A web-based application for optimization of single reservoir operation

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In spite of the large number of optimization techniques reported in the literature, traditional operation models are still in wide use for reservoir planning and management studies. Optimal operation of reservoir systems, however, requires computer optimization modeling tools to provide information for their rational operating decisions. Recent improvements in high-speed computers and the Internet encourage researchers and practitioners to become familiar with and use of modern techniques and tools more frequently. In this article, a web-based application (WBA) was developed for reservoir operation using an optimization approach. This article presents and tests a set of operational objectives to optimally operate a single reservoir using a web-based platform. All practitioners and students can use this free WBA to share their data, findings, and models while simultaneously solving their reservoir operation problems. Practical use of the WBA is illustrated by developing and running a model based on real-world reservoir data.

Keywords: *web-based application, reservoir operation, online optimization tool*

Web technology presents a convenient and cost-effective way to analyze, store, retrieve, and share information and models. Generally speaking, a web-based application (WBA) is an online tool that can be publically accessible on a web page for specific purposes and applications (Bhargava et al, 2007). The main advantage of a WBA is its simultaneous accessibility from multiple locations from anywhere there is Internet availability. This advantage has led to widespread applications in resource planning (Tarantilis et al, 2008), education (Driscoll, 2010), medicine (Graber & Mathew, 2008), environmental management (Fitz-Rodríguez et al, 2010), and other diverse areas. Besides providing information, the Internet is also effective for global service delivery by providing an attractive opportunity for sharing information interactively, simultaneously, and securely at a limited cost because of an open architecture.

Salewicz and Nakayama (2004) presented a web-based decision support system for analyzing various policy alternatives in a large international river. A web-based water conservation calculator was designed for British Columbia (http://waterbucket.ca/wuc/2014/03/09/a-water-conservation-strategy-for-british-columbia/) to illustrate how specific conservation measures yield both fiscal and physical water consumption savings. Cahn and coworkers (2011) introduced a WBA to assist growers in making decisions on irrigation and nitrogen fertilizer management that was made accessible from smart phones, tablet computers, and desktop computers. It also maintains and shares irrigation, fertilizer, and soil test records for multiple fields and farms.

Reservoir operators must decide on the amount of water to be released now and the water to be retained for future use. These decisions are often made after receipt of available and/or forecasted information at the beginning of the current period.

Reservoir operation policy, which determines the release of water from a reservoir as a function of stated variables (i.e., reservoir storage and inflow during the current period), may be derived using optimization techniques. In practice, many feasible operating policies may exist; therefore, mathematical optimization techniques may help identify the most desirable ones (Yeh, 1985). The optimum operation policy may be derived for reservoir operation that results in the best value of an objective function (e.g., minimizing water deficit) during the planning horizon. Labadie (2004) presented an extensive review of optimization techniques used to derive a reservoir's optimum operation policies. In spite of the large number of modern optimization techniques available in the literature, traditional models still remain the most widely used tools for reservoir planning and management studies. Optimal reservoir system operation requires computer optimization modeling tools to provide information for rational operational decisions. Among these optimization techniques, genetic algorithms (GAs) have received significant attention. Although GAs and some other metaheuristic methods are available in commercial mathematical software packages, their practical use by reservoir operators is not common. Despite intensive research and development in the application of gradient-based and metaheuristic optimization models for reservoir operation, the gap between the theory and practice has not been completely bridged (Labadie, 2004). Mathematical complexity, enormous range and varieties of optimization methods, and customized programming requirements are some of the reasons for this disparity. Although some of the hindrances for applying optimization to reservoir management problems have been reduced by introducing decision support systems, easier and user-friendly approaches are needed to promote its application. Addressing these hindrances through extensive application of modern optimization techniques, both in academic and professional environments, the proposed WBA may significantly promote successful implementation of training and decision supports. Those applying the systems do not need an extensive knowledge of computer coding and commercial or academic software packages.

This article introduces a WBA called ResOS (http://jpsbook.com/resos.aspx) that researchers, agencies, and students can use for common modern optimization methods to generate reservoir operation rules. ResOS assists users who are unfamiliar with computer programming in taking advantage of metaheuristic optimization methods that produce optimum operation policies for reservoir operation. It also helps students understand and investigate performance criteria and the influence of multiple types of objective functions associated with reservoir operation problems.

ResOS was developed in a web developer program[1] using a free web framework.[2] It includes control toolkit[3] components that provide a dynamic and user-friendly environment. ResOS does not require a software download or installation on the client side and does not depend on the user's operating system. The only requirement is the ability to access http://jpsbook.com/resos.aspx. Multiple users can simultaneously use ResOS on any type of operating system or device (e.g., smart phone, laptop) that has a web browser installed.

