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Determination of Pipe Diameters for Pressurized Irrigation Systems Using Linear Programming and Artificial Neural Networks

Ezgi KURTULMUS[a]*, Ferhat KURTULMUS[a], Hayrettin KUSCU[a], Bilge ARSLAN[a], Ali Osman DEMIR[a]

[a]*Department of Biosystems Engineering, Faculty of Agriculture, Bursa Uludag University, 16059, Bursa, TURKEY*

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Corresponding Author: Ezgi KURTULMUŞ, E-mail: ezgikaberli@uludag.edu.tr
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ABSTRACT
Pressurized irrigation systems are widespread among other alternatives in Mediterranean countries. Since the initial investment costs of pressurized irrigation systems are quite high, it is crucial to determine design parameters such as pipe diameter. Most of the current optimization techniques for pipe diameter selection are based on linear, non-linear, and dynamic programming models. The ultimate aim of these techniques is to produce solutions to problems with less cost and computation time. In this study, a novel approach for determining pipe diameter was proposed using Artificial Neural Networks (ANN) as an alternative to existing models. For this purpose, three pressurized irrigation systems were investigated. Different ANN architectures were created and tested using hydrant level parameters of the irrigation systems, such as irrigated area per hydrant, hydrant discharge, pipe length, and hydrant elevation. Different training algorithms, transfer functions, and hidden neuron numbers were tried to determine the best ANN model for each irrigation system. Using multilayer feed-forward ANN architecture, the highest coefficients of determination were found to be 0.97, 0.93, and 0.83 for irrigation systems investigated. It was concluded that pipe diameters could be determined by using artificial neural networks in the planning of pressurized irrigation systems.

Keywords: Machine learning, Optimization techniques, Irrigation water management, Network performance analysis, Hydraulic parameters

1. Introduction

Limited water resources impose people for modernizing irrigation systems to provide equal rights to all users and to save water. One of the main reasons for not using water effectively in irrigation networks is that water losses are very high in the systems. In light of this fact, initially, water-saving measures should be taken thoroughly in agriculture. Firstly, it is imperative to install water transmission and distribution systems that will minimize water losses. Therefore, pressurized irrigation systems instead of open channel systems must be established in new irrigation projects.

The design of pressurized irrigation systems is a complicated, and time-consuming process. For this reason, many hydraulic parameters and factors must be considered. This process consists of mainly five stages: (1) optimization of network layout to reduce total cost of network, (2) hydrant discharge calculation considering plot sizes (3) determination of design flow each pipeline, (4) calculation of the optimum pipe size diameters to minimize the investment and energy costs, (5) network performance analysis for different operating conditions to specify the potential supply failure situations of the network or of the pumping plant (Alandi et al. 2007).

The initial investment costs of pressurized irrigation systems are relatively high. A reason for this might be that the majority of the expenses are vastly spent on pipe costs. Since the size of the pipes is directly related to the pipe prices, the selection of the optimum pipe diameter is significant in terms of both project cost and system performance when designing the network.

With advances in computer technology, optimization techniques have been used by many researchers to solve complex equations and the design of hydraulic parameters efficiently. The classical optimization techniques such as linear programming (LP), non-linear programming, and dynamic programming have been commonly used for many years. Especially in large and complicated network systems, classical optimization techniques can be time-consuming to find an optimal solution. Therefore, metaheuristic optimization techniques have been proposed, such as Genetic algorithms, simulated annealing, tabu search, ant-colony optimization, and harmony search (Schaake & Lai 1969; Alperovits & Shamir 1977; Lansey & Mays 1989; Simpson et al. 1994; Cunha & Sousa 1999; Geem et al. 2002; Maier et al. 2003; Cunha & Ribiero 2004).

Artificial Neural Network (ANN) is a machine learning method gaining popularity for solving complex problems in recent years. Unlike many machine learning methods, the core idea behind ANN is to reveal the hidden interactions between features (variables) that consist of the data. An ANN learns by using numerical values that can be observed or experienced previously. Accordingly, they can predict the data that the ANN model has not seen before with its hidden network structure. This approach allows the ANN to simulate the biological nervous system. An input layer of the ANN contains neurons corresponding to the number of features in training data. Target output values are represented by one neuron in an output layer. Hidden layers are located between the input and output layers. Neurons collect information that reaches them via transfer functions and transmit it to the subsequent neurons they are connected to (Omid et al. 2009). ANNs can reveal potential and hidden correlations between the variables that make up the data. Contrary to conventional models, an ANN model can produce satisfactory results even if there are several miscalculated neuron weights. In addition to these advantages, ANN models also can learn using the outputs of multiple traditional models looking for a solution to the same problem, thereby producing better predictions by combining the solving power of different models. ANN-based approaches were reported for possible solutions to various issues in non-agricultural water networks. One of the problems that were tried to be solved with ANN was to detect bursts and leaks in urban water networks (Mounce & Machell 2006; Arsene et al. 2012). Besides, some efforts were reported for non-agricultural purpose water networks such as assessment of the water flow rate and pressure losses (Czapczuk & Dawidowicz 2018; Dawidowicz et al. 2018), pipe failure detection (Shirzad & Safari 2019), and infrastructure aging risk assessment (Cantos & Juran 2019). As of preparing this paper, there was only one study accomplished by Dawidowicz (2018) investigating to determine pipe diameters based on ANN for urban water networks to the best of the authors' knowledge. However, the literature was in lack of optimization techniques in determining pipe diameters for agricultural irrigation networks using ANN.

The aim of present study was to investigate the possibilities of determining the pipe diameter, which is an important system design parameter in pressure irrigation systems using ANN as an alternative to the currently used models. For this purpose, three different pressurized irrigation systems operated with the on-demand method were selected, and different ANN architectures were created and tested with the hydrant level parameters of the system such as irrigated area, hydrant discharge, pipe length, and hydrant elevation above sea level.

