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Development of Real-Time Conjunctive Use Operation Rules for Aquifer-Reservoir Systems

Elahe Fallah-Mehdipour · Omid Bozorg Haddad · Saeed Alimohammadi · Hugo A. Loáiciga

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Abstract Real-time operation rules are strategies that use prior and current system states to achieve desired conditions in future periods. Commonly, these rules are based on estimates of current and future inflows, current aquifer and reservoir storages, hydraulic heads, power plant capacities and energy demands, and water demand values from users. This paper proposes the development and implementation of a linear real-time operation rule for lumped and distributed aquifer-reservoir systems. A fixed length gene genetic programming (FLGGP) approach is applied to find linear operation rules for a lumped aquifer- reservoir system and compared to an approach using genetic algorithms (GA). Results obtained with the FLGGP are significantly better (over 30 %) than those calculated with GA. The added functions and mathematical operators of the FLGGP create more effective operation rules in a conjunctive aquifer-reservoir system. In addition, lumped and distributed model performances are compared. Results obtained show reliability higher and vulnerability lower for water allocations in distributed aquifer-reservoir systems than those corresponding to lumped systems.

Keywords Fixed length gene genetic programming · Aquifer-reservoir system · Real-time operation · Optimization

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1 Introduction

Growing demand under limited water resources has increased in many parts of the world. Iran is one of the arid and semi-arid countries where there are serious problems to supply water demands that include municipal, agricultural, and industrial users. Therefore, optimizing the use of existing water resources is one of the best methods to cope with water scarcity.

Recently, several optimization techniques have been developed and applied in various fields of water resources systems such as reservoir operation (Bozorg Haddad et al. 2011a; Fallah-Mehdipour et al. 2012a, 2013a), hydrology (Orouji et al. 2013), project management (Bozorg Haddad et al. 2010a; Fallah-Mehdipour et al. 2012b), cultivation rules (Bozorg Haddad et al. 2009; Noory et al. 2012), pumping scheduling (Bozorg Haddad et al. 2011b), hydraulic structures (Bozorg Haddad et al. 2010b), water distribution networks (Bozorg Haddad et al. 2008; Seifollahi-Aghmiuni et al. 2011, 2013), operation of aquifer systems (Bozorg Haddad and Mariño 2011), site selection of infrastructures (Karimi-Hosseini et al. 2011), and algorithmic developments (Shokri et al. 2013). Only a few of these works dealt with the development of real-time conjunctive use operation rules for aquifer-reservoir systems.

The Food and Agricultural Organization (FAO 1993) presented examples of the conjunctive use of surface and groundwater that minimize the undesirable physical, environmental, and economic effects of the separate management of these two water resources.

Buras (1963) applied aquifers and reservoir resources to supply agricultural demands by probabilistic dynamic programming (PDP). Mobasheri and Sharon (1969) employed nonlinear programming (NLP) to determine the best alternative for a conjunctive system. Nishikawa (1998) developed a simulation-optimization model for the optimal management of the city of Santa Barbara’s water resources during a drought. These investigations used gradient-based optimization methods to determine the best operational alternative. Gradient-based methods may converge to local optimal solutions instead of global ones when solving complex programs. Karamouz et al. (2004) developed a dynamic programming (DP) optimization model for conjunctive use planning to supply agricultural water demands, reduce pumping costs, and control groundwater table fluctuations. Although the latter authors applied DP successfully, it is known that DP is beset by dimensionality problems in complex applications. Alimohammadi et al. (2009) proposed a cyclic storage system (CSS) for available water management in both surface impoundments and groundwater aquifers to maximize the efficient use of available resources with minimum cost.

Gradient based methods and DP are two optimization techniques that can be used to determine optimal solutions. However, the corresponding modeling requirements and computational time can be prohibitive when solving conjunctive optimization problems, which tend to be highly nonlinear. Moreover, the probability of finding global optima is lower than that of finding local optima. For these reasons evolutionary algorithms that can determine optimal/near-optimal solutions by random search have gained popularity in the optimization community (Fallah-Mehdipour et al. 2011a) and are currently extensively applied in water-resources engineering (e.g. Fallah-Mehdipour et al. 2011b, 2013b; Noory et al. 2012; Orouji et al. 2013; Ahmadi et al. 2014 and Beygi et al. 2014).

Yang et al. (2009) used an integrated tool involving: (1) multi-objective genetic algorithm (MOGA), (2) constrained differential dynamic programming (CDDP) and (3) a groundwater simulation model for conjunctive use of surface and subsurface water in southern Taiwan. Afshar et al. (2010) proposed surface and subsurface impoundment subsystems that minimize most of the complexities associated with large-scale surface impoundments for water supply purposes. They implemented a hybrid two-stage genetic algorithm-linear programming (GA-LP) solution algorithm Safavi et al. (2010) employed artificial neural networks (ANN) as a simulator and GA as an optimizer in the optimal operation of surface and ground water resources for the Najafabad plain in west-central Iran. Safavi and Esmikhani (2013) developed a support vector machine (SVM) model as a simulator of surface water and groundwater interaction model while GA was used as the optimization method. Rezapour Tabari and Soltani (2013) applied the non-dominated sorting genetic algorithm (NSGA-II) to calculate the optimal trade-off between maximization of minimum reliability and minimization of costs due to water supply, aquifer reclamation, and violation of reservoir capacity constraints. The sequential genetic algorithms (SGA) was also implemented and used for comparison with the NSGA-II model.

Genetic programming (GP) is a subset of evolutionary algorithms that is commonly used as a black- box method to calculate best relations between different input(s) and output(s). Savic et al. (1999) introduced GP as an evolutionary computing method for a rainfall-runoff model. Rabunal et al. (2007) proposed GP to model rainfall and runoff in an urban basin. They showed that the methodology can be used to solve similar problems by combining GP and ANN. Sivapragasam et al. (2008) used GP to route complex flood hydrographs in a channel reach along the Walla River, USA. Wang et al. (2009) used autoregressive moving-average (ARMA) models, ANN, adaptive neural-based fuzzy inference system (ANFIS), GP, and SVM for forecasting river flow. Fallah-Mehdipour et al. (2013c) applied GP to rough stage hydrograph in open channels.

This paper develops and applies a fixed length gene genetic programming (FLGGP) algorithm to find optimal operating rules for lumped and distributed aquifer- reservoir systems. Results show the superior efficiency of the FLGGP rules compared to those derived from common linear rules. Moreover, aquifer modeling based on lumped and distributed models are compared in respect to their capacities to allocate optimal volumes of water to meet demands.

