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Multi-objective optimization to manage reservoir water quality and quantity via selective withdrawal and watershed control

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ABSTRACT

A new approach was presented to manage simultaneously reservoir outflow quantity and quality. Two strategies were used to control reservoir outflow quality: (1) reservoir inflow control with Best Management Practices (BMPs) in the watershed and (2) outflow management by reservoir operational strategy. Soil and Water Assessment Tool (SWAT) model was linked to a reservoir water quality simulation model (CE-QUAL-W2), the linked watershed-reservoir model was coupled with Multi-Objective Particle Swarm Optimization algorithm (MOPSO) to find the best set of decisions to optimize the reservoir outflow quality and quantity objectives. The approach was applied to Alavian reservoir and its watershed, in Iran, for a 6-year time horizon. The results show the proposed approach could reduce reservoir outflow phosphorus concentration while increasing downstream water supply. The implemented BMPs outperformed the reservoir operational strategy in terms of reservoir outflow quality reducing outflow phosphorus concentration up to 45% comparing with current conditions. Among the four applied BMPs, filter strips had more effect on reducing nutrient loads.

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1. Introduction

Reservoir water quality degradation is a common problem caused by nutrients from upstream watersheds. Mitigating these water quality problems requires effective policies to manage both the reservoir and upstream watersheds. Such policies can be realized by (1) optimizing Best Management Practices (BMPs) (Arabi et al., 2008) in the upstream watershed to reduce the burden of nutrients and (2) adapting reservoir operation policies such as selective withdrawal. Coupled simulation and optimization models can help implement a framework that establishes water quantity and quality objectives for optimal reservoir operational strategies and optimal selection and placement of BMPs in the watershed. In recent years, different simulation-optimization models have been used to reduce pollutant loads at watersheds through management strategies (Arabi et al., 2006; Maringanti et al., 2008; Kaini et al., 2012; Alami et al., 2017). In these studies, a hydrology model was coupled with an optimization model to simulate the effects of the watershed management strategies on watershed outflow quality, while the effect of the watershed management strategies on the reservoir water quality was not examined. Other studies have also been carried out by integrating reservoir simulation models with an optimization algorithm to derive reservoir optimal policies in regards to water quantity and quality objectives (Dhar and Datta 2008; Shirangi et al., 2008; Schardong et al., 2012; Castelletti et al., 2008, 2014; Soleimani et al., 2016; Saadatpour et al., 2017). The mentioned literature considered one of the two control strategies (i.e., the reservoir operational strategy) to manage water quality issues in reservoirs while the entry of the point and non-point source pollutants into the reservoirs is the main cause of reservoirs health problem. Some previous studies linked watershed and reservoir models to simulate the effects of the watershed management strategies on reservoir water quality.

Wang et al. (2005) coupled Artificial neural network Agricultural Non-Point Source (AnnAGNPS) watershed and Hydrologic Simulation Program Fortran (BATHTUB) lake models to simulate response to changes in different watershed landuse and management scenarios. Wu et al. (2006) used a watershed model (HSPF) and a receiving water quality model (CE-QUAL-W2) to evaluate alternative (BMPs) strategies at a watershed level and the resultant receiving water quality. Karamouz et al. (2010) linked the Soil and Water Assessment Tool (SWAT) to a system dynamic model to assess BMPs implementation in the watershed and reservoir phosphorus concentration in the Aharchai River watershed. To develop a cost-effective optimization model, a linked watershed-reservoir model was coupled with genetic algorithm to find optimal selection and placement of BMPs in the watershed with minimum cost. The approach could reduce the phosphorus concentration of the reservoir to the standard level. Ciou et al. (2012) developed an optimization model for finding the optimal location of structural BMPs at the watershed scale for the Feitsui Reservoir and its watershed in northern Taiwan. They integrated a watershed water quality simulation model (HSPF) with a reservoir water quality model (CE-QUAL-W2). The integrated watershed-reservoir model was coupled with genetic algorithm to design cost-effective combination of BMPs. The outcomes obtained from the integrated model efficiently showed its capability in improving reservoir water quality by adopting watershed approach. Yazdi et al. (2017) developed a watershed-reservoir system to the Seimare reservoir and its upstream watershed to evaluate 6 water quality protection scenarios in the watershed to control the upstream point and non-point sources of pollution. Overall, the aforementioned investigations were concerned with only watershed management strategies to control reservoir water quality while using multi-level outlets and improved reservoir operation rule may further enhance water quality. The literature review revealed that watershed management or reservoir operation approaches has been used separately, while none employed both watershed management and reservoir operation simultaneously to manage reservoir water quality. Development of a systematic approach to water quality and quantity management in the reservoir is to model watershed nutrient loading and link the watershed model to a reservoir model, and then to couple the linked watershed-reservoir system with an optimization algorithm to assess the many combined management alternatives to find a set of desirable decisions. The main contribution of the current research is linking a time continuous distributed watershed model (i.e., SWAT) to a two dimensional hydrodynamic and water quality model (i.e., CE-QUAL-W2) to develop a direct cause-and-effect relationship between upstream activities and downstream water quality, and optimizing the BMPs and the reservoir operational strategies simultaneously with a multi-objective algorithm (i.e., PSO). The proposed approach was applied to the Alavian reservoir and its upstream watershed in the northwestern part of Iran. In order to assess the effectiveness of the two control strategies (i.e., reservoir operational strategies through selective withdrawal scheme, and watershed control strategies) results from proposed methodology was compared with current conditions of the reservoir. A brief description of the materials and methods consisting of the case study area, proposed methodology, simulation models, model performance criteria, and optimization tools are presented in Section 2. The problem formulation (section 3) is followed by the application of the models and detailed analysis of the results and finally conclusions are presented.

