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Journal
Journal of Irrigation and Drainage Engineering, 142(3)

ISSN
0733-9437

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

Publication Date
2016-03-01

DOI
10.1061/(asce)ir.1943-4774.0000969

Peer reviewed

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Application of the SVR-NSGAII to Hydrograph Routing in Open Channels

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

Abstract: Flow routing is used to simulate or predict downstream hydrographs on the basis of the features of upstream flow hydrographs. This paper combines support vector regression (SVR) and the nondominated sorting genetic algorithm II (NSGAII) into a hybrid hydrologic routing model called SVR-NSGAII in this paper for the prediction of a downstream flow hydrograph in simple and compound channels. The SVR-NSGAII hydrologic routing predictions are compared with those from hydraulic models in simple and compound channels. This paper's results indicate that the SVR-NSGAII predicts the downstream hydrograph flow in a simple and compound channel, with approximately 94 and 98% accuracy, respectively. **DOI: 10.1061/(ASCE)IR.1943-4774.0000969.**

Author keywords: Flow routing; Open channels; Support vector machine; Nondominated sorting genetic algorithm.

Introduction

Recent publications dealing with newly developed models for the optimization and simulation of water resources systems have addressed topics, such as reservoir operation (Ashofteh et al. 2013b, 2015a, c), design operation of pumped-storage and hydropower systems (Bozorg Haddad et al. 2014b), levee layouts and design (Bozorg Haddad et al. 2015b), hydrology (Ashofteh et al. 2013a), qualitative management of water resources systems, (Bozorg Haddad et al. 2015a), and algorithmic developments (Ashofteh et al. 2015b). However, few of these models have focused on the application of support vector regression (SVR) and the nondominated sorting genetic algorithm II (NSGAII) (SVR-NSGAII) or hydrograph routing in open channels.

Flow routing procedures used to simulate or predict a downstream hydrograph can be accomplished into hydrologic or hydraulic methods. Hydrologic routing methods simulate the flow hydrograph downstream on the basis of the continuity equation and functions relating to storage, outflow, and possibly inflow. In contrast, hydraulic routing methods model the flow hydrograph on the basis of the continuity and momentum equations, but they have many parameters that must be calibrated and channel characteristics to be incorporated in the analysis. Recently, artificial intelligence (AI) algorithms, such as the artificial neural network (ANN) (Peters et al. 2006), support vector machine (SVM) (Han et al. 2007), and genetic programming (GP) (Fallah-Mehidpour et al. 2013) were used to simulate downstream hydrographs on the basis of the features of upstream hydrographs. These AI algorithms are classifiable as hydrologic routing methods.

Concerning hydraulic routing methods, Saint-Venant (1871) introduced the dynamic wave equations. These equations have been widely used for flood forecasting in routing and software packages, such as *MIKE11* and *HEC-RAS* (Néelz and Pender 2009). However, these hydraulic equations are nonlinear and require numerical solutions. Mahmood and Yevjevich (1975) and Montes (1998) presented a comprehensive investigation on historical developments in numerical modeling of unsteady open channel flows. Proust et al. (2009) developed a new one-dimensional (1D) model called the independent subsections method (ISM) that computes the water profiles in each subsection of compound channels for uniform flow. Moreover, Proust et al. (2010) reported on the energy losses under nonuniform conditions in compound channels. Moghaddam and Firouzi (2011) developed the dynamic flood wave routing in natural rivers through the implicit numerical method. They presented a solution for the full Saint-Venant equations with the Preissmann implicit finite-difference scheme for hypothetical flood routing problems in a wide rectangular river and compared the solution of the developed model with *HEC-RAS*. Costabile and Macchione (2012), Tsakiris and Bellos (2014), and Costabile and Macchione (2015) provide more comprehensive views of hydraulic routing methods.

Concerning hydrologic routing methods, McCarthy (1938) developed a flood routing procedure for the Muskingum River in Ohio, now called the Muskingum method. Software packages, such as *HEC-1* (USACE 1998), apply the Muskingum method, whereby the outflow hydrograph is calculated for a given inflow hydrograph. Similar to hydraulic routing models, the parameters of the Muskingum method must be calibrated by using a set of observed inflow and outflow hydrograph data. The calibration of Muskingum-type methods plays a key role in its predictive accuracy. Many researchers, therefore, have addressed the estimation of Muskingum parameters with various techniques. The genetic algorithm (GA) (Mohan 2009), particle swarm optimization (PSO) (Chu and Chang 2009), immune clonal selection algorithm (ICSA) (Luo and Xie 2010), Nelder-Mead simplex algorithm (NMSA) (Barati 2011), harmony search (HA) (Geem 2011), differential evolution (DE) (Xu et al. 2012), Microsoft *Excel* solver (Barati 2013), hybrid harmony search algorithm (HHSA) (Karahan et al. 2013), metaheuristic algorithms (Orouji et al. 2013), GP (Orouji et al. 2014), and

[1]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, Santa Barbara, CA 93106-4060. E-mail: Hugo.Loaiciga@ucsb.edu

Note. This manuscript was submitted on June 2, 2015; approved on August 11, 2015; published online on December 16, 2015. Discussion period open until May 16, 2016; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Irrigation and Drainage Engineering***, © ASCE, ISSN 0733-9437.

modified honey bee mating optimization (MHBMO) (Niazkar and Afzali 2015) have been applied to estimate the Muskingum parameters. In spite of such previous studies, increasing the accuracy of the Muskingum method with a rapid convergence rate remains an active area of research, to which this paper contributes.

