Cyclic storage approach for conjunctive operation of surface and ground water systems (Case study: ZarrinehRoud catchment area)

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Abstract

In this research, the problem of optimal conjunctive operation of surface and ground water system is investigated considering cyclic storage approach. This problem is solved here using mathematical programming and some efficient meta heuristic algorithms. For this purpose, the mathematical model of this system is defined and firstly solved by nonlinear programming (NLP) method. In addition, the performance of artificial bee colony (ABC) algorithm, genetic algorithm (GA), gravitational search algorithm (GSA) and particle swarm optimization (PSO) algorithms are also studied to solve this problem. Here, two case studies, means a hypothetical benchmark system and conjunctive use of Buchan dam reservoir and Miandoab aquifer located in the catchment area of Urmia Lake (ZarrinehRoud catchment area) as a real problem, are considered to study the performance of proposed methods. For the hypothetical benchmark system, the results show that the optimal operating cost and related computational time are equal to 5.2428 Billion Rials and 5400 second, respectively, obtained using the NLP method. In addition, the operation costs are increased 26.36%, 26.1%, 44.91% and 21.28% in comparison with result of NLP method using ABC, GA, GSA and PSO algorithms, respectively. However, the computational time is extremely decreased in comparison with the related value of NLP method using these algorithms. For the real benchmark system, the results show that the optimal operating cost and related computational time are equal to 139.0145 Billion Rials and 259200 second, respectively, obtained using the NLP method. In addition, the operation costs are increased 43.74%, 32.32%, and 50.57% in comparison with result of NLP method using ABC, GA and PSO algorithms, respectively. However, the computational time is extremely decreased in comparison with related value of NLP method using this algorithm. Furthermore, the water demands of these problems are fully stratified using proposed methods. The obtained results show the efficiency and affectivity of the used method to solve more this complex optimization problem.

Key words: Conjunctive operation; Cyclic storage approach; Meta heuristic algorithms; ZarinehRoud catchment area.

1. Introduction

Water is one of the basic human needs since ancient times. In other words, water has been always considered as a source of human life. In ancient times, the required water was supplied directly from surface water or ground water resources. Nowadays, due to increasing the population and the human well-being, the surface water resources can not satisfy the human demands alone. Therefore, new methods have been proposed to supply the water demands. These days, the conjunctive and integrated operation of surface and groundwater resources has been proposed by researchers to solve this problem. In general, the conjunctive operation can be done using several methods, depending on the components of the defined system. The most complete form of an integrated system can include all subsystems such as rivers, surface reservoirs and aquifers and artificial recharging systems in which sufficient hydraulic connection should be exist between all subsystems. This form of system definition is generally called cyclic storage system (Alimohammadi et al., 2009) .

During 1960 up to 1980, different researches were done in the field of simulation and conjunctive operation of surface and ground water in which most of them were done using traditional and classical methods including mathematical and dynamic programming. Paper of Buras (1963) was one of the initial researches in this field. In this study, dynamic programming (DP) was used to optimize the combined system of a dam and and aquifer to supply the water demands of two agricultural areas. Bredehoeft and Young (1970) used the simulation-optimization approach to optimize the operation of a combined river-aquifer system in which this research work was completed eleven years later considering the risk. Nieswand and Granstorm (1971) used linear programming (LP) method and chance chance-constrained approach to optimize the conjunctive use of surface and ground waters in New Jersey. Chaudhry et al. (1974) used a deterministic dynamic programming (DDP) method to optimize the design and operation of the conjunctive use for Indus Basin. Rushton and Tomlinson (1981) simulated the conjunctive use of a dam-aquifer system. In this study, five scenarios were presented and their performance was investigated and compared. Lettenmaier and Burges (1982) investigated the performance of a hypothetical cyclic storage system using the Monte

Carlo simulation model. Hantush and Marino (1989) proposed a chance-constrained approach for managing the operation of a combined river-aquifer system. In this study, an approximate solution method was used to determine the water level in a well near the river. Latif and Douglas James (1991) used LP method to optimize the cultivation pattern for a farm using a conjunctive use model. Onta et al. (1992) used a stochastic dynamic programming (SDP) method to optimize the operation of a river-aquifer system and investigated the performance of the system using simulation model. In this research, different scenarios were ranked using multi-criteria decision making (MCDM) method. Matsukawa et al. (1992) proposed a model to optimize the conjunctive use of a dam-aquifer-river system, emphasizing the importance of daily changes of river water levels. Yan and Smith (1994) proposed different equations for calculating various components such as evaporation and transpiration, recharging aquifer with rainfall, infiltration, and so on. In addition, a comprehensive model for simulating the combined surface and groundwater systems was proposed and formulated based on the South Florida water management model using three-dimensional finite differences method. Wang et al. (1995) used a quantitative-qualitative parametric simulation model to simulate the conjunctive use of surface and groundwater in the California. Peralta et al. (1995) used an interpolation method to solve the optimization model and formulate the conjunctive operation of surface and groundwater in the Mississippi Plain. In this study, different scenarios of system operation were investigated for the next fifty years (1990-2039). Reichard (1995) used a distributed model to optimize the conjunctive operation of the river-aquifer system. In this study, minimizing the auxiliary resource to supply the water demands and minimizing the change of pumping rate were considered as objective functions. Ejaz and Peralta (1995) proposed a model to maximize the profits of conjunctive operation of surface and ground water for a catchment including water quality constraints. In this study, three models were applies in which one of them was used for routing the surface flow. In addition, the MODFLOW model was used to simulate the aquifer and generate response coefficients. Finally, the QUAL2E model was used to qualitatively simulate the water surface flow. Philbrick and Kitanidis (1998) investigated the operation optimization problem of a hypothetical system that includes a dam and an aquifer (pumping from aquifers and recharging into aquifers) using DP method. In order to optimize the conjunctive use of the California water resources system in drought conditions, Nishikawa (1998) used the single response matrix method to simulate the groundwater behavior and the LINDO software to solve a LP model. Başagaoglu and Mariño (1999) proposed a distributed parametric model to optimize the conjunctive operation of a combined system including a dam, river, aquifer, pumping well and power supply well. Barlow and Dickerman (2001) proposed a model for numerical simulation and conjunctive management models of the Hunt– Annaquatucket Pettaquamscutt Stream-Aquifer System in Rhode Island. In this study, MODFLOW model was used to determine the response coefficients and LINNDO software was used to solve the LP model. The main issues and problems of the planning, design, construction and management of both surface and groundwater resources were investigated by Wrachien and Fasso (2002). In this study, the environmental impacts of conjunctive management of surface and ground water and the limitations of the approaches for sustainable development, as well as the importance of researches, technological development and effective participation of governments and stakeholders were investigated. In order to supply the urban demands of Jakarta in Indonesia, Syaukat and Fox (2004) proposed a model for conjunctive operation of surface and ground water emphasizing the components of the urban water system. In this study, LP method was used to optimize the operation policies of surface and ground water resources. Due to increasing the agricultural and domestic water demand in the Varada catchment area in India, Ramesh and Mahesha (2009) developed an optimization model for the conjunctive use of surface and ground water resources. In this study, LP method was used to determine the optimal allocation of surface and ground considering hydraulic constraints. Singh (2014) investigated the problem and related methods of conjunctive use of surface and ground water resources to achieve sustainable irrigation for agricultural lands. In addition, the conjunctive use of surface and ground water to manage the use of low-quality water and increasing the water level of aquifers were also investigated. Wu et al. (2015) used a surrogate approach called dynamic coordinate search to optimize the conjunctive use of surface and ground water resources in order to supply the agricultural water demand. Li et al. (2016) proposed a model for regulating the surface and groundwater allocation in arid regions of northwestern China. In this model, current year water information was used to optimize the water resources allocation of the next year. Milan et al. (2018), at first, used a linear fuzzy optimization model to find the optimal solution of conjunctive use of surface and ground water resources problem. Then, amount of water extraction from groundwater were determined using the obtained results of fuzzy inference system. In this study, MODFLOW model was used to simulate groundwater and two fuzzy optimization methods were developed to minimize the water shortage. Pérez-Uresti et al. (2019) developed a multi-objective optimization model to supply the water demand. Maximizing the profits, minimizing the water derivation from groundwater resources, and minimizing the initial investment were considered as the objective function of this model.

Due to the special capabilities of new methods (including meta heuristic algorithms and hybrid methods) and the limitations of traditional and classical methods, nowadays, the use of these methods for solving complex problems has been increased. Therefore, these algorithms should also be used to solve the conjunctive use of surface and ground water resources optimization problem. In the following, the related researches in the field of conjunctive use of surface and ground water resources are presented using these methods. Karamouz et al. (2008) used genetic algorithm (GA) to investigate the conflict of water quality and quantity allocation considering water allocation priorities and the existing of surface and ground water. In this study, maximizing the net profit of agricultural products according to the allowable amount of aquifer water oscillation, pumping costs and the impact of water shortages on the quality of products were considered as objective functions of the model. Jahanpour et al. (2013) combined a dynamic semi distributed system simulation model with a genetic algorithm to propose a new approach to simulating-optimizing the management of conjunctive use of surface and groundwater. Peralta et al. (2014) used multi-objective genetic algorithm to find the optimal solution for the simultaneous use of dam reservoir, river, and aquifer considering nonlinear hydraulic and economic constraints. In this model, water interaction between the river, aquifer, dam reservoir, river diversion and return flow from the demand area have been fully simulated and optimized for multiple operation time periods. Safavi and Enteshari (2016) used artificial neural network (ANN) model and ant colony optimization algorithm to propose a simulator-optimizer model for conjunctive use of surface and groundwater to supply the water demands of agricultural area. Minimizing the shortage of water supply for three irrigation areas located in Najafabad plain was considered as objective function of the model. Rezaei et al. (2017) proposed a new algorithm named optimization of fuzzy multi-objective particle swarm optimization (f-MPSO) algorithm for conjunctive surface and ground water use management in Najafabad plain of Iran for 10 years operation time period. Fu et al. (2017) proposed a hybrid model for improving the integrated management of surface and groundwater resources by combining the interval parameter programming method, fuzzy programming method and one-dimensional water quality model. Wang et al. (2018) proposed a new approach named centroid-based type-2 fuzzy-probabilistic programming approach for management of the conjunctive use of surface and groundwater. Yousefi et al. (2018) used the PSO algorithm to solve the optimization problem of the conjunctive use of surface and ground water for Varamin plain irrigation network in Iran. In the proposed improved model, the PSO algorithm along with an additional weighting method and multi-objective PSO algorithm were used to find optimal solutions. In general, it is difficult to develop and propose a comprehensive model for water resources management due to the multidimensional and large scale size of the problem. Therefore, Al-jawad et al. (2019) used a multi-objective optimization algorithm to solve this problem. In this study, social, economic, and environmental conditions and, surface and groundwater resources and watershed infrastructure of the basin were considered.

Rewiring the literature in the field of conjunctive use of surface and ground water shows that using new and effective meta heuristic algorithms to solve this complex optimization problem is an attractive research field for water resource management researchers. Therefore, in this research, the performance of some applicable and effective meta heuristic algorithms is studied to solve the optimization problem of conjunctive use of surface and ground water for ZarrinehRoud catchment basin using the cyclic storage approach. It should be noted that this approach is an effective and new approach which is rarely used by researches and, therefore, it is used here for solving a real case study in Iran. These facts are innovations of this research.

2. Optimization model of cyclic storage system operation

In this section, the mathematical optimization model of a cyclic storage system operation is presented. In order to define this model, it is necessary to define the decision variables, objective function and all constraints. The objective function of the proposed model is to minimize the operating and maintenance costs of the system to supply the water demand.

Here, the maintenance and operation costs include the operation cost of system elements including conveyance cost from dam reservoir to demand and artificial recharge areas, conveyance cost from aquifer to dam reservoir, diversion cost from river to demand and artificial recharge areas, pumping and recharging wells and deficit costs for not supplying the predefined demands. The mathematical formulation of the objective function of the problem is presented as follows (Alimohammadi et al., 2009):

$$\begin{aligned}\text{O.F.} = \text{Minimize } PVC_{OMR} &= CW + CAR + CDEF + COMRD + COMRCD + \\ &OMRCAR + COMRDivD + COMRDivAR + COMRP\end{aligned} \tag{1}$$

Where,

$$CW = \sum_{t=1}^{NT}\sum_{k=1}^{NK}\left[\frac{(u_{CW}(t,k) * (l_W(k) + \bar{s}_W(t,k)) * q_W(t,k))}{(1+r_S)^t}\right] \tag{2}$$

$$u_{CW}(k,t) = \frac{(uelif * ucen * hour(t) * 3600/efp)}{kqv(t)} \tag{3}$$

$$kqv(t) = \frac{(hour(t) * 3600)}{10^{-6}} \tag{4}$$

$$CAR = \sum_{t=1}^{NT}\sum_{k=1}^{NK}\left[\frac{u_{CAR}(t,l) * q_{ar}(t,l)}{(1+r_S)^t}\right] \tag{5}$$

$$CDEF = \sum_{t=1}^{NT}\left[\frac{u_{CDEF}(t) * def(t)}{(1+r_S)^t}\right] \tag{6}$$

$$COMRD = u_{OMRD} * CD \tag{7}$$

$$COMRCD = \sum_{t=1}^{NT}\left[\frac{u_{OMRCD}(t) * R_d^s(t)}{(1+r_S)^t}\right] \tag{8}$$

$$COMRCAR = \sum_{t=1}^{NT}\left[\frac{u_{OMRCAR}(t) * R_{ar}^s(t)}{(1+r_S)^t}\right] \tag{9}$$

$$COMRDivD = \sum_{t=1}^{NT}\left[\frac{u_{OMRDivD}(t) * DivD(t)}{(1+r_S)^t}\right] \tag{10}$$

$$COMRDivAR = \sum_{t=1}^{NT}\left[\frac{u_{OMRDivAR}(t) * DivAR(t)}{(1+r_S)^t}\right] \tag{11}$$

$$COMRP = \sum_{t=1}^{NT}\left[\frac{u_{OMRP}(t) * R_s^g(t)}{(1+r_S)^t}\right] \tag{12}$$

