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Forecasting dam water inflows with fuzzy support vector regression using a rainy season-based membership function

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Abstract

Establishing proper management of dam water inflows is essential for successful planning and irrigation. This research aimed to forecast the water inflow into the Queen Sirikit Dam, located in Pha Leud Sub-district, Tha Pla District, Uttaradit Province, Thailand. The dam was constructed across the Nan River. The research proposes a new method that uses fuzzy support vector regression (FSVR) based on a generalized bell-shaped membership function that depends on the rainy season. Moreover, a comparison was made between this method and FSVR based on the linear function of time, which is commonly used, as well as classical support vector regression (SVR). The predictive ability of the models was evaluated using 10-fold cross-validation on 3,700 samples. The results indicate that FSVR based on a generalized bell-shaped membership function is more effective than the other two methods, with a mean absolute error (MAE) of 15.6247 m^3/s and R-square (R^2) of 0.7984. This shows an improvement over the linear membership function, which had an MAE of 17.2566 m^3/s and an R^2 of 0.7555. Meanwhile, the classical SVR model had an MAE of 23.6997 m^3/s and an R^2 of 0.6741. These findings suggest that FSVR based on a generalized bell-shaped membership function is an effective approach for forecasting dam water inflows. Consequently, it will be highly beneficial for the efficient management of the dam, including drainage or warning announcements to downstream populations.

Keywords: Water inflow, Fuzzy support vector regression, Forecasting, Membership function

1. Introduction

The inflow of water into dams is crucial for effective planning and irrigation management, as it indicates the water quantity and dam capacity. Accurately forecasting dam water inflows is essential for reliable flood warning systems. However, predicting dam water inflows can be challenging due to various factors, including rainfall in the dam area, rainfall above the dam, and evaporation rate, which are influenced by the climate and topography of the dam's location.

Several studies have utilized back-propagation (BP) neural networks in water resources management [1-4]. However, BP neural networks face difficulties in selecting numerous controlling parameters, such as relevant input variables, hidden layer size, learning rate, and momentum term. To address these issues, Vapnik et al. introduced support vector regression (SVR) [5]. SVR has solved the problem of nonlinear regression estimation and demonstrated excellent performance in time series prediction [6, 7]. In [8], the integration of fuzzy membership with corresponding training data points improved SVR's performance, leading to the development of fuzzy support vector regression (FSVR). FSVR has shown superior proficiency compared to SVR [9-13].

BP neural networks and SVR are commonly used for dam water level prediction [14, 15]. However, in the field of computational intelligence, SVR is considered more effective than BP Neural Networks for time series prediction [16-18]. Building upon this, [19] utilized FSVR with a linear function of time to predict runoff and compared its capabilities with SVR. The results demonstrated that FSVR outperformed SVR, making it a preferred tool for water level prediction [20, 21].

Therefore, this research proposes a new method that employs FSVR based on a generalized bell-shaped membership function. This membership function is defined to adapt to changes in water inflow into dams, which fluctuate during the rainy season. The research aims to predict water inflow into the Queen Sirikit Dam, located in Pha Leud Sub-district, Tha Pla District, Uttaradit Province, Thailand. Additionally, the forecasting system in this study focuses on providing predictions for the next three days, as it takes three days for the dam to release maximum capacity water to accommodate the inflow. Accurately predicting water inflow into the Sirikit Dam through this forecasting system will greatly benefit the effective management of the dam. It will enable proper preparation for water level expectations, such as implementing drainage systems or issuing warning announcements to downstream populations.

2. FSVR for forecasting

In this section, we describe the concept and formulation of FSVR in the context of a regression problem. The challenge in regression lies in dealing with divergences among the training points, where some points hold more significance than others. To address this, a fuzzy membership value, denoted as s_i, is assigned to each training point x_i, with a range of $0 \leq s_i \leq 1$.

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To enhance the conventional SVR and incorporate fuzzy membership values, FSVR is developed. The fuzzy membership value s_i represents the training point's attitude towards the mapping function, while the value $(1 - s_i)$ holds no practical significance.

For a given data set S, each data point is associated with a fuzzy membership value, as shown in equation (1):

$$(x_1, y_1, s_1) \dots (x_i, y_i, s_i) \tag{1}$$

where $x_i \in R^n$ represents the input vector, $y_i \in R$ denotes the desired value, and $\lambda \leq s_i \leq 1$ is the fuzzy membership value associated with each data point ranging from $i = 1, \dots n$ and λ is a sufficiently small value greater than 0. The FSVM regression optimizes the following problem [8], as shown in equations (2) and (3):

$$\min_{w,\xi_i,\xi_i^*} \frac{1}{2} \left\| \vec{w} \right\|^2 + C \sum_{i=1}^{n} s_i (\xi_i - \xi_i^*) \tag{2}$$