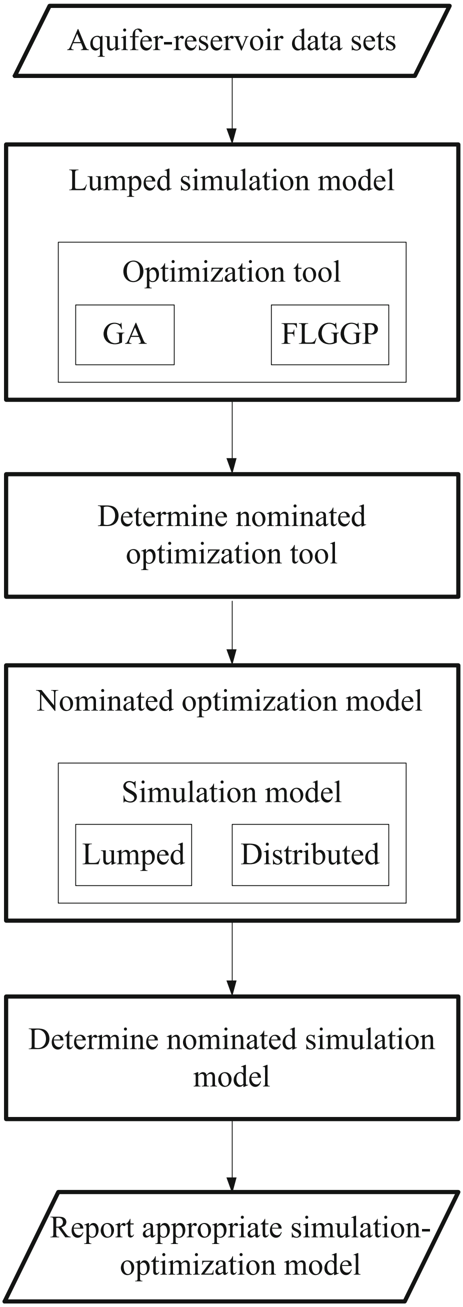
2 Methodology

A combination of simulation and optimization is applied to derive the optimal operation of an aquifer-reservoir system. Firstly, the aquifer is simulated using a lumped model. This model is coupled with GA and FLGGP as the optimization tools. Secondly, the GA and FLGGP tools are applied in distributed modeling of the aquifer-reservoir system. Figure 1 summarizes this paper's methodology.

3 Simulation of a Conjunctive System

The conjunctive use of surface and ground water resources is an interactive allocation problem that poses challenging complexities for water resources planning and

Fig. 1 Flowchart of the paper's methodology



management. Aquifers and reservoirs are water resources available to supply municipal, agricultural, and industrial water demands, and their conjunctive use is exploited in this paper.

4 Reservoir Modeling

Reservoirs hold large volumes of water. They are operated to meet downstream water demands. The continuity equation is central to reservoir operation:

$$S_{t+1} = S_t + I_t - RD_t - SP_t - Loss_t \tag{1}$$

where S_t and S_{t+1} = storage volume of the reservoir at the beginning of the t^{th} and the $t+1$th periods ($10^6 \times \text{m}^3$), respectively; I_t = inflow to the reservoir during the t^{th} period ($10^6 \times \text{m}^3$); RD_t = released water volume from the reservoir during the t^{th} period ($10^6 \times \text{m}^3$); SP_t = volume of spilled water over the reservoir's dam during the t^{th} period ($10^6 \times \text{m}^3$); and $Loss_{it}$ = volume of water lost from the reservoir during the t^{th} period ($10^6 \times \text{m}^3$).

The storage S_t is constrained as follows:

$$S_{Min} \leq S_t \leq S_{Max} \tag{2}$$

in which, S_{Min}, S_{Max} = minimum and maximum allowable storage volumes, respectively.

5 Aquifer Modeling

An aquifer is a natural, subsurface, water body in which hydraulic head evolves driven by hydrological and hydrogeological processes. Lumped and distributed models are employed for hydraulic head modeling.

6 Lumped Aquifer Models

In lumped models the total inputs to and outputs from an aquifer are calculated and the variation of aquifer volume during the t^{th} period, ΔV_t, is determined as follows:

$$\Delta V_t = \alpha \times River_t - RG_t + \sum_{i=1}^{I} \beta_i \left(RG_{i,t-1} + RD_{i,t-1} \right) + \gamma \times P_t \tag{3}$$

where α= river infiltration during the t^{th} period (percent); $River_t$= river flow during the t^{th} period ($10^6 \times \text{m}^3$); RG_t= groundwater discharge during the t^{th} period ($10^6 \times \text{m}^3$); β_i= return flow from i^{th} water-demand sector to the aquifer; $RG_{i,t-1}$ and $RD_{i,t-1}$= allocated water to the i^{th} demand sector during the t-1th period from aquifer and reservoir ($10^6 \times \text{m}^3$), respectively; I= number of demand sectors; P_t= precipitation during the t^{th} period ($10^6 \times \text{m}^3$); and γ= precipitation percolation during the t^{th} period (percent). According to Eq. (3), a percentage of water allocated to each demand sector during each period returns to the aquifer during the next period.

The value of the aquifer's hydraulic head in each period, h_t is a function of $Area$= aquifer area; S=aquifer storage coefficient (or storativity), and the variation of hydraulic head in each period, Δh_t is calculated by using the following equations:

$$\Delta h_t = \frac{\Delta V_t}{Area.S} \tag{4}$$

$$h_{t+1} = h_t + \Delta h_t \tag{5}$$

The drop in aquifer head through the operational period is:

$$h_1 - h_{N+1} \le \chi \tag{6}$$

in which, χ= an allowable threshold of hydraulic variation and N= number of operational periods.

7 Distributed Aquifer Model

Two-dimensional groundwater flow in a confined, isotropic, and heterogeneous aquifer is approximated by the following equation (Bozorg Haddad et al. 2013):

$$\frac{\partial}{\partial x}\left(Tr\frac{\partial h}{\partial x}\right) + \frac{\partial}{\partial y}\left(Tr\frac{\partial h}{\partial y}\right) \pm W = S\frac{\partial h}{\partial t} \tag{7}$$

in which, Tr= aquifer transmissivity; h= hydraulic head; S=storativity; W= the net of recharge and discharge within each areal unit of an aquifer model, e.g., a cell in a finite-difference grid; W is positive (negative) if it represents recharge (discharge) in the aquifer; and x, y= spatial coordinates, and t=time.

The flow Eq. (7) is solved numerically, most commonly with the method of finite differences (FDM). Figure 2 depicts a typical finite-difference cell (i, j) in a confined aquifer showing groundwater fluxes through its perimeter and cell geometry. The water-balance

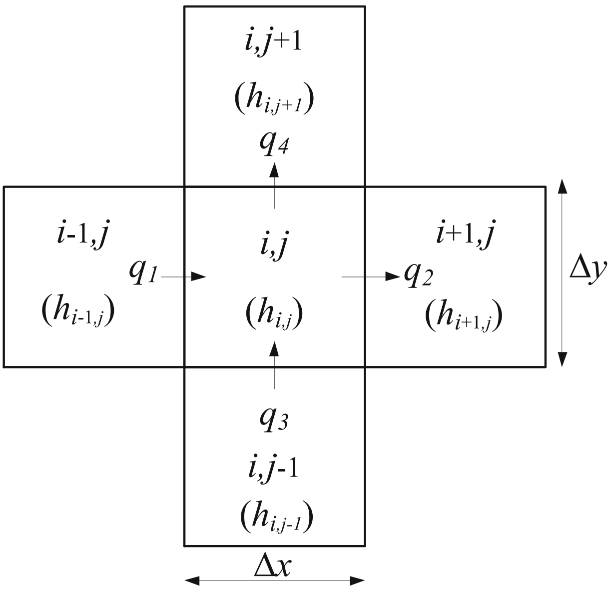


Fig. 2 A typical finite-difference cell depicting groundwater fluxes and geometry

equation for the cell (i, j) is:

$$q_2 - q_1 + q_4 - q_3 + W \times \Delta x \times \Delta y = S\frac{\partial h}{\partial t} \times \Delta x \times \Delta y \tag{8}$$

in which, q_1, q_2, q_3 and q_4= groundwater flows through the walls of cell (i, j); Δx and Δy= horizontal and vertical differences in the ADIM network, respectively.

