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Estimation of Energy Dissipation in Non-Aerated Flow Regimes over Stepped Spillways Using Advanced Soft Computing Techniques

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A B S T R A C T

Stepped spillways have garnered significant attention due to their high efficiency in dissipating flow energy, primarily attributed to the presence of steps that enhance turbulence and energy loss. A stepped spillway consists of a sequence of vertical drops extending from the crest at the upstream end to the stilling basin at the downstream. Under high discharge conditions, the flow regime transitions into non-aerated skimming flow, characterized by substantial energy levels that necessitate careful management. Accurate estimation of energy dissipation is essential for the safe and economical design of downstream energy dissipators. In this study, 154 experimental data points from physical models of stepped spillways were utilized, encompassing a broad range of hydraulic conditions by varying parameters such as the drop number, spillway slope, number of steps, critical depth-to-step height ratio, and Froude number. To predict the energy dissipation, several soft computing techniques were applied, including Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Support Vector Regression (SVR). The models' predictive capabilities were assessed using key statistical performance metrics, including the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). Comparative analysis of the results demonstrated that the ANN model exhibited superior accuracy over the other models, achieving R^2, RMSE, and MAE values of 0.99, 0.96, and 0.67, respectively. The findings underscore the potential of soft computing models, particularly ANN, as powerful predictive tools in hydraulic engineering applications. The proposed modeling approach offers an effective means for estimating energy dissipation in stepped spillways, facilitating optimized and cost-effective design of hydraulic structures.

1. Introduction

Spillways are critical components in dam infrastructure, serving to discharge excess reservoir volume exceeding the dam's storage capacity to the downstream environment. This discharge is characterized by a substantial kinetic energy flux, thus necessitating dedicated energy dissipation mechanisms. Management of the high-energy flow has consistently presented a significant challenge in hydraulic structure design, as inadequate energy dissipation can precipitate detrimental effects, including downstream channel erosion, structural abrasion, and scour at the dam foundation. While downstream energy dissipation systems, particularly stilling basins, are conventionally employed to mitigate this energy, pre-emptive energy reduction within the spillway itself can substantially decrease the energy load imposed on downstream structures. This approach, in turn, may facilitate a reduction in the construction costs associated with downstream energy dissipation infrastructure [1, 2].

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Stepped spillways, commonly employed in large dams, have demonstrated effective energy dissipation of high-velocity flows. These spillways are, in essence, a type of hydraulic structure that has garnered significant attention due to their ability to control flood flows and attenuate substantial potential energy. Furthermore, their implementation leads to a reduction in the required dimensions of the stilling basin [3, 4]. Stepped spillways, with a long history in hydraulic engineering dating back approximately 3500 years, remain the subject of extensive research. This is because the precise hydrodynamic mechanisms governing flow energy dissipation and turbulent flow patterns within these structures have not yet been fully modeled and explained, particularly under varying geometric and flow conditions [5].

Stepped spillways with diverse configurations are widely employed to dissipate the kinetic energy of flow at the outlet and, consequently, to reduce the dimensions of downstream energy dissipation structures. The hydraulic behavior of these structures is highly dependent on the inflow rate, and as the flow rate increases, the flow regime transitions from nappe flow to skimming flow [6]. Numerous experimental studies have investigated the performance of stepped spillways, considering parameters such as staircase and channel geometry, inlet flow conditions, the type of construction materials, and other relevant factors. Based on the results obtained from research [7-10], the flow hydraulics in these spillways can be categorized into three distinct regimes, based on the ratio of critical depth to step height: nappe flow, transition flow, and skimming flow (Fig. 1). It should be noted that in the nappe flow regime, energy dissipation is generally more effective. However, in long stepped spillways, the total energy dissipation under a steady skimming flow regime is greater due to the higher flow velocities. The characteristics of the vortices formed are influenced by factors such as the spillway slope, step geometry, and overall geometric dimensions [11, 12]. In this section, each of these three flow regimes will be briefly described [13].