2. Material and Methods

2.1. Case Study

Alavian dam and its upstream watershed are located in the East Azerbaijan Province in the northwest of Iran, and are a part of the Urmia Lake basin. The watershed is located between 37°11'- 38°28'N and 46° - 46°25'E, covering a catchment area for the dam of about 313 km^2 up to the Dam (Figure 1). The height of the dam is 70 m from the river bed and 80 m from the dam foundation. The Alavian reservoir has a volume of 60 million cubic meters (MCM) and a surface area of 2.7 km^2 at a normal water level. Two outlets of this dam are located at 1530 m and 1545 m above sea level and can be used for selective withdrawal. Alavian dam was constructed on the Sufichay

River in order to provide municipal drinking water in Maragheh City, and water for irrigation of 10,000 ha of agricultural lands of Maragheh plain and its surrounding gardens. Finally it supplies the hydroelectric power plant (Mahab Ghodss, 1990). During recent years, reservoir water quality has been degraded due to the entry of excessive nutrients into the reservoir which could cause reservoir eutrophication. Total nitrogen to total phosphorus ratio (TN: TP) has been used as an indicator for estimating which nutrient limits algal growth. Ratios greater than 10:1 are indicative of phosphorus limitation (U. S. EPA, 2000). The average ratio of (TN: TP) in the Alavian reservoir water was between 12 and 124 based on the available data. Consequently, phosphorus is the limiting factor in the reservoir. Total phosphorus was approximated by phosphate (i.e., dissolved phosphorus), as other types of phosphorus, such as suspended phosphorous was insignificant in the reservoir. In this study, SWAT model was used to simulate the surface runoff and transportation of nutrient loads in the watershed and CE-QUAL-W2 model was used to simulate the reservoir water quality. Digital elevation model (DEM) from the Iranian surveying organization with 1:25000 scale, the FAO–UNESCO global available soil data with 1:5000,000 scale, landuse map of the watershed generated using MODIS satellite imageries and climate data were used to setup SWAT model. The weather-generator variables produced by the Iranian Meteorological Organization included daily rainfall, daily minimum and maximum air temperature, and wind speed which were available at Maragheh synoptic station. The measured data for the water flow and water quality during the years 1999-2012 at TazehKand-Alavian station were used for calibration and validation of SWAT model. To decrease the initial condition impacts, first four years of the simulation from 1999 to 2002 were considered as a warmup period. The calibration period was considered from 2003 to 2008 and the validation period from 2009 to 2012. Temperature and water quality data were collected at 3 sites within the reservoir from October 2006 to July 2009 for 23 different times to support CE-QUAL-W2 model calibration and validation. The calibration period was from October 2006 to April 2007 and the validation period from May 2007 to July 2009.

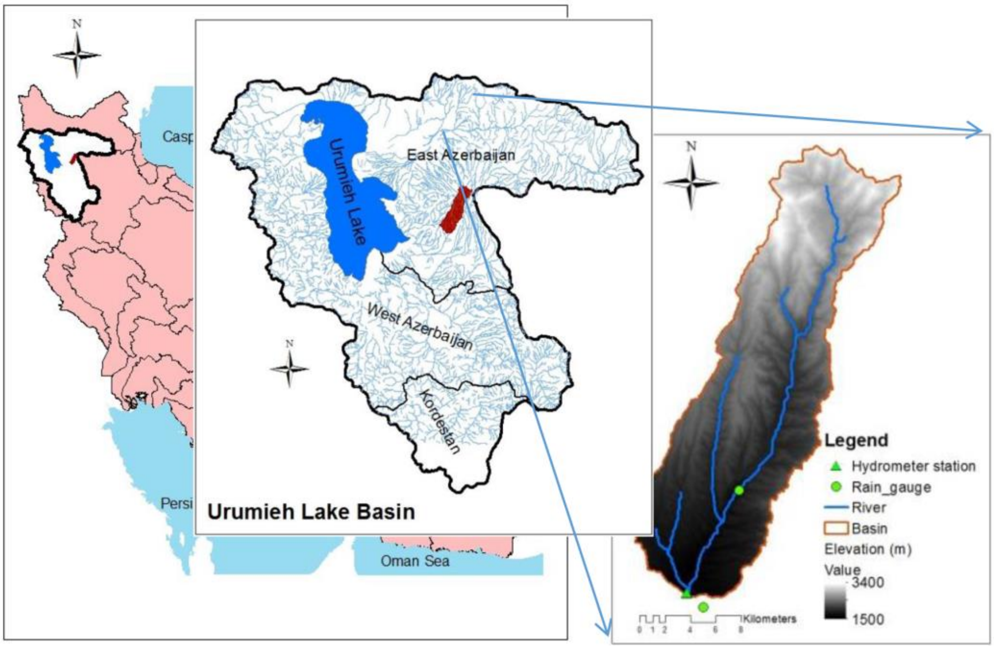

Fig. 1. Geographical location of Alavian reservoir watershed

2.2. Proposed Methodology

The proposed methodology in this study contains two steps: simulation and coupled simulation-optimization. Simulation step consists of calibration of watershed model (SWAT), reservoir water quality model (CE-QUAL-W2), and integrating watershed-reservoir approach through an intermediate program (this program extracts required outputs from SWAT model and converts them into acceptable CE-QUAL-W2 inputs). DEM, landuse data, soil data, and climate data are the input data to set up SWAT model. Observed flow and nutrient concentrations were used in SWAT model calibration and validation. CE-QUAL-W2 model needs the reservoir bathymetry data, initial conditions, and boundary conditions to simulate reservoir water quality. Flow and converted nutrient loads from the calibrated SWAT model and the observed outflow from the reservoir were used as the boundary conditions. The values of the reservoir water quality parameters at time t=0 were set as the initial conditions. In coupled simulation-optimization step, the calibrated and linked (SWAT)-(CE-QUAL-W2) simulation system was coupled with Multi-Objective Particle Swarm Optimization (MOPSO) algorithm to find optimal strategies (Figure 2). In the following sections, all main components of Figure 2 are explained in details. The Pareto Front as a set of non-dominated solutions in multi-objective optimization problems would be analyzed to assess the efficiency of the two control strategies (reservoir operational strategy through selective withdrawal scheme and watershed control strategy).