Subject to:

$$\begin{aligned} & y_i - w^T \varphi(x_i) - b \leq \varepsilon + \xi_i \\ & w^T \varphi(x_i) + b - y_i \leq \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \geq 0 \ ; 1 \leq i \leq n \end{aligned} \tag{3}$$

where the parameter $\xi = [\xi_1 \ \xi_2 \dots \xi_n]^T$ and $\xi_i^* = [\xi_1^* \xi_2^* \dots \xi_n^*]^T$ are slack variables that represent upper and lower constraints on the system's outputs, respectively, and they are positive values. The function $\varphi(x_i)$ represents the mapping function to a high-dimensional space, derived from the input space x through a nonlinear transformation. The parameters w and b are the weight and bias of the support vector, and the constant $C > 0$ determines the trade-off between deviations larger than ε are the flatness of f. The optimization problem is then resolved, and the weight vector can be computed as shown in equations (4) and (5):

$$w = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) \Phi(x_i) \tag{4}$$

where α_i, α_i^* $i = 1,2, \dots n$ are the Lagrange multipliers and $K(x, x_n) = \Phi(x)\Phi(x_n)$ is the kernel function that satisfies the Mercer condition [22]. In this work, the radial basis kernel function was selected and defined as shown in equation (5):

$$K(x, x_n) = exp(-\|x - x_n\|^2 / 2\sigma^2) \tag{5}$$

The optimal hyperplane is defined as shown in equation (6):

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(x_i, x) + b \tag{6}$$

Many researchers prefer to specify the lower bound of fuzzy membership values as $\lambda > 0$ [23] and let the fuzzy membership $s_i$be a function of time t_i. In this case, the data in the first position x_1 is considered less important, and we assign $s_1 = f(t_1) = \lambda$, while the data at the last position x_n is considered more important, and we assign $s_n = f(t_n) = 1$. As mentioned earlier, the concept of importance is defined based on the passage of time. The most recent input is assigned a magnitude of 1, while the oldest input has the lowest magnitude $\lambda > 0$, as described by equation (7):

$$s_i = f(t_i) = \frac{1-\lambda}{t_n - t_1} t_i + \frac{t_n \lambda - t_1}{t_n - t_1} \tag{7}$$

The generalized bell-shaped membership function is well-known a well-known symmetric bell shape. In [24], this function is applied with three parameters: the width of the bell curve denoted as a, a positive number denoted as b, and the center of the curve in the universe of discourse denoted as c. It can be defined using equation (8):

$$s(i) = bell(t_i : a, b, c) = \frac{1}{1 + \left| \frac{t_i - c}{a} \right|^{2b}} \tag{8}$$

3. Method of FSVR for forecasting

3.1 Process

The input data and output data set should be standardized to the same range, typically [0,1]. This ensures consistency in the algorithm's computations. However, it is important to note that after the algorithm has been applied, the output values should be converted back to their original ranges. Table 1 shows examples of the raw data.

Table 1 Examples of input and output data

Day	Input Data					Output Data
	Rain Fall Dam (mm)	Rainfall Dam North (mm)	Capacity (m^3)	Water Level (MSL)	Reservoir Release (m^3/s)	Inflow (m^3/s)
20-Jul-17	3.919564	2.96	3,215	131	31.77	31.77
21-Jul-17	30.06596	29.48	3,233	131	35.93	35.93
22-Jul-17	67.39604	67.17	3,254	131	30.68	30.68
23-Jul-17	20.95472	21.33	3,270	131	34.95	34.95
24-Jul-17	35.92145	34.97	3,290	131	28.12	28.12

3.2 Data collection

The Queen Sirikit Dam is situated in Pha Leud Sub-district, Tha Pla District, Uttaradit Province, which is in the northern part of Thailand. It is constructed across the Nan River, as depicted in Figure 1. The dam serves various purposes such as irrigation, flood control, and hydroelectric power production. It has a surface area of 259 km^2 and a reservoir capacity of 9,510 million m^3, and it is currently in active use [25].

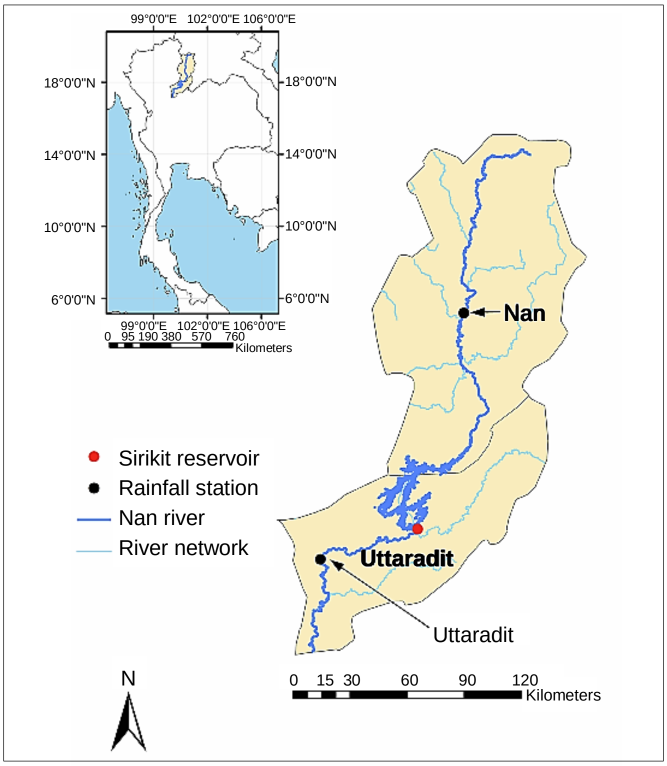


Figure 1 Location of Sirikit Dam [26].