Concerning AI, Savic et al. (1999) asserted the advantages of GP over ANNs in the flow prediction of the Kirkton catchment, Dundee, Scotland, and Deka and Chandramouli (2005) relied on a fuzzy neural network (FNN) to forecast the river flow in the Brahmaputra River. Peters et al. (2006) evaluated the performance of ANN in the routing hydrograph with the *HEC-RAS* results. Han et al. (2007) applied SVM with a linear and radial base function (RBF) to rout floods in the Bird Creek catchment. They reported that selecting the optimal combinations of input variables is a most challenging problem in the AI tool, such as SVM for flood routing. Sivapragasam et al. (2008) evaluated the accuracy of nonlinear Muskingum models in multipeaked hydrographs and proposed GP as an alternative technique to route single-peaked and multipeaked flood hydrographs. Fallah-Mehdipour et al. (2013) applied GP to rout a stage hydrograph in simple and compound open channels. They compared the accuracy of the GP hydrologic routing model to those of the *HEC-RAS* and the characteristic dissipative Galerkin procedure in one-dimension (CCDG-1D) hydraulic routing models. The results indicated that GP exhibited an acceptable performance in routing stage hydrographs. Further discussion about the application of AI in water resources management (WRM) is provided by Bozorg Haddad et al. (2013, 2014a), Garousi-Nejad and Bozorg Haddad (2015), and Aboutalebi and Garousi-Nejad (2015).

A review of previous publications reveals that hydraulic routing methods, such as *HEC-RAS* and CCDG-1D, are more accurate than hydrological routing methods, but they require lots of information related to channel geometry and specifications that imply a high computational burden. In contrast, hydrologic routing methods, such as the Muskingum method, can calculate the output hydrograph with less data than hydraulic methods, but lower accuracy than the latter methods, and their performance depends strongly on the proper calibration of their parameters. Recently, Bozorg Haddad et al. (2015c) proposed a seven-parameter Muskingum model for flood routing. Increasing the number of the Muskingum model's parameter leads to improved predictive accuracy, but raises the complexity of parameter estimation.

This paper applies SVR-NSGAII, introduced by Aboutalebi and Bozorg Haddad (2015) and Aboutalebi et al. (2015), to predict the downstream flow hydrographs on the basis of upstream hydrographs. The SVR predicts the downstream hydrograph in the current time on the basis of an upstream hydrograph in the current and previous times. The SVR-NSGAII combines the features of SVR and the NSGAII to calibrate routing parameters and choose input variables for predicting downstream flow hydrographs. The major advantage of SVR-NSGAII relative to other routing methods is that it simultaneously generates several models with which to predict downstream hydrographs in terms of a Pareto frontier while performing autocalibration and parsimonious parameter selection.

Hydraulic Routing Methods

Hydraulic routing methods calculate streamflow as a function of space and time on the basis of the continuity and momentum equations for open channels. One of the merits of these methods is their better accuracy than that of hydrologic routing methods. In contrast, one of the disadvantages of hydraulic methods is simulating flow hydrographs based extensively on data about river geometry, such as cross-sectional shape, bed form, longitudinal form, and branching.

HEC-RAS

The United States Army Corps of Engineers developed *HEC-RAS*. It is equipped to model the hydraulics of water flow through natural rivers and other channels. The basic computational procedure of *HEC-RAS* for steady flow is on the basis of the solution of the one-dimensional energy equation. Therefore, *HEC-RAS* is a one-dimensional hydrodynamic model. For unsteady flow, *HEC-RAS* solves the full, dynamic, 1D Saint-Venant equation using an implicit, finite-difference method. This paper compares the *HEC-RAS* routing results with those obtained with the SVR-NSGAII hydrologic routing model in a simple channel.

CCDG-1D

Tuitoek and Hicks (2001) modeled unsteady flow in compound channels with the aim of controlling floods. They developed a model called CCDG-1D on the basis of the Saint-Venant equations of flow, with the incorporation of terms to account for the momentum transfer phenomenon to route unsteady flow in compound channels. Tuitoek and Hicks (2001) provide more information on the CCDG-1D model. This paper compares the results obtained from the prediction of flow hydrographs in compound channels calculated with the CCDG-1D hydraulic model and the SVR-NSGAII hydrologic model. The downstream hydrographs computed with *HEC-RAS* in simple channels and with CCDG-1D in compound channels are used as benchmark data sets for evaluating the performance of the SVR-NSGAII.

Hydrologic Routing Methods

Hydrologic routing methods simulate the downstream hydrograph on the basis of data about the upstream hydrograph and consider the flow hydrograph as a function of time at a particular river location.

SVM

Vapnik (1995) invented the first version of the SVM theory. The SVM uses an error and kernel function to recognize patterns that are used in classification or regression analysis of a given data set (Bozorg Haddad et al. 2013, 2015a). The regression version of SVM is called SVR, which is briefly described next.

