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CIVIL & ENVIRONMENTAL ENGINEERING | RESEARCH ARTICLE

Simulation and prediction for energy dissipaters and stilling basins design using artificial intelligence technique

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Abstract: Water with large velocities can cause considerable damage to channels whose beds are composed of natural earth materials. Several stilling basins and energy dissipating devices have been designed in conjunction with spillways and outlet works to avoid damages in canals' structures. In addition, lots of experimental and traditional mathematical numerical works have been performed to profoundly investigate the accurate design of these stilling basins and energy dissipaters. The current study is aimed toward introducing the artificial intelligence technique as new modeling tool in the prediction of the accurate design of stilling basins. Specifically, artificial neural networks (ANNs) are utilized in the current study in conjunction with experimental data to predict the length of the hydraulic jumps occurred in spillways and consequently the stilling basin dimensions can be designed for adequate energy dissipation. The current study showed, in a detailed fashion, the development process of different ANN models to accurately predict the hydraulic jump lengths acquired from different experimental studies. The results obtained from implementing these models showed that ANN technique was very successful in simulating the hydraulic jump characteristics occurred in stilling basins. Therefore, it can be safely

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Mostafa Ahmed Moawad Abdeen graduated with honors in Civil Engineering Department from Cairo University, EGYPT; Master of Science in Engineering Mechanics at Cairo University, EGYPT; Doctor of Engineering in Engineering Mechanics at Yokohama National University, JAPAN. He was an associate professor of Engineering Mechanics 2004 at Dept. of Eng. Mathematics and Physics, Faculty of Engineering, Cairo University, professor of Engineering Mechanics 2012 at Dept. of Eng. Mathematics and Physics, Faculty of Engineering, Cairo University, and head of Engineering Mechanics Group 2013 at Dept. of Eng. Mathematics and Physics, Faculty of Engineering, Cairo University. He was involved in research field with the group: Engineering Mechanics, Computational Mechanics, Solid Mechanics, Fluid Mechanics, Heat and Mass Transfer, Artificial Intelligence Techniques. This paper is one of the important papers to design accurately water structures to avoid any damages caused by water jumps.

PUBLIC INTEREST STATEMENT

Water with large velocities can cause considerable damage to channels whose beds are composed of natural earth materials. Several stilling basins and energy dissipating devices have been designed in conjunction with spillways and outlet works to avoid damages in canals' structures. The dimensions of these structures have to be designed very accurately and their length mainly depends on the length of the hydraulic jump occurred in them. The current study utilized the artificial intelligence to predict these hydraulic structures' lengths. The authors could successfully model the jump lengths using the artificial neural networks in six types of different hydraulic structures. In addition, they provided an easy tool for the design engineers to safely design their energy dissipaters' structures.

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utilized in the design of these basins as ANN involves minimum computational and financial efforts and requirements compared with experimental work and traditional numerical techniques such as finite difference or finite elements.

Subjects: Applied Mathematics; Applied Physics; Environmental Management

Keywords: energy dissipaters; stilling basins design; hydraulic jump; artificial neural networks

1. Introduction

Stilling basins and energy dissipating devices in conjunction with spillways, outlet works, and canal structures have been extensively investigated experimentally throughout the literature. Specifically, hydraulic jumps phenomenon associated with these structures have received lots of research attention throughout experimental works and traditional numerical modeling to accurately identify the different characteristics associated with the hydraulic jumps. Experimental researchers have agreed about the high cost and limited results for the applications associated with the identification of the hydraulic jumps characteristics and consequently provide safe design for stilling basins and energy dissipating devices. On the other hand, the traditional modeling research group has agreed on the complexity of their numerical modeling techniques toward obtaining accurate identification of the hydraulic jumps dimensions.

New technological modeling techniques such as artificial intelligence have proven its capability in simulating and predicting the behavior of different physical phenomena in most of the engineering fields. Artificial neural network (ANN) is one of the artificial intelligence techniques that has been utilized in civil engineering in general and in the water field area specifically.