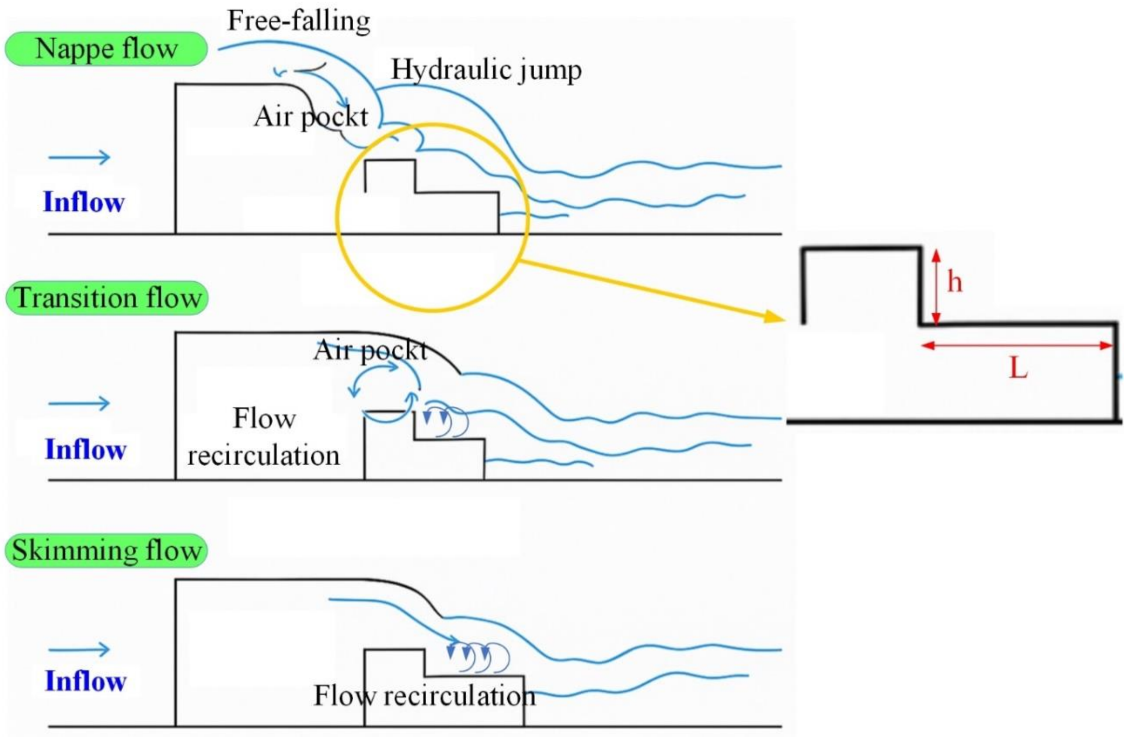

Fig. 1 Classification of three distinct flow regimes in stepped spillways.

A) Nappe Flow: Nappe flow is a type of flow occurring over a stepped spillway with a low slope and low discharge, characterized by a series of free-falling jets that impact the subsequent step. This flow regime is referred to as nappe flow. In other words, in the nappe flow regime, the total height of the spillway is divided into a series of vertical cascades, and the flow is observed as a chain of free-falling waterfalls. Energy dissipation in this case occurs due to the interaction of the flow with the air and the formation of a complete or incomplete hydraulic jump on each step.

B) Skimming Flow: At high flow rates, the flow skims over the outer edges of the steps, such that the step edges form a virtual bed over which the water descends. Beneath this virtual bed, rotating vortices are formed. This type of flow is called skimming flow or pseudo-smooth flow. If the spillway is long, the flow becomes frothy at the toe of the spillway, and the flow appears as white water. In this type of flow, the majority of energy dissipation occurs due to the generation of rotating currents beneath the false bed.

C) Transitional Flow: Regions of flow occur between the regimes of nappe flow and skimming flow, known as transitional flow. Visually, this type of flow is highly irregular, and its hydraulic characteristics change significantly along the spillway. It is associated with intense water dispersion and sudden waves.

Numerous researchers have employed numerical methods and laboratory models to assess and estimate energy dissipation in stepped spillways. Tabbara et al. (2005) conducted a computational simulation of the flow over stepped spillways. Using finite element method codes, these researchers modeled the flow over a stepped spillway. The study aimed to estimate the main characteristics related to flow, namely identifying the water surface profile, improving the understanding of corner vortex dynamics, and quantifying energy dissipation. The stepped spillway used in this experiment consisted of four steps. The results obtained from all simulations indicated that the predicted water surface profile and the estimated energy dissipation rate were in good agreement with experimental measurements [14].

Feldman and Chanson investigated three parameters: energy dissipation, flow resistance, and air-water interfaces. The results of this experimental study indicated that, in skimming and transitional flow regimes, the free surface of the flow was quite smooth and clear in the initial steps. Significant aeration occurred when the void spaces of the steps induced turbulence that extended to the free water surface. Furthermore, the findings suggested that step height and discharge rate had no impact on the parameters being examined. A comparison between the use of stepped spillways and conventional spillways demonstrated that, at a constant flow rate, stepped spillways exhibit greater aeration and higher energy dissipation [15]. Hamedi et al. conducted a study to investigate energy dissipation using both stepped spillways and an end sill simultaneously. Their results indicated that the combined use of these two elements significantly enhances energy loss in transitional and skimming flow regimes. Furthermore, the energy dissipation rate was found to be greater in transitional flows compared to skimming flows. Laboratory results demonstrated that optimal energy dissipation occurs when the ratio of step length to step height is between 0.7 and 1. Outside of this range, energy dissipation decreases due to the potential for the hydraulic jump to occur over multiple steps [16].

