Hydraulic optimization of corrugated stilling basin with adverse slope

Tooraj Honar, Nafiseh Khoramshokooh and Mohammad Reza Nikoo

ABSTRACT

In this paper, perhaps for the first time, a data-driven simulation–optimization model is developed based on experimental results to find the effects of state and decision variables on the optimum characteristics of a stilling basin with adverse slope and corrugated bed. The optimal design parameters of the stilling basin are investigated to minimize the length of the hydraulic jump and ratio of the sequent depths of the jump while the relative amount of energy loss is maximized. In order to model the relationship between design variables of the bed, the experimental results are converted to a data-driven simulation model on the basis of a multilayer perceptron (MLP) neural network. Then, the validated MLP model is used in a genetic algorithm optimization model in order to determine the optimum characteristics of the bed under the hydraulic jump considering the interaction between the bed design variables and the hydraulic parameters of the flow. Results indicate that the optimum values of bed slope and the diameter of the corrugated roughness (2*r*) can be considered as −0.02 and 20 millimetres, respectively.

Key words | adverse slope, corrugated bed, genetic algorithm optimization model, hydraulic jump, MLP neural network simulation model

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INTRODUCTION

Hydraulic jump is generally observed in open channels and its governing conditions follow up the rules of rapid varied flow (Nikmehr & Tabebordbar 2010; Jalil *et al.* 2015). This frequently occurring phenomenon needs to be widely investigated as a result of its most important role, i.e. energy dissipation for outlet works of hydraulic structures (Afzal *et al.* 2011; Jalil *et al.* 2015). In fact, excess energy is an important factor to be dissipated in order to avoid erosion in open channels and preserve hydraulic structures. On the other hand, hydraulic jumps are usually confined through the stilling basins. Thus, it would be an important subject to consider the criteria and provisions for design of the stilling basins (Pagliara *et al.* 2008). So, it is important to optimize stilling basin characteristics in order to obtain its best hydraulic operation.

Classical jump is a kind of jump which occurs in wide rectangular horizontal channels and has been extensively investigated (Murzyn *et al.* 2005; Carollo *et al.* 2009). Regarding the existing natural rough beds, many studies have been conducted to clarify the role of bed roughness on hydraulic jump characteristics (Leutheusser & Schiller 1975; Izadjoo & Shafai Bejestan 2007; Pagliara *et al.* 2008; Abbaspour *et al.* 2009; Bejestan & Neisi 2009; Neluwala *et al.* 2013). The main results indicate that a rough bed causes more energy loss while reducing distance to the jump from the gate compared with smooth beds. Some of the studies were also carried out on uniform artificial rough beds in which the boundary roughness reduces both the sequent depth and length of the hydraulic jump (Ead & Rajaratnam 2002; Smart *et al.* 2002; Nikmehr & Tabebordbar 2010).

Adverse slope can have a definite effect on increasing the amount of dissipated energy (Pourabdollah *et al.* 2014). Nikmehr & Tabebordbar (2010) have utilized four adverse slopes up to −0.005 in order to study hydraulic jump

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behavior on an adverse slope (F jumps) (Kindsvater 1944). Other similar studies about hydraulic jump behavior on adverse slopes can be found in Defina & Susin (2003) and Parsamehr *et al.* (2017). The main results demonstrate that an adverse slope acts like an obstacle along the channel, reducing sequent depths ratio and hydraulic jump length.

Some studies have investigated sequent depths ratio in channels with rough beds, such as Leutheusser & Schiller (1975), Pagliara *et al.* (2008) and Roushangar *et al.* (2017). Hence, the amounts of the sequent depths ratio and the length of jump upon a smooth bed are more than those upon a rough bed for the same condition of slope and Froude number. Accordingly, the hydraulic jump has been also studied upon corrugated beds by Abbaspour *et al.* (2009), Tokyay *et al.* (2011), Neluwala *et al.* (2013) and Hassanpour *et al.* (2017). One important result of the above-mentioned studies states that the height of corrugation from crest to trough and its wave length have remarkable effects on hydraulic jump behavior on corrugated beds (Afzal *et al.* 2011). To investigate the effects of roughness and adverse slope simultaneously, Parsamehr *et al.* (2017) have assessed those effects on hydraulic jump characteristics through experimental research. On the other hand, as mentioned above, there are many studies that have investigated hydraulic jumps on adverse slopes but there is no unit of research to consider a stilling basin with adverse slope and corrugated bed simultaneously using experimental or even mathematical models. The mentioned research studies would be efficient solutions for reliable design of stilling basins downstream of transversal hydraulic structures, but optimizing the stilling basin design variables leads to its best hydraulic operation.

