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Design of Basin Irrigation System using Multilayer Perceptron and Radial Basic Function Methods

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Abstract: The common use of an artificial neural network model has been in water resources management and planning. The length, width, and discharge of a basin were measured in this study utilizing field data from 160 Dashti Hawler existing projects. Multilayer Perceptron (MLP) and Radial Basic Function (RBF) networks were employed in the basin irrigation assessment. Input factors included the soil type, the conveyance system effectiveness, and the root zone depth. 130 projects were used for calibration, while the remaining 30 were used for validation. When developing the basin irrigation system, the models' aforementioned indicators' performance was evaluated using the coefficient of determination (R^2), mean absolute error (MAE), relative error (RE), and Nash Sutcliff efficiency (NSE). For the basin's length, width, and discharge, the (R^2) values for the MLP model were determined to be 0.97, 0.97, and 0.96, respectively, whereas the corresponding values for the RBF model were 0.88, 0.89, and 0.89. Compared to the RBF model, the values of (MAE) for basin length, width, and discharge for the MLP model were determined to be 8.99, 8.52, and 42.58, respectively. However, the (NSE) values for the models mentioned above were 0.95, 0.96, and 0.94, as well as 0.65, 0.66, and 0.66 for the basin's length, width, and discharge, respectively. When it comes to building the irrigation system for the basin, the MLP is more precise than RBF depending on the values of (R^2), (MAE), and (NSE). Finally, the ANN approach uses additional design options quickly examine which model is computationally efficient.

تصميم نظام الري الحوضي باستخدام طريقة برسترون متعدد الطبقات والدالة الأساسية الشعاعية

عبدالواحد علي قاسم، خليل كريم حمدامين
قسم الموارد المائية / كلية الهندسة / جامعة صلاح الدين / اربيل - العراق.

الخلاصة

تم استخدام نموذج الشبكة العصبية الاصطناعية (ANN) على نطاق واسع في العقود الماضية في تخطيط وإدارة الموارد المائية. في هذه الدراسة، تم استخدام النموذجين (MLP) و (RBF) في تصميم الري بالأحواض باستخدام البيانات الميدانية لـ 160 مشروعًا في سهل اربيل، ومن ثم إيجاد قيم الطول والعرض وتصريف الحوض. تم استخدام العديد من المتغيرات كمدخلات مثل نوع التربة وكفاءة النقل المياه وعمق المنطقة الجذرية وما إلى ذلك. تم تقسيم البيانات إلى مجموعتين، 130 لمعايرة النموذج، والباقي 30 للتحقق. تم استخدام المعامل (R^2) و(MAE) و(NSE) لتقييم الأداء للنماذج المذكورة أعلاه في تصميم نظام الري بالاحواض. كانت قيم (R^2) لنموذج (MLP) لطول وعرض وتصريف الحوض هي 0.97 و0.97 و0.96 على التوالي، بينما لنموذج (RBF) كانت 0.88 و0.89 و0.89 على التوالي. بينما قيم (MAE) لنموذج (MLP) كانت 3.35 و2.85 و16.79 على التوالي، اما بالنسبة لنموذج (RBF) لطول الحوض وعرضه التصريف كانت 8.99 و8.52 و42.58 على التوالي. بينما كانت قيم (NSE) للنماذج المذكورة 0.95هي و0.96 و0.94 بالإضافة إلى 0.65 و0.66 و0.66 على التوالي لطول وعرض وتصريف الحوض لنموذج (RBF). اعتمادًا على قيم (R^2) و (MAE) و (NSE) التي تم الحصول عليها في هذه الدراسة؛ يمكن الاستنتاج بأن نموذج (MLP) أكثر دقة من نموذج (RBF) في تصميم نظم ري السطحي باستخدام الاحواض.

الكلمات الدالة: نظام الري بالاحواض، استقرار المنحدر، قلب الطين.