Husain et al. employed the Smoothed Particle Hydrodynamics (SPH) method to investigate the pressure distribution on steps of stepped spillways within the non-aerated flow region. The numerical results obtained from this study indicated a good agreement between the velocity and water surface profiles at various sections and the experimental results presented in the literature. The experiments further revealed that stepped spillways, in addition to energy dissipation, protect the structure's surface from cavitation due to the self-aeration process, which introduces air bubbles into the flow [17]. Hou et al. simulated aeration and energy dissipation in stepped spillways using the Random Number Generation (RNG) model and the Volume of Fluid (VOF) method. They utilized a 1:60 scale laboratory model for their simulations. The results indicated that computer numerical simulations can accurately estimate energy dissipation and aeration. Furthermore, they found that an increased contraction ratio at the gate leads to greater energy dissipation. However, with respect to aeration, an increased contraction ratio initially enhances aeration on the first few steps before subsequently reducing it [18]. Shahheydari et al. investigated the flow over stepped spillways using the Flow-3D software, employing the VOF method to define the surface flow profiles. For this purpose, 112 spillway models were designed, encompassing two different step sizes, six configurations, four distinct flow rates, and four different profile slopes. These models were subjected to varying flow rates to measure energy dissipation and the discharge coefficient. The results indicated an inverse relationship between the discharge coefficient and energy dissipation; as energy dissipation increased, the discharge coefficient decreased [19].

Khatibi and Salmasi investigated energy dissipation on gabion stepped spillways using artificial intelligence, genetic algorithms, and regression equations, conducting several experiments. In their study, they employed multiple variables, including discharge, two different slopes, and various gabion materials. They analyzed 74 data points under two flow regimes: skimming and transitional. Eighty percent of the data was used for training, while twenty percent was used for testing. Analysis of the results indicated that artificial neural network (ANN) models demonstrated higher reliability in estimating energy dissipation compared to genetic algorithms and regression models. Accordingly, the coefficient of determination (R^2) and root mean square error (RMSE) were used to evaluate the performance of the different models [20]. Focusing on flow rate and channel slope, Mostafa et al. investigated energy dissipation in stepped spillways under transition and skimming flow regimes. Simulated flow rates ranged from 0.72 L/s to 2.569 L/s. With channel slopes of 15°, 30°, and 45° examined, results indicated that, on average, the 45° slope exhibited the highest energy dissipation in the stepped spillways [21]. Tabari and Tavakoli investigated the influence of stepped spillway geometry on flow patterns and energy dissipation, seeking to establish a relationship between energy dissipation and critical depth. Their findings, obtained through Flow-3D simulations, indicated that increased energy dissipation resulted from decreased discharge, fewer steps, and increased step height [2].

Accurately estimating energy dissipation in spillways is a critical subject that has been extensively studied by various researchers. In this context, approaches based on machine learning models have not only demonstrated acceptable accuracy in predicting energy dissipation in stepped spillways but have also succeeded in modeling the intricate patterns that occur in these processes by considering various parameters and statistical analyses. These methods offer higher accuracy compared to traditional techniques and possess the capability to process large datasets, features that significantly enhance their value as powerful tools in the design and optimization of energy dissipation systems, especially in civil engineering and water engineering projects.

Hanbay and colleagues predicted flow conditions over stepped chutes using an Adaptive Neuro-Fuzzy Inference System (ANFIS). In their research, the number of steps, slope, and critical flow depth were used as input data for the ANFIS model to predict flow conditions over stepped spillways. The model's performance was evaluated using cross-validation, achieving an accuracy of 99.01%, demonstrating the high potential of ANFIS in hydraulic systems. This study encompassed all three flow regimes: nappe, skimming, and transition. The results indicated that flow over stepped spillways is turbulent, leading to significant air entrainment. Therefore, it is crucial to accurately predict hydraulic conditions for the design of a stepped structure [22]. Roushangar et al. (2014) utilized ANN and genetic programming (GEP) models to model energy dissipation. To determine the optimal percentage split for training and testing data, they employed three different data allocation strategies. Ultimately, the model using 65% of the data for training and 35% for testing demonstrated the best performance. The resulting values of Correlation Coefficient (R), Nash-Sutcliffe index (NS), and RMSE obtained under all three flow regimes indicated that the artificial neural network (ANN) model yielded values of 0.968, 0.936, and 2.9, respectively, while the GEP model produced values of 0.968, 0.937, and 2.85, respectively [23]. Salmasi and Özger investigated the hydraulic characteristics of stepped spillways through experimentation, the development of models to describe the data, and the testing of model accuracy. In their research, an ANFIS model was employed to correlate input and output variables, specifically energy dissipation. The inputs to this model consisted of five variables: the number of steps, the spillway slope, the Froude number, the critical depth, and the drop number. Furthermore, two metrics, R^2 and RMSE, were used to compare the performance of different models. Ultimately, the R^2 value for the ANFIS model was calculated to be 0.966 [13]. Ekmekcioğlu et al. evaluated Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and ANN models for predicting energy dissipation in stepped spillways, using laboratory data. Their results indicated that ensemble-based intelligence models outperformed individual machine learning methods in predicting energy dissipation [24]. Baharvand et al. predicted the rate of energy dissipation and its variations in stepped vertical overfalls under various geometric and hydraulic conditions using two models: Random Forest Regression (RF) and Support Vector Regression (SVR). An examination of 27 geometric scenarios revealed that the energy dissipation rate in this type of spillway gradually increases with relative water depth. Furthermore, the RF model demonstrated superior performance compared to the Support Vector Regression method [25].

