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Authors
Aboutalebi, Mahyar
Haddad, Omid Bozorg
Loáiciga, Hugo A

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Optimal Monthly Reservoir Operation Rules for Hydropower Generation Derived with SVR-NSGAII

Mahyar Aboutalebi, M.ASCE[1]; Omid Bozorg Haddad[2]; and Hugo A. Loáiciga, F.ASCE[3]

Abstract: A novel tool is proposed that couples the nondominated sorting genetic algorithm (NSGAII) with support vector regression (SVR) and nonlinear programming (NLP) to optimize monthly operation rules for hydropower generation. The SVR-NSGAII is applied to calculate the optimized release for hydropower generation by minimizing (1) the error committed by the SVR in extracting the optimized operation rule, and (2) the number of input variables used as predictors (the parsimony feature) in a regression model. The SVR calculates the optimized reservoir release for hydropower generation based on input variables and parameters values that are found by the NSGAII. An evaluation of results obtained for the Karoon-4 reservoir of Iran indicates that the SVR-NSGAII is well suited to calculate the optimal hydropower reservoir operation rule in real time with approximately 90% accuracy. **DOI: 10.1061/(ASCE)WR.1943-5452.0000553.** *© 2015 American Society of Civil Engineers.*

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Introduction

Hydropower is a clean energy source. Its share of electricity generation is 20% worldwide. Thus the importance of optimization hydropower production by implementing efficient reservoir operation rules is of utmost interest.

Various optimization techniques have been developed and applied in the field of water resources systems such as reservoir operation (Bozorg Haddad et al. 2011a; Fallah-Mehdipour et al. 2011b, 2012a, 2013a), hydrology (Orouji et al. 2013), project management (Bozorg Haddad et al. 2010b; Fallah-Mehdipour et al. 2012b), cultivation rules (Bozorg Haddad et al. 2009; Noory et al. 2012; Fallah-Mehdipour et al. 2013b), pumping scheduling (Bozorg Haddad et al. 2011b), hydraulic structures (Bozorg Haddad et al. 2010a), water distribution networks (Bozorg Haddad et al. 2008a; Fallah-Mehdipour et al. 2011a; Seifollahi-Aghmiuni et al. 2011, 2013), operation of aquifer systems (Bozorg Haddad and Mariño 2011), site selection of infrastructures (Karimi-Hosseini et al. 2011), and algorithmic developments (Shokri et al. 2013). Only a few of these works dealt with the application of hybrid methods such as nondominated sorting genetic algorithm with support vector regression (SVR-NSGAII) for deriving optimal monthly operation rules for hydropower production.

Algorithms used to derive optimal reservoir operation rules fall into three categories, namely, mathematical programming techniques (MPTs) such as linear programming (LP), dynamic programing (DP), and nonlinear programing (NLP); artificial intelligence (AI), which includes artificial neural network (ANN) and support vector machine (SVM); and evolutionary algorithms (EAs) such as genetic algorithm (GA) and particle swarm optimization (PSO). Hybrids of AI and MPT or EA have recently surfaced and are becoming popular in water resource management.

Related to MPT, Simonovic (1992), Wurbs (1993), and Yeh (1985) presented comprehensive overviews on the MPT used for optimal operation of reservoirs. Yoo (2009) applied LP to maximize hydropower generation. Moieni et al. (2011) presented a fuzzy rule-based model derived from stochastic dynamic programming (SDP) model to calculate a steady-state policy for hydropower reservoirs operation. The proposed model was applied to the hydropower operation of the Dez Reservoir in Iran and the results were compared with those obtained with SDP. Marano et al. (2012) applied DP to optimize the management of a hybrid power plant. Results indicated that the integration of compressed energy storage (CAES) technology increased the economic benefit of renewable sources and reduced CO_2 emissions.

More comprehensive reviews and comments on the extraction of reservoir operation rules based on MPT are found in Liu et al. (2014) and Yin et al. (2014).

Related to AI, Saad et al. (1994) illustrated an application of ANN to obtain optimal operation rule in a five-reservoir system. Cancelliere et al. (2002) applied ANN to the derivation of the operating rules of the Pozzillo Reservoir on the Salso River located in Italy. Paulo and Toshiharu (2007) applied stochastic fuzzy neural network (SFNN) coupled with a GA-based model to derive the reservoir operation strategies considering water quantity and quality objectives. Mousavi et al. (2007) compared the capability of ordinary least-squares regression (OLSR), fuzzy regression (FR), and adaptive network-based fuzzy inference system (ANFIS) in deriving reservoir operation rules for the Dez reservoir in Iran. Ji et al. (2014) used SVM to derive optimal operation rule for reservoir operation. The parameters of SVM were calibrated with a grid search and cross-validation technique. More details about hydropower optimization based on based on AI methods are provided by Madani (2011).

[1]M.Sc. Graduate Student, Dept. of Irrigation and Reclamation Engineering, Faculty of Agricultural Engineering and Technology, College of Agriculture and Natural Resources, Univ. of Tehran, Karaj, 14378-35693 Tehran, Iran. E-mail: Aboutalebi@ut.ac.ir

[2]Associate Professor, Dept. of Irrigation and Reclamation Engineering, Faculty of Agricultural Engineering and Technology, College of Agriculture and Natural Resources, Univ. of Tehran, Karaj, 31587-77871 Tehran, Iran (corresponding author). E-mail: OBHaddad@ut.ac.ir

[3]Professor, Dept. of Geography, Univ. of California, Santa Barbara, CA 93106-4060. E-mail: Hugo.Loaiciga@ucsb.edu

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Concerning EA, Oliveira and Daniel (1997) proposed monthly operating rules based on the GA for a multireservoir system. Jalali et al. (2007) introduced a multicolony ant algorithm (MCAA) to solve for the operation of a 10-reservoir system by maximizing the total efficiency of producing hydropower energy during 12 periods of operation. Gradient-based NLP methods can solve problems with smooth nonlinear objectives and constraints. However, because of the dependence of NLP on initial estimated solution, these methods can fail to find feasible solutions in large and highly nonlinear hydropower multireservoir optimization problems, or converge to local, nonglobal solutions (Barton et al. 1998; Cai et al. 2001; Bozorg Haddad et al. 2008b). Because of these limitations of NLP to achieve a solution to maximize the hydropower production in a multireservoir system, Bozorg Haddad et al. (2008b) proposed the honeybee mating optimization (HBMO) algorithm to the operation of multireservoir system. Ostadrahimi et al. (2012) presented and tested a set of operation rules for a multireservoir system, using a multiswarm version of particle swarm optimization (MSPSO) approach and compared the results of the rule-based reservoir operation with the Hydrologic Engineering Center (HEC) Prescriptive Reservoir Model (PRM) (Hydrologic Engineering Center 2003). More discussion about the application of metaheuristic and EA in water-resources management (WRM) are provided by Reed et al. (2000), Yuan et al. (2008), Nicklow et al. (2010), Afshar (2012), and Bolouri-Yazdeli et al. (2014).