1.INTRODUCTION

Basin systems, furrows, and borders are the three main categories that constitute surface irrigation. Surface irrigation has been widely used globally. Due to its simple nature, complex technologies and related applications are uninvolved. In comparison to the irrigation methods, more initial work is required. All surface system types have advantages and disadvantages, mostly dependent on various variables, such as climate, soil features, crop type, size, fields shape, water supply sources, and initial costs required for the development [1]. In this study, a basin system was designed, considered the most popularly used type of surface irrigation, probably in areas with layouts of smaller fields. In case the leveling of a field has been the same in all directions with an inclusion of a dyke, which is important for preventing runoff, the surface is then can be considered as a basin [2]. Generally, the soils with moderate or relatively slower infiltration are favorable for basin irrigation, those with deep root zone, and fields with spaced crops with the flooding water requirement. Basin irrigation is considered one of the best ways to leach salts from the soil profiles, reaching the deep groundwater. Thus, in the last two decades, several models have been introduced and developed to help design the surface irrigation system. In the current study, two types of artificial neural networks were used MLP and RBF models. Artificial neural networks (ANN) have been extensively employed in recent technical developments to solve issues related to water resources. An ANN was used to represent the intricate hydrological processes required to connect the inputs and outputs using mathematical functions without being aware of their connection [3]. Artificial neural networks (ANN) or connection systems are computer systems generally based on the biological neural networks comprising animal brains. The basis of an ANN is a system of linked artificial neurons that imitates the neurons in a biological brain. Like synapses in the human brain, each connection may transmit a signal to nearby neurons. After digesting signals provided to it, an artificial neuron may signal neurons that are attached to it. Each neuron's output is determined by some nonlinear function of the sum of its inputs, where the signal at a connection is a real integer. The connections' weight often changes as learning progresses, and the weight alters the signal's intensity at the receiver in terms of increasing or decreasing. The neural network is not an algorithm but a framework that allows several machine learning algorithms to cooperate and handle large amounts of complicated data. Such systems study examples to learn how to accomplish tasks, typically without any task-specific rules being implemented [4]. Multilayer perceptron, a feed-forward neural network design with unidirectional connections between subsequent levels, is included among the consecutive layers. In feed-forward networks, the signal flow is strictly in the feed-forward direction from input to output units. There are no feedback links, although the data processing can span several layers of units. This type may be separated into feed-forward neural networks with a single layer and/or several layers [5]. Recently, applying the aforementioned model in hydrological and irrigation systems modeling was increased [6, 7]. Raju et al. (2006) applied three models; i.e., the ANN, separate linear programming (LP), and non-dominated irrigation planning strategies; on the Jayakwadi irrigation project, in Maharashtra, India, as a case study [8]. Ekhmaj et al. (2007) determined a pattern that can be used to wet the land while using the trickle scheme that comes under ANN. These models are based on numerical calculations, and it was found that the ANN strategy generated quite more precise results than other models [9]. Umair et al. (2010) have utilized an intelligent system that can be controlled with the help of ANN technology. It helps operate irrigation scheduling and mainly depends on the metrological data as input variables [10]. Mattar et al. (2015) used the feed-forward neural network technology. This method benefits from the back-propagation training algorithm, which was developed to give a precise estimate of the infiltrating water volume utilized for furrow irrigation. Six experiments were combined to produce 159 data points for this purpose obtained from previously written works [11]. The time needed for watermelon crop watering was determined by Rocha Neto et al. (2015) using the ANN and volumetric water balance (VWB). The experiment was conducted at Lower Acara, a region within a Brazilian irrigation perimeter [12]. Dela Cruz et al. (2017) integrated the feed-forward back-propagation ANN model into the proposed Smart Farm Automated Irrigation System (SFAIS) to improve water usage in crops [13]. Through the use of ANN and nonlinear regression (NLR) techniques, Karimi et al. (2020) developed equations to estimate the up and down wetted regions surrounding the dripper location [14]. The main objectives of this study are the possibility of basin irrigation design by using different types of artificial neural network approach, which is computationally efficient. Also, to determine the length (L), breadth (W), and discharge (Qb) of the irrigation basin to build an irrigation system using the Radial Basic Function (RBF) and Multilayer Perceptron (MLP) models. Consumptive use (Cu), water holding capacity (WHC), root zone depth (RZD), depletion percentage (Dp), application efficiency (Ea), roughness coefficient (n), main canal conveyance efficiency (Ec1), conveyance efficiency of other canals (Ec2), and available discharge (Qa) were used as input data of the models.