Where, PVC_{OMPR} = Total operation and maintenance costs of system elements, *COMRD*= Operation cost of dam reservoir, *COMRCD*= operation cost of conveyance from dam reservoir to demand area, *COMRCD*= operation cost of conveyance from dam reservoir to artificial recharge area, *COMRP*= operation cost of conveyance from aquifer to dam reservoir, *COMRDivD*= operation cost of diversion from river to demand area, *COMRDivAR*= operation cost of diversion from river to artificial recharge area, *CW*= the pumping operational cost, *CAR*= groundwater recharge operation cost, *CDEF*= deficit costs for not supplying the predefined demands (CDEF) presenting the cost of supplying demand from other replacement resources, *kqv(t)*= the function to convert discharge (m3/s) to volume (MCM), *ucen*= unit cost of energy, *efp*= pumping efficiency, *uelif* = energy required to pump a unit volume of water to a unit height, *hour (t)*= Total number of hour for operation time period *t*, $l_w(k)$= initial drawdown (or lift) for pumping well *k*, $\bar{s}_w(t,k)$ = average change of groundwater level for pumping well *k* in operation time period *t*; $q_w(t,k)$= pumping rate for pumping well *k* in operation time period *t*, $u_{CW}(t,k)$ = unit pumping cost of unit volume of water to a unit height for pumping well *k* in operation time period *t*, $u_{CAR}(t,l)$ = unit recharging cost for recharge well *l* in operation time period *t*, r_s= seasonal discount rate, $q_{ar}(t,l)$= recharge rate for recharging well *l* in operation time period *t*, $R_s^g(t)$ = the water volume value transferred from the aquifer to the dam reservoir in operation time period *t*, *DivD(t)* = the river water volume value diverted to the demand area in operation time period *t, DivAR(t)*= the river water volume value diverted to the artificial recharge area in operation time period *t, def (t)* =Water deficit (shortage) in operation time period *t,* $R_d^s(t)$ = the water volume value transferred from the dam reservoir to demand area in operation time period *t*, $R_{ar}^s(t)$ = the water volume value transferred from the dam reservoir to artificial recharge area in operation time period t, U_{OMRD}= unite operation constant accounting for the dam reservoir, U_{OMRCD}= Unite operation constant accounting for conveyance from dam reservoir to demand area, U_{OMRCAR}= Unite operation constant accounting for conveyance from dam reservoir to artificial recharge area, U_{OMRP}= Unite operation constant accounting for conveyance from dam reservoir to aquifer, $U_{OMRDivD}$= Unite operation constant accounting for transferring from the dam reservoir to demand area, $U_{OMRDivAR}$= Unite operation constant accounting for transferring from the dam reservoir to artificial recharge area, U_{CDEF}= Unite operation constant accounting for supplying demand from other replacement resources or decreasing the benefit due to not supplying the predefined demands (CDEF), *NT*= total number of operation time periods, *NK*= total number of pumping wells, and NL= Total number of recharging wells.

In order to fully describe the optimization model, all constraints should be defined including mass balance and system component capacity constraints (equations 13 to 19), supplying demand constraints (equation 20), pumping and recharging well constraints (equations 21 to 27), capacity of aquifer and change in ground water level constraints for lumped system (equations 28 to 36), river-aquifer interactions constraints (equations 37 to 38) and river hydraulics constraints (equations 39 to 46). The mathematical formulations of maintained constraints are presented as follows (Alimohammadi et al., 2009: McDonald and Harbaugh, 1986; Afshar et al., 2008)

$$S^s(t+1) = S^s(t) + Q^s(t) + R_s^g(t) - E^s(t) - R_d^s(t) - R_{ar}^s(t) - R_{riv}^s(t) \tag{13}$$

$$S^s(NT+1) \le S^s(1) \tag{14}$$

$$A^s(t) = f(S^s(t)) \tag{15}$$

$$E^s(t) = \frac{ep(t)}{1000} \cdot \frac{[A^s(t) + A^s(t+1)]}{2} \tag{16}$$

$$S_{\min} \le S^s(t) \le CapD \tag{17}$$

$$R_d^s(t) \le CapCD \tag{18}$$

$$DivD(t) \le CapDivD \tag{19}$$

$$R_d^s(t) + R_d^g(t) + DivD(t) = \eta(t) \cdot ANDM - def(t) \tag{20}$$

$$R_{ar}^{s}(t) \le CapCAR \tag{21}$$

$$DivAR(t) \le CapDivAR \tag{22}$$

$$R_{s}^{g}(t) \le CapP \tag{23}$$

$$\sum_{k=1}^{NK} q_{w}(t,k) = R_{d}^{g}(t) + R_{s}^{g}(t) \tag{24}$$

$$\sum_{l=1}^{NL} q_{ar}(t,l) = R_{ar}^{s}(t) + DivAR(t) \tag{25}$$

$$q_{w}^{\min}(t,k) \le q_{w}(t,k) \le q_{w}^{\max}(t,k) \tag{26}$$

$$q_{ar}^{\min}(t,l) \le q_{ar}(t,l) \le q_{ar}^{\max}(t,l) \tag{27}$$

$$\mathrm{S^{g}(t+1) = S^{g}\ (t) + \sum_{l=1}^{NL} q_{ar}}(t,l)\ \text{-} \sum_{\mathrm{k=1}}^{\mathrm{NK}} \mathrm{q_{w}}(t,k) + \frac{\mathrm{q_{raq}}(t,r)}{kqv(t)} + \mathrm{(rets * y(t)) + \frac{prc(t) \times seep \times AQA}{1000}} \tag{28}$$

$$\alpha_{\min} S^{g}(1) \le S^{g}(NT+1) \le \alpha_{\max} S^{g}(1) \tag{29}$$

$$S^{g}(t+1) - S^{g}(t) = \Delta S^{g}(t) \tag{30}$$

$$\Delta S^{g}(t) = S_{y} \times AQA - dh^{g}(t) \tag{31}$$

$$h^{g}(t+1) = h^{g}(t) + dh^{g}(t) \tag{32}$$

$$(h_{f}(t,k))^{2} - (h_{s}(t,k))^{2} = \sum_{k(l)=1}^{NK(NL)} \frac{q_{w}(t,k) - q_{ar}(t,l)}{\pi \times k} \tag{33}$$

$$S_{w}(t,k) = h_{f}(t,k) - h_{s}(t,k) \tag{34}$$

$$\overline{S}_{w} = \frac{s_{w}(t-1,k) - s_{w}(t,k)}{2} \tag{35}$$

$$S_{w}^{\min} \le S_{w}(t,k) \le S_{w}^{\max} \tag{36}$$

$$q_{raq}(t,r) = \begin{cases} C_{riv}(r).[h_{riv}^{s}(t,r) - h_{riv}^{g}(t,r)] & if \quad h_{riv}^{g}(t,r) > h_{riv}^{bot}(t,r) \\ C_{riv}(r).[h_{riv}^{s}(t,r) - h_{riv}^{bot}(t,r)] & if \quad h_{riv}^{g}(t,r) \le h_{riv}^{bot}(t,r) \end{cases} \tag{37}$$

$$C_{riv}(r) = \frac{K(r) \times L(r) \times W}{M(r)} \tag{38}$$

$$ql_{riv}(t,r) = \left(\frac{Area(r) \times prc(t)}{1000} - DivD(t) - DivAR(t) + retr \times y(t) \right) \times .kqv(t) + q_{raq}(t,r) \tag{39}$$

$$q_{riv}^{in}(t,1) = \frac{R_{riv}^{s}(t)}{kqv(t)} \tag{40}$$

$$q_{riv}^{out}(t,r) = ql_{riv}(t,r) + q_{riv}^{in}(t,r) \tag{41}$$

$$q_{riv}^{out}(t,r) = q_{riv}^{in}(t,r+1) \tag{42}$$

$$h_{riv}^{in}(t,r) = f\left(q_{riv}^{in}(t,r)\right) \tag{43}$$

$$h_{riv}^{out}(t,r) = f\left(q_{riv}^{out}(t,r)\right) \tag{44}$$

$$h_{riv}(t,r) = \frac{h_{riv}^{in}(t,r) + h_{riv}^{out}(t,r)}{2} \tag{45}$$

$$q_{riv,\min}^{out}(t,r) \le q_{riv}^{out}(t,r) \le q_{riv,\max}^{out}(t,r) \tag{46}$$

Where, $S^{s}(t)$ =water storage volume of the dam reservoir at the start of operation time period *t*, $S^{s}(t+1)$ =water storage volume of the dam reservoir at the end of operation time period *t*, $Q^{s}(t)$ =water inflow volume into the dam reservoir at the operation time period *t*, ,*t*dam reservoir at the operation time period ofvolume evaporation= $E^{s}(t)$ r = dam reservoi*CapD* minimum water storage volume of the dam reservoir, $S_{\min}$ = storage capacity, *CapCD* =capacity of conveyance from dam reservoir to demand area, *CapDivD* =capacity of river diversions to demand area, *CapCAR* = capacity of conveyance from dam reservoir to artificial recharge, *CapP*= capacity of conveyance from aquifer to reservoir, *CapDivAR*= capacity of river diversions to artificial recharge area, $A^s(t)$ = the reservoir surface area at operation time period *t* as a function of $S^s(t)$; *ep(t)* is the evaporation height at the operation time period *t*; $R_d^g(t)$ = The water volume value transferred from the aquifer to the demand area in operation time period *t*, $\eta(t)$ = a coefficient defining seasonal distribution of demand; *ANDM* = annual demand volume; $q_w^{\max}(t,k)$ = maximum pumping rate for pumping well *k* in operation time period *t*, $q_w^{\min}(t,k)$ = minimum pumping rate for pumping well *k* in operation time period *t*, $q_{ar}^{\max}(t,l)$ = maximum recharge rate for recharging well *l* in operation time period *t*, $q_{ar}^{\min}(t,l)$ = minimum recharge rate for recharging well *l* in operation time period *t*, $S^g(t)$=water storage volume of the aquifer at the start of operation time period $t, S^g(t+1)$=water storage volume of the aquifer at the end of operation time period *t*, $q_{raq}(t,r)$ = interaction between river reach *r* and the aquifer in operation time period *t*, *rets* = fraction of water percolating into the aquifer from water transferred to the demand area, *seep*= fraction of precipitation percolating into the aquifer, *prc(t)*= the precipitation height in operation time period *t (mm)*, *AQA*= rainfall area of the plain, $\alpha_{\min}$ = minimum coefficient for balancing the storage volume of the aquifer, $\alpha_{\max}$ = maximum coefficient for balancing the storage volume of the aquifer, $\Delta S^g(t)$ = change of water storage volume of the aquifer in operation time period t; S_y =Specific Yield; $dh^g(t)$ = change of water level (height) of the aquifer in operation time period *t*; $h^g(t)$ = water level (height) of the aquifer at the start of operation time period *t*; $h^g(t+1)$ = water level (height) of the aquifer at the end of operation time period *t*; $h_f(t,k)$ = initial Piezometric height (elevation) before pumping from well *k* in operation time period *t,* $h_s(t,k)$ = Piezometric height (elevation) after pumping from well *k* in operation time period *t, k*= hydraulic conductivity of aquifer, $S_w(t,k)$= groundwater level drop of pumping well *k* in operation time period *t*, $S_w^{\min}$= maximum groundwater level drop of pumping well, $S_w^{\max}$= minimum groundwater level drop of pumping well, $C_{riv}(r)$ = the river conductance of river reach *r* (as a function of the semi pervious streambed hydraulic conductivity, length, width and thickness), *K(r)*= the semi pervious streambed hydraulic conductivity of river reach *r, L(r)* = the semi pervious streambed length of river reach *r, W(r)* = the semi pervious streambed width of river reach *r*, *M(r)* = the semi pervious streambed thickness of river reach *r*, $h_{riv}^{s}(t,r)$= the elevation of river surface water for river reach *r* at operation time period *t*, $h_{riv}^{g}(t,r)$= the elevation of aquifer water table below for river reach *r* at operation time period *t*, $h_{riv}^{bot}(r)$ = the elevation of semi pervious` streambed bottom of river reach *r*, $ql_{riv}(r,t)$ = summation of lateral inflows or outflows along the river reach *r*, Area= plan area of river reach *r*, *retr* = fraction of water percolating into the river from water transferred to the demand area, $q_{riv}^{in}(t,r)$ = river inflow of river reach *r* in operation time period *t,* $q_{riv}^{out}(r,t)$ = river outflow of river reach *r* in operation time period *t*, $h_{riv}^{in}(t,r)$= river inflow depths of river reach *r* in operation time period *t,* $h_{riv}^{out}(r,t)$ = river outflow depths of river reach *r* in operation time period *t,*river water depth of $= h_{riv}(t,r)$ river reach *r* in operation time period *t,*of river = minimum river outflow $q_{riv,\min}^{out}(t,r)$ reach *r* in operation time period *t,* $q_{riv,\max}^{out}(t,r)$ = maximum river outflow of river reach *r* in operation time period *t* and other parameters were defined before.

This defined problem is a constrained optimization problem in which several methods have been proposed for satisfying the constraints. For this purpose, here, penalty method is used. In this method, the amount of constraints violation is calculated when the solution is infeasible and it is multiplied to the fix penalty coefficient and added to original objective function value for minimization problem.

$$O.F._P = \begin{cases} O.F. + Penal \times \sum_{g=1}^{G} CSV_g & if\ \ soulution is \inf easible \\ O.F. & otherwise \end{cases} \quad (47)$$

3. Case study

In order to investigate the proposed methods, in this research, two benchmark marks problem are solve using the proposed method. In the section, details o these two case studies are presented.