To the extent of the authors' knowledge, the literature on designing stilling basins lacks the application of simulation–optimization models in order to optimize the characteristics of stilling basins with adverse slope and corrugated bed. On the other hand, no study has been carried out to investigate the simultaneous effects of upstream Froude number, flow discharge and the mentioned decision variables on the optimization objectives, i.e. length of the hydraulic jump, sequent depths ratio and relative energy loss. Length of the stilling basins definitely depends on length of the hydraulic jump and the sequent depths ratio. Obviously, both of the above-mentioned parameters are better to get minimized in order to have the stilling basin design variables at their acceptable amounts. Accordingly, optimal design of the bed slope of the stilling basin and diameter of bed roughness is done in this study through an artificial neuron network (ANN) simulation model and genetic algorithm optimization model.

METHODS

Two principal characteristics of stilling basins are bed slope and the diameter of bed roughness. The purpose of this study is to develop a simulation–optimization model in order to specify the two mentioned features considering the flow characteristics. Figure 1 depicts stages of the suggested methodology to determine the optimal characteristics of the stilling basin. The proposed methodology contains three steps. In the first step, the essential data and information for design of the stilling basin based on the physical model are gathered (Ahmadi 2013). In the second step, the multi-layer perceptron (MLP) neural network meta-model is trained and validated according to the collected data of step 1. Finally, in the third step, the validated MLP meta-model is coupled with the genetic algorithm optimization model in order to create the simulation–optimization model to determine detecting the bed slope and bed roughness diameter of the stilling basin considering the hydraulic jump features.

MLP neural network model

The MLP neural network model is one of the most common architectures of neural networks and belongs to a general class of structures called feedforward neural networks. The MLP neural network has been used in around 90% of the developed ANNs in the research fields of hydraulic structures (Nikoo *et al.* 2015; Nikoo *et al.* 2017), hydrology (Azzellino *et al.* 2015) and other water-related issues (Coulibaly *et al.* 2000; Farhadi *et al.* 2016; Zangooei *et al.* 2016). The MLP neural network model contains several layers in which there are neurons with a nonlinear activation function (Ruck *et al.* 1990; Karlik & Olgac 2011). According to the architecture of the MLP neural network model, each neuron of the layers, except the first layer, is connected to the neurons of the previous layers. On the one hand, the output parameters of every layer are utilized as the input

