

Prediction of wind drift and evaporation losses of a sprinkler irrigation system using principal component analysis and artificial neural network technique

Samy A Marey^{1,3*}, Mohamed SA El Marazky^{2,3} and Abdulwahed M Aboukarima^{2,3}

¹Sciences, Technology and Innovation Unit, Rector's for Graduate Studies & Scientific Research, King Saud University, PO Box 2454, Riyadh 11451, Saudi Arabia

²Department of Agricultural Engineering, College of Food and Agriculture Sciences, King Saud University, PO Box 2460, Riyadh 11451, Saudi Arabia

³Agricultural Engineering Research Institute (AEnRI), Agricultural Research Centre, Egypt

ABSTRACT

Principal component analysis was merged with the artificial neural network (ANN) technique to predict wind drift and evaporation losses (WDEL) from a sprinkler irrigation system. For this purpose, field experiments were conducted to determine WDEL under different conditions. Data from field experiments and previous studies were used as sample data to train the ANN model. Three models were developed to predict WDEL. In the first model (ANN1), 9 neurons (riser height, main nozzle diameter, auxiliary nozzle diameter, discharge rate of the main nozzle, discharge rate of the auxiliary nozzle, operating pressure, wind speed, air temperature and relative humidity) were used as the input layer. In the second model (ANN2), 7 neurons (riser height, operating pressure, wind speed, air temperature and relative humidity, diameter ratio and discharge ratio) were used as the input layer. The third model (ANN3) used a multivariate technique (PC1, PC2, and PC3). Results revealed that the ANN3 model had the highest coefficient of determination ($R^2 = 0.8349$). The R^2 values for the ANN1 and ANN2 models were 0.7792 and 0.4807, respectively. It can be concluded that the ANN3 model has the highest predictive capacity.

Keywords: sprinkler irrigation systems, neural networks, modelling, evaporation and drift losses

INTRODUCTION

The popularity of sprinkler irrigation systems is increasing in different parts of the world. Sprinkler systems are mainly used because of their high efficiency and flexibility in applying small amounts of water (Mohamed et al., 2016). The application of the right amount of water and the uniformity of distribution of water over the field are important issues for such systems (Michael, 1978). In an experiment on cumin using sprinkler and surface irrigation in Egypt, sprinkler irrigation reduced the amount of irrigation water by 47%, increased irrigation efficiency by 53%, and increased crop yield by 11% (Bondok and El-Sharkawy, 2014). Design and operation factors affect the performance of sprinkler irrigation systems. Operation factors include operational pressure at the nozzle, wind speed, air temperature, and relative humidity. Design factors include riser height, sprinkler type, number of nozzles, nozzle diameters, sprinkler spacing, and the design pressure and its variability (Fukui et al., 1980; Kincaid et al., 1996; Playan et al., 2005; Tarjuelo et al., 1999; Zapata et al., 2007).

During operation of a sprinkler irrigation system, a significant part of the water discharged by the system does not reach the crop canopy. This unaccounted-for water is referred to as 'wind drift and evaporation losses' (WDEL), and is expressed as a percentage of the gross volume of irrigation water. WDEL has been assessed using laboratory tests, field tests and different analyses. The first analysis of WDEL was published by Frost and Schwalen (1955, 1960). They developed a nomograph to estimate WDEL as a function of sprinkler characteristics, operating pressure, and climatic factors.

Several studies have been conducted to develop sprinkler irrigation simulation models that can be used to estimate water distribution patterns of irrigation systems under real or controlled conditions (Sayyadi et al., 2012). These models can minimize the use of field tests and can improve the design and management of sprinkler irrigation systems. Models often focus on irrigation uniformity, which is an important performance indicator commonly used in the design and evaluation of sprinkler irrigation systems. Pressure-nozzle relations, sprinkler heads and spacing, and wind conditions are key variables affecting uniformity.

Relevant efforts have been devoted to experimentally characterize WDEL under various operating conditions. These experiments are costly and time-consuming. Thus, modelling WDEL stands as an adequate approach. The artificial neural network (ANN) technique has proved capable of successfully addressing problems that differ widely in nature (Hota, 2014; Arif et al., 2012; Hardaha et al., 2012; Karasekreter et al., 2012; Ahmadaali et al., 2013; Nithya and Srinivasan, 2015; Da Rocha Neto et al., 2015). This is due to its ability to describe complex real-world problems, especially when the relationships between the dependent and independent variables are unclear. Moreover, the appeal of utilizing ANN also lies in its remarkable information processing characteristics, specifically, nonlinearity, high parallelism, fault tolerance, and learning and generalization capabilities (Basherr and Hajmeer, 2000). The most generally used type of neural network is the multilayer feedforward neural network (Balas et al., 2010).