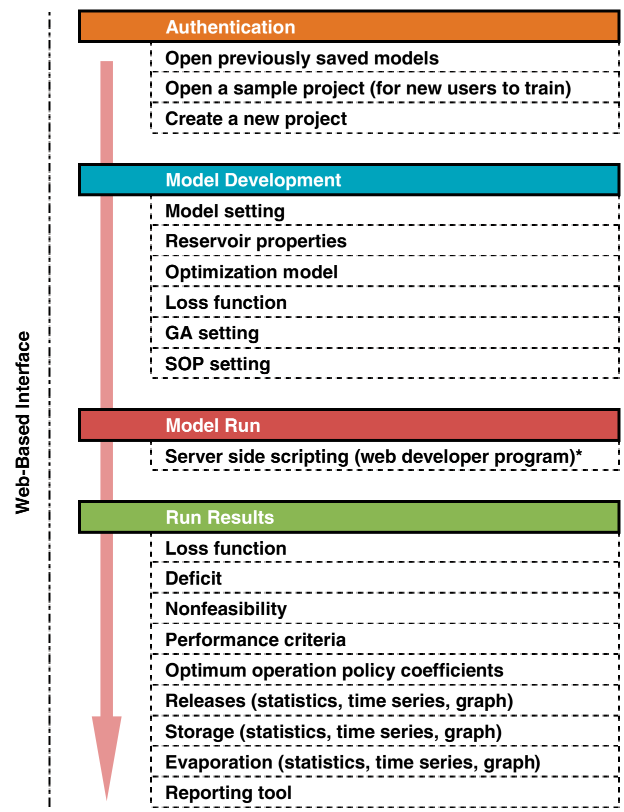
The ResOS calculation modules are executed on the web server; consequently, the user's computing system (e.g., central processing unit, memory) are not used to run the model. As a result, even a very low-performance computer or device can use ResOS with no loss of functionality or calculation speed. Anyone who is able to browse the Internet, regardless of device, can use the program. Reservoir operators, agencies, and students have permanent and unlimited access to ResOS.

This article is organized as follows. First, the ResOS conceptual framework is explained (Figure 1). Significant topics such as the optimization method and loss functions (LFs) are demonstrated in the model development section, whereas performance criteria including reliability, resiliency, and vulnerability are discussed in the results section. Next, a real-world case study is solved using ResOS, and the results are interpreted. A conclusion and ideas for future development of ResOS are presented last.

AUTHENTICATION

The goal of ResOS is to obtain optimum operation policies for custom reservoirs. Reservoir operation rules might be updated peridically as new information becomes available. For example, reservoir inflow and/or downstream demands may change over time, which calls for a new operational rule. It is of prime importance for users to be able to store, open, and update model data. The online ResOS databank makes it possible for users to manage their input data over time. For training purposes, a sample model is provided that derives operation rules for Ekbatan Dam in Iran. The model and data have already been solved and loaded as the default model for ResOS.

FIGURE 1 Conceptual framework of ResOS



GA—generic algorithm, SOP—standard operating procedure

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MODEL DEVELOPMENT

Model setting. Basic model data including planning time and other input data such as natural inflow to the reservoir, demands, and evaporation coefficients are identified in this subsection.

Reservoir properties. A reservoir's physical properties such as depth-volume-area curves, minimum and maximum operational capacities, and initial storage at the beginning of the planning time are entered in this subsection.

Reservoir operation models. Standard operating procedure (SOP) is the simplest and possibly the most prevalently rule employed to operate reservoirs (Loucks et al, 1981). In each period, when sufficient water is available, SOP satisfies the whole target demand of the period, even if no storage is preserved for subsequent periods. During times when there is not enough water available in the reservoir, an SOP supplies only whatever is available. Application of an SOP minimizes total deficits over the entire planning time; nevertheless, sequential periods with severe deficit values are most likely to happen during times of peak demand and drought.

An SOP prescribes an operation policy (Eq 1) that determines release volume (e.g., million cubic metres, MCM) from a reservoir in period t ($R(t)$) as a function of reservoir storage volume at the beginning of the period ($S(t)$), the natural volume of inflow to the reservoir during the period ($Q(t)$), the demands of the period ($D(t)$), and the maximum allowed storage of the reservoir (S_{max}).

$$R(t) = \begin{cases} S(t) + Q(t) & S(t) + Q(t) < D(t) \\ D(t) & \text{if} \quad D(t) < S(t) + Q(t) < D(t) + S_{max} \\ S(t) + Q(t) - S_{max} & S(t) + Q(t) > D(t) + S_{max} \end{cases} \tag{1}$$

On the other hand, optimization methods search for the optimal operation policy that minimizes or maximizes predefined objective functions that may include, but are not limited to, total deficits, reliability, and total yield. Labadie (2004) categorized the various optimization methods applied in reservoir operation optimization studies into implicit stochastic optimization, explicit stochastic optimization, real-time control with forecasting, and metaheuristic programming.