3.1. Hypothetical simple case study

Here, a hypothetical and simple cyclic storage system and its details are presented. This system is presented in figure 1 in which it consists of a dam reservoir, a free aquifer and a river by considering hydraulically interaction with aquifer, a demand area and a pumping well that also acts as a recharging well. A seasonal time series of river flow is presented in table 1 considering eight months (two year) operation time period.

In the defined hypothetical problem, the area of aquifer is 80 square kilometers (km^2). This aquifer is homogeneous and its hydraulic conductivity (K) is 0.0009 m/s and its storativity (S) is 0.14. As an initial condition, it is assumed that the water elevation in all parts of the aquifer is constant and equal to 10 meters below the ground elevation. The river is assumed to be a rectangular channel with a length of 40,000 meters, a width of 20 meters, a Manning coefficient of 0.02 and a longitudinal slope of 0.0001. In the river, the stage-discharge relation is assumed to be Q = 3h in which the Q is river flow discharge (cubic meter per second, m^3/s) and h is the river flow depth (m). The aquifer is separated from the river by a semipervious streambed layer considering 2 meter thickness with and hydraulic conductivity of 0.000001 m/s. The demand area is located in the center of the system with the annual demand value of 40 million cubic meters (m^3). This demand can be supplied from the three sources of direct transfer from the dam reservoir, pumping from the aquifer and diversion of the river flow. The values of the water inflow flow to the dam reservoir, the seasonal demand distribution and the average annual precipitation are presented in Table 1. Here, 5 percent of precipitation can percolate into the aquifer. In addition, 10 percent of water delivered to the demand area can percolate into the aquifer and while 10 percent of the former can be returned to the river. Furthermore, it is assumed that the initial water aquifer elevation is equal to river surface elevation.

Unite operation constants accounting for each sub-system of this problem are considered as: U_{OMRD} = 0.05, U_{OMRCD} = 0.02, U_{OMRCAR} = 0.01, U_{OMRP} = 0.02, $U_{OMRDivD}$ = 0.02, $U_{OMRDivAR}$= 0.01, and U_{CDEF} = 3. In addition, upper and lower bounds of parameters and other data such as pumping cost data are considered as: $q_w^{\max}(t,k) = 5$, $q_w^{\min}(t,k) = 0$, $q_{ar}^{\max}(t,k) = 5$, $q_{ar}^{\min}(t,k) = 0$, $S_w^{\min} = -10$, $S_w^{\min} = 10$, $q_{riv,\max}^{out}(t,r) = 5$, $q_{riv,\min}^{out}(t,r) = 0.2$, $l_w(k)$= 10, *ucen*= 0.00000778, *efp*= 0.75 %, *uelif* =0.0028, and r_s= 8

3.2. Real world case study

In ordered to evaluation of the performance of proposed method to find the optimal solution for the cyclic storage system problem, here, a part of the catchment area of Lake Urmia (ZarrinehRoud catchment area) has been investigated as a real world case study during operation time period from 2005 to 2015. ZarrinehRoud catchment area is one of the water-rich basins in Urmia Lake catchment area, which is located in the northwest of the Iran. In general, ZarrinehRoud is one of the most important rivers for the catchment area of Lake Urmia in which the general slope of this river is from southeast to northwest. The maximum height of this basin is 3300 meters above sea level. The initial tributaries of this river originate from the snow-capped mountains of Chehel Cheshmeh in Kurdistan and finally move into Lake Urmia. The ZarrinehRoud River is about 250 km long in which the distance from the Chehel Cheshmeh Mountains to the Buchan Dam is about 100 km and the distance from the Buchan Dam to Lake Urmia is about 150 km.

Buchan Dam is located in 35 km southeast of Buchan city in the West Azerbaijan Province. This dam is constructed to supply the agricultural demand of Miandoab plain and part of Malekan, Bonab, Ajabshir and Azarshahr plains. In addition, this dam is used to supply most of the drinking water of Tabriz. The length of the dam crown is 520 meters and its height is 50 meters. As the dam's height increased in 2005, the total water storage volume of the reservoir was increased to 764 million cubic meters (MCM). Therefore, the active storage of the dam reservoir is now 629 MCM. The location and details of this test example is presented in the figure 2.

Usually, the water level or surface of the dam reservoir can be determined as a nonlinear function of the water storage volume leading to the height-surface-volume curves. Here, the mathematical form of this function for Buchan Dam is presented as:

$$A^s(t) = -0.0001 S^s(t)^2 + 0.1256 S^s(t) + 2.6996 \qquad (48)$$

Where, all the parameters were defined before.

Here, the area of the aquifer is 1255.98 km^2. The type of aquifer is an alluvial with an average thickness of 300 meters. In addition, the specific yield of this aquifer is 2% and its hydraulic conductivity is equal to 0.000000386 meters per second. Furthermore, the initial water storage volume of the aquifer in the first operation period is equal to 7536 MCM. The difference between the initial water level of the aquifer and the ground elevation is equal to 2 meters. Here, a rectangular cross section is assumed for river with the width of 50 meters.

In order to modeling this case study, the river is divided into two reaches. The first reach is considered from the dam to the beginning of the aquifer and the second one is considered from the beginning of the aquifer to the end of the aquifer. The length of the first reach is equal to 75.23 km and the second one is equal to 71.64 km. In addition, the semi pervious streambed thickness of river is assumed to be 2 meters. According to information obtained from Regional Water Company of West Azarbaijan, 28% of the water transferred to the demand area percolates into the aquifer. In addition, 5% of the total water transferred to the demand area enters in to the second river reach. Furthermore, the 4.44% of the precipitation percolates into the aquifer. The annual water demand of agricultural areas located at the downstream of the dam is 964 MCM in which it is supplied by the Buchan Dam, the ZarrinehRoud River and the Miandoab aquifer. The drinking water and industrial demands of Miandoab city are also about 36 MCM. Due to water shortage and supplying drinking water problem of the Tabriz, Azarshahr, Ajabshir and Bonab cities, about 100 MCM of water is transferred to these areas from Buchan Dam every year. The water inflow into dam reservoir, precipitation height and evaporation values from 2005 to 2015 year are presented in figures 3, 4 and 5, respectively.

4. Methodology

In this research, based on the cyclic storage approach, the problem of optimal conjunctive operation of surface and ground water system problem is solved using mathematical programming and four meta-heuristic algorithms called GA, GSA, PSO and ABC algorithms. Therefore, in this section, a briefly descriptions of these algorithms are presented.

4.1. Genetic Algorithm

At first, Holland (1975) proposed GA, based on natural evolution of alive creatures. By creating the specified numbers of chromosomes population representing the problem solutions, the current generation is formed. Generally, each solution is named individual. In each generation, the fitness value is determined for every individual based on the objective function value of the problem. In general, superior individual can be selected using fitness values. By determining all individual fitness, the individuals are chosen, using their corresponding probability to their relative fitness, for mating and creating next generation. These processes should be continued until stop criterion is reached (Holland, 1975).

In GA, three operators named selection, crossover, and mutation are generally used to obtained best solution. Selection operator is used to choose some of the individuals, named parents, for creating next generation in which some of the most useful selection operator are Roulette wheel, tournament, and uniform selections. Crossover operator is generally used to create new chromosomes in which they are combination of their parent's genes characteristics. Finally, mutation operator is used to create new genetically structure by replacing one gene with another gene.

4.2. Particle Swarm Optimization (PSO) algorithm

Particle swarm optimization (PSO) algorithm is proposed by simulating the natural behaviors ruling over birds and poultry. At first, Eberhart and Kennedy (1995) simulated the swarm movement which is causes in two conditions of local and global neighborhood. In this algorithm, particles represent the solutions of the problem in which each particle defines by tow parameters of location and velocity movement. By considering initial location and velocity for each particle, the new velocity and particle location are updated using different defined parameters such as the weight inertia, cognitive and social parameters. These processes should be continued until stop criterion is reached.

It should be noted that, in order to inappropriate exploration in the search space of the problem leading to best solution, in this algorithm, the particle velocity should be limited to the maximum and minimum values.

4.3. Artificial Bee Colony (ABC) algorithm

Finding the food resource is one of the social lives of honey bee in which it was used to proposed ABC algorithm by Karaboga and Basturk (2005). In this algorithm, artificial bee colony collects information from surroundings such as real bee behavior to collect information for finding food. Here, bees are divided to three groups named employed bees (EB), onlooker bees (OB) and scout bees (SB). Initially, the EB goes toward the food resources and then come back to hive by collecting information. This information can be offered with other bees and therefore the OB can easily find food resources that have the greater probability for amount of nectar according to the food resources probability. Furthermore, the SB searches the food resources randomly without using other bee’s information (Karaboga and Basturk, 2005).

In ABC algorithm, random solutions represent (food resources in which they are initially generated. The objective functions of these solutions are determined representing the amount of nectar for every food resource. Due to this fact that new initial solution maybe better that current solution, another initial solution can randomly be chosen by EB and therefore the new solutions can be generated at the next iterations. The objection function values of these new solutions are determined and they are replaced with pervious ones or rejected due to objective function values. In the next stage of this algorithm, the OB moves toward the food resources with greater probability values considering the nectar information of the EB. Here, some food resources are investigated several times by OB related to probability values. These processes should be continued until stop criterion is reached (Naveena et al., 2015).

4.4. Gravitational search algorithm (GSA)

Based on the natural gravitation law named newton's gravitation law a new algorithm named GSA is proposed by Rashedi et al. (2009). In GSA, the complex of planets is represented by the explorer agents in which the position of optimal solutions attracts the agents like black hole. Here, each solution is represented by each agent. By comparing all solutions, the optimal solution is chosen as maintained follow. Based on the physics rules, in GSA, the gravitation and movement rules are used for simulation.

In GSA, each agent defines by parameters of location, velocity and acceleration movement. By calculating the inserted force of agents, using defined equations based on the physics rules, only a few (superior) agents are considered for the GSA process in order to improve the exploration feature to find the best solution. By calculating the inserted force, the acceleration and velocity of the agents can be calculated. Therefore, the new agent location can be determined using new agent velocity value. In other words, by defining the search space of problem and the parameters, agents are evaluated and their movements are determined and updating over the iterations. Then, GSA parameters such as active, passive and inertia gravitational masses and gravitational constant are updated for the next iteration. These processes should be continued until stop criterion is reached (Moeini et al., 2017).

5. Results and discussion

In order to investigate the performance of the maintained algorithm to solve optimization problem of conjunctive operation of surface and ground water system considering cyclic storage approach, here, two hypothetical and real (ZarrinedRouud catchment area) test examples are solved and the results are presented and compared. For comparison purpose, LINGO software is also used to solve these problems using NLP method. Table 2 shows the obtained results (optimal details of operation cost) of solving optimization models using NLP method. It should be noted that the computational times are equal to 5400 and 259200 second for solving the hypothetical and real test examples, respectively.

Generally, each algorithm contains of some parameters in which the sensitivity analysis should be initially done to find the best values of them. The best values of parameters of each algorithm are presented as follow. The best values of GA parameters for hypothetical (real) test example are as: mutation probability = 0.1 (0.12); crossover probability = 0.9 (0.88); and selection= Roulette wheel. In addition, the best values of ABC parameters for hypothetical (real) test example are as: *ndim*= 3(8); and *limit*= 6500 (100000). Furthermore, the best values of PSO parameters for hypothetical (real) test example are as: W_{max}= 1(1); W_{min}= 0.99 (0.9); C_1= 1(1); and C_2= 1 (1). Finally, the best values of GSA parameters for both test examples are as: $\alpha = 8$; R=1; and G_0= 500. Here, 100,000 function evaluations (multiple numbers of iteration and population) are chosen for each algorithm considering number of 1000 iterations and 100 populations. In addition, all the results are presented here using 10 times run of the program in which some of them may be infeasible.

All the results such as the minimum, maximum and average solution cost values (Bilion Rillas), normalized standard deviation, computational time (second) and the number of feasible solutions in 10 runs are presented in Table 3. Comparison of the results shows that the best and worth results of hypothetical test example are obtained using PSO algorithm and GSA, respectively, in comparison with the result of NLP method. In addition, the operation costs are increased 26.36%, 26.1%, 44.91% and 21.28 % in comparison with the result of NLP method using ABC, GA, GAS and PSO algorithms for solving hypothetical test example, respectively. However, the computational time is extremely reduced using meta heuristic algorithm in comparison with NLP method. In other words, the computational time are decreased 99.73%, 99.82%, 99.32%, and 99.78% in comparison with the result of NLP method using ABC, GA, GAS and PSO algorithms for solving hypothetical test example, respectively. Furthermore, comparison the results of table 4 shows that the best and worth results of real test example (ZarrinehRoud catchment area) are obtained using GA and GSA, respectively, in comparison with the result of NLP method in which all of the obtained solutions are infeasible using GSA. In other words, the operation costs are increased 50.57%, 32.23%, and 43.74% in comparison with the result of NLP method using ABC, GA, and PSO algorithms for solving real test example, respectively. However, the computational time is extremely reduced using meta heuristic algorithm in comparison with NLP method. In other words, the computational times are decreased 99.95%, 99.91%, and 99.90% in comparison with the result of NLP method using ABC, GA, and PSO algorithms for solving real test example, respectively. Finally, it is worth noting that near optimal solutions with lesser computational time are obtained for both test examples using meta heuristic algorithm. Table 4 and 5 show that the obtained results (optimal details of operation cost) of solving the optimization models of hypothetical and real test examples, respectively, using meta heuristic algorithm.