SVR

Vapnik (1998) modified SVM for a regression analysis involving the prediction or simulation of time series. The linear form of SVR is as follows:

$$f(\mathbf{x}) = \mathbf{w}^{Tr} \cdot \mathbf{x} + b \tag{1}$$

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

The SVR attempts to minimize the differences between the observed data and the estimated data. Therefore, SVR minimizes an optimization problem whose objective function is decreasing the error function proposed by Vapnik (1998), which is called e-insensitive loss function. This error function ignores errors for data that are situated within the epsilon distance (ε) from the fitting line. The optimization problem is as follows:

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

$$\text{Subject to } (w_i \cdot x_i + b) - y_i < \varepsilon + \xi_i^+, \quad i = 1, 2, \ldots, m$$

$$y_i - (w_i \cdot x_i + b) \leq \varepsilon + \xi_i^-, \quad i = 1, 2, \ldots, m, \quad \xi^+, \xi^- \geq 0 \quad (3)$$

where C = penalty coefficient; m = number of training data sets; ξ_i^-, ξ_i^+ = violation of the ith training point that is situated out of the ε distance from the fitting line; and w_i, x_i, and y_i = ith weight variable, input variable, and observed target variable in the training data set, respectively.

The variables $\mathbf{w}$ and b are calculated by solving Eqs. (2) and (3). Their calculated values are substituted in Eq. (1), and $f(x)$ is computed. By means of several kernel functions that map the data set to the linear separable space, SVR can be modified to predict or simulate the nonlinear time series. Therefore, Eq. (1) is rewritten as follows for this purpose:

$$f(\mathbf{x}) = \mathbf{w}^{Tr} \cdot K(\mathbf{x}, x_i) + b \quad (4)$$

$$K(\mathbf{x}, x_i) = \exp\left(-\frac{|\mathbf{x} - x_i|^2}{2\gamma^2}\right) \quad i = 1, 2, \ldots, m \quad (5)$$

where $K(\mathbf{x}, x_i)$ denotes the kernel function, which is RBF in this study, where γ is the RBF parameter. The most common kernel function is RBF, which has one parameter called γ. In addition to the kernel function parameter, there are ε and C as SVR parameters. Many researchers, e.g., Han and Cluckie (2004), Cherkassky and Ma (2004), and Aboutalebi et al. (2015), studied the SVR parameters and showed that defining the SVR parameters' values correctly plays an important role in the accuracy of SVR.

NSGAII

Deb (2001) suggested a multiobjective evolutionary algorithm on the basis of a nondominated sorting and elitist selection theory called NSGAII. In the first step, the NSGAII creates a random parent population and computes the objective functions corresponding to this population. In the second step, the offspring population is generated on the basis of mating operators, namely, crossover and mutation, and the objective functions are calculated for the offspring population. The number of crossover and mutated populations is related to the probability of crossover and mutation. After generating the offspring population, in the third step, the parent and offspring population are combined and sorted on the basis of a ranking process called the nondominated sorting theory. Therefore, the members of the combined population can be shown sets called Pareto fronts, in which the members with Rank 1 are called Front 1, i.e., the best front. In the fourth step, the members of each front are sorted on the basis of the crowding distance measure computed for these members. Each member of the combined population has two indexes: one for rank and the other for crowding distance. In the final step, the combined population is truncated in the same manner as the parent population, and the new parent population is transferred to the next iteration for generating new offspring and sorting processes. These steps are repeated until convergence to an optimal solution is achieved.

SVR-NSGAII

Aboutalebi and Bozorg Haddad (2015) proposed a new method called SVR-NSGAII to predict the monthly inflow to a hydropower reservoir. Aboutalebi et al. (2015) calculated the operation rule of the hydropower reservoir using SVR-NSGAII. In the SVR-NSGAII method, NSGAII determines the best input variables for prediction purposes, and the optimized SVR parameters and SVR predict or simulate the time series assumed as the target variable on the basis of the chosen input variables. In this paper, SVR-NSGAII is used to predict the downstream hydrograph in open channels on the basis of the features of the upstream hydrograph in simple and compound channels. Fig. 1 shows a flowchart of the SVR-NSGAII.

On the basis of Fig. 1, the downstream hydrographs for simple and compound open channels are first simulated using *HEC-RAS* and CCDG-1D, respectively. Afterward, the simulated hydrographs are selected as the benchmark observed data for creating the SVR training and testing data sets. These data sets include the downstream discharge and depth hydrographs at the current time and one to three time intervals prior as the input variables (possible predictors), and the predicted downstream discharge hydrograph is considered as the target or output variable. Next, the data set is divided into two categories, namely, the training data set (75% of the data points on the basis of random selection) and the testing data set (25% of the data points on the basis of random selection). Afterward, SVR-NSGAII is applied to the data set while the names of the input variables and the SVR parameters are considered as decision variables, and minimizing the number of input variables and errors of SVR in the testing data set are considered as the objective functions. In other words, first, the decision variables that include the name of the input variables and SVR parameters are randomly created as the primary population. After generating the decision variables, SVR is run and the objective functions are calculated for each member of the population. Next, the SVR-NSGAII enters the main loop. In the main loop and in each iteration, the decision variables are corrected according to the described NSGAII process (mutation and crossover) and SVR is run on the basis of the corrected decision variables. This process continues until the stopping criterion is satisfied. Finally, the results are shown as Pareto fronts or frontiers. Therefore, SVR-NSGAII is a tool in which NSGAII is tasked with selecting the effective predictors used and providing the best value of the SVR parameters by minimizing the error function of SVM [root mean square error (RMSE)] and the number of input variables according to the parsimonious feature of prediction.