In addition to the cited publications, many studies discussed the capability of the hybrids of AI with MPT or EA in WRM such as combinations of SVM and GA or PSO (Su et al. 2014; Sudheer et al. 2014) to derive reservoir operation rules (Hasebe and Nagayama 2002; Ponnambalam et al. 2003). Liu et al. (2006) combined DP and neural network simplex (DPNS) to obtain refilling operation rules in the Gorges Reservoir of the Yangtze River.

The review of previous pertinent publications reveals that AI tools such as ANN and SVM are used as regression models to predict reservoir operation rules. The accuracy or performance of those tools is assessed based on error indexes such as the root-mean-square error (RMSE) calculated with predicted and optimized reservoir releases, where optimized releases are obtained using DP or NLP or other optimization methods. In any regression model, however, one is confronted with two problems. The first is defining the best values regression parameters, and the second is defining the input regression variables used as the predictors among the large number of possible variables, known as the model selection problem. Several techniques have been used to tackle the first regression problem (parameter selection), such as trial and error, cross validation, proposed equations, and metaheuristic algorithms. Metaheuristic algorithms have high precision and are computationally efficient, they are widely used in finding the best regression parameters. The second regression problem, identifying optimal regressor or predictor variables, usually is handled by examining various combinations of input variables or resorting to the use of statistical criteria such as the Akaike information criterion (AIC). The latter two techniques become excessively burdensome to apply effectively when there is a very large number of possible input variables in a regression problem. Moreover, considering all the possible variables as input variables leads to impractical complexity and often leads to inadmissible regression solutions. For this reason, the parsimony principle—that of using the smallest possible number of parameters for designing a regression problem while preserving acceptable accuracy of the solution—becomes a proper solution strategy.

This paper proposes a new tool named SVR-NSGAII to calculate optimal reservoir operation rules for hydropower production, in conjunction with NLP. SVR predicts the optimal release in the current period based on historical data such as inflow, reservoir storage, and released volume in previous times. The NSGAII provides SVR parameters and selects historical (regression) variables as (regression) predictors among many input data in terms of two objectives, minimizing the prediction error of SVR and minimizing the number of input variables (predictors). In other words, the decision variable in this problem has two parts, selection of the SVR parameters and of the input variables. The first objective of NSGAII searches the best values of the SVR parameters and the second objective searches the best combination of input variables used as the predictors. The first objective function is used to achieve accuracy and the second objective achieves parsimony in parameter selection. The major advantage of SVR-NSGAII relative to other methods is that it simultaneously achieves the best values of SVR parameters and the best parsimonious combination of input (regressor or predictor) variables in optimization reservoir operation rules for hydropower production.

Problem Definition

The objective function is the minimization of the sum of the squared hydropower production deficits

$$\text{Minimize Def} = \sum_{t=1}^{T}\left(1-\frac{P_t}{\text{PPC}}\right)^2 \tag{1}$$

where Def = relative deficit of hydropower generation; P_t = power produced during the tth period (MW); PPC = installed capacity of the reservoir's power plant (MW), and T = number of operation periods. P_t is calculated as follows:

$$P_t = \gamma \times E \times \frac{R_t}{\text{PF} \times M_t} \times \frac{(H_t - \text{TW})}{1{,}000} \tag{2}$$

where γ = unit weight of water (kg/m^3); E = efficiency of the hydropower plant; R_t = release of the reservoir during the tth period (10^6 m^3); PF = power factor of the generating installation; M_t = units conversion coefficient during the tth period; H_t = water level at the turbine inlet during the tth period (m); and TW = tailwater level (m).

The constraints of the optimization model are as follows:

Continuity equation

$$S_{t+1} = S_t + Q_t - \text{Sp}_t - R_t - \text{Ev}_t \times \frac{(A_t + A_{t+1})}{2} \tag{3}$$

Constraints on reservoir storage

$$S_{\min} \le S_t \le S_{\max} \tag{4}$$

Constraints on reservoir releases

$$R_{\min} \le R_t \le R_{\max} \tag{5}$$

Constraints on power production

$$0 \le P_t \le \text{PPC} \tag{6}$$

Constraints on reservoir spillage

$$\text{Sp}_t = \begin{cases} S_{t+1} - S_{\max} & \text{if } S_{t+1} > S_{\max} \\ 0 & \text{if } S_{t+1} \le S_{\max} \end{cases} \tag{7}$$

where S_t, S_{t+1} = reservoir storage at the beginning of tth and $t+1$st periods, respectively (10^6 m^3); Q_t = inflow to the reservoir during the tth period (10^6 m^3); Sp_t = spillage volume of the hydropower reservoir during the tth period (10^6 m^3); Ev_t = reservoir evaporation during the tth period (m); A_t, A_{t+1} = reservoir's water area at the beginning of the tth and $t+1$st periods, respectively (km^2); $S_{\min}$, $S_{\max}$ = minimum and maximum permitted reservoir storage, respectively (10^6 m^3); and $R_{\min}$, $R_{\max}$ = minimum and maximum permitted reservoir releases, respectively (10^6 m^3).

H_t and A_t are defined as area-storage formulas

$$H_t = p_0 \times S_t^4 + p_1 \times S_t^3 + p_2 \times S_t^2 + p_3 \times S_t + p_4 \tag{8}$$

$$A_t = q_0 \times S_t^4 + q_1 \times S_t^3 + q_2 \times S_t^2 + q_3 \times S_t + q_4 \tag{9}$$

where p_0, p_1, p_2, p_3, and p_4 = constant coefficients that convert S_t to H_t; and q_0, q_1, q_2, q_3, and q_4 = constant coefficients that convert S_t to A_t.

Methodology

A brief review of SVM, SVR, NSGAII, and SVR-NSGAII is presented in the following.

Support Vector Machine

SVM theory was first investigated by Vapnik (1995). SVM is commonly applied to data classification, regression analysis, and clustering analysis (Maity et al. 2013; Bozorg Haddad et al. 2013, 2014). The regression form of SVM (i.e., SVR) is briefly outlined.