Regarding water engineering field, several researchers have incorporated ANN technique in hydrology, groundwater, hydraulics, and reservoir operations to simulate their problems. In (Abdeen, 2006), a study for the development of ANN models to simulate flow behavior in open channel infested by submerged aquatic weeds has been presented. Guven, Gunal, and Cevik (2006) presented a study for the prediction of pressure fluctuations on sloping stilling basins using neural networks (NNs). Specifically, the authors developed an ANN model to predict the pressure fluctuations pattern beneath hydraulic jump occurring on sloping stilling basins. A study for estimating the scour characteristics downstream of a ski-jump bucket using NNs had been presented by Azmathullah, Deo, and Deolalikar (2005). Specifically, the authors developed NN structure as well as its connection weights and functions to predict the depth, location of maximum scour, and the width of scour hole. Water distribution systems using ANN had been investigated in Mansoor and Vairavamoorthy (2005). Specifically, the authors presented a modified network analysis program where nodal outflows were developed as function of pressure and secondary network characteristics. On the other hand, Abdin and Abdeen (2005) presented a study for predicting the impact of subsurface heterogeneous hydraulic conductivity on the stochastic behavior of well draw down in a confined aquifer using ANNs. Several ANN models were developed in this study to predict the unsteady two-dimensional well draw down and its stochastic characteristics in a confined aquifer.

Regarding the applicability of ANN in other engineering fields, several researchers have incorporated ANN to simulate the internal properties of different engineering materials. The internal properties of light weight aggregate concrete were investigated in Abdeen and Hodhod (2010). Abdeen and Abbas (2010) predicted the dynamic response of the seated human body using ANNs. The acoustic properties of some tellurite glasses using ANN technique were simulated and predicted in Gaafar, Abdeen, and Marzouk (2011). Moreover, the effect of natural and steel fibers on the performance of concrete using ANNs was studied in Hodhod and Abdeen (2011). These studies showed the wide applicability of ANN, not only in water research field, but also in other engineering research areas. Goh, Kulhawy, and Chua (2005) presented a comprehensive Bayesian neural network algorithm to model the relationship between the soil undrained shear strength, the effective overburden stress, and the undrained side resistance alpha factor for drilled shafts. Hossein Alavi, Hossein Gandomi, Mollahassani, Akbar Heshmati, and Rashed (2010) presented a study for the utilization of ANNs to

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predict the maximum dry density and optimum moisture content of soil-stabilizer mix. Alavi and Gandomi (2011) derived new models to predict the peak time domain characteristics of strong ground motions utilizing a novel hybrid method coupling ANN and simulated annealing (SA), called ANN/SA. Mollahasani, Alavi, Gandomi, and Rashed (2011) derived a new model to estimate undrained cohesion intercept (c) of soil using multilayer perceptron of ANNs.

It is quite clear from the previously presented literature that ANN technique showed its applicability in simulating and predicting the behavior of different engineering hydraulics as well as material problems. However, its utilization for the identification of hydraulic jump's characteristics is still limited and requires more applicable research. Therefore, the presented study is aimed toward enriching this area of research and consequently helping field engineers to adopt ANN hydraulics modeling in their stilling basins and energy dissipating designs by predicting the hydraulic jumps' characteristics occurring on stilling basins.

2. Problem description

The current paper investigates the applicability of utilizing the ANN technique in predicting the hydraulic jumps' characteristics, specifically its length, occurred in different experimental works performed by Bureau of Reclamation within the United States Department of Interior and published in The Engineering Monograph No. 25, Hydraulic Design of Stilling Basins and Energy Dissipaters (1984).

The experimental program carried out by this organization included six test flumes to obtain the experimental data for the hydraulic jumps. Throughout the research presented in the current manuscript, ANN technique was applied to each of the six experimental flumes' data to obtain one specific ANN model for each flume that is capable of predicting its hydraulic jump's length with an acceptable and high accuracy. These models can thereafter be utilized in serving the field hydraulic engineers in their design of the stilling basins where hydraulic jumps occur.