In the case of nonlinear, nonconvex optimization problems with constrained feasible space, gradient-based optimization techniques may fail to address feasible space and optimal solutions. Furthermore, to apply classical gradient-based optimization techniques, the objective function must be differentiable in the decision space. Computing derivatives consumes a considerable amount of time. Metaheuristic programming, which is the last generation of optimization methods, is neither restricted to differentiable objective functions nor to the linearizing assumptions of model equations. In addition, there is no concern for numerical instabilities associated with matrix inversion that can occur in traditional optimization approaches such as linear programming. Furthermore, a holistic search pattern of metaheuristic algorithms reduces the probability to become entrapped in local optima compared with gradient-based methods (Jahanpour et al, 2013a).

ResOS currently includes a GA as the optimization method. Similar to other metaheuristic search algorithms, a GA strives to locate feasible and near-optimal solutions and/or global optimal solutions under a large number of function evaluations. It has been successfully used to optimize discrete or continuous variables while searching a broad area of the decision space (Jahanpour et al, 2013a; Afshar et al, 2010).

In optimizing reservoir operation policy, the optimum values of reservoir releases over the planning time are searched. To develop a reservoir operation rule, the release from the reservoir in $R(t)$ may be assumed to be a function of two easily monitored key variables of the system: the reservoir storage at the beginning of $S(t)$ and the natural inflow to the reservoir in the same period ($Q(t)$). In this case, the release equation is shown in Eq 2, in which a, b, and c are the dimensionless decision parameters that are to be optimized.

$$R(t) = aS(t) + bQ(t) + c \tag{2}$$

The optimal values of these three parameters determine the optimal value of releases during the operation period. Once the rule is optimized for an LF, the reservoir is then simulated for the obtained rule. Furthermore, users have the option to optimize historical releases without following a rule. In this case, releases are not defined as a function of system key parameters, and release values themselves will be the decision parameters of the optimization problem.

The objective of the optimization modules (i.e., GA) is to minimize a user-selected objective function defined as the LF. LFs are the objective function of the optimization problem. The optimization problem can be formulated as follows:

$$\text{Min } f = \text{LF} \tag{3}$$

Subject to

$$S(t+1) = S(t) + Q(t) - E\,(S(t), S(t+1)) - R(t);\ \forall t \tag{4}$$

$$S_{min} \le S(t) \le S_{max};\ \forall t \tag{5}$$

$$0 \le R(t);\ \forall t \tag{6}$$

$$E\,(S(t), S(t+1)) = e(t)\ \frac{A(S(t)) + A(S(t+1))}{2};\ \ \forall t \tag{7}$$

$$A(S(t)) = pS(t)^i + qS(t)^j + k; \tag{8}$$

$$S(1) = S_0 \tag{9}$$

in which E is evaporation loss from the reservoir (MCM); $\forall t$ indicates all periods, S_{min} is the minimum reservoir storage (MCM), $e(t)$ is the evaporation in period t (m), A is surface area of the reservoir lake (km^2); S_0 is the initial reservoir storage (MCM), and $p, q, i, j,$ and k are dimensionless user-defined parameters to define the area storage curve of the reservoir.

ResOS uses a GA to solve the optimization problem defined by Eqs 3–9. GA commences its search for the optimal values of the decision parameters by generating a set of initial trial solutions. All solutions in every generation are evaluated according to an objective function selected by the user. In this study, the objective function is addressed by an LF, which will be discussed later in the article. The optimization methods search for a solution by which the value of the objective function, LF, is minimized. Solutions are reproduced from previous generations by three genetic operators—selection, crossover, and mutation—to create the next generation. In any generation, solutions with the best objective function (elites) are guaranteed to survive for the next generation. The evolutionary process of GA continues until a stopping criterion is reached. Stopping criteria consist of the maximum number of generations, time limits, and stall generations (generations with no significant improvement in the objective function value) (Jahanpour et al, 2013b).

LFs. Selection of an LF requires an explicit statement of the reservoir's operational objectives (e.g., to maximize reliability measures and/or minimize the deviation from target storage/releases) (Datta & Burges, 1984). To determine the ability of an operation policy that satisfies the objectives, an LF is defined—in fact, the value of the LF numerically describes the performance of the operation policy in satisfying the project objectives.

There are unsolved questions concerning the best choice of an LF for reservoir operation, which include the issues of concavity, convexity, or symmetry of the LF equation. Some researchers (Klemeš, 1978; Hashimoto et al, 1982) have defined the LF as the deviation from a predefined demand value. Stedinger (1978) believes it is unrealistic to penalize positive deviations (excessive water supply) from demand values, whereas Klemes (1978) uses a quadratic form of the LF in which positive deviations from demand values are penalized as much as negative deviations (Eq 11). When Klemeš's definition of an LF is accepted, the loss can be assumed to be zero in the vicinity of the target, implying negligible losses for small deviations from this particular value and increasingly higher loss values for larger deviations (Datta & Burges, 1984). Various studies have considered more hydrological, economical, and even political measures in LF calculations (Jahanpour et al, 2013a; Afshar et al, 2010; Jenkins et al, 2003).

