

## EXTENDED ABSTRACT

# Investigating the Rate of Flow Energy Loss in Zigzag Weirs Using Methods Based on Soft Computing

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### Keywords:

Zigzag weir, Energy loss, Artificial Neural Network, Support Vector Machine, Random Forest algorithm.

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## 1. Introduction

In a significant number of past studies, the discharge coefficient of labyrinth weirs has been investigated, the study on energy loss of labyrinth weirs has been done in a limited way and except for a few types of research (Mohammadzadeh-Habili et al. 2018; Hagiabi et al. 2022) has not been done extensively yet. Therefore, considering the uncertainty governing the problem in this research, it seems necessary to conduct new research in the field of intelligent modeling and soft computing of the relative energy loss in labyrinth weirs in different plan forms. For this purpose, in the present study, the energy loss of labyrinth weirs with a triangular and trapezoidal plan has been investigated based on experimental data using intelligent models of Artificial Neural Networks (ANN), Support Vector Machine (SVM), and Random Forest (RF) algorithm.

## 2. Methodology

### 2.1. Experimental study

In this research, the research data of Mohammadzadeh-Habili et al. (2018) have been used. The experiments were carried out in a channel 8 meters long, 0.4 meters wide, and 0.6 meters depth. The experiments were carried out in the range of head from 0.009 to 0.114 meters. Labyrinth weirs with triangular and trapezoidal single and double-cycle plans were used at the weir height of 0.12 meters. A magnetic flowmeter with an error of  $\pm 0.5\%$  was used to measure the flow.

### 2.2. Support Vector Machine

The Support Vector Machine model (SVM) was used as a supervised learning model for classification and estimation (Vapnik, 1995). The SVM is an impressive learning machine that uses the principle of induction of structural error minimization and leads to a general optimal solution.

### 2.3. Artificial Neural Network

An Artificial Neural Network method (ANN) generally consists of input, hidden and output layers. A neuron can be a non-linear mathematical function, as a result, a neural network formed by the community of these neurons can also be a completely complex and non-linear system. In the neural network, each neuron acts independently and the overall behavior of the network is the result of the behavior of many neurons. It is possible to design a data structure that acts like a neuron-using computer programming. By creating a network of these interconnected artificial neurons and creating a training algorithm for the network and applying these algorithms, it can be trained.

### 2.4. Random Forest

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Random forest is a supervised learning algorithm. As the name suggests, this algorithm creates a random forest. The work of making a forest using trees is often done by bagging. The main idea of the bagging method is that the combination of learning models increases the overall results of the model.

### 3. Results and discussion

In order to choose the best model among SVM, ANN, and RF models, the best results of each group are shown in Figure (1). According to Figure (1-a), it can be seen that for the RF model, the values are within the relative error range of  $\pm 9.36\%$ . The value of RMSE and Mean RE% for this model is 0.0193 and 1.91%, respectively. For the SVM-RBF model, the data are within the relative error range of  $\pm 5.34\%$ . This model has provided favorable results compared to the RF model. The RMSE and Mean RE% for the SVM-RBF model are 0.0153 and 1.38%, respectively. The results of the ANN-MLP method have statistically better results compared to the previous two models and are close to the experimental results. For the ANN-MLP method, the data are within the percentage relative error range of  $\pm 2.80\%$ . The values of the above statistical indicators are 0.0070 and 0.73% for this model, respectively. The correlation coefficient for the above models in the test phase is 0.898, 0.907, and 0.969, respectively. The comparison of the relative energy loss obtained from different models and the experimental results indicates a better overlap of the data in the ANN method with the experimental results.

### 4. Conclusions

In the current research, modern data mining methods of support vector machine (SVM), artificial neural network (ANN), and random forest (RF) were used in predicting the relative energy loss of labyrinth weirs. For all the mentioned models, 70% of the data were randomly used for the training phase and 30% for the test phase. In the SVM model, the results of the examination of different kernels showed that the radial basis function (RBF) kernel has favorable results compared to other Polynomial, Linear, and Sigmoid kernels compared to the experimental results. The statistical indices of correlation coefficient (R), root mean square error (RMSE), mean percentage relative error (Mean RE%), and Kling Gupta Efficiency (KGE) for the SVM-RBF model in the test phase are 0.907, 0.0153, 1.38% and 0.744, respectively. In the ANN method with MLP and RBF networks, the ANN-MLP method has more accurate results than the other type of network. So, for the ANN-MLP method,  $R=0.969$ ,  $RMSE=0.007$ ,  $Mean\ RE\%=0.73\%$  and  $KGE=0.969$ . The results in the random forest model have provided weaker results compared to the other two models. ANN-MLP method has better results compared to SVM and RF models and is closer to experimental results.

### 5. References

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