DE	ABC	HS	SCE	SIMPSA
P_1	201	198.1	197.6	221.86	206.12	222.28	289.64	329.84	294.35	224.21	291.05
P_2	351	380	386.0	351.29	371.19	315.61	235.59	362.54	262.92	329.46	319.36
P_3	150	150.1	150.1	159.29	152.15	184.37	180.30	371.95	237.76	162.14	311.32
P_4	1497	1462	1460.6	1433.14	1463.41	1427.48	1441.18	574.16	1276.97	1499.90	1003.44
P_5	155	150.0	150.2	157.00	151.42	151.09	150.00	454.98	220.63	150.05	337.64
P_6	1387	1406.6	1406.9	1415.29	1406.62	1430.79	1413.04	972.65	1350.72	1390.99	1170.68
P_7	150	150.2	150.1	150.86	150.09	150.23	150.42	275.62	160.55	150.00	206.78
P_8	–	–	–	–	–		–	–	–	–	–
P_9	–	–	–	–	–	–	–	–	–	–	–
Total pumping (m^3/day)	3891	3897.0	3901.5	3888.71	3901.70	3881.86	3861.97	3341.74	3803.88	3906.74	3640.27
Number of simulations	–	–	20,000	10,000	10,000	10,000	10,000	15,000	10,000	50,000	10,000

[a] Cheng et al. (2000).
[b] Park and Aral (2004).
[c] Ataie-Ashtiani and Ketabchi (2011).

Table 9
Problem 2b: Comparison of optimal solution results for the system of 8 wells.

Decision variable (m^3/day)	Optimal solution results										
	SMGA[a]	MOGA[b]	CACO[c]	Present study							
				GA	CACO	PSO	DE	ABC	HS	SCE	SIMPSA
P_1	255	221.7	222.8	284.00	317.34	417.72	383.63	416.55	370.73	305.53	330.39
P_2	402	579.8	587.6	489.33	421.05	150.04	246.96	286.41	330.96	404.68	373.77
P_3	–	–	–	–	–	–	–	–	–	–	–
P_4	728	733.2	658.5	644.67	704.29	1,028.47	879.85	264.55	723.38	793.95	813.24
P_5	232	178.4	203.1	231.67	251.28	151.70	165.91	264.69	218.83	192.79	303.64
P_6	1500	1402.9	1499.9	1494.33	1485.46	1499.88	1493.78	1060.41	1455.74	1499.05	985.34
P_7	185	215.9	197.0	192.67	182.84	151.05	177.63	271.78	194.80	188.86	271.00
P_8	158	154.4	150.2	163.33	158.79	150.02	154.20	359.04	177.73	150.07	232.44
P_9	150	151.1	150.1	155.67	150.50	150.02	158.49	266.36	158.86	150.01	156.95
Total pumping (m^3/day)	3610	3637.4	3669.2	3655.67	3671.55	3698.90	3660.44	3189.82	3631.03	3684.93	3466.77
Number of simulations	–	–	20,000	10,000	10,000	10,000	10,000	15,000	10,000	50,000	10,000

[a] Cheng et al. (2000).
[b] Park and Aral (2004).
[c] Ataie-Ashtiani and Ketabchi (2011).

time denotes the time required for each simulation and total computational time need for each EA are given as seconds in this Table. The total required time is considered for the purpose of comparison to measure the speed of EAs which mostly consistent with the number of simulations The number of simulations has a considerable impact on total required time because the required simulation numbers of considered EAs are different (See Tables 7–11). However, the processing time of each problem is in the approximately same order for proposed EAs as seen in Table 12. Hence, the reduction of the number of required simulations has a significant role in the final efficiency, as the simulation time of real SWI numerical models is considerable. For example, a simulation time of 55 min for a single run of a real-case SWI numerical model with a relatively coarse discretization was reported by Ataie-Ashtiani et al. (2013a).