Support Vector Regression

SVR identifies a linear function that relates dependent (predicted) variables and independent (regressor or predictor) variables by minimizing a generalized error function. SVR provides a suitable regression model for extracting reservoir operation rules from noisy data that may contain outliers (Ji et al. 2014).

The main equation of SVR used for prediction (the output data) is a linear function, which is as follows:

$$f(\mathbf{x}) = \mathbf{w}^{\mathrm{Tr}} \cdot \mathbf{x} + b \tag{10}$$

where $\mathbf{x}$ = vector of input variables; $\mathbf{w}$ = weighting vector of the input variables; b = bias of $\mathbf{w}^{\mathrm{Tr}} \cdot \mathbf{x}$ with respect to $f(\mathbf{x})$; Tr denotes the transpose sign; and $f(\mathbf{x})$ = output variable estimated by SVR.

In order to avoid the overfitting deficit, Vapnik (1998) considered an error function called epsilon insensitive function (e-insensitive function). This function is

$$|y - f(x)| = \begin{cases} 0 & \text{if } |y - f(x)| \le \kappa \\ |y - f(x)| - \kappa = \xi & \text{otherwise} \end{cases} \tag{11}$$

where y = observed output variable; κ = permitted error threshold so that a prediction error less than κ is ignored; and ξ = considered penalty for the prediction errors that are outside of the range $(-\kappa, +\kappa)$.

The main goal of SVR optimization is to minimize the e-insensitive function and the $\mathbf{w}$ vector

$$\text{Minimize } \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{m}(\xi_i^- + \xi_i^+) \tag{12}$$

$$\begin{aligned} \text{subject to } & (w_i \cdot x_i + b) - y_i < \kappa + \xi_i^+, \quad i = 1, 2, \ldots, m \\ & y_i - (w_i \cdot x_i + b) \le \kappa + \xi_i^-, \quad i = 1, 2, \ldots, m \\ & \xi^+, \xi^- \ge 0 \end{aligned} \tag{13}$$

where C = penalty coefficient; m = number of training (calibrating) data (sample size); ξ_i^-, ξ_i^+ = violation of the ith training point that are located below and above the range $(-\kappa, +\kappa)$, respectively; and w_i, x_i, and y_i = ith weight, the value of input variable, and the observed value of output variable in the training data set.

The decision variables of Eqs. (12) and (13) are $\mathbf{w}$ and b. In other words, $\mathbf{w}$ and b are provided after completing the SVR training process. The estimated $\mathbf{w}$ and b are replaced into Eq. (10) to obtain predictions $[f(x)]$ based on input variables (x).

Eq. (10) is a linear regression. SVR can be generalized to a nonlinear function by means of several kernel functions. The most common kernel function is the radio basis functions (RBFs) (Han and Cluckie 2004; Su et al. 2014). The nonlinear regression form of SVR and RBF is written as follows:

$$f(\mathbf{x}) = \mathbf{w}^{\mathrm{Tr}} \cdot K(\mathbf{x}, x_i) + b \tag{14}$$

$$K(\mathbf{x}, x_i) = \exp\left(-\frac{|\mathbf{x} - x_i|^2}{2\gamma^2}\right) \quad i = 1, 2, \ldots, m \tag{15}$$

where $K(\mathbf{x}, x_i)$ = kernel function (RBF in this study); and γ = RBF parameter. The key task of SVR is to determine the values of the parameters κ, C, and the kernel function parameter (γ). Huang and Wang (2006) showed that the parameters values play an important role in the performance of SVR.

Nondominated Sorting Genetic Algorithm

The NSGAII was developed by Deb (2001). It is a popular method for multiobjective optimization based on nondominated sorting and elitist selection. The NSGAII starts with the generation of a random parent population and the objective functions are calculated for this population. Next, the children population is created based on two operators, namely, crossover and mutation, and the objective functions are calculated for the children population. Then, the combined population that includes parent and children is classified into fronts (Front 1 is the best front) based on a ranking process called nondominated sorting. Afterward, the crowding distance is computed for the members of each front and these members are sorted based on the crowding distance. Finally, after the classifying and sorting process, the combined population is truncated in the same manner as the parent population, and the new population is ready to generate a children population for the next iteration.

Combined SVR-NSGAII

The proposed algorithm couples SVR and NSGAII and is described in pseudocode in Fig. 1.

As shown in Fig. 1, Step 1 is about initializing the variables that are used in the pseudocode. In Step 2 the initial population is generated. The initial population includes chromosomes and each chromosome has two parts including the input variables vector (IV) and the SVR parameters vector (SPV). In Step 2, for example, when the generation number (GN) is 1, the first part (the name of the input variables, which is coded between 1 and 48) and the second part (SVR parameters) of Chromosome 1 (that is randomly generated) are [1, 5, 10, 35, and 48] and [$C = 10$, $k = 5$, and $\gamma = 0.5$] (Lines 1 and 2 in Step 2), respectively.

Then, SVR is executed (Line 3) and the RMSE of the SVR as the first objective function and the number of input variables (five input variables in this example) as the second objective function are calculated (Lines 4 and 5). Next, the first and second objective functions are merged (Line 6) and the algorithm returns to Line 1

```
Step 1. Initialize the input variables vector (IV), the SVR parameters vector (SPV), the parent vector
(PV), the offspring vector (OV), the collect vector (CV), the generation number (GN), target vector of
SVR (TVS), observed vector (OBV), cost vector (CTV) and the maximum iteration number (Max it).
Step 2: while GN< terminal generation number
 (1)  Generation random population for IV(GN) and SPV(GN)
 (2)  Combine IV(GN) and SPV(GN) via PV(GN)=IV(GN) U SVP(GN)
 (3)  Run SVR
 (4)  Calculate RMSE between TVS and OBV as g1
 (5)  Calculate the number of IV as g2
 (6)  CTV(GN)=[ g1, g2]
      End while
 Step 3
 (7)   Apply non-dominated Sorting
 (8)   Calculate crowding distance
 (9)   Sorting Population
 Step 4: while Max it < terminal iteration
            While (GN) < terminal generation number
               (10) Generate OV (GN) based on mutation and crossover from PV (GN)
               (11) Run SVR
               (12) Calculate RMSE between TVS (GN) and OBV (GN) as g1
               (13) Calculate the number of IV (GN) as g2
               (14) CTV (GN) = [g1, g2]
            End while
               (15) PV=Merge PV and OV
               (16) Apply non-dominated Sorting
               (17) Calculate crowding distance
               (18) Sorting Population
               (19) Truncate PV to GN
End while
```

Fig. 1. Pseudocode of SVR-NSGAII

in Step 2 and generates the next chromosome as long as the GN exceeds then initial population size (the initial population equals 100 in this paper). Afterward, the NSGAII prepares the new population for the main loop (Step 4) by applying nondominated sorting, crowding distance, and sorting population to the initial population (Lines 7 to 9).