Building upon prior research and the significant role machine learning models have played in enhancing the accuracy of hydraulic variable predictions, this study aims to investigate and predict energy dissipation rates in stepped spillways under skimming flow conditions. Specifically, laboratory experimental data pertaining to stepped spillways were utilized to evaluate the performance of three artificial intelligence models: ANN, ANFIS, and SVR. By comparing the accuracy of the results obtained from these models, this research seeks to achieve the most precise estimation of energy dissipation in stepped spillways possible, thereby informing the design and optimal dimensioning of stilling basins downstream of the spillway from a broader perspective.

2. Methodology

To investigate energy dissipation in stepped spillways, all experimental activities in this study were conducted based on the results of tests performed in the Hydraulics Laboratory of Shahid Chamran University of Ahvaz [13]. In this research, various parameters affecting energy dissipation in stepped spillways were examined and analyzed, and the data were evaluated using statistical methods.

2.1. Properties of a physical model

Laboratory activities in this study were conducted in two distinct channels. Channel 1 had a width of 0.5 meters, a length of 8 meters, and a height of 1.6 meters. Channel 2 had a width of 0.25 meters, a length of 10 meters, and a height of 0.6 meters. The flow through the channels was controlled at the downstream end by a gate, designed to induce a hydraulic jump at the toe of the spillway, enabling flow measurements in that specific region. Consequently, discharge rates were measured using a calibrated V-notch weir (with a 53-degree angle) located downstream of the channel. The water flow rate was supplied by a pump with a maximum capacity of 50 liters per second. The flow rate ranged from 7 to 50 liters per second, with an accuracy of ±0.9 liters per second. The upstream water level was measured using a point gauge with an accuracy of ±0.1 millimeters. All measurements were taken along the channel axis. In each experiment, the water depth was measured 0.6 meters downstream of the chute (y_0) and after the hydraulic jump (y_2). The shallow, aerated flow at the toe of the spillway made accurate measurement of the flow depth (y_1) difficult. The geometric characteristics of the physical models of constructed stepped spillways are presented in the study by [13].

2.2. Calculation of energy dissipation using dimensional analysis and experimental data

In this study, energy dissipation has been calculated using dimensional analysis and experimental data. A total of 154 experiments were conducted under the skimming flow regime and for different slopes (15, 25, and 45 degrees). Furthermore, in these experiments, 7 types of step numbers and different flow rate values were used. The measurements performed in each experiment included flow rate values and two flow depths. The upstream energy head (E_0), downstream energy head (E_1), and relative energy dissipation ($\Delta E/E_0$) were calculated as follows:

$$E_0 = w + y_0 + \frac{V_0^2}{2g} = w + y_0 + \frac{q^2}{2g(w+y_0)^2} \tag{1}$$

$$E_1 = y_1 + \frac{V_1^2}{2g} = y_1 + \frac{q^2}{2gy_1^2} \tag{2}$$

$$\frac{\Delta E}{E_0} = \frac{E_0 - E_1}{E_0} = 1 - \frac{E_1}{E_0} \tag{3}$$

Where, g is the acceleration due to gravity, w is the total spillway height, measured with a point gauge after the installation of the spillway in the flume, y_0 is the flow depth measured at a set distance upstream of the spillway and above the spillway crest, q is discharge per unit width, and V_0 is the approach velocity. The downstream flow depth, y_1, was calculated using the concept of conjugate depth (y_2), expressed as:

$$y_1 = \frac{y_2}{2}(\sqrt{1 + 8Fr_2^2} - 1) \tag{4}$$

where, Fr_2 is the Froude number and is calculated as:

$$Fr_2 = \frac{V_2}{gy_2} \tag{5}$$

Based on the defined relationships and variables, and using Buckingham's Π −theorem, the relative energy dissipation can be estimated using the following equation:

$$\frac{\Delta E}{E_0} = f(DN, S, N, \frac{y_c}{h}, Fr_1) \tag{6}$$

In this context, $y_c = (q^2/g)^{\frac{1}{3}}$, $DN = q^2/gH_w^3$, H_w is equal to the height of the spillway, and $Fr_1 = V_1/\sqrt{gy_1}$ represent the critical depth, the drop number, and the Froude number, respectively. The average flow velocity at each cross-section was calculated using the relation $V = q/y$, where the discharge per unit width is defined as $q = Q/b$. In this expression, Q denotes the total discharge, b is the width of the weir crest, and y corresponds to the flow depth at the respective cross-section.