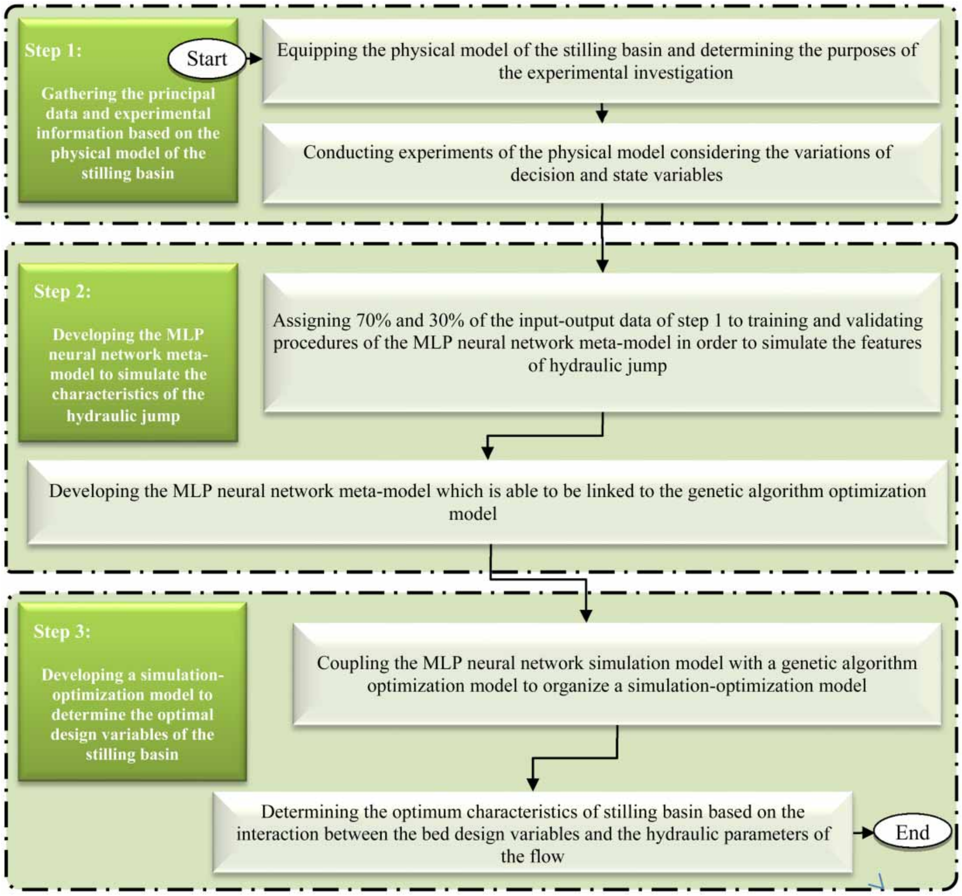


Figure 1 | Framework of the proposed data-driven simulation–optimization methodology for optimal design of stilling basin features with adverse slope and corrugated bed.

data of the subsequent layer. Weights of the neurons are also designated through the feedforward calculating processes (Zhang *et al.* 2003; Nikoo *et al.* 2015). It is remarkable to note that in this research study, there are four input variables of the MLP neural network meta-model including two decision variables, namely, the bed slope and the diameter of the semicircular PVC strips as artificial bed roughness and also two state variables, including the Froude number of the upstream flow and flow discharge.

Figure 2 illustrates the general architecture of the developed MLP neural network model with specified input and output variables. As is shown, the developed MLP neural network model used in this paper contains four input variables, four neurons in a hidden layer and finally three output variables. The Levenberg–Marquardt algorithm with tangent sigmoid activation function is also used as the training strategy of the MLP neural network models for the hidden layer. It is important to notice that the activation function of the output layer is linear. On the other hand, for different sets of data, the three objectives of optimization (length of the hydraulic jump, sequent depths ratio and relative energy loss) were checked to have reasonable amounts. Also the discretization process is done between the maximum and minimum scenarios of the existing criteria in

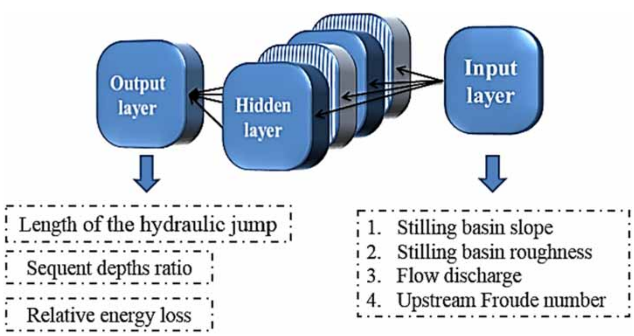


Figure 2 | The architecture of the developed MLP neural network model with input–output variables.

order to be sure that the number of model samples is sufficient and no extrapolation is done.

In the present research, a shuffled sampling strategy was used to divide the dataset into train and test sections. So, an independent generation of samples without any bias of the dataset is acquired. In addition, it was investigated that the range of the training set encompassed the test data. There are some studies that have used this way to divide the dataset (Govindaraju 2000; Reitermanov 2010; Ehsani *et al.* 2016; Alizadeh *et al.* 2017).

The MLP neural network meta-models are utilized in order to determine the interaction between the flow and hydraulic jump features and the stilling basin characteristics. The MLP neural network meta-models are then linked to the genetic algorithm optimization model in order to determine the optimal design variables of the stilling basin. Details of applying the optimization model are presented in the next section.

Genetic algorithm optimization model

The effective conditions on design of hydraulic structures should be taken into account in order to maximize the optimal design validity as much as possible. The optimal design of hydraulic structures causes the hydraulic characteristics of the flow to be in their best states. Hydraulic jumps upon a stilling basin have three important features, namely, length of the hydraulic jump, sequent depths ratio and flow energy loss. As mentioned, the hydraulic jump must be confined through the stilling basin. Thus, the length of the hydraulic jump and sequent depths ratio should be at their minimum possible values considering the economic justifications. On the other hand, erosion of the hydraulic structures and relevant problems are from the substantial subjects that should be taken into consideration in hydraulic designs. So, the energy loss of the flow through the hydraulic jump must have its maximum amount to preserve the structures from erosion and failure. Hence, these three mentioned parameters are objectives of the optimization with important effects on design of the decision variables. As a result of the different effects, three weights are assigned to each objective on the basis of expert opinions. These weights are multiplied by the objectives, separately, and the three items are summed up to obtain a unique objective function. The objective function features of the optimization model and constraints of the decision variables are presented as below:

$$\min h = \left(w_1 \times \frac{\sum_{dQ=1}^{Q}\sum_{dFr=1}^{Fr} HJL^{dQ,dFr}}{\max HJL^{dQ,dFr}}\right) + \left(w_2 \times \frac{\sum_{dQ=1}^{Q}\sum_{dFr=1}^{Fr} SDR^{dQ,dFr}}{\max SDR^{dQ,dFr}}\right) - \left(w_3 \times \frac{\sum_{dQ=1}^{Q}\sum_{dFr=1}^{Fr} REL^{dQ,dFr}}{\max REL^{dQ,dFr}}\right) \quad (1)$$

$$\sum_{i=1}^{3} w_i = 1 \quad (2)$$

$$HJL = g(x_1, x_2, Q, Fr_1) \quad (3)$$

$$SDR = h(x_1, x_2, Q, Fr_1) \quad (4)$$

$$REL = k(x_1, x_2, Q, Fr_1) \quad (5)$$

$$x_{L_i} \le x_i \le x_{U_i} \quad \forall i = 1, 2 \quad (6)$$

where x_i refers to the ith decision variable, $i = 1$ for bed slope of the stilling basin, and $i = 2$ for the diameter of the semicircular PVC strips as artificial roughness [L]; dQ (flow discharge [L^3T^{-1}]) and dFr (upstream Froude number) are two state variables; $g(x_1, x_2, Q, Fr_1)$, $h(x_1, x_2, Q, Fr_1)$ and $k(x_1, x_2, Q, Fr_1)$ are estimated functions obtained from the nonlinear meta-models and calculate the hydraulic jump length (HJL[L]), sequent depths ratio (SDR) and relative energy loss (REL), respectively; $w_i \ \forall \ i = 1, 2$ are weights assigned to hydraulic optimization objectives, i.e. HJL, SDR and REL; and x_{L_i} and x_{U_i} refer to the lower and the upper values of the ith design decision variables. It is remarkable to note that the mentioned meta-models are created using the MLP neural network simulation model which are then linked to a powerful genetic algorithm optimization model. In addition, the simulation–optimization methodology used in this research can be utilized in other different situations in which there are more decision variables with a nonlinear relationship between the input and output data.

Experimental investigations on the physical model

In this research study, the experimental test results of Ahmadi (2013) are utilized as the input data of the developed MLP neural network models. These experiments are done in

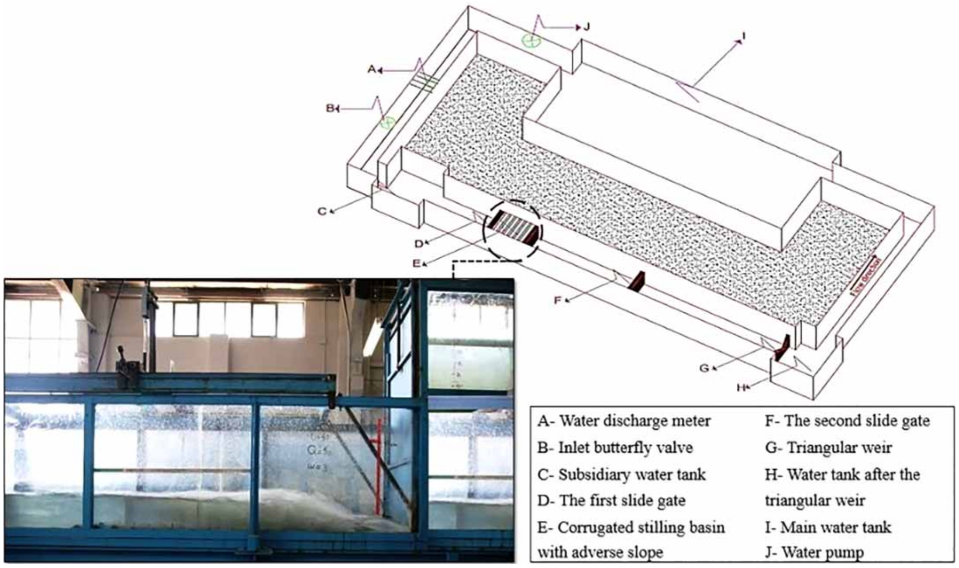


Figure 3 | The experimental flume with stabilized hydraulic jump on the corrugated bed with adverse slope.

the hydraulic sediment laboratory in Shiraz University, Iran. As is illustrated in Figure 3, experiments are performed in a rectangular flume with length and width of 15 and 0.705 metres, respectively, with a main water reservoir of 12 cubic metres capacity. A metal slide gate is utilized at the beginning of the flume in order to create a supercritical flow. The second metal slide gate is prepared about 5 metres after the first one to control and fix the hydraulic jump. The adverse bed slopes of the stilling basin are set using a metal sheet 2 metres long and 2 millimetres wide.