2. Material and Methods

2.1. Study areas

In this study, three different sized pressurized irrigation system data were used to re-estimate pipe diameters with ANN: (1) Gulluce-Dolluk; (2) Devecikonagi; and (3) Yolcati. The Gulluce-Dolluk and Devecikonagi pressurized irrigation systems are located within the Mustafakemalpasa district's borders in the Marmara Region, 90 km from Bursa city center. These systems supply irrigation water from Devecikonagi Dam (Figures 1 and 2). The Devecikonagi pressurized irrigation system's irrigation water is taken from the Devecikonagi Dam via the transmission line and pumped to a water collection pool at the highest point (103.6 m) of the irrigation area by using a pump. A pressurized pipe irrigation system then delivers water to the hydrants from the water collection pool. The Yolcati (Gobelye) pressurized irrigation network is located in the Marmara Region, 20 km from Bursa city center, within the boundaries of Bursa Uludag University Campus in Turkey (Figure 3). The Yolcati Pond is used for irrigation purposes of Bursa Uludag University, within the Nilufer District of the central Bursa. Irrigation water is conveyed to hydrants with a piped irrigation system by pumping from the sluice gate to the reservoir located on the highest point of irrigation area by two electro pumps. Then it is distributed to the irrigated area from the reservoir with the help of gravity. The properties of three different pressurized irrigation systems used in this study are shown in Table 1.

Table1-The properties of pressurized irrigation systems used in this study.

Study areas / ***System parameters***	***Gulluce-Dolluk***	***Devecikonagi***	***Yolcati***
Coordinate	40° 10' N, 28° 23' E	39° 54' N, 28° 34' E	40°02′ N, 28°23′ E
Irrigated area (ha)	5820	360	125
Discharge (l s^{-1})	5035	528	217
Upstream elevation (m)	77	103.6	140
Total hydrant number	741	63	54
Pipe material	HDPE (High-density polyethylene)	HDPE	HDPE

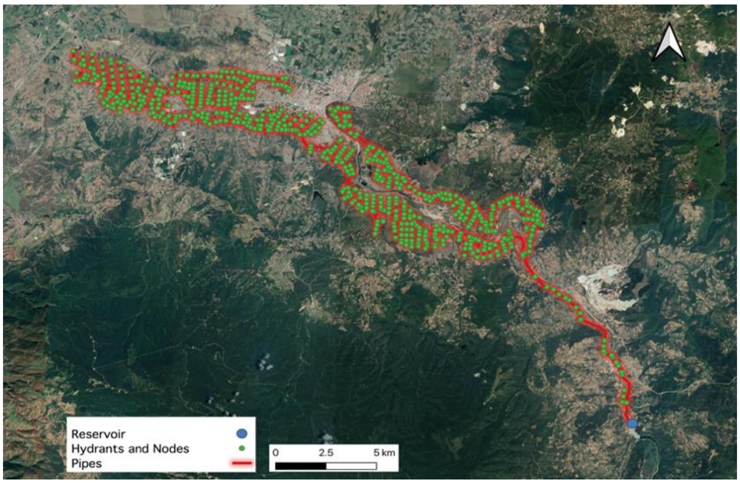


Figure 1- The layout of Gulluce-Dolluk pressurized irrigation network

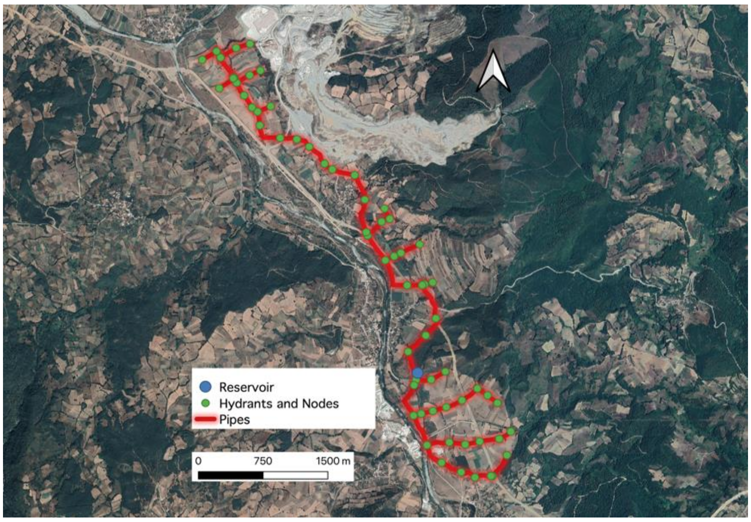


Figure 2- The layout of Devecikonagi pressurized irrigation network

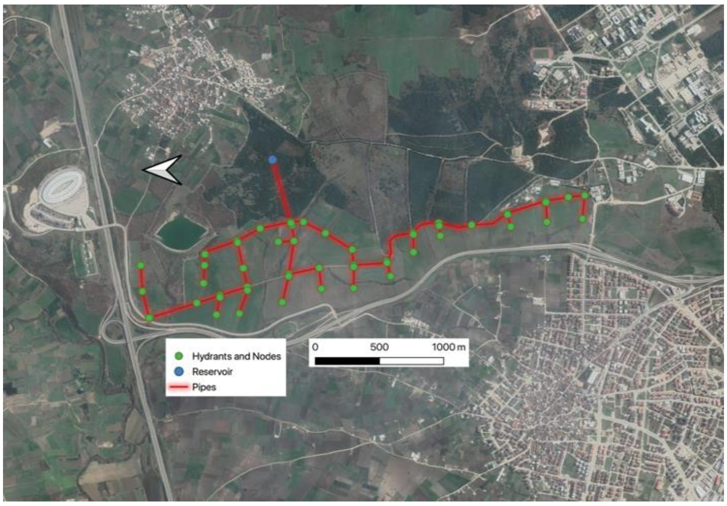


Figure 3- The layout of Yolcati pressurized irrigation network

2.2. Software

The use of ANN requires the preparation of data with an appropriate number of training examples. For this purpose, hydraulic data was collected from three different pressurized irrigation systems, and hydraulic calculations were made to create the training data for ANN. For this reason, COPAM (Combined Optimization and Performance Analysis Model) software, by

Lamaddalena & Sagardoy (2000), was applied. The ANN models were implemented and tested with Matlab (2020a, The MathWorks, Inc., Natick, Massachusetts) software.