The performance of an ANN usually depends on data representation. An important characteristic is that data is not correlated (Sratthaphut et al., 2013). In fact, correlated data reduce the distinctiveness of data representation and introduce confusion in the ANN model during the learning process (Mohamad-Saleh and Hoyle, 2008). In addition, many input variables may cause poor generalization performance (Pakath

* To whom all correspondence should be addressed.

e-mail: samarey@ksu.edu.sa

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and Zaveri, 1995; Walczak and Cerpa, 1999). These problems can be solved by combining a feedforward neural network with principal component analysis (Zhang et al., 2006; He and Ma, 2010; Farajpour, 2012; Padma et al., 2014). Principal component analysis transforms the original dataset into a set of uncorrelated variables that capture all the variance of the original dataset (Dunteman, 1989). Wang et al. (2003) used a combination of neural networks and principal component analysis to enhance forecasting of air quality. Omid et al. (2010) used an approach based on combining principal component analysis and ANN to design an intelligent sorting system for pistachio nuts. Noori et al. (2010) also compared two common methods of ANN and principal component analysis to predict river flow.

The application of neural networks to sprinkler irrigation has received very little attention by the research community. As an example, a multilayer feedforward neural network with 2 input parameters (wind speed and wind direction) was employed by Sayyadi et al. (2012) to simulate the effects of wind on the distribution pattern of a single sprinkler under a centre pivot or block irrigation system. A multi-layer perceptron neural network with a back propagation-training algorithm was used; furthermore, 2 hidden layers (20 neurons in the first hidden layer and 6 neurons in the second hidden layer) and a tangent-sigmoid transfer function were utilized. The selected structure produced a coefficient of determination (R^2) of 0.929 for the test subset. In another study by De Menezes et al. (2015), an ANN model used operating pressure, wind speed, wind direction, and sprinkler nozzle diameter to estimate the uniformity of a sprinkler irrigation system. Field trials were performed with one sprinkler operating in a grid of 16×16 collectors with spacing of 1.5 m and different combinations of nozzle diameters, pressure, and wind conditions. The ANN model showed adequate agreement with experimental data, with a correlation coefficient ranging from 0.92 to 0.97. Zhang and Qie (2007) applied a radial basis function neural network model to estimate sprinkler irrigation uniformity.

In this study, multilayer feedforward artificial neural networks and hybrid artificial neural networks with principal component analysis are introduced for the prediction of WDEL in a sprinkler irrigation system. Hybrid artificial neural networks utilize principal component analysis to enhance the overall performance of the multilayer feedforward neural network. Results were evaluated to examine the applicability of these models to the generation of accurate predictions of WDEL from a sprinkler irrigation system. Thus, this study aims to investigate the use of ANN combined with principal component analysis in modelling sprinkler irrigation performance.

MATERIALS AND METHODS

Field experiments site and procedures for sprinkler tests

Field experiments were conducted at the experimental farm of the College of Food and Agriculture Sciences, King Saud University, Riyadh, (latitude: 24.67°N, longitude: 46.69° E), Saudi Arabia, during the period of February to April, 2017. Soil samples were randomly collected from the experimental sites at 0–60 cm depth and air dried, sieved through a 2.0 mm sieve, and taken for routine analysis (Page et al., 1982). The soil texture was sandy loam, and additional soil physical properties are presented in Table 1.

The experiments were executed in an area of 324 m² (18×18 m) using an isolated sprinkler system. The brass impact sprinkler model RC130-BY (Riegos Costa, Lleida, Spain) (Note: The use of the trade name does not imply recommendation or endorsement of this product) was used in the experiments. It was installed 2 m above ground level using a riser pipe. The main and auxiliary nozzles were manufactured in plastic, and installed using a bayonet-type coupling. The auxiliary nozzle used in all tests had an internal diameter of 2.5 mm. The water discharged from the sprinklers was collected in pluviometers located in 4 lines and 6 perpendicular rows, with distances of 1.5 m between the line and 0.75 m between the containers (Fig. 1). The pluviometers were cylindrical, with a diameter of 230 mm and a height of 230 mm. Windbreak trees with lengths of 6–8 m were used to minimize the effect of the wind surrounding the



Figure 1
Measuring of sprinkler base pressure

Soil layer depth (cm)		0–20	20–30	30–60	Average
PSD* (%)	Sand	74.81	72.64	70.35	72.60
	Silt	11.77	11.65	14.82	12.75
	Clay	13.42	15.71	14.83	14.65
Soil texture class		Sandy loam	Sandy loam	Sandy loam	Sandy loam
Field capacity ($m^3 \cdot m^{-3}$)		14.74	17.27	15.90	15.97
Permanent wilting point ($m^3 \cdot m^{-3}$)		5.32	6.54	6.58	6.15
Bulk density ($g \cdot cm^{-3}$)		1.64	1.61	1.59	1.61

*PSD: particle size distribution (%)

experimental area. The experiments were conducted based on the recommendations of Merriam and Keller (1978) and the relevant International Standards: ASAE S330.1 (ASAE, 1987), ISO 7749/1 (ISO, 1995) and ISO 7749/2 (ISO, 1990).