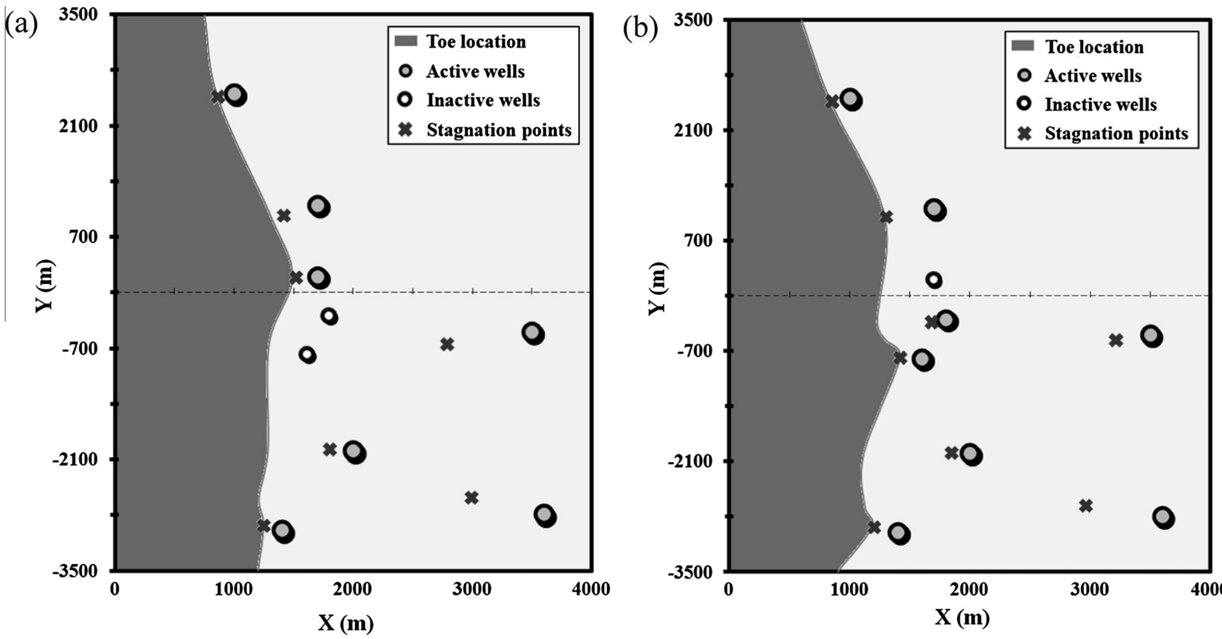

Fig. 7. SWI in the condition of (a) Problem 2a and (b) Problem 2b.

Table 10
Problem 3: Comparison of optimal solution results.

Decision variable (Mm^3/year)	Optimal solution results									
	LP[a]	Present study								
		LP	GA	CACO	PSO	DE	ABC	HS	SCE	SIMPSA
P_1	0	0	0.01	0	0.01	0.03	0.04	0	0.04	0.01
P_2	0	0	0.01	0	0	0.02	0.15	0	0.12	0.05
P_3	0	0	0.04	0	0.01	0.09	0.25	0	0.15	0.06
P_4	0	0	0.02	0	0.03	0	0.17	0	0.13	0.05
P_5	0	0	0.01	0	0	0	0.03	0	0.08	0
P_6	0	0	0.05	0	0.02	0.07	0.31	0	0.31	0.08
P_7	0	0	0.43	0.27	0.49	0.29	0.38	0.54	0.52	0.57
P_8	1.06	0	0.77	0.66	0.29	0.48	0.80	1.07	0.61	0.73
P_9	0	0	0.52	0.30	0.55	0.10	0.38	0.53	0.79	0.52
P_{10}	0	0	0.07	0	0.10	0.04	0.16	0	0.12	0.12
P_{11}	0.8	0.68	0.68	0.67	0.57	0.60	0.74	0.45	0.55	0.54
P_{12}	1.59	2.02	1.35	1.68	1.61	1.57	0.89	1.47	1.16	1.28
P_{13}	1.16	1.60	1.18	1.23	1.29	1.34	1.12	1.00	1.04	1.20
P_{14}	1.59	2.02	1.39	1.83	1.58	1.62	0.75	1.49	0.91	1.17
P_{15}	0.8	0.68	0.46	0.37	0.43	0.74	0.84	0.44	0.47	0.63
Total cost (MU/year)	14.44	13.76	14.61	14.04	14.39	14.58	16.47	14.34	15.76	14.87
Number of simulations	–	–	90,000	60,000	60,000	300,000	60,000	300,000	300,000	60,000

[a] Bear (1979).