2.3. Data evaluation using soft computing models

In this study, the data processing for estimating energy dissipation was performed using three soft computing models: ANN, ANFIS, and SVR. These soft computing models, implemented in the MATLAB environment, leverage machine learning techniques to predict the desired output. Soft computing models are a subset of artificial intelligence that process input data by learning underlying patterns through training. After the training phase, the models generalize the learned information and apply rule-based inference on the test data, enabling them to accurately estimate the target variable—in this case, energy dissipation.

An ANN can be trained for a specific task by adjusting the connection weights between its components. Typically, trained neural networks operate such that a given input is mapped to a desired target output. The network adjusts the weights iteratively based on the difference between the actual output and the target, continuing this process until the output closely matches the target. Generally, a large number of input-target pairs is required to effectively train the network. In the present study, the transfer functions transig and purelin were employed in the neural network architecture. The trainlm algorithm was utilized for training, which updates the weights and biases by leveraging the Levenberg-Marquardt optimization method to achieve efficient and accurate convergence. Further details regarding this model can be found in the studies by Tabari and Azari [26].

The ANFIS is a type of artificial neural network based on the Takagi-Sugeno fuzzy inference model. This model operates according to a set of if-then fuzzy rules and has the capability to learn and approximate nonlinear functions. In the present study, the function trndata was employed for training the data, while chkdata was used for validating and detecting potential overfitting in the dataset. Furthermore, the fuzzy inference system was generated using the genfis algorithm, which applies subtractive clustering for rule extraction. Finally, the fuzzy inference computations were performed using the evalfis function. A more comprehensive analysis of this model is presented in the research conducted by Jafari et al. [27].

SVR is a supervised learning method widely used for both classification and regression tasks. The core principle of SVR is to find a linear decision boundary that maximizes the margin between data points, effectively achieving robust separation. In general, implementing an SVR prediction model requires the selection of three key parameters by the user: the epsilon (ε) parameter, the regularization parameter (C), and the kernel function. Proper tuning of these parameters significantly enhances the model's predictive performance. The kernel function defines the transformation of data into a new feature space, enabling the model to capture complex nonlinear relationships. The regularization parameter C controls the trade-off between minimizing the training error and maintaining model simplicity by limiting the size of the model weights. In this study, the Radial Basis Function (RBF) kernel was employed, with C set to 100, ε set to 0.05, and the kernel parameter (often denoted as gamma) set to 5. A detailed exposition of this model is available in the work of Tabari and Sanayei [28].

2.4. Performance evaluation criteria of the models

Following the completion of experimental and computational procedures, the reliability of the model outputs was assessed using three criteria: the coefficient of determination (R^2), Root Mean Square Error ($RMSE$), and Mean Absolute Error (MAE). The coefficient of determination quantifies the degree of correlation between two sets of data. In this study, it is defined as the square of the correlation coefficient between the predicted and the actual energy dissipation values, thus ranging between 0 and 1. An R^2 value of 0 indicates that the dependent variable (energy dissipation) cannot be predicted from the independent variables—namely, the drop number, weir slope, number of steps, critical depth relative to step height, and Froude number. Conversely, an R^2 equal to 1 implies that the independent variables can perfectly predict the energy dissipation without any error. Hence, the closer the R^2 The value is 1, the higher the accuracy of the prediction.

The RMSE measures the average magnitude of the difference between the predicted values by the model and the observed actual values. It serves as an effective metric for comparing prediction errors over a dataset and is calculated as shown in Equation (7).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(E_t - E\prime)^2}{n}} \tag{7}$$

In this relation, E_t represents the energy dissipation measured from laboratory experiments, E' denotes the energy dissipation predicted by the soft computing models, and n is the total number of samples. The RMSE is calculated by first squaring the difference between the predicted and actual values, then averaging these squared differences over all samples, and finally taking the square root of this average. Because the errors are squared before averaging, RMSE assigns greater weight to larger errors, making it particularly sensitive to outliers. Therefore, RMSE is especially useful when large prediction errors are particularly undesired.

RMSE values range from zero to infinity, where values closer to zero indicate smaller prediction errors and consequently higher model reliability. In other words, in this study, a lower RMSE value signifies that the model provides more accurate estimates of energy dissipation and thus demonstrates greater trustworthiness.

Mean Absolute Error (MAE) measures the average magnitude of errors in a set of predictions, regardless of their direction. Unlike squared error metrics, MAE is a linear measure that assigns equal weight to the absolute difference of each individual sample. Essentially, MAE represents the average of the absolute differences between the predicted values and the observed values (e_i) and is computed as defined in Equation (8).

$$MAE = \frac{\sum_{i=1}^{n}|e_i|}{n} \tag{8}$$

Similar to RMSE, the MAE can take values ranging from zero to infinity, where smaller values closer to zero indicate lower prediction errors. Using both RMSE and MAE together provides insight into the variance of errors within the estimated dataset. Generally, RMSE is always greater than or equal to MAE. The greater the difference between these two metrics, the higher the variance among individual prediction errors. Conversely, if RMSE and MAE are equal, it implies that all individual errors have the same magnitude.

