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Research Article

River Flow Estimation from Upstream Flow Records Using Support Vector Machines

Halil Karahan,[1] Serdar Iplikci,[2] Mutlu Yasar,[1] and Gurhan Gurarslan[1]

[1] *Department of Civil Engineering, Faculty of Engineering, Pamukkale University, 20070 Denizli, Turkey*
[2] *Department of Electrical and Electronics Engineering, Faculty of Engineering, Pamukkale University, 20070 Denizli, Turkey*

Correspondence should be addressed to Halil Karahan; hkarahan@pau.edu.tr

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A novel architecture for flood routing model has been proposed and its efficiency is validated on several problems by employing support vector machines. The architecture is designed by including the inputs and observed and calculated outflows from the previous time step output. Whole observed data have been used for determining the model parameters in the heuristic methods given in the literature, which constitutes the major disadvantage of the existing approaches. Moreover, using the whole data for training may lead to overtraining problem that causes overfitting of estimations and data. Therefore, in this study, 60–90% of the data are randomly selected for training and then the remaining data are used for validation. In order to take the effects of the measurement errors into consideration, the data are corrupted by some additive noise. The results show that the proposed architecture improves the model performance under noisy and missing data conditions and that support vector machines can be powerful alternative in flood routing modeling.

1. Introduction

Flood routing is important in the design of flood protection measures in order to estimate how the proposed measures will affect the behavior of flood waves in rivers so that adequate protection and economic solutions can be found [1]. Flood routing models may be classified as either hydrologic or hydraulic. The hydraulic models solve the Saint-Venant equations by using a numerical method such as finite difference or finite element methods. A great deal of studies based on hydraulic models was developed by various researchers for flood routing [2–8]. These models require the measurement of flow depth and discharges. If detailed topographical surveys of channel cross-sections and roughness at close intervals are not available, hydraulic models are not suitable to serve the purpose of flood routing. In this case, hydrologic models may be used because they can cope with sparse spatial data [9].

Hydrologic models are based on the storage continuity equation and another equation which usually expresses the storage volume as a linear or nonlinear function of inflow and outflow discharges. The Muskingum method is the most widely used hydrologic flood routing method owing to its simplicity [10]. Many researchers made studies on the parameter estimation of Muskingum flood routing models [11–14]. Performances of the Muskingum models depend on the selection of the appropriate storage equation and the optimal parameter estimation of these models. Even if the parameters of storage equation are determined as optimum, every flood event may not be adequately represented. In particular, this problem occurs in a flood event containing more than one peak and/or having substantially lateral flow.

In order to overcome this problem, data-driven flood routing models based on support vector machines (SVM) need to be developed. SVM is based on statistical learning theory and structural risk minimization principle and can solve any regression problems without getting stuck into local minima. They achieve the global solution by transforming the regression problem into a quadratic programming (QP) problem and then solving it by a QP solver. Finding global solution and possessing higher generalization capability constitute the major advantages of the SVM algorithms over other regression techniques [15]. In the last decade, SVM-based algorithms have been developed very rapidly and have

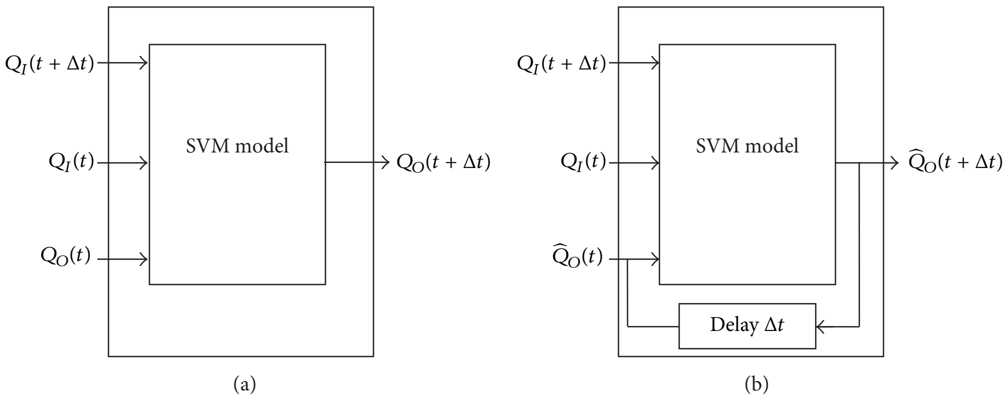

FIGURE 1: (a) Training phase and (b) prediction phase.

been applied to many areas [16, 17]. In particular, the SVM have been used for modeling and prediction purposes for solving some problems in the hydrology area of research and application [18–29].