In this case, if we consider 5000 and 1500 simulations for SCE and CACO, respectively (Table 11) and considering the abovementioned simulation time for a single run, a difference of 3200 h for simulation time is estimated for these two EAs. Hence more efficient simulation–optimization strategy requires fewer simulations and therefore less computational time to reach the optimal solution.

Based on the results of this study, GA performs poorly than other EAs despite its extensive use in CGMPs. Table 12 reveals the higher performance and robustness of SCE, CACO, and PSO to find the high-quality solutions. On two problems, SCE and on another two out of five problems, CACO are first while in the remaining problem, PSO obtains the best solution. SCE has one of the superlative places for all problems except for the case of Problem 3 which is a complex problem containing 15 decision variables. Hence, on average, CACO is superior in the problems with higher decision variables, besides the having one of the top places among the EAs. For instance, CACO shows the better solutions (up to 17%) than the poor one in Problem 3 which has the highest decision variables among the CGMPs of this study. These results are similar to those of Afshar et al. (2006), Madadgar and Afshar (2009), and Ataie-Ashtiani and Ketabchi (2011). ABC shows the poor results in all Problems, while GA in Problem 1, SIMPSA in Problem 2, SCE in Problem 3, and HS in Problem 4 are the second poor EA in terms of solution quality.

PSO on Problems 1 and 4, and SIMPSA on Problems 2 are the fastest. In Problem 3, GA is the fastest with lowest total time. Although SCE is more successful in the solution of the considered problems due to find the high-quality solutions, its computational time is not competitive and therefore, it restricts SCE applicability compared to CACO and PSO. For example, in Problem 4, SCE needs 8145 s while 2158.5 s is sufficient for PSO. CACO and PSO can be chosen in terms of both abovementioned criteria to application in CGMPs. It should be noted that CACO employs only one control parameter to be set with respect to other superlative EAs (see

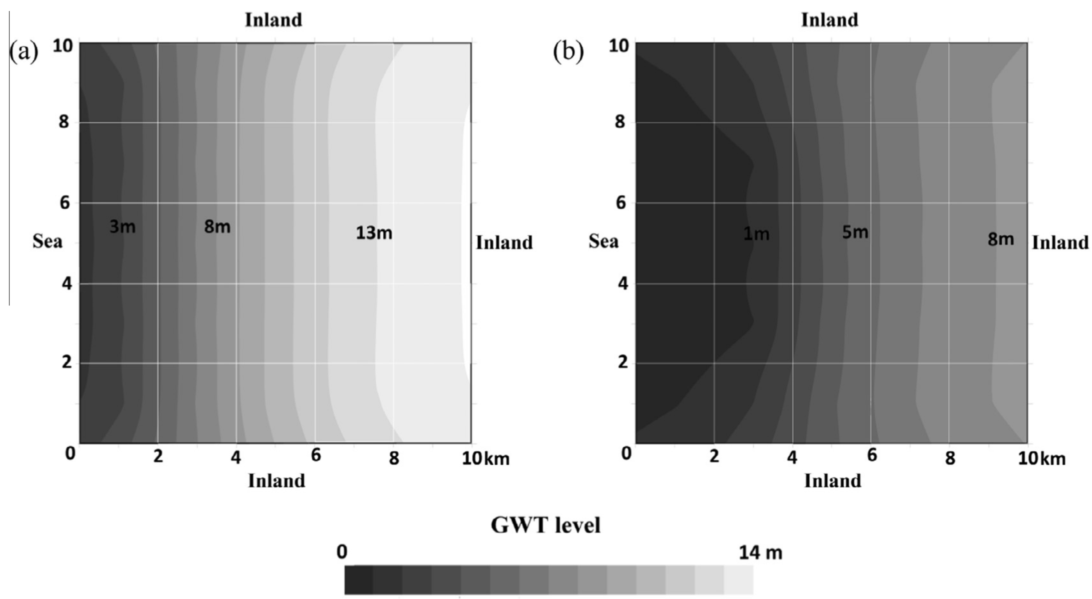

Fig. 8. GWT in Problem 3 (a) no-pumping condition and (b) with optimal pumping condition.

Table 11
Problem 4: Comparison of optimal solution results.

