Comparison of Multivariate Regression and Artificial Neural Networks for Peak Urban Water-Demand Forecasting: Evaluation of Different ANN Learning Algorithms

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Abstract: For the past several years, Cyprus has been facing an unprecedented water crisis. Four options that have been considered to help resolve the problem of drought in Cyprus include imposing effective water use restrictions, implementing water-demand reduction programs, optimizing water supply systems, and developing sustainable alternative water source strategies. An important aspect of these initiatives is the accurate forecasting of short-term water demands, and in particular, peak water demands. This study compared multiple linear regression and three types of multilayer perceptron artificial neural networks (each of which used a different type of learning algorithm) as methods for peak weekly water-demand forecast modeling. The analysis was performed on 6 years of peak weekly water-demand data and meteorological variables (maximum weekly temperature and total weekly rainfall) for two different regions (Athalassa and Public Garden) in the city of Nicosia, Cyprus. 20 multiple linear regression models, 20 Levenberg-Marquardt artificial neural network (ANN) models, 20 resilient back-propagation ANN models, and 20 conjugate gradient Powell-Beale ANN models were developed, and their relative performance was compared. For both the Athalassa and Public Garden regions in Nicosia, the Levenberg-Marquardt ANN method was found to provide a more accurate prediction of peak weekly water demand than the other two types of ANNs and multiple linear regression. It was also found that the peak weekly water demand in Nicosia is better correlated with the rainfall occurrence rather than the amount of rainfall itself.

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Introduction

Water supply systems around the world have become stressed in recent years due to a combination of factors including rapid population growth, increased per capita water consumption, and the effects of climate change. For the past several years Cyprus has been facing an unprecedented water crisis. There has been minimal rainfall since 2003, reservoirs in the country are at less than 10%, and its two newly built desalination plants have been unable to supply sufficient quantities of water (Gabriel 2008). In addition to reduced supplies of water, recent trends indicate that both average and peak water demand have been increasing.

It has been estimated that there is approximately 462 m^3 of water per inhabitant in Cyprus (Artemis 2006). To put this in perspective, thresholds of 1,000 and 500 m³ of water per inhab-

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itant have been deemed to correspond, respectively, to "water stress" and "water scarcity" levels (Sivakumar 2004). Rainfall on the island averages 460 mm, a 15% drop from 1970. Overabstraction from aquifers has been estimated to be between 29 and 40 MCM per year, and due to water scarcity and multiyear droughts, this has led to a near exhaustion of the "cushioning" effects of the aquifers as well as seawater intrusion (Socratous 2005).

It is anticipated that climate change will have a number of impacts in Cyprus: a mean summer temperature increase of 5° C by 2070–2100, a mean summer precipitation change of -4 mm/ month by 2070–2100, and an increase in the duration and intensity of droughts (Lange 2007). Intense precipitation events could result in excess surface runoff rather than infiltration to groundwater, and rising seawater levels could increase flooding and seawater ingress, resulting in the contamination of surface and groundwater bodies.

Water shortages have been a long-standing problem in Cyprus. In 1991, the deficit was so acute (75 MCM) that a 20% reduction in domestic water supply and a 30–70% reduction in irrigation water supply were imposed. A similar scenario occurred between 1996 and 2000 (with deficits between 68 and 114 MCM), and a similar scenario is unfolding in 2008 (Tsiourtis 2004).

The annual water demand in Cyprus is approximately 69% for agriculture, 25% for domestic (20% for inhabitants and 5% for tourism), 1% for industry, and 5% for the environment (Savvides et al. 2001). The 2001 overall water demand was 265.9 MCM, while the projected demand for 2010 is 290.5 MCM and 313.7

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issue of increasingly high overall and peak water demand and decreasing amounts of water, it will be necessary to pursue new strategies. Among many possibilities, this could involve a combination of the following: implementing effective water-demand reduction programs, imposing effective water use restrictions, optimizing water supply systems through real-time control by hybrid expert systems, and developing sustainable alternative water source strategies. An important aspect of these initiatives is the accurate forecasting of short-term water demands and, in particular, peak water demands.
Despite the relative importance of peak water demand and, in particular, peak water-demand forecasting, limited detailed research has been devoted to this topic, including factors driving peak water demand and different forecasting methods (Day and Howe 2003). The motivation for this research was therefore to study three important issues that have not, to the best knowledge of the authors, been explored in detail in the short-term water-

study three important issues that have not, to the best knowledge of the authors, been explored in detail in the short-term waterdemand literature: (1) the use of resilient back-propagation (RP) and conjugate gradient Powell-Beale (CGPB) ANNs for urban short-term water-demand forecasting, (2) the use of ANNs for peak (as opposed to average or total) weekly water demand in an area with very acute water scarcity, and (3) the determination of whether rainfall occurrence or rainfall amount is a more significant variable in modeling peak water-demand forecasts.