This research utilizes the data collected on a daily average basis, incorporating the following features: rainfall in the dam area (mm), rainfall above the dam area (mm), the dam's water capacity (m^3), the water level of the dam (mean sea level: MSL), reservoir release (m^3/s), and the inflow of the dam (m^3/s). The raw data was collected between 2011 and 2021, as demonstrated in Figure 2 to Figure 7.

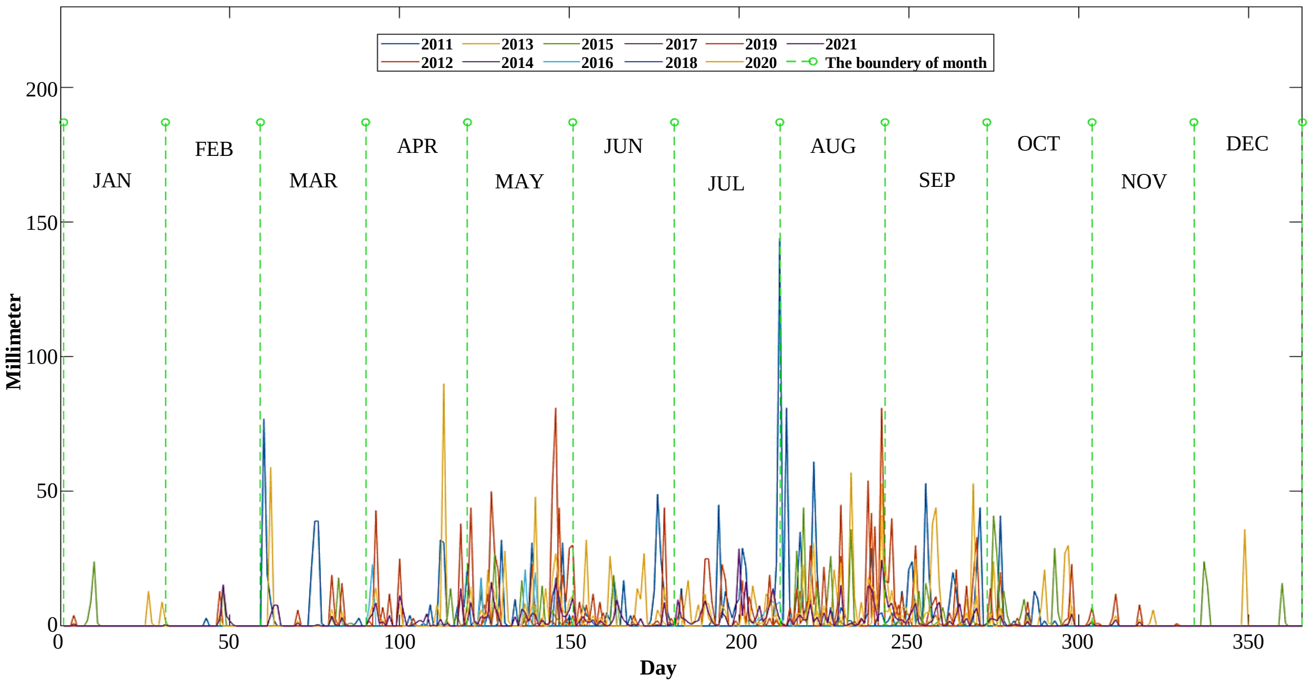


Figure 2 Data set of rainfall in the dam area.