2. MATERIAL AND METHODS

2.1. Basin Irrigation System

Since tail-water cannot enter the areas already in use and slopes are often extremely little or nonexistent, basin irrigation designs are simpler than furrow and border designs. Recession and water depletion occur simultaneously and are relatively consistent throughout the basin. The flow-pushing force is only as strong as the hydraulic slope of the water surface because longitudinal and transverse slopes are minimal or zero [15]. Determining whether the basins must be square or rectangular spaces with bunds built around them to regulate irrigation water. Depending on the crop, the available water supply, the features of the soil's infiltration, and other local elements, the area's size may vary significantly. Large-sized basins may be uneconomical and ineffective regarding irrigation efficiency for loam and sandy loam soils with significant infiltration capacity. However, the check basin's field can be expanded for clay soils with lower infiltration rates. The slope of the ground is the primary limiting factor for basin width; when the slope is steep, the width should be modest or significant earthwork should be done to level the land [1]. Three parameters should be found in the basin irrigation design, length, width, and discharge, which are shown in Fig. 1. The basins length (L) may be calculated by Eq. (1):

$$L = \frac{60 * Qu * T_L}{Da + 37 * n^{0.375} * T_L^{0.1875} * Qu^{0.5625}} \quad \textbf{(1)}$$

where Qu is unit discharge, n is roughness coefficient, depending on the types of crops and the status of the surface, T_L is water advance time to the end of the basin, Da is the average accumulated depth of infiltration at the time T_L. While the basin width (W) can be estimated by:

$$N_B = 1300 / L \quad \textbf{(2)}$$

$$W = 1300 / N_B \quad \textbf{(3)}$$

where N_B is the number of basins along with the direction of the field width B. This Eq. is used when the length and width of the basin are equal, and then the width should be adjusted:

$$N_{B\text{-}adj} = 1300/W \quad \textbf{(4)}$$

$$W_{adj} = 1300 / N_{B\text{-}adj} \quad \textbf{(5)}$$

The basin discharge (Qb) is estimated by:

$$Q_b = Q_u \times W_{adj} \quad \textbf{(6)}$$

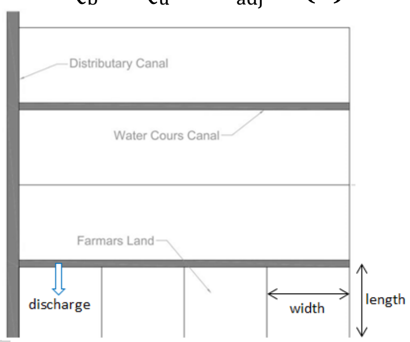


Fig. 1 Parameters of Basin Irrigation System.

2.2. Models Description

In this study, MLP and RBF models have been profoundly utilized to design basin irrigation systems and find the required basin length, width, and discharge.

2.2.1. MLP Model

The input, hidden, and output layers of neurons are the three basic layers of the MLP model, as shown in Fig. 2. Weight is the strength that joins these layers. There are two sets of weights: input-hidden layer weights (wj,i) and hidden-output layer weights (wk,j). Due to these weights, the network is enabled with a high degree of flexibility and can easily respond to data. The total is then processed via a nonlinear function called an activation function or transfer function after each input is typically given a different weight.

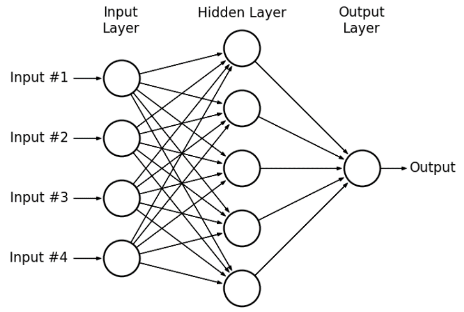


Fig. 2 The Multilayer Perceptron Network Structure.