Optimization Model

The SVR-NSGAII optimization model used for predicting discharge hydrographs is as follows:

$$\text{Min } g_1 = \text{RMSE}[y, f(x)] = \sqrt{\sum \frac{1}{n}[y - f(x)]^2} \quad (6)$$

$$\text{Min } g_2 = M \quad (7)$$

$$1 < M \leq 8 \quad (8)$$

where g_1 = accuracy of prediction simulation by SVR on the basis of RMSE for the testing data set; g_2 = number of input variables (M); n = number of testing data points; y = observed variable, i.e., simulated hydrograph calculated with *HEC-RAS* in simple channels and with CCDG-1D in compound channels; and $f(x)$ = estimated target variable, i.e., predicted downstream discharge hydrograph by SVR. In addition to the RMSE, one statistical index is considered to evaluate the accuracy of SVR-NSGAII

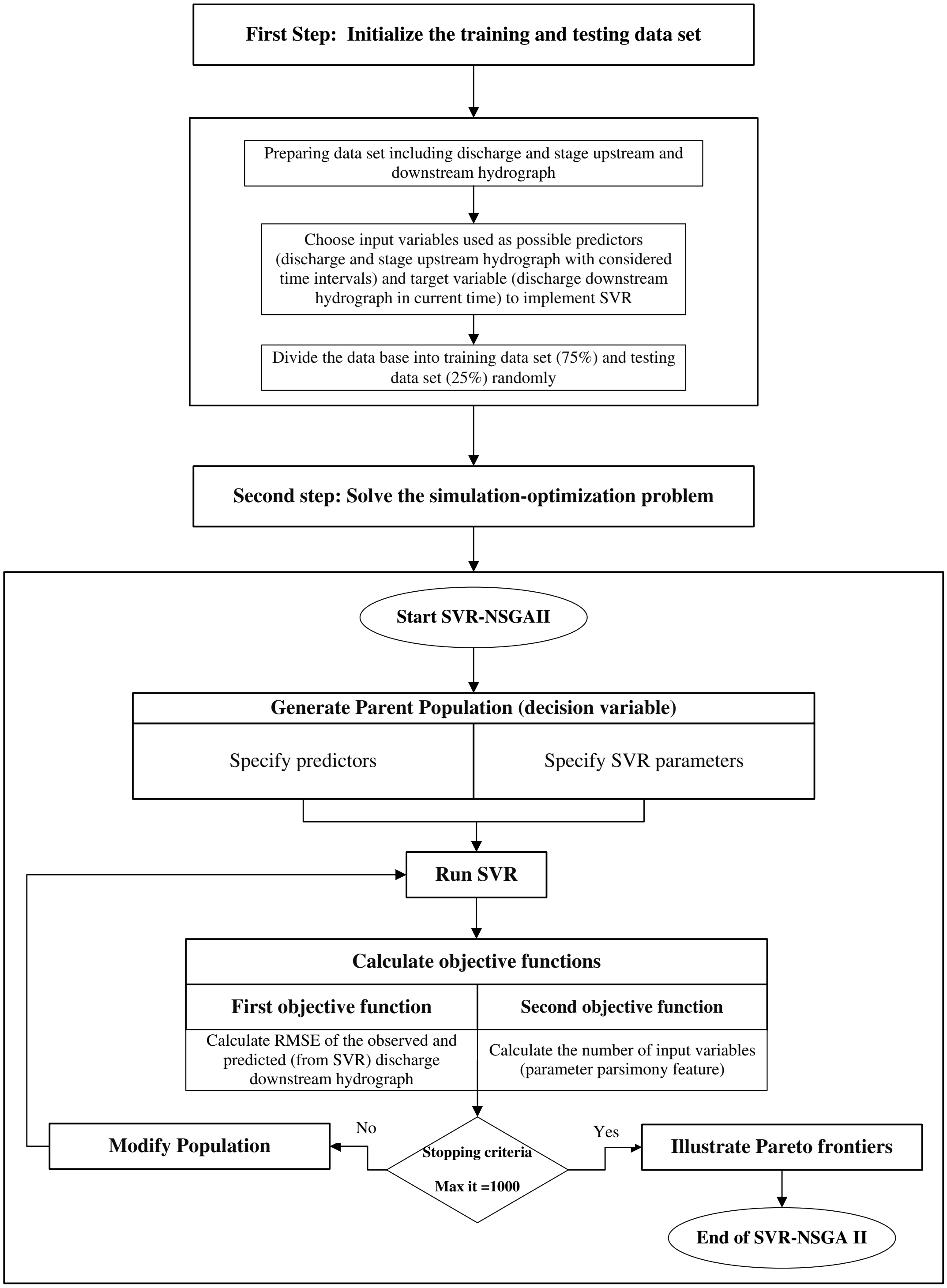

Fig. 1. Flowchart of SVR-NSGAII to predict downstream hydrographs

$$R^2 = 1 - \left\{ \frac{\sum [y - f(x)]^2}{\sum (y - \bar{y})^2} \right\} \tag{9}$$

where R^2 = determination coefficient.

In this study, the best NSGAII parameters were obtained after a preliminary sensitivity analysis, with several short runs. These parameters were used to execute the long runs of the optimization model. Moreover, the values of the parameters fall within the recommended ranges suggested in previous studies (Aboutalebi et al. 2015; Aboutalebi and Bozorg Haddad 2015). Table 1 lists the NSGAII parameters and the ranges of the SVR parameters.