Obtained operational parameters of optimization model solution of hypothetical and real (ZarrinehRoud catchment area) test examples are presented in figures 6 and 7, respectively, using different methods. It is worth noting that in the hypothetical test sample, the amount of water inflow into the dam reservoir is high in the first year, and in the second year this value decreases significantly. In addition, comparison the results of figure 6 shows that the system prefers to supply the water of demand area from the reservoir and river in the first year, and from the aquifer in the second year, for hypothetical test example. Therefore, in the first year, the amount of water in the aquifer is stored for using in the second year. In addition, artificial recharge area is recharged form both reservoir and the river in the first, second and third seasonal operation time periods in which these periods are watery periods. On the other hand, in these three periods, no pumping is done from the aquifer. Furthermore, the amount of water spill from the dam reservoir is the highest value in the third operation time period, which is the most watery period. For the hypothetical test example, it is assumed that the dam reservoir is initially empty ($S(1)$=0) and the maximum values of reservoir storage volume is obtained in the fourth operation time period which is equal to 19.9 MCM. In addition, in the first year, the groundwater storage volume is increased due to artificial recharging the groundwater and no pumping from the aquifer to supply the demand area. However, in the second year, the groundwater storage volume is decreased due to pumping from the aquifer to demand area and lack of surface water for artificial recharging of aquifer. In addition, the positive values of change of the groundwater storage volume show the increasing of water storage volume and the negative values show the decreasing. Furthermore, groundwater level of the aquifer is initially assumed to be 10 meter in which the groundwater level is increased by increasing the ground water storage volumes and it is decreased by decreasing this parameter. In figure 6, positive values show the lateral river inflow and negative one show the lateral river outflow along the river. Furthermore, the positive values of $q_{raq}(t,r)$ show the transferred water from river reach *r* to the aquifer in operation time period *t* and the negative ones show the transferred water from aquifer to the river reach *r* in operation time period *t*. Finally, investigating the values of river outflow of river reach *r* in operation time period *t* ($q_{riv}^{out}(r,t)$) shows that this value is equal to downstream demand in all operation time period expect for third operation time period that the water inflow value is very high.

Comparison the results of figure 7 shows that, in each year, the maximum reservoir storage volumes are occurred in April and May and the minimum values are occurred in December and January due to the reason presented follows. The precipitation of this study area is mostly in the form of snow, and therefore the warming of the air in April and May causes the snow to melt leading to increasing the water inflow values to dam reservoir. In addition, supplying the water demands of the demand area by pumping from the aquifer reduces the water storage volumes of the aquifer, but the high water level of the river causes the aquifer to return to an almost full capacity state expect for third and forth years. This is due to the low values of water inflow into dam reservoir and the consequent decrease in the amount of water release from reservoir into the river, and as a result, the water level of the river is not high. However, this fact is not completely possible leading to worst solutions in comparison with NLP results. In addition, the volume of surface water is decreased in the last months of the each year and, therefore, the water demand of demand area is supplied by pumping from the aquifer leading to maximum reduction of water storage volume of groundwater in these months. Comparison the obtained results of figure 7 show that the groundwater level varies between 298 and 273 meters. Furthermore, the river outflow of river reach one is related to water spilled from the reservoir and, therefore, this parameter only increases when the dam is relatively full and the water inflow in to the dam reservoir is extremely high. Otherwise, the constant value of 5 MCM will be out of the first river reach into the second one. In addition, the lateral rive flow of the second river reach is affected by the precipitation, water transferred from the river to the demand area, the water interaction between the river and the aquifer, and return water from the region. By using NLP method to solve this model, the amount of lateral flow of the second river reach is positive; it means that the river water level increases so that it is possible to recharge the aquifer and prevent the reduction of groundwater storage. However, by using meta heuristic algorithm to solve this model, the amount of lateral flow of the second river reach is negative; it means that the river water level decreases so that it is impossible to recharge the aquifer. In addition, the interaction between the river and the aquifer is in the most cases such that the river water level is higher than the water level of the aquifer leading to recharging the aquifer from river and prevent excessive groundwater level drop.

Finally, figures 8 and 9 show convergence curves of minimum obtained solutions using different meta hubristic for hypothetical and real test examples, respectively. The results of figure 8 show the better convergence characteristics of ABC algorithm in comparison with other meta heuristic algorithm algorithms. It is seen from this figure that best solution cost of the generation obtained with PSO algorithm stays way below that of other maintained algorithms. In addition, the results of figure 9 show the better convergence characteristics of GA in comparison other meta heuristic algorithms. It is seen from this figure that best solution cost of the generation obtained with GA stays way below that of other maintained algorithms.

6. Conclusion remarks

In this research, a new approach named cyclic storage approach was proposed to investigate the problem of optimal conjunctive operation of surface and ground water system. At first, the mathematical model of this system was defined and solved using NLP method. In addition, the performance of four applicable meta hubristic algorithms means ABC, GA, GSA and PSO algorithms were also studied to solve this problem. A hypothetical benchmark system and conjunctive use of Buchan dam reservoir and Miandoab aquifer located in the catchment area of Urmia Lake (ZarrinehRoud catchment area), as a real problem, were considered to investigate the performance of proposed methods. Summarizing the obtained results showed that proposed approaches was an effective method for sustainable operation of the system. In addition, optimal solutions were obtained using NLP method, but the computational time was very high. Furthermore, near optimal solutions were obtained using meta hubristic algorithms. However, the computational time was extremely decreased in comparison with related value of NLP method by using meta heuristic algorithm.

- Declarations

- **Conflict of Interest:**

Both authors declare that he and she have no conflict of interest.

- **Funding Source:**

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- **Ethical approval:**

This article does not contain any studies with human participants or animals performed by any of the authors.

- **Data availability**

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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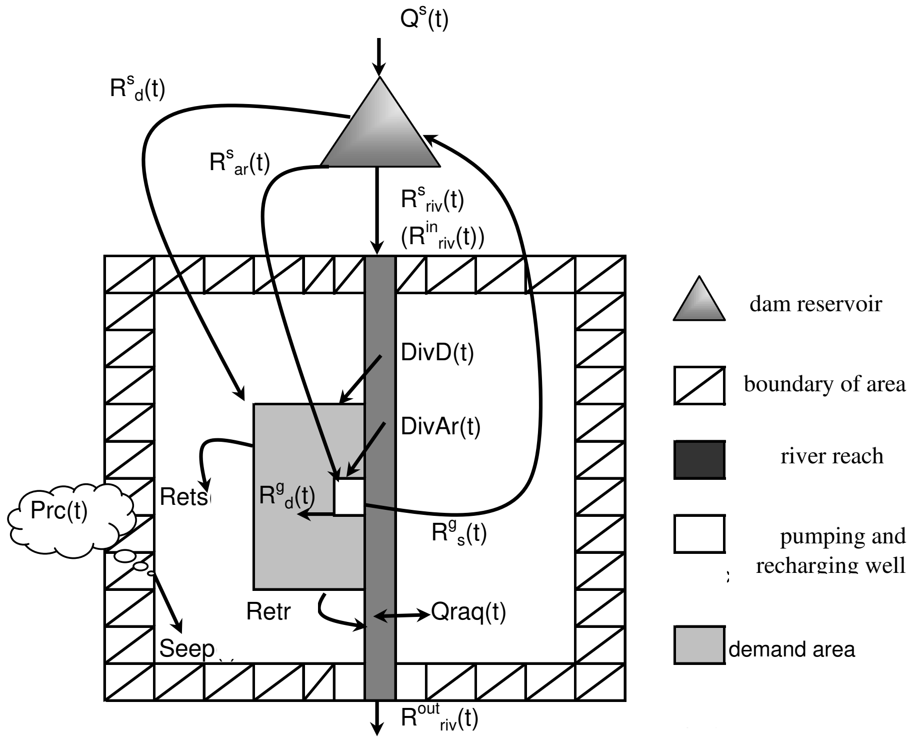


Figure 1: Details of hypothetical case study (Alimohammadi et al., 2009)

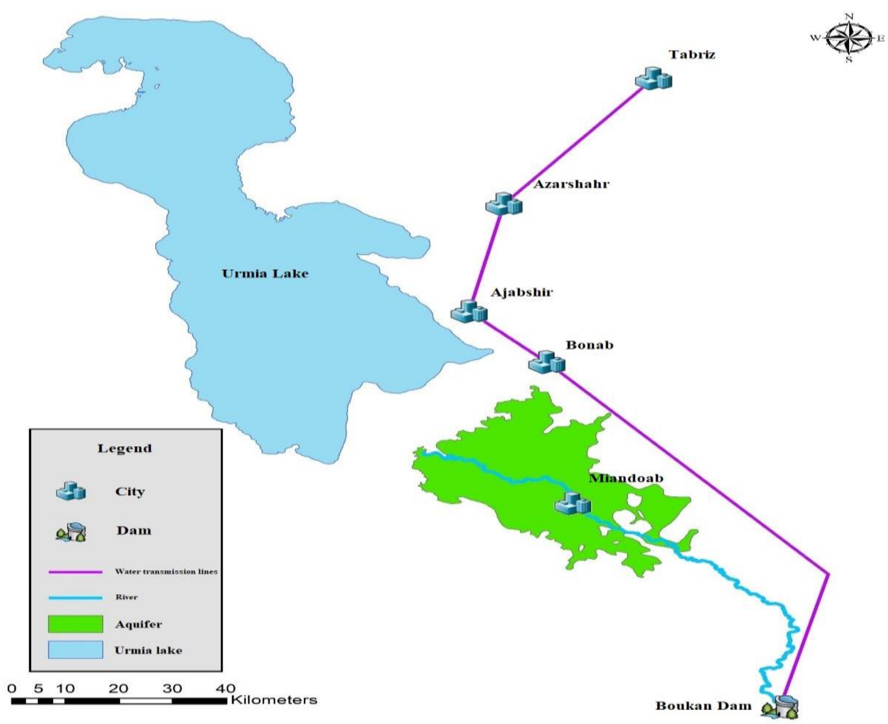


Figure 2: Schematic location and details of real case study

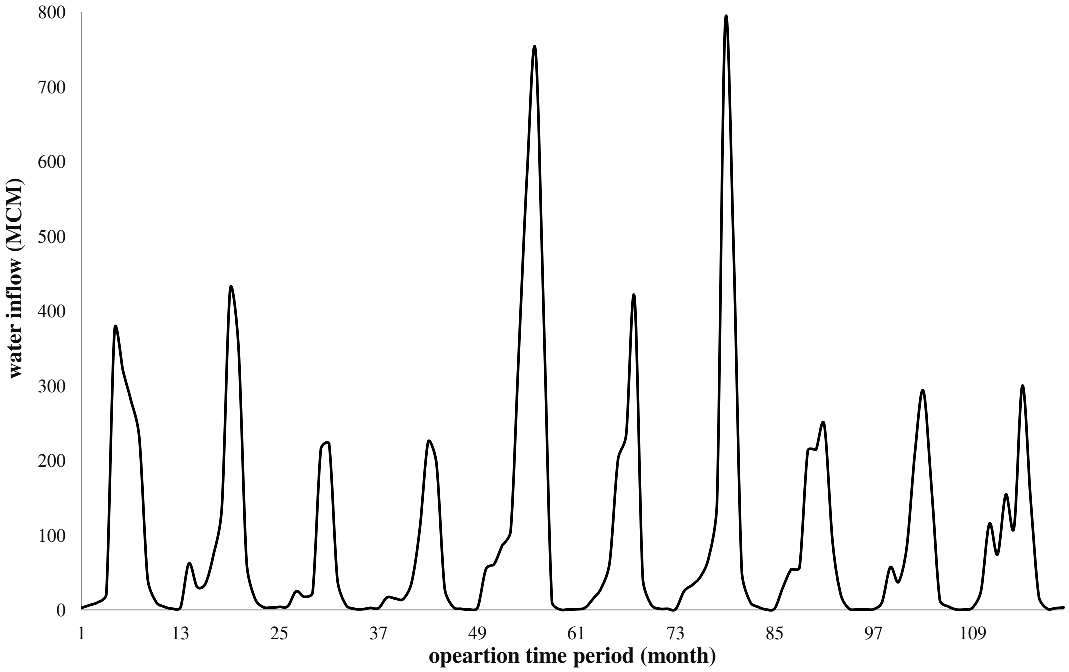


Figure 3: Observed water inflow values of Buchan dam reservoir form 2005 to 2015

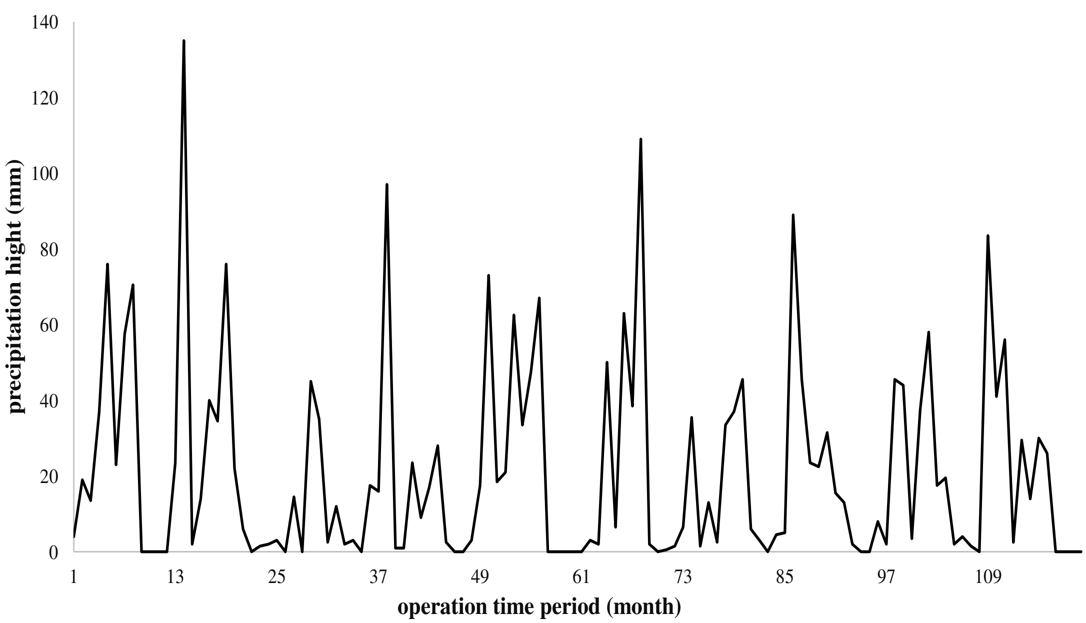


Figure 4: Precipitation height values of ZarrinehRoud catchment area form 2005 to 2015