The output of a node (neuron) is determined by its activation function or transfer function in response to a set of inputs. Only nonlinear activation functions enable such networks to calculate nontrivial issues using only a few nodes. This result is then utilized as an input for the following node until a desired solution for the original problem is discovered [16]. Numerous kinds, including the logistic sigmoid, softmax, and hyperbolic tangent, may be used. Without training, a neural network cannot be utilized to make predictions. During training, the network is typically shown input and target pairings one at a time so that it may learn from them. The neural network is requested to estimate using the weights as they are right now, and its performance is then evaluated using an error function criterion. If the performance was poor compared to the previous attempt, the network weights were modified to deliver the appropriate or proper output [17]. The error function indicates how closely the network predictions are to the objectives and, consequently, how much weight adjustment should be applied by the training algorithm in the iteration and used to assess a neural network performance during training. Consequently, the error function serves as the training algorithms' eyes to determine how well a network works given its present stage of training and, as a result, how much change to the value of its weights should be made [18]. Error function types are some of the squares and cross-entropy used for the MLP model. Eq. (7) derives output results from multilayer perceptron artificial neural networks [19]:

$$Y_{(k)} = f_o\left[\sum_{j=1}^{m}\left(w_{k,j} * f_h\left(\sum_{i=1}^{n}\left(w_{j,i} * x_i\right) + b_j\right)\right) + b_k\right] \quad \textbf{(7)}$$

where $Y_{(k)}$ is the output variable, x_i is the input variable, $w_{j,i}$ is the weight of input-hidden, $w_{k,j}$ is the weight of hidden-output layers, b_j is the bias of the hidden layer, b_k is the bias of the output layer, n is the number of input variables, m is the number of neurons in the hidden layer, k is the number of output variables, f_h is the activation function of the hidden layer, and f_o is the activation function of the output layer.

2.2.2. *RBF Model*

Fig. 3 shows the radial basis function neural networks. The design is compared to a typical feed-forward back-propagation network. This type can be created faster, although it frequently calls for more neurons [20].

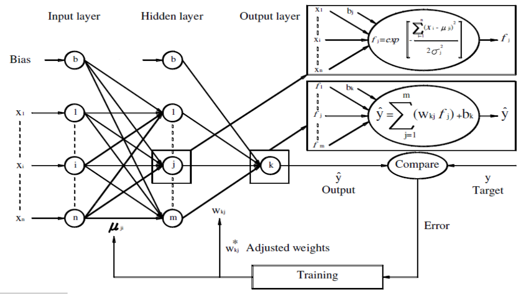


Fig. 3 Typical Radial Basis Network Function Structure.

The radial basis function was used to transfer the input to a hidden layer format. The output from this Eq. represents the response of the network and is represented by Eq. (8):

$$Y_k = \sum_{j=1}^{m}\left(w_{k,j} * f_j\left(exp\left(-\frac{\sum_{i=1}^{n}\left(x_i-\mu_{j,i}\right)^2}{2\sigma_j^2}\right)\right)\right) + b_k \quad \textbf{(8)}$$

where $\hat{Y}_k$ is the output variable, x is the input variable, μ is the center of the Gaussian, σ is the standard deviation, n is the number of neurons in the inputs layer, $w_{k,j}$ is the weight of the connection between the hidden neuron j and the output neuron k, b is the bias, and m is the number of neurons in the hidden layer.

2.2.3. *Field Data*

The variables used as input data of the aforementioned models were consumptive use (Cu), water holding capacity (WHC), root zone depth (RZD), depletion of water percentage (Dp), the application efficiency (Ea), roughness coefficient (n) depending on the crop type and the status of surface area, the conveyance efficiency of the main canal (Ec1), conveyance efficiency of other canals (Ec2), and available discharge (Qa). In addition, the types of crops used here are summer crops. Table 1 shows the range of each variable obtained from the Directorate of Irrigation-Erbil.

Table 1 The Range of the Available Data of the Dashti Hawler Projects that used as Input Variables.

Variable	Unit	Min. value	Max. value
Consumptive use (Cu)	mm/day	0.76	9.50
Water Holding Capacity (W.H.C)	mm/cm	0.3	1.5
Root Zone Depth (R.Z.D)	Cm	60	100
Depletion Percentage (Dp)	%	70	70
Application Efficiency (Ea)	%	80	92
Roughness Coefficient (n)		0.04	0.25
Available Discharge (Qa)	lit/sec	2000	10000
Conveyance Efficiency (Ec1)	%	95	95
Conveyance Efficiency (Ec2)	%	90	90

2.2.4. Evaluation of Model's Performances

Four different statistical criteria were used to evaluate the accuracy of the predictions made by the two models. The model's effectiveness was assessed using the following metrics: Nash Sutcliff efficiency, mean absolute error, relative error, and coefficient of determination. From Eq. (9) [21], the coefficient of determination (R^2) may be derived from:

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O-\bar{O}).(P-\bar{P})}{\sqrt{\sum_{i=1}^{n}(O-\bar{O})^2.\sum_{i=1}^{n}(P-\bar{P})^2}}\right]^2 \qquad \textbf{(9)}$$

where O is the observed data, P is the predicted data, n is the number of data, $\bar{O}$ is the average of observed data, and $\bar{P}$ is the average of predicted data.

