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Artificial neural networks aided conceptual stage design of water harvesting structures☆

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Summary The paper presents artificial neural networks (ANNs) based methodology for ascertaining the structural parameters of water harvesting structures (WHS) at the conceptual stage of design. The ANN is trained using exemplar patterns generated using an in-house MSExcel based design program, to draw a functional relationship between the five inputs design parameters namely, peak flood discharge, safe bearing capacity of strata, length of structure, height of structure and silt factor and four outputs namely, top width, bottom width, foundation depth and flood lift representing the structural parameters of WHS. The results of the study show that, the structural parameters of the WHS predicted using ANN model are in close agreement with the actual field parameters. The versatility of ANN to map complex or complex unknown relationships has been proven in the study. A parametric sensitivity study is also performed to assess the most significant design parameter. The study holistically presents a neural network based decision support tool that can be used to accurately estimate the major design parameters of the WHS at the conceptual stage of design in quick time, aiding the engineer-in-charge to conveniently forecast the budget requirements and minimize the labor involved during the subsequent phases of analysis and design.

Introduction

The water harvesting structure (WHS) is either broad crested or sharp crested weir, meant for storing water catering to the drinking water needs of the nearby locality and augment the ground water resources. Growing water crisis and the need to tap the overflowing water sometimes creates immense pressure on the administrative machinery to take immediate action to construct the WHS. In these circumstances the authority empowered to take decisions for the structural and financial feasibility of the structure, has to decide the structural parameters immediately. The vague nature of information available at the conceptual stage of design, make the design activities heuristic in

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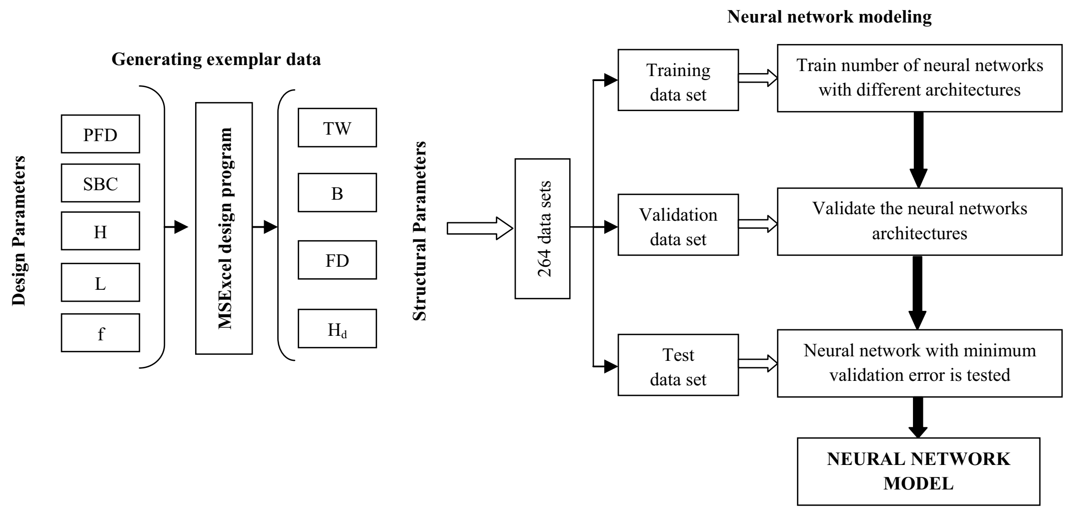

Figure 1 Flowchart of the methodology adopted for the conceptual stage design of the WHS.

nature, relying more on the experience and knowledge of the designer than on computation (Ferreira and Gil, 2012). Since at the conceptual stage, because of the time constraints it is not possible to explore all feasible alternatives (Rafiq et al., 2003) hence, a decision support tool at this stage plays an important role in effectively bridging the gap between vaguely structured conceptual design and finally conceived detailed design.

Paucity of commercially available decision support tools to aid conceptual design catering to a particular problem, has created immense interest among the researchers to harness the capabilities of soft computing tools. One of most popular soft computing techniques is the artificial neural networks (ANNs). Inspired by the structure and working of the human brain, ANNs have been in vogue, particularly since last two decades due to their remarkable ability to learn and draw logical inferences based on the information provided to them during their training phase. Despite ANNs wide applications in the field of pattern recognition, function approximation, classification and control systems (Haykin, 2009), these have not been so far harnessed for the conceptual stage design of WHS. The study presents an ANN based methodology for design of WHS that integrates the experiences of the designer to aid the conceptual stage of design.