Figure 4 indicates the semicircular PVC strips with diameters of $2r = 32$, 40 and 50 millimetres located on the

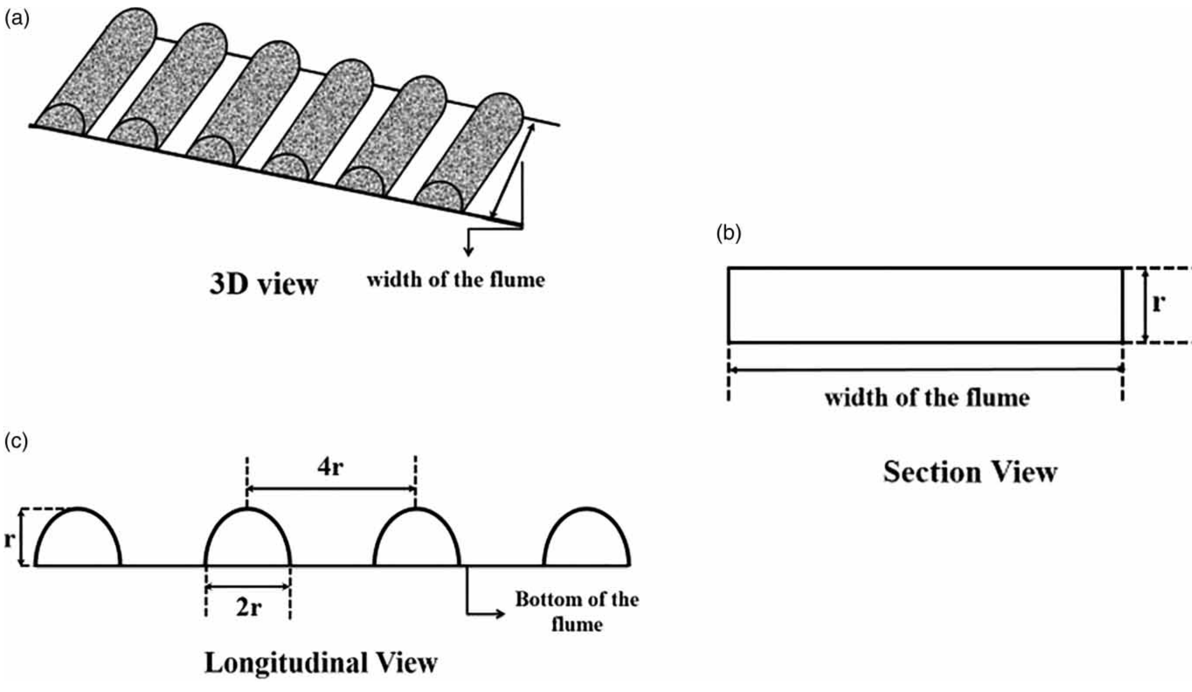


Figure 4 | Schematic view of the corrugated bed of the stilling basin: (a) 3D view, (b) section view, (c) longitudinal view.

metal sheet with specified intervals to create three separate corrugated beds. The 3D view, section view and longitudinal view of the corrugated bed are illustrated in Figure 4(a)–4(c), respectively.

Eventually, experiments are done with four slopes of 0, −0.01, −0.015 and −0.02 and three various flow discharges equal to 40, 45 and 50 litres per second. The three mentioned flow discharges are combined with three different opening values of the first metal slide gate, which leads to nine different values of upstream Froude numbers.

In total, 144 experiments are done in which the effects of variation in state and decision variables (flow discharge, upstream Froude number, bed slope and bed roughness diameter) are tested on the hydraulic jump length, sequent depths ratio and relative energy loss of the flow.

RESULTS AND DISCUSSION

As mentioned, the hydraulic simulation of the stilling basin is done based on the MLP neural network model. Results of the experimental tests done on the physical model were used to train and validate the MLP neural network meta-models. Of the obtained results, 70% and 30% (100 and 44 subsets) are used for training and validating the MLP neural network simulation models, respectively. It should be stated that the

