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# Firefly optimization algorithm effect on support vector regression prediction improvement of a modified labyrinth side weir's discharge coefficient

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ABSTRACT

A principal step in designing dividing hydraulic structures entails determining the side weir discharge coefficient. In this study, Firefly optimization-based Support Vector Regression (SVR-FF) is introduced and examined in terms of predicting the discharge coefficient of a modified labyrinth side weir. Ten non-dimensional parameters of various geometrical and hydraulic conditions are defined as the input parameters for the SVR-FF and the side weir discharge coefficient is defined as the output. Improvements in SVR prediction accuracy are determined by comparing SVR-FF with the traditional SVR model. The results indicate that the SVR-FF model with *RMSE* of 0.035 is about 10% more accurate than SVR with *RMSE* of 0.039. Thus, combining the Firefly optimization algorithm with SVR increases the prediction model performance.



## 1. Introduction

Side weirs are commonly used as part of various hydraulic structures in flood control, dividing, irrigation, drainage, etc. De Marchi [1] performed the first study on the mathematical explanation of side weirs. The equation obtained based on the constant specific assumption of the upstream and downstream of a side weir is as follows:

$$-\frac{dQ}{dx} = \frac{2}{3}Cd\sqrt{2g}(y-w)^{1.5} \tag{1}$$

where $Cd$ is the discharge coefficient, $dQ/dx$ is the variation of discharge along the main channel, $w$ is the weir height and $y$ is the flow depth. In these side weirs, the effective parameters are the Froude number in the beginning section of the side weir ($Fr_1$), weir height ($w$), upstream flow depth ($Y_1$), weir length ($L$) and main channel width ($b$).

Traditional side weirs are rectangular. Many studies have concerned determining the discharge coefficient of rectangular side weirs [2–11]. One of the most economical alternatives when overflow occurs in a channel and when there are limitations to increasing tributary channel width is to use more efficient side weirs with a higher discharge coefficient. Side weir shape modification significantly affects [12–16], and can potentially increase side weir performance by 1.5 to 4.5 times [17].

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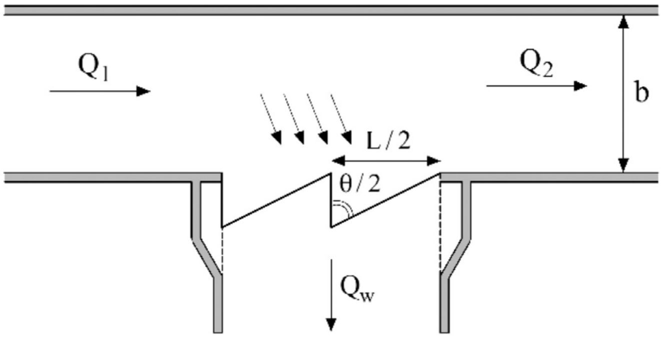


**Fig. 1.** Schematic overview of the modified labyrinth side weir [31].

Owing to the complex relations of the discharge coefficient in various geometric and hydraulic conditions, soft computing methods are widely employed for discharge coefficient prediction [17–23]. Emiroglu et al. [24] used the adaptive neuro-fuzzy inference system (ANFIS) to estimate the discharge capacity of triangular labyrinth side weirs. The authors revealed that ANFIS is more accurate than multiple nonlinear and linear regression models in estimating the discharge coefficient. Support vector machines (SVMs) are among the newest soft computing learning algorithms that are extensively applied in the computing, hydrology and environmental fields [25–28]. More recently, the Firefly optimization algorithm combined with the SVM method has been successfully applied in various complex multi-variable problems [29,30].

In this study, a hybrid Firefly optimization-based Support Vector Machine (SVR-FF) is used to estimate the discharge coefficient of a modified labyrinth side weir [31]. The discharge coefficient of a modified labyrinth side weir is influenced by various geometric parameters, such as the weir's height, length and included angle, as well as hydraulic parameters, such as upstream Froude number and the depth of flow. By employing these effective parameters, ten non-dimensional input variables are applied and run in the numerical models. To evaluate the extent of numerical model improvement, the SVR-FF results are compared with the traditional SVR model. According to the results obtained, the Firefly optimization algorithm can successfully improve support vector machine model performance.

## 2. Materials and method

### 2.1. Modified labyrinth side weir characteristics

The datasets from Borghei and Parvaneh's [31] experimental study are used to verify the SVR-FF and SVR models (Fig. 1). Borghei and Parvaneh's experiments were done in a glass channel built with length, height and width of 11, 0.66 and 0.4 m, respectively. Various weir heights ($w$), weir apex angles ($\theta$), weir lengths ($L$) and side weir upstream Froude numbers ($F_1$) are examined in the present study. The variation intervals of each investigated parameter are given in Table 1.

According to Table 1, the entire dataset comprises 200 samples, 50% of which are considered for the training phase and the remaining 50% for the testing phase. The odd data numbers are used for training and the even numbers for testing.

### 2.2. Firefly optimization-based support vector regression

The Support Vector Machine (SVM) is a powerful algorithm that performs much better compared to other neural network methods in both regression and classification [32–35]. SVM formulation was developed and described entirely by

**Table 1**
Variations of geometric and hydraulic parameters for the modified labyrinth side weir [31].

| $\theta/2$(°) | $L$(m) | $w$(mm) | $w/Y_1$ | $Q_1$(m$^3$/s) | $F_1$ | No. of runs |
|---|---|---|---|---|---|---|
| 30 | 0.3 | 5,07,51,00,150 | 0.46-0.83 | 0.019-0.030 | 0.19-0.96 | 40 |
| | 0.4 | 5,07,51,00,150 | | | | |
| 45 | 0.3 | 5,07,51,00,150 | 0.46-0.83 | 0.019-0.030 | 0.19-0.96 | 55 |
| | 0.4 | 5,07,51,00,150 | | | | |
| | 0.6 | 5,01,00,150 | | | | |
| 60 | 0.3 | 5,07,51,00,150 | 0.46-0.83 | 0.019-0.030 | 0.19-0.96 | 50 |
| | 0.4 | 50, 100,150 | | | | |
| | 0.6 | 50, 100,150 | | | | |
| 70 | 0.3 | 5,07,51,00,150 | 0.46-0.83 | 0.019-0.030 | 0.19-0.96 | 55 |
| | 0.4 | 5,07,51,00,150 | | | | |
| | 0.6 | 5,01,00,150 | | | | |