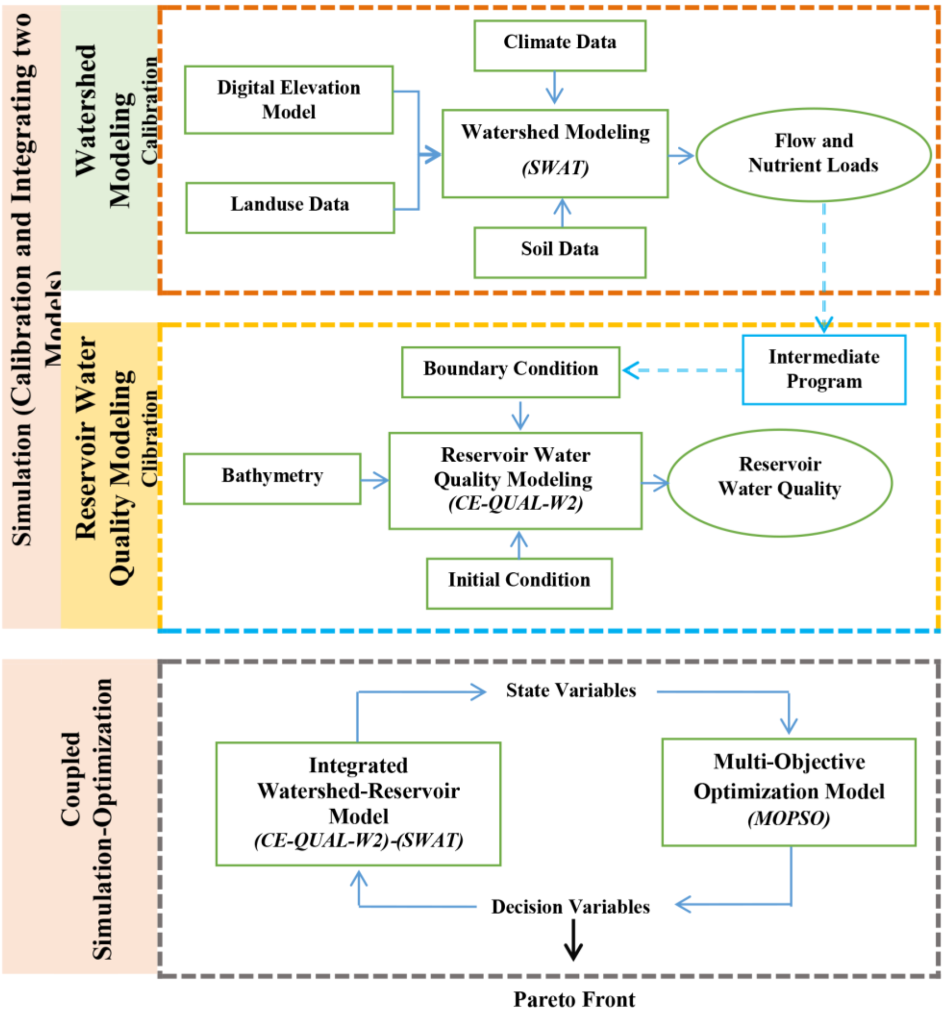

Fig. 2. the calibrated and linked (SWAT)-(CE-QUAL-W2) simulation system was coupled with Multi-Objective Particle Swarm Optimization (MOPSO) algorithm to find optimal strategies.

2.3. Watershed Modeling

SWAT is a time continuous, semi-distributed and physically based watershed scale model, which has been developed by USDA Agricultural Research Service (Arnold et al., 1998). SWAT can simulate the flow, sediment, and nutrient loads; however, it needs various sources of information and empirical parameters. Climate data, landuse and soil maps, and DEM are essential data to setup SWAT model (Figure 1). In this model, the watershed is firstly divided to several sub-basins based on stream network, and then each sub-basin is divided into some hydrological response units (HRU) with unique soil, slope, and landuse combinations. SWAT uses QUAL2E model (Brown and Barnwell, 1987) to simulate and route nutrients in the stream. In this study, SWAT model was selected due to its widespread application and its capability to predict the impact of watershed management practices and climate change on hydrology, sedimentation, and nutrient loads, which has been confirmed in former studies (Arabi et al., 2006; Gitau et al., 2006; Parajuli, 2012; Zhu et al., 2015). Integration of different structural and non-structural BMPs is possible in SWAT model. In this study 4 different structural BMPs were applied to control pollutants load. i) Detention pond (DP) is placed in sub-basin to retain flow and can reduce pollutants load. The fraction of the sub-basin drains to the pond (Pnd-Fr), pond area (Pnd-Psa) and pond volume (Pnd-Pvol) are parameters related to DP in SWAT. ii) Filter strips (FS) are designed in HRU and can decrease sediment and pollutants. In order to represent FS in SWAT model, the width of edge of field filter strip (FILTERW) is modified. iii) Parallel terraces (PT) designed in HRU, are presented to the model by modifying the soil conservation service curve number (CN2), Universal soil loss equation (USLE) support practice factor (USLE-P) and average slope length (SLSUBBSN) parameters (Arabi, 2008). iv) Grade stabilization structures (GSS) are applied to decrease the channel slope; accordingly sediment trapping would be increased. GSS is presented to SWAT with modifying the channel segment $(\mathrm{CH}-\mathrm{S2})$ and channel erodibility factor $(\mathrm{CH}-\mathrm{EROD})$. The unit costs of four BMPs were estimated based on current implementation costs in the region which are stated in the bids and contracts documents (Table 1).

Table1. The unit cost of four BMPs applied in this study

BMP	Description	Unit	Unit Cost (US$*)
1	Detention ponds (DP)	*ha-m*	5000
2	Grade Stabilization Structures (GSS)	*Each*	8000
3	Parallel Terraces (PT)	*ha*	1400
4	Filter Strips (FS)	*ha*	650

*Current Exchange Rates

2.4. Reservoir Water Quality Modeling

CE-QUAL-W2 is a two dimensional, longitudinal/vertical, hydrodynamic, and water quality model, developed by the US Army Engineer Research and Development Center. Due to the lateral homogeneity assumption, it is applicable for long and narrow water bodies. The model uses finite difference numerical method to solve governing equations and can simulate water surface elevations, velocities, temperatures, and water quality. The capabilities of model include long term simulations, head boundary conditions, multiple branches and water bodies, variable grid spacing, multiple inflows and outflows, ice cover calculations, selective withdrawal calculations, and time-varying boundary conditions. CE-QUAL-W2 has been used for the past two decades as a tool for water quality managers to evaluate the effects of management strategies on many different waterbodies (Cole and Wells, 2015).