MCM for 2020 (Savvides et al. 2001). In order to address the

It has been shown that the peak water-demand process is often stochastic and nonlinear (Gutzler and Nims 2005). As such, the forecasting of peak water demand is complex and thus the use of different types of ANNs, which are capable of modeling nonlinear systems, needs to be explored. The issue of whether rainfall occurrence or rainfall amount is a more significant variable in modeling short-term water demand has been investigated by Jain et al. (2001), Bougadis et al. (2005), and Adamowski (2008), but they arrived at differing conclusions. Therefore, this issue was further investigated in this study for peak weekly water demand.

In this research, three different types of multilayer perceptron artificial neural networks [each using a different learning algorithm, namely, Levenberg-Marquardt (LM), RP, and CGPB algorithms] were developed and compared with a conventional method [multiple linear regression (MLR)] for peak weekly water-demand forecasting.

Previous Research

MLR Analysis and Time Series Analysis

A variety of techniques has been used in short-term water-demand forecasting, including regression analysis and "time series" analysis. Simple regression and MLR are frequently used river flow forecasting methods. They have the advantage that they are comparatively simple and can easily be implemented. However, they are somewhat limited in their ability to forecast in certain situations, especially in the presence of nonlinear relationships and high levels of noisy data. Examples of short-term water-demand forecast modeling using regression analysis include Howe and Linaweaver (1967), Oh and Yamauchi (1974), Hughes (1980), Anderson et al. (1980), and Maidment and Parzen (1984).

Most "time series" models belong to the class of linear time series forecasting, because they postulate a linear dependency of the future value on the past values. A critique of univariate time series models is that they do not consider climatic variables during the modeling process since they only explore the relationship between present and past floods. However, the time series technique is nevertheless very useful where climatic data are not available. The most popular univariate models are the autoregressive moving average (ARMA) model and its derivatives, which include the autoregressive (AR), autoregressive integrated moving average (ARIMA), seasonal ARIMA, periodic ARMA, threshold AR, and fractionally integrated ARMA models. Maidment et al. (1985) used short-term time series models for daily municipal water use as a function of rainfall and air temperature. Maidment and Miaou (1986) applied this model to the water consumption from nine cities in the United States. Some other examples of short-term water-demand forecast modeling using time series analysis include Smith (1988), Miaou (1990), Zhou et al. (2000), Jain et al. (2001), Bougadis et al. (2005), and Adamowski (2008).

Artificial Neural Network Analysis

Artificial neural networks have recently begun to be used for short-term water-demand forecasting. A number of studies have compared the use of artificial neural networks for short-term urban water-demand forecasting with other forecasting methods. Most studies used traditional gradient-descent feedforward backpropagation ANNs.

Jain et al. (2001) developed gradient-descent ANN models and compared them to regression and time series models. It was found that the occurrence of rainfall was a more significant variable than the amount of rainfall itself in the modeling of short-term water demand, and that the ANN models outperformed both the regression and time series models. Jain and Ormsbee (2002) examined regression, time series analysis, and gradient-descent ANN models for daily water-demand forecasting and found that the ANN models were slightly more accurate than the time series and the regression-disaggregation models. Pulido-Calvo et al. (2003) examined regression, time series, and gradient-descent ANN models for total daily water demand for Fuente Palmera, Spain, and found that the ANN model outperformed all the other models. Bougadis et al. (2005) explored regression, time series, and gradient-descent ANN models for weekly water demand and found that the ANN models consistently outperformed the regression and time series models. They found, in contrast to Jain et al. (2001), that the weekly water demand is better correlated with the amount of rainfall rather than the rainfall occurrence. Adamowski (2008) compared regression, time series, and gradient-descent ANN models for peak daily water-demand forecasting and found that the ANN models were more accurate than the other models, and that the peak daily water demand is better correlated with the rainfall occurrence rather than the amount of rainfall itself.