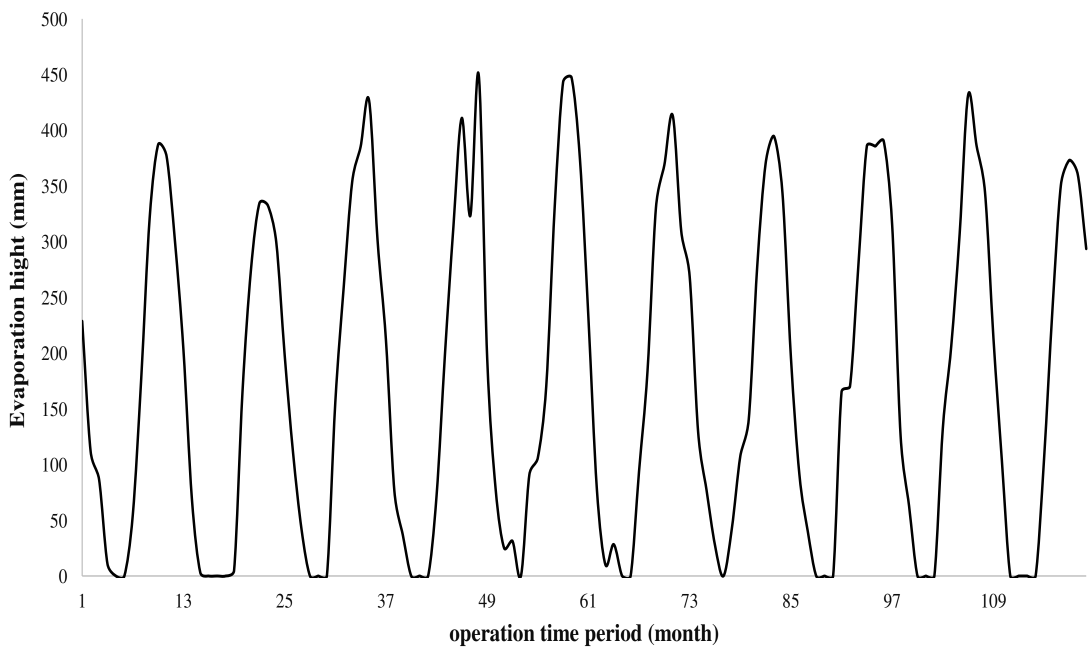
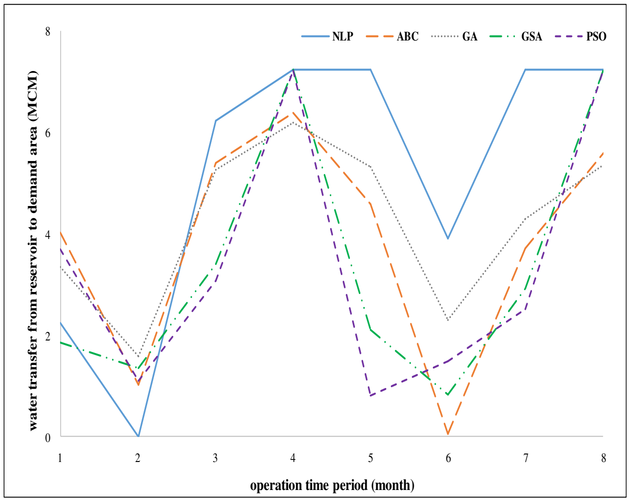
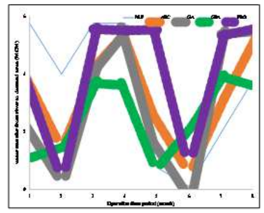


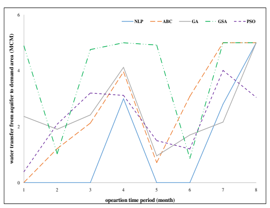
Figure 5: Evaporation hight of Buchan dam reservoir form 2005 to 2015