2.1. Experimental work

As mentioned previously, six test flumes were experimentally investigated to obtain accurate data for the different characteristics of the hydraulic jumps occurred in the stilling basins. Flumes A–E, as shown in Figures 1–6, contained overflow sections so that the jet entered the stilling basin at an angle to the horizontal. The degree of the angle varied in each test flume. In Flume F, the entering jet was horizontal, since it emerged from under a vertical slide gate. Each flume served a useful purpose either in verifying the similarity of flow patterns of different physical size or in extending the range of the experiments started in one flume and completed in others. The different flume sizes and arrangements also made it possible to determine the effect of flume width and angle of entry of the flow. Each flume contained a head gage, a tail gage, a scale for measuring the length of the jump, a point gage for measuring the average depth of flow entering the jump, and a means of regulating the tail water depth.

The discharge in all cases was measured through the laboratory venturi meters or portable venturi orifice meters. The tail water depth was measured by a point gage operating in a stilling well. The tail
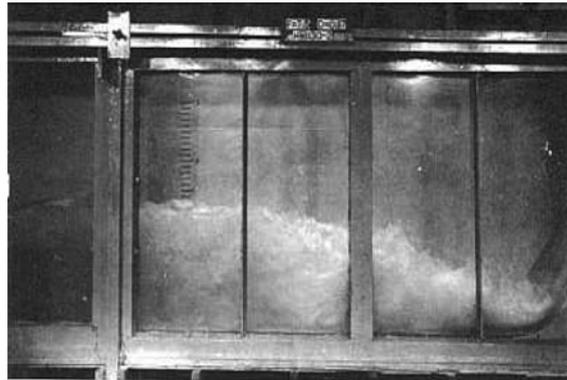
Figure 1. Tests Flume A.

Notes: Width of basin 1.5 m, drop 0.9 m, and discharge 0.17 m³/s.
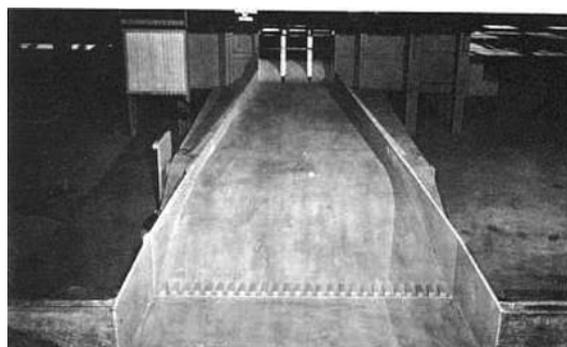
Figure 2. Tests Flume B.

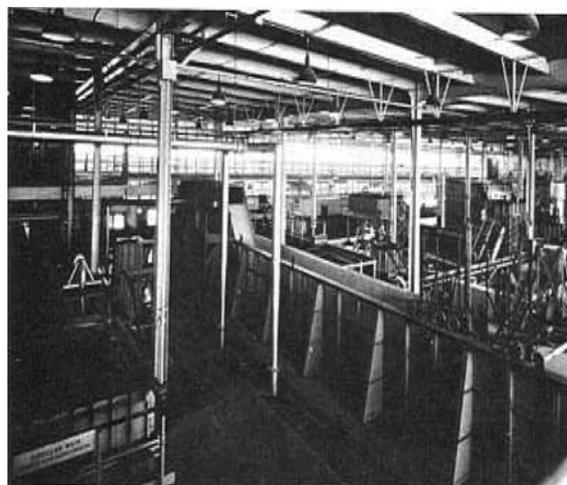Notes: Width 0.6 m, drop 1.7 m, and discharge 0.34 m³/s.

Figure 3. Tests Flume C.

Notes: Width 0.45 m, drop 3 m, discharge 1.5 m³/s, and slope 2:1.

Figure 4. Tests Flume D.

Notes: Width 1.2 m, drop 3.65 m, discharge 0.8 m³/s, and slope 0.8:1.

water depth was regulated by an adjustable weir at the end of each flume. The reader can refer to The Engineering Monograph No. 25, Hydraulic Design of Stilling Basins and Energy Dissipaters, 1984 for further details description about the entire experimental program.
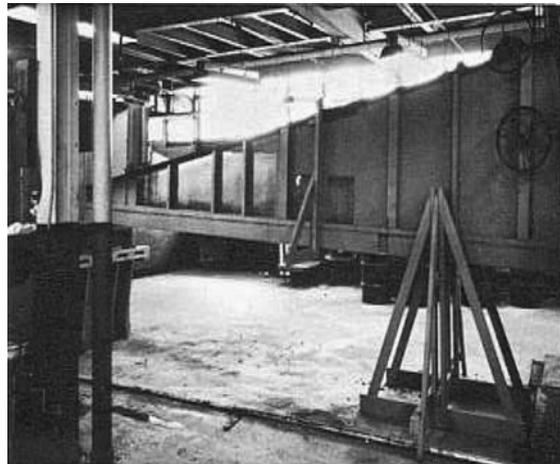
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Figure 5. Test Flume E.