There have also been a number of studies that compared different types of artificial neural networks for short-term urban water-demand forecasting. Heller and Singh Thind (1994) found cascade correlation ANNs to be more accurate than gradientdescent ANNs, Chen et al. (2005) found Chebyshev ANNs to be more accurate than gradient-descent ANNs, Pulido-Calvo et al. (2007) found LM ANNs to be more accurate than MLR, Yue et al. (2007) found particle swarm optimization ANNs to be more accurate than gradient-descent ANNs, and Ghiassi et al. (2008) found dynamic ANNs to be more accurate than gradient-descent ANNs and autoregressive integrated moving average time series analysis.

A number of studies comparing different types of ANNs have also been completed for flood and rainfall-runoff forecasting applications. Those studies that compared LM ANNs with other types of ANNs (conjugate gradient, Bayesian regularization, cascade correlation, gradient descent, variable learning rate, and momentum back-propagation) found that the LM ANNs outperformed the other types of ANNs (Aqil et al. 2007; Cigizoglu and Kisi 2005; Kişi 2007; Liu et al. 2007). Those studies that compared radial basis function (RBF) ANNs with other types of ANNs (namely, gradient-descent ANNs) arrived at a variety of conclusions. Some studies found that the RBF ANNs slightly outperformed the traditional gradient-descent ANNs (Piotrowski et al. 2006; Huang et al. 2003). Other studies found that the RBF ANNs had approximately the same level of accuracy as the gradient-descent ANNs (Jayawardena 1997; Fernando and Jayawardena 1998; Jayawardena et al. 1998; Dawson et al. 2002), while still other studies found that the gradient-descent ANNs outperformed the RBF ANNs (Dawson and Wilby 1999).

From the above flood and rainfall-runoff forecasting studies, it can be seen that the traditional gradient-descent ANNs have approximately the same performance as the RBF ANNs, the LM ANNs have better performance than most other types of ANNs, and that there are very few studies that have explored the use of conjugate gradient ANNs, and no studies that have explored the use of CGPB and RP ANNs.

In this study, it was decided to compare three types of ANNs: LM, RP, and CGPB. RP and CGPB ANNs were tested because, to the best knowledge of the authors, they have not been explored in literature for use in forecasting short-term urban peak water demand even though they have a number of advantages. LM ANNs were tested because they have been shown to be highly accurate for short-term irrigation water-demand forecasting (Pulido-Calvo et al. 2007) and flood and rainfall-runoff forecasting (Aqil et al. 2007; Cigizoglu and Kisi 2005; Kişi 2007; Liu et al. 2007), and as such it was deemed that it would be useful to compare RP and CGPB ANNs with an ANN method (LM) that has already been shown to be very accurate in other forecasting applications. MLR was also used in this study because it is one of the most widely used techniques for water-demand forecasting and as such is ideal for comparative purposes with the newer ANN methods.

Study Areas and Data

Nicosia Water Supply System

The Water Board of Nicosia buys water from the Water Development Department and is responsible for distributing potable water services to over 200,000 people (83,129 water meters). The total capacity of the reservoirs is 70,000 m³ (equivalent to 2-day supply) and the entire water supply system operates under gravity. In 2005, water production in Nicosia was estimated at 18 MCM, water consumption at 16.96 MCM (with domestic use accounting for 13 MCM), and actual average daily consumption per person at 159 L (Local water supply, sanitation and sewage: Country report-Cyprus 2005). Unaccounted water was estimated at approximately 24.4%. The sources for domestic water supply in Nicosia are desalination (45.5%), groundwater (28.8%), and surface water (25.7%). Water shortages have seriously harmed the distribution system due to pressure being off and on, which has lead to an increase in the number of leaks (Local water supply, sanitation and sewage: Country report—Cyprus 2005).

In order to address the issue of increasingly high overall and peak water demand and decreasing amounts of water in Nicosia, it will be necessary to pursue new strategies. Among many possibilities, this could involve a combination of the following: implementing effective water-demand reduction programs, imposing effective water use restrictions, optimizing water supply systems through real-time control by hybrid expert systems, and developing sustainable alternative water source strategies. An important aspect of these initiatives is the accurate forecasting of short-term water demands and, especially, peak water demands. In particular, the city of Nicosia has identified peak weekly waterdemand forecasts as being very important to help them address increasingly high overall and peak water demand and decreasing amounts of water in Nicosia.