2.3. Hydraulic calculations

Three different configurations are available with COPAM; calculation of discharge, calculation of pipe diameter, and analysis. There are two modules (Clément and random) in the structure of discharge calculation, a module (optimization) under the structure of pipe diameter calculation, and two modules (configurations and hydrants) under the analysis structure. In COPAM, pipe diameters are determined using an optimization process called Labye's iterative discontinuous method (ELIDM), which is an extension for several flow regimes models (SFR) (Labye 1981; Ait-Kadi et al. 1990). Further details about COPAM software can be found in Lamaddalena (1997), Lamaddalena & Sagardoy (2000) and Calejo et al. (2008).

COPAM has a software module for calculating an irrigation network's optimum pipe diameter under several different flow configurations and single flow regime conditions. ELIDM, used by COPAM, implements linear programming methods to cover several different flow regimes.

The ELIDM model uses the Darcy equation to calculate the pipes' friction coefficient (Eq. 1).

$$Y = 0.000857\ (1 + 2\gamma D^{-0.5})^2\ Q^2 D^{-5}\ L = u\ Q^2\ L \tag{1}$$

Where; γ, roughness parameter of Bazin (expressed by m0.5); Q, pipe discharge ($m^3\ s^{-1}$); u, dimensional coefficient of resistance ($m^{-1}\ s^2$); L, the length of pipe (m). Bazin's roughness coefficient was taken as 0.05 for HDPE pipes used (Lamaddalena & Sagardoy 2000). AKLA model was used for each hydrant's reliability analysis according to a minimum pressure head Hmin of 25 m.

2.4. Artificial neural network (ANN)

In this study, multi-layered feed-forward artificial neural network structures were employed to determine the pipe diameters of pressurized irrigation systems. While designing the prediction models, one hidden layer was used along with an input and an output layer since a hidden layer is enough to solve many complex problems. The use of more than one hidden layer is required in rare cases. However, this situation would cause the network to learn excessively and negatively affect the ability to generalize (Wang & Paliwal 2006; Nazghelichi et al. 2011). Different training algorithms can be used to update neuron weights in ANNs. The training algorithm used may affect the performance of ANN (Beale et al. 2014). Therefore, in this study, four different training algorithms were employed to determine the best ANN architecture that provides the highest prediction success in irrigation networks tested. The training algorithms used in the experiments are shown in Table 2 (Garg & Bansal 2015; Pakalapati et al. 2019).

Table 2- The training algorithms used in the experiments

Training algorithm	***Abbreviation***
Bayesian regularization backpropagation	Trainbr
Levenberg-Marquardt	Trainlm
Resilient backpropagation	Trainrp
Scaled conjugate gradient	Trainscg

The number of neurons in the hidden layer plays a crucial role in the creation of ANN models. There is no generally accepted rule for determining the number for ANNs. However, in a few studies, empirical methods were established to determine the number of neurons (Heaton 2015; Priddy & Keller 2005). In this study, while creating ANN architectures, the numbers of neurons up to 40, with five intervals starting from five, were tried. Their performances in predicting the diameter of network pipes were investigated. Another factor that affects ANN performances is the transfer function. While the linear transfer function was used in the output layer of the ANNs created, the tangent-sigmoid and logarithmic-sigmoid transfer functions were employed separately in the hidden layer. Table 3 shows the ANN architectures employed in the present study. The equations of these transfer functions are given in Eq. 2, 3, and 4 (Lertworasirikul & Tipsuwan 2008).

$$\mathrm{logsig}(x) = \frac{1}{(1+\mathrm{e}^{-x})} \tag{2}$$

$$\mathrm{tansig}(x) = \frac{2}{(1+\mathrm{e}^{-2x})} - 1 \tag{3}$$

$$\mathrm{purelin}(x) = x \tag{4}$$

Table 3- The ANN architectures employed in the present study

	Training algorithm																															
	Trainbr								*Trainlm*								*Trainrp*								*Trainscg*							
	Number of neurons																															
	5	10	15	20	25	30	35	40	5	10	15	20	25	30	35	40	5	10	15	20	25	30	35	40	5	10	15	20	25	30	35	40
Transfer function	Tangent-sigmoid																															
	Logarithmic-sigmoid																															

The hydraulic data of Gulluce-Dolluk, Devecikonagi and Yolcati irrigation networks were used in the training and testing of the ANNs. The variables used in the training of the ANNs were start point, end point, irrigated area (ha), hydrant discharge (l s^{-1}), pipe length (m), and hydrant elevation (m). Assuming that each variable used affects determining a pipe diameter, the ANN models were expected to use hidden correlations between variables in deciding a proper diameter of a pipeline. Figure 4 shows a representative model of the ANN scheme concept in the study. There were 741 hydrants and nodes data in the Gulluce-Dolluk irrigation system, 63 in the Devecikonagi irrigation system, and 54 in the Yolcati irrigation system. For each irrigation system, there were 3 data sets, namely, training set (50% of total data), validation set (25%), and test set (25%) (Sigtia & Dixon 2014; Ucar et al. 2020). Those data sets were constructed randomly before the experiments. During the networks' training, the training and validation sets were used to update the neuron weights. The prediction performances of the trained ANN were evaluated using the test data set that the network had never seen during the training phase. Since the variable value ranges were quite different for each variable, before training, all the variables were normalized in the range of 0 to 1 to increase the prediction success. Matlab initializes the neurons' weight values randomly at the beginning of the training of any network. This causes each training to yield a different prediction model, even if the number of hidden layers and other network parameters remain unchanged. To cope with this variation, a constant random state was used to give all ANN models experimented equal chance.