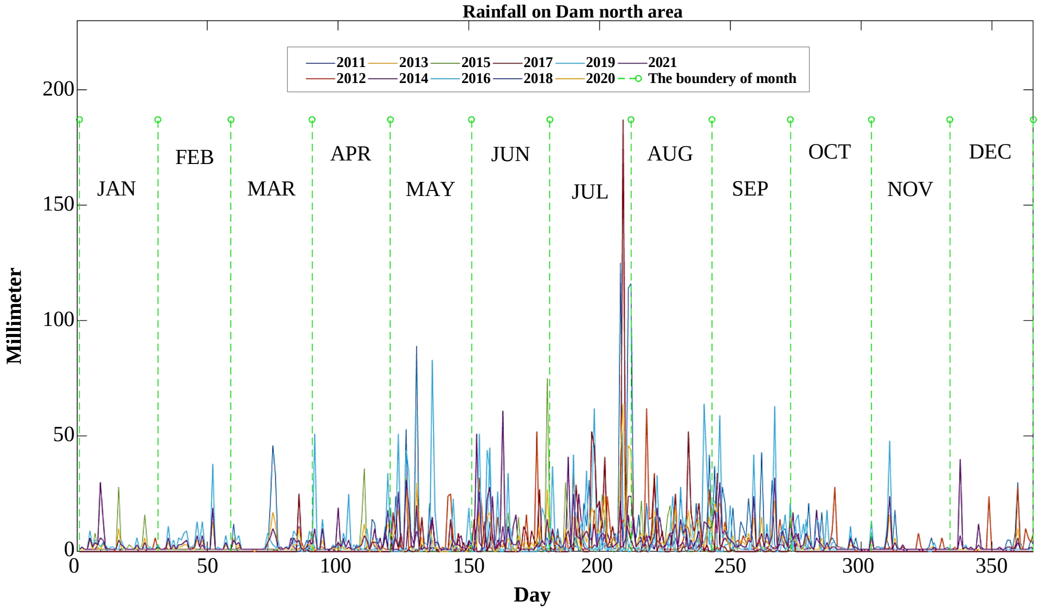


Figure 3 Data set of rainfall above the dam area.

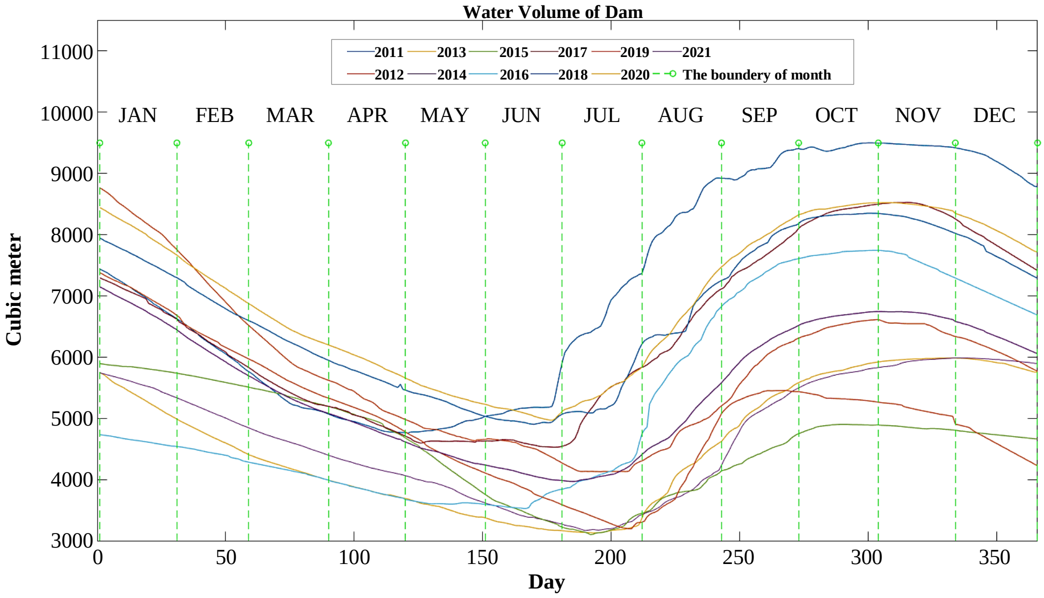


Figure 4 Data set of the dam's water capacity.

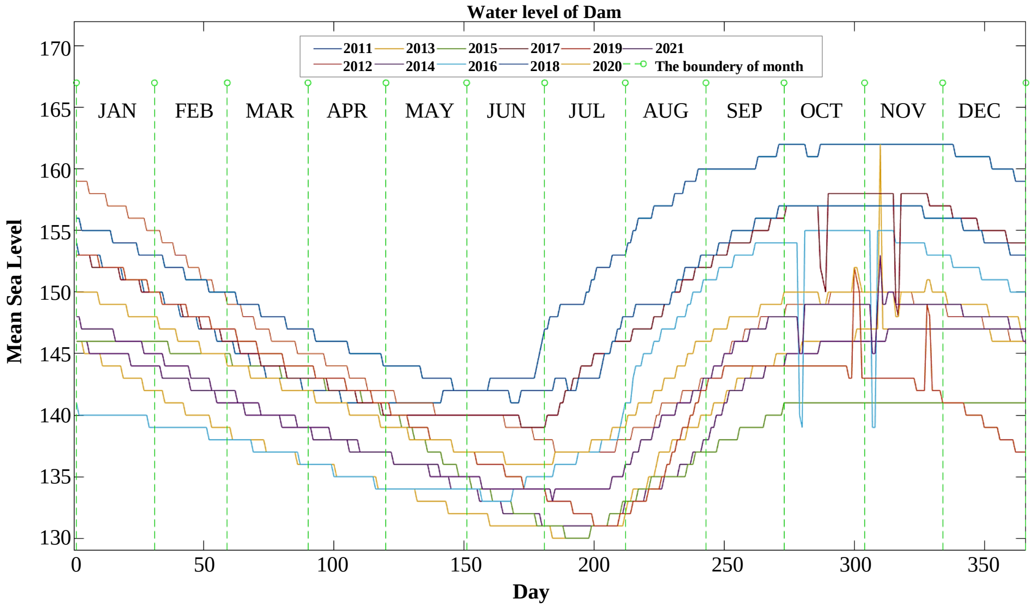


Figure 5 Data set of the water level of the dam.