In Step 4, which is the main loop (outer loop), according to the crossover and mutation function, the algorithm continues to modify and update the chromosomes (Line 10). Then, as indicated by Lines 3 to 6 in Step 2, the SVR runs and the accuracy of SVR (RMSE) and the number of input variables are calculated and merged (Lines 10 to 14) and the algorithm returns to Line 10 to update and modify the next chromosome until the GN is larger than the initial population size. After the end of the inner loop, the parent and offspring are merged and as indicated by Lines 7 to 9 in Step 3, the nondominated sorting, crowding distance, and sorting population are applied to the updated population and finally the population is truncated to size of the GN (Lines 15 to 19). At this time, Iteration 1 of the main loop is finished and the algorithm returns to Line 10 to start the next iteration until the maximum number of iterations (Max it) reaches the terminal iteration number (= 1,000 in this application)

Case Study

The SVR-NSGAII tool is applied to the Karoon-4 reservoir basin in Iran. The basin area of the Karoon-4 reservoir is approximately 12,831 km^2. Its dam is used to generate hydropower. It is located 180 km southwest of the city of Shahrekord, Iran.

A flowchart of the SVR-NSGAII algorithm is shown in Fig. 2, where it is depicted that first the optimization model for the long-term operation of the Karoon-4 reservoir is solved by using NLP (with software *Lingo 11.0*). After solving this optimization problem, the optimized release (monthly) is selected as the benchmark observed data for creating the SVR training (calibration) and testing data set. This data set includes the monthly storage, inflow, evaporation, and optimized release for hydropower generation during the operation period. In order to extract the operation rule with SVR-NSGAII the monthly storage, inflow, evaporation, and optimized release variables with time delays ranging from 1 to 12 time periods (that is, variables' values at times $t-1, t-2, \ldots, t-12$) are considered as the input variables (predictors) and the optimized release at the current time (t) is taken as the output variable. Then, the data set is divided into two categories, namely, the training (calibration) data set (75% of the data points, based on random selection) and the testing data set (25% of the data points based on random selection). Afterward, according to Fig. 1, SVR-NSGAII is applied to the data set while the SVR parameters and the names of input variables are considered as decision variables, and the RMSE and the number of input variables are considered as the objective functions (to be minimized). In other words, in each iteration of the SVR-NSGAII, the decision variables that include the SVR parameters and the name of input variables are created. Next, the decision variables are corrected according to the described NSGAII process (mutation and crossover). The SVR-NSGAII is

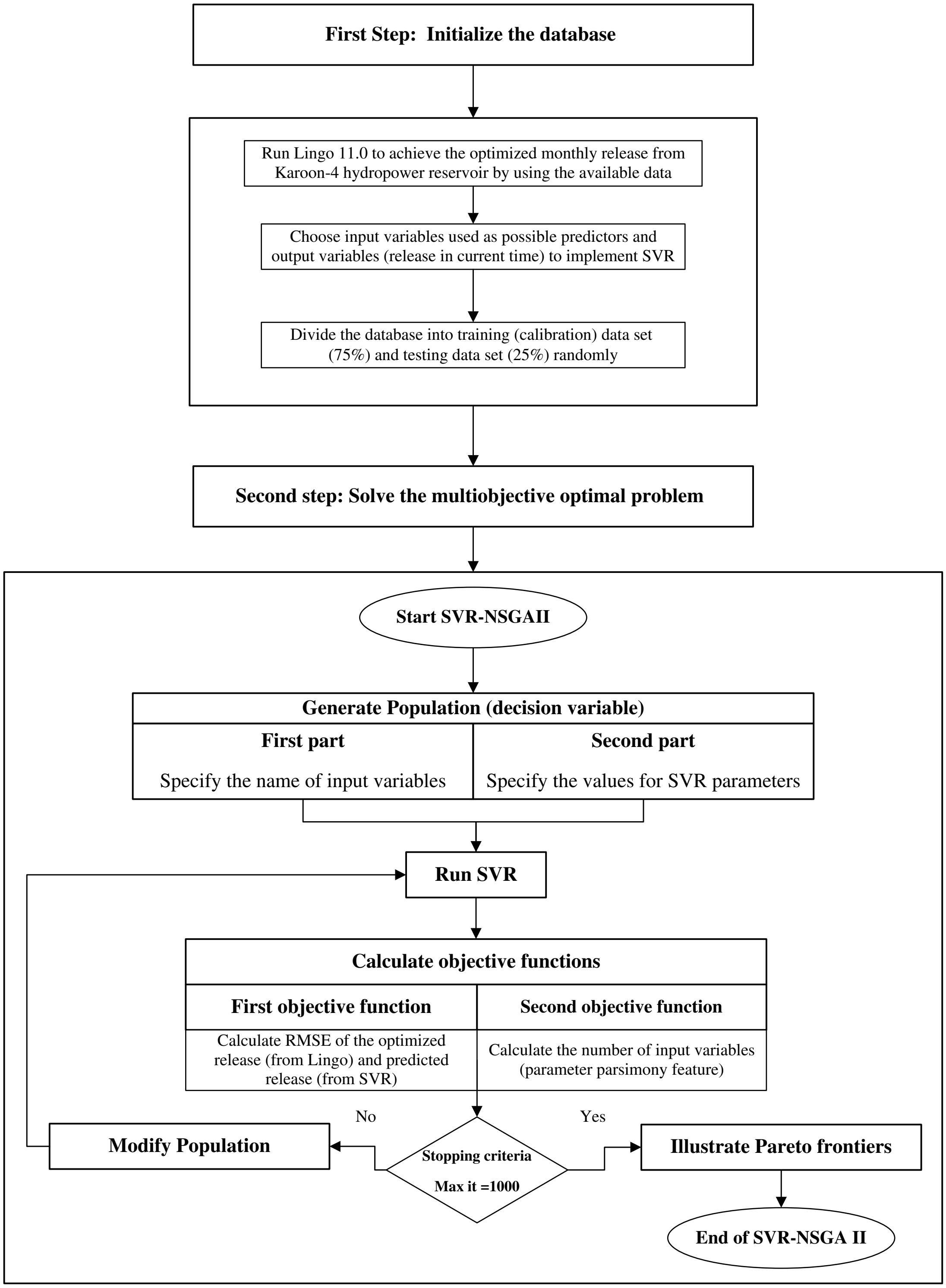

Fig. 2. Flowchart of the implemented SVR-NSGAII to derive optimal operation rule

a tool in which SVR is tasked with calculating the optimized release based on historical variables and the NSGAII is tasked with finding the best value of the SVR parameters and selecting the effective input variables used as the predictors by minimizing the error function of SVR (RMSE) and the number of input variables (according to the parsimonious feature of prediction). Finally, the results are shown as Pareto fronts (or frontiers).