2.5. Model performance criteria

Four criteria were used to assess the performance of the SWAT and CE-QUAL-W2 model.

- Nash Sutcliffe coefficient of efficiency (NSE), Equation 1, is a normalized statistic that determines the relative magnitude of the residual variance compared to the measured data (Nash and Sutcliffe, 1970).

$$NSE = 1 - \left(\frac{\sum_{i=1}^{n} (S_i - O_i)^2}{\sum_{i=1}^{n} \left(O_i - O_{avg}\right)^2} \right) \quad (1)$$

in which O_{avg} is the mean of the observed values; $\mathrm{O_i}$ and $\mathrm{S_i}$ are the observed and simulated values respectively; and n is the number of values. The model performance is considered to be good for values of NSE>0.75, while for values of 0.36<NSE<0.75, model performance is considered to be satisfactory (Motovilov et al., 1999).

- Percent bias (PBIAS), Equation 2, is a measure of the average tendency of the simulated values to be higher or lower than their observed values. The optimal PBIAS value is 0; positive and negative values of PBIAS indicate a model bias toward underestimation and overestimation, respectively (Gupta et al., 1999).

$$PBIAS = \frac{\sum_{i=1}^{n}(O_i - S_i) \times 100}{\sum_{i=1}^{n}(O_i)} \quad (2)$$

The performance rating for PBIAS is constituent specific. Model performance can be evaluated as satisfactory if PBIAS ± 25% for streamflow, PBIAS ± 55% for sediment, and PBIAS ± 70% for nitrate nitrogen (N-NO_3), and mineral phosphorus (P-PO_4) (Moriasi, 2007).

- RMS error (RMSE)-observations standard deviation ratio (RSR) as:

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{i=1}^{n}(S_i - O_i)^2}}{\sqrt{\sum_{i=1}^{n}\left(O_i - O_{avg}\right)^2}} \quad (3)$$

where $STDEV_{obs}$ is the standard deviation of the observed values. The optimal RSR value is 0. The model performance is considered to be unsatisfactory for values of RSR>0.7 (Moriasi, 2007).

- Absolute Mean Error (AME) as:

$$AME = \frac{\sum_{i=1}^{n}|S_i - O_i|}{n} \quad (4)$$

where O_i and S_i are the observed and simulated values, respectively; and n is the number of values. The model evaluation criteria should be adjusted based on the quality and quantity of measured data, evaluation time step, and project scope and magnitude. Typically, model simulation results are poorer for shorter time steps than for longer time steps (Moriasi, 2007). In this study, observed flow, total suspended solids, nitrate nitrogen (N-NO_3), and mineral phosphorus (P-PO_4) values were considered to evaluate SWAT model performance for daily time steps. Historical measured daily water surface elevation, water temperature, and water quality data were used to assess CE-QUAL-W2 model performance.

2.6. Multi-Objective Particle Swarm Optimization

Because of the multiplicity of decision variables, the nonlinearity, and complexity of the cause-effect relationships among water quality parameters, and time delay between cause and effect in water quality issues, the use of a linked watershed-reservoir model in the coupled simulation-optimization approach can be an appropriate tool for providing optimal reservoir operation and determining combination of BMPs in the watersheds. As a result, in this study, Multi-Objective Particle Swarm Optimization (MOPSO) algorithm was employed to develop a trade-off curve (i.e., Pareto Front) between the defined objective functions.

Particle Swarm Optimization (PSO), introduced by Kennedy and Eberhart (1995) has shown to be a powerful competitor to other evolutionary algorithms (Sedki and Ouazar, 2011; Kamali and Niksokhan, 2017). PSO is a population-based algorithm in which optimal solutions are searched through a combination of individual learning and social behavior. In PSO, the movement of the particles toward the optimum is governed by equations similar to the followings:

$$V_i(t) = w \times V_i(t-1) + c_1 \times r_1(t) \times \left(pbest_i - x_i(t)\right) + c_2 \times r_2(t) \times \left(gbest^t - x_i(t)\right) \quad (5)$$

$$x_i(t) = x_i(t-1) + V_i(t) \quad (6)$$

where w is inertia weight, r_1, r_2 are random variables between [0,1], and c_1, c_2 are acceleration constants. x, and V are the position and velocity of particle i in iteration t, respectively. $pbest$, and $gbest$ are personal best positions of each particle and global best position of all particles, respectively. A number of multi objective extensions of PSO algorithm have been proposed since late 1990s. This study implements an approach proposed by Coello et al. (2004). They used a global repository in which non-dominated solutions are stored. Additionally, they proposed an adaptive grid approach to choose a solution from repository as a leader for each particle to guide the search.

2.7. Problem Formulation

Usually, simulation models are developed to achieve the answer of 'what if' and optimization models answer the question of 'what is the best' under a given set of conditions. Consequently, the optimal water resource management alternatives may not be attained using either simulation or optimization techniques alone. Thus, the combined use of simulation and optimization models is important to address both questions simultaneously (Singh, 2014). In this study, a multi-objective optimization algorithm was used to manage the reservoir water with quality and quantity objectives as:

$$ObjectFunction = F(f_{BMPCOST}, f_{quality}, f_{quantity}) \quad (7)$$

$$Minimize\colon f_{BMPCOST} = \sum_i \sum_j CBMP_{ij} \quad (8)$$

$$(9)$$

$$Minimize\colon f_{quality} = \sum_{Dt=1}^{endofsimulationday} P_{outflow}^{Dt} - P_{Standard} \quad \forall\ Dt$$

$$P_{outflow}^{Dt} = \begin{cases} P_{Standard} & P_{outflow}^{Dt} > P_{Standard} \\ P_{outflow}^{Dt} & else \end{cases}$$

$$(10)$$

$$Minimize\colon f_{quantity} = \sum_{t=1}^{endofsimulationmonth} \left(\frac{Demand^t - Q_{outflow}^t}{Demand^t}\right)^2 \quad \forall\ t$$