Mean Absolute Error (MAE) is a measure of the difference between two continuous variables, predicted versus observed values. Considering this type, the most appropriate model has the least value; and can be measured by Eq. (10) [21]:

$$MAE = \frac{1}{n}.\sum_{i=1}^{n}|O-P| \qquad \textbf{(10)}$$

The relative error (RE) is the ratio of the absolute error to the actual measurements. The relative error indicates how good the results are compared to the actual measurement and can be found using Eq. (11).

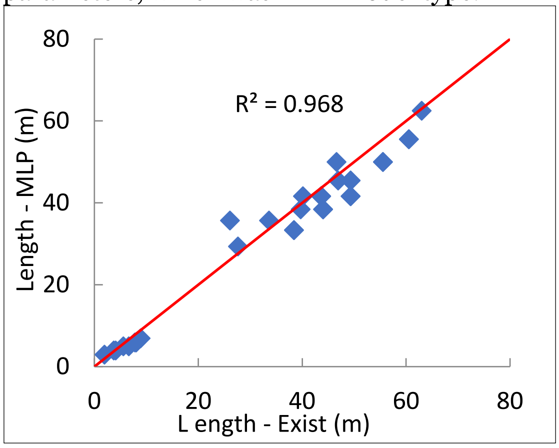
$$RE = |P - O| \,/\, O \qquad \textbf{(11)}$$

Nash Sutcliff efficiency (NSE) comes under the category of normalized statistics, which helps determine the relative magnitude of the residual variance and measured data variance. When the value of NSE = 1, it showed a perfect match of the model concerning the observed data. When NSE = 0, it depicts that the model predictions are correct and cohere with the mean of the observed data and may be found by the following Eq.

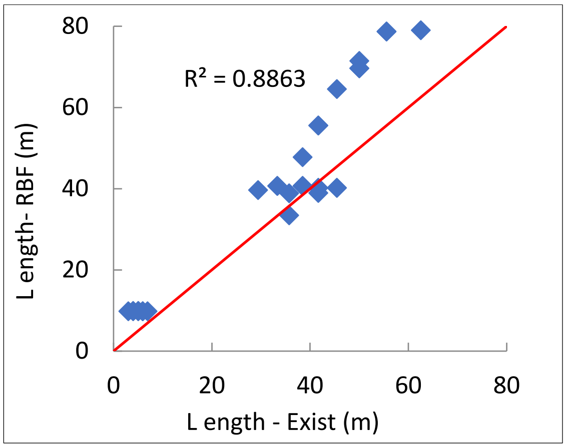
$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(O-P)^2}{\sum_{i=1}^{n}(O-\bar{O})^2}\right] \qquad \textbf{(12)}$$

3. RESULTS AND DISCUSSION

The MLP and RBF models were utilized using (Matlab version 2008) and (SPSS version 23.0). These models were used to calibrate and validate the models for designing a basin irrigation system and finding the design length, width, and discharge of the basin. For both models, the 160 available data were divided into two sets, i.e., 130 for calibration and 30 for validation. The best models of the MLP were (6, 4, and 3), where 6 is the input nodes number, 4 is the hidden nodes number, and 3 is the nodes number for the output layer. The hidden layer's activation function was discovered to be a hyperbolic tangent function, while the output layer's activation function was found to be an identity function. To avoid overtraining, maximum training epochs were estimated automatically, and the gradient descent approach was used to describe the optimization process. In the validation stage, the (R^2) values for output values of the MLP model for the length (L), width (W), and discharge (Qb) were found to be 0.97, 0.97, and 0.96, respectively, as shown in Figs. (4-6) and Tables (2-4). While for the RBF model, (R^2) values were found to be 0.88, 0.89, and 0.89, respectively. However, the values of MAE for the MLP model were found to be 3.35, 2.85, and 16.79, respectively, and for the RBF model were found to be 8.99, 8.52, and 42.58, respectively. Furthermore, the values of (RE) for the output of the MLP model were found to be 0.08, 0.09, and 0.08 for length, width, and basin discharge, respectively, as shown in Tables (2-4), and for the RBF model were found to be 0.25, 0.29, and 0.27, respectively. In addition, the values of (NSE) of the MLP model were found to be 0.95, 0.96, and 0.94, respectively, and equal to 0.65, 0.66, and 0.66 for the RBF model, respectively. The most suitable model was attained by comparing the results with provided data due to higher values of (R^2) and NSE and lower values of MAE and (RE) for the above design parameters, which was MLP model type.