The implicit finite-difference form of the groundwater flow equation for cell (i, j) of a confined aquifer is obtained by using Darcy's law in Eq. (8) and replacing derivatives with their finite-difference approximations (Bear 1979):

$$\begin{aligned}&\left(Tr_{i+1,j} + Tr_{i,j}\right)/2 \times \left(\frac{h^t_{i+1,j} - h^t_{i,j}}{\Delta x^2}\right) - \left(Tr_{i-1,j} + Tr_{i,j}\right)/2 \times \left(\frac{h^t_{i,j} - h^t_{i-1,j}}{\Delta x^2}\right) + \dots \\ &\left(Tr_{i,j+1} + Tr_{i,j}\right)/2 \times \left(\frac{h^t_{i,j+1} - h^t_{i,j}}{\Delta y^2}\right) - \left(Tr_{i,j-1} + Tr_{i,j}\right)/2 \times \left(\frac{h^t_{i,j} - h^t_{i,j-1}}{\Delta y^2}\right) + \dots \\ &\frac{W_{i,j}}{\Delta x \times \Delta y} = S \times \left(\frac{h^t_{i,j} - h^{t-1}_{i,j}}{\Delta t}\right)\end{aligned} \tag{9}$$

for all cells i, j in the aquifer domain, in which entity$_{r,s}$ denotes the value of a variable or parameter in cell r, s=i-1, i, i+1, j-1, j, j+1 according to the finite-difference geometry shown in Fig. 2. The system of Eq. (9) is solved with numerical schemes such as the alternating direction implicit method (ADIM, see, Bear 1979, for a review). Karahan and Ayvaz (2005) proposed an iterative alternating direction implicit method (IADIM) to solve for hydraulic heads in Eq. (9). The IADIM is adopted in this work.

8 Optimization Tools

This paper compares the capabilities of two optimization tools, GA and FLGGP, in calculating optimal operational rules of a conjunctive system. These algorithms emulate mathematically biological processes such as evolutionary adaptation to calculate optimal or near optimal solutions of optimization problems.

9 Genetic Algorithm (GA)

The GA is one of the oldest random-search algorithms (Orouji et al. 2013). It starts the search process for an optimal solution by generating a population of strings called chromosomes. There is an objective function corresponding to each chromosome. Chromosomes move toward better solutions in an iterative searching process based on the calculated value of the objective function. Each iteration in the GA algorithm is named a generation. In each generation, chromosomes are selected from the current population based on their calculated objective function and modified to form a new population. There are two main processes in the GA: (1) selection using roulette wheel, competition, and tournament methods, and (2) reproduction using crossover and mutation operators. New chromosomes (children) are performed from randomly selected chromosomes (parents) by the crossover operator. In mutation operator, new random decision variables are generated in each chromosome by the mutation operator. The aforementioned process continues up until reaching a stopping criterion, which is commonly a specified maximum number of generations.

10 Fixed Length Gene Genetic Programming (FLGGP)

The FLGGP is an evolutionary computation algorithm based on the GA. This algorithm uses GA and genetic programming (GP) advantages to overcome their individual limitations. This paper uses a fixed-length linear string of chromosomes that improves the performance of GP.

The FLGGP performs random iterative searches for optimal solutions of an optimization problem in a manner akin to GA (Fallah-Mehdipour et al. 2013d) but with the advantage of adding functions and operators than enhance its capacity to evaluate mathematical expressions. In the FLGGP, each section chromosome represents a polynomial equation of a subsystem relation. Several input variables and one output variable are considered in each section. For example, if a system includes input (x') and output (y') variables, the mathematical expression $y'=[a(F((x')^b))+c]^d$ represents a section. Figure 3 shows this FLGGP chromosome. In this structure, a, b, c, and d as the 1st, 3rd, 5th and 6th gene are numerical variables and the 2nd gene is a mathematical function such as sin, cos, log, and exp. The 4th gene is a mathematical operator from {+,−,×,÷} set. Various types of mathematical equations such as linear, nonlinear, exponential and logarithmic can be considered in this polynomial structure. A chromosome is extended by adding more sections if there is more than one sub-system. Figure 4 presents a chromosome structure in a problem with two subsystems considering two sections. $y_1' = \left[a_1\left(F_1\left((x')^{b_1}\right)\right) + c_1\right]^{d_1}$ and $y_2' = \left[a_2\left(F_2\left((x')^{b_2}\right)\right) + c_2\right]^{d_2}$ are two sub-system relations extracted from the chromosome. There is an objective function for each chromosome. Other searching processes of the FLGGP (involving levels such as selection, crossover, and mutation) are identical to those used by the GA.

11 Case Study

Iran is an arid country that has insufficient surface water resources to meet water demands, especially in the warm season. Thus, consumers resort to groundwater resources, predominantly in municipal regions of Iran. Tehran, Iran's capital, is a major water user, accounting for a demand of about 340×10^6 m^3, supplied from the Karaj dam. However, water demands downstream of Karaj dam equals 767×10^6 m^3, which exceeds the annual average inflow to Karaj dam of about 415×10^6 m^3. The Karaj aquifer is a groundwater resource used as supplemental water supply to meet demand sectors. Figure 5 displays water sources and water uses in the Tehran-Karaj regions. There is no available infrastructure to meet the municipal water demand of Tehran with groundwater from the Karaj aquifer.

12 Application of the Lumped Model

A lumped model considers an aquifer as an integrated body in which the water budget and hydraulic changes are calculated using the volumes of input to and output from the aquifer. In

a	*F*	b	+	*c*	d

Fig. 3 Chromosomal structure of FLGGP with one set of input and output dataset

a_1	F_1	b_1	+	c_1	d_1	a_2	F_2	b_2	+	c_2	d_2

Fig. 4 Chromosomal structure of FLGGP with two sections

this case study, the Tehran municipal sector, municipal, and agricultural sectors of the Karaj region have first, second, and third priorities in having their demands met, respectively. The objective function is as follows:

$$Min. \sum_{t=1}^{T} 100 \left(\frac{De_t^{Tehran} - R_t^{Tehran}}{De_t^{Tehran}} \right)^2 + 10 \left(\frac{De_t^{Karaj} - R_t^{Karaj}}{De_t^{Karaj}} \right)^2 + \left(\frac{De_t^{Agri} - R_t^{Agri}}{De_t^{Agri}} \right)^2 \quad (10)$$

in which, De_t^{Tehran}, De_t^{Karaj} and De_t^{Agri}= volume of water demand of the Tehran municipal sector, other municipal, and agricultural sectors of the Karaj region, respectively; and R_t^{Tehran}, R_t^{Karaj} and R_t^{Agri}= allocated water to the Tehran municipal sector, other municipal, and agricultural sectors of the Karaj region, respectively. Water-supply priorities are reflected by the weighing factors 100, 10, and 1 for Tehran's, municipal, and agricultural sectors, respectively, in the objective function.