Exemplar data and methodology

The conceptual stage of design presented in the study incorporates two stages. The first stage deals with generation or collection of exemplar patterns. The exemplar data for training ANN have been generated using an in-house MSExcel based design program. The design parameters namely, peak flood discharge (PFD), safe bearing capacity of strata (SBC), length of overflow (L), height of structure (H) and silt factor (f) were varied. Using different combinations of the design parameters, 264 exemplar data comprising of top width (TW), flood lift (H_d), bottom width (B) and foundation depth (FD) representing the structural parameters of WHS were generated.

The second stage is related to ANN modeling wherein, the available data is split into three disjoint sets namely, training, validation and test data sets. Subsequently, the training of various neural network architectures using a training data set is performed and all the trained neural networks are validated using the validation data set. The trained neural network with least validation error is selected as the mathematical model for conceptual design of WHS and further tested using test data set for computing the final network error. Finally, the prediction ability of the neural network model is evaluated by presenting it with the actual data. The flowchart for the adopted methodology is presented in Fig. 1.

Development of ANN model for conceptual design of WHS

A neural network is characterized by its architecture that represents the pattern of connection between the nodes, its method of determining the connection weights and transfer function (Fausett, 2008). In the present study a feed-forward back-propagation neural network that primarily consists of three layers: a layer of ''input'' neurons connected to a layer of ''hidden'' neurons which is connected to a layer of ''output'' neurons. The neural network model for the present study is developed using five input neurons namely, PFD, SBC, H, L and f and four output neurons namely, TW, B, FD and H_d. The ''hidden layers'' and ''hidden layer'' neurons have been varied to create a number of neural network architectures.

The training of neural network involves updating the neural network weights. This has been achieved using the Levenberg-Marquardt training algorithm, which is the most efficient and fastest converging algorithm (Hagan and Menhaj, 1994). The transfer function attached to the hidden layer neurons introduces non-linearity into the neural network and enables the neural network to learn nonlinear relationships between input and output vectors (Shamseldin et al., 2002). Log-sigmoid transfer function which is the most widely used transfer function (Ozkan and Erbek, 2003) has