The fact that the whole observed data has been used for determining the model parameters in the abovementioned heuristic methods constitutes the major disadvantage of these approaches. This may lead to overtraining problem that degrades generalization capability [34]. In order to prevent overtraining, some part of the data is used for training and the remaining part is spared for validation. Thus, in this study, 60–90% of the data are randomly selected for training (for determining model parameters) and then the remaining unseen data are used for validation. Therefore, in this study, novel model architecture has been proposed and its efficiency is validated on several problems. This is organized as follows.

In the next section, first, the proposed training and prediction procedures are introduced and then the training algorithm is explained in detail for SVM in the following subsection. In Section 3, the three numerical applications are investigated to show the efficiency of the proposed method by comparing SVM to other methods when all data are used for training and also to each other when only some portion of the data is used for training. The simulation results are discussed in Section 4.

2. Model Development

In this study, we have employed SVM in flood routing modeling for prediction of its future behavior. For this purpose, as can be seen in Figure 1(a), an SVM model of the flood routing is obtained in the training phase by using a training set T as given by

$$T = \{Q_I(t+k\Delta t), Q_I(t+(k-1)\Delta t), Q_O(t+(k-1)\Delta t); Q_O(t+k\Delta t)\}_{k=1}^{k=N}, \tag{1}$$

where $Q_I(t)$ and $Q_O(t)$ are the measured input and output flow rates at time t, respectively, Δt is the time interval between the successive measurements, and N is the number of training data. For sake of the simplicity, the data set T can be represented more compactly as $T = \{\mathbf{x}_k; y(k)\}_{k=1}^{k=N}$, where $\mathbf{x}_k \in X \subseteq \mathfrak{R}^3$ is the kth input data point in the input space and $y(k) \in Y \subseteq \mathfrak{R}$ is the corresponding output value; that is,

$$\mathbf{x}_k[Q_I(t+k\Delta t), Q_I(t+(k-1)\Delta t), Q_O(t+(k-1)\Delta t)]^T; \quad y(k) = Q_O(t+k\Delta t). \tag{2}$$

In the modeling phase, to obtain a model that represents the relationship between the input and output data points is desired. The training data set T is to be used to obtain an approximate model of the flood. Once the SVM model of the flood routing is obtained, then its future behavior can be predicted by the mechanism depicted in Figure 1(b), where the predicted output of the model is delayed by Δt and then fed back to the model itself as the third input thereby making the model more realistic to predict the flood.

In this section, the ε-SVR algorithm, SVM regression algorithm used in this study, is described briefly. The primal form of an SVM regression model is given by (3), which is linear in a higher dimensional feature space $\boldsymbol{F}$.

Consider

$$\hat{y}(\mathbf{x}_i) = \langle \mathbf{w}, \boldsymbol{\Phi}(\mathbf{x}_i)\rangle + b, \tag{3}$$

where $\mathbf{w}$ is a vector in the feature space $\boldsymbol{F}$, $\boldsymbol{\Phi}(\cdot)$ is a mapping from the input space to the feature space, b is the bias term, and $\langle\cdot\rangle$ is the inner product operation in the feature space. The SVM regression algorithm looks upon the regression problem as an optimization problem in dual space, where the model is given by

$$\hat{y}(\mathbf{x}_i) = \sum_{j=1}^{N} \alpha_j K(\mathbf{x}_i, \mathbf{x}_j) + b, \tag{4}$$

where α_j's are the coefficients of each training data point and $K(\mathbf{x}_i, \mathbf{x}_j)$ is a kernel function. The kernel function handles the inner product in the feature space; that is, $K(\mathbf{x}_i, \mathbf{x}_j) = \langle \boldsymbol{\Phi}(\mathbf{x}_i), \boldsymbol{\Phi}(\mathbf{x}_j)\rangle$, and hence the explicit form of $\boldsymbol{\Phi}(\mathbf{x})$ does not need to be known. In this study, we have used the radial basis kernel function given by

$$K(\mathbf{x}_i, \mathbf{x}_j) = K_{ij} = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}\right), \tag{5}$$