Data

Many variables influence water demand, most of which can be grouped into two classes: socioeconomic and climatic variables. Studies have demonstrated that socioeconomic variables are responsible for the long-term effects on water demand, while climatic variables are mainly responsible for short-term seasonal variations in water demand (Miaou 1990).

This study used climatic variables and past water demand. More specifically, the data used in this study consisted of weekly total rainfall (mm), maximum weekly temperature (°C), and peak weekly water demand (ML/d). The peak weekly water demand for a specific week was the peak hour water demand in that week. Two sets of water-demand data and one set of climatic data were used. The first set of water-demand data was from Athalassa in Nicosia, while the second set of water-demand data was from the Public Garden in Nicosia.

Water-demand data were provided by the Water Board of Nicosia, and meteorological data were provided by the Meteorological Service of Cyprus. The water-demand series record was available from 2002 to 2007. For the Public Garden region, the mean weekly rainfall over this time period was 7.16 mm (with a standard deviation of 15.35 mm), while the mean weekly temperature over this time period was $25.85 \,^{\circ}\text{C}$ (with a standard deviation of $6.12 \,^{\circ}\text{C}$). For the Athalassa region, the mean weekly rainfall over this time period was 7.03 mm (with a standard deviation of $14.48 \,$ mm), while the mean weekly temperature over this time period was $26.34 \,^{\circ}\text{C}$ (with a standard deviation of $8.25 \,^{\circ}\text{C}$). There were no special events (such as a large pipe break or tournaments) that could have invalidated the data in either of the regions.

For the ANN models, the water demand and meteorological data series were divided into a training/calibration set (the first 70% of the data sets from 2002 to 2007), a validation set (the next 10% of the data sets from 2002 to 2007), and a testing set (the last 20% of the data sets from 2002 to 2007). For the MLR models, the water demand and meteorological data series were divided into a training/calibration set (the first 70% of the data sets from 2002 to 2007) and a testing set (the last 30% of the data sets from 2002 to 2007).

Model Development

MLR Analysis

Ten MLR models for the Athalassa region [MLR-(A)] and ten MLR models for the Public Garden region [MLR-(PG)] were developed for weekly peak water-demand forecasts and can be seen in Table 1.

Cross-correlation coefficients between peak weekly water demand and each variable were calculated. This information was

Table	1. Performance	Statistics	for MLR	Models	1-10 fo	r Athalassa	and Public	Garden,	Nicosia
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Model	Parameters	R^2 training	R^2 testing	RMSE (ML/d)	AARE	Max ARE
		Athalassa		. ,		
MLR-1(A)	WD(t-1), T, T(t-1), R, R(t-1), CR, CR(t-1)	0.8501	0.8138	0.1916	2.4594	12.2336
MLR-2(A)	WD(t-1), T(t)	0.7967	0.7749	0.2092	2.8324	14.0489
MLR-3(A)	WD(t-1), T(t), T(t-1)	0.8347	0.8153	0.2048	2.5634	12.9539
MLR-4(A)	WD(t-1), T(t), R(t)	0.8101	0.7910	0.2061	2.7447	13.0094
MLR-5(A)	WD(t-1), T(t), T(t-1), R(t)	0.8408	0.8186	0.1963	2.5257	12.1704
MLR-6(A)	WD(t-1), T(t), CR(t)	0.8034	0.7597	0.2075	2.8008	13.3840
MLR-7(A)	WD(t-1), T(t), T(t-1), CR(t)	0.8380	0.8073	0.1982	2.5388	12.5230
MLR-8(A)	WD(t-1), T(t), T(t-1), R(t-1)	0.8403	0.8180	0.2009	2.5443	12.7667
MLR-9(A)	WD(t-1), T(t), T(t-1), R(t-2)	0.8351	0.8152	0.2023	2.5581	12.8799
MLR-10(A)	WD(t-1), T(t), T(t-1), T(t-2)	0.8383	0.8196	0.1952	2.5143	11.9900
		Public Garden				
MLR-1(PG)	WD(t-1), T, T(t-1), R, R(t-1), CR, CR(t-1)	0.8385	0.8133	0.1932	2.4806	12.5852
MLR-2(PG)	WD(t-1), T(t)	0.7981	0.7749	0.2125	2.8135	14.2099
MLR-3(PG)	WD(t-1), T(t), T(t-1)	0.8265	0.8133	0.2065	2.5879	14.5574
MLR-4(PG)	WD(t-1), T(t), R(t)	0.7986	0.7722	0.2083	2.8244	14.1343
MLR-5(PG)	WD(t-1), T(t), T(t-1), R(t)	0.8295	0.8091	0.1982	2.5736	14.3795
MLR-6(PG)	WD(t-1), T(t), CR(t)	0.8033	0.7708	0.2095	2.8024	13.3425
MLR-7(PG)	WD(t-1), T(t), T(t-1), CR(t)	0.8285	0.8124	0.2001	2.5667	14.0009
MLR-8(PG)	WD(t-1), T(t), T(t-1), R(t-1)	0.8275	0.8162	0.2023	2.5836	14.3986
MLR-9(PG)	WD(t-1), T(t), T(t-1), R(t-2)	0.8288	0.8134	0.2041	2.5744	14.3059
MLR-10(PG)	WD(t-1), T(t), T(t-1), T(t-2)	0.8316	0.8157	0.1963	2.5347	13.9153