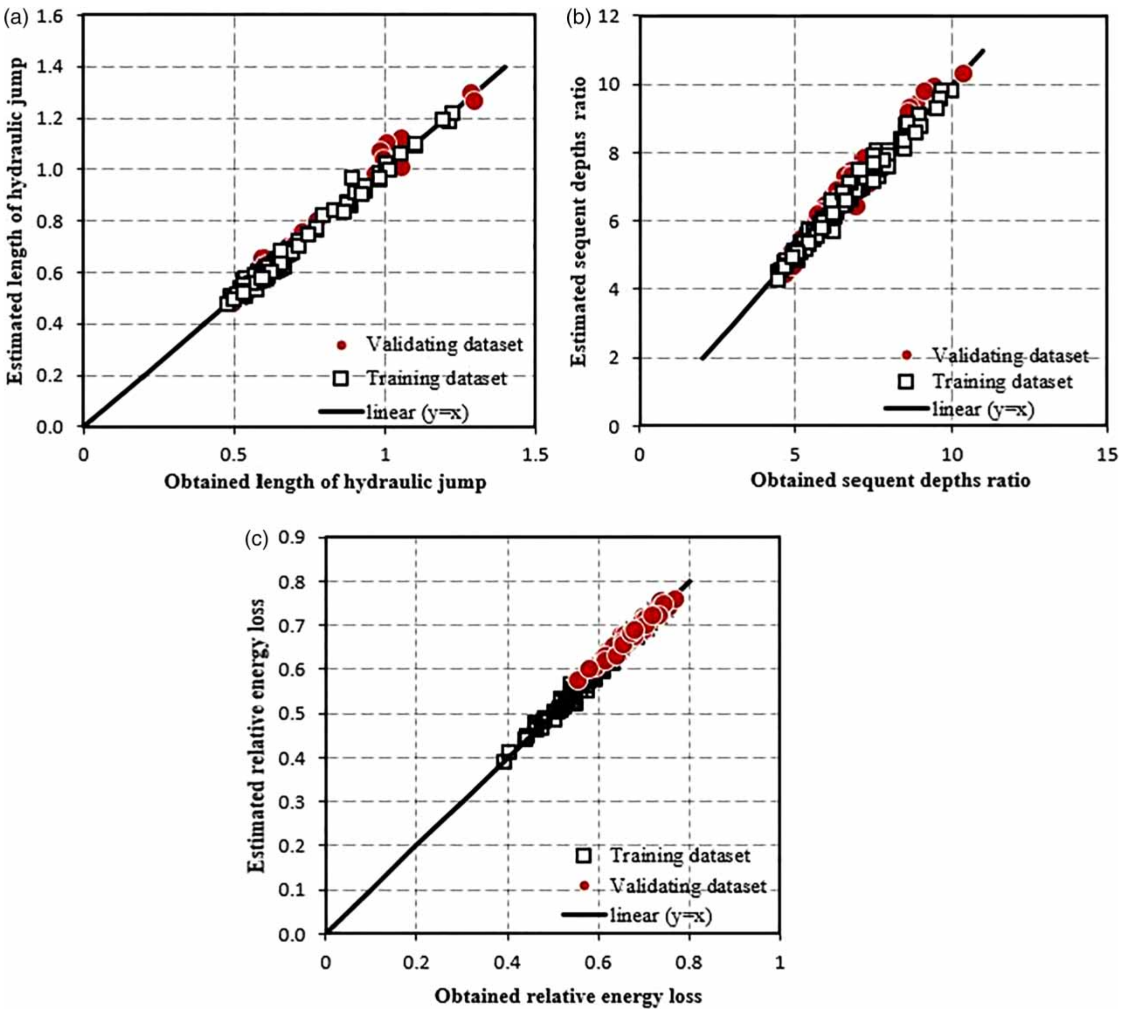


Figure 5 | The results of the developed MLP neural network models to estimate (a) length of the hydraulic jump, (b) the sequent depths ratio, (c) the relative energy loss of the flow for training and validating datasets.

training data were utilized to approximate the precision of the proposed models. Also, the early stopping method was applied in order to prevent overfitting problems (Doan & Liong 2004; Piotrowski & Napiorkowski 2013).

The input data of the MLP neural network simulation models were bed slope, roughness diameter of the stilling basin, flow discharge and upstream Froude number. The output data of the developed MLP neural network meta-models would be length of the hydraulic jump, the sequent depths ratio and the relative energy loss of the flow.

The validation results of the developed MLP neural network simulation models to determine the length of the hydraulic jump and sequent depths ratio are presented in Figure 5(a) and 5(b), respectively. Figure 5(c) illustrates the efficiency of the MLP neural network simulation model for estimation of the relative energy loss of the flow for training and validation stages. These figures confirm the remarkable performance of the ANN model in simulating hydraulic jump characteristics.

Figure 6 indicates the acceptable amounts of the statistical measures including correlation coefficient and mean absolute relative error. Results show that the MLP neural network models have an acceptable accuracy for simulating the features of hydraulic jump. According to correlation coefficient error index results, the acceptable amounts of R^2 show the accuracy of the MLP neural network models. The other error index is mean absolute relative error and its amounts are below 5 for the MLP neural network models, which is an acceptable range.