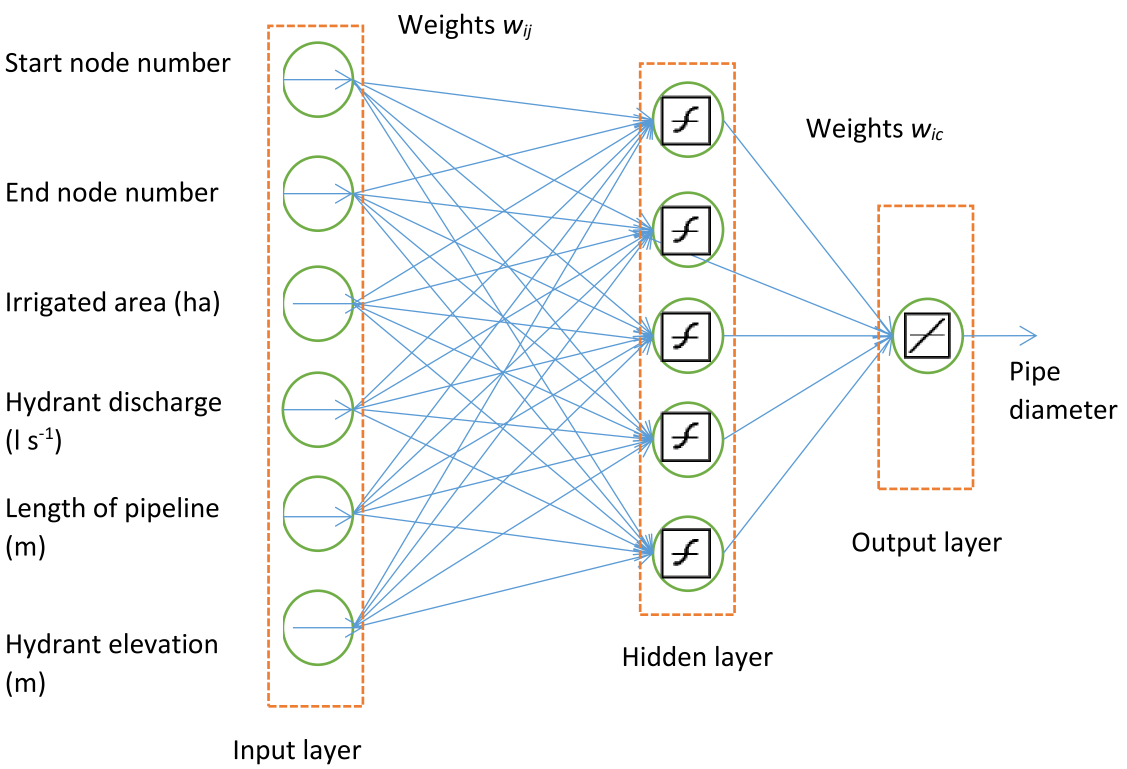


Figure 4- A hidden layered feed-forward ANN model

In the ANN models' training, mean square error (MSE) was used as a performance function. The error goal and the maximum number of epochs were set to 0.001 and 1000, respectively. In the experiments, to prevent overfitting, a training process stopped when the error goal was reached, the course of the validation error remained constant, or the validation error did not decrease over five iterations. The best ANN models were determined in predicting pipe diameters based on the highest determination coefficient (R^2), the lowest root mean square error (RMSE), and the mean absolute percentage error (MAPE) values for the test data set.

3. Results and Discussion

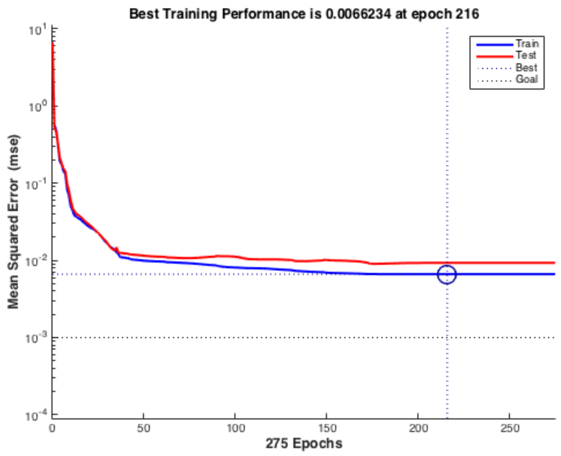
In the experiments, three real-world irrigation networks were investigated. A total of 64 different ANN architectures were employed for each irrigation network using eight different neuron numbers, four training algorithms, and two activation functions. Thus, the most successful ANN models were determined for each irrigation network.

3.1. The gulluce-dolluk pressurized irrigation system

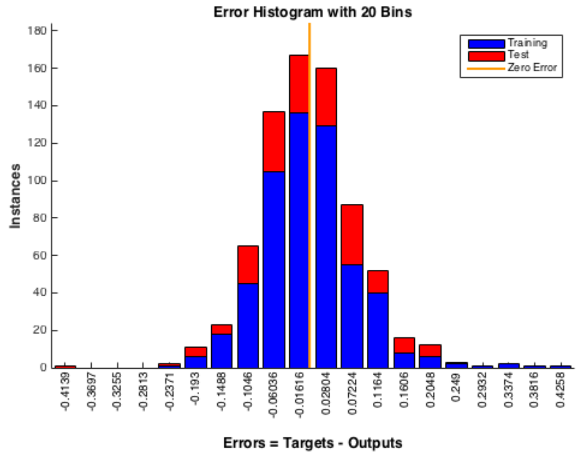
A total of 741 available network sections were used for training and testing the ANN models based on the Gulluce-Dolluk irrigation network. Table 4 shows prediction successes on 185 test samples of ANN models tested with different model parameters. According to the results, the best prediction performances were observed using the ANN models with the trainbr algorithm and 15 neurons. Both transfer functions yielded very similar performance metrics. The R^2 value was obtained as 0.97 for both transfer functions providing very close error metrics. The lowest RMSE and MAPE values were also obtained for those highest R^2 scores. The MAPE values were found between 20% and 50% for these models. According to Moreno et al. (2013), these scores are interpreted as a reasonable prediction. Figure 5a shows the best performed ANN model's training record in predicting pipe diameters of the Gulluce-Dolluk irrigation network. A smooth decrease in training and testing error was obtained during the training of this ANN model. This model yielded the best training performance at the training iteration 216. The error histogram of this ANN model was shown in Figure 5b. As a useful performance indicator, it was observed that most of the error distributed close to zero error line in the error space. For this ANN model, Figure 5c shows a plot representing the linear regression of target pipe diameters relative to predicted ones on the test data set. The regression plot also supported that this ANN model was very accurate. For the experiments related to Gulluce-Dolluk, the second-best performance was obtained from the trainlm algorithm with an R^2 value of 0.96. It was also inferred from the experiments that high prediction performances were provided by the ANN models having 15 neurons in their hidden layers. The learning algorithm trainrp was an exception in this regard since the highest R^2 (0.92) was observed using 30 neurons in the hidden layer.