Decision variable (m^3/day)	Optimal solution results								
	NSGA-II [a]	Present study							
		GA	CACO	PSO	DE	ABC	HS	SCE	SIMPSA
P_1	41	121.17	101.19	100.28	95.58	96.60	100.50	96.17	94.67
P_2	500	277.83	368.85	378.49	373.97	327.20	351.23	378.66	378.55
P_3	223	291.83	242.21	191.45	263.37	253.24	236.49	259.12	258.50
P_4	0	44.33	49.88	63.97	27.56	43.07	42.25	43.32	43.05
Total pumping (m^3/day)	764	735.17	762.12	734.19	760.49	720.11	730.47	777.27	774.78
Number of simulations	–	1500	1500	1500	3000	2500	1500	5000	3000

[a] Kourakos and Mantoglou (2011).

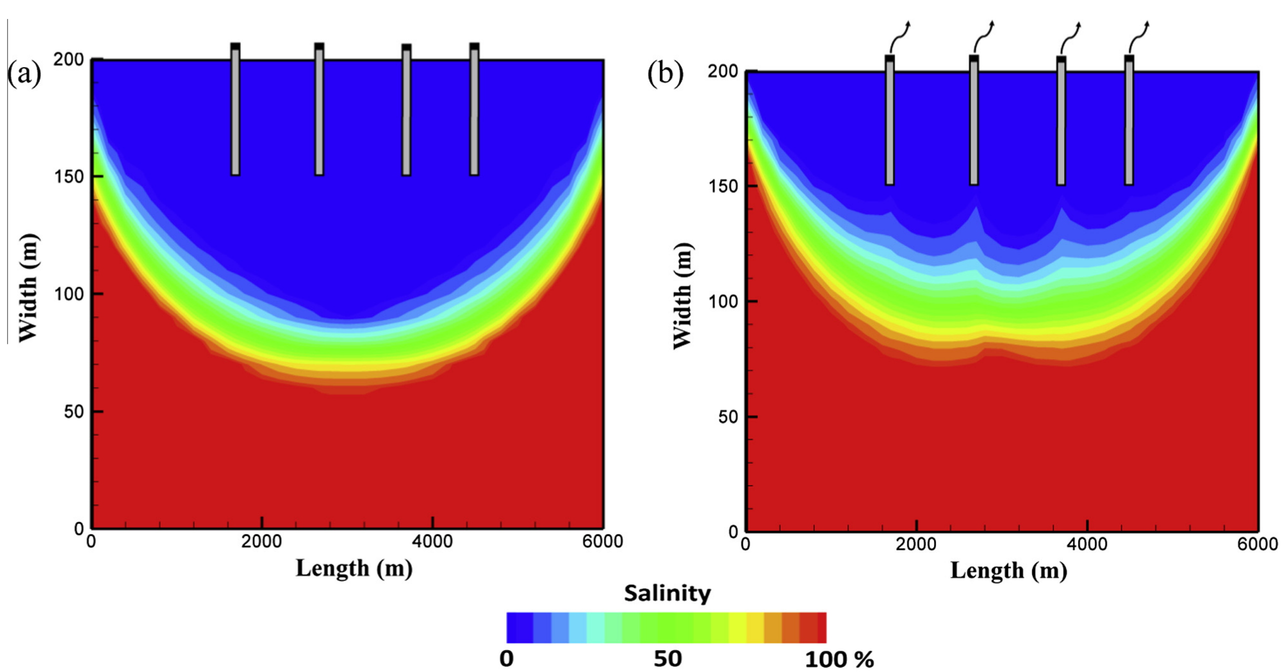

Fig. 9. Steady-state salinity distributions for Problem 4 (a) no-pumping and (b) with pumping.

Table 12
Statistical results of 30 independent runs obtained by EAs.