Experiments were conducted at 3 different operating pressures (200, 300, and 400 kPa) with 3 main nozzle diameters (4.0, 4.5, and 5.0 mm). Each treatment was replicated 9 times, resulting in 81 experiments. Each experiment lasted for 30 min (irrigation time), plus the preparation and measuring time. A graduated glass cylinder was used to measure the water stored in each collector. Dead calm conditions could not be achieved, since the tests were performed under open-air conditions.

A manual valve and a manometer were installed at the head control of the experiment (Fig. 1) to control the operating pressure in the sprinkler. The operating pressure of the sprinkler was recorded using a pressure transducer model PS series (Gems Sensors Inc., Basingstoke, Hampshire, UK) connected to a data logger (E120, Dixon, Addison, IL, USA) installed in the pipe riser 200 mm below the sprinkler nozzles. Pressure data was recorded at a 5 min interval.

Wind speed, air temperature, and relative humidity were monitored by an automatic meteorological station located in a plot adjacent to the experimental site during the tests. A 3-cup rotor anemometer Series A-100 and a wind direction sensor model 024-L (Campbell Scientific Ltd., Shepshed, UK) were used to measure the wind speed and direction, respectively. A combined probe was used to measure the temperature and relative humidity (model CS-215, Campbell Scientific Ltd., Shepshed, UK). The meteorological variables were recorded every 5 min by a data-logger of model CR10X (Campbell Scientific Ltd, Shepshed, UK). For each test of the solid-set experiment, WDEL was assessed from the irrigation depth (ID) collected in the pluviometers. WDEL was estimated as the percentage of the water emitted by the sprinklers (IDe) but not collected inside the pluviometers (Dechmi et al., 2003; Playán et al., 2005; Sanchez et al., 2010a), according to the following equations:

$$WDEL = \left[\frac{IDe - ID}{IDe} \right] \times 100 \quad (1)$$

$$IDe = Q \times \frac{t}{(S_s \times S_l)} \times 100 \quad (2)$$

where Q is the discharge ($L \cdot s^{-1}$), t is the operating time (s), and S_s and S_l are the side and lateral distances between two sprinklers, respectively. Q was assessed by collecting the water discharged by the sprinkler into a tared container. The discharge was calculated by dividing the weight of the collected volume by the time of filling.

Previous studies used for modelling of WDEL

A WDEL ANN model was developed using 148 observations collected from 5 published datasets (Abo-Ghobar, 1993; Dechmi et al., 2003; Bavi et al., 2009; Sanchez et al., 2010b; Sanchez et al. 2011). From these studies, different parameters (riser height (X1), main nozzle diameter (X2), auxiliary nozzle diameter (X3), wind speed (X4), air temperature (X5), operating pressure (X6), relative humidity (X7), water discharge by main nozzle (X8) and water discharge by auxiliary nozzle (X9), were evaluated. A summary of the field data and no. of data points reported in these studies is presented in Table 2, along with the

TABLE 2
Summary of the field data used in the model's development and collected from previous studies

Input variables	Output variable									No. of data points	Country	References	
	X1	X2	X3	X4	X5	X6	X7	X8	X9				WDEL
(m)	(mm)	(mm)	(m·s ⁻¹)	(°C)	(kPa)	(%)	(L·s ⁻¹)	(L·s ⁻¹)	(L·s ⁻¹)	(%)	(---)		
1	5.5–6.1	3.0–4.2	2.33–3.65	34–42	200–300	42.0–56.7	0.41–0.50	0.10–0.12	0.10–0.12	22.6–34.0	6	Saudi Arabia	Abo-Ghobar (1993)
2.3	4.4	2.4	0.6–6.5	12–31	300	31–64	0.26	0.08	0.08	6–39.6	23	Spain	Dechmi et al. (2003)
2	7.32	3.32	3–10	19–45	345.1–443.7	17.43–89.86	0.78–0.88	0.16–0.18	0.16–0.18	4.4–8.7	37	Iran	Bavi et al. (2009)
2.3	4	2.4	0.8–5.6	19–27	290–355	44–68	0.10–0.33	0.04–0.12	0.04–0.12	3–33	30	Spain	Sanchez et al. (2010b)
2	4.0–4.8	2.4	0.4–8.0	5.0–7.1	230–420	40–86	0.19–0.37	0.07–0.09	0.07–0.09	2.4–35.6	37	Spain	Sanchez et al. (2011)