Note: MLR=multiple linear regression, A=Athalassa, PG=Public Garden, R^2 =coefficient of determination, RMSE=root-mean-square error, AARE = average absolute relative error, Max ARE=maximum absolute relative error, WD(t)=demand at time t, T(t)=temperature at time t, R(t)=rainfall at time t, and CR(t)=occurrence or nonoccurrence of rainfall at time t.

used to aid in selecting input variables for the MLR and ANN models. The cross correlation between the peak weekly water demand at time *t* and each of the other variables (peak water demand, maximum temperature, total rainfall, and occurrence or nonoccurrence of rainfall) was performed from times *t* (current week) to *t*-5 (5 weeks ago). Based on the cross-correlation results, the MLR (and ANN) models were developed using a combination of the following variables: peak water demand for the previous week WD(t-1), maximum temperature for the current week T(t), maximum temperature for the previous week R(t), total rainfall for the previous week R(t), total rainfall for the previous week R(t-1), total rainfall for the current week CR(t), and occurrence or nonoccurrence of rainfall for the previous week CR(t-1).

An example of one of these models is MLR-1(A), which is a function of the peak water demand from the previous week WD(t-1), the maximum temperature of the current day T(t), the maximum temperature of the previous week T(t-1), the total rainfall of the current week R(t), the total rainfall of the previous week R(t-1), the occurrence/nonoccurrence of rainfall for the current week CR(t), and the occurrence/nonoccurrence of rainfall for the previous week CR(t-1), and is shown by

$$WD(t) = B_0 + B_1 WD(t-1) + B_2 T(t) + B_3 T(t-1) + B_4 R(t) + B_5 R(t-1) + B_6 CR(t) + B_7 CR(t-1)$$
(1)

All of the MLR models were first trained (to determine the regression coefficients) using the data in the training set (the first

70% of the data) and then tested using the testing data set (the last 30% of the data), and compared using the four statistical measures of goodness of fit.

Artificial Neural Network Analysis

Multilayered perceptrons (MLPs) are the simplest and most commonly used neural network architectures. MLPs can be trained using many different learning algorithms. In this research, MLPs were trained using LM, RP, and CGPB learning algorithms. There are a number of advantages associated with using the LM, RP, and CGPB learning algorithms. Furthermore, as was mentioned earlier, two of these learning algorithms (RP and CBPB) have not been explored for use in short-term urban water-demand forecasting.

The LM algorithm (Levenberg 1944; Marquardt 1963), like the quasi-Newton methods, was developed to approach secondorder training speed without having to compute the Hessian matrix. The LM algorithm has been found to be the fastest method for training moderate-sized feedforward neural networks, although it requires a greater amount of memory than other algorithms (Karul et al. 2000).

Multilayer networks usually use sigmoid transfer functions in the hidden layers. The slopes of sigmoid functions have to approach zero as the input becomes large. This can be problematic when the steepest descent is used to train a multilayer network with sigmoid functions because the gradient can have a very small magnitude. This in turn can result in small changes in the weights and biases, even though the weights and biases are far