Table 4- Performance results of the ANN models in predicting the pipe diameters of Gulluce-Dolluk

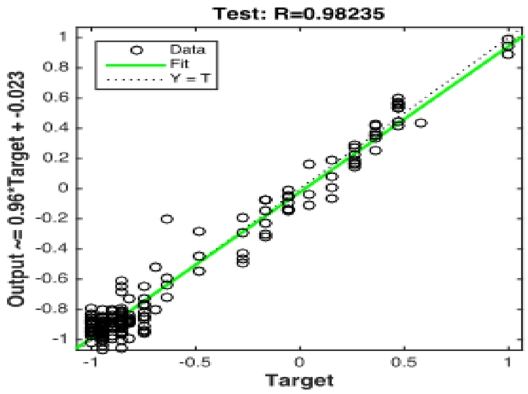
Training algorithm	*N. of neurons in hidden layer*	*R*	*R^2*	*RMSE*	*MAPE*	*R*	*R^2*	*RMSE*	*MAPE*
		Transfer function Tangent-sigmoid				Transfer function Logarithmic-sigmoid			
Trainbr	5	0.97	0.94	113.29	0.30	0.96	0.92	126.24	0.33
	10	0.95	0.91	149.56	0.36	0.97	0.93	125.66	0.31
	15	**0.98**	**0.97**	**91.04**	**0.28**	**0.98**	**0.97**	**90.98**	**0.27**
	20	0.95	0.90	160.87	0.29	0.96	0.92	145.00	0.32
	25	0.79	0.61	483.21	0.35	0.83	0.69	398.53	0.30
	30	0.86	0.75	350.53	0.29	0.96	0.92	167.45	0.29
	35	0.97	0.94	127.80	0.32	0.94	0.89	169.64	0.35
	40	0.97	0.94	128.96	0.31	0.94	0.88	174.68	0.40
Trainlm	5	0.97	0.93	117.05	0.33	0.96	0.93	118.67	0.32
	10	0.93	0.87	211.84	0.34	0.94	0.89	173.27	0.33
	15	**0.98**	**0.96**	**93.74**	**0.29**	**0.98**	**0.96**	**100.25**	**0.30**
	20	0.96	0.92	144.44	0.37	0.96	0.92	144.32	0.36
	25	0.95	0.90	159.82	0.36	0.91	0.83	217.70	0.36
	30	0.96	0.92	151.46	0.37	0.97	0.94	137.59	0.30
	35	0.96	0.93	133.41	0.33	0.97	0.94	124.25	0.30
	40	0.96	0.92	141.57	0.36	0.96	0.93	135.77	0.38
Trainrp	5	0.90	0.81	196.61	0.60	0.89	0.80	203.41	0.58
	10	0.91	0.83	209.71	0.45	0.93	0.87	172.94	0.45
	15	0.93	0.86	181.27	0.47	0.93	0.87	174.90	0.47
	20	0.92	0.85	193.05	0.53	0.87	0.76	257.72	0.53
	25	0.89	0.80	230.00	0.49	0.94	0.89	170.74	0.47
	30	0.95	0.89	181.05	0.49	0.96	0.92	153.96	0.43
	35	0.94	0.88	176.18	0.43	0.95	0.90	159.74	0.37
	40	0.93	0.86	177.02	0.53	0.93	0.85	185.25	0.51
Trainscg	5	0.82	0.67	258.66	0.70	0.82	0.68	255.63	0.69
	10	0.86	0.74	286.98	0.51	0.88	0.75	267.07	0.50
	15	0.95	0.90	152.24	0.41	0.74	0.54	334.43	0.91
	20	0.89	0.79	234.14	0.63	0.84	0.70	291.20	0.66
	25	0.90	0.80	232.73	0.48	0.92	0.85	201.13	0.52
	30	0.87	0.76	268.12	0.52	0.93	0.87	198.64	0.53
	35	0.77	0.60	318.31	0.68	0.84	0.71	269.05	0.58
	40	0.89	0.79	220.76	0.60	0.81	0.66	280.07	0.70



(a)



(b)



(c)

Figure 5- Training record (a), error histogram (b), and regression plot (c) related to the best ANN model performed for Gulluce-Dolluk irrigation network

3.2. The devecikonagi pressurized irrigation system

The Devecikonagi was another irrigation network studied in this study. Using 63 available sections, different ANN models were trained and tested. For this irrigation network, only 16 test sections were available. In the real-world, there are many irrigation networks with such a small number of sections. Furthermore, it was an important task to reveal the performance of neural network models predicting pipe diameters with fewer sections or pipelines. The performance results of the experiments related to this irrigation network were given in Table 5. The highest R^2 value (0.93) was obtained using the trainscg algorithm, 20 neurons, and the tangent-sigmoid transfer function. The second-highest performance metric (R^2= 0.89) for this experiment group was obtained with the trainbr algorithm using the same number of neurons. The MAPE values, obtained between 0.1-0.2, showed that these models performed good predictions (Moreno et al. 2013). Figure 6a shows that the best training performance was reached at epoch 20. This experiment's error histogram showed that the error is mainly distributed between -0.9528 and 0.5842 (Figure 6b). In Figure 6c, the regression plot related to the best-performed model also shows that model fits well with a slight shift from the perfect fit.