No.	Range	Number of decision variables	Optimal solution results [b]									
			LP	Factor [a]	GA	CACO	PSO	DE	ABC	HS	SCE	SIMPSA
Problem 1	P[0,0.127] x[-600,600] y[0,1200]	10	9486.60	Mean (MU/year)	9517.68	9486.62	9488.22	9486.72	9781.33	9488.65	9486.63	9499.19
				Max (MU/year)	9581.67	9486.87	9491.00	9487.00	9962.50	9492.80	9486.64	9512.10
				Min (MU/year)	9488.89	9486.60	9486.63	9486.62	9595.00	9486.64	9486.61	9490.50
				Dev (MU/year)	29.09	0.067	1.46	0.12	105.83	2.09	0.01	7.93
				P-Time (s)	6.0×10^{-4}	1.8×10^{-3}	7.9×10^{-4}	8.9×10^{-4}	1.5×10^{-4}	2.2×10^{-4}	1.6×10^{-4}	2.9×10^{-4}
				T-Time (s)	60.0	18.0	7.9	44.5	12.0	17.6	24.0	23.2
Problem 2a	P[150,1500]	7	-	Mean (m^3/day)	3888.71	3901.70	3881.86	3861.97	3341.74	3803.88	3906.74	3640.27
				Max (m^3/day)	3905.02	3909.25	3907.92	3883.03	3494.46	3824.13	3925.04	3780.15
				Min (m^3/day)	3870.10	3897.16	3867.02	3779.78	3165.36	3780.29	3902.04	3531.76
				Dev (m^3/day)	13.31	2.80	18.13	36.94	91.61	18.77	10.23	95.82
				P-Time (s)	0.302	0.293	0.274	0.256	0.261	0.237	0.144	0.179
				T-Time (s)	3020.0	2930.0	2740.0	2560.0	3915.0	2370.0	7200.0	1790.0
Problem 2b	P[150,1500]	8	-	Mean (m^3/day)	3655.67	3671.55	3698.90	3660.44	3189.82	3631.03	3684.93	3466.77
				Max (m^3/day)	3671.05	3723.05	3699.45	3695.37	3191.31	3656.15	3722.63	3534.19
				Min (m^3/day)	3633.20	3643.45	3698.09	3606.26	3185.82	3569.07	3648.48	3382.07
				Dev (m^3/day)	14.64	24.56	0.74	37.10	2.31	37.93	36.72	63.19
				P-Time (s)	0.401	0.314	0.308	0.276	0.298	0.295	0.161	0.194
				T-Time (s)	4010.0	3140.0	3080.0	2760.0	4470.0	2950.0	8050.0	1940.0
Problem 3	P[0,3]	15	13.76	Mean (MU/year)	14.61	14.04	14.39	14.58	16.47	14.34	15.76	14.87
				Max (MU/year)	15.19	14.47	14.82	14.81	16.97	14.48	16.32	15.13
				Min (MU/year)	14.26	13.78	13.93	14.44	15.49	14.16	15.10	14.65
				Dev (MU/year)	0.22	0.18	0.30	0.15	0.42	0.09	0.36	0.16
				P-Time (s)	5.9×10^{-4}	3.6×10^{-3}	2.4×10^{-3}	2.3×10^{-3}	6.1×10^{-3}	9.8×10^{-4}	6.1×10^{-4}	9.3×10^{-4}
				T-Time (s)	53.1	216.0	144.0	690.0	366.0	294.0	183.0	55.8
Problem 4	P[0,600]	4	-	Mean (m^3/day)	735.17	762.12	734.19	760.49	720.11	730.47	777.27	774.78
				Max (m^3/day)	766.01	777.44	760.45	766.12	746.70	757.60	777.43	776.31
				Min (m^3/day)	703.00	729.96	692.87	741.44	687.37	708.75	777.08	771.83
				Dev (m^3/day)	20.17	20.34	28.47	9.38	26.17	19.27	0.18	2.05
				P-Time (s)	1.442	1.500	1.439	1.436	1.618	1.639	1.629	1.590
				T-Time (s)	2163.0	2250.0	2158.5	4308.0	4045.0	2458.5	8145.0	4770.0

[a]Mean: mean of the optimal values; Max: maximum of the optimal values; Min: minimum of the optimal values; Dev: standard deviation of the optimal values; P-Time: processing time; T-Time: total time.
[b]Higher performance is indicated by darker. The best solution for each EA are shown with black cell.

Table 6). Clearly, this characteristic causes an easy parameter setting procedure in comparison to other EAs. This feature is considered as one of the advantages of any EAs (Pourtakdoust and Nobahari, 2004; Karaboga and Akay, 2009).