Table 1: Comparison of the observed and computed outflows for Wilson data.

Time (h)	Input (cms)	Output (cms)	NLMM-L [30]	VPWFDM-L [31]	FIS [32]	SVM
0	22	22	22	22	22.0	22.00
6	23	21	21.71	20.66	20.9	20.93
12	35	21	22.02	21.5	21.0	20.98
18	71	26	26.08	25.79	26.0	25.92
24	103	34	33.51	33.71	34.0	34.04
30	111	44	42.83	44.65	44.0	43.97
36	109	55	55.44	54.37	57.1	55.04
42	100	66	66.67	65.72	66.2	65.96
48	86	75	75.77	75.78	75.0	75.06
54	71	82	82.12	82.55	82.0	81.93
60	59	85	84.78	84.65	85.4	84.95
66	47	84	83.42	84.07	84.0	84.08
72	39	80	79.44	79.36	80.0	79.93
78	32	73	72.48	72.67	73.0	72.92
84	28	64	64.08	63.75	64.0	64.02
90	24	54	54.58	54.53	54.0	54.04
96	22	44	45.22	44.87	44.0	43.96
102	21	36	36.34	36.24	35.9	36.04
108	20	30	29.21	29.5	29.9	29.96
114	19	25	24.21	24.56	25.3	25.04
120	19	22	20.96	21.31	21.7	21.96
126	18	19	19.41	19.39	19.1	19.04
SSE			9.823	5.178	4.830	0.056

where $\|\cdot\|$ is the Euclidean norm and σ is the width parameter. In the model (4), a training point $\mathbf{x}_j$ corresponding to a nonzero α_j value is referred to as the *support vector*. The ε-SVR algorithm employs Vapnik's ε-insensitive loss function $L(\varepsilon, y, \hat{y})$ given by

$$L(\varepsilon, y, \hat{y}) = \begin{cases} 0 & y - \hat{y} \le \varepsilon \\ y - \hat{y} & y - \hat{y} > \varepsilon \end{cases} \tag{6}$$

and formulates the primal form of the regression problem as follows:

$$\min_{\mathbf{w},b,\xi,\xi^*} P_\varepsilon = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{N}\left(\xi_i + \xi_i^*\right), \tag{7}$$

subject to the constraints

$$\begin{gathered} y(\mathbf{x}_i) - \langle \mathbf{w}, \mathbf{\Phi}(\mathbf{x}_i)\rangle - b \le \varepsilon + \xi_i, \quad i = 1,\ldots,N \\ \langle \mathbf{w}, \mathbf{\Phi}(\mathbf{x}_i)\rangle + b - y(\mathbf{x}_i) \le \varepsilon + \xi_i^*, \quad i = 1,\ldots,N \\ \xi_i, \xi_i^* \ge 0, \quad i = 1,\ldots,N, \end{gathered} \tag{8}$$

where ξ_i's and ξ_i^*'s are slack variables, ε is the upper value of tolerable error for the output, and C is a regularization parameter that provides a compromise between the model complexity and the degree of tolerance to the errors larger than ε. Dual form of the optimization problem becomes a quadratic programming (QP) problem as follows:

$$\begin{aligned} \min_{\beta,\beta^*} D_\varepsilon = {} & \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}K_{ij}\left(\beta_i - \beta_i^*\right)\left(\beta_j - \beta_j^*\right) + \varepsilon\sum_{i=1}^{N}\left(\beta_i + \beta_i^*\right) \\ & - \sum_{i=1}^{N} y(\mathbf{x}_i)\left(\beta_i - \beta_i^*\right), \end{aligned} \tag{9}$$

subject to the constraints

$$0 \le \beta_i,\ \beta_i^* \le C, \quad \sum_{i=1}^{N}\left(\beta_i - \beta_i^*\right) = 0, \quad i = 1,\ldots,N. \tag{10}$$