range in the experimental variables and the range of observed WDEL. Abo-Ghobar (1993) reported using 10 types of impact sprinklers of different nozzle diameters. The system was operated for 1 to 2 h per run, depending on the nozzle size, in order to collect a sufficient amount of water in the catch cans. Dechmi et al. (2003) used nozzle diameters of 4.4 mm (main) and 2.4 mm (auxiliary). The system was installed 2.30 m above ground level. The nozzle operating pressure was kept constant during the season at 300 kPa, and resulted in a wetted radius of 11 m. Bavi et al. (2009) used nozzle diameters of 7.32 mm (main) and 3.32 mm (auxiliary), and the riser was installed at 2 m above ground level. The system was operated at 3 pressure levels, of 345.1, 394.4, and 443.7 kPa. Sanchez et al. (2010b) used a main 4.0 mm main nozzle with a jet-straightening vane. The auxiliary nozzle was 2.4 mm in diameter. Sanchez et al. (2011) used a main nozzle of 4.0–4.8 mm. The sprinkler also included an auxiliary nozzle of 2.4 mm. An ample range of pressure, from 230 to 420 kPa, was tested. All tests lasted for 2 h and were performed under low wind conditions.

Modelling WDEL from a sprinkler

Three paths are described that are involved in the selection of an ANN model for the estimation of WDEL. These paths are presented in Fig. 2. Path 1 presented data describing the effect of the collected 9 parameters on the drift and evaporation losses. In Path 2, the mathematical calculation was applied to reduce the parameters to be 7 parameters: riser height, diameter ratio, water discharge ratio, operating pressure, wind velocity, air temperature and air relative humidity and the data were divided to create 2 datasets, 1 for training and 1 for testing. However, the diameter ratio (X10) and discharge ratio (X11), are as follows:

$$X_{10} = \frac{X_2}{X_3} \quad (3)$$

$$X_{11} = \frac{X_8}{X_9} \quad (4)$$

Table 3 illustrates the maximum, minimum, mean, and standard deviation of the main and the created parameters in the dataset used for the training and testing phases of the ANNs. However, in Path 3, the principal component analysis was applied to reduce the parameters to a set of 3 parameters. Then, an appropriate ANN model was developed that used different input variables to model WDEL. The estimates were compared to the original data, and error estimates and correlation coefficients were obtained for each method. The ANN model was selected that had a low error criteria and high correlation coefficients.

Principal component analysis (PCA)

PCA is a multivariate technique used to reduce the dimensions of a dataset consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the dataset (Sharma, 1996; Özkan and Mendes 2004). This is achieved by transforming the set of original variables to a new set of variables, the principal components (PCs), which are ordered so that the first few retain most of the variation present in all of the original variables (Jolliffe, 2002). As PCAs have been explained in detail elsewhere (Johnson and Wichern, 1982; Sharma, 1996), limited information about them will be provided in this section. However, transforming a p -dimensional vector $XT = [X_1, X_2, \dots, X_p]$ into PCs designates an orthogonal rotation in p -space. Hence, a new vector