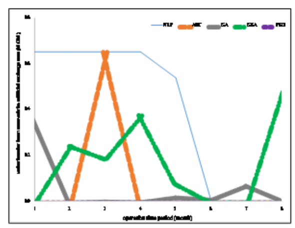




a) Rsd

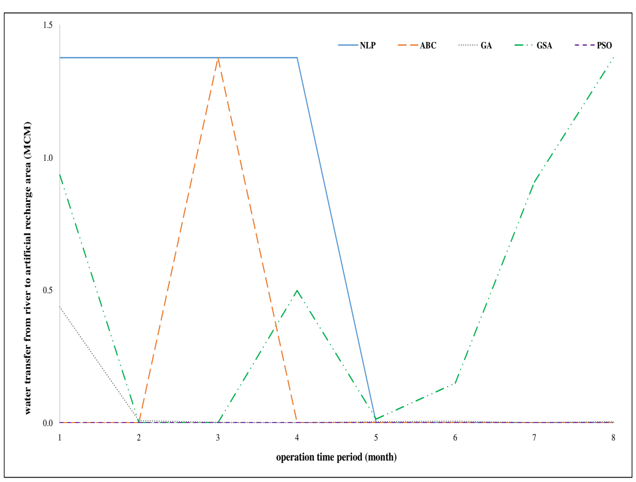
b) DivD

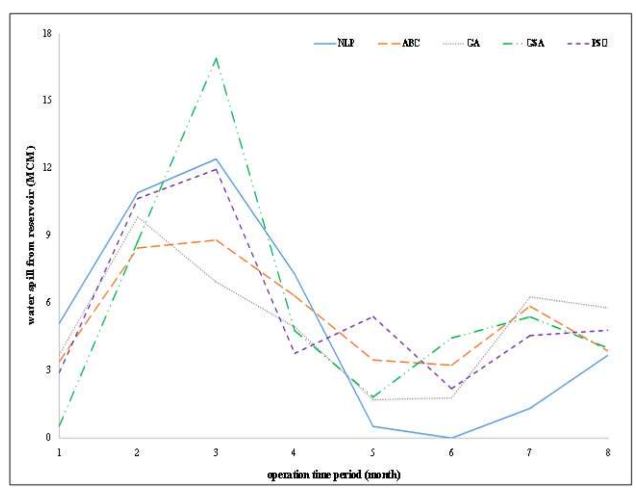




c) Rgd

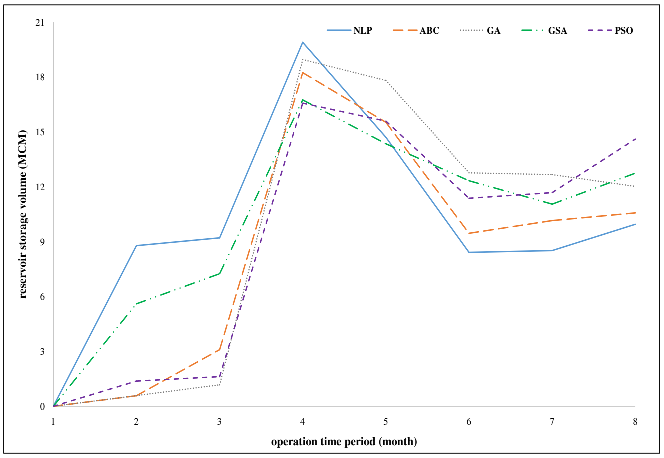
d) Rsar



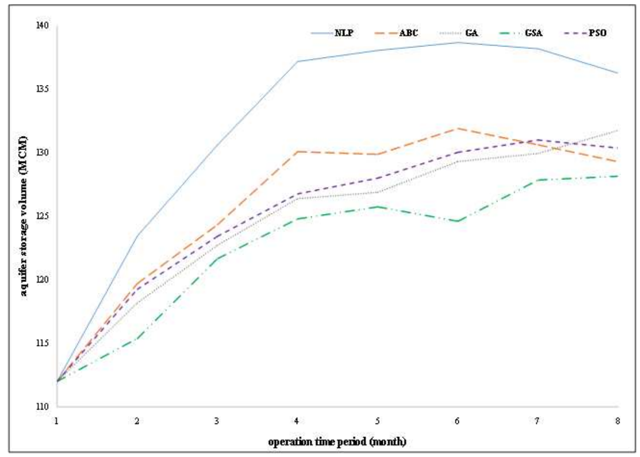


e) DivAR

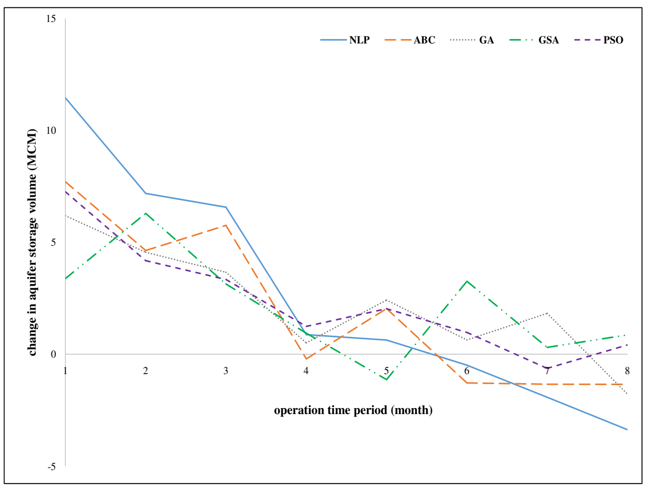
f) Rsriv



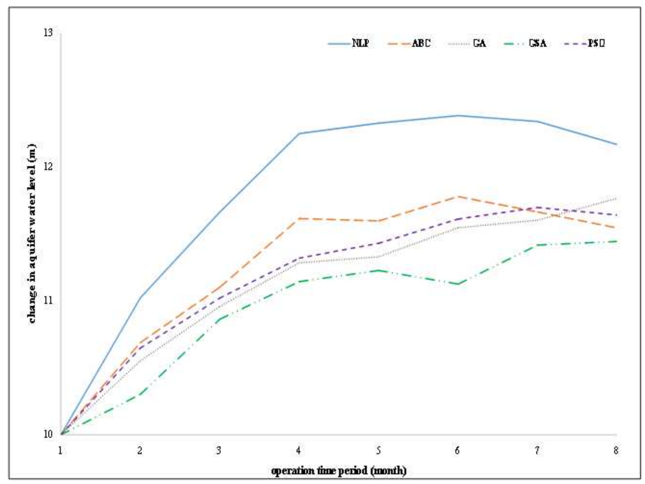
g) Ss



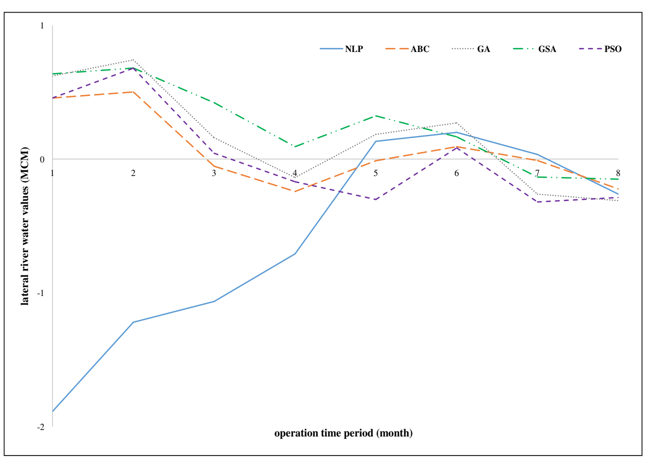
h) Sg



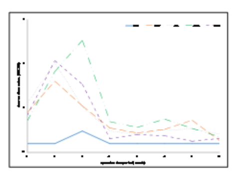
i) DeltaSg



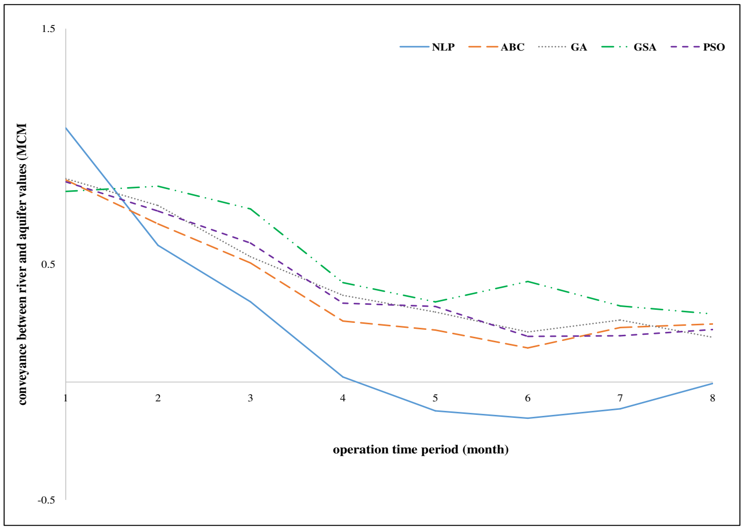
j) Hg



k) qlriv

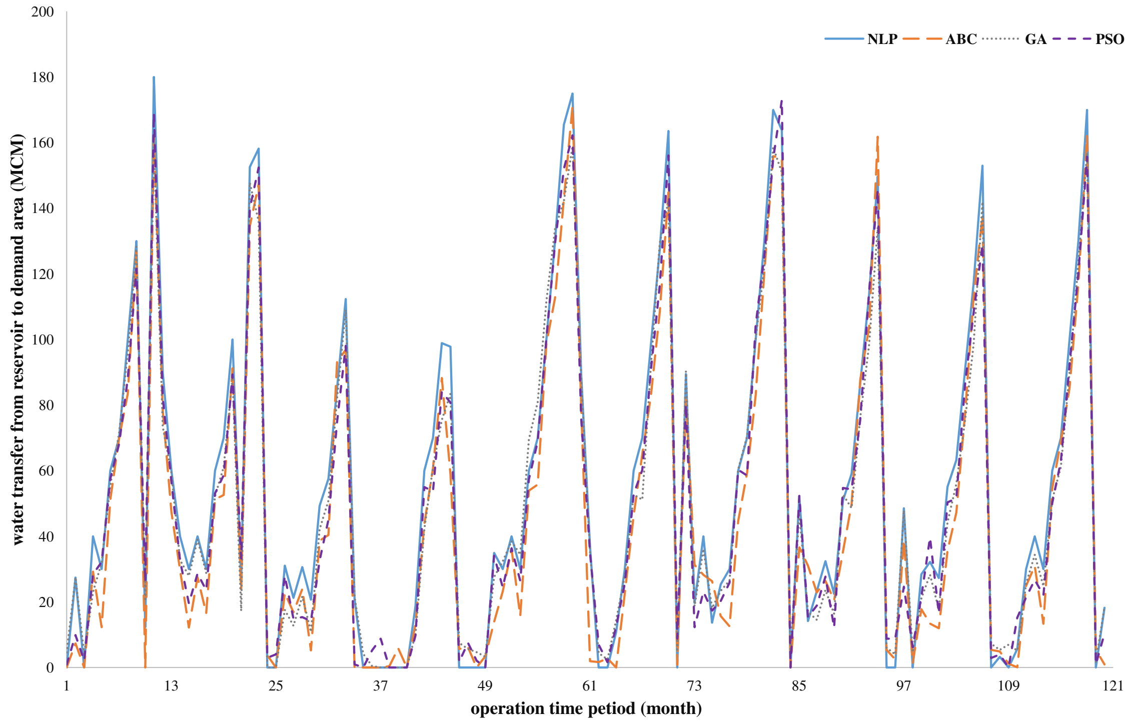


l)qoutriv



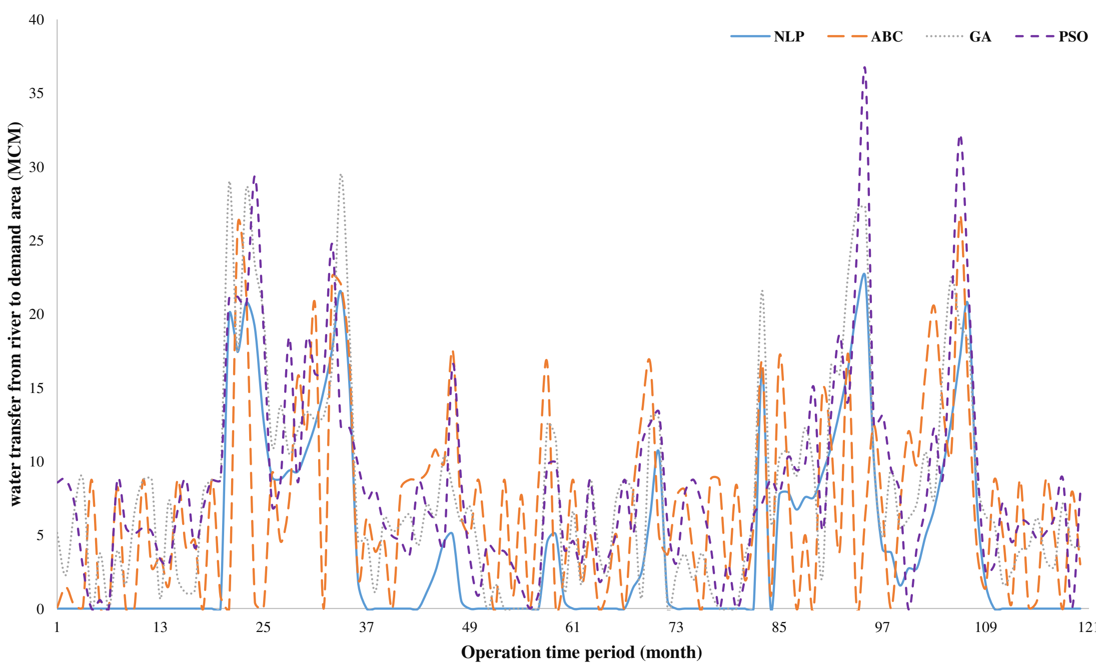
m) qraq

Figure 6: Obtained operational parameters of optimization model for hypothetical test example using different methods



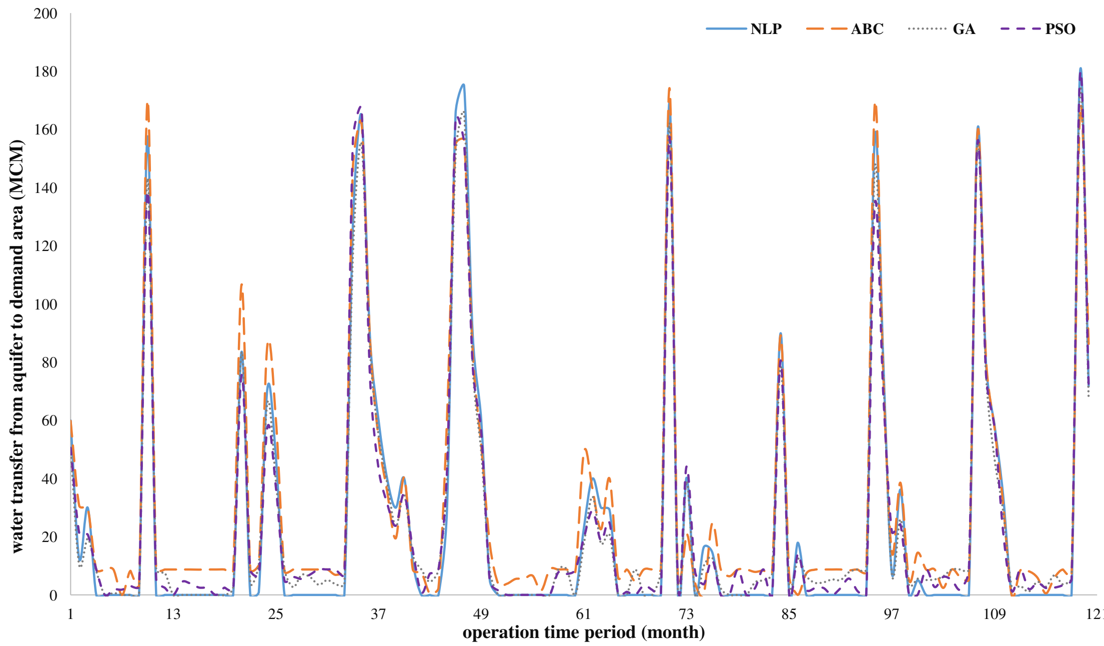
200
180
160
140
120
100
80
60
40
20
0
water transfer from reservoir to demand area (MCM)
NLP
ABC
GA
PSO
1
13
25
37
49
61
73
85
97
109
121
operation time petiod (month)

a) Rsd

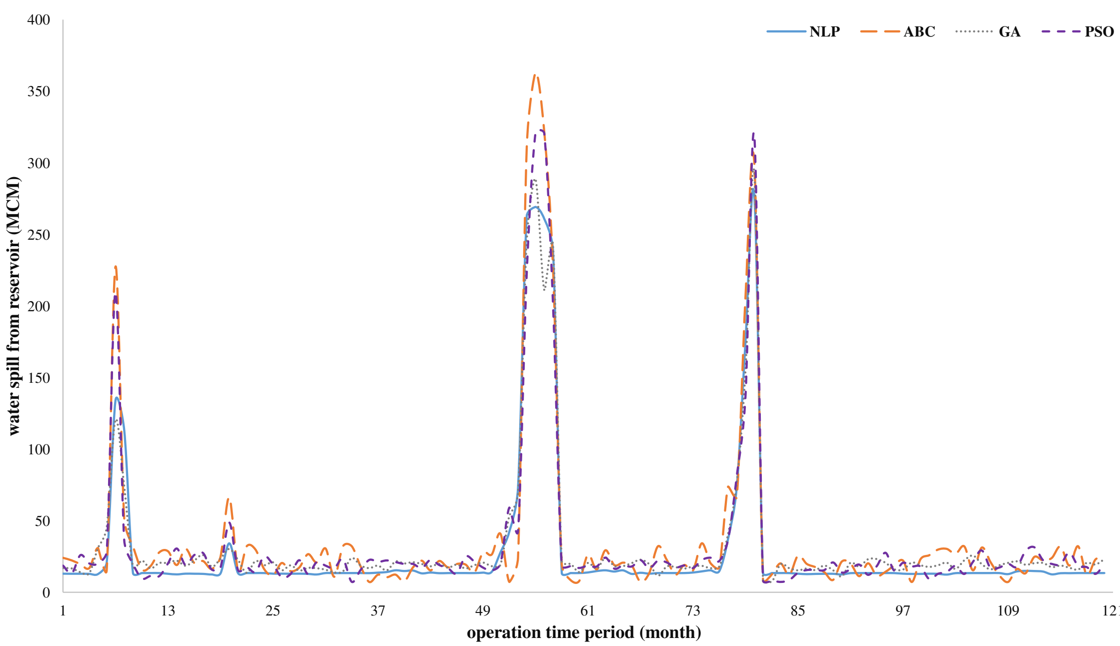


40
35
30
25
20
15
10
5
0
water transfer from river to demand area (MCM)
NLP
ABC
GA
PSO
1
13
25
37
49
61
73
85
97
109
121
Operation time period (month)

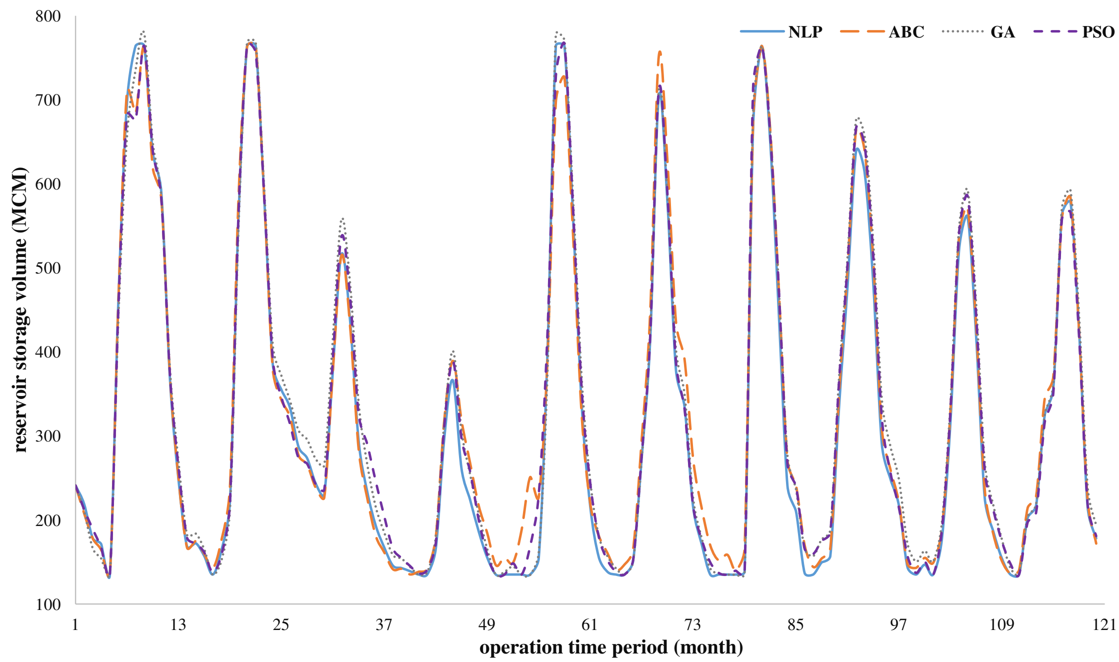
b) DivD


NLP
ABC
GA
PSO
water transfer from aquifer to demand area (MCM)
operation time period (month)

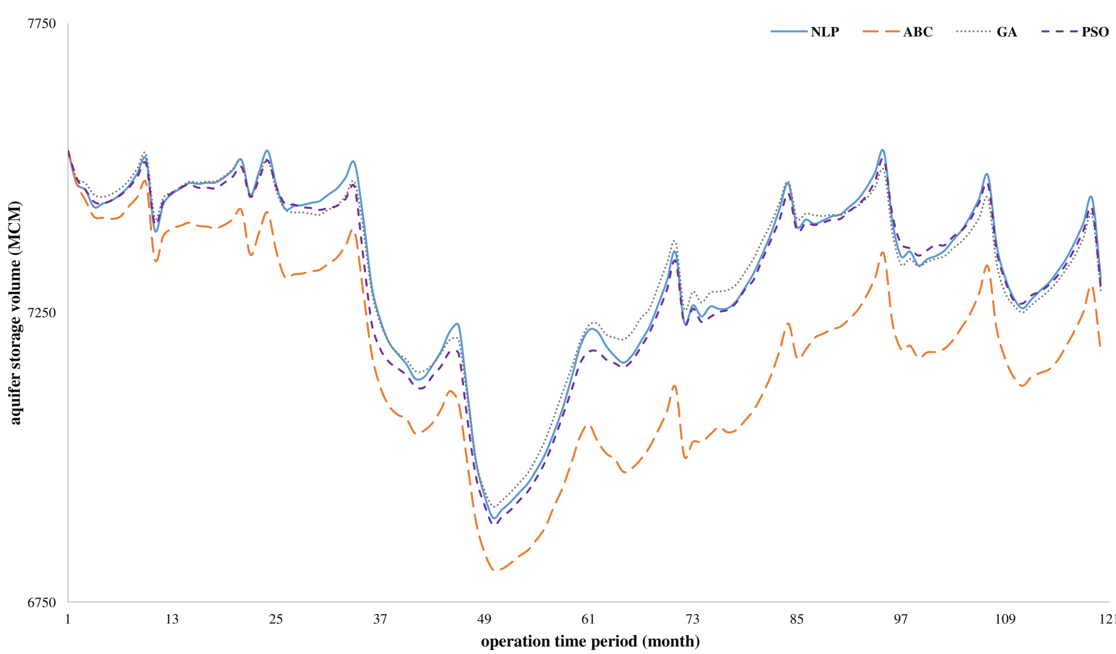
c) Rgd


NLP
ABC
GA
PSO
water spill from reservoir (MCM)
operation time period (month)