Users must understand what happens and what results they obtain in terms of the selected LF while trying to create operation policies for a reservoir. Operation policies are derived to optimize the value of a selected LF; in other words, minimizing an LF is the target for operating a reservoir and an optimized operation policy is the instruction for operating the reservoir so that this target can be reached. The user has the option to choose an LF from four built-in LFs offered by ResOS:

$$\mathrm{LF1} = \sum_{t=1}^{NT} \max\,(D(t) - R(t), 0) \tag{10}$$

$$\mathrm{LF2} = \sum_{t=1}^{NT} \left(\frac{D(t) - R(t)}{D_{\max}}\right)^2 \tag{11}$$

$$\mathrm{LF3} = \frac{\mathrm{NF}}{\mathrm{NT}} \tag{12}$$

$$\mathrm{LF4} = \sum_{t=1}^{NT} \max\,(S_{\text{lowest}} - S(t), 0) + \max\,(S(t) - S_{\text{highest}}, 0) \tag{13}$$

in which NT is the total number of operational periods, $D_{\max}$ is the maximum value of demands over the entire planning horizon, NF is the number of periods in which the release from the reservoir does not fully satisfy the demand, and S_{lowest} and S_{highest} are the minimum and the maximum desirable storage of the reservoir, respectively.

If LF1 (Eq 10) is selected, the optimized operation policy minimizes the total deficit in the entire planning horizon. When LF2 (Eq 11) is used, the optimum operation policy simultaneously minimizes both deficits and excess releases from the reservoir. In other words, LF2 penalizes both insufficient and excessive water supply to a demand area, whereas LF1 considers only deficits as losses and does not penalize excessive supplies.

LF3 (Eq 12) minimizes the risk of system failure by defining the probability that a failure occurs in satisfying the demand in the planning time. If LF3 is selected, the optimum operation policy minimizes the number of periods with a deficit (failure periods). In this case, periods with very small and very large deficits are given the same value in the objective function.

In some reservoirs with fisheries, aquaculture, or recreation or tourism activities, deviation from the target storage is undesirable. To control reservoir storage, an LF may be defined to penalize any deviation of reservoir storage from particular target values. LF4 (Eq 13) is used to derive operation policies that minimize the total deviations from target storage values.

GA setting. In the GA setting section of ResOS, users may insert selected values for tunable model parameters of a GA. Although there is no universal definition, GAs are characterized by (1) generation of initial population, (2) fitness evaluation and chromosome ranking, (3) selection for mating to create offspring, and (4) mutation to maintain diversity. These elements are repeated until a suitable (called near-optimal) solution is obtained. By mixing important genes between parent alternatives via selection schemes and mutations, superior offspring are expected. These two operators introduce stochastic behavior into the process; therefore, even for a fixed number of generations, the same results in different runs are not expected because of different values from a random number generators.

As discussed previously, GAs are stochastic, and users need to design applications to minimize random seed variability (i.e., attain more or less similar results regardless of the randomly generated initial search population). Although an increase in population size and number of generations can improve search reliability for a single random seed, it may not be totally eliminated for a limited number of function evaluations.

Considering the large number of available selections and operators, algorithm operators should carefully select options to best suit the model's properties and goals. Realizing the appropriateness, benefits, and limits of the common selection and operators, this study uses tournament selection, a simulated binary crossover (Deb & Agrawal, 1995), and a uniform mutation operator. Nicklow and co-workers (2010) provide a comprehensive review of state-of-the-art GA methods and their applications in water resources planning and management.

MODEL RUN

ResOS was developed using a free web framework[2], which is a server-side scripting technique that allows applications to run on a server to avoid consuming a user's resources. In server-side scripting, the server computer provides all of the necessary computing resources before sending a page, including computation results, back to the client device for display. After model development completion, the user may run the model. Optimization methods, because of their metaheuristic nature, take time to converge into a solution, whereas the SOP simulation runs almost instantly.

RUN RESULTS

Once a run procedure is finished, results appear in the results section of the program, and include values of the selected LF, deficit, nonfeasibility (only for optimization), and optimum operation policy coefficients. Statistics, time series, and graphs of the reservoir releases, storage, and evaporation variations are also provided.

Performance criteria. Operation policies obtained from the optimization and SOP approaches need to be evaluated to determine their performance. Performance criteria are often used to evaluate and compare alternative management policies. Water-demand