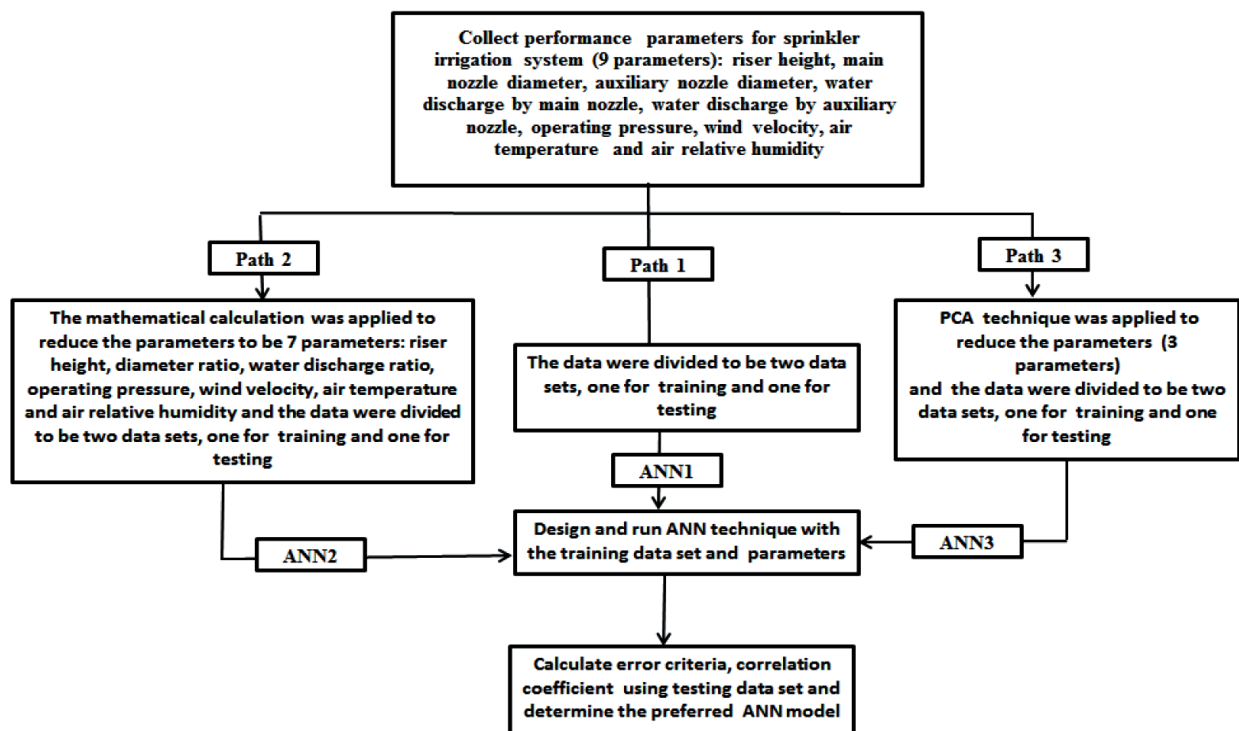


Figure 2

Flow chart describing the process used to select the preferred ANN model for estimating the wind drift and evaporation losses (WDEL) from a sprinkler irrigation system

Statistical criteria	Main parameters									Created parameters	
	(X1) (m)	(X2) (mm)	(X3) (mm)	(X4) (m·s ⁻¹)	(X5) (°C)	(X6) (kPa)	(X7) (%)	(X8) (L·s ⁻¹)	(X9) (L·s ⁻¹)	(X10) (---)	(X11) (---)
Minimum	1.00	4.00	2.40	0.30	5.00	175.0	17.43	0.10	0.04	1.31	0.43
Maximum	2.30	7.32	4.20	10.19	45.40	443.7	89.86	0.88	0.90	2.20	5.56
Mean	2.04	4.89	2.62	2.77	23.06	316.6	52.85	0.38	0.11	1.85	3.48
Standard deviation	± 0.21	± 1.14	± 0.38	± 2.12	± 7.46	± 68.5	± 13.46	± 0.20	± 0.06	± 0.21	± 0.85

can be obtained $YT = [Y1, Y2, \dots, Yp]$ with elements that are uncorrelated, and with a decreasing variance from the first to last element. Each $Y_j, j = 1, \dots, p$ is a linear combination of $X_j, j = 1, \dots, p$ with a vector of constants or weighting factors of $aTj = [a1j, a2j, \dots, apj], j = 1, \dots, p$, namely, $Y_j = a1jX1 + a2jX2 + \dots + apjXp, j = 1, \dots, p$.

The units of the variables could have an effect on PCA. Owing to differences in the units of variables used in PCA, the SPSS software (SPSS Inc., 2008) was used to pre-process the data according to the following formula:

$$T = \frac{(Z - \bar{Z})}{S_d} \quad (5)$$

where: Z are the original values of the input and output parameters, T is the normalized value, \bar{Z} is average value, and S_d is standard deviation. The correlation matrix of parameters was used to obtain the eigenvalues and weights of the variables (Mendes, 2011). In this study, the PCA was performed on 9 parameters to rank their relative significance and to describe their interrelation patterns. The Kaiser–Meyer–Olkin (KMO) value was used to measure the sample adequacy, and the Bartlett’s test of sphericity was applied to verify the applicability of PCA (Pallant et al., 2007). KMO is a measure of sampling adequacy that varies between 0 and 1, with values closer to 1 considered good and those below 0.50 considered unacceptable. The KMO value can be increased in many ways, such as increasing the sample size or increasing the number of variables. If the average correlations among the variables are high or the numbers of factors are diminished, the value of KMO becomes large (Hair et al., 2003). The Kaiser rule states that only those components or factors which have eigenvalues greater than 1 (Gaur and Gaur, 2006) should be selected. The Bartlett’s sphericity test is used to test the null hypothesis that the correlation matrix is an identity matrix or all correlations are zero; the significance level of the Bartlett’s test should also be lower than 0.05. In this study, PCs with eigenvalues greater than 1 were selected (Kaiser, 1960). Communalities measure the amount of variance that a variable shares with all the other variables in the analysis. This is also the proportion of each variable’s variance explained by the principal components. It is also noted that the communality can be defined as the sum of squared factor (component) loadings. A large communality means a large amount of the variance in a parameter is extracted by the factor solution. In other words, parameters with high values are well represented in the common factor space while low value variables are not well represented (Malhotra, 2004). The eigenvalue is the variance explained by a component or factor. A

low eigenvalue contributes little to the explanation of variances in the set of variables being analysed. The component matrix table shows the component loadings that are the correlations between the parameters and the components. The first component is generally more highly correlated with the variables than the second component and so on. Loadings above 0.5 were considered high, whereas those below 0.4 were considered low. PCA analysis was carried out using the SPSS software (SPSS Inc., 2008).