The validated MLP simulation meta-model was coupled with the proposed genetic algorithm optimization model in order to determine the optimum features of the stilling basin. The final consequences pertaining to the objectives of the optimization and the mentioned values for the optimal design of the stilling basin are presented in Table 1. The results state that the optimum bed slope for design of the stilling basin is equal to -0.02 and also that the optimum diameter of the semicircular PVC strips, as the artificial roughness, would be 20 millimetres.

The sensitivity analysis was then carried out in order to investigate the effects of changing the weights of the objectives ω_i where $i = 1, 2, 3$, on the results of the simulation–optimization model. To illustrate, the single objective optimization model was executed using different sets of weights and then the results were compared in order to see

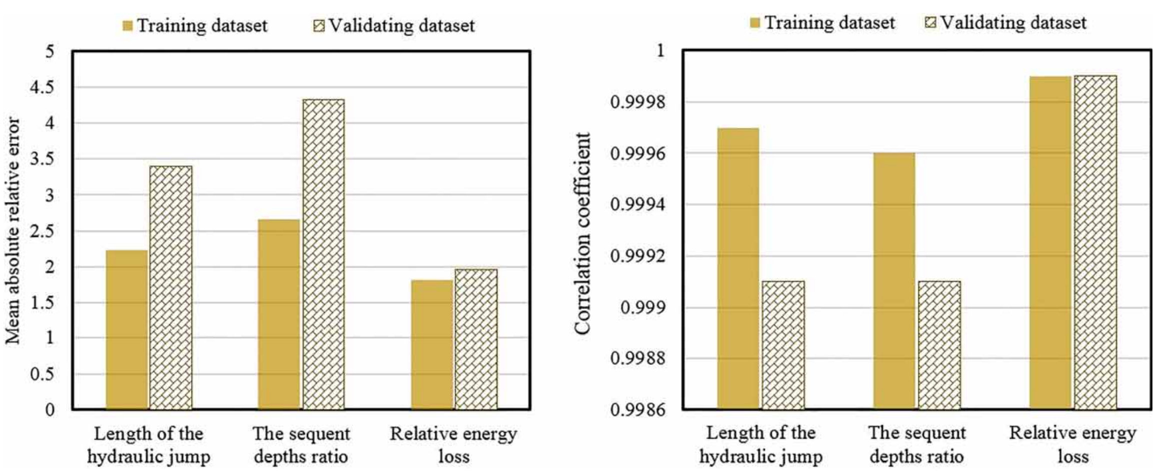


Figure 6 | The statistical error indices of the MLP neural network meta-models in training and validating datasets.

Table 1 | The optimal values pertaining to the objectives of the optimization and decision variables

Optimal design decision variables (x_i ∀ $i = 1, 2$)		Optimization objectives (h_i ∀ $i = 1, 2, 3$)		
Slope of the stilling basin (x_1)	**Roughness diameter of the stilling basin (x_2, mm)**	**Length of the hydraulic jump (h_1, m)**	**The sequent depths ratio (h_2)**	**The relative energy loss (h_3)**
-0.02	20	0.5	4.78	0.553

the relative changes of stakeholders' priorities. As is shown in Figure 7, set A of the weights specifies the condition in which all weights related to the objectives of the optimization are nearly the same. In set B of weights and comparing with set A, by increasing the assigned weight of the relative energy loss (w_3), the amounts of hydraulic jump length and sequent depths ratio reduce while the relative energy loss of the flow increases. Also in set C of weights and according to set A, increasing the weight of the sequent depths ratio (w_2) has no remarkable effect on variations of the three objectives of the optimization.