TABLE 1 Natural inflow and demands time series

		October	November	December	January	February	March	April	May	June	July	August	September	Annual
Natural Inflow *MCM*	2009	28.13	12.39	9.62	6.20	5.02	3.48	4.42	3.21	2.67	2.70	2.98	3.88	84.70
	2010	26.81	19.75	4.93	1.49	0.47	0.21	2.65	2.48	3.89	2.80	2.90	3.86	72.24
	2011	9.99	10.51	4.58	3.28	0.01	0.44	0.70	1.68	2.51	3.42	3.86	9.87	50.85
	2012	9.99	6.51	4.58	3.28	3.44	0.61	2.76	4.04	3.11	2.15	2.41	2.26	45.14
	2013	2.22	1.46	1.28	1.34	0.19	0.00	0.00	1.86	1.53	1.39	1.76	3.99	17.02
Demand *MCM*		12.50	12.50	12.50	8.75	7.25	5.00	5.00	5.00	5.00	5.00	5.00	6.50	90.00

reliability, resiliency, vulnerability, and sustainability index are widely used for this purpose. According to Hashimoto et al (1982), water demand reliability defines the probability of meeting the water demand during the simulation period. Vulnerability expresses the severity of failure after it happens. Resiliency expresses a system's adoption potential to varying conditions and is defined as the probability of system recovery from a period of failure (Hashimoto et al, 1982). According to Sandoval-Solis et al. (2011), the sustainability index may also be used to evaluate alternative policies from water users and environmental perspectives. ResOS uses the following mathematical definitions for reliability, resiliency, and vulnerability criteria to evaluate the operation policies:

$$\text{Reliability} = 1 - \frac{\text{NF}}{\text{NT}} \tag{14}$$

$$\text{Resiliency} = \frac{\text{NSF}}{\text{NT}} \tag{15}$$

$$\text{Vulnerability} = \max\left(\frac{\text{Deficit}(t)}{\text{Demand}(t)}\right) \text{ for } t = 1 \text{ to NT} \tag{16}$$

in which NSF is the number of the times when a failure happens after a satisfactory period, Deficit(t) is the water deficit in period t, and Demand(t) is water demand in period t.

All the three criteria may change between 0 and 1. Although higher values of reliability and resiliency are more desirable, smaller values of vulnerability are more favorable. A high value for reliability indicates that the water demand is fully satisfied in a large number of periods. A high value for resiliency shows that the operation policy performs well in recovering rapidly from a failure period (i.e., the period in which water shortage occurs) into a win period (i.e., the period in which all water demand is supplied). On the other hand, a high value of the vulnerability criterion indicates that, at lease in one period, a large portion of water demand has not been met. Therefore, the optimization model intends to maximize the reliability and resiliency while trying to minimize the vulnerability.

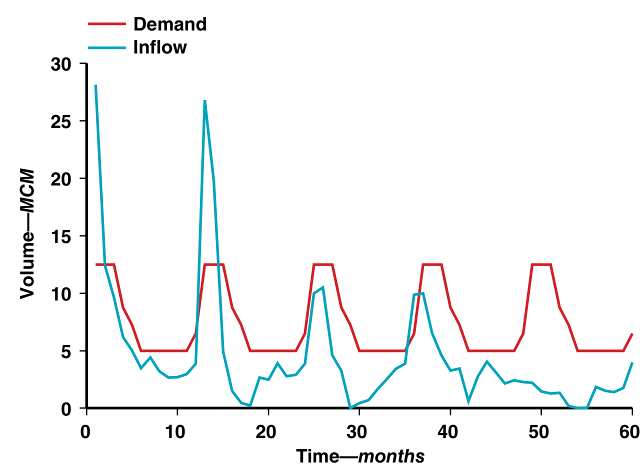
CASE STUDY

ResOS capabilities are demonstrated here by using it to generate operation policies for the Ekbatan Dam located in the upstream of Yalfan River, Iran (latitude 34.7565537, longitude 48.6003889).

Historical river-flow data between 2009 and 2013 have been used as monthly inflow to the reservoir. As shown in Table 1, the first two years were fairly wet, and their annual inflows exceeded the average annual inflow of entire years, which is 54 MCM (million cubic metres). On the other hand, the next three years were relatively dry, and their annual inflows dropped below the annual average. As Figure 2 shows, inflow to the reservoir decreased, whereas demand values repeated during the planning time. During the five-year management period, the total inflow to the reservoir was 270 MCM, whereas the total water demand during this period was estimated to be 450 MCM. Obviously, there is not enough natural inflow to the system to fully satisfy all water demands; therefore, periods of shortage will occur. Minimum and maximum operational capacities of the reservoir were 0 and 50 MCM, respectively. It was assumed that the reservoir was empty at the beginning of the planning time. Although for simplicity, the evaporation loss has been disregarded in this case study, it was easy to include it in the model setup. The model is capable of accounting for evaporation losses once the monthly evaporation rate and elevation-storage and elevation-area data (or curves) are available.