The optimization model for SVR-NSGAII is formulated as follows:

$$\text{Min } g_1 = \text{RMSE}[y, f(x)] = \sqrt{\sum \frac{1}{n}[y - f(x)]^2} \tag{16}$$

$$\text{Min } g_2 = M \tag{17}$$

$$1 < M \leq 48 \tag{18}$$

where g_1 = accuracy of prediction simulation by SVR based on the RMSE for testing data; g_2 = number of input variables (M);

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n = number of testing data points; y = observed variable (optimized released achieved with Lingo); and $f(x)$ = estimated output variable (optimized release estimated with SVR).

In addition to the RMSE, one statistic index is considered to evaluate the accuracy of SVR-NSGAII

$$R^2 = 1 - \left\{ \frac{\sum [y - f(x)]^2}{\sum (y - \bar{y})^2} \right\} \tag{19}$$

where R^2 = determination coefficient.

The parameters of NSGAII and the ranges of the SVR parameters are listed in Table 1.

Results and Discussion

The optimization model of the Karoon-4 hydropower reservoir operation was solved with *Lingo 11.0* considering 576 months (48 years from 1957 to 2005) as the period of operation. The value of the objective function for this period equals 44.8. Next, the data containing inflow, storage volume, release, and evaporation variables with 1- to 12-month delay times are considered the possible predictors, and the release of the current month (the predicted variable) are input to SVR-NSGAII. The following regression model is used to calculate the operation rule of the Karoon-4 reservoir with SVR-NSGAII:

$$R'_t = f(Q_{t-1}, \ldots, Q_{t-12}, S_{t-1}, \ldots, S_{t-12}, \mathrm{Ev}_{t-1}, \ldots, \mathrm{Ev}_{t-12}, R'_{t-1}, \ldots, R'_{t-12}) \tag{20}$$

where R'_t = optimized release during month t; and R'_{t-1} = optimized release during month $t-1$, which is calculated with *Lingo 11.0*. There are 48 possible predictors considered in the regression model [Eq. (20)] to predict R'_t. Solving the optimization problem with SVR-NSGAII yields the SVR parameters and the effective predictors in form of Pareto frontiers. The Pareto frontiers with hypervolumes indicator (HI) (Zitzler and Thiele 1998) that measure the size of the space covered or the size of dominated space are shown in Fig. 3.

It is seen in Fig. 3 that the range of g_1 (RMSE) that is calculated for the testing data is between 21.5 and 35.4 and the range of g_2 (number of input variables) is between 1 and 9. In other words, only one to nine variables were selected by SVR-NSGAII among the 48 input variables that were considered as possible predictors. Also, the results in Fig. 3 show that RMSE is reduced by increasing the number of input variables from 1 to 9.

Table 2 lists the values of the decision variables with the objective functions for each Pareto point. It is seen in Table 2 that the Pareto solution suggests nine points or combinations (A through I) for extracting the operation rule. In other words, this Pareto solution provides the different combinations that can be used to predict the optimized release from the reservoir based on the available variables and the accuracy required. Also, the Pareto provides the best values of SVR parameters for each suggested combination. For example, if the operator decides to use the combination E for predicting R'_t, the selected regressors are Q_{t-1}, Q_{t-8}, Ev_{t-1}, S_{t-2}, and R'_{t-1}. The SVR is then run with the optimal parameters (κ, C, γ) that correspond to the five predictors in combination E.

Fig. 4 depicts the accuracy of regression for the combinations (or points) A, E, G, and I using training, testing, and the total data sets. It is seen in Fig. 4 that every combination has acceptable accuracy using training data, but only Models A, E, and G have acceptable accuracy using testing data. Despite minimizing the RMSE in the testing process, it seems that Model I suffers from overfitting in the training process, which leads to an increase in the error of SVR in the testing process. Considering these findings,

Table 1. Ranges of the SVR-NSGAII Parameters

Parameter	Range or value
Range of C in SVR	(0,100)
Range of κ in SVR	(0,10)
Range of γ in SVR	(0,1)
Probability of mutation in NSGAII	0.2
Probability of crossover in NSGAII	0.7
Number of members of the initial population	100
Maximum number of iterations (max it)	1,000

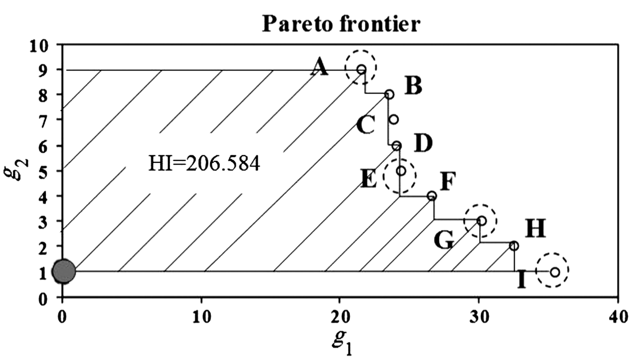

Fig. 3. Pareto frontier calculated with SVR-NSGAII

Table 2. Decision Variables with the Values of the Objective Functions Calculated with SVR-NSGAII