Artificial neural network (ANN)

The ANN has been used in sprinkler irrigation systems for the prediction of water distribution patterns. The back-propagation algorithm has emerged as one of the most widely used learning procedures for multilayer networks in the irrigation field (Sayyadi et al., 2012; De Menezes et al., 2015). In Fig. 3, a three-layer multi-input ANN model is presented; the corresponding structure is $m-q-1$, where m is the number of inputs, q is the number of neurons in the hidden layer, and 1 represents the one output unit. Let $X_i (i = 1, 2, \dots, m)$ denote the set of input vector of neurons, and Y denote the output of the network. Between the inputs and the output, there is a layer of processing units called hidden units. $Z_j (j = 1, 2, \dots, q)$ denotes the output of the hidden layer neurons, W_{ij} is the weight that connects the node i in the input layer neurons to the node j in the hidden layer, V_j is the weight that connects the node j in the hidden layer neurons to the node in the output layer. Haykin (1999) gives the input of all neurons in the hidden layer

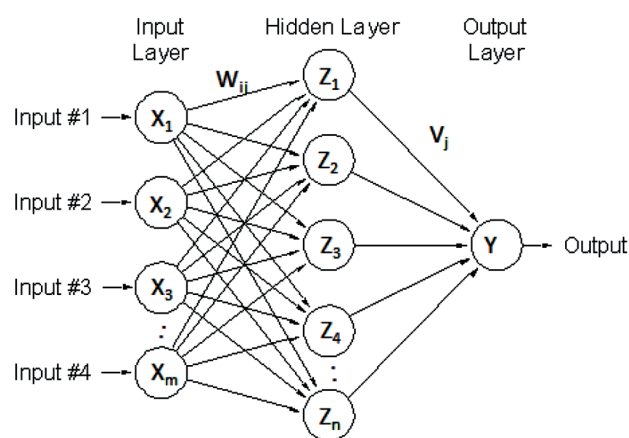


Figure 3
A three-layer multi-input ANN model

$$net_j = \sum_{i=1}^q W_{ij} X_i - \theta_j \quad i = 1, 2, \dots, q \quad (6)$$

The output of hidden neuron is given by:

$$Z_j = f_H(net_j) = f_H\left(\sum_{i=1}^q W_{ij} X_i - \theta_j\right) \quad i = 1, 2, \dots, q \quad (7)$$

where θ_j is the threshold of neurons in the hidden layer. The sigmoid function in the hidden layer f_H is selected in this study as the activation function. The output of the hidden layer is given as follows:

$$Y = f_T\left(\sum_{j=1}^m V_j Z_j - \theta_T\right) \quad (8)$$

where θ_j is the threshold of neurons in the output layer and f_H is the activation function in the output layer.

In this study, a feedforward artificial neural network model was developed. The model was built with the help of the commercially available QNET 2000 software (Vesta Services, 2000). This software supports a standard back-propagation algorithm for training purposes. QNET 2000 operates via a graphical user interface (GUI) that enables the user to load the training and test sets, design the network architecture, and feed values for the training parameters. The ANN models proposed in this study were supposed to be m - $Hn1$ -1, which implies m neurons in the input layer. $Hn1$ is the number of neurons in the first hidden layer, and 1 represents the one neuron in the output layer. There were 9 neurons in the input layer for the ANN1 model and one in the output layer; 7 neurons in the input layer for the ANN2 model and one in the output layer; and 3 neurons in the input layer for the ANN3 model and one in the output layer. The whole dataset (229 data points) was randomly divided into 216 data points and 13 data points, for training and testing purposes, respectively.

At the beginning of the training process, the weights were initialized with a set of random values. The goal of learning is to determine a set of weights that will minimize the error function. As training proceeds, the weights are systematically updated according to a training rule. The ANN model with the highest correlation coefficient and lowest training error was selected as the best model. The optimal number of hidden neurons in the ANN was determined based on the trial-and-error method.

Evaluation of model predictive capacity

The coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) were determined to assess the accuracy of the proposed models. The MAE and RMSE were determined as follows:

$$MAE = \frac{1}{N_d} \times \sum_{i=1}^{i=N_d} |WDEL_{ia} - WDEL_{ip}| \quad (9)$$

$$RMSE = \sqrt{\frac{1}{N_d} \times \sum_{i=1}^{i=N_d} (WDEL_{ia} - WDEL_{ip})^2} \quad (10)$$

where $WDEL_{ia}$ and $WDEL_{ip}$ are actual and predicted wind drift and evaporation losses from a sprinkler irrigation system, respectively; N_d is the number of data points in the test dataset. MAE measures the average magnitude of errors in a set of forecasts without considering their direction.

RESULTS AND DISCUSSION

Results of principal component analysis

Table 4 shows the correlation coefficients of the nine parameters. The correlation coefficients are high; therefore, this study is proposing the PCA technique for two reasons: firstly, it removes the correlation among the independent parameters and, secondly, it reduces the number of parameters to a minimum (Ismail and Abdullah, 2016). The null hypothesis of the Bartlett's sphericity test is that the input variables are uncorrelated. This null hypothesis was rejected with a statistical significance of 5%. The Kaiser-Meyer-Olkin (KMO) parameter, a measure of sample adequacy, was found to be 0.588.