Notes: Width 1.2 m, drop 0.15–0.45 m, and discharge 3 m³/s.

Figure 6. Test Flume F.

Adjustable tilting type, maximum slope 12°, width 0.3 m, and discharge 1.5 m³/s.

2.2. Data categories utilized for the ANN

As reported by the Bureau of Reclamation, 1984, observation of the hydraulic jump throughout its entire range required tests in all the previously described six test flumes. Specifically, this involved about 125 tests for discharges of 0.3–8.5 m³/s.

The number of flumes used enhanced the value of the results and made it possible to observe the degree of similitude obtained for the various sizes of jumps. Greatest reliance was placed on the results from the larger flumes, since the action in small jumps is too rapid for the eye to follow and, also, friction and viscosity become a measurable factor. This was demonstrated by the fact that the length of jump obtained from the two smaller flumes, A and F, was consistently shorter than that observed for the larger flumes. These jump lengths' realizations are the main outputs' type for the several developed ANN models within the current presented study.

3. Numerical models

ANN is a numerical model depends on a certain number of neurons in different layers. Every neuron acts very closely to the real neuron of the human brain. Each layer has a different function than the others. The input layer with its neurons gets the information from the external world (given data), while the hidden layers are working as detectors of these data. The output layer is the final layer of the network and it produces the required results as described in a very detailed fashion in Abdeen (2001) and Kheireldin (1998). Neuralyst software (Shin, 1996) is used to design the ANN models in the present work.

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Table 1. Test flumes (cases) characteristics				
Test flume (case)	**Width characteristics**	**Width value (m)**	**Flow discharge characteristics**	**Flow discharge range (m³/s)**
Test Flume A	Maximum	1.5	Relatively small	0.9–1.5
Test Flume B	Intermediate	0.61	Intermediate	0.9–2.4
Test Flume C	Second minimum	1.5	Small	0.3–1.35
Test Flume D	Second large	0.46	Variable up to maximum	0.9–8.65
Test Flume E	Second large	1.21	Intermediate	0.74–3.05
Test Flume F	Minimum	0.3	Minimum range	0.21–1.05

4. Simulation cases

To investigate and model the hydraulic jump length using ANN technique, the experimental work performed by the Bureau of Reclamation in USA and published in 1984 was utilized in the current study. As mentioned previously, the experimental work included six flumes to capture different possible impacts of flow discharges and physical flumes' dimensions on the hydraulic jumps' length. Consequently, the current study adopts six simulation cases and develops six ANN models, one for predicting the hydraulic jump length in each experimental flume considering the other five flumes' data for training the ANN model. Table 1 summarizes all test flumes (cases) characteristics regarding their physical dimension (width) and flow discharge ranges. It is quite clear that the adopted cases for ANN development and investigation include wide range of physical dimension for the flumes and flow discharges that are expected to produce robust models that can be applied in the field for the design of stilling basins of similar characteristics.

5. Numerical models design

To develop an NN model toward simulating any physical phenomenon such as the impact of different flow discharges or physical dimensions on the hydraulic jumps length within the experimental flume mentioned previously, first, input and output variables have to be determined. Input variables are chosen according to the nature of the problem and the type of data that would be collected in the field if this was a real-field experiment. To clearly specify the key input variables for each NN simulation model and its associated outputs, Table 2 is designed to summarize all NN key input variables and outputs for all six simulation cases.

On the other hand, if the developed ANN models were to be applied to a field application, not laboratory experiment, the type of input data needs to be collected would be the same as they are listed in Table 2. Similarly, the set of output variables required for the training of the ANN models would also need to be collected and reported as they were measured in the field corresponding to their input variables conditions.