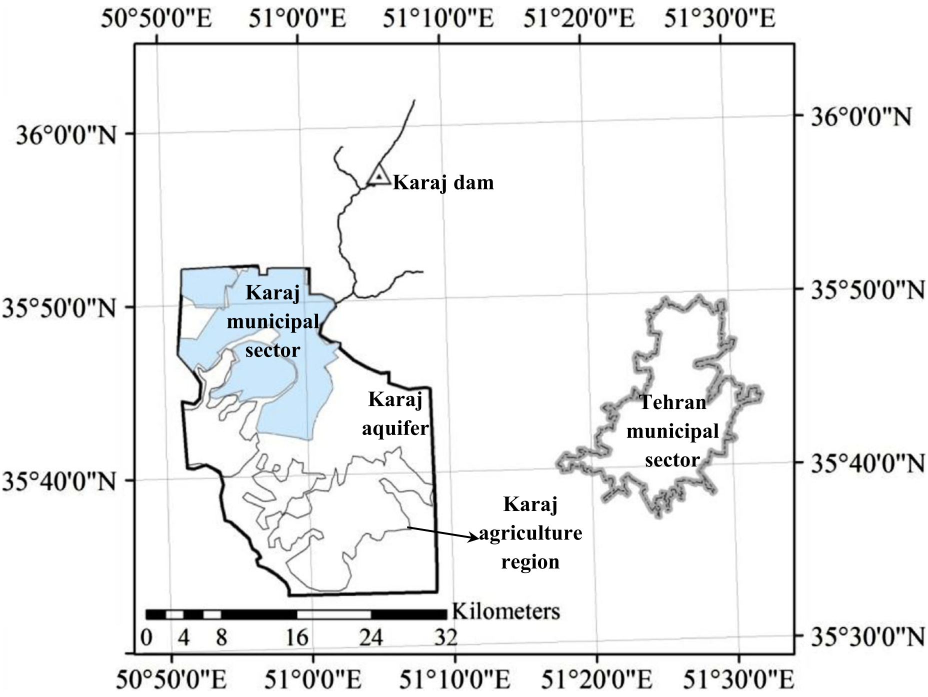


Fig. 5 Water resources and demand regions in the Tehran-Karaj region

General mathematical equations are used to determine operation rules for the reservoir and aquifer models when using lumped models, as follows:

$$RD_t = Z_1(S_t, I_t, h_t, De_t) \tag{11}$$

$$RG_t = Z_2(S_t, I_t, h_t, De_t) \tag{12}$$

$$De_t = De_t^{Tehran} + De_t^{Karaj} + De_t^{Agri} \tag{13}$$

in which Z_1 and Z_2= optimal operation rules for the reservoir and aquifer, respectively, and all other variables previously defined (see Eqs. (1), (2), (10)). Operators calculate optimal volumes of water released from the reservoir and extracted water from the aquifer by knowing S_t, Q_t, h_t and De_t that represent the water system's conditions.

Linear operating rules are used by GA to calculate releases from the reservoir (RD_t) and extraction from an aquifer (RG_t), as follows:

$$RD_t = a_1 I_t + a_2 S_t + a_3 h_t + a_4 De_t + a_5 \tag{14}$$

$$RG_t = a_6 I_t + a_7 S_t + a_8 h_t + a_9 De_t + a_{10} \tag{15}$$

The coefficients in Eqs. (14) and (15), $\{a_1,\ldots,a_{10}\}$ are present in a chromosome and are optimized by the GA. Thus, a linear operation pattern is dictated to the system.

If the operating rules are derived by the FLGGP, two mathematical Eqs. (16) and (17) with no predefined pattern are added to the conjunctive model:

$$RD_t = (b_1 \sin(I_t) \times b_2 \cos(S_t) + b_3 h_t + b_4 \exp(De_t))^{b_5} \tag{16}$$

$$RG_t = \left(\frac{b_6 \exp(I_t) \times b_7 \cos(S_t)}{b_8 \sin(h_t) - b_9} + b_{10}(De_t)\right)^{b_{11}} \tag{17}$$

The numerical variables ($\{b_1,\ldots,b_{11}\}$), mathematical operators ($\{+,-,\times,\div\}$), and functions ($\{\sin,\cos,\exp\}$) are present in the FLGGP rules.

The operation rules herein calculated are for water allocation. The volume of water released from the reservoir plus groundwater extraction, RD_t+RG_t, is allocated to users according to their assigned priorities.

The language for interactive general optimization (LINGO) NLP software was applied to determine the best solution to the aquifer- reservoir system's long-term operation. The calculated objective function was 1001.89. A second solution was obtained for the real-time operation of the reservoir-aquifer system. The linear operation rules considered Eqs. (14) and (15) in finding the real-time operation solution with the GA. Being a random-search method, GA may find different solutions in different runs. Five different runs were carried out with 1000 generations and 10 chromosomes. The statistical results are listed in Table 1. The minimum (best) calculated objective function value is 14.60 % smaller (better) than the average value. The optimal operation rule for the best calculated objective function is:

$$RD_t = 0.260(I_t) + 0.282(S_t) + 0.023(h_t - 1000) + 0.036(De_t) + 1.960 \quad \forall t = 1, 2, \ldots, N \tag{18}$$

$$RG_t = 0.003(I_t) + 0.059(S_t) + 0.013(h_t - 1000) + 0.097(De_t) + 0.033 \quad \forall t = 1, 2, \ldots, N \tag{19}$$

Equations (18) and (19) are optimal linear operating rules for conjunctive water use. The FLGGP algorithm was used to derive operational rules without any predefined mathematical pattern. 10 chromosomes and 1000 generations were used in FLGGP as done with the GA. The FLGGP relies on a random-based search and different runs must be carried out. Table 2 lists the FLGGP results. The best (minimum) value of the objective function equals 2115.85. Equations (20) and (21) are optimal operation rules associated with the minimum value of the objective function:

$$RD_t = \left\{ \begin{array}{l} 0.524\cos\left[(I_t)^{0.380}\right] + 0.888(S_t)^{0.655} - 1.222(h_t - 1000)^{1.381} \\ +0.009\sin\left[(De_t)^{0.86}\right] + 1.965 \end{array} \right\}^{1.215} \quad \forall t = 1, 2, \ldots, N \tag{20}$$

$$RG_t = \left\{ \begin{array}{l} 0.361\cos\left[(I_t)^{0.695}\right] - 1.800\sin\left[(S_t)^{0.421}\right] + 1.372(h_t - 1000)^{0.149} \\ +0.201\cos\left[(De_t)^{1.850}\right] + 1.599 \end{array} \right\}^{1.514} \quad \forall t = 1, 2, \ldots, N \tag{21}$$

The minimum value with the FLGGP is 32.58 % smaller than that calculated with the GA. Moreover, because of the mathematical operators and functions used in calculating operation rules with FLGGP, its coefficient of variation is 43.48 % larger than the GA's.