Initial communalities are estimates of the variance in each variable accounted for by all components or factors. For principal components extraction, this is always equal to 1.0 for correlation analyses (<https://www.ibm.com>) and, as shown in Table 5, variance ranges from 0.46 to 0.95 and can be reduced to factors. However, the initial eigenvalues for the first, second, and third components were 4.9, 1.2, and 1.0, respectively (Table 6). The percentage variance thus explained by each of the three components was about 54.3, 13.5, and

TABLE 4
The matrix of correlation coefficient

	X1	X2	X3	X4	X5	X6	X7	X8
X1	1.000							
X2	-0.366	1.000						
X3	-0.566	0.881	1.000					
X4	-0.176	0.487	0.377	1.000				
X5	-0.255	0.662	0.691	0.067	1.000			
X6	0.125	0.396	0.291	0.190	0.242	1.000		
X7	0.038	-0.311	-0.310	-0.249	-0.320	-0.058	1.000	
X8	-0.223	0.963	0.840	0.440	0.664	0.555	-0.296	1.000
X9	-0.342	0.798	0.910	0.275	0.692	0.492	-0.299	0.869

Parameters	Extraction
Riser height	0.79
Main nozzle diameter	0.90
Auxiliary nozzle diameter	0.95
Water discharge by main nozzle	0.76
Water discharge by auxiliary nozzle	0.66
Operating pressure	0.77
Riser height	0.46
Main nozzle diameter	0.94
Auxiliary nozzle diameter	0.89

11.2, respectively, with a cumulative percentage of 78.9. The three selected PCs were fed to the proposed ANN prediction model to estimate WDEL.

As shown in Table 7, the first component had high loadings (highlighted in bold) for 5 parameters, namely, main nozzle diameter, auxiliary nozzle diameter, water discharge by the auxiliary nozzle, air temperature, and air relative humidity. For the second component, riser height and operating pressure were strongly associated. For the third component, water discharge by the main nozzle and wind velocity were strongly associated. Although there are many criteria for selecting components, for the output analysis, only 3 components were selected based on the Kaiser criterion. The component score coefficient matrix of the first 3 factors that were used in the ANN model is shown in Table 8.

The composite score F , that is, the sum of the product of each factor and its contribution to the total variance, is:

$$F = 0.54296 \times PC1 + 0.13538 \times PC2 + 0.11161 \times PC3 \quad (11)$$

Results of wind drift and evaporation losses from a sprinkler irrigation system by ANN models

After testing various ANN architectures by varying the activation function, number of hidden units, and number of neurons in the hidden layers, the MLP (multilayer perceptron) with the sigmoid activation function produced the best prediction values of all three tested ANN models. The training results of the three ANN models are presented in Table 9 and Table 10. The mean absolute error, root mean square error, and coefficient of determination of the three ANN models in estimating the WDEL from a sprinkler irrigation system after the testing stage are presented in Table 11. The predictive capacity of each model is evaluated by its error values, as shown in Table 11 and Fig. 4.

ANN3 showed the lowest MAE and RMSE and the highest R^2 , followed by ANN1. The training speed was highly dependent on the number of input variables, and was the highest in ANN1 (25 233 K), followed by ANN2 (22 700 K) and ANN3 (14 576 K), while the lowest training speed was observed in ANN3. As the accuracy of ANN3 in predicting WDEL was higher than the accuracy of ANN1 and ANN2, it can be concluded that ANN3 (with PCs as input variables)

Component	Initial Eigenvalues		
	Total	% of variance	Cumulative %
PC1	4.9	54.3	54.3
PC2	1.2	13.5	67.8
PC3	1.0	11.2	78.9
PC4	0.9	10.2	89.2
PC5	0.4	5.3	94.5
PC6	0.3	3.0	97.5
PC7	0.2	2.1	99.6
PC8	0.04	0.4	99.9
PC9	0.001	0.01	100

Parameter	Component		
	PC1	PC2	PC3
Riser height	0.421	0.778	0.076
Main nozzle diameter	0.946	0.000	0.044
Auxiliary nozzle diameter	0.944	0.233	0.074
Water discharge by main nozzle	0.464	0.042	0.734
Water discharge by auxiliary nozzle	0.754	0.070	0.297
Operating pressure	0.481	0.714	0.164
Wind velocity	0.397	0.006	0.550
Air temperature	0.949	0.199	0.026
Air relative humidity	0.923	0.050	0.185