Several NN architectures are designed and tested for each of the six simulated cases investigated in the current study to finally determine the best network model to simulate and predict, very accurately, the hydraulic jump length based on minimizing the root mean square error. Table 3 shows the final NN models for each simulation case and their associated number of neurons.

Table 2. Key input and outputs variables for all six NN simulation cases					
Simulation case	**Input variables**				**Output variable**
All cases (Test Flumes A–F)	Flow discharge (m³/s)	Flume width (m)	Jump upstream depth (m)	Jump downstream depth (m)	Hydraulic jump length (m)

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Table 3. The design of the developed NN models for all the simulated cases							
Simulation case	Number of layers	Number of training epochs	Number of neurons in each layer				
			Input	1st hidden	2nd hidden	3rd hidden	Output
Test Flume A	4	39223	4	3	3		1
Test Flume B	5	567608	4	4	3	2	1
Test Flume C	4	82418	4	4	3		1
Test Flume D	3	161472	4	3			1
Test Flume E	4	62010	4	4	4		1
Test Flume F	5	108963	4	3	2	4	1

Table 4. Training parameters for all the ANN models	
Training parameter	Value used for all ANN models
Learning rate (LR)	0.5
Momentum (M)	0.7
Training tolerance (TRT)	0.005
Testing tolerance (TST)	0.01
Input noise (IN)	0
Function gain (FG)	1
Scaling margin (SM)	0.1
Learning algorithm	Back propagation with float calculation method
Epochs per update	1.0
Epoch limit	0.0
Activation function	Hyperbolic activation function

The input and output layers represent the key input and output variables described previously in Table 2 for each simulation case. Regarding the adopted activation function within the current developed ANN models, it is important to mention here that the developed models for test Flumes A, B, C, and D incorporated the hyperbolic activation function while ANN models for test Flumes E and F utilized the sigmoid and linear activation functions, respectively.

Table 4 presents the different parameters' values for all network models developed in the current study for all the simulation cases according to their tasks.

The definitions of each parameter can be found clearly in any NN text book (Alavi & Gandomi, 2011).

6. Results and discussion

This section is mainly devoted to present each of ANN model's prediction results as well as their accuracy for each of the simulation cases (test flumes) described in the previous sections. The accuracy of each model's prediction was evaluated based on the percentage relative error computed for each single data value according to Equation 1 as follows:

$$\text{PRE} = \left(\text{Absolute Value } (\text{ANN\_PR} - \text{AMV})/\text{AMV} \right) \times 100 \tag{1}$$

where PRE is the percentage relative error, ANN_PR is the prediction results using the developed ANN model, and AMV is the actual measured value
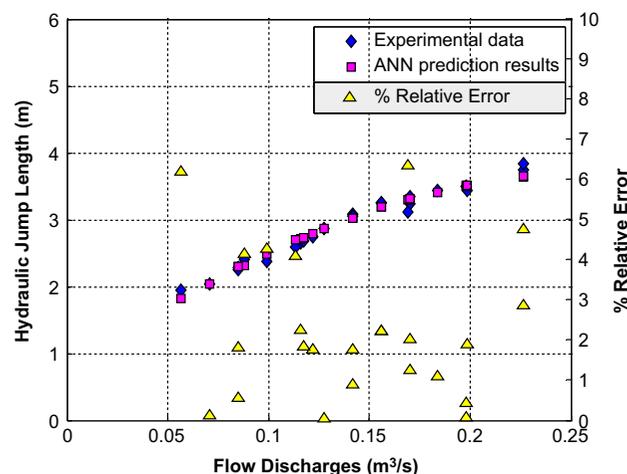
6.1. Test Flume A

Test Flume A is characterized by the maximum width value among all tested flumes with relatively small water flow discharges as mentioned in Table 1. The ANN model designed to predict the