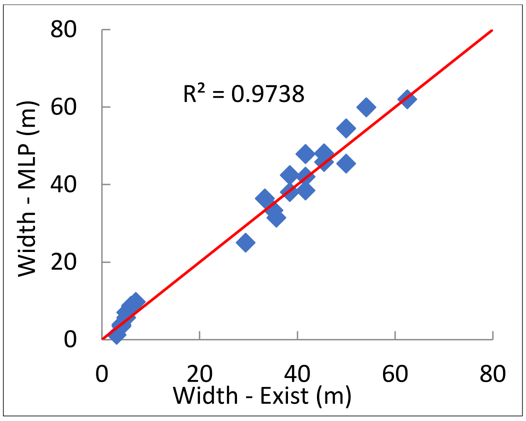


MLP Model

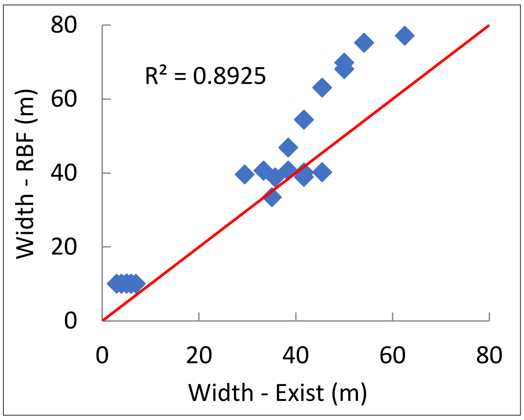


RBF Model

Fig. 4 Determination Coefficients (R2) for the Length of the Basin using MLP and RBF Models.

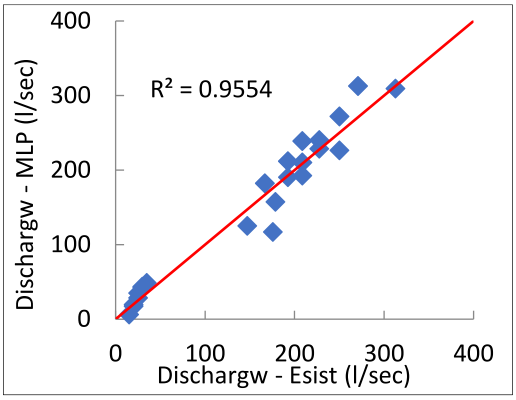


MLP Model

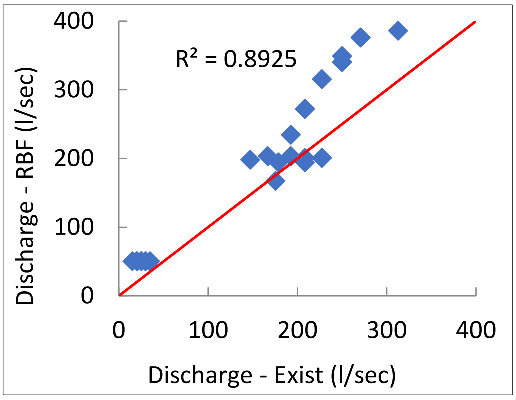


RBF Model

Fig. 5 Determination Coefficients (R2) for the Width of the Basin using MLP and RBF Models.



MLP Model



RBF Model

Fig. 6 Determination Coefficients (R^2) for Basin Discharge using MLP and RBF Models.

Table 2 Determination Coefficients (R^2), (MAE), (RE), and (NSE) for the Length of the Basin using MLP and RBF Models.