Solution of the QP problem gives the optimum values of β_i's and β_i^*'s. The value of b in the model is determined as follows: the condition $y(\mathbf{x}_i) - \hat{y}(\mathbf{x}_i) = \varepsilon$ is satisfied for each support vector $\mathbf{x}_i$ for which the condition $0 \le \beta_i - \beta_i^* \le C$ holds. If α_j is defined to be the new coefficient of $\mathbf{x}_j$ for $j = 1,\ldots,N$ as $\alpha_j = \beta_j - \beta_j^*$, then we obtain an SVM model as given by (4). Furthermore, if the support vectors are considered only, then the model becomes

$$\hat{y}(\mathbf{x}_i) = \sum_{\substack{j=1 \\ j\in \mathrm{SV}}}^{\#\mathrm{SV}} \alpha_j K\left(\mathbf{x}_i, \mathbf{x}_j\right) + b, \tag{11}$$

Table 2: Comparison of the observed and routed outflows for Viessman and Lewis data.

Time (h)	Input (cms)	Output (cms)	NLMM-L [30]	VPWFDM-L [31]	SVM
0	166.2	118.4	166.2	118.40	118.40
1	263.6	197.4	166.2	182.23	198.71
2	365.3	214.1	263.25	262.43	215.39
3	580.5	402.1	346.87	362.43	403.06
4	594.7	518.2	505.25	496.97	519.25
5	662.6	523.9	563.12	559.30	526.01
6	920.3	603.1	620.77	633.91	604.67
7	1568.8	829.7	773.8	803.13	831.03
8	1775.5	1124.2	1109.49	1150.33	1122.98
9	1489.5	1379	1381.64	1417.85	1377.61
10	1223.3	1509.3	1460.43	1433.22	1508.11
11	713.6	1379	1389.1	1345.15	1378.08
12	645.6	1050.6	1133.57	1115.25	1049.46
13	1166.7	1013.7	890.74	968.99	1012.38
14	1427.2	1013.7	982.97	994.50	1012.35
15	1282.8	1013.7	1167.97	1022.09	1014.47
16	1098.7	1209.1	1236.21	1216.84	1207.94
17	764.6	1248.8	1192.89	1231.67	1246.96
18	458.7	1002.4	1019.78	1023.80	1000.48
19	351.1	713.6	743.04	689.20	714.04
20	288.8	464.4	501.27	473.12	466.09
21	228.8	325.6	345.06	351.18	327.39
22	170.2	265.6	245.18	266.89	266.12
23	143	222.6	168.87	194.24	224.38
			73399.33	26185	43.37

where #SV stands for the number of support vectors in the model [19, 35] The SVM model is sparse in the sense that the whole training data are represented by only support vectors. The parameters of ε-SVR are the maximum tolerable error ε at the output, the regularization parameter C, the number of training patterns N, and the width parameter σ. The major advantage of the ε-SVR algorithm is that it allows for the determination of the maximum total training error beforehand by choosing a proper ε value.

3. Numerical Applications

In this study, we have tested modeling and prediction performance of the proposed SVM structure on three different flood problems. For each problem, we have gathered some artificial and real-world data for modeling purposes. In this comparative work, we have split our comparisons into two cases. In Case I, in order to have a basis for fair comparisons to other methods, all of the gathered data are used for only training of SVM structure. In Case II, only some portions, μ, of the data are used for training, while remaining data are spared for validation and then the SVM approach is compared to other models given in the literature. For both cases in the training phase, all variables in each data set are normalized to the interval [0, 1] and then an appropriate data set for training is formed. Afterwards, SVM model is obtained to give least possible training plus validation errors.