A model for the case study was developed using the previously mentioned data, then the model was run in terms of each of the

FIGURE 2 Demands and inflow to reservoir over time



MCM—million cubic metres

TABLE 2 Summary of the simulation results with SOP and the optimized rules for different LFs

	LF1 (Eq 10)		LF2 (Eq 11)		LF3 (Eq 12)		LF4 (Eq 13)	
	SOP	Optimized Rule (GA)	SOP	Optimized Rule (GA)	SOP	Optimized Rule (GA)	SOP	Optimized Rule (GA)
LF	180	180	82.74	5.05	0.75	0.45	1200.00	147.37
Deficit—*MCM*	180	180	180	188	180	187	180	196
Reliability	0.250	0.417	0.250	0.083	0.250	0.550	0.250	0.033
Resiliency	0.0667	0.2857	0.0667	0.0364	0.0667	0.5926	0.0667	0.0172
Vulnerability	1.000	0.990	1.000	0.922	1.000	0.998	1.000	0.806

GA—generic algorithm, LF—loss function, SOP—standard operating procedure

four LFs. A GA was used to generate four near-optimum operation policies for the reservoir, each corresponding to one of the LFs (Eqs 10–13). A summary of the results is shown in Table 2.

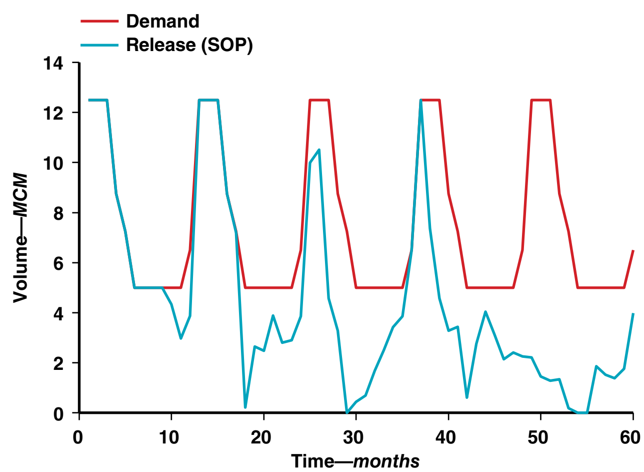
In terms of each of the four LFs, near-optimum rules have been derived by an optimization procedure and simulated using the optimized rule and SOP. For each run, results including the values of the LF, deficit, reliability, resiliency, and vulnerability were obtained, as shown in Table 2. In the following sections, the results are discussed by comparing the performance of the SOP operation rule and the near-optimum operation rules while considering different LFs.

LF1. As expected, while trying to minimize the total deficit (Eq 10), the optimization model has resulted in the same total deficit as that of the SOP. Although the time variation and distribution of the deficits vary for the two operation rules, the values of the LFs are equal. In this case, a total deficit of 189 MCM is expected to occur during the five-year simulation period. This LF merely targets the total deficit value over the planning time and does not penalize for exceeding release values. Release values achieved by the optimized rule did not exceed the water demand values in any period. Release values obtained from the SOP and optimized rule, with the objective function defined as LF1, are shown in Figures 3 and 4, respectively. Although both rules resulted in the same total deficit and vulnerability values, the optimized rule came up with more desirable reliability (0.417 compared with 0.250) and resiliency (0.2857 compared with 0.0667) values than those of the SOP.

When LF1 is selected, it is not logically possible to find any solution with a smaller total deficit than that of the SOP. As explained previously, although the SOP guarantees the minimum total deficit, its solutions may be inferior in other performance criteria. For this case study, as shown in Table 2, both the SOP and optimization methods have the same total deficits and LF values of 180, yet the optimized operation policy has significantly better values of reliability and resiliency compared with the SOP. The higher reliability value of the optimized rule indicates that, compared with the SOP, fewer periods with a shortage might be expected. Furthermore, a higher resiliency value for the optimized operation policy shows that this policy is faster in recovering from a failure to a win period.

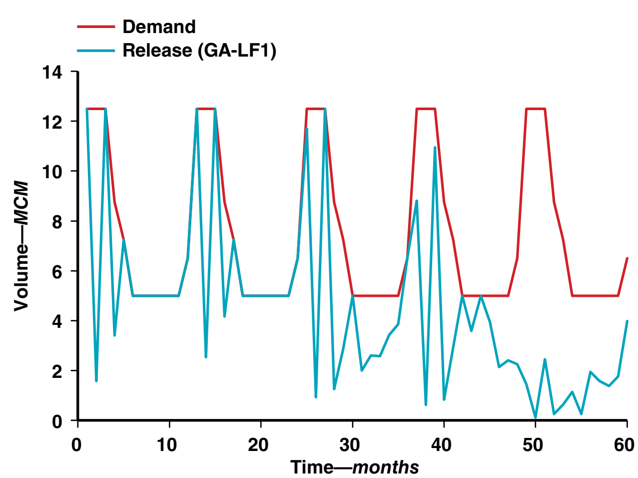
LF2. When considering LF2 (Eq 11) as the objective function of the minimization problem (GA), the optimum solution is the one