3. Results and discussions

After identifying the dataset, the relationship between the five variables DN, S, N, y_c/h, Fr_1 and $\Delta E/E_0$ was examined to determine which variable has the strongest direct linear correlation with energy dissipation. Scatter plots of each input variable against the output were also generated for visualization (Fig. 2). Pearson's correlation coefficient was used to quantify the strength of the linear relationship. This coefficient ranges from -1 to +1, with values closer to either extreme indicating a stronger linear correlation. Negative correlation values indicate an inverse relationship, meaning that as energy dissipation increases, the corresponding variable decreases, and vice versa. A correlation coefficient of zero indicates the absence of any linear relationship between energy dissipation and the variable in question. According to the scatter plots and correlation coefficients, the linear relationship between energy dissipation and the variables y_c/h, Fr_1, and DN is inverse, whereas it is direct with spillway slope (S) and number of steps (N). In other words, to achieve greater energy dissipation in stepped spillways, the critical depth to step height ratio (y_c/h), Froude number (Fr_1), and drop number should increase, while the spillway slope and number of steps should decrease. Among these, the drop number exhibits the strongest correlation with energy dissipation, whereas the Froude number and number of steps show the weakest correlation. Therefore, to enhance energy dissipation, priority should be given to reducing the drop number. To effectively reduce DN, the spillway height should be increased primarily, followed by an increase in spillway width.

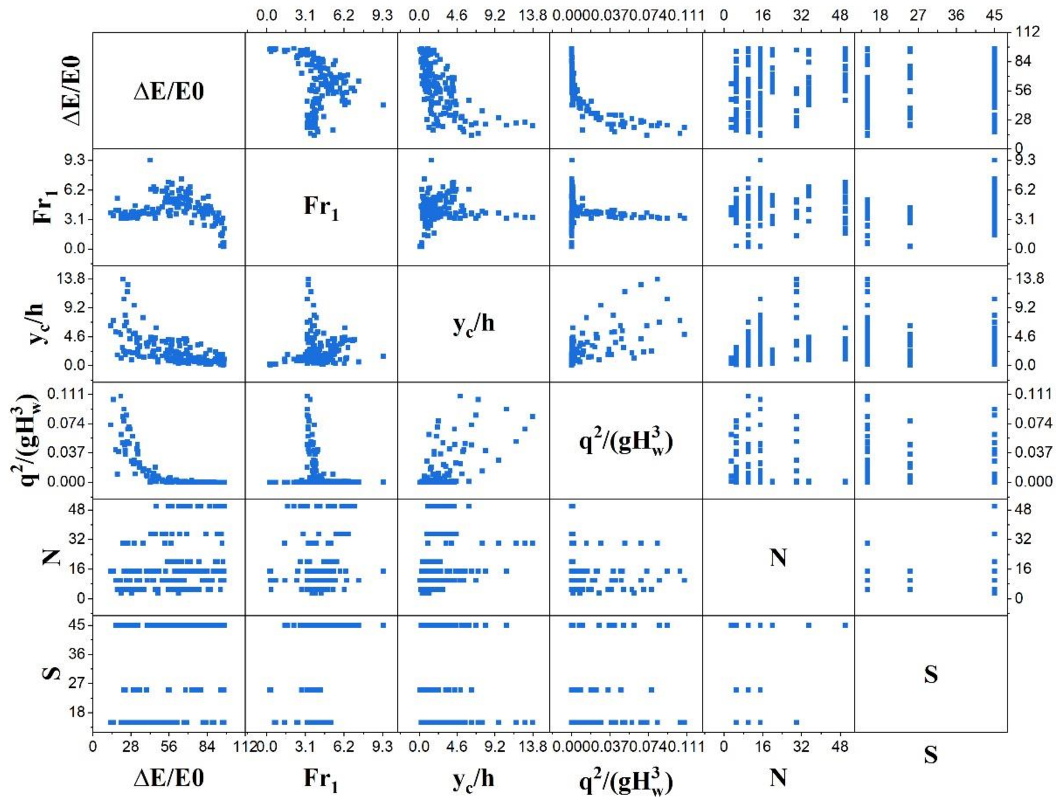

Fig. 2. Scatter plot of the parameters influencing the rate of energy dissipation.

Based on the performance evaluation criteria of the models, the ANN demonstrated the highest correlation with the actual energy dissipation data (Table 1). Analysis of the RMSE, which emphasizes the magnitude of errors for each individual prediction, showed that the ANN model did not produce any large errors across all 154 estimates. Moreover, the comparison between RMSE and MAE values across the models, and the close agreement between these two metrics in the ANN model, indicate that the errors were consistently small and uniform across all samples. Although the SVR and ANFIS models also provided reasonable estimates of energy dissipation, their relatively high RMSE values and the considerable disparity between RMSE and MAE suggest greater variance in prediction errors, meaning the error magnitudes were not consistent across all predictions.

Table 1 Comparison of the performance of the investigated soft models.