3.1. Application to Wilson Data [36]. Data sets reported by Wilson are known to present a nonlinear relationship between weighted discharge and storage and used extensively in the literature as a benchmark problem. The number of data in this example is 22. The comparison of the SVM to other methods with respect to the prediction performances for Example 1 is given in Table 1.

The Wilson flood data were modeled by Karahan et al. (2014) using a nonlinear Muskingum model incorporating lateral flow (NLMM-L) and SSE value was found as 9.823. Chu (2009) presented the combined application of fuzzy inference system (FIS) and Muskingum model in flood routing. Chu (2009) found the SSE value as 4.830. More recently, Karahan et al. (2014) have proposed a variable-parameter nonlinear Muskingum model incorporating lateral flow with a weighted finite difference method [VPWFDM-L] and applied this model to Wilson data. Karahan et al. (2014) have reported the SSE value as 5.178. When the SVM model is employed for the same flood data, the SSE value has been found as 0.056, which is much better than that of other methods.

Table 3: Comparison of the observed and routed outflows for the River Wyre data.

Time (h)	Input (cms)	Output (cms)	LMM-L [33]	NLMM-L [30]	SVM
0	2.6	8.3	8.3	8.3	8.300
1	4.2	9	8.2	8.51	9.092
2	12.3	9.9	8.1	8.79	10.020
3	25.4	10.2	12.7	10.94	10.338
4	24.1	18.9	27.9	20.28	19.063
5	20.3	35.9	39.9	37.54	35.980
6	23.3	51.8	45.7	49.07	51.815
7	27.7	59.4	52.2	55.11	59.327
8	27.7	63.3	61.4	62.5	63.279
9	26.9	69.6	68.9	71.44	69.482
10	24.8	76.7	74.7	78.03	76.649
11	26.9	82	77.2	82.07	82.051
12	33.7	85.3	79.8	83.72	85.234
13	33.9	89	87.8	87.43	88.901
14	27.8	94.6	95.5	95.49	94.514
15	20.8	98.8	97.7	100.88	98.683
16	15.6	98	94.4	99.29	97.902
17	11.9	91.8	87.9	92.06	91.728
18	9.5	82.3	79.8	82.22	82.217
19	7.8	72	71.5	71.75	72.086
20	6.5	61.9	63.6	61.91	61.824
21	5.8	53	56.1	53.12	53.068
22	5	45.6	49.6	45.47	45.560
23	4.8	39.2	43.7	39.14	39.259
24	4.5	33.8	38.8	33.76	33.764
25	4.1	29.3	34.6	29.55	29.363
26	3.7	26.2	30.9	26.12	26.085
27	3.4	23.5	27.7	23.2	23.496
28	3.2	21.2	24.8	20.67	21.289
29	2.9	19.2	22.3	18.52	19.367
30	2.8	17.7	20.1	16.71	17.747
31	2.6	16.4	18.2	15.12	16.527
SSE			468.840	53.708	0.253

3.2. Application to Viessman and Lewis Data [37]. This example is based on inflow and outflow hydrographs exhibiting linear characteristics and presents a relatively difficult prediction problem for flood routing, where there exist two successively active floods. The number of data in this example is 24.

Table 2 shows the comparison results numerically. It is obviously seen that the SVM method outperforms others in prediction of the flood dynamics, which can be attributed to the proposed training and prediction structures and also the generalization potentials of SVM approach.

As can be seen from Table 2, the SSE values are obtained as 73399.33 for the NLMM-L model, 26185 for the VPWFDM-L model, and 43.37 for the SVM model, respectively. It is observed from the results of Table 3 that the SSE value (0.253) obtained by the SVM model for the River Wyre data is better than those obtained when the LMM-L and NLMM-L models are used.

3.3. Application to River Wyre [33]. For the River Wyre data, the flood volume between the inflow and the outflow sections is 25 km, along which there are lateral flows that considerably contribute to the flood [33]. Moreover, the input hydrograph has multiple peaks. The number of data in this example is 32.