First Case Study

The first case study is hypothetical flow in a wide rectangular channel 29 km long and 120 m wide, with a 0.00061 bed slope. Moghaddam and Firoozi (2011) introduced this case study in dynamic flood wave routing. They routed the downstream discharge with the Preissmann implicit scheme (PIS) and then compared the

Table 1. Ranges of the SVR-NSGAII Parameters

Parameter	Range or value
Range of ε (SVR's parameter)	(0, 1)
Range of γ (SVR's parameter)	(0, 10)
Range of C (SVR's parameter)	(0, 100)
Probability of crossover (NSGAII's parameter)	0.25
Probability of mutation (NSGAII's parameter)	0.75
Number of individuals of the initial population	100
Maximum number of iterations (stopping criterion)	1,000

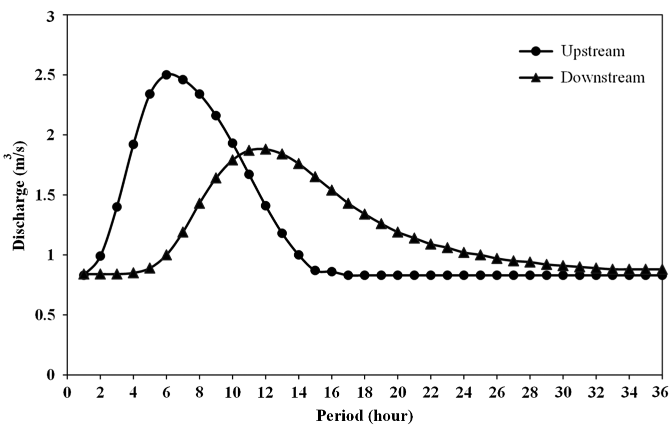

Fig. 2. Upstream and downstream discharge hydrographs of first case study

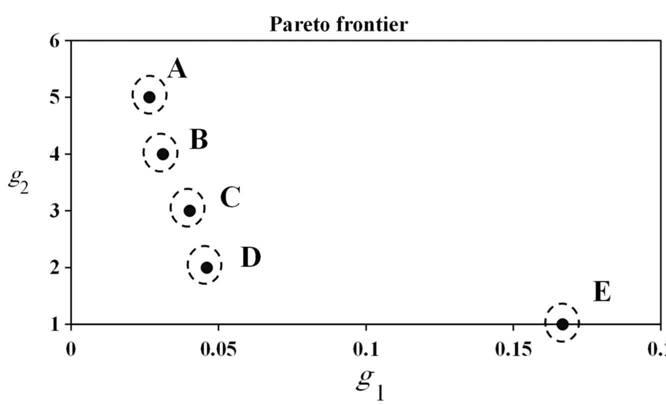

Fig. 3. Pareto frontier calculated with SVR-NSGAII for first case study

results of PIS to the *HEC-RAS* results (benchmark downstream hydrograph). Using this case study, Fallah-Mehdipour et al. (2013) applied GP to predict downstream hydrographs and compared the GP results to the routed hydrographs computed by the *HEC-RAS* model. Fig. 2 shows the upstream and downstream discharge hydrographs considered in this case study.

To compare the capability of SVR-NSGAII as a hydrologic routing method with *HEC-RAS* as a hydraulic method, the current discharge and stage of the upstream hydrograph with one to three prior time intervals are the possible predictors and the current discharge hydrograph at the downstream is the target variable. The following regression model is used to calculate the downstream discharge hydrograph with SVR-NSGAII:

$$QD_t = f(QU_t, \ldots, QU_{t-3}, SU_t, \ldots, SU_{t-3}) \tag{10}$$

where QD_t = discharge at the downstream section at time t; QU_t = discharge at the upstream section at time t; and SU_t = stage at the upstream section at time t. According to Eq. (10), there are eight possible predictors considered in the regression model to predict QD_t. After solving the optimization problem with SVR-NSGAII, the SVR parameters and effective predictors are determined in the form of a Pareto frontier, as shown in Fig. 3.

Fig. 3 reveals that SVR-NSGAII identified five models to predict the downstream discharge hydrograph, whereby each model has its specific predictors, SVR parameters, and accuracy. The range of g_1 (RMSE), which is the error between the hydrographs calculated by SVR-NSGAII and *HEC-RAS*, ranges from 0.026 to 0.166, and the range of g_2, i.e., the number of input variables, is from 1 to 5. Therefore, among the eight possible predictors, only one to five variables were selected by SVR-NSGAII. Also, the accuracy of the proposed model increases, and RMSE is reduced with the increasing number of effective input variables.

Table 2 lists the values of the decision variables with the objective functions for each Pareto point. Table 2 shows that the Pareto solution suggests five points or models (A–E) for predicting the downstream discharge hydrograph. In other words, this Pareto solution provides alternative models that can be used to predict the downstream discharge hydrograph on the basis of the available variables and accuracy required. Also, the Pareto provides the best values for the SVR parameters for each suggested model. For example, if the analyst decides to use Model D for prediction, the selected predictors are SU_t and QU_t and the optimal parameters for SVR (κ, C, γ) are 0.016, 46, and 4.07, respectively.