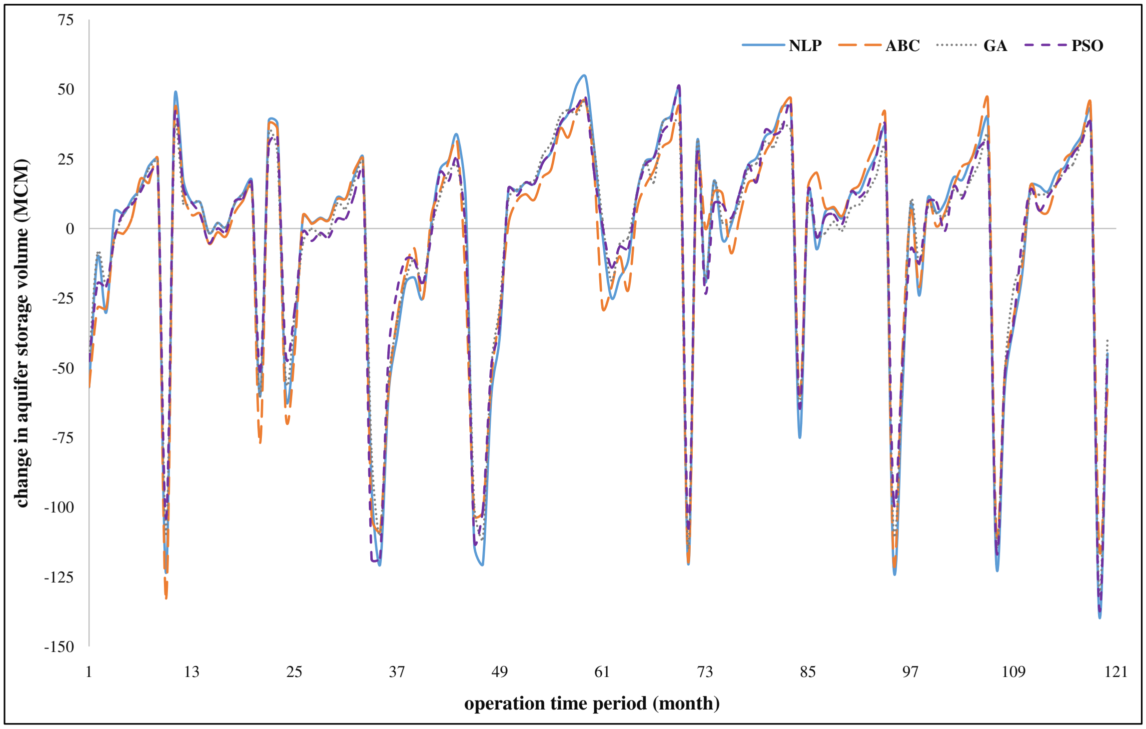
d) Rsriv


NLP
ABC
GA
PSO
800
700
600
500
400
300
200
100
reservoir storage volume (MCM)
1
13
25
37
49
61
73
85
97
109
121
operation time period (month)

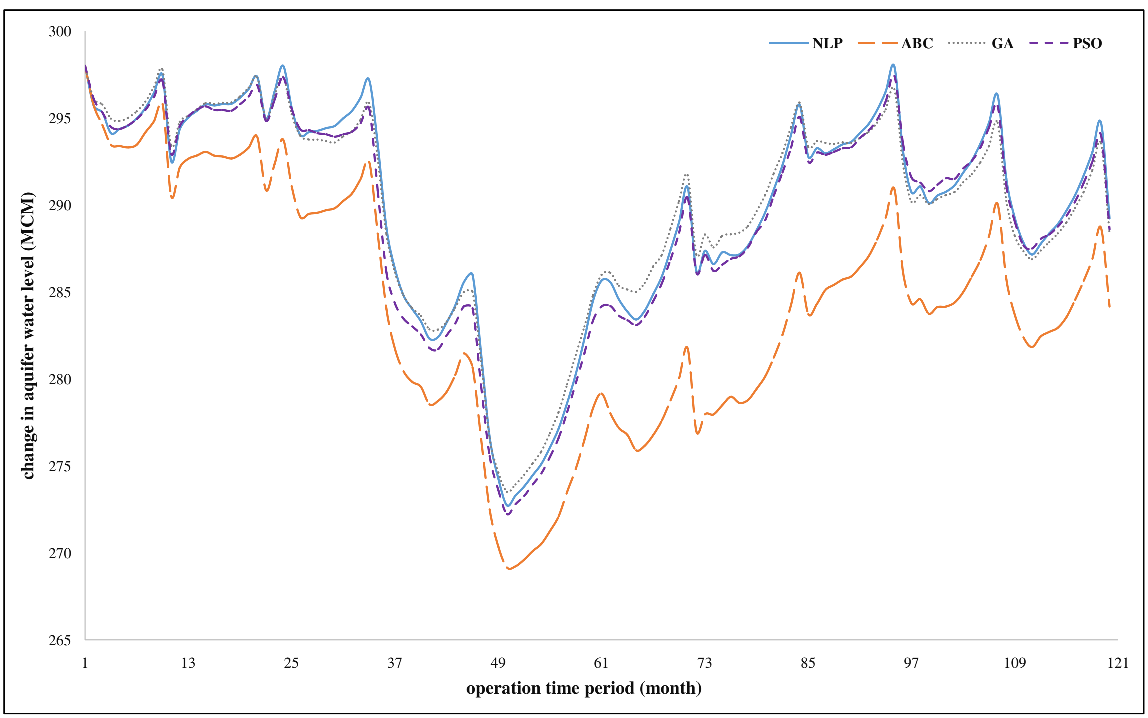
e) Ss


NLP
ABC
GA
PSO
7750
7250
6750
aquifer storage volume (MCM)
1
13
25
37
49
61
73
85
97
109
121
operation time period (month)