Parameter	Component		
	PC1	PC2	PC3
Riser height	-0.106	0.062	0.637
Main nozzle diameter	0.163	0.113	-0.005
Auxiliary nozzle diameter	0.206	-0.003	-0.192
Water discharge by main nozzle	-0.186	0.714	0.008
Water discharge by auxiliary nozzle	0.254	-0.219	-0.050
Operating pressure	0.154	-0.092	0.589
Wind velocity	0.130	-0.538	0.015
Air temperature	0.190	0.055	0.161
Air relative humidity	0.244	-0.099	0.044

*Extraction method: principal component analysis and rotation method: Varimax with Kaiser Normalization Component Scores

ANN models	Input parameters	Architecture	Learning rate	Momentum coefficient	Training speed (CPS)	Iteration number
ANN1	X1, X2, X3, X4, X5, X6, X7, X8, X9	9-15-1	0.024551	0.8	25 233 K	100 000
ANN2	X1, X6, X7, X8, X9, X10, X11	7-15-1	0.012381	0.8	22 700K	100 000
ANN3	PC1, PC2, PC3	3-15-1	0.056174	0.8	14 576 K	100 000

ANN models	Mean absolute error (%)	Root mean square error (%)	Correlation coefficient
ANN1	3.499481	4.798766	0.8513
ANN2	6.021407	7.716723	0.5754
ANN3	3.358815	4.400021	0.8869

ANN models	Mean absolute error (%)	Root mean square error (%)	Coefficient of determination (R ²)
ANN1	5.252466	6.23325	0.7792
ANN2	5.200981	6.201125	0.4807
ANN3	2.045736	3.151156	0.8349

contributes to reducing the training speed. These results indicate that ANN3 is the most efficient among the three tested models.

CONCLUSIONS

The accuracy in predicting WDEL is important for the design of sprinkler irrigation systems. This study has demonstrated that an accurate prediction of WDEL can be obtained with a hybrid approach combining PCA and ANN. The goal of utilizing this combination was to capture different patterns of the independent variables. The PCR-ANN model provided a better result than the ANN model based on the selected parameters. This combination method is to be recommended because it improved the prediction of WDEL. Hybrid combinations may have other applications in the irrigation field.

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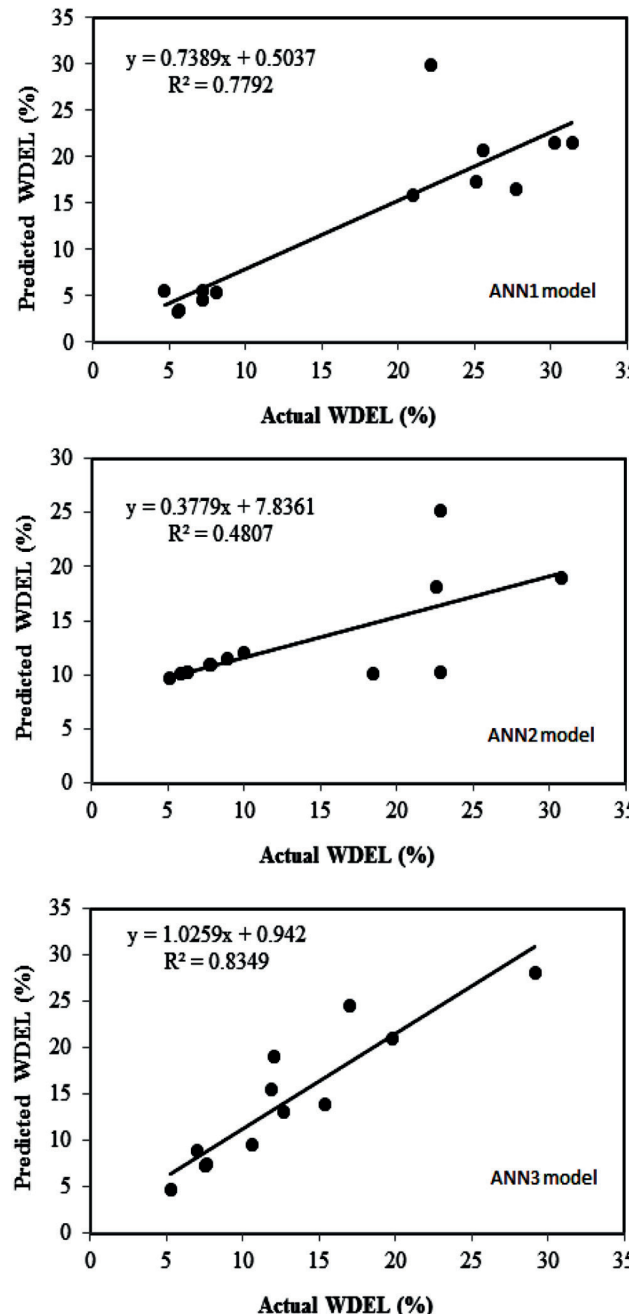


Figure 4
Relationship between actual WDEL and WDEL predicted by the three ANN models

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