Table 5- Performance results of the ANN models in predicting the pipe diameters of Devecikonagi

Training algorithm	*N. of neurons in hidden layer*	*R*	*R^2*	*RMSE*	*MAPE*	*R*	*R^2*	*RMSE*	*MAPE*
		Transfer function Tangent-sigmoid				Transfer function Logarithmic-sigmoid			
Trainbr	5	0.56	0.32	103.13	0.35	0.56	0.32	96.23	0.33
	10	0.88	0.78	74.01	0.25	0.88	0.77	74.27	0.25
	15	0.78	0.61	104.88	0.37	0.79	0.62	98.31	0.35
	20	**0.94**	**0.89**	**53.59**	**0.18**	0.94	0.89	54.15	0.18
	25	0.49	0.24	143.09	0.28	0.62	0.38	121.13	0.25
	30	0.73	0.53	107.74	0.27	0.75	0.57	103.82	0.29
	35	0.83	0.68	70.27	0.20	0.87	0.76	70.67	0.22
	40	0.69	0.48	104.91	0.26	0.62	0.38	118.26	0.26
Trainlm	5	0.67	0.44	63.27	0.23	0.82	0.67	50.05	0.19
	10	0.80	0.64	112.10	0.43	0.93	0.86	71.00	0.18
	15	0.36	0.13	164.84	0.59	0.68	0.46	124.63	0.48
	20	0.76	0.58	107.57	0.32	0.91	0.82	66.68	0.23
	25	0.53	0.28	144.30	0.31	0.68	0.47	115.25	0.33
	30	0.57	0.32	162.36	0.56	0.50	0.25	142.86	0.54
	35	0.75	0.56	123.30	0.34	0.78	0.62	92.28	0.22
	40	0.56	0.32	124.62	0.30	0.63	0.40	113.22	0.28
Trainrp	5	0.34	0.12	108.55	0.40	0.55	0.31	86.98	0.36
	10	0.83	0.68	89.65	0.29	0.88	0.77	76.58	0.29
	15	0.74	0.54	105.40	0.42	0.79	0.63	127.83	0.53
	20	0.93	0.87	60.77	0.20	0.90	0.81	75.31	0.24
	25	0.73	0.53	114.89	0.27	0.65	0.42	119.72	0.25
	30	0.63	0.40	141.71	0.42	0.80	0.64	122.78	0.47
	35	0.67	0.45	97.68	0.25	0.40	0.16	152.49	0.42
	40	0.29	0.08	174.50	0.49	0.70	0.49	102.45	0.31
Trainscg	5	0.65	0.42	64.28	0.24	0.63	0.39	67.06	0.24
	10	0.74	0.54	109.67	0.42	0.86	0.75	88.13	0.32
	15	0.80	0.64	110.49	0.44	0.89	0.79	115.20	0.52
	20	**0.96**	**0.93**	**48.29**	**0.17**	0.85	0.73	90.95	0.33
	25	0.69	0.48	129.06	0.27	0.74	0.55	116.60	0.25
	30	0.55	0.30	135.84	0.42	0.60	0.37	123.31	0.45
	35	0.71	0.51	131.53	0.36	0.36	0.13	124.20	0.32
	40	0.71	0.51	104.70	0.22	0.70	0.50	103.66	0.31

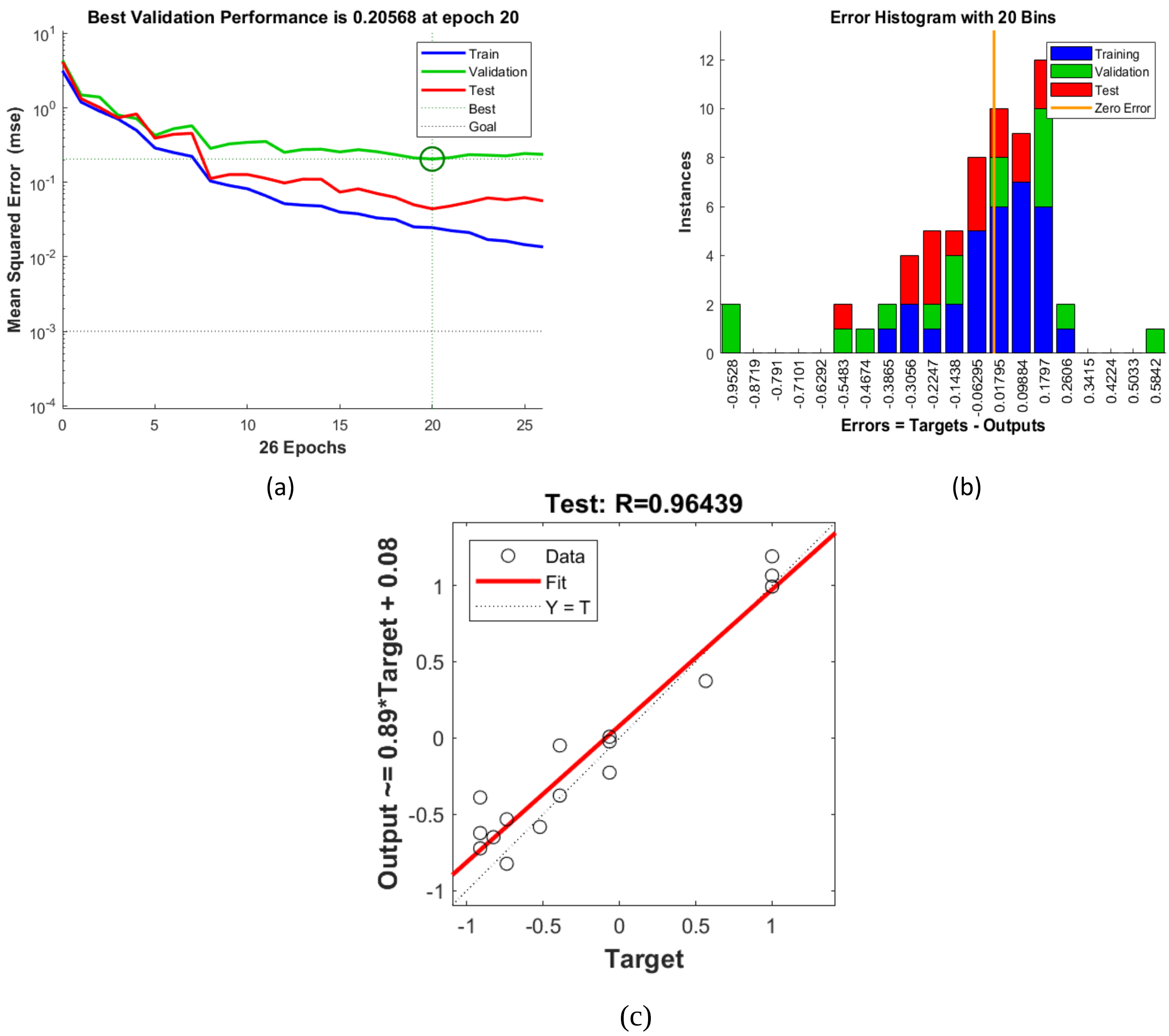


Figure 6- Training record (a), error histogram (b), and regression plot (c) related to the best ANN model performed for Devecikonagi