Subject to the following constraints:

$$(11)$$

$$(Q_{inflow}^{Dt}, P - PO_4^{Dt}, N - NO_3^{Dt}) = SWAT(Pnd - Fr, Pnd - Psa, Pnd - Pvol, FILTERW, CN2, USLE - P, SLSUBBSN, CH - S2, CH - EROD)$$

$$(12)$$

$$P_{outflow}^{Dt} = CE - QUAL - W2(Q_{inflow}^{Dt}, P - PO_4^{Dt}, N - NO_3^{Dt}, Q_{outflow}^t, \alpha)$$

$$(13)$$

$$Demand_{Municipal}^t \leq Q_{outflow}^t \leq Demand^t \quad \forall\ t$$

$$(14)$$

$$S_{min} \leq S_{Dt} \leq S_{max} \quad \forall\ Dt$$

$$(15)$$

$$Q_{outflow}^t = RE_1^t + RE_2^t \quad \forall\ t$$

where, $f_{BMPCOST}$ is the total cost of BMPs applied in the watershed. $CBMP_{ij}$ is the cost of a j type of BMP applied in sub-basin i or HRU i. $f_{quality}$ and $f_{quantity}$ are quality and quantity objective functions. $P_{outflow}^{Dt}$ is the reservoir outflow phosphorus concentration at day Dt, and $P_{Standard}$ is the concentration of standard phosphorus. According to *USEPA* (2000), the standard phosphorus concentration for eutrophic level in the reservoir was set as 0.02 mg/L. $Demand^t$ is the downstream water demands at month t. $Q_{outflow}^t$ is the allocated water to the downstream demands at month t (decision variable). Q_{inflow}^{Dt}, $P - PO_4^{Dt}$, and $N - NO_3^{Dt}$ are the watershed discharge, mineral phosphorus load, and nitrate nitrogen load at day Dt input to the reservoir which are calculated by SWAT model based on BMP parameters (decision variables) in Table 2. α is the bottom outlet withdrawal ratio (decision variable). $P_{outflow}^{Dt}$ is calculated by CE-QUAL-W2 model based on the Q_{inflow}^{Dt}, $N - NO_3^{Dt}$, and $P - PO_4^{Dt}$ which are simulated by SWAT model and also based on $Q_{outflow}^t$ and α. $Demand_{Municipal}^t$ is municipal water demand. S_{Dt} is the reservoir storage at day Dt. S_{min} and S_{max} are minimum and maximum reservoir storage. RE_1^t and RE_2^t are releases from two outlets. The quality objective function $(f_{quality})$, which determines the reservoir outflow phosphorus concentration violation from the standard phosphorus concentration, is expected to minimize the reservoir outflow phosphorus concentration. $Q_{outflow}^t$ is one of the decision variables in this study which affects reservoir outflow water quality, and also downstream water demand satisfactions. The quantity objective $(f_{quantity})$, which measures the downstream water demand deficit, is considered to increase the downstream agricultural and environmental demand satisfaction. The defined problem in Equation 7 was solved for a 6-year time horizon.

Table 2. BMP type and decision variables used in the watershed model

BMP TYPE	Parameters	SWAT input file	Pre-BMP (from calibration)	Post-BMP
Detention Pond	*Pnd-Fr*	*.pnd*	0	0.9
	Pnd-Psa	*.pnd*	0	(0.005, 0.0075) of each subbasin area
	Pnd-Pvol	*.pnd*	0	Depth of Pnd (2, 3 (m)) * Pnd_Psa
Filter Strip	*FILTERW*	*.hru*	0	20
Parallel terraces	*CN2*	*.mgt*	varies	(CN2)-6
	USLE-P	*.mgt*	0.35-0.5	a
	SLSUBBSN	*.hru*	10-150	a
Grade Stabilization Structure	*CH-S2*	*.rte*	varies	Reduced by 10%
	CH-EROD	*.rte*	0.44	0.001 (nonerodable)

a: (Arabi et al., 2008)

Figure 3 shows the flowchart of the proposed (SWAT)–(CE-QUAL-W2)-(MOPSO) model. The integrated model was developed in a way that it can apply the principles of the simulation–optimization approach, where the optimization model repeatedly calls the simulation model to find the optimum solution of the problem and to simulate the state variables. The whole solution procedure is sequentially reiterated to find a new solution until the global (or near global) solutions are achieved. In this study, reaching to the 50th iteration was considered as the stopping criterion.