Large groundwater extraction has lowered the average hydraulic head in the Karaj aquifer. Figure 6 depicts more than 10 m of drawdown over a 15-year period. The annual average aquifer head must be increased by 25 % to meet Iran's law of economic, social, and cultural development. Application of optimal operation rules can reduce aquifer drawdown while simultaneously supplying water users. Figure 6 shows that the GA and FLGGP control the trend of aquifer hydraulic head.

Although Eqs. (20) and (21) are optimal operation rules of conjunctive use, these rules include deterministic and stochastic variables. In real-time operation, stochastic

Table 1 Results of GA and statistical measures for linear operating rules calculated with the lumped model

Number of run	1	2	3	4	5
Objective function	3138.51	4373.49	3372.97	3770.36	3720.69
Statistical measures	Minimum	Average	Maximum	Standard deviation	Coefficient of variation
	3138.51	3675.21	4373.49	468.54	0.13

Table 2 Results of FLGGP and statistical measures calculated with the lumped model

Type of variable	Number of run	1	2	3	4	5
Stochastic and deterministic	Objective function	2115.85	3534.46	2764.89	3400.68	2215.76
	Statistical measures	Minimum	Average	Maximum	Standard deviation	Coefficient of variation
		2115.85	2806.33	3534.46	653.96	0.23
Deterministic	Number of run	1	2	3	4	5
	Objective function	2245.94	2121.98	3936.16	4457.28	3735.96
	Statistical measures	Minimum	Average	Maximum	Standard deviation	Coefficient of variation
		2121.98	3303.07	4457.28	1045.61	0.32

variables should be estimated by prediction models to apply in the operation rules. The estimated values directly affect the operational procedures that govern reservoir and aquifer. Inappropriate selection of a prediction model impacts system performance and increases the computational burden in optimization. Optimal simultaneous derivation of an operation rule and prediction model reduces probabilistic estimation errors.

The aforementioned process needs an appropriate tool with the capability to predict inflow in Eqs. (20) and (21) and derive rule curves at the same time. To accomplish this, the FLGGP is run with S_t, h_t, and De_t as the deterministic variables, and past inflow I_{t-1} is used to predict the present-period I_t. Table 2 presents results of five runs and their statistical characteristics considering the aforementioned variables. It is apparent form Table 2 that the minimum value of the calculated objective function using deterministic variables is only 0.29 % larger (worse) than the corresponding

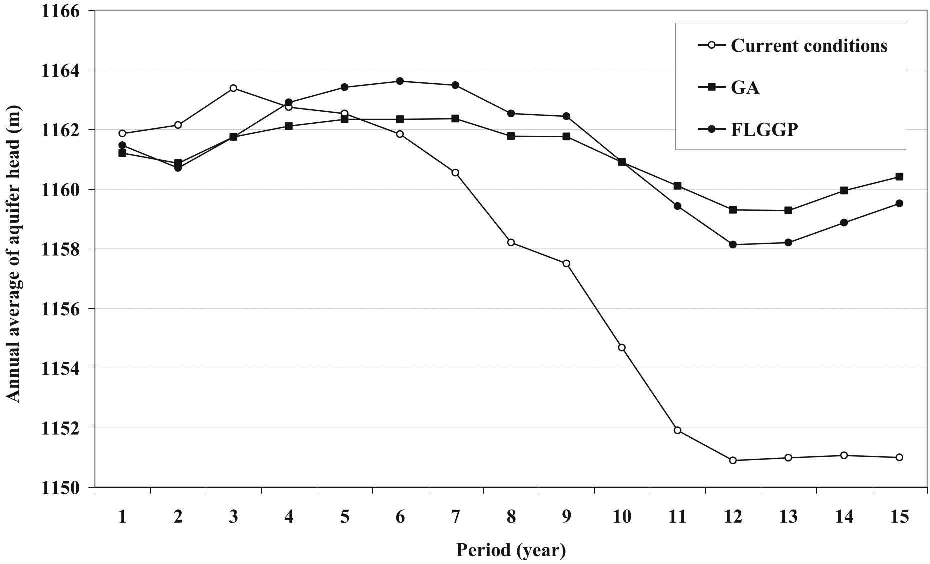


Fig. 6 Comparison of aquifer head under current conditions and with the application of operation rules

value using deterministic and stochastic variables. Equations (22) and (23) are the optimal operation rule curves corresponding to the minimum value of the objective function when prediction of river inflow is effected:

Reservoir operation rule:

$$RD_t = \left\{ \begin{array}{l} 1.546\cos\left[(I_{t-1})^{0.452}\right] + 0.809(S_t)^{0.525} + 1.158(h_t - 1000)^{0.030} \\ +0.006\cos\left[(De_t)^{2.84}\right] + 2.31 \end{array} \right\}^{1.494} \quad (22)$$
$$\forall t = 1, 2, \ldots, N$$

Aquifer operation rule:

$$RG_t = \left\{ \begin{array}{l} 1.589\sin\left[(I_{t-1})^{0.374}\right] - 0.671\cos\left[(S_t)^{0.033}\right] + 0.210(h_t - 1000)^{0.426} \\ +1.06\cos\left[(De_t)^{0.85}\right] + 2.209 \end{array} \right\}^{1.608} \quad (23)$$
$$\forall t = 1, 2, \ldots, N$$

Table 3 lists results that allow comparison of the consequences on system conditions calculated with the two types of operation rules calculated with FLGGP. More information about these types of FLGGP rules can be found in Bolouri-Yazdeli et al. (2014).

It is seen in Table 3 that there is no considerable difference between the aforementioned rules except for the time-base reliability of supplying Karaj municipal water. However, the volumetric reliability of the FLGGP rule using deterministic variables is 2.20 % larger than the corresponding value calculated when using deterministic and stochastic variables. This result demonstrates that the volume of allocated water to Karaj municipal sector in different periods is approximately equal when calculated by the two types of operation rules. Figure 7 displays the storage volume in the Karaj reservoir using two FLGGP rules based on the: (1) deterministic and stochastic variables (that is, with inflow prediction), and (2) deterministic variables. Figures 8, 9, and 10 show allocated water to the Tehran municipal, Karaj municipal, and Karaj agricultural sectors, respectively. It is evident from the latter Figures that is no considerable difference in the supply of water to these sectors.

Results of optimal operation of the conjunctive system using FLGGP rules confirmed the capability of this algorithm to achieve appropriate system states. Moreover, FLGGP rules based on the deterministic variables produce operation rules that are nearly almost indistinguishable from those calculated with the rules that apply an inflow prediction model.