Point	Selected predictors									SVR parameters			Objective function	
										κ	C	γ	g_1	g_2
A	Q_{t-1}	Q_{t-3}	Ev_{t-1}	S_{t-1}	S_{t-2}	S_{t-3}	R'_{t-1}	R'_{t-3}	R'_{t-8}	0.007	62	0.167	21.579	9
B	Q_{t-1}	Q_{t-8}	Ev_{t-1}	S_{t-1}	S_{t-3}	S_{t-8}	R'_{t-1}	R'_{t-3}	—	0.010	62	0.232	23.579	8
C	Q_{t-1}	Q_{t-3}	Ev_{t-1}	S_{t-1}	S_{t-2}	S_{t-3}	R'_{t-1}	—	—	0.003	63	0.186	23.812	7
D	Q_{t-1}	Q_{t-8}	Ev_{t-1}	S_{t-1}	S_{t-3}	R'_{t-1}	—	—	—	0.005	64	0.188	24.018	6
E	Q_{t-1}	Q_{t-8}	Ev_{t-1}	S_{t-2}	R'_{t-1}	—	—	—	—	0.004	64	0.610	24.429	5
F	Q_{t-1}	S_{t-3}	Ev_{t-1}	R'_{t-1}	—	—	—	—	—	0.006	64	0.620	26.552	4
G	Q_{t-1}	S_{t-1}	R'_{t-1}	—	—	—	—	—	—	0.028	60	1.696	30.142	3
H	Q_{t-1}	R'_{t-1}	—	—	—	—	—	—	—	0.003	61	8.483	32.473	2
I	R'_{t-1}	—	—	—	—	—	—	—	—	0.046	58	1.976	35.434	1

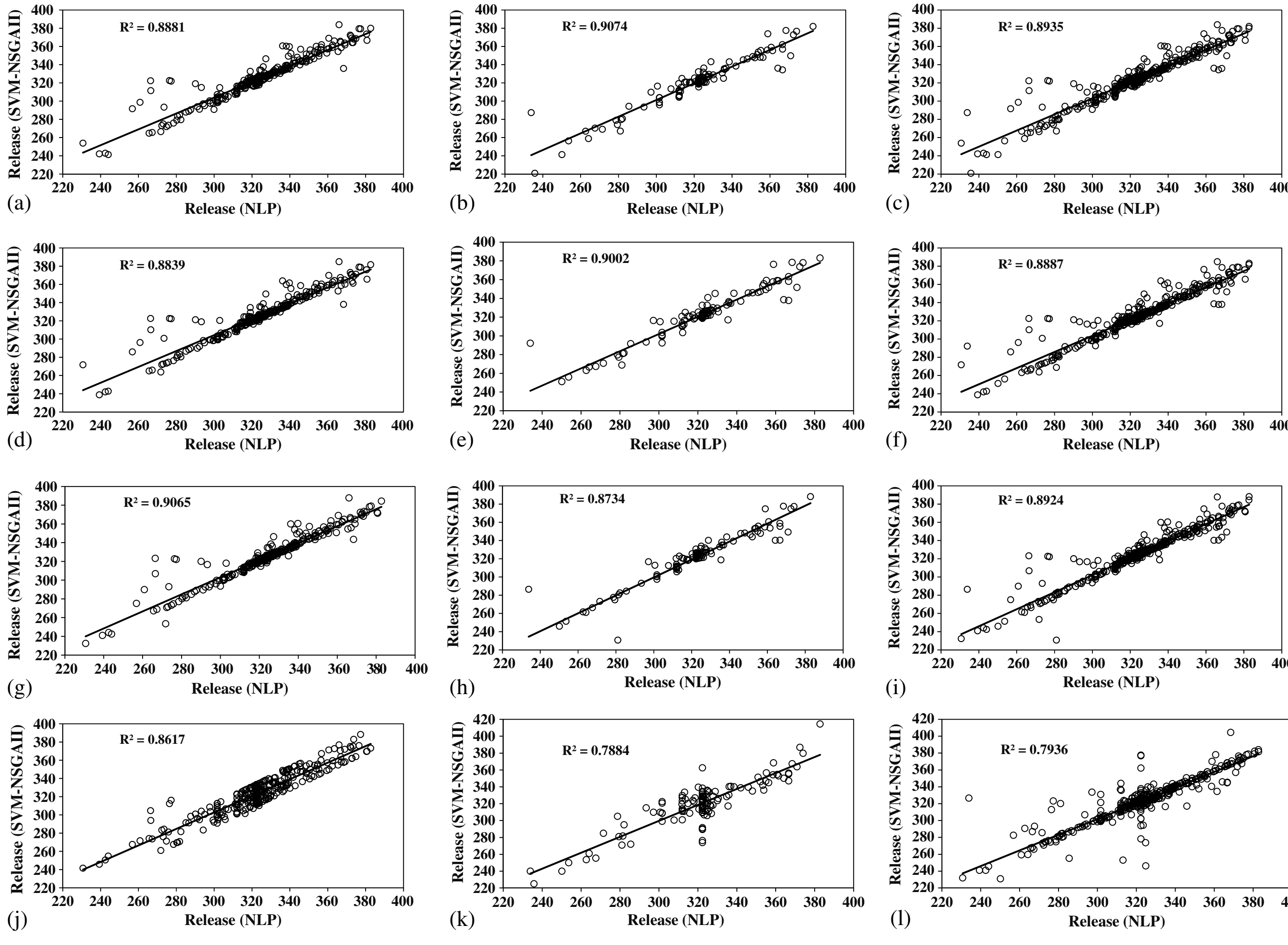

Fig. 4. Results of release (NLP) versus release (SVR-NSGAII) for (a) point A of frontier in training (calibration); (b) point A of frontier in testing; (c) point A of frontier in total data set; (d) point E of frontier in training (calibration); (e) point E of frontier in testing; (f) point E of frontier in total data set; (g) point G of frontier in training (calibration); (h) point G of frontier in testing; (i) point G of frontier in total data set; (j) point I of frontier in training (calibration); (k) point I of frontier in testing; (l) point I of frontier in total data set

combinations A through G are recommended for use in the prediction of R_t'.

Concluding Remarks

A novel method, the SVR-NSGAII, was used to derive the optimized reservoir operation rule for hydropower generation based on NLP. The NSGAII chooses the best input variables among 48 input variables that are possible predictors, and calculates the best values of the SVR parameters. The SVR extracts the optimized reservoir release for hydropower production based on a database that is determined by the NLP method and historical data. The key merit of SVR-NSGAII is its ability to determine the various combinations of parameters and predictor variables that reservoir operators can use to optimize the future reservoir release. The SVR-NSGAII has two other attractive features: parsimonious parameterization and parameter optimization. The SVR-NSGAII determines the best combinations of calibrated parameters and smallest number of predictor variables to be used in reservoir operation. This paper's application results have shown that the combinations that are determined with SVR-NSGAII to calculate the operation rule of the Karoon-4 hydropower reservoir have approximately 90% accuracy in terms of their R^2.