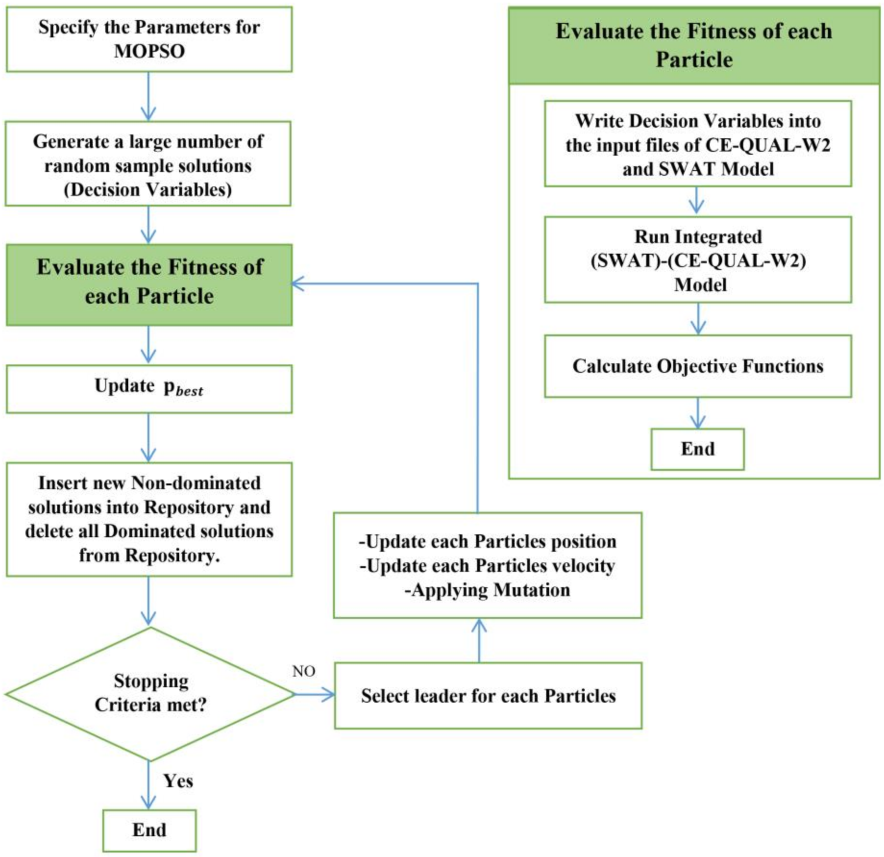

Fig. 3. Flowchart of the developed simulation-optimization part

2.8. Application of the Model

2.8.1. Model Setup

In this study, the watershed was divided into 41 sub-basins using a threshold value of 400 ha. These sub-basins were further divided into 144 HRUs based on the landuse, soil, and slope. The SWAT model was calibrated for the watershed in daily time step using flow and total suspended solid load, nitrate nitrogen (N-NO_3) and mineral phosphorus (P-PO_4) data observed at the TazehKand-Alavian station, located at the outlet of the watershed. The main objective of SWAT model set-up was to simulate nutrient loads entry into the reservoir. There was a data limitation in model calibration of sediment and nutrients. Availability of observed sediment and nutrients data were one of the major limitations as only 87 and 20 sediment data were used for calibration and validation periods, respectively. Also only 40 and 20 nitrate nitrogen (N-NO_3) and mineral phosphorus (P-PO_4) samples were used respectively for calibration and validation periods. The sequential uncertainty fitting algorithm (SUFI-2) was used for calibration and validation of SWAT model (Abbaspour et al., 2007). Model performance measures for simulations of flow, total suspended solids, nitrate nitrogen (N-NO_3) and mineral phosphorus (P-PO_4) in calibration and validation periods are presented in Table 3. The model performance was generally satisfactory for calibration and validation periods. Figure 4 shows simulated and observed flow time series. Comparing two series in the Figure 4 shows that the daily simulated flows almost match the daily observed values. This being said, the model underestimated the peak flows. This could be contributed to errors in input data, errors in observed data, or errors in the model itself.

Table 3. SWAT model performance measures for simulations of flow, total suspended solids, Nitrate nitrogen (N-NO_3) and Mineral phosphorus (P-PO_4) in Calibration and validation periods

Specification	Calibration			Validation		
Variable	**NSE**	**PBIAS(%)**	RSR	**NSE**	**PBIAS(%)**	**RSR**
Discharge	0.73	-8.6	0.52	0.65	-11.5	0.59
TSS load	0.58	13.8	0.65	0.59	-12.4	0.64
N-NO_3 load	0.47	-4.5	0.72	0.45	16	0.74
P-PO_4 load	0.51	15.2	0.7	0.48	18.7	0.72

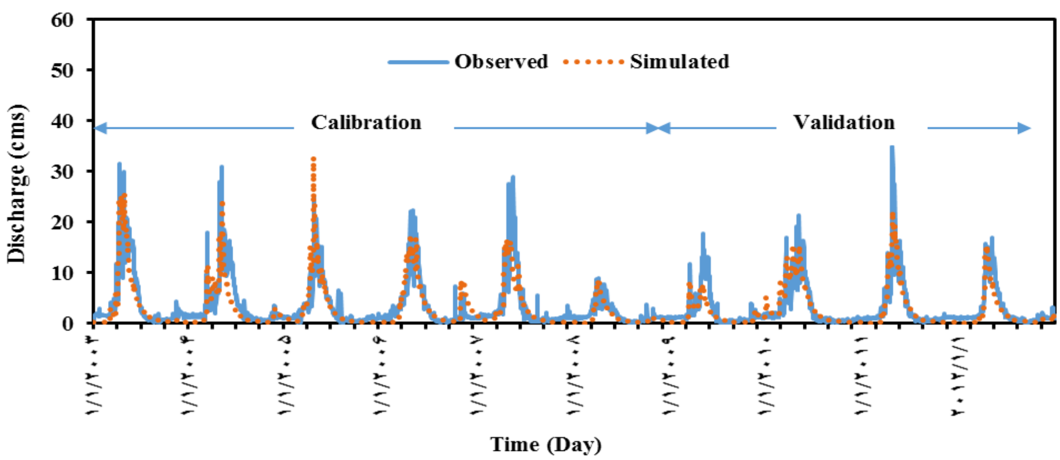

Fig. 4. Observed and simulated daily flow time series at the watershed outlet

Based on the shape and topography of the reservoir, it was configured as a one-branch and divided into 16 segments with a length of 110 to 250 m. Each segment was divided into 33 layers with 2 m depth in the water column for modeling with CE-QUAL-W2. Watershed flow, sediment, and nutrient loads from the SWAT model were extracted and converted into acceptable CE-QUAL-W2 input format by the intermediate program that was developed in Matlab in this study. Calibration process of the CE-QUAL-W2 model was started with the water balance. Recorded daily data were used to calibrate and validate water level time series (Figure 5). The AME were 0.28 m and 0.36 m for calibration and validation periods, respectively. For hydrodynamic calibration of the model, the gradient of the horizontal or longitudinal concentration of conservative constituent was investigated. Salinity is the only conservative constituent and historically used for hydrodynamic calibration. Since salinity usually is not measured in freshwater, most studies have used temperature as a first step in hydrodynamic calibration, followed by the examination of the dissolved oxygen (Cole et al., 2015). Temperature gradients were used to calibrate the hydrodynamics in the reservoir and then, the model was examined by the dissolved oxygen gradients. Calibration and verification results of the reservoir modeling indicated a good match between the simulated and observed water temperature and dissolved oxygen gradients. The AME between the observed and simulated temperature and dissolved oxygen on the sampling days for the calibration period were about 1.26 ºC and 1.3 mg/L, respectively; while, for the validation period they were approximately 1.4 ºC and 1.6 mg/L. Figures 6 and 7 show the vertical profiles of the simulated and observed water temperature and dissolved oxygen for some of the sampling days. In addition to the temperature and dissolved oxygen, two other water quality data, including nitrate/nitrite, and phosphorus were calibrated to investigate the characteristics of water quality. The AME between the observed and simulated phosphorus and nitrate values on the sampling days were about 0.005 mg/L P and 0.1 mg/L N, respectively; while for the validation period they were approximately 0.007mg/L P and 0.11 mg/L N. The comparison between the observed data and simulated temperature proved that the thermal changes in the reservoir would initiate after the air temperature increases on March. Thermal stratification would be gradually formed during the warm months of the year, usually in June. The stable thermal stratification and the maximum temperature difference between the lower and upper layers of the reservoir would occur in mid-July to mid-August. At this time, water temperature in the upper layer may increase up to 20 ºC and in the lower layer may reach to 5 ºC. According to the vertical gradients of the water temperature, the thermocline layer is located at a depth of approximately 10 m below the water surface with an approximate thickness of 7 m.