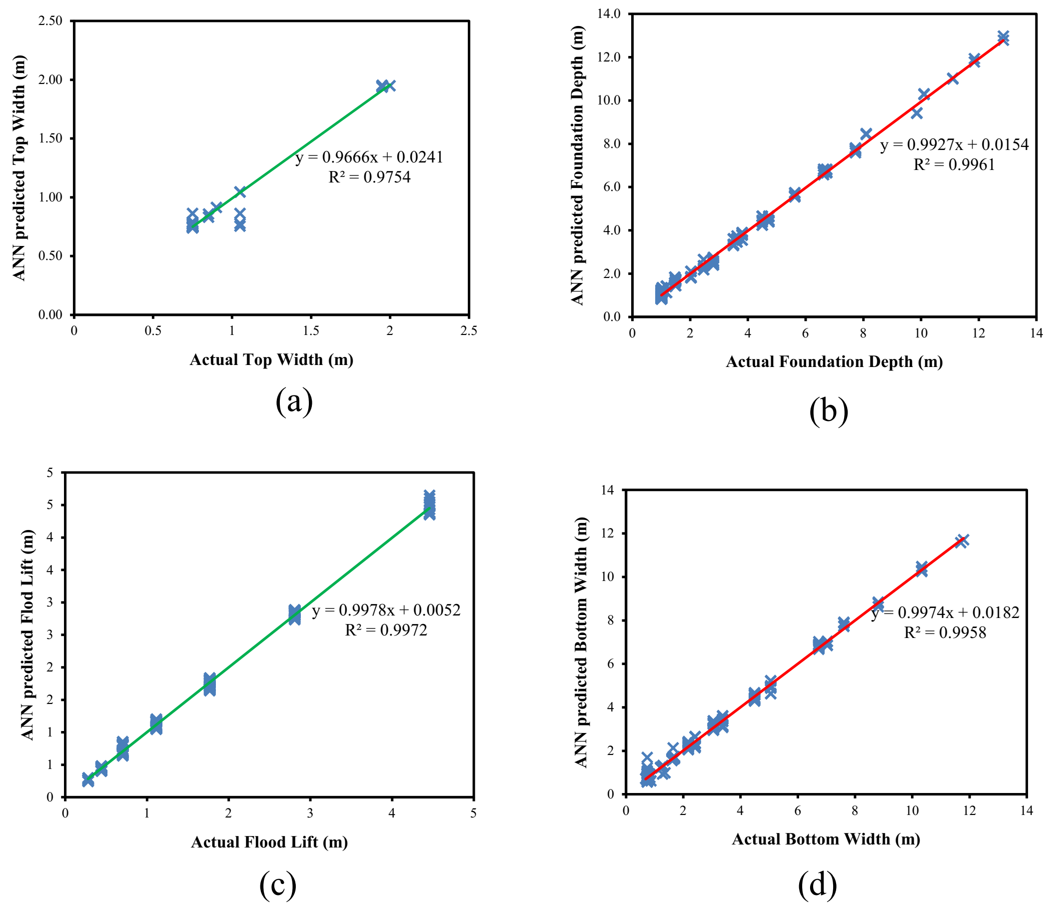

Figure 2 Regression plots for trained neural network model.

been used in the hidden layers to introduce non-linearity and a linear transfer function has been used in output layer for comparing the predicted values with the actual values.

Results and discussion

A number of neural network architectures were trained using the training data set and subsequently validated using validation data set. The network error was evaluated in terms of mean squared error (MSE). The neural network architecture having two hidden layers with six neurons in the first layer and seven neurons in the second layer provided the least validation error. The selected trained neural network model designated as 5-6-7-4 was further tested to evaluate the final network error.

The entire data comprising of 264 datasets was employed for judging the prediction ability of the neural network model (5-6-7-4). The regression plots drawn for ANN predicted values and the actual values for four structural parameters namely, top width (TW), foundation depth (FD), flood lift (H_d) and bottom width (B) shown in Fig. 2(a)—(d) reveal a close agreement between actual and ANN model predicted values with coefficient of determination (R^2) in the range 0.995 and 0.997.

The neural network models are considered as statistical regression models. The prediction ability of the trained neural network model was compared with that of first order and second order regression models by evaluating the coefficient of determination (R^2) and mean square error (MSE). The results shown in Table 1 indicate that ANN model is far superior to the conventional statistical models.

Table 1 Comparison of ANN model with first order and second order regression models.

Structural parameter	Artificial neural network (ANN) model		First order regression model		Second order regression model	
	R^2	MSE	R^2	MSE	R^2	MSE
Top width (TW)	0.975	0.000839	0.131	0.029445	0.359	0.021718
Foundation depth (FD)	0.996	0.024853	0.777	1.502255	0.963	0.239256
Bottom width (B)	0.997	0.002987	0.873	0.133673	0.988	0.012431
Flood lift (H_d)	0.995	0.024399	0.606	2.251066	0.814	1.062604