Performance criteria	Training			Testing		
Model name	**MAE**	**RMSE**	R^2	**MAE**	**RMSE**	R^2
ANN	1.0605	1.6405	0.994	0.6766	0.9643	0.996
ANFIS	4.0962	5.2334	0.9522	4.0962	5.9834	0.9668
SVR	0.0590	2.0265	0.973	0.0592	2.0554	0.971
Regression model			$R^2 = 0.908$ for all data			
Salmasi and Özger (2014)			0.974			0.9667

To evaluate and compare the results obtained from the three machine learning approaches, the scatter matrix of the examined models along with their pairwise calculated values is presented in Fig. 3. The horizontal and vertical axes in each subplot represent the predicted values by the models and the actual values or predictions from other models, respectively. As shown, the ANN model exhibits a highly compact and close clustering of points around the diagonal line, indicating its high accuracy in predicting actual values. This model effectively captures the fluctuations and overall trend of energy dissipation. In the ANFIS model, the scatter points also align around the diagonal, but with a slightly more dispersed distribution compared to ANN, reflecting lower accuracy and higher variance in errors for ANFIS predictions. Although the SVR model generally follows the trend, its scatter points display a wider spread and greater deviations from the ideal line, indicating larger errors and instability in some predictions. Comparative scatter plots between model predictions reveal that ANN and SVR demonstrate greater consistency with the calculated values than ANFIS. Therefore, the presented scatter results, consistent with statistical performance metrics, confirm that ANN is the superior model for predicting energy dissipation in this study.

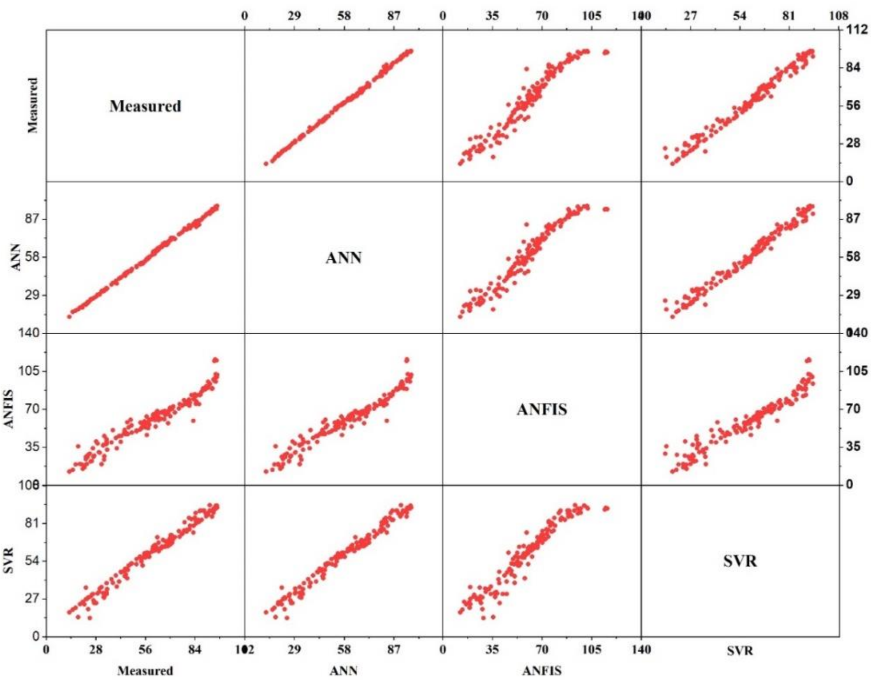

Fig. 3. Scatter plot of the parameters influencing the rate of energy dissipation

The Ridgeline plot serves as a powerful and intuitive visualization tool for evaluating the predictive performance of machine learning models in estimating energy dissipation rates in spillways. By displaying the probability density distributions of each model's predictions in a stacked and parallel manner, this plot facilitates a detailed comparison of the shape, spread, and central tendency of the data. In addition to highlighting statistical differences among models, the Ridgeline plot visually emphasizes the alignment or deviation of model predictions relative to the observed measured data. Therefore, it is an effective tool for assessing model reliability and selecting the most accurate model for predicting energy dissipation in hydrodynamic spillway studies. Based on Fig. 4, the probability density distributions of predictions from the three examined machine learning models (ANN, ANFIS, and SVR) can be evaluated in comparison with the distribution of the measured data for energy dissipation estimation. The overlap analysis of the curves indicates that the ANN model demonstrates the highest agreement with the measured data distribution, as both the shape and peak location of its prediction distribution closely resemble those of the actual data. This serves as a strong indicator of the ANN model's high accuracy in reproducing the true pattern of energy dissipation. In contrast, despite exhibiting convergent distributions, the SVR and ANFIS models show notable deviations from the measured data, particularly the ANFIS model, whose distribution is comparatively broader and differs more substantially from the observed data. Therefore, it can be concluded that among the models studied, the ANN possesses superior capability in replicating the statistical distribution of energy dissipation data, leading to more accurate predictions. This enhanced performance likely stems from the ANN's ability to capture complex and nonlinear relationships inherent in the real data.