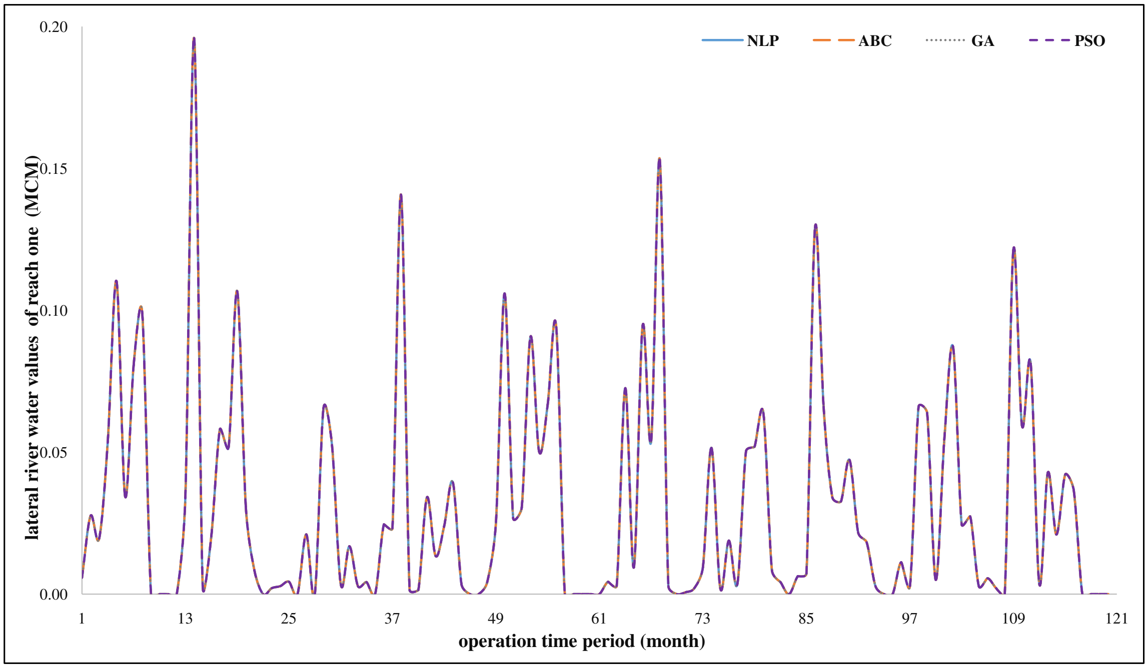
f) Sg



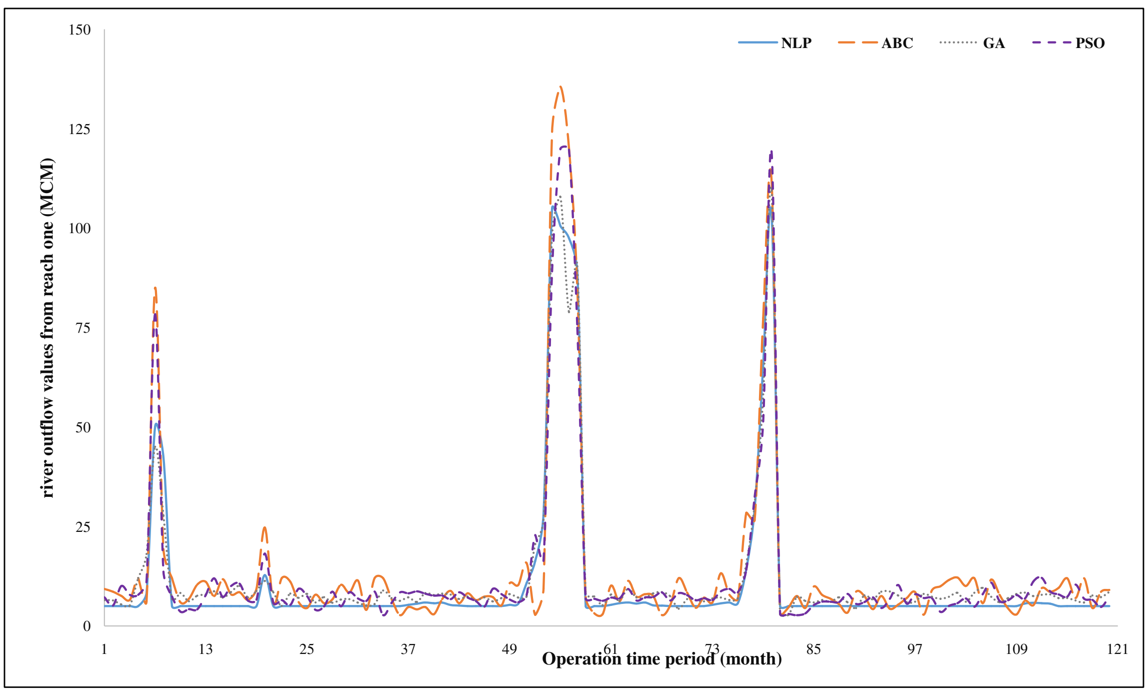
g) DeltaSg



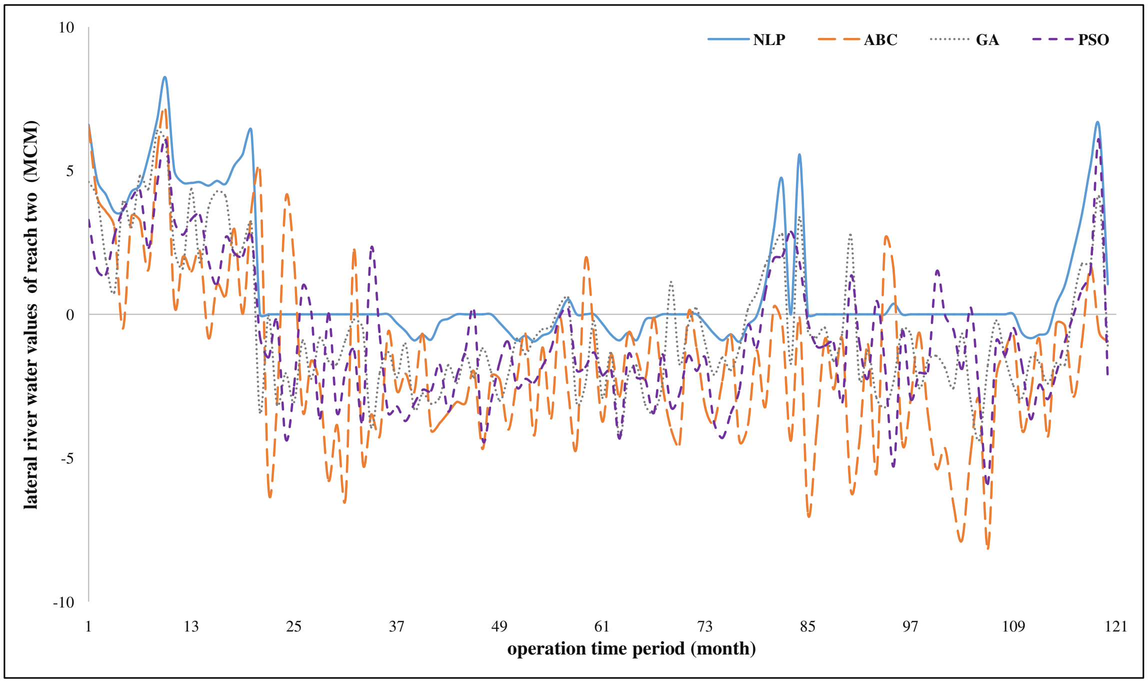
h) Hg



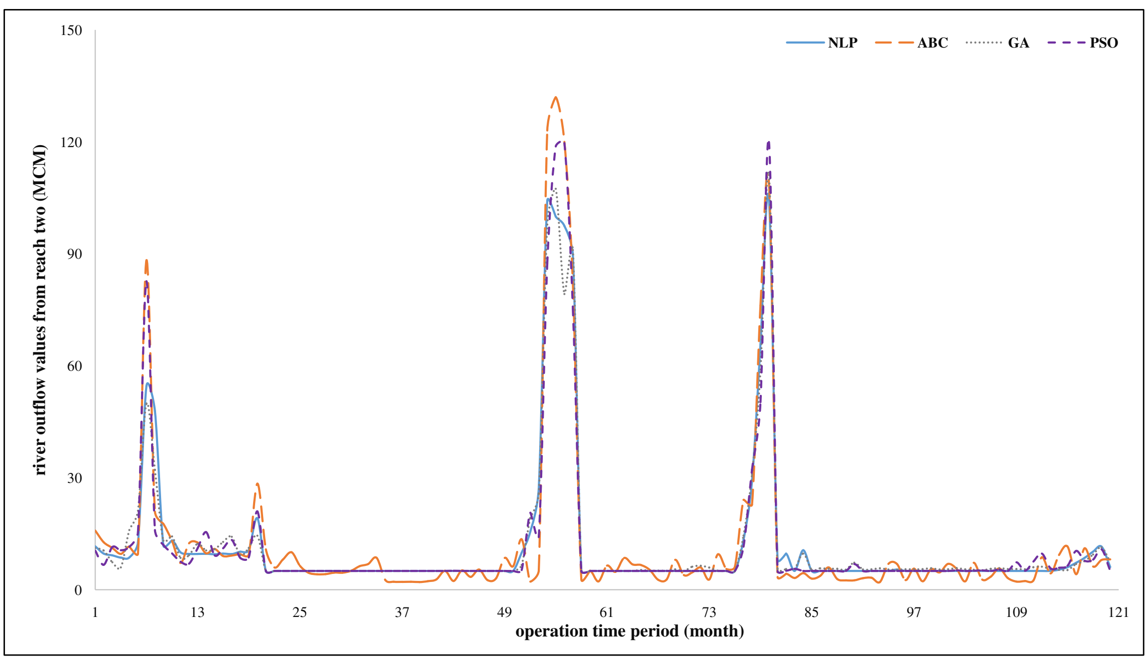
i) qlriv1



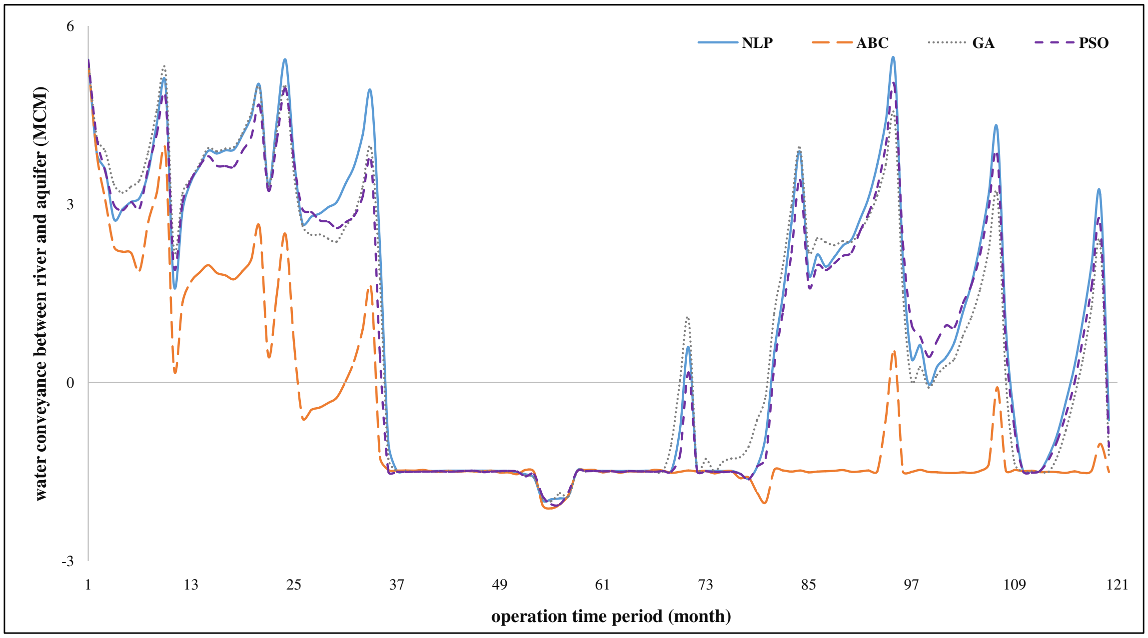
j) qoutriv1



k) qlriv 2



l) qoutriv2



m) qraq

Figure 7: Obtained operational parameters of optimization model solution for real test example (Zarinehdroud catchment area) using different methods

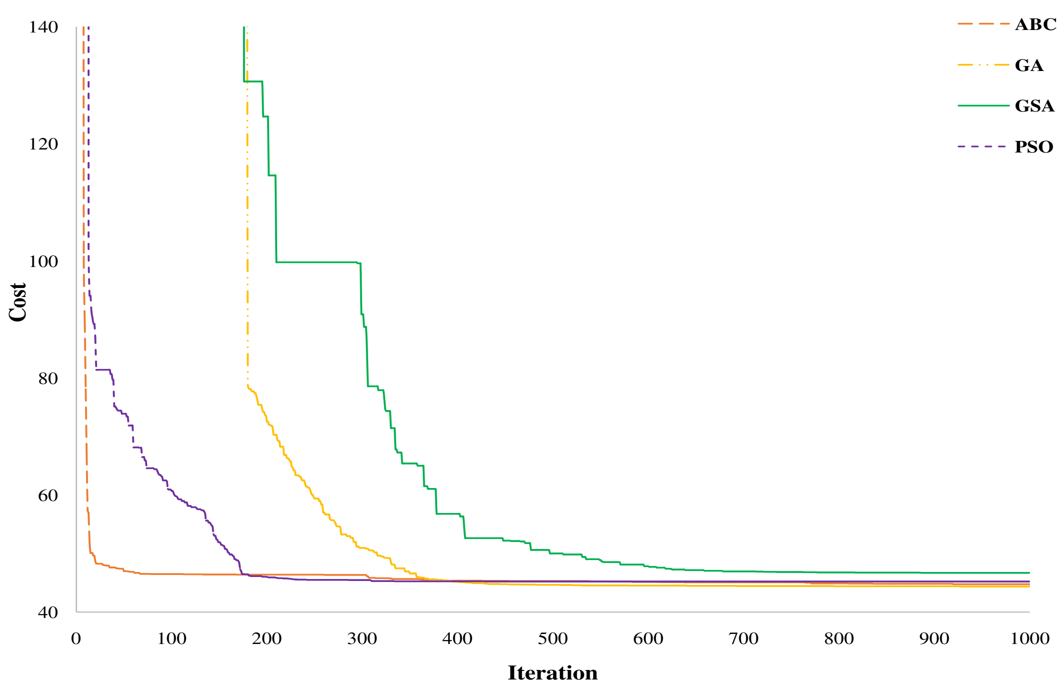
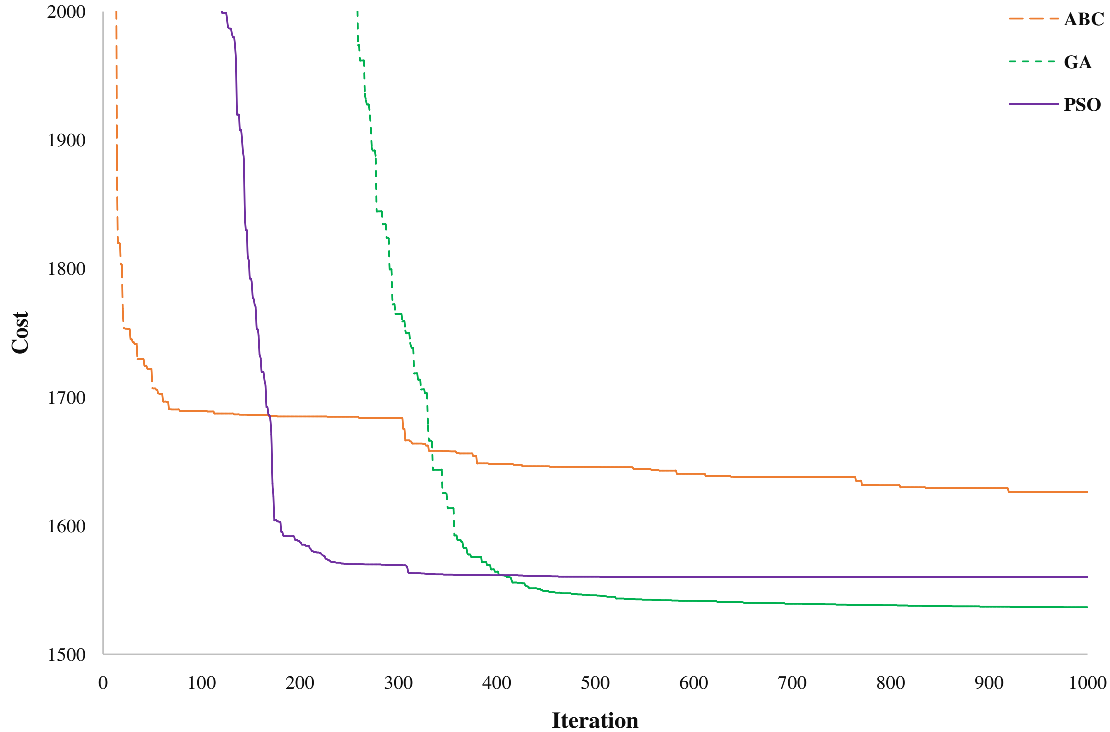


Figure 8: Convergence curves of the best solution of hypothetical test example using different algorithms



Figurse 9: Convergence curves of the best solution of real test example (Zarinehdroud catchment area) using different algorithms

Table 1: Details and parameter values for hypothetical case study

Parameters \ Season		Autumn	Winter	Spring	Summer	Annual
Inflow (MCM)	First year	8	12	30	10	60
	Second year	2	4	10	1	17
Precipitation (mm) (Both years)		60	72	150	18	300
Demand distribution (Both years)		0.2	0.1	0.3	0.4	1

Table 2. Obtained details of operation cost for hypothetical and real test examples using NLP method

Component	Operation cost

	Hypothetical test example	Real test example
Reservoir	1.4925	68.76
Transfer from reservoir to demand area	0.6167	38.0599
Transfer from aquifer to demand area	2.5448	25.3493
Transfer from reservoir to artificial recharge area	0.0253	0.000
Transfer from aquifer to reservoir	0.000	0.000
Diversion from river to demand area	0.4471	6.8427
Diversion from river to artificial recharge area	0.0456	0.000
Pumping	0.000	0.000
Recharge	0.0708	0.000
Deficit	0.000	0.0026
Total operation cost	5.2428	139.0145

Table 3: The obtained results of both test examples using meta heuristic algorithms

Test example	Algorithm	Operation cost			normalized standard deviation	number of feasible solutions	Computational time (s)
		Minimum	Maximum	Average			
hypothetical	GA	7.0947	8.2977	7.8059	0.3588	10	9.75
	GSA	9.5165	10.4955	9.9124	0.2533	10	36.76
	ABC	7.1191	8.0947	7.6768	0.2998	10	14.4
	PSO	6.6598	8.8473	7.4679	0.5914	10	12.1
real	GA	205.3968	225.5085	213.407	5.3267	10	225.9
	GSA	in	in	in	----	0	---
	ABC	281.2568	352.288	306.7029	9.6351	10	138.3
	PSO	247.1	268.3187	258.4189	4.3268	10	265.5

Table 4. Obtained details of operation cost for hypothetical test examples using meta heuristic algorithms

Component	Operation cost			
	GA	GSA	ABC	PSO
Reservoir	1.4925	1.4925	1.4925	1.4925
Transfer from reservoir to demand area	0.4731	0.3696	0.4385	0.3798
Transfer from aquifer to demand area	4.7401	7.2854	4.4468	4.3079
Transfer from reservoir to artificial recharge area	0.0041	0.0096	0.0052	0.000
Transfer from aquifer to reservoir	0.000	0.000	0.000	0.000
Diversion from river to demand area	0.3519	0.2976	0.4001	0.4796
Diversion from river to artificial recharge area	0.0042	0.0261	0.0109	0.000
Pumping	0.000	0.000	0.000	0.000
Recharge	0.0083	0.0357	0.0161	0.000
Deficit	0.0205	0.000	0.3090	0.000
Total operation cost	7.0947	9.5165	7.1191	6.6598

Table 5. Obtained details of operation cost of real test examples using meta heuristic algorithms

Component	Operation cost		
	GA	ABC	PSO
Reservoir	68.76	68.76	68.76
Transfer from reservoir to demand area	30.0267	9.1942	15.3148
Transfer from aquifer to demand area	72.2574	158.1462	114.2368
Transfer from reservoir to artificial recharge area	0.000	0.000	0.000
Transfer from aquifer to reservoir	0.000	0.000	0.000
Diversion from river to demand area	34.2573	40.1441	48.3298

Diversion from river to artificial recharge area	0.000	0.000	0.000
Pumping	0.000	0.000	0.000
Recharge	0.000	0.000	0.000
Deficit	0.0954	5.0123	0.4587
Total operation cost	205.3968	281.2568	247.1