Fig. 4 depicts R^2, with concern for the accuracy of the suggested Models A–E using training, testing, and total data sets. According to Fig. 4, it is obvious that Models A–D have acceptable accuracy using the testing data set, but the R^2 of Model E is inferior to that of the other suggested models and is under 90% in the testing data set. Considering these findings, Models A–D are recommended to predict the downstream discharge hydrograph in simple channels.

Table 2. Effective Predictors and the Values of the Objective Functions for Each Model Calculated with SVR-NSGAII in the First Case Study

						SVR parameters			Objective functions	
Model	Effective predictors					ε	C	γ	g_1	g_2
A	SU_t	SU_{t-1}	QU_{t-3}	QU_{t-2}	QU_t	0.008	47	5.245	0.026	5
B	SU_t	SU_{t-1}	QU_{t-2}	QU_t	—	0.010	59	4.957	0.031	4
C	SU_t	QU_{t-2}	QU_t	—	—	0.008	47	5.271	0.041	3
D	SU_t	QU_t	—	—	—	0.016	46	4.074	0.046	2
E	QU_t	—	—	—	—	0.079	42	5.357	0.166	1

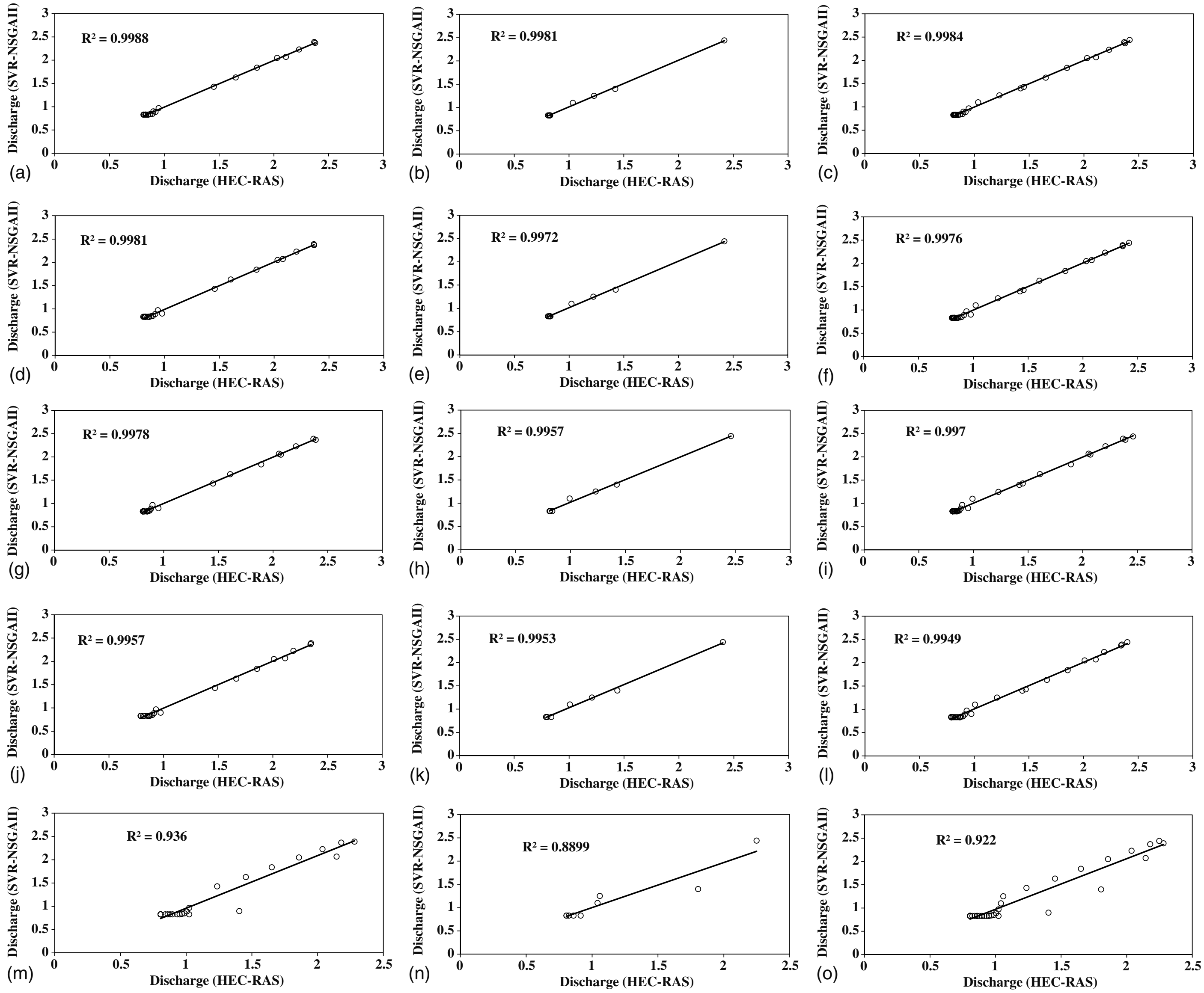

Fig. 4. Results of downstream discharge hydrographs routed with *HEC-RAS* versus discharge hydrographs predicted with SVR-NSGAII for (a) Point A of frontier in training; (b) Point A of frontier in testing; (c) Point A of frontier in total data set; (d) Point B of frontier in training; (e) Point B of frontier in testing; (f) Point B of frontier in total data set; (g) Point C of frontier in training; (h) Point C of frontier in testing; (i) Point C of frontier in total data set; (j) Point D of frontier in training; (k) Point D of frontier in testing; (l) Point D of frontier in total data set; (m) Point E of frontier in training; (n) Point E of frontier in testing; and (o) Point E of frontier in total data set