Figure 7. Comparison between experimental data and ANN model prediction results as well as percentage relative error for test Flume A.
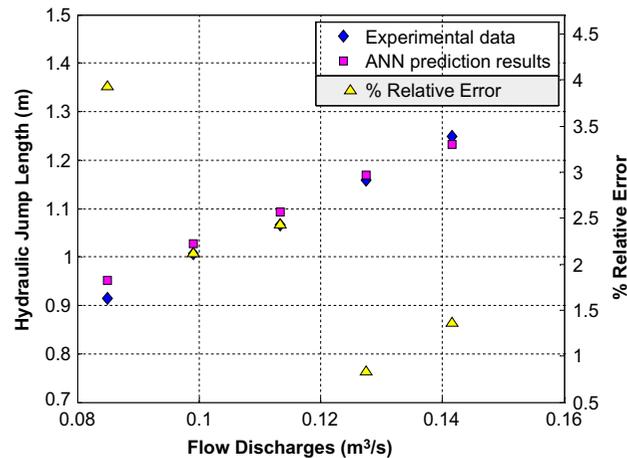
hydraulic jump length within this flume was trained using the other five flumes data and the model's network design is described in Table 3. Figure 7 shows comparison between the experimental data for this flume and the ANN model predicted results as well as the percentage relative error between these two series. The results presented in this figure show that the developed ANN model was very successful in predicting the hydraulic jump length for this flume with maximum percentage relative error less than 4%.

6.2. Test Flume B

Test Flume B is characterized by intermediate width value among all tested flumes with intermediate water flow discharges as mentioned in Table 1. The ANN model designed to predict the hydraulic jump length within this flume was trained using the other five flumes data and the model's network design is described in Table 3. Figure 8 shows comparison between the experimental data for this flume and the ANN model predicted results as well as the percentage relative error between these two series. The results presented in this figure shows that the developed ANN model was very successful in predicting the hydraulic jump length for this flume with maximum percentage relative error less than 7%.
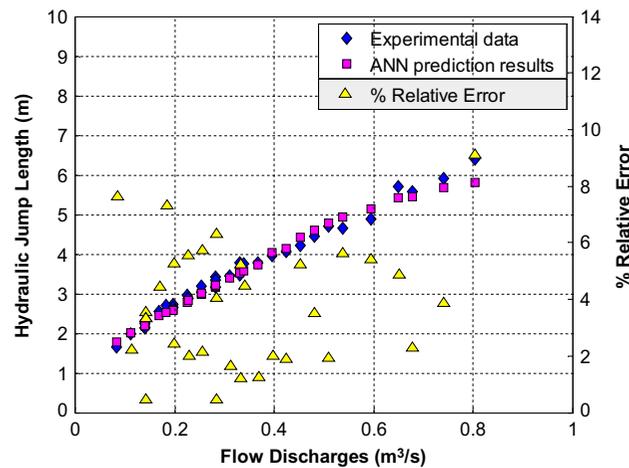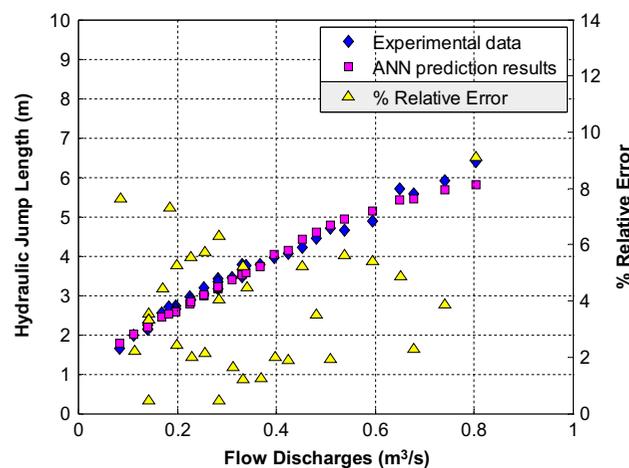
6.3 Test Flume C

Test Flume C is characterized by second minimum width value among all tested flumes with small water flow discharges as mentioned in Table 1. The ANN model designed to predict the hydraulic jump length within this flume was trained using the other five flumes data and the model's network

Figure 8. Comparison between experimental data and ANN model prediction results as well as percentage relative error for test Flume B.