Table 3 Objective function and performance criteria calculated with FLGGP rules

Rule type	Objective function	Demand sector	Time-base reliability	Volumetric reliability	Resiliency	Vulnerability
Using deterministic and stochastic variables	2115.85	Tehran municipal	53.63	85.13	0.146	17.88
		Karaj municipal	40.22	88.03	0.206	8.69
		Karaj agriculture	0.00	51.32	0.00	51.01
Using deterministic variables	2121.98	Tehran municipal	50.84	83.16	0.07	18.56
		Karaj municipal	50.84	89.97	0.123	10.09
		Karaj agriculture	0.00	56.03	0.00	52.78

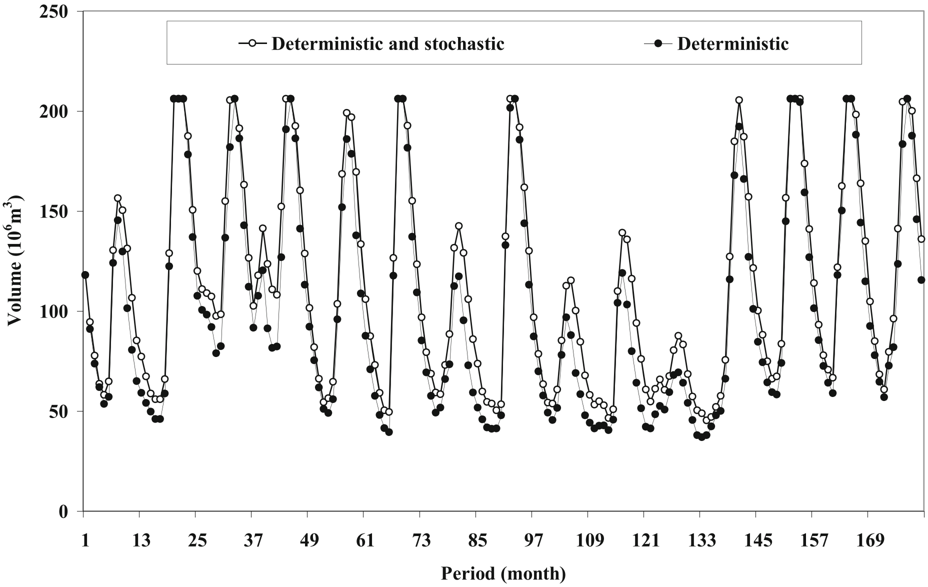


Fig. 7 Storage volume of Karaj reservoir using two FLGGP rules

13 Application of the Distributed Model

The Karaj aquifer is a confined aquifer that involves 1026 grid cells each with area equal to 1×10^6 m^2. Figure 11 displays the IADIM network for the Karaj aquifer. The calibrated parameters for the Karaj aquifer were those calculated by Bozorg Haddad et al. (2013). Each cell has an operation rule for reservoir allocation and one for aquifer allocation. Cells were divided into

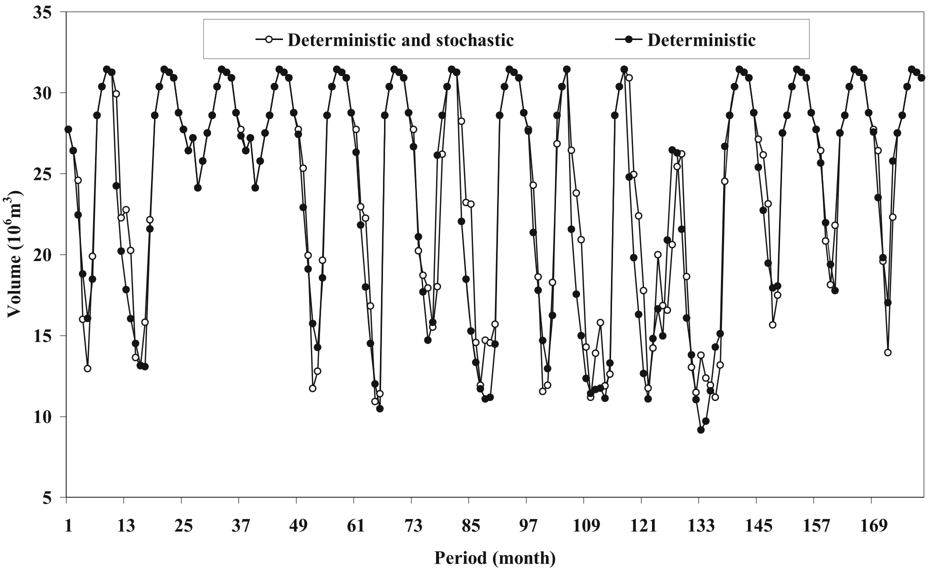


Fig. 8 Allocated water to Tehran municipal sector using two FLGGP rules

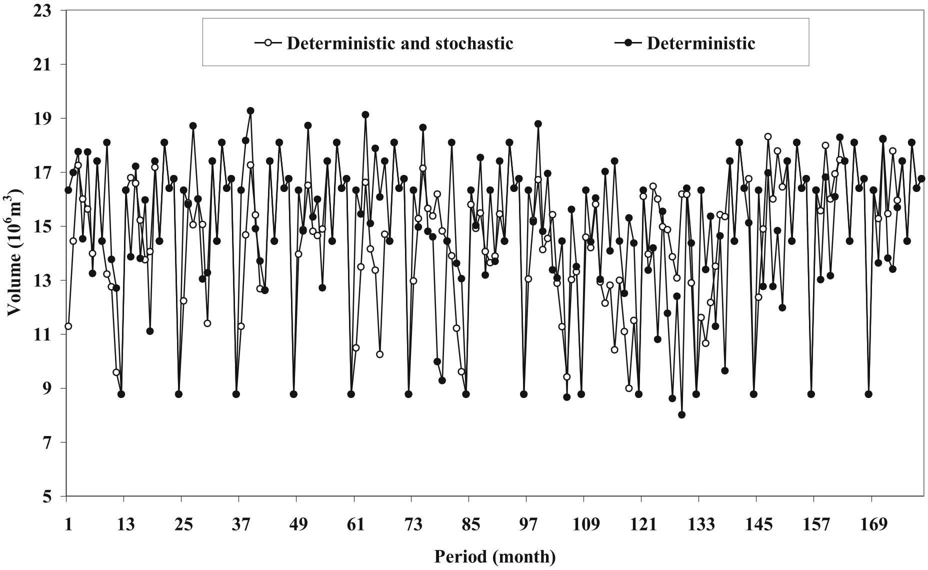


Fig. 9 Allocated water to Karaj municipal sector using two FLGGP rules

six categories $\{C_1,\ldots,C_6\}$. The first three categories $\{C_1,C_2,C_3\}$ and the second three $\{C_4,C_5,$ $C_6\}$ rules correspond to the Karaj municipal and Karaj agricultural sector, respectively. Recall that there is no available infrastructure to meet the municipal water demand of Tehran with groundwater from the Karaj aquifer. Categories $\{C_1,C_4\}$, $\{C_2,C_5\}$ and $\{C_3,C_6\}$ correspond to cells in which less than 10 %, between 10 and 50 %, and more than 50 % of the cell area