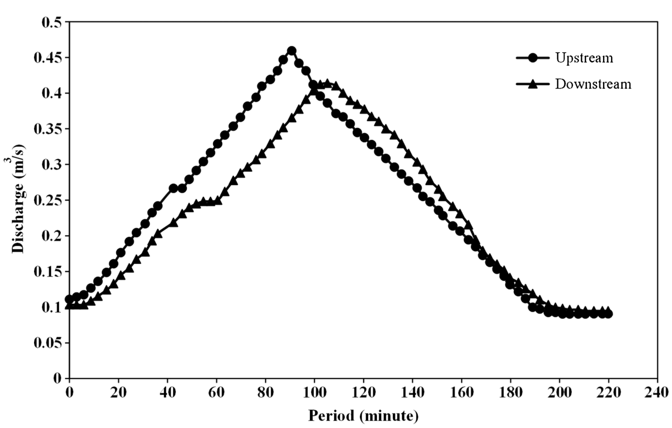

Fig. 5. Upstream and downstream discharge hydrographs of second case study

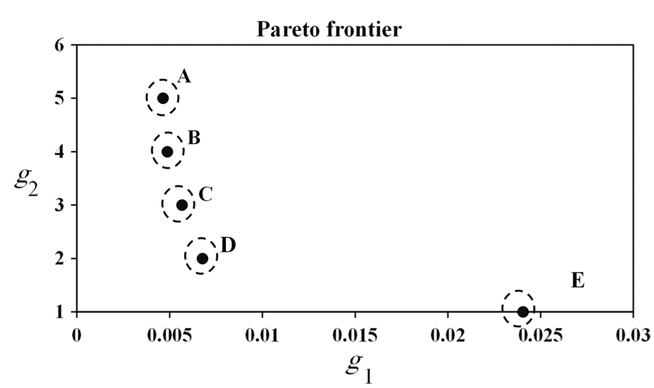

Fig. 6. Pareto frontier calculated with SVR-NSGAII for second case study

Table 3. Effective Predictors and the Values of the Objective Functions for Each Model Calculated with SVR-NSGAII in the Second Case Study

Model	Effective predictors					SVR parameters ε	SVR parameters C	SVR parameters γ	Objective functions g_1	Objective functions g_2
A	SU_t	SU_{t-2}	QU_{t-3}	QU_{t-1}	QU_t	0.0021	16	8.332	0.0046	5
B	SU_t	QU_{t-3}	QU_{t-2}	QU_t	—	0.0041	12	8.754	0.0048	4
C	SU_t	QU_{t-1}	QU_t	—	—	0.0034	14	8.802	0.0056	3
D	QU_{t-1}	QU_t	—	—	—	0.0033	17	9.001	0.0067	2
E	QU_t	—	—	—	—	0.0504	11	7.954	0.0240	1