Figure 9. Comparison between experimental data and ANN model prediction results as well as percentage relative error for test Flume C.

design is described in Table 3. Figure 9 shows comparison between the experimental data for this flume and the ANN model predicted results as well as the percentage relative error between these two series. The results presented in this figure show that the developed ANN model was very successful in predicting the hydraulic jump length for this flume with maximum percentage relative error less than 5%.

6.4. Test Flume D
Test Flume D is characterized by second large width value among all tested flumes with variables water flow discharges that vary from intermediate values (3.0 cfs) up to maximum value (28.37 cfs) as mentioned in Table 1. The ANN model designed to predict the hydraulic jump length within this flume was trained using the other five flumes data and the model's network design is described in Table 3. Figure 10 shows comparison between the experimental data for this flume and the ANN model predicted results as well as the percentage relative error between these two series. The results presented in this figure show that the developed ANN model was very successful in predicting the hydraulic jump length for this flume with maximum percentage relative error equals 9%.
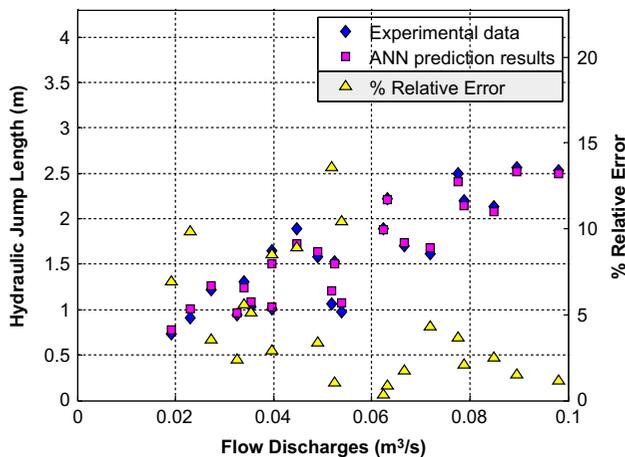
6.5. Test Flume E
Test Flume E is characterized by second large width value among all tested flumes with intermediate water flow discharges between 2.4 and 10.0 cfs as mentioned in Table 1. The ANN model designed to predict the hydraulic jump length within this flume was trained using the other five flumes data and the model's network design is described in Table 3. Figure 11 shows comparison between the

Figure 10. Comparison between experimental data and ANN model prediction results as well as percentage relative error for test Flume D.

Figure 11. Comparison between experimental data and ANN model prediction results as well as percentage relative error for test Flume E.
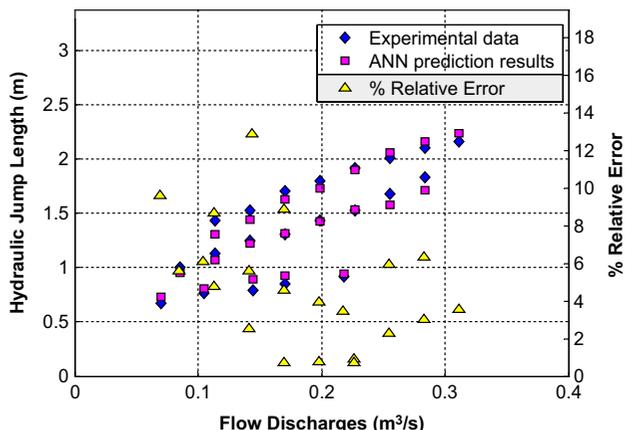
experimental data for this flume and the ANN model predicted results as well as the percentage relative error between these two series. The results presented in this figure show that the developed ANN model was very successful in predicting the hydraulic jump length for this flume with maximum percentage relative error less than 13%.

6.6. Test Flume F

Test Flume F is characterized by minimum width value among all tested flumes with minimum water flow discharges that range between 0.68 and 3.46 cfs as mentioned in Table 1. The ANN model designed to predict the hydraulic jump length within this flume was trained using the other five flumes data and the model's network design is described in Table 3. Figure 12 shows comparison between the experimental data for this flume and the ANN model predicted results as well as the percentage relative error between these two series. The results presented in this figure show that the developed ANN model was very successful in predicting the hydraulic jump length for this flume with maximum percentage relative error less than 14%.