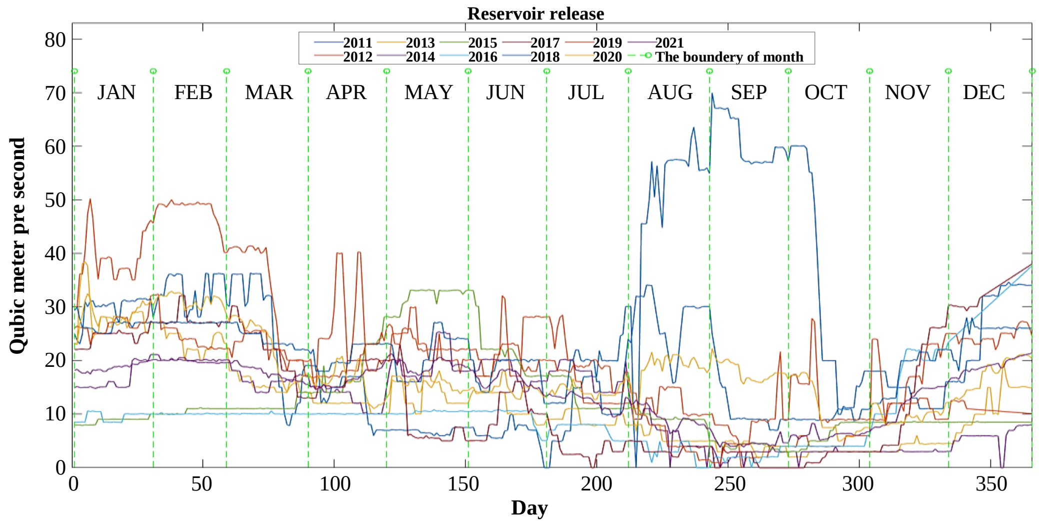


Figure 6 Data set of the reservoir release.

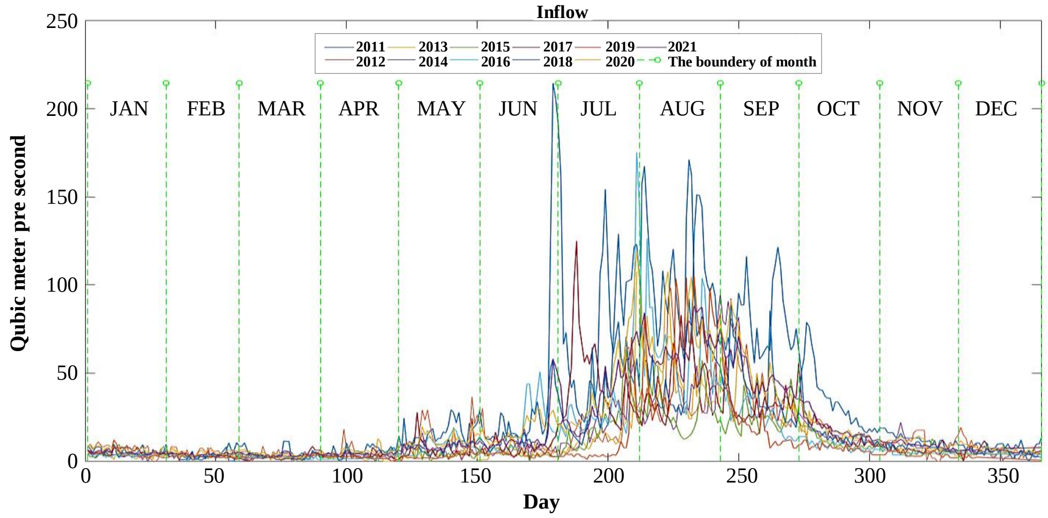


Figure 7 Data set of the inflow of the dam.

3.3 FSVR based on the generalized bell-shaped membership function

The study proposed a generalized bell-shaped membership function. This function assigns a crucial fuzzy membership value of 1 at the center of the shape, gradually decreasing towards 0 at both ends. Figures 2 and 3 depict bell-shaped curves that resemble the data set of rainfall. Hence, the generalized membership function is employed. Furthermore, the rainfall data set indicates a rainy season occurring from May to October each year, spanning from 2011 to 2021. Consequently, the parameters a, b, and c were adjusted to match the shape during the rainy season (May to October). The resulting parameter values are as follows: a = 53, b = 5, and c = 212, as illustrated in Figure 8.