3. Results and discussion

After models calibration, the developed watershed-reservoir management model ((SWAT)-(CE-QUAL-W2)-(MOPSO)) was applied to Alavian reservoir and its results compared to current conditions. Minimization of the BMPs implementation cost, the downstream water demand deficits, and the reservoir outflow phosphorus concentration violation of the standard phosphorus concentration were defined as the objective functions. In the watershed model, out of 144 HRUs, 62 were qualified for filter strip implementation, this is due to the fact that only HRUs with agricultural landuse were considered qualified for filter strip implementation. Parallel terraces were applicable to 18 HRUs based on landuse and slope of HRUs. Detention pond and grade stabilization structure were applicable in 41 subbasins. The number of decision variables in the watershed model is presented in table 4.

Table 4. Number of decision variables in the watershed model

BMP TYPE	Number of Parameters	Numberof eligible subbasins or HRUs	decision variables
Detention Ponds	3	41	123
Filter Strips	1	62	62
Parallel terraces	3	18	54
Grade Stabilization Structures	2	41	82
		Total	321

In the reservoir model, the decision variables were allocated monthly water to the downstream demands ($Q^{t}_{outflow}$, 72 decision variables) and the bottom outlet withdrawal ratio (α , 72 decision variables). Simulation period duration was 72 months. Therefor the number of decision variables was 465 (321+72+72). The final Pareto front with 35 non-dominated solutions was derived with 100 particles and 50 iterations. Solutions with the best downstream water demand satisfaction, the best outflow phosphorus concentration, and the minimum cost of BMPs implementation from the Pareto front are presented in Table 5.

Table 5. The selected best solutions under the third scenario

Objectives	Cost of the BMPs Implementation ($) (Eq. 8)	Downstream Water Demand Deficit (Eq. 10)	Outflow P Concentration Violation of the Standard P (mg/L) (Eq. 9)
Minimum cost of the BMPs implementation solution	97026.46	429.76	50.52
The best downstream water demand satisfaction solution	121787.8	354.69	46.10
The best outflow P concentration solution	223925	461.78	29.78

Detailed observations of the results showed that among the considered BMPs, filter strip is the most selected BMPs in the Pareto front, this is due to the fact that filter strip was more effective to reduce nutrient loads entering the reservoir. The time series showing the reservoir water surface elevation and allocated water to the downstream demands in the solutions with the best downstream water demand satisfaction, and the best outflow phosphorus concentration are demonstrated in Figure 5. Additionally, the time series of the reservoir inflow and downstream water demands are presented in figure 5. The results indicated that, in the solution with the best outflow phosphorus concentration, variables are optimized with regard to qualitative conditions thus; more water volume has been discharged regardless of future demands. This would result in decreasing downstream supply. In fact, in the best downstream water demand satisfaction solution, release from the reservoir focuses more on downstream requirements and storage of water volume in the reservoir. In other words, in this solution, in the periods when the reservoir inflow is lower, more water is stored in the reservoir to meet future demands. In order to examine the efficiency of BMPs implementation on reservoir water quality, the effect of BMPs implementation on the obtained Pareto front solutions were eliminated and their new values were recalculated. The Differences between new water quality objective values and their previous values over the water quality objective function value in current conditions (51 mg/L) were considered as the improvement percentage over current conditions. Figure 6 shows the improvement percentage of water quality objectives in the Pareto front with considering BMPs in the watershed. It is clear from Figure 6 that the optimized combinations of BMPs in the Pareto front would improve water quality objectives up to 45%, if compared with current conditions. Additionally, the amount of improvement percentage increases as the cost of BMPs (the number of BMPs) is increased.

4. Conclusion

In this paper, a coupled simulation-optimization model was developed to examine the effectiveness of the two control strategies consisting of the reservoir operation strategy through selective withdrawal scheme, and BMPs implementation in the upland watershed on downstream water quality. The hydrological SWAT model and the hydrodynamic and water quality model CEQUAL-W2 were integrated to simulate the water quality and quantity processes in the watershed and reservoir, respectively. The linked watershed-reservoir model was coupled with Multi-Objective Particle Swarm Optimization (MOPSO) engine to simulate and find the optimal combination of the BMPs in the watershed and the optimal reservoir operational strategies through selective withdrawal scheme. The results indicated that BMPs implementation in the watershed would enhance the reservoir water quality better than the reservoir operation strategy through selective withdrawal scheme. Furthermore, the optimized combinations of BMPs in the Pareto front would improve water quality objectives up to 45%, if compared with the current conditions. Detailed observations of the results revealed that among the applied BMPs in study, filter strip has more effect on reducing nutrient loads and it is the most chosen BMP option in the selected solutions; while parallel terraces and grade stabilization structures are the least selected options in the study area. This is due to the fact that filter strips was more effective to reduce nutrient loads entry into the reservoir. The proposed approach can be further applied to derive the optimal combination of the (BMPs) in the watershed and the optimal reservoir operational strategies through selective withdrawal scheme encompassing salinity, nutrient loads, and other water quality issues in reservoirs.