3.3. The yolcati pressurized irrigation system

This network has a few numbers (54) of pipeline sections. According to the experiments, the best prediction result (R^2= 0.83) was obtained using the training algorithm of trainbr (Table 6). The trainbr algorithm was responsible for the second-best performance metric (0.73). Apart from these, the rest of the training algorithms yielded R^2 values below 0.6 with this irrigation network. For this experiment group, the most successful predictions were observed with 10 neurons and the tangent-sigmoid transfer function. The best training performance was reached at epoch 20 for the model with the highest R^2 (Figure 7a). This experiment's error histogram showed that the prediction errors were distributed in a wide range (Figure 7b), which was an unwanted and a relatively low-performance result. The regression plot related to the best-performing model also shows that the model fits not as good as the other networks investigated in this research (Figure 7c).

Table 6- Performance results of the ANN models in predicting the pipe diameters of Yolcati

Training algorithm	*N. of neurons in hidden layer*	*R*	*R^2*	*RMSE*	*MAPE*	*R*	*R^2*	*RMSE*	*MAPE*
		Transfer function Tangent-sigmoid				Transfer function Logarithmic-sigmoid			
Trainbr	5	0.73	0.53	59.03	0.24	0.73	0.53	58.99	0.24
	10	**0.85**	**0.73**	**70.90**	**0.24**	0.85	0.72	72.48	0.25
	15	0.51	0.26	84.48	0.27	0.51	0.26	84.40	0.27
	20	0.80	0.64	64.20	0.25	0.80	0.64	64.17	0.25
	25	0.47	0.22	77.34	0.30	0.50	0.25	75.14	0.30
	30	0.45	0.20	67.76	0.30	0.45	0.20	67.82	0.30
	35	0.63	0.40	65.06	0.32	0.27	0.08	87.54	0.41
	40	0.72	0.52	57.14	0.23	0.72	0.52	57.17	0.23
Trainlm	5	0.66	0.44	72.45	0.31	0.67	0.45	59.79	0.30
	10	0.68	0.47	171.92	0.79	0.66	0.44	115.85	0.39
	15	0.44	0.20	95.23	0.26	0.28	0.08	123.69	0.35
	20	-0.59	0.35	158.97	0.74	0.44	0.19	94.09	0.39
	25	0.67	0.45	65.69	0.26	0.61	0.37	69.59	0.29
	30	0.14	0.02	142.67	0.73	0.29	0.08	104.87	0.46
	35	0.05	0.00	139.25	0.67	0.19	0.04	109.00	0.56
	40	0.48	0.23	111.29	0.49	0.53	0.28	89.46	0.44
Trainrp	5	0.75	0.56	62.26	0.24	0.76	0.58	55.17	0.22
	10	**0.91**	**0.83**	**75.43**	**0.26**	0.84	0.71	86.12	0.27
	15	0.38	0.14	100.81	0.26	0.25	0.06	115.44	0.34
	20	0.14	0.02	131.55	0.61	0.58	0.33	87.19	0.40
	25	0.35	0.12	108.10	0.35	0.64	0.41	68.07	0.33
	30	0.04	0.00	106.35	0.50	0.31	0.10	77.35	0.41
	35	0.21	0.04	154.05	0.61	0.35	0.12	87.20	0.37
	40	0.51	0.26	147.12	0.58	0.67	0.44	98.99	0.48
Trainscg	5	0.72	0.52	56.66	0.26	0.72	0.52	57.50	0.26
	10	0.73	0.54	96.99	0.36	0.67	0.44	98.58	0.34
	15	0.31	0.09	104.12	0.33	0.29	0.09	110.23	0.37
	20	0.55	0.31	94.52	0.49	0.63	0.39	85.72	0.37
	25	0.53	0.28	83.55	0.30	0.47	0.22	86.67	0.35
	30	-0.11	0.01	138.88	0.74	0.04	0.00	90.13	0.38
	35	0.43	0.18	127.75	0.61	0.50	0.25	90.42	0.48
	40	0.56	0.31	99.76	0.47	0.57	0.33	72.11	0.36