FIGURE 3 Releases obtained by SOP



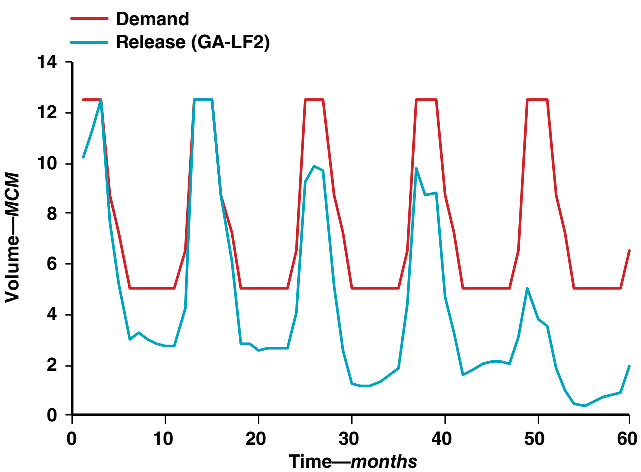
MCM—million cubic metres, SOP—standard operating procedure

FIGURE 4 Releases obtained by GA (LF1)



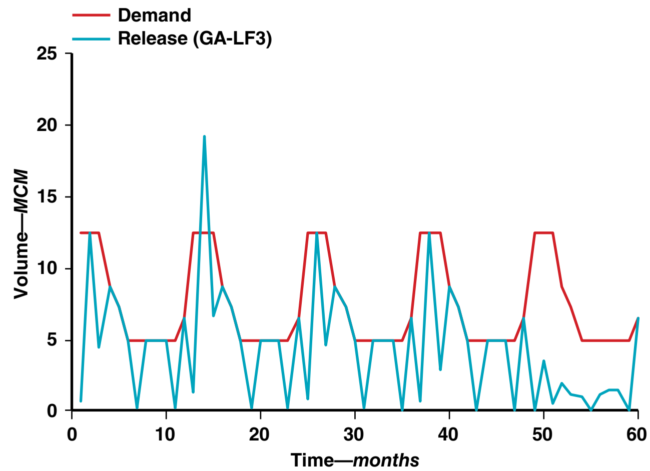
GA—generic algorithm, LF—loss function, MCM—million cubic metres, SOP—standard operating procedure

FIGURE 5 Releases obtained by GA (LF2)



GA—generic algorithm, LF—loss function, MCM—million cubic metres, SOP—standard operating procedure

FIGURE 6 Releases obtained by GA (LF3)



GA—generic algorithm, LF—loss function, MCM—million cubic metres, SOP—standard operating procedure

that results in releasing values with the minimum sum of squared deviations from demand values. It means that release values that are bigger and smaller than their corresponding demand values are equally penalized. Figure 5 shows that the near-to-optimum release values have the minimum total deviations from the demand values although more failure periods have occurred in the planning time. As expected, the optimization model has resulted in a much better LF value (5.05 compared with 82.74); however, the reliability and resiliency have dropped significantly. These drops in the two performance criteria are offset by a moderate reduction in the vulnerability index.

In fact, following the optimized operation policy, periods of failure are longer than those in the SOP, which reduces the value of resiliency for the optimized operation policy. Nevertheless, as shown in Figures 3 and 5, the severity of the failures caused by the optimized rule are lower than those of the SOP (Table 2). Consequently, the value of the vulnerability criterion is smaller (better) for the optimized operation policy compared with that of the SOP. This behavior is justified by recognizing that the SOP tends to satisfy demands only as much as possible and does not care about possible future dry periods in which there is nothing left in the reservoir to be released.

LF3. This LF (Eq 12) is preferred when there is a tendency to minimize the risk of the occurrence of failure periods by maximizing the reliability of the system (Eq 14). This LF should be selected when managers tend to maximize the number of win periods.

The near-optimum release values in this case are shown in Figure 6. As expected, compared with all other cases, the highest reliability of 0.550 has been achieved along with a total deficit slightly exceeding that of the SOP—meaning that in 55% of periods, the optimized rule has been able to fully satisfy the demands. This policy also has the best resiliency value among all other cases, meaning that it can recover from failed periods to win periods faster than other policies. In all cases, when release exceeds demand in some periods, it is assumed that the excess release is captured in the downstream storage and does not cause damage to that downstream storage.

LF4. When choosing LF4 (Eq 13) as the objective of the minimization algorithm, GA searches for operation policies that keep the reservoir storage value within a prespecified (user-determined) range. This LF is often considered when reservoir management controls the reservoir water level for recreational and tourism activities and does not consider water supply to the demand area. As a result, a high value of deficit and low values of reliability and resiliency criteria are expected when following operation policies obtained by this LF (Table 2). The optimization method produced an operation policy (Figure 7) that controls the reservoir storage values (Figure 8). Monthly storage values for both the optimized operation policy and the SOP are shown in Figure 8. The reason for this unacceptable SOP performance is that this operation rule merely considers satisfying the demands; therefore, the reservoir storage may fall to the minimum pool level. For illustrative purposes, the minimum pool level is assumed to correspond to zero effective storage (Figure 8).