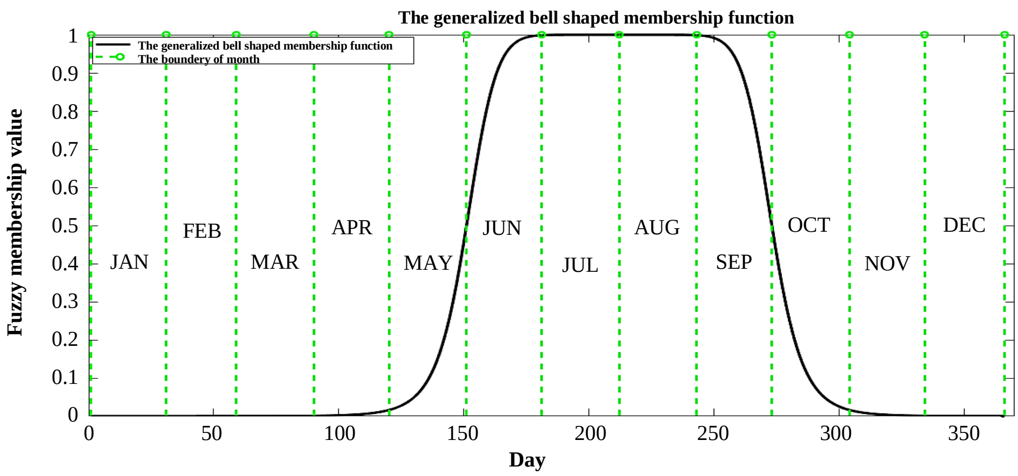


Figure 8 Generalized bell-shaped membership function.

3.4 Performance criteria

The mean absolute error (MAE) and R-squared (R^2) were utilized as performance criteria for water inflow prediction. The MAE quantifies the errors between the predicted and actual observations, and it can be defined by equation (9). Additionally, the R^2 is a measure of the proportion of the variance in the dependent variable that is explained by an independent variable in a regression model. It can be defined using equation (10).

$$MAE = \left(\frac{\sum_{i=1}^{n}|d-p|}{n}\right) \tag{9}$$

$$R^2 = 1 - \frac{\sum(d_i-p_i)^2}{\sum(d_i-\bar{d})^2} \tag{10}$$

where $i = 1, \ldots, n$ indicates the index of each data point entry, p represents the outcome of the prediction, and d denotes the inflow water for the next three days, which represents the desired value. The mean value of compressive strength is denoted by $\bar{d}$.

4. Experimental and results

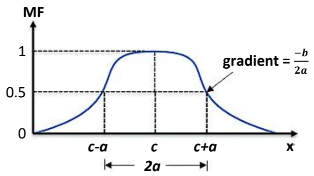
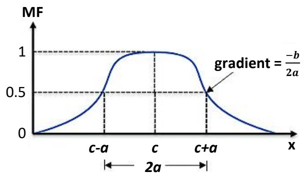
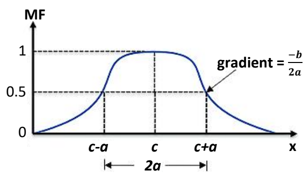
4.1 Experimental data

The data set utilized in this research was collected through daily data collection spanning from 2011 to 2021. A 10-fold cross-validation method was employed using a data set consisting of 3,700 samples. These samples were divided into a training data set comprising 3,350 samples and a testing data set comprising 350 samples. Additionally, the data set from 2021 was used as a blind test set. The data was employed to develop a predictive model for dam water inflow using FSVR based on a generalized bell-shaped membership function. Furthermore, FSVR based on a linear function of time and classical SVR were also demonstrated.

4.2 Data configuration for training

Each sample point in the data input consists of five features: (1) Data set of rainfall in the dam area, (2) Data set of rainfall above the dam area, (3) Data set of the dam's water capacity, (4) Data set of the water level of the dam, and (5) Data set of the reservoir release. The forecasting system provides predictions for the next three days. Therefore, the data inputs for the current day (Day 1) will correspond to the desired output of water inflow on the fourth day (Day 4), as shown in Table 2.

Table 2 Data set preparation for FSVR for forecasting in the next three days

Features Input (x_i)	**Membership Function (s_i)**		**Desired Output (y_i)**
	Generalized Bell-Shaped	**Linear Function of the Time**	
1/1/2011 2/1/2011 ⋮ 28/12/2011		λ > 0	4/1/2011 5/1/2011 ⋮ 31/12/2011
1/1/2012 2/1/201 ⋮ 28/12/2012		0.75	4/1/2012 5/1/2012 ⋮ 31/12/2012
⋮	⋮	⋮	⋮
1/1/2020 2/1/2020 ⋮ 28/12/2020		1	4/1/2020 5/1/2020 ⋮ 31/12/2020

4.3 Adjusting parameters for training

FSVR relies on two significant parameters: C and σ. C determines the distance of the plane, while σ is a parameter of the kernel function. In this study, the values of C and σ were adjusted using the 10-fold cross-validation method to obtain an optimal model. Initially, σ was set to 0.1 and tested with 60 different values of C. Then, the value of σ was changed to 0.15 and tested again with the same 60 values of C. This process was repeated for all 18 values of σ. The combination of C and σ that resulted in the smallest MAE was chosen. The range of σ varied from 0.1 to 0.95 in increments of 0.05, while C ranged from 50 to 3,000 in increments of 50.