In the literature, the River Wyre flood data were first modeled by O'Donnell (1985) using a linear Muskingum model incorporating lateral flow (LMM-L) and the SSE value was found as 468.840. Recently, Karahan et al. (2014) have applied NLMM-L model to River Wyre flood data and have reported the SSE value as 53.708. It is observed from the results that the SSE value (0.253) obtained by the SVM model for the River Wyre data is better than those obtained when the LMM-L and NLMM-L models are used.

3.4. Verification of Model Robustness. In Sections 3.1–3.3, the SVM models have been obtained by using whole data and then compared to other methods in the literature. The

Table 4: Average SSE values of the SVM approach for Wilson data, Viessman and Lewis data, and River Wyre data.

Data	μ	$\delta = 0$	$\delta = 0.01$	$\delta = 0.05$	$\delta = 0.10$
Wilson	0.9	1.389	1.627	2.013	2.691
	0.8	3.486	4.120	4.160	7.738
	0.7	7.284	8.473	8.835	10.818
	0.6	12.540	14.872	17.878	21.755
Viessman and Lewis	0.9	12460.720	14446.716	18456.445	21172.915
	0.8	34631.312	48888.423	50163.966	58837.181
	0.7	83005.647	84387.246	112145.221	100247.301
	0.6	124339.197	124324.518	118768.183	131235.761
River Wyre	0.9	5.760	9.895	11.922	7.788
	0.8	218.236	55.846	70.096	289.540
	0.7	291.692	161.367	133.620	363.987
	0.6	331.883	271.468	239.053	440.319

results have shown that there is good agreement between the predicted and measured outflows for the three examples under investigation. However, it is possible that there may be some erroneous and/or missing measurements in practical applications. In order to test the performance of the proposed SVM model under such conditions, input data have been corrupted by additive uniformly distributed noise with zero mean. The noisy data are obtained as [38, 39]

$$Q_I^*(t) = Q_I(t) + \lambda\delta Q_I(t), \tag{12}$$

where $Q_I(t)$ and $Q_I^*(t)$ stand for the noiseless and noisy input flow rates at time t, respectively, λ represents the measurements errors that are distributed uniformly between −1 and 1, and δ is a noise level scalar between 0.0 and 0.1. In this study, various noise level conditions, namely, 0.01, 0.05, and 0.10, are considered and also it is assumed that some portions (10 to 40 percent) of the data are missing in order to investigate the effects of the missing data on the model performance. In order to get more reliable results, the tests have been performed at least 100 times for each case and then their average SSE values have been given in Table 4.

As can be seen from Table 4, only μ portion of data is used for training, while its remaining part is spared for validation. The test data are selected randomly out of the whole data set. It is observed from numerical results that the SVM method provides excellent prediction performance when there is no measurement noise ($\delta = 0$) and the nearly whole data are used ($\mu = 0.9$). On the other hand, as the level of the measurement noise and the portion of the missing data are increased, the model performance decreases expectedly. Still, in the worst case ($\delta = 0.1$ and $\mu = 0.6$) the proposed SVM method provides acceptable performance.

4. Conclusions

In this study, a novel architecture for flood routing model has been proposed and its efficiency is validated on three different flood routing problems by employing SVM approach. Proposed model is designed including the inputs and observed and calculated outflows from the previous time step output, thereby making the model more realistic. The SVM approach has been implemented to capture the dynamics of the investigated floods from the observed data. In this study, higher generalization capabilities have motivated us to employ the SVM structure. After completing the learning phase, the model has been performed to predict the routing outflows. The proposed model has also been compared to the different models in the literature.

The simulation results have revealed that when combined with the powerful modeling tools, such as SVM, the proposed architecture exhibits excellent modeling and prediction performances for flood routing problems under investigation. The results have also demonstrated that the proposed model provides better prediction performance than the ones existing in the literature when whole data are used for training. Furthermore, SVM approach has been employed when only some portions (60–90%) of the data are used for training, and it has been observed that SVM maintains its prediction performance up to an acceptable level even if only 60% of the data are used for training under noisy condition. Consequently, the proposed model possesses higher applicability potential in forecasting outflows with different inflow patterns and thus it can be employed for solving flood routing problems.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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