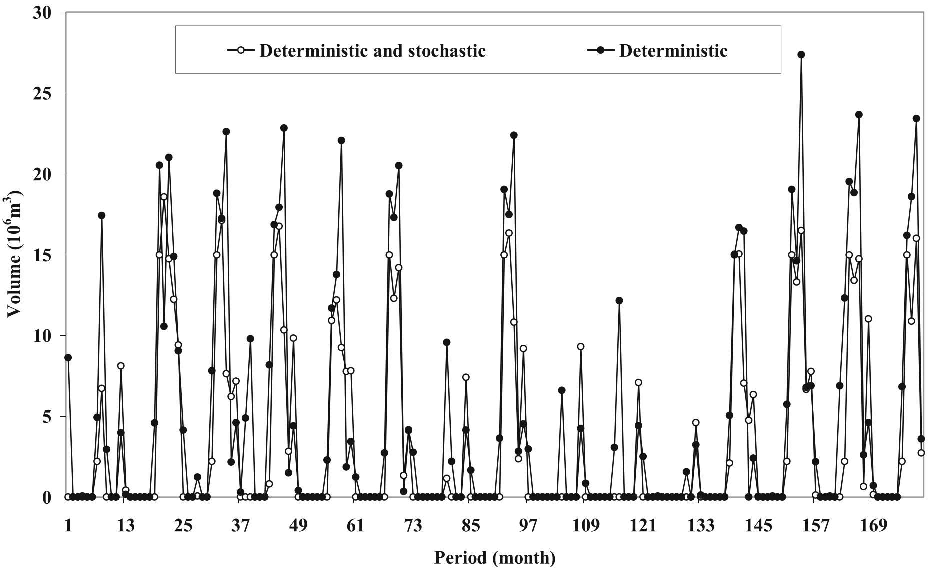


Fig. 10 Allocated water to Karaj agriculture sector using two FLGGP rules

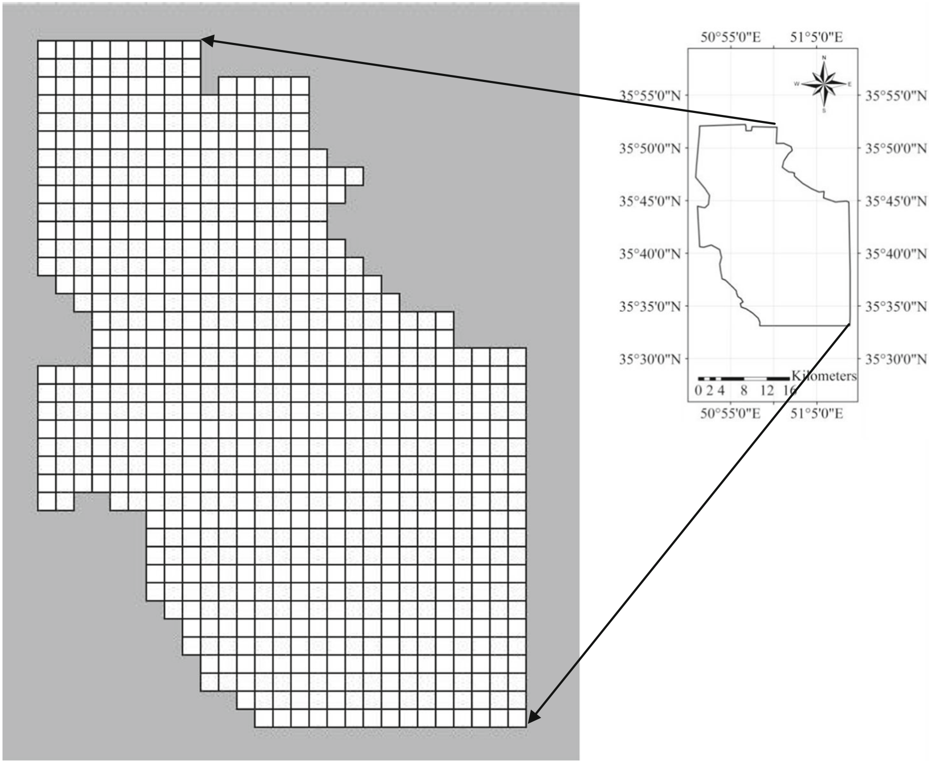


Fig. 11 IADIM network for the Karaj aquifer

covers a specific water-demand sector. The objective model used with the distributive models is:

$$Min.\left(100\sum_{t=1}^{N}\left(\frac{De_t^{Tehran}-R_t^{Tehran}}{De_t^{Tehran}}\right)+10\sum_{i=1}^{38}\sum_{j=1}^{27}\sum_{t=1}^{N}\left(\frac{De_{(i,j,t)}^{Karaj}-R_{(i,j,t)}^{Karaj}}{De_{(i,j,t)}^{Karaj}}\right)^2+\sum_{i=1}^{38}\sum_{j=1}^{27}\sum_{t=1}^{N}\left(\frac{De_{(i,j,t)}^{Agri}-R_{(i,j,t)}^{Agri}}{De_{(i,j,t)}^{Agri}}\right)^2\right) \tag{24}$$

The FLGGP implemented 5 runs with 10 chromosomes and 1000 iterations. Table 4 lists the FLGGP results and their statistical characteristics. The corresponding optimal operation rules are:

Table 4 Results of FLGGP and statistical measures calculated with the distributed model

Number of run	1	2	3	4	5
Objective function	7.1132E05	7.1144E05	7.2495E05	7.9213E05	6.9190E05
Statistical measures	Minimum	Average	Maximum	Standard deviation	Coefficient of variation
	6.9190E05	7.0633E05	2495E05	1142E04	0.02

Reservoir operation rule:

$$RD_{(i,j,t)} = \begin{cases} 9.55E{-}04(I_{t-1})^{0.52}{-}3.63E{-}02\sin(S_t) + 5.01E{-}05\left(h_{(i,j,t)}{-}1000\right) \\ +1.87E{-}06\left(De^{Karaj}_{(i,j,t)}\right)^{7.31E-06} + 2.90E{-}03 & (i,j)\in C_1 \\ \left\{\begin{array}{l} 9.37E{-}02(I_{t-1})^{0.21} \times 9.59E{-}04\left[(S_t)^{1.18}\right] + 2.63E{-}05\left(h_{(i,j,t)}{-}1000\right) \\ +9.55E{-}06\left(De^{Karaj}_{(i,j,t)}\right)^{9.09E-06} + 5.47E{-}03 \end{array}\right\}^{1.3} & (i,j)\in C_2 \\ 9.80E{-}04(I_{t-1}) + 5.96E{-}05\left[(S_t)^{1.3}\right] + 1.67E{-}05\cos\left(h_{(i,j,t)}{-}1000\right) \\ \times 3.26E{-}06\left(De^{Karaj}_{(i,j,t)}\right)^{9.79E-06} + 9.88E{-}03 & (i,j)\in C_3 \\ \left\{\begin{array}{l} 9.87E{-}05(I_{t-1}) + 2.619E{-}05\left[(S_t)^{-0.2}\right] + 3.35E{-}06\left(h_{(i,j,t)}{-}1000\right) \\ +7.45E{-}06\left(De^{Agri}_{(i,j,t)}\right)^{5.17E-06} + 6.80E{-}06 \end{array}\right\}^{1.42} & (i,j)\in C_4 \\ 9.94E{-}05(I_{t-1}) + 7.79E{-}06\sin(S_t) + 7.15E{-}06 \times \cos\left(h_{(i,j,t)}{-}1000\right) \\ +9.36E{-}06\left(De^{Agri}_{(i,j,t)}\right)^{5.54E-07} + 9.04E{-}06 & (i,j)\in C_5 \\ 3.05(I_{t-1}) + 7.44\left[(S_t)^{0.25}\right]{-}5.00E{-}06\left(h_{(i,j,t)}{-}1000\right) \\ +2.94E{-}06\left(De^{Agri}_{(i,j,t)}\right)^{8.75E-07} + 4.80E{-}06 & (i,j)\in C_6 \end{cases}$$

$$t = 1, 2, \ldots, N,\ i = 1, 2, \ldots, 38,\ j = 1, 2, \ldots, 27 \qquad (25)$$