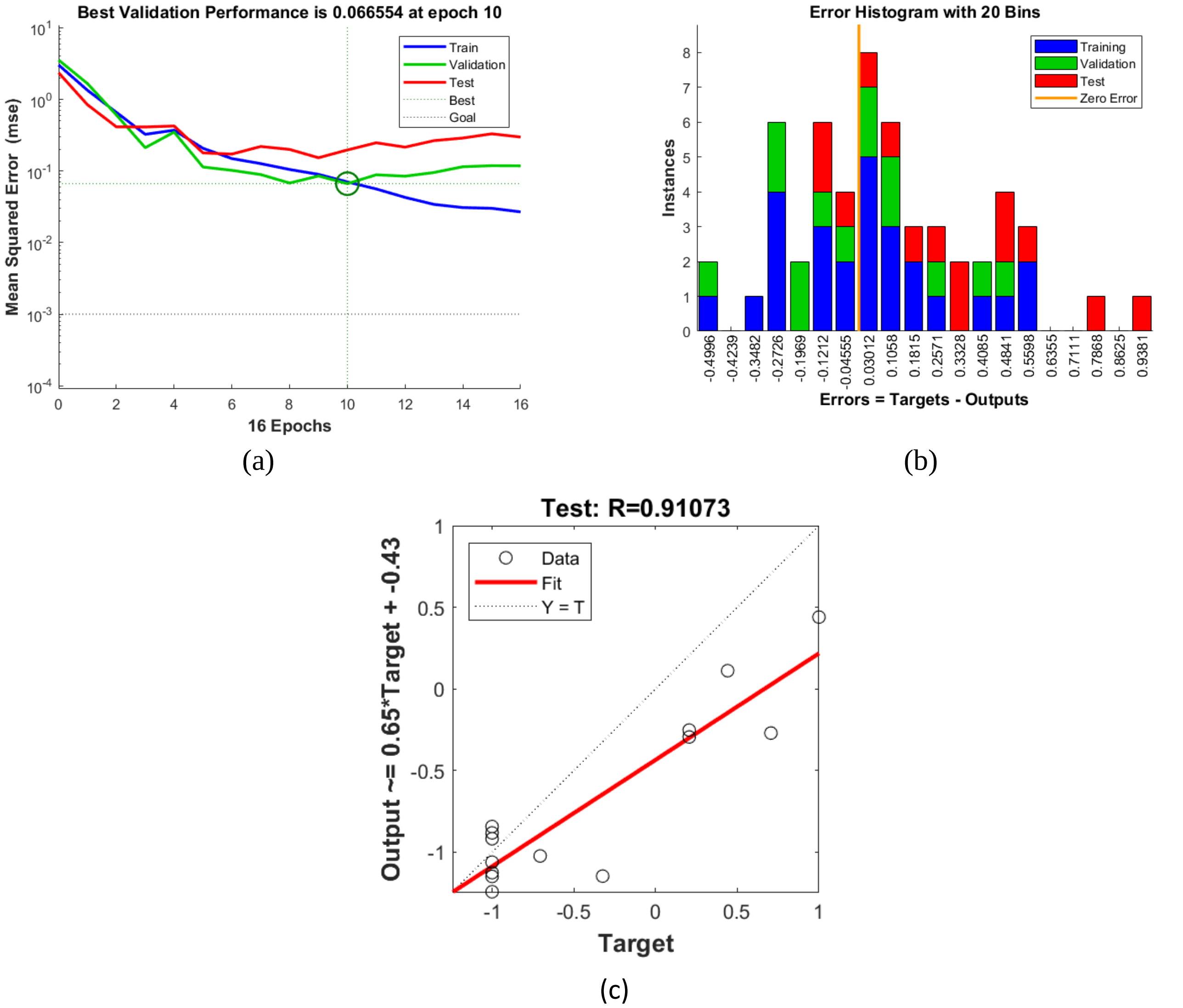


Figure 7- Training record (a), error histogram (b), and regression plot (c) related to the best ANN model performed for Yolcati

The ANN models yielded decimal numbers in the experiments, as seen in Table 7, illustrating the target and predicted pipe diameters. The pipe sections in the table were chosen randomly from the test data sets. The predicted pipe diameters were standardized as commercially available integer values, pointing out the proposed method's potential usage. The last row of Table 6 shows the pipe diameters obtained from the Network Optimization Program (NOP) used by The Republic of Turkey, the General Directorate of State Hydraulic Works (SHW). The NOP is an out-of-date program operated on MS-DOS, and it has some drawbacks, such as it is not possible to add all the pipes in production (Wang & Dal, 2017). When comparing the ANN results and the NOP results, an R^2 value of 0.95 was obtained (RMSE = 143.85, MAPE = 0.16) with a correlation coefficient (R) of 0.98. Although the results of the NOP should not be considered as a reference (ground-truth) for model verification, these findings were remarkable because statistically similar values were obtained using the ANN model and a classical method.

Table 7- Target and predicted values for pipe diameters

		Pipe Diameter (mm)			
Study Area	***Pipe section number***	***Hydraulic data***	***Predicted (ANN)***	***Predicted (standardized)***	***NOP***
Gulluce-Dolluk	50	1400	1407.95	1400	1900
	244	160	156.88	160	200
	575	1000	998.54	1000	1000
	621	450	450.40	450	500
	709	160	216.18	200	225
Devecikonagi	4	600	598.30	600	600
	15	355	371.83	355	350
	27	250	235.85	225	250
	53	355	364.51	355	355
	56	280	283.16	280	280
Yolcati	2	315	237.21	250	450
	24	110	84.83	90	160
	28	160	106.16	110	160
	35	355	299.01	315	400
	54	110	88.72	90	110

In this study, pressurized irrigation systems of different sizes were investigated to predict pipe diameters using ANN. In the Yolcati irrigation, using the least numbers of hydrants, pipe diameter prediction success was lowest with a R^2 value of 0.83. In the Gulluce-Dolluk irrigation having 741 hydrants, the pipe diameter prediction was done with the highest R^2 value of 0.97. Thus, it can be concluded that as the number of data increases in the training data set, pipe diameter estimation success also increases. Although it may not be fair to make a one-to-one comparison with the related papers employing ANN to optimize or analyze water networks, some points are worth discussing. While the approach developed in this study was to take the problem as a regression task, Dawidowicz (2018) addressed the problem as a classification task to determine the pipe diameters for urban water networks. Sadly, a prediction score was not reported in the researcher's study. However, a confusion matrix was available to compute the overall accuracy of the prediction model. Using a relatively large database of 36 urban water networks, the prediction model's overall accuracy could be computed as 0.998 based on the confusion matrix reported. In this paper, relatively high prediction scores were also obtained. Unfortunately, pressurized irrigation networks usually are not abundant, and they do not have as many nodes as urban water distribution networks. These may make it challenging to model agricultural irrigation networks with ANN compared to urban water networks. Nevertheless, the results obtained in this study were promising in terms of modeling agricultural irrigation networks using ANN.

4. Conclusions

The initial investment costs of pressurized irrigation systems are quite high, in addition, the calculation of pipe diameter in system design is very important for the performance of the irrigation system. Different ANN models were trained and tested to predict pipe diameters of three irrigation systems. Tested networks had different sizes. It was a promising result of a model fit success of 0.83 for an irrigation network with relatively low hydraulic data. The highest model success was obtained for the Gulluce-Dolluk irrigation system with an R^2 value of 0.97. Considering these findings, it was concluded that ANN could be a versatile tool to determine the pipe diameters of pressurized irrigation networks if a decent number of training samples is available. Although it is difficult to integrate a new system parameter into traditional models, new system parameters can be easily integrated into the ANN-based model implementations. Since the core idea of tubular networks is the same as the pressurized irrigation networks, the findings of the present work should also guide future studies related to the drinking water networks. Future studies should include the usage of a large hydraulic database covering a vast number of conditions to train the ANN models that can make more accurate predictions for design parameters of irrigation networks.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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