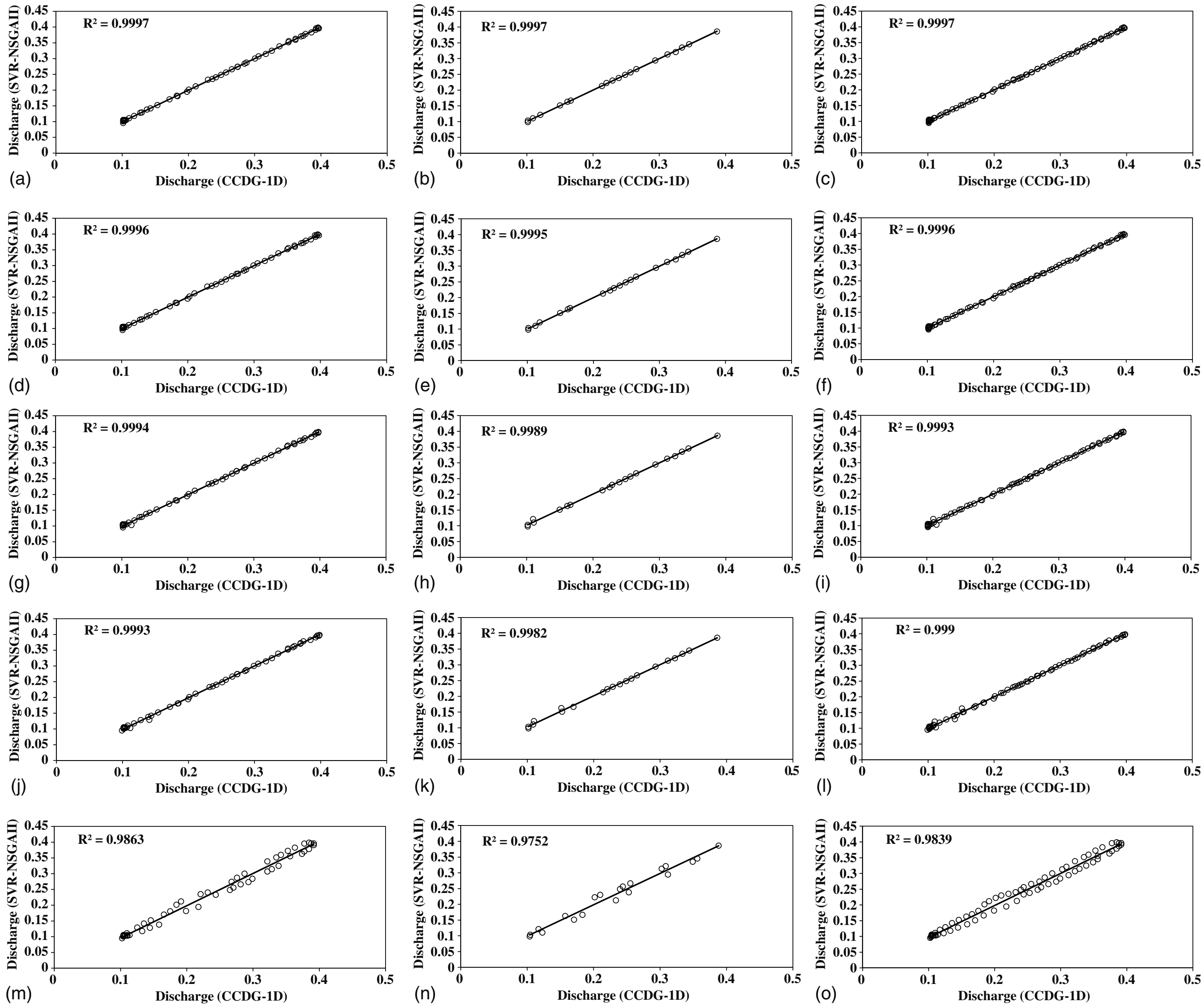

Fig. 7. Results of downstream discharge routed with CCDG-1D versus discharge predicted with SVR-NSGAII for (a) Point A of frontier in training; (b) Point A of frontier in testing; (c) Point A of frontier in total data set; (d) Point B of frontier in training; (e) Point B of frontier in testing; (f) Point B of frontier in total data set; (g) Point C of frontier in training; (h) Point C of frontier in testing; (i) Point C of frontier in total data set; (j) Point D of frontier in training; (k) Point D of frontier in testing; (l) Point D of frontier in total data set; (m) Point E of frontier in training; (n) Point E of frontier in testing; and (o) Point E of frontier in total data set

Second Case Study

The second case study examines discharge hydrographs in a compound channel. Tuitoek and Hicks (2001) reported the downstream hydrograph routed with the hydraulic model CCDG-1D. The length, width, and depth of the main channel are 120 m, 1.25 m, and 0.39 m, respectively, and the left and right floodplains are 3 and 1.5 m wide, respectively. Manning's roughness coefficient for both the main channel and floodplains was set equal to

0.012, and the bed slope is 0.019%. Fig. 5 shows the upstream and downstream discharge hydrograph of this case study.

To compare the capability of the hydrologic SVR-NSGAII method with that of the hydraulic CCDG-1D method, the regression model cited in the first case study was used to calculate the downstream discharge hydrograph t with SVR-NSGAII. Therefore, similarly to what was done in the first case study, there are eight possible predictors to predict the downstream flow QD_t in the compound channel. The routing optimization problem for the compound channel was solved with SVR-NSGAII. Fig. 6 shows the results, including the SVR parameters and identified predictors, in the form of a Pareto frontier.

Fig. 6 shows that the SVR-NSGAII identified five models to predict QD_t in the compound channel, and each model features specific predictors, SVR parameters, and accuracy. The range of g_1 (RMSE), which is the error between the hydrographs calculated with SVR and CCDG-1D, ranges from 0.0046 to 0.0240, and the range of g_2, i.e., the number of input variables, ranges from 1 to 5 in the case in this study. Among the eight predictors, only one to five variables were chosen by SVR-NSGAII. Similar to the first case study, the accuracy of the proposed models increases and RMSE is reduced with the increasing number of prediction variables.

Table 3 illustrates the values of the decision variables associated with the objective functions for each Pareto point. Table 3 shows that the Pareto solution suggests five points or models (A–E) for predicting the downstream discharge hydrograph. Fig. 7 shows the R^2 for the suggested Models A–E using training, testing, and total data sets. It is evident in Fig. 7 that the models have acceptable accuracy using the training data, but Models A–D are more accurate with the testing data set than Model E. Therefore, Models A–D are recommended for predicting the downstream discharge hydrograph in compound channels.

Concluding Remarks

The hydrologic SVR-NSGAII routing model was used to predict the downstream discharge hydrograph in simple and compound channels and was compared with hydraulic methods. The routed downstream hydrograph was computed with *HEC-RAS* in simple channels and CCDG-1D in compound channels and was used as the benchmark data set for evaluating the SVR-NSGAII method. The upstream stage and discharge of hydrographs at the current time and three prior time intervals were the possible predictors, and the discharge of the downstream hydrograph was the target variable. The NSGAII selected the combinations of predictors among eight possible predictors and computed the optimal values of the SVR parameters. The SVR predicted the downstream hydrograph on the basis of the predictors and the SVR parameters' values provided by NSGAII. The key merit of SVR-NSGAII is its ability to identify various models to predict the downstream hydrograph. Each of these identified models features attractive attributes: parsimonious parameterization and parameter optimization. The results of the application SVR-NSGAII in routing downstream hydrographs have shown that the majority of the models suggested by SVR-NSGAII have an approximately 96% accuracy in terms of their R^2.

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