References

Afshar, M. H. (2012). "Large scale reservoir operation by constrained particle swarm optimization algorithms." *J. Hydro-Environ. Res.*, 6(1), 75–87.

Barton, P. I., Allgor, R. J., Feehery, W. F., and Galan, S. (1998). "Dynamic optimization in a discontinuous world." *Ind. Eng. Chem. Res.*, 37(3), 966–981.

Bolouri-Yazdeli, Y., Bozorg Haddad, O., Fallah-Mehdipour, E., and Marino, M. A. (2014). "Evaluation of real-time operation rules in reservoir systems operation." *Water Resour. Manage.*, 28(3), 715–729.

Bozorg Haddad, O., Aboutalebi, M., and Garousi-Nejad, I. (2014). "Discussion of hydrolicmatic stream flow prediction using least square support vector regression." *ISH J. Hydraul. Eng.*, 20(3), 274–275.

Bozorg Haddad, O., Aboutalebi, M., and Marino, M. A. (2013). "Discussion of prediction of missing rainfall data using conventional and artificial neural network techniques." *ISH J. Hydraul. Eng.*, 19(2), 76–77.

Bozorg Haddad, O., Adams, B. J., and Mariño, M. A. (2008a). "Optimum rehabilitation strategy of water distribution systems using the HBMO algorithm." *J. Water Supply Res. Technol.*, 57(5), 327–350.

Bozorg Haddad, O., Afshar, A., and Mariño, M. A. (2008b). "Design-operation of multi-hydropower reservoirs: HMBO approach." *Water Resour. Manage.*, 22(12), 1709–1722.

Bozorg Haddad, O., Afshar, A., and Mariño, M. A. (2011a). "Multireservoir optimisation in discrete and continuous domains." *Proc. Inst. Civ. Eng. Water Manage.*, 164(2), 57–72.

Bozorg Haddad, O., and Mariño, M. A. (2011). "Optimum operation of wells in coastal aquifers." *Proc. Inst. Civ. Eng. Water Manage.*, 164(3), 135–146.

Bozorg Haddad, O., Mirmomeni, M., and Mariño, M. A. (2010a). "Optimal design of stepped spillways using the HBMO algorithm." *Civ. Eng. Environ. Syst.*, 27(1), 81–94.

Bozorg Haddad, O., Mirmomeni, M., Zarezadeh Mehrizi, M., and Mariño, M. A. (2010b). "Finding the shortest path with honey-bee mating optimization algorithm in project management problems with constrained/unconstrained resources." *Comput. Optim. Appl.*, 47(1), 97–128.

Bozorg Haddad, O., Moradi-Jalal, M., and Mariño, M. A. (2011b). "Design-operation optimisation of run-of-river power plants." *Proc. Inst. Civ. Eng. Water Manage.*, 164(9), 463–475.

Bozorg Haddad, O., Moradi-Jalal, M., Mirmomeni, M., Kholghi, M. K. H., and Mariño, M. A. (2009). "Optimal cultivation rules in multi-crop irrigation areas." *Irrig. Drain.*, 58(1), 38–49.

Cai, X., McKinney, D. C., and Lasdon, L. (2001). "Solving nonlinear water management models using a combined genetic algorithm and linear programming approach." *Adv. Water Resour.*, 24(6), 667–676.

Cancelliere, A., Giuliano, G., Ancarani, A., and Rossi, G. (2002). "A neural networks approach for deriving irrigation reservoir operating rules." *Water Resour. Manage.*, 16(1), 71–88.

Deb, K. (2001). "A fast and elitist multiobjective genetic algorithm: NSGAII." *IEEE Trans. Evol. Comput.*, 6(2), 182–197.

Fallah-Mehdipour, E., Bozorg Haddad, O., Beygi, S., and Mariño, M. A. (2011a). "Effect of utility function curvature of Young's bargaining method on the design of WDNs." *Water Resour. Manage.*, 25(9), 2197–2218.

Fallah-Mehdipour, E., Bozorg Haddad, O., and Mariño, M. A. (2011b). "MOPSO algorithm and its application in multipurpose multireservoir operations." *J. Hydroinf.*, 13(4), 794–811.

Fallah-Mehdipour, E., Bozorg Haddad, O., and Mariño, M. A. (2012a). "Real-time operation of reservoir system by genetic programming." *Water Resour. Manage.*, 26(14), 4091–4103.

Fallah-Mehdipour, E., Bozorg Haddad, O., and Mariño, M. A. (2013a). "Developing reservoir operational decision rule by genetic programming." *J. Hydroinf.*, 15(1), 103–119.

Fallah-Mehdipour, E., Bozorg Haddad, O., and Mariño, M. A. (2013b). "Extraction of multicrop planning rules in a reservoir system: Application of evolutionary algorithms." *J. Irrig. Drain. Eng.*, 10.1061/(ASCE)IR.1943-4774.0000572, 490–498.

Fallah-Mehdipour, E., Bozorg Haddad, O., Rezapour Tabari, M. M., and Mariño, M. A. (2012b). "Extraction of decision alternatives in construction management projects: Application and adaptation of NSGA-II and MOPSO." *Expert Syst. Appl.*, 39(3), 2794–2803.

Han, D., and Cluckie, I. (2004). "Support vector machines identification for runoff modeling." *Proc., 6th Int. Conf. on Hydroinformatics*, S. Y. Liong, K. K. Phoon and V. Babovic, eds., World Scientific, Singapore.

Hasebe, M., and Nagayama, Y. (2002). "Reservoir operation using the fuzzy and neural network and fuzzy systems for dam control and operation support." *Adv. Eng. Software*, 33(5), 245–260.

Huang, C. L., and Wang, C. J. (2006). "A GA-based feature selection and parameters optimization for support vector machines." *Expert Syst. Appl.*, 31(2), 231–240.

Hydrologic Engineering Center. (2003). "HEC-PRM prescriptive reservoir model." U.S. Army Corps of Engineers, Davis, CA.

Jalali, M. R., Afshar, A., and Mariño, M. A. (2007). "Multi-colony ant algorithm for continuous multi-reservoir operation optimization problem." *Water Resour. Manage.*, 21(9), 1429–1447.

Ji, C.-M., Zhou, T., and Huang, H.-T. (2014). "Operating rules derivation of Jinsha reservoirs system with parameter calibrated support vector regression." *Water Resour. Manage.*, 28(9), 2435–2451.