There are very few studies reported in the literature on the subject of the relative efficiency and robustness of various EAs. Some important examples are Karaboga and Akay (2009), Ma et al. (2013), Civicioglu and Besdok (2013), and Pham and Castellani (2014), however none of them are in groundwater resources management problems. Karaboga and Akay (2009) used 50 benchmark functions in order to test the performance of ABC in comparison with GA, DE, PSO based on repeated 30 times runs as similar as this study. Based on their results, ABC was better than GA, PSO, DE. In our study, ABC has the poorest level among the all EAs in solving CGMPs despite the Karaboga and Akay (2009) results and it shows the necessities of comparative study in each field of optimization problems. Ma et al. (2013) also established that DE and PSO were better than GA under certain conditions of their considered benchmark functions. Based on our results, DE results are superior in four out of five problems while PSO performs better in three of them. Civicioglu and Besdok (2013) compared the EAs of Cuckoo search, PSO, DE, ABC by testing over 50 different benchmark functions. Cuckoo search and DE supplied more robust results than the PSO and ABC in their study. The results of the present study show similar trend for DE and ABC, but do not confirm the superiority of DE to PSO for three out of five problems. Pham and Castellani (2014) compared GA, PSO, ABC, and bee's algorithm to 25 benchmark functions. Their results supported the superiority of PSO relative to GA, but contradict with our findings regarding ABC performance.

Ayvaz (2009) proposed a combined MODFLOW and HS model for groundwater resources management purposes and compared HS to the previously published results of GA, SA, SCE and some of their variants. Their results showed the superiority of SCE and in some cases, HS, and SA in comparison with each other, as confirmed the most results of this study. As can be comprehended from obtained results and available literature, although some efforts have been made in scientific applications and in particular using benchmark test functions, the efficient choice of EAs are still an open challenge for coastal groundwater managers. The results of this paper address some elements of this need for having comparative assessments. Also, it can be utilized as the basis for the choice of appropriate EAs in similar applications. While CACO and PSO are shown efficient in this study, it is important to emphasize that this result is generally problem-dependent. For this reason, in this study, it is tried to utilize the wide range of benchmark CGMPs to dominate this issue. The methodology of EA's selection can be opted by the assessments similar to methodology considered in this study for CGMPs.

4.2. Future research challenges

The other challenges remaining in this context are briefly scrutinized here. Considering this first comparative study in the field of CGMPs, further extensive evaluations of combined simulation–optimization algorithms seems required. One of the main challenges and opportunities for future research is the need for developing, evaluating, and implementing the available methodologies for the combined simulation–optimization models of coastal aquifers to real-case and large-scale problems. Future research efforts can also be focused on other EAs and their variants. For instance, other EAs such as memetic algorithm and cuckoo search (e.g., Elbeltagi et al., 2005; Civicioglu and Besdok, 2013) may provide better solutions for the specific type of problems than EAs of this paper. In addition, high-performance computational tools or some efficient techniques such as parallel processing (e.g., Coumou et al., 2008; Pedemonte et al., 2011) and surrogate models (e.g., Ataie-Ashtiani et al., 2014) can be applied to improve the efficiency of combined simulation–optimization models by reduction the computational time. Accelerating the convergence speed of EAs is one of the other necessities. Afshar et al. (2006) improved the convergence speed of CACO by implementing the elitist strategy in its algorithm. Zecchin et al. (2007) investigated four variants of ACOs and discuss how these EAs match to their problems. Another opportunity is hybridizing the techniques of EAs by coupling them (e.g., Kaveh and Talatahari, 2009). By this technique, researchers can integrate the advantages of the efficient steps of a particular EA into others which are weak in proposed steps, and therefore obtain improved EAs. Kaveh and Talatahari (2009) hybridized the capabilities of PSO, ACO, and HS. PSO was applied for global optimization, ACO was used to update positions of particle to reach the feasible solution space, HS handled variable constraints in their EA, and consequently a more efficient EA in terms of convergence speed was achieved for their application. Dealing with the multi-objective functions in optimization procedure which a more realistic approach, is another important issue. Some examples include Reed et al. (2013) and Ataie-Ashtiani et al. (2014). Reed et al. (2013) evaluated the performances of ten benchmark multi-objective EAs for a representative suite of water resources applications. Ataie-Ashtiani et al. (2014) identified the Pareto-optimal solutions via a combined ANN-GA to solve complex real-case CGMPs considered in Kish Island, Iran.