Aquifer operation rule:

$$RG_{(i,j,t)} = \begin{cases} \left(\begin{array}{l} 1.29E{-}03(I_{t-1})^{-0.16} + 1.07E{-}04(S_t) + 8.89E{-}05\left(h_{(i,j,t)}{-}1000\right) \\ -4.25E{-}06\left(De^{Karaj}_{(i,j,t)}\right)^{6.47E-06} + 9.79E{-}04 \end{array}\right)^{1.06} & (i,j)\in C_1 \\ 9.29E{-}02(I_{t-1})^{-0.3} + 2.07E{-}04(S_t) + 8.89E{-}05\left(h_{(i,j,t)}{-}1000\right)^{3.6} \\ +7.21E{-}06\left(De^{Karaj}_{(i,j,t)}\right)^{4.55E-06} + 6.70E{-}03 & (i,j)\in C_2 \\ -3.77E{-}04(I_{t-1})^{-0.2}{-}8.52E{-}06(S_t)^{1.02} + 1.01E{-}04\left(h_{(i,j,t)}{-}1000\right) \\ \times 9.31E{-}07\left(De^{Karaj}_{(i,j,t)}\right)^{4.06E-06} + 7.96E{-}01 & (i,j)\in C_3 \\ \left[\begin{array}{l} 1.37E{-}06(I_{t-1}) + 7.21E{-}05(S_t)^{0.90}{-}1.07E{-}06\left(h_{(i,j,t)}{-}1000\right) \\ -1.19E{-}06\left(De^{Agri}_{(i,j,t)}\right)^{7.67E-06}{-}6.54E{-}06 \end{array}\right]^{1.07} & (i,j)\in C_4 \\ \left[\begin{array}{l} 8.91E{-}04(I_{t-1})^{-0.9} + 3.34E{-}03(S_t)^{0.206} + 6.99E{-}06\left(h_{(i,j,t)}{-}1000\right) \\ +6.47E{-}07\left(De^{Agri}_{(i,j,t)}\right)^{8.33E-06} \times 8.92 \end{array}\right]^{0.87} & (i,j)\in C_5 \\ \left[\begin{array}{l} 9.05E{-}04(I_{t-1})^{-0.1} + 6.10E{-}05(S_t) + 6.18E{-}06\left(h_{(i,j,t)}{-}1000\right)^{0.8} \\ +2.94E{-}06\left(De^{Agri}_{(i,j,t)}\right)^{8.75E-07} + 8.59E{-}06 \end{array}\right]^{0.12} & (i,j)\in C_6 \end{cases} \qquad (26)$$

$$t = 1, 2, \ldots, N,\ i = 1, 2, \ldots, 38,\ j = 1, 2, \ldots, 27$$

Table 5 lists performance criteria calculated for the distributive model. These criteria allow comparison between the lumped and distributive models. The results listed in Table 5 establish that the time-base and volumetric reliability of the distributed model for the Tehran municipal sector are 63.92 and 11.24 % larger (better) than the corresponding values calculated with the lumped model. The volumetric reliability of the Karaj municipal sector with the distributed model is 6.89 % better than the value calculated with the lumped model. However, the time-base reliability associated with supplying 100 % of water demand is zero for the Karaj municipal sector. This means that there is a small deficit that is distributed among all periods. This deficit does not take place with respect to the time-base reliability associated with supplying 90 % of water demand. This demonstrates that the vulnerability of water supply

Table 5 Performance criteria by FLGGP rules calculated with the distributed model

% of demand supplied	Demand sector	Time-base reliability	Volumetric reliability	Resiliency	Vulnerability
100	Tehran municipal	83.33	92.51	0.20	25.27
	Karaj municipal	0.56	92.25	0.00	1.17
	Karaj agriculture	6.67	37.71	0.06	47.53
90	Tehran municipal	84.44	93.42	0.21	22.18
	Karaj municipal	100.00	100.00	0.00	0.00
	Karaj agriculture	11.11	40.82	0.11	42.02

to the Karaj municipal sector achieved with the distributed model is considerably smaller than that calculated with the lumped model.

Figure 12 depicts observed hydraulic head and yield of optimal operation obtained with FLGGP. It is shown in Fig. 12a and b that the initial and final aquifer hydraulic head are considerably different under real conditions because of the excessive groundwater extraction by existing wells. In contrast, the FLGGP operation rules produce acceptable (allowable) variations of the hydraulic head simultaneously with the supply of water demands.

14 Concluding Remarks

Conjunctive-use water resources systems integrate surface and water resources to meet water demands and other objectives. This paper presented a conjunctive-use model for aquifer and reservoir operation in Iran. The conjunctive-use model had two versions of aquifer representation. The first modeled the Karaj aquifer as a lumped system. The second version modeled the Karaj aquifer as a distributed system. Optimal operating rules were derived with FLGPP and GA for the lumped- and distributed-conjunctive models for aquifer-reservoir water allocation in the Karaj-Tehran region of Iran. This paper's results demonstrated that the calculated objective function with FLGGP is 32.58 % smaller (better) than that calculated

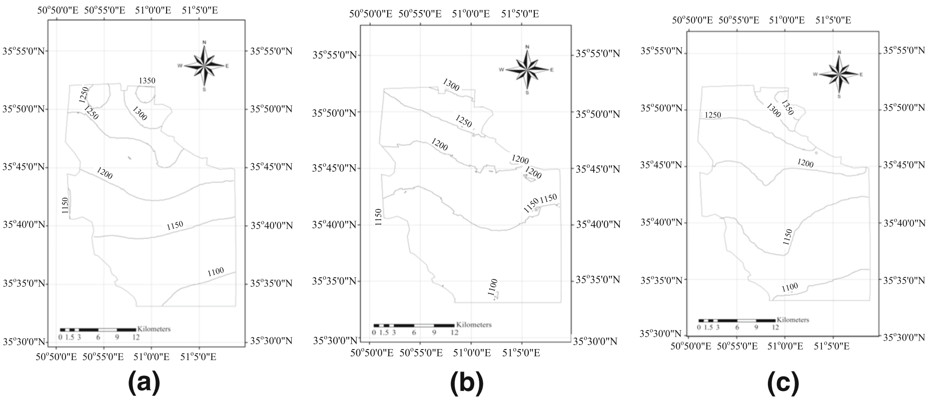


Fig. 12 Contour lines of hydraulic head (*h*, in m) at: **a** initial period of operation under real condition, **b** final period of operation under real condition, and **c** final period of optimal operation with FLGGP

with GA. Thus, FLGGP proved superior in the calculation of optimal aquifer-reservoir operation rules. The response of the Karaj aquifer response was simulated with the calculated operation rules based on distributed aquifer modeling. The simulation results indicated that the distributed aquifer model increases water-supply system performance criteria concerning the satisfaction of water demands compared to the lumped aquifer model.

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