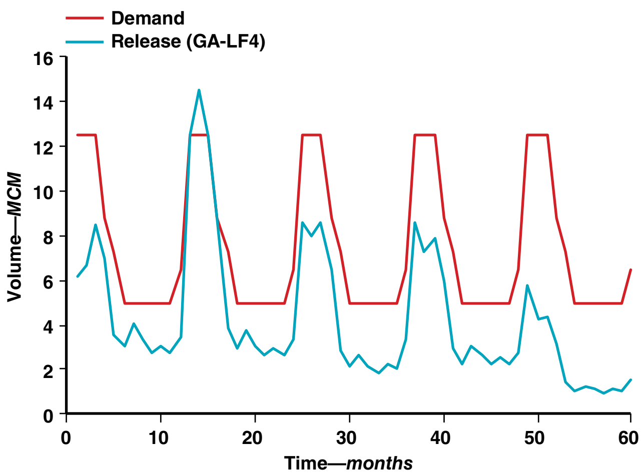
In many cases, when other LFs are considered by managers, an SOP is not able to provide desirable solutions. However, the optimization method (GA) was found to be flexible when dealing with various LFs and showed better performance.

In spite of availability of modern optimization models and proposed web-based models for operators, the Ekbatan reservoir is managed using the traditional SOP model. The existing gap between theory and practice has not been completely removed. It is possible that the proposed WBA may significantly promote the application of advanced modeling techniques in training and real-world cases such as Ekbatan reservoir.

CONCLUSION

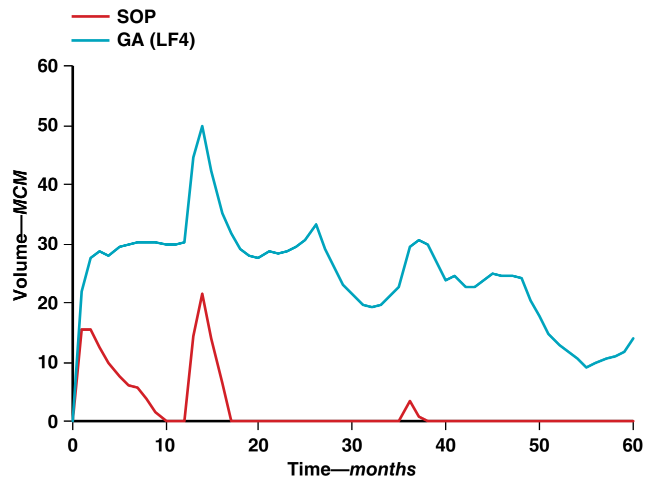
There is an ever-increasing need for modern metaheuristic optimization techniques in many areas of water resources

FIGURE 7 Releases obtained by GA (LF4)



GA—generic algorithm, LF—loss function, MCM—million cubic metres, SOP—standard operating procedure

FIGURE 8 Monthly storage values: SOP versus GA (LF4)



GA—generic algorithm, LF—loss function, MCM—million cubic metres, SOP—standard operating procedure

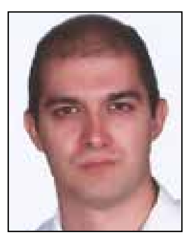
management, such as operation of reservoirs. Experts and students need to share data, models, and analysis tools in a user-friendly environment that makes analysis and evaluation more convenient and simpler than using sophisticated commercial software packages.

ResOS makes it possible for agencies and experts to implement and for students to investigate predefined LFs and optimization methods to produce reservoir operation policies. Users may implement the GA embedded in ResOS and become familiar with and take advantage of this modern metaheuristic method in solving water resources–management problems.

The WBA introduced in this article supports the entire process of generating operation policies of reservoirs, including model-setting adjustment, definition of reservoir properties, selection of an optimization method, LF definition, and adjustment of optimization algorithm settings. As a case study, ResOS was tested to generate operation policies for an actual reservoir in Iran, and the results were discussed. Successful development of this version of ResOS demonstrates the general feasibility of such research and the basis for further development.

In the current version of ResOS, users have to select one of the predefined LFs as the optimization model's objective function. Work is under way to provide an option for users to define a custom LF by combining previous LF formats. For example, users will be able to define a custom LF in which both the issues of deficits and reservoir storage changes are considered with a custom degree of importance. Including more features such as operation costs in LF evaluation is another idea for extending the ability of ResOS to deal with more sophisticated reservoir operation problems. Other metaheuristic optimization methods such as honey-bee mating optimization (Haddad et al, 2006) have also shown advantages for optimizing reservoir operation. Honey-bee mating optimization is a metaheuristic approach to optimization in which the search algorithm is inspired by the process of honey-bee mating. Adding metaheuristic optimization methods is another improvement for the next version of ResOS; this will help users take advantage of modern optimization methods and also compare the performance of methods when considering various LFs in reservoir operation–policy optimization.

ABOUT THE AUTHORS



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FOOTNOTES

[1]Visual Web Developer 2010, Microsoft Corp., Redmond, Wash.
[2]ASP.NET 4.0, Microsoft Corp., Redmond, Wash.
[3]AJAX Control Toolkit, CodePlex, Microsoft Corp., Redmond, Wash.

PEER REVIEW

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