Karimi-Hosseini, A., Bozorg Haddad, O., and Mariño, M. A. (2011). "Site selection of raingauges using entropy methodologies." *Proc. Inst. Civ. Eng. Water Manage.*, 164(7), 321–333.

LINGO 11.0 [Computer software]. Chicago, Lindo.

Liu, P., Guo, S., Xiong, L., Li, W., and Zhang, H. (2006). "Deriving reservoir refill operating rules by using the proposed DPNS model." *Water Resour. Manage.*, 20(3), 337–357.

Liu, P., Li, L., Chen, G., and Rheinheimer, D. E. (2014). "Parameter uncertainty analysis of reservoir operating rules based on implicit stochastic optimization." *J. Hydrol.*, 514, 102–113.

Madani, K. (2011). "Hydropower licensing and climate change: Insights from cooperative game theory." *Adv. Water Resour.*, 34(2), 174–183.

Maity, R., Bhagwat, P., and Bhatnagar, A. (2013). "Potential of support vector regression for prediction of monthly streamflow using endogenous property." *Hydrol. Processes*, 24(7), 917–923.

Marano, V., Rizzo, G., and Tiano, F. A. (2012). "Application of dynamic programming to the optimal management of a hybrid power plant with wind turbines, photovoltaic panels and compressed air energy storage." *Appl. Energy*, 97(1), 849–859.

Moeini, R., Afshar, A., and Afshar, M. H. (2011). "Fuzzy rule-based model for hydropower reservoirs operation." *Int. Electr. Power Energy Syst.*, 33(2), 171–178.

Mousavi, S. J., Ponnambalam, K., and Karray, F. (2007). "Inferring operating rules for reservoir operations using fuzzy regression and ANFIS." *Fuzzy Set Syst.*, 158(10), 1064–1082.

Nicklow, J., et al. (2010). "State of the art for genetic algorithms and beyond in water resources planning and management." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)WR.1943-5452.0000053, 412–432.

Noory, H., Liaghat, A. M., Parsinejad, M., and Bozorg Haddad, O. (2012). "Optimizing irrigation water allocation and multicrop planning using discrete PSO algorithm." *J. Irrig. Drain. Eng.*, 10.1061/(ASCE)IR.1943-4774.0000426, 437–444.

Oliveira, R., and Daniel, P. L. (1997). "Operating rules for multi-reservoir systems." *Water Resour. Res.*, 33(4), 839–852.

Orouji, H., Bozorg Haddad, O., Fallah-Mehdipour, E., and Mariño, M. A. (2013). "Estimation of Muskingum parameter by meta-heuristic algorithms." *Proc. Inst. Civ. Eng. Water Manage.*, 166(6), 315–324.

Ostadrahimi, L., Mariño, M. A., and Afshar, A. (2012). "Multi-reservoir operation rules: Multi-swarm PSO-based optimization approach." *Water Resour. Manage.*, 26(2), 407–427.

Paulo, C., and Toshiharu, K. (2007). "Deriving reservoir operational strategies considering water quantity and quality objectives by stochastic fuzzy neural networks." *Adv. Water Resour.*, 30(5), 1329–1341.

Ponnambalam, K., Karray, F., and Mousavi, F. (2003). "Minimizing variance of reservoir systems operations benefits using soft computing tools." *Fuzzy Sets Syst.*, 139(2), 451–461.

Reed, P., Minsker, B., and Goldberg, D. (2000). "Designing a competent simple genetic algorithm for search and optimization." *Water Resour. Res.*, 36(12), 3757–3761.

Saad, M., Turgeon, A., Bigras, P., and Duquette, R. (1994). "Learning disaggregation technique for the operation of long-term hydroelectric power system." *Water Resour. Res.*, 30(11), 3195–3202.

Seifollahi-Aghmiuni, S., Bozorg Haddad, O., Omid, M. H., and Mariño, M. A. (2011). "Long-term efficiency of water networks with demand uncertainty." *Proc. Inst. Civ. Eng. Water Manage.*, 164(3), 147–159.

Seifollahi-Aghmiuni, S., Bozorg Haddad, O., Omid, M. H., and Mariño, M. A. (2013). "Effects of pipe roughness uncertainty on water distribution network performance during its operational period." *Water Resour. Manage.*, 27(5), 1581–1599.

Shokri, A., Bozorg Haddad, O., and Mariño, M. A. (2013). "Algorithm for increasing the speed of evolutionary optimization and its accuracy in multi-objective problems." *Water Resour. Manage.*, 27(7), 2231–2249.

Simonovic, S. P. (1992). "Reservoir systems analysis: Closing gap between theory and practice." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)0733-9496(1992)118:3(262), 262–280.

Su, J., Wang, X., Liang, Y., and Chen, B. (2014). "A GA-based support vector machine model for prediction of monthly reservoir storage." *J. Hydrol. Eng.*, 10.1061/(ASCE)HE.1943-5584.0000915, 1430–1437.

Sudheer, Ch., Maheswaran, R., Panigrahi, B. K., and Mathur, S. (2014). "A hybrid SVM-PSO model for forecasting monthly streamflow." *Neural Comput. Appl.*, 24(6), 1381–1389.

Vapnik, V. (1995). *The nature of statistical learning theory*, Springer, New York.

Vapnik, V. N. (1998). *Statistical learning theory*, Wiley, New York.

Wurbs, R. A. (1993). "Reservoir-system simulation and optimization models." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)0733-9496(1993)119:4(455), 455–472.

Yeh, W. W.-G. (1985). “Reservoir management and operation models: A state of-the-art review.” *Water Resour. Res.*, 21(12), 1797–1818.

Yin, X.-A., Yang, Z.-F., Petts, G. E., and Kondolf, G. M. (2014). “A reservoir operating method for riverine ecosystem protection, reservoir sedimentation control and water supply.” *J. Hydrol.*, 512, 379–387.

Yoo, J.-H. (2009). “Maximization of hydropower generation through the application of a linear programming model.” *J. Hydrol.*, 376(1), 182–187.

Yuan, X., Wang, L., and Yuan, Y. (2008). “Application of enhanced PSO approach to optimal scheduling of hydro system.” *Energy Convers. Manage.*, 49(11), 2966–2972.

Zitzler, E., and Thiele, L. (1998). “Multiobjective optimization using evolutionary algorithms—A comparative study.” *Lecture notes in computer science 1498: Parallel problem solving from nature—PPSN V*, A. E. Eiben, T. Back, M. Schoenauer and H.-P. Schwefel, eds., Springer, Berlin, 292–301.