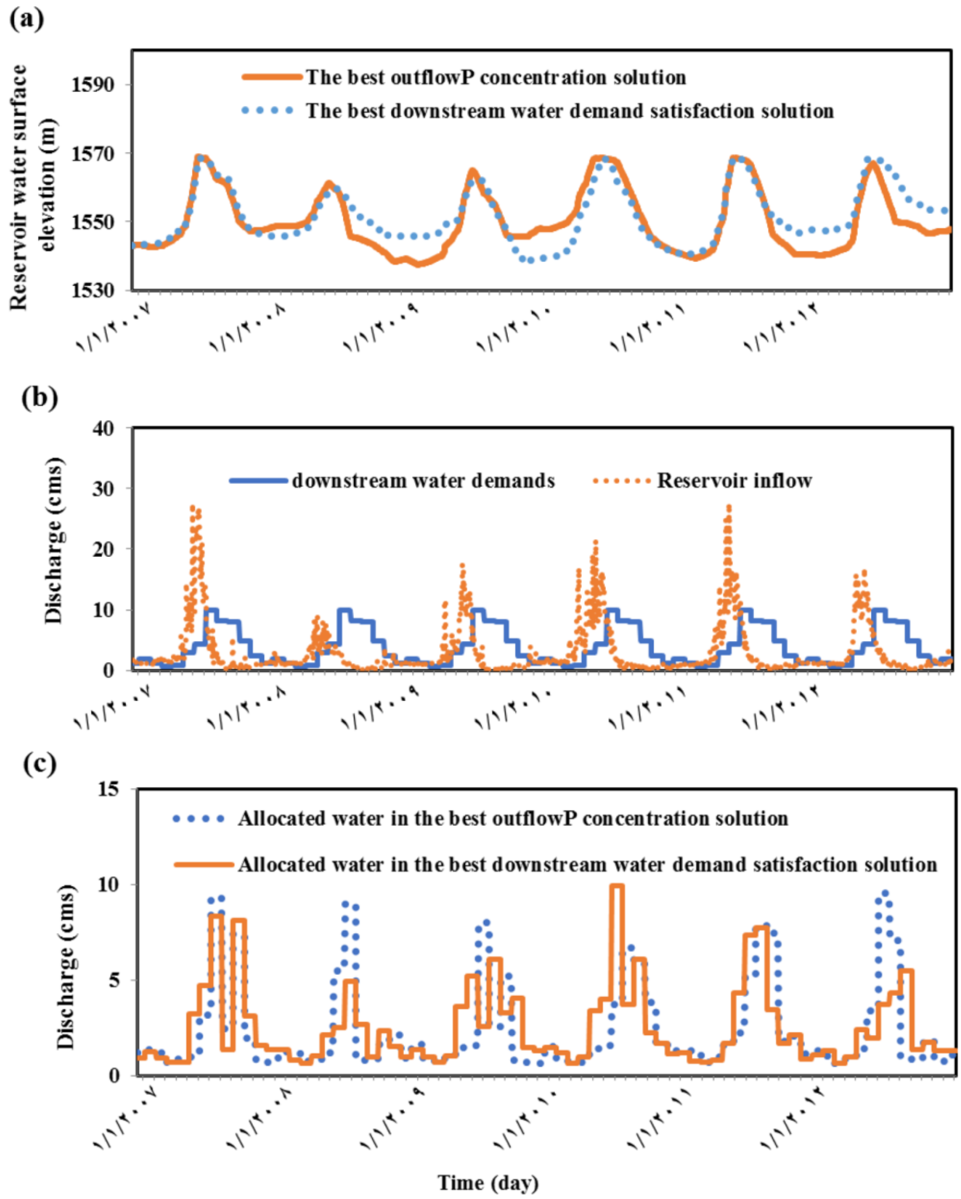

Fig. 5. a) The time series of the reservoir water surface elevation in the best downstream water demand satisfaction and the best outflow phosphorus concentration solutions; b) the time series of the downstream water demand and reservoir inflow; c) allocated water in the best downstream water demand satisfaction and the best outflow phosphorus concentration solutions

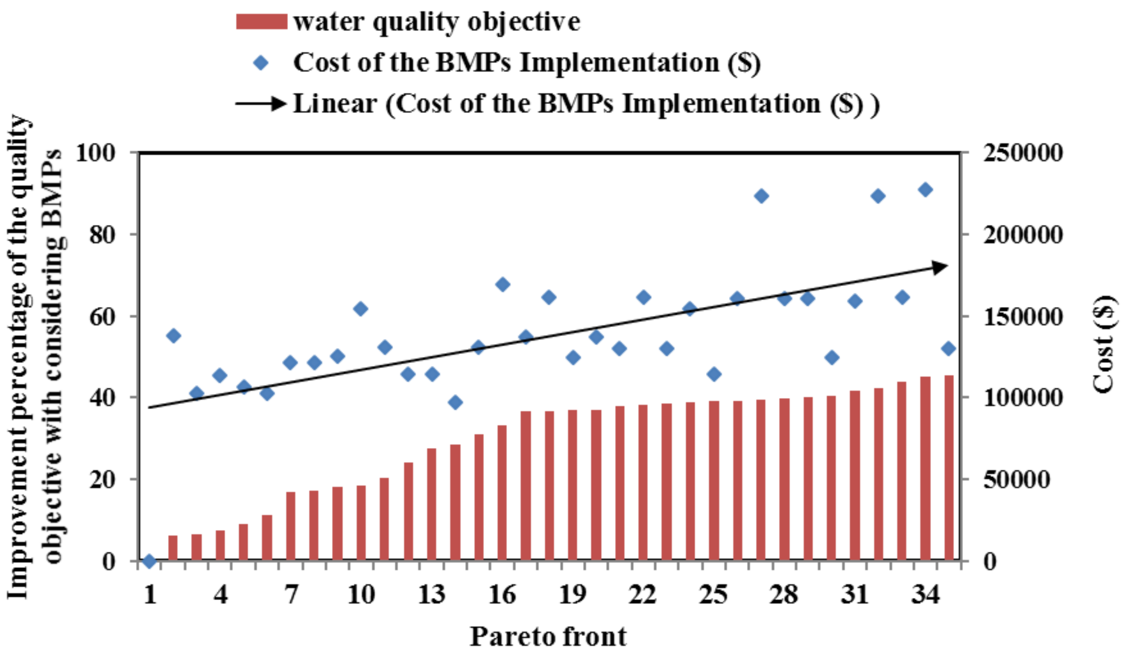

Fig. 6. The improvement percentage of water quality objective function in the Pareto front with considering BMPs in the watershed

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