To address the complexities of real-world problems the uncertainties in parameters and processed shall be infolded. The work of Sreekanth and Datta (2011) is an example of incorporating uncertainty in the process. Considering the recent works on improving the efficiency of Monte Carlo procedure, there are promising research opportunities in this regard. Recently Rajabi and Ataie-Ashtiani (2014) investigated the implementation of Monte Carlo simulations for the propagation of uncertainty in SWI numerical models, which often becomes computationally unaffordable for real cases. More efficient sampling strategies, which required fewer simulations and less computational time to reach a certain level of accuracy, were suggested in their studies. Moreover, Rajabi et al. (2014) proposed the application of non-intrusive polynomial chaos expansions for uncertainty propagation analysis in SWI numerical modeling studies. They showed that non-intrusive polynomial chaos expansions provided a reliable and yet computationally efficient surrogate of the original numerical model. Conceptualizing some global and significant concerns such as the effects of climate change (e.g., Ketabchi et al., 2014; Mahmoodzadeh et al., 2014) is one of areas which demand further examinations to identify how these impacts change the coastal groundwater management. As these issues (e.g., climate change-induced sea-level rise and variations in recharge rates) are essentially uncertain, stochastic conceptualization is compelled to properly distinguish between the various impacts and different SWI underlying factors (Werner et al., 2013).

5. Conclusions

This paper presents the results of the application of eight EAs to four benchmark CGMPs with different degree of difficulty. Pumping rate schemes and proposed limits, well locations, operating cost, GWT level, SWI toe location, and salt concentration are examples of the objective functions and constraints considered in the proposed CGMPs. In all problems and their associated simulation and optimization formulation presented here, a combined simulation–optimization approach has been used to obtain decisions for coastal groundwater management and particularly the SWI protection of coastal regions. To set the most efficient parameter values of EAs, a trial and error approach using the number of preliminary experiments has been adopted. Surveying the literature indicates that just a few of EAs have been applied in the resolving of CGMPs and commonly focused on a certain EA application, mostly GAs. Therefore, there is a need for a systematic and comprehensive evaluation of a wide range of EAs applications for CGMPs. This investigation seems to be the first effort in this regard. This paper is also the first attempt to apply PSO, ABC, HS, and SCE to resolving groundwater optimization problems and especially CGMPs. Also, CACO, DE, and SIMPSA which have rarely been utilized in this field are tried.

On the basis of the findings of this investigation, the following points can be compiled in conclusion:

- The applicability and capabilities of each EA toward CGMPs are compared in terms of results quality and required computational time. The comparisons show that the performance of SCE, CACO, and PSO is outstanding compared to the other EAs examined according to the quality of solutions whereas ABC show the least fitting results. Also, CACO seems better than SCE in complex CGMPs with higher decision variables. Moreover, GA finds imperfect solutions in comparison with some of the other applied EAs, despite the wide application to solve CGMPs in former works. In terms of required computational time, PSO and SIMPSA are ranked in the first places. Nevertheless SCE is the slowest EA, even up to four times compared to the fastest EA.
- CACO and PSO are recommended for application in CGMPs. These EAs are the fastest and also generally outperform all other EAs in terms of solution quality. Also, among the superlative EAs, CACO has only one control parameter to be set. This is an advantage of CACO because it has an easy parameter setting procedure than other EAs.
- The future opportunities and challenges in this field are: implementing other EAs and their variants, investigating the stochastic objective functions and constraints including uncertainty analyses, considering the multi-objective purposes, hybridizing EAs, applying the high-performance techniques such as parallel processing and surrogate models, investigating the real-case and large-scale problems, and considering the significant impacts such as climate change effects.

In summary, this paper clearly demonstrates that the inclusion of new EAs such as SCE, CACO, and PSO leads to improve the efficiency of considered approaches in many CGMPs. To conclude, a deep understanding of the efficiency and robustness of EAs might help the coastal groundwater managers to select the efficient EAs. It is noteworthy that the proposed methodology and also considered EAs are applicable to real-case and large-scale CGMPs or even in different types of problems. However, particular attention should be endowed to the problem-dependent behavior of EAs.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jhydrol.2014.11.043.

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