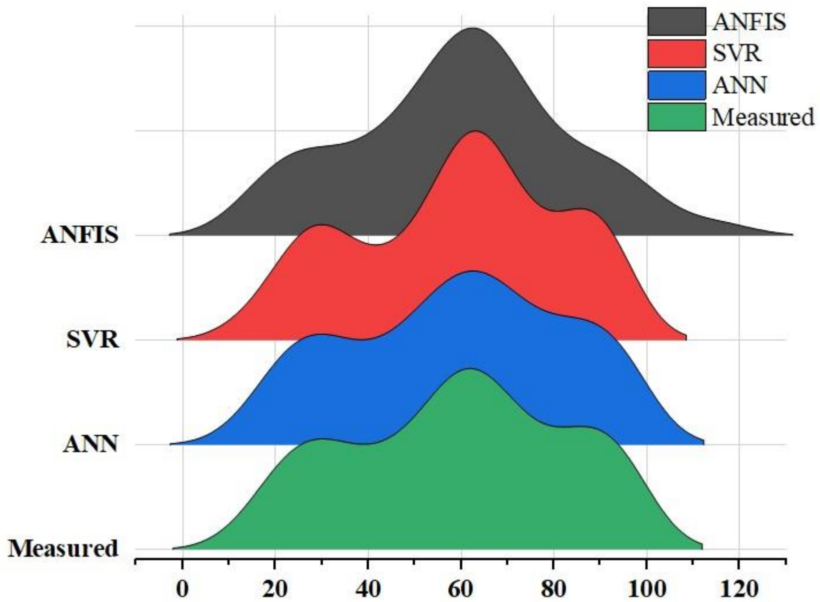

Fig. 4. Ridgeline plot comparing the prediction distributions of three machine learning models with measured data for estimating the rate of energy dissipation.

4. Conclusions

In this study, to estimate energy dissipation in stepped spillways, laboratory data pertaining to actual energy dissipation were initially collected. Subsequently, utilizing these data and five key hydraulic parameters – the drop number, spillway slope, number of steps, ratio of critical depth to step height, and upstream Froude number – as input variables, three machine learning models, namely ANN, ANFIS, and SVR, were trained independently. The dataset employed comprised 154 laboratory samples, with 85% allocated for training, 5% for validation, and 10% for evaluating model performance. The performance of the models in estimating energy dissipation was assessed and compared using the statistical indices of coefficient of determination, root mean squared error, and mean absolute error. Based on comprehensive statistical analyses and advanced machine learning models developed to accurately estimate energy dissipation rates in stepped spillways, the key findings of this research are summarized as follows:

- The results of this study demonstrate that the use of stepped spillways significantly enhances energy dissipation of water flow over dams. Laboratory results indicate that energy dissipation is approximately 60%. Statistical analysis revealed that the DN exhibits the strongest linear correlation with the energy dissipation rate; a decrease in DN leads to an increase in energy dissipation. Considering the DN calculation formula, increasing the height and width of the steps can be an effective strategy to achieve this. While other variables examined also showed significant correlation coefficients, analysis of scatter plots suggests that using these variables alone is insufficient for accurate energy dissipation prediction. Therefore, a comprehensive model that considers all parameters simultaneously is deemed necessary.
- Performance evaluation of soft computing models indicated that the ANN model exhibits the highest correlation with actual energy dissipation data.
- Analysis of the RMSE index reveals that the ANN model does not exhibit significant error in any of its 154 estimations. This indicates high accuracy of the model in estimating energy dissipation values across all samples.
- Comparison of RMSE and MAE values in the ANN model shows a remarkable proximity between these two indices. This convergence indicates a uniform and negligible distribution of error across all samples, reducing the likelihood of outliers in

the estimations.

- Although SVR and ANFIS models also provided acceptable estimations of energy dissipation, the higher RMSE value compared to MAE in these models indicates greater error variance and heterogeneity in prediction accuracy. In other words, the magnitude of error in the predictions of these models has a greater dispersion across different samples.

Given the increasing significance and widespread application of stepped spillways in energy dissipation downstream of hydraulic structures, the need for more extensive research in this area is becoming increasingly apparent. In this context, it is noteworthy that, in addition to the five variables examined in the present study, other variables such as step material and flow velocity can also be incorporated into the analysis. Furthermore, to achieve more accurate energy dissipation estimations, it is suggested to integrate soft computing models and metaheuristic algorithms to optimize the tuning parameters of machine learning approaches. This hybrid approach not only enhances modeling accuracy but also enables the identification of complex and nonlinear patterns present in the data.

Statements & declarations

Author contributions

Milad Taji: Conceptualization, Methodology, Formal analysis, Resources, Original Draft

Masoud Morsali: Conceptualization, Formal analysis, Resources, Writing

Mehdi Eilbeigi: Conceptualization, Investigation, Writing

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Data availability

The data presented in this study are available on request from the corresponding author.

Declarations

The authors declare no conflict of interes.

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