It can be easily seen from Figures 7 to 12 that all ANN models, designed and developed for the different simulation cases, could predict the hydraulic jump lengths in all these simulation cases separately when they are trained with different set of data. On the other hand, Table 5 summarizes the maximum percentage relative error results produced from the different models and shows that this percentage was 13.55% in simulating case F and 12.88% for case E while the other four simulation cases recorded less than 10%. In addition, Table 5 shows the correlation coefficient (*R*) for the

Figure 12. Comparison between experimental data and ANN model prediction results as well as percentage relative error for test Flume F.

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Table 5. Summary of percentage relative errors and correlation coefficient for each simulation case							
Test flume (case)	Width characteristics	Width value (m)	Flow discharge characteristics	Flow discharge range (m³/s)	Maximum percentage relative error (%)	(R) test	(R) train
A	Maximum	1.5	Relatively small	0.9–1.5	3.93	0.998	0.998
B	Intermediate	0.61	Intermediate	0.9–2.4	6.34	0.988	0.999
C	Second minimum	1.5	Small	0.3–1.35	4.76	0.996	0.998
D	Second large	0.46	Variable up to maximum	0.9–8.65	9.08	0.99	0.998
E	Second large	1.21	Intermediate	0.74–3.05	12.88	0.99	0.998
F	Minimum	0.3	Minimum range	0.21–1.05	13.55	0.993	0.998

Table 6. Summary of testing and training data numbers used for the development of each model		
Test flume (case)	Number of training data points	Number of testing data points
A	115	5
B	96	24
C	105	15
D	87	33
E	99	21
F	98	22

testing and training cases for all five experiments. All these results give an indication that ANN can successfully, with high acceptable accuracy, simulate hydraulic jump phenomenon with much less computational efforts compared with the other traditional numerical approaches.

For the sake of full describing the developed model, Table 6 shows the number of testing and training data used in developing each of the models for all cases.

7. Summary and conclusion

Stilling basins and energy dissipating devices are essential in protecting open channels from the damages that can be caused by large water velocities. Lots of experimental and traditional mathematical numerical works have been performed to profoundly investigate the accurate design of these stilling basins and energy dissipaters. The most important element in this design is the identification of the hydraulic jump lengths occurred when spillways and outlet works are constructed to dissipate the energy associated with high water velocities. Traditional numerical approaches for the determination of hydraulic jumps' lengths involve lots of computational efforts and they are time consuming.

The current research introduced the utilization of one of artificial intelligence techniques to, accurately, determine the hydraulic jumps' lengths with minimum numerical efforts. Specifically, ANN was adopted in the current manuscript for this determination in six experimental flumes. Several ANN models were tested for each of the six simulation cases to finally design one model for each case. The designed ANN model for each case was trained, first, utilizing the data from the other five simulation cases. Thereafter, this case-specific model is tested to predict the hydraulic jump's length for its own case data. As it was presented in the results and discussion section, all ANN designed models were very successful in predicting their cases hydraulic jumps' lengths with high accuracy. The maximum percentage relative error encountered in all six simulation flumes was 13.55% in the minimum characteristics flume. In addition, it was observed from the current study that the numerical computations involved in the utilization of the ANN were much less than those required for the adaptations of the traditional numerical techniques.

Therefore, it can be concluded that ANN technique can be safely adopted as a supporting tool in the design of various stilling basins and energy dissipaters that are associated with hydraulic jumps occurrence. Due to its simple implementation procedures, field and design engineers can easily be encouraged to adopt this ANN technique in their design and field works that involve stilling basins and energy dissipaters design and construction. On the other hand, future research could address the robustness of the developed ANN models using sensitivity and parametric analyses.

8. Guidelines for applying the ANN to a field scale channel

As mentioned previously, if the ANN models were to be applied to a field application, not laboratory experiment, the type of input data needs to be collected from the field would be the same as they are listed in Table 2. Similarly, the set of output variables required for the training of the ANN would also need to be collected and reported as they were measured in the field corresponding to their input variables conditions. However, in most of real-field earth open channels, the natural cross-section might not be rectangular. Therefore, full cross-sections' dimensions should be considered among the input variables and not only the channel width as it is presented in Table 2.

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