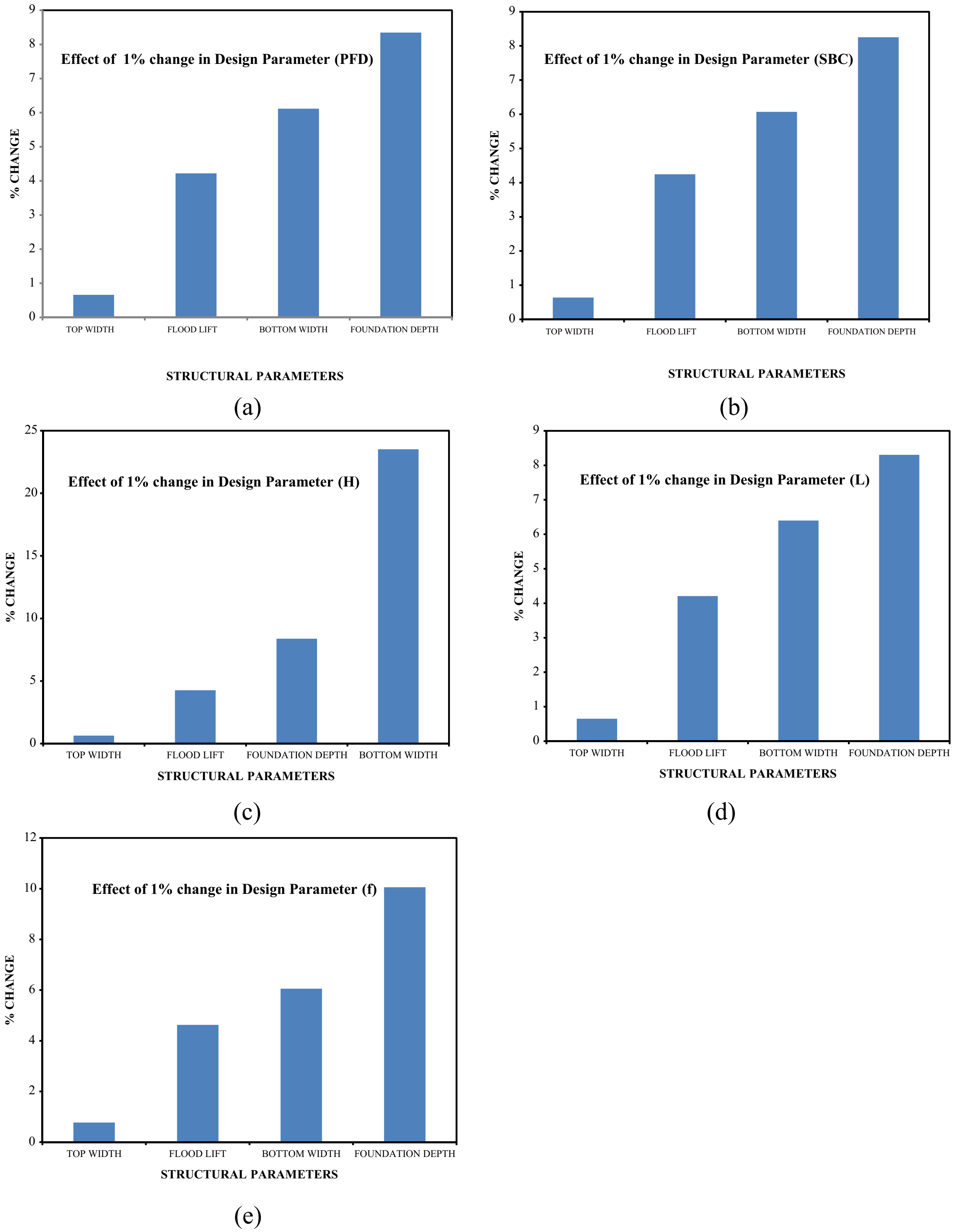

Figure 3 Sensitivity analysis of output parameters due to variation in input parameters.

The sensitivity analysis is performed to find the most important input parameter. Fig. 3(a)—(e) shows the percentage variation in the structural parameter namely, top width (TW), foundation depth (FD), flood lift (H_d) and bottom width (B) when 1% variation is brought about in the design parameter namely, peak flood discharge (PFD), safe bearing capacity (SBC), height (H), length (L) and silt factor (f).

The sensitivity analysis reveals that the height of the structure (H) is the most predominant design parameter influencing the structural parameters of WHS. Its 1% variation leads to 23.51% variation in the bottom width of the structure. This due to the fact that in water resources structure the bottom width governs the stresses at the foundation level. As the height of the structure increases, stresses at foundation level increase demanding higher base width to counteract the increase in stress. Moreover the silt factor (f), peak flood discharge (PFD), length (L) and safe bearing capacity (SBC) have a predominant effect on the foundation depth (FD). All the input parameters have a least influence on the top width (TW) of the structure. This is due to the fact that the overall stability and stress distribution at the foundation level of the structure is governed by its bottom width.

Conclusions

The study reflects the capabilities of ANN computational model mimicking the functioning of a human brain to, successfully aid a designer at the conceptual stage of design in making sensible decisions thereby mitigating the chances of design and analysis cycles at the later stages. The ANN model is shown to accurately predict the structural parameters of WHS and will thus supplement the decision making ability of the designer enabling him to derive a precise estimation of resource requirements right at the initial design stage. Moreover the designer can quickly and accurately predict the structural parameters of a WHS without having to undergo a detailed analysis. A well conceptualized initial design will thus save time and human resources to arrive at the final stage of design.

A comparison of R^2 and MSE values reveals that ANN surpasses the prediction capabilities of the regression models. The uniformity in the R^2 values for top width, foundation depth, bottom width and flood lift illustrates ANN's stability and robustness to change in the input data which allows it to take into account all kinds of possibilities giving an accurate functional relationship.

The parametric sensitivity study helped to extract the most important design parameter. It is seen that 1% variation in the height of the structure has the greatest impact on the bottom width. All other input parameters like silt factor, peak flood discharge, length and safe bearing capacity influence the foundation depth of the structure. Top width parameter is least affected by the change in the input parameters.

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