4.4 The resulting

After adjusting the parameters, it was found that setting σ = 0.7 as the core characteristic, with C = 1000 and ε = 0.00001, yielded the smallest average MAE at 10-fold cross-validation on the testing data set. Additionally, the FSVR parameters were tested with two different membership functions: the generalized bell-shaped function with parameters a = 53, b = 5, c = 212, and the linear function of the time parameter λ, ranging from 0.1 to 1. The MAE and R^2 results are presented in Table 3 and Table 4, respectively. The findings indicate that testing data set 7 demonstrates the highest R^2 and lowest MAE value among the methods, except for the classical SVR on training data set 8, which yields the lowest MAE value due to overfitting. This suggests that the model based on testing data set 7 performs promisingly. Figure 9 depicts the predicted water inflows for the dam based on testing data set 7.

Table 3 MAE values of comparative method (m^3/s)

Data Set	SVR		FSVR			
			Linear Function of the Time		Generalized Bell-Shaped MF	
	Training Data	Testing Data	Training Data	Testing data	Training Data	Testing Data
Data set 1	15.3447	18.3919	14.2108	15.2947	9.2479	13.2708
Data set 2	14.391	17.7287	12.3116	16.1034	9.8400	15.5711
Data set 3	14.8045	24.2028	13.1731	18.5105	13.8195	17.0729
Data set 4	13.5034	21.4445	13.3277	19.3106	13.0546	16.4663
Data set 5	13.7800	15.7559	5.8789	10.8103	5.2327	9.8986
Data set 6	13.0682	15.1782	8.7393	9.7600	7.4485	8.8531
Data set 7	13.6997	***15.1318***	***6.2506***	***8.3906***	***5.1546***	***6.3726***
Data set 8	***12.8775***	19.1454	7.3295	15.4382	7.4791	12.9826
Data set 9	14.2122	17.2128	9.3319	9.732	8.8915	8.8393
Data set 10	13.6986	16.5587	10.4858	11.4999	9.1603	8.8958
Average MAE	13.938	18.0751	10.1039	13.485	***8.93287***	11.82231

Table 4 R^2 values of comparative method

Data Set	SVR		FSVR			
			Linear Function of the Time		Generalized Bell-Shaped MF	
	Training Data	Testing Data	Training Data	Testing Data	Training Data	Testing Data
Data set 1	–0.4463	0.4107	0.5406	0.5048	0.8773	0.4713
Data set 2	0.5160	0.4144	–0.5234	0.6693	–0.6868	0.4721
Data set 3	0.4635	–0.5552	0.5109	0.4537	0.4375	–0.5562
Data set 4	0.4780	0.5034	0.5550	0.4755	0.5726	0.5568
Data set 5	0.4733	0.4021	–0.6878	0.4086	–0.6300	0.5184
Data set 6	–0.5714	0.55000	–0.6447	0.5019	–0.7730	0.6475
Data set 7	***0.6030***	***0.5697***	***0.8306***	***0.7822***	***0.8907***	***0.8508***
Data set 8	0.5518	0.5512	0.6757	0.4397	0.6726	0.5582
Data set 9	0.4727	–0.5491	0.6694	0.3855	0.5139	0.8970
Data set 10	–0.5267	0.4599	0.5966	–0.4774	0.6720	0.6571

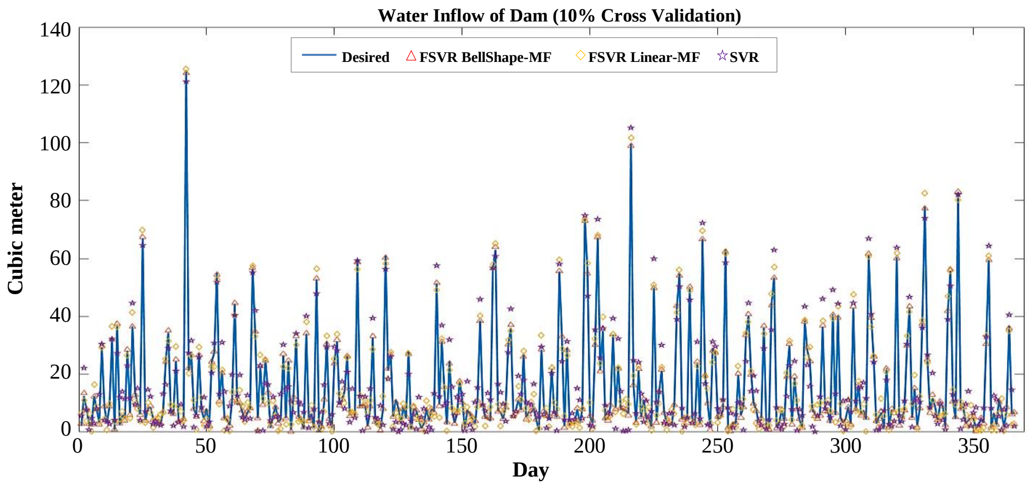


Figure 9 Prediction of water inflow for the dam based on data set 7.