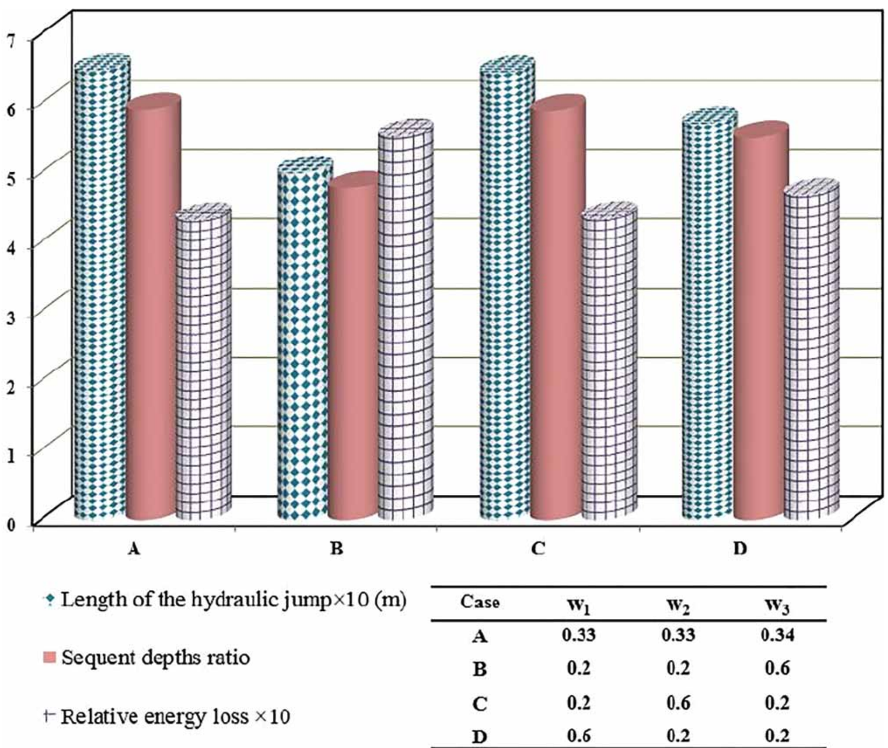
On the other hand, in all cases of weights, the roughness diameter of the stilling basin, as a decision variable, is constant. In other words, as Figure 8 indicates, the bed roughness is independent of the variations of the weights assigned to optimization objectives. Regarding the effects of different weights assigned to the objectives of the optimization, different results can be achieved by stakeholders. This result can help decision-makers to choose correct weights for the objectives of the optimization which are compatible with their viewpoints.

CONCLUSIONS

In this research study, a simulation–optimization approach is proposed to determine the optimal characteristics of a stilling basin. The bed slope and the diameter of the semi-circular PVC strips as artificial roughness are optimized considering the hydraulic features of the flow and the hydraulic jump upon the stilling basin. The intended methodology designates the minimum amounts for the hydraulic jump length and the sequent depths ratio and also maximizes the relative energy loss of the flow. Consequences of the present research study indicate the appropriate efficiency of the methodology for optimal design of the features of the stilling basin.

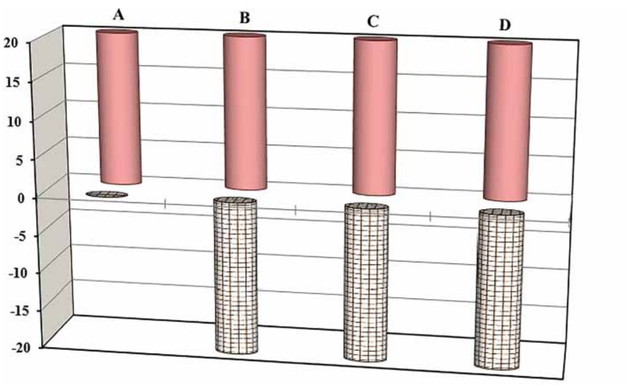
The concise advantages of the mentioned simulation–optimization methodology can be discussed as follows:

- Determining the optimal properties of the stilling basin considering the fluid flow characteristics and the hydraulic jump features, i.e. flow discharge and the upstream Froude number.



Case	w_1	w_2	w_3
A	0.33	0.33	0.34
B	0.2	0.2	0.6
C	0.2	0.6	0.2
D	0.6	0.2	0.2

Figure 7 | The sensitivity analysis to investigate the effects of changing weights of the objectives on the results of the simulation–optimization model.



Case	w_1	w_2	w_3
A	0.33	0.33	0.34
B	0.2	0.2	0.6
C	0.2	0.6	0.2
D	0.6	0.2	0.2

Figure 8 | The sensitivity analysis to investigate the effects of changing weights of the objectives on the results of the simulation–optimization model.

- Using the hydraulic jump length and the sequent depths ratio as two objective functions of the developed optimization model causes economic discussions to be taken into account through the stilling basin optimal design procedure leading to more reliable and cost-effective consequences.

As further research based on the present study, it could be proposed to develop a multi-objective optimization model considering the cost and hydraulic objectives in order to optimize the design parameters of stilling basins regarding viewpoints of different stakeholders. Furthermore, available uncertainties of the optimal design of stilling basins can be considered in future studies to acquire more accurate results. In addition, the mathematical modelling of a stilling basin with adverse slope and corrugated bed can be investigated as a further step of research in order to compare the results with the present study.

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