Statistical evaluation types	Calibration stage		Validation stage	
	MLP	RBF	MLP	RBF
R^2	0.98	0.86	0.97	0.88
MAE	4.24	13.93	3.35	8.99
RE	0.07	0.22	0.08	0.35
NSE	0.98	0.65	0.95	0.65

Table 3 Determination Coefficients (R2), (MAE), (RE), and (NSE) for the Width of the Basin using MLP and RBF Models.

Statistical evaluation types	Calibration stage		Validation stage	
	MLP	RBF	MLP	RBF
R^2	0.99	0.86	0.97	0.89
MAE	3.69	13.65	2.85	8.52
RE	0.07	0.22	0.09	0.38
NSE	0.99	0.66	0.96	0.66

Table 4 Determination Coefficients (R^2), (MAE), (RE), and (NSE) for Basin Discharge using MLP and RBF Models.

Statistical evaluation types	Calibration stage		Validation stage	
	MLP	RBF	MLP	RBF
R^2	0.99	0.86	0.96	0.89
MAE	18.63	68.62	16.79	42.58
RE	0.07	0.22	0.08	0.36
NSE	0.99	0.66	0.94	0.66

Finally, Eq. (7) may be rearranged as follows:

$$\boldsymbol{Y_{(k)}} = \left[\sum_{j=1}^{4}\left(\boldsymbol{w_{k,j}} * \boldsymbol{tanh}\left(\sum_{i=1}^{6}\left(\boldsymbol{w_{j,i}} * \boldsymbol{x_i}\right) + \boldsymbol{b_j}\right)\right) + \boldsymbol{b_k}\right] \qquad \textbf{(13)}$$

In this Eq., when k=1, the value of $Y_{(1)}$ is considered the basin length (L). When k=2, the value of $Y_{(2)}$ is considered the basin discharge (Qb). Also, when k=3, the result $Y_{(3)}$ is considered the basin width (w).Tables (5, 6) show the values of weights between the input and hidden layers ($w_{j,i}$), between the hidden and output layers ($w_{k,j}$), the bias of the hidden layer (b_j), and the bias of the output layer (b_k). These values can be used in Eq. (13) to obtain the design parameters.

Table 5 Values of weights and bias between nodes of the input and hidden layers for the MLP model.

		Hidden Layer Nodes			
		H1	H2	H3	H4
Input Layer Nodes	(Bias)	-0.2844	-0.0177	-1.6200	-0.8825
	n	0.1288	-0.0922	-0.4072	-0.1849
	Q	0.0619	-0.1836	0.6816	-0.0349
	RZD	-0.4075	0.0785	0.8065	0.7712
	WHC	0.8811	1.3656	0.6530	0.9473
	Ea	0.4393	-0.2654	-0.4556	-0.4683
	Cu	0.1865	-0.0020	0.2271	-0.2339

Table 6 Values of weights and bias between nodes of the hidden and output layers for the MLP model.

		Output Layer Nodes		
		L	Qp	W
Hidden Layer	(Bias)	0.3757	0.3854	0.3703
	H1	-0.3167	-0.3961	-0.3974
	H2	0.8846	0.9583	0.9596
	H3	0.6423	0.7275	0.7002
	H4	0.4199	0.3184	0.3305

4. CONCLUSIONS

The challenge in this research was to test the possibility of basin irrigation design by using an artificial neural network, which is often used for predicting, with some attempts here and there to use it for design in different engineering applications. The models used in this research are only specific to the research study area or any similar regions, provided that the upper and lower limits of the input data in the design are shown in Table 1. In addition, few input data have been deleted by the model because they are fixed values here, such as depletion percentage and conveyance efficiency; however, this does not mean that they were removed from the design, as they must be considered in the design and not to be changed, since it could lead to the model failure. In this study, two methods named MLP and RBF were used to design the basin irrigation system to find the basin's length (L), width (W), and discharge (Qb) at the condition that the necessary conditions for designing this method of irrigation are met. It was concluded that the MLP model results were more accurate than the RBF model for designing the basin irrigation system and finding the area measurements that account for the basin length and width. This result was due to higher values of (R^2) and (NSE), and lower values of (MAE) and (RE). Also, it was found that the basin discharge for both models provided extremely close results. Using the MLP and RBF models to design other types of irrigation systems, such as furrows and borders, is recommended.

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