The statistical results of the blind test, based on the testing data set 7 model, are presented in Table 5 and Figure 10. Among the various methods, FSVR utilizing the generalized bell-shaped membership function exhibited the highest accuracy. It achieved an MAE of 15.6247 m^3/s and an R^2 of 0.7984. This performance is superior to the linear membership function, which had an MAE of 17.2566 m^3/s and an R^2 of 0.7555. In comparison, the SVR model had an MAE of 23.6997 m^3/s and an R^2 of 0.6741.

Table 5 MAE and R^2 values of comparative method

Blind Test Data Set	SVR	FSVR	
		Linear Function of the Time	Generalized Bell-Shaped MF
MAE (m^3/s)	23.6997	17.2566	15.6247
R^2	0.6741	0.7555	0.7984

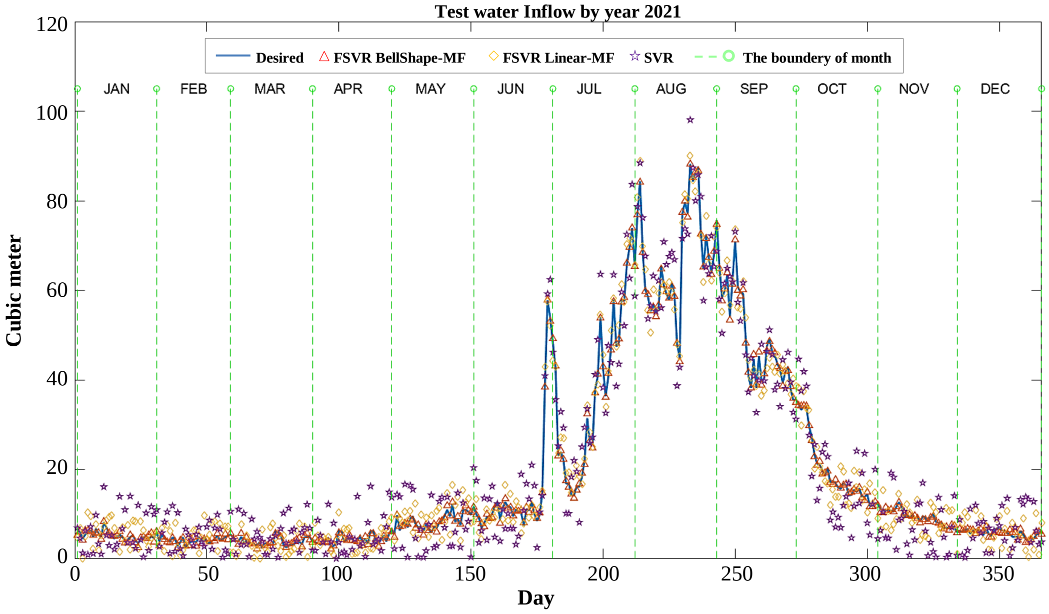


Figure 10 Result of the water inflow prediction for the next three days in the year 2021 (blind test data)

5. Conclusion

This research proposes a new method that utilizes FSVR based on the generalized bell-shaped membership function to estimate the water inflow of the Queen Sirikit Dam, located in Pha Leud Sub-district, Tha Pla District, Uttaradit Province, Thailand. A comparison with FSVR based on the Linear function of time and classical SVR is also demonstrated. The predictive ability of these models was evaluated using 10-fold cross-validation on 3,700 samples.

Based on the desired output of the 2021 data set, which served as a blind test set, the FSVR employing the generalized bell-shaped membership function exhibited the highest accuracy. It achieved an MAE of 15.6247 m^3/s and an R^2 of 0.7984. This is an improvement over the Linear function of time, which resulted in an MAE of 17.2566 m^3/s and an R^2 of 0.7555. In comparison, the SVR model had an MAE of 23.6997 m^3/s and an R^2 of 0.6741. This difference in performance can be attributed to the fact that SVR methods assign equal weight to all data points, while FSVR assigns different weights based on their importance, as determined by the fuzzy membership grade. The membership functions used in this study include the linear function of time, which is commonly used, and the proposed generalized bell-shaped membership function. The linear function of time was observed to diminish the significance of x_1 when the number of samples x_1 with i being large. This implies that certain data samples have a minimal impact on water inflow, such as during periods of low or no rainfall. The generalized bell-shaped membership function addresses this issue by adjusting parameters to accommodate extremely significant data samples during the rainy season (May to October) and slightly significant data samples during periods of low or no rainfall.

These findings suggest that FSVR based on the generalized bell-shaped membership function is an effective approach for forecasting dam water inflows. It can significantly contribute to efficient dam management, including drainage operations and downstream population warning announcements.

6. Acknowledgments

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