Table 2.	Performance	Statistics	for ANN	Models	1 - 5	for	Athalassa,	Nicosia
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Model	Parameters	R^2 training	R^2 validation	R^2 testing	RMSE (ML/d)	AARE	Max ARE
LM-1(A)	WD(t-1), T, T(t-1), R, R(t-1), CR, CR(t-1)	0.9526	0.8923	0.9462	0.1255	2.1467	11.1821
RP-1(A)	WD(t-1), T, T(t-1), R, R(t-1), CR, CR(t-1)	0.9257	0.8939	0.9257	0.1842	2.4620	12.3675
CGPB-1(A)	WD(t-1), T, T(t-1), R, R(t-1), CR, CR(t-1)	0.9473	0.8971	0.9418	0.1626	2.0949	11.9275
LM-2(A)	WD(t-1), T(t)	0.9374	0.8739	0.9173	0.1735	2.3642	11.0312
RP-2(A)	WD(t-1), T(t)	0.9199	0.8869	0.9426	0.1936	2.4717	15.8176
CGPB-2(A)	WD(t-1), T(t)	0.9195	0.8796	0.9313	0.1929	2.5443	15.2643
LM-3(A)	WD(t-1), T(t), T(t-1)	0.9569	0.8971	0.9396	0.1395	1.9821	15.7640
RP-3(A)	WD(t-1), T(t), T(t-1)	0.9265	0.8783	0.8993	0.1843	2.4989	11.8496
CGPB-3(A)	WD(t-1), T(t), T(t-1)	0.9463	0.8970	0.9423	0.1604	2.1763	14.2667
LM-4(A)	WD(t-1), T(t), R(t)	0.9525	0.8869	0.9557	0.1504	2.0216	16.0445
RP-4(A)	WD(t-1), T(t), R(t)	0.9354	0.8727	0.9510	0.1776	2.3827	14.9018
CGPB-4(A)	WD(t-1), T(t), R(t)	0.9139	0.8752	0.9494	0.1859	2.5712	14.4451
LM-5(A)	WD(t-1), T(t), T(t-1), R(t)	0.9653	0.9279	0.9091	0.1278	1.7649	12.4000
RP-5(A)	WD(t-1), T(t), T(t-1), R(t)	0.9254	0.9034	0.9327	0.1812	2.4273	11.3539
CGPB-5(A)	WD(t-1), T(t), T(t-1), R(t)	0.9123	0.8986	0.9143	0.1805	2.6825	13.2094

Note: A=Athalassa, LM=Levenberg-Marquardt, RP=resilient back-propagation, CGB=conjugate gradient Powell-Beale, R^2 =coefficient of determination, RMSE=root-mean-square error, AARE=average absolute relative error, Max ARE=maximum absolute relative error, WD(t)=demand at time t, T(t)=temperature at time t, R(t)=rainfall at time t, and CR(t)=occurrence or nonoccurrence of rainfall at time t.

from their optimal values. The purpose of the RP training algorithm (Riedmuller and Braun 1993) is to eliminate the harmful effects of the magnitudes of the partial derivatives. In the RP training algorithm, the sign of the derivative is used to ascertain the direction of the weight update, while the magnitude of the derivative does not have an effect on the weight update. A separate update value determines the size of the weight change. The update value for each weight and bias is increased by a specific factor when the derivative of the performance function with respect to that weight has the same sign for two successive iterations. The update value is decreased by a specific factor when the derivative with respect to that weight changes sign from the previous iteration. If the weights are oscillating, the weight change will be reduced, and if the weight continues to change in the same direction for several iterations, then the magnitude of the weight change will be increased ((Matlab help files 2005). The RP training algorithm is usually much faster than the standard steepest descent algorithm, and requires only a small increase in memory.

The back-propagation algorithm adjusts the weights in the steepest descent direction, which is the direction in which the performance function decreases most rapidly. Although the function decreases most rapidly along the negative of the gradient, this does not necessarily result in the fastest convergence. In the conjugate gradient algorithms a search is performed along conjugate directions, which usually results in faster convergence than steepest descent directions. The conjugate gradient algorithm with Powell-Beale restarted method (Beale 1972; Powell 1977) is used to improve the convergent rate and the performance of the neural model. The Powell-Beale variation of the conjugate gradient has two main features. First, the algorithm uses a test to determine when to reset the search direction to the negative of the gradient. Second, the search direction is computed from the negative gradient, the previous search direction, and the last search direction before the previous reset.

To develop an ANN model, the primary objective is to arrive at the optimum architecture of the ANN that captures the relationship between the input and output variables. The task of identifying the number of neurons in the input and output layers is normally simple as it is dictated by the input and output variables considered to model the physical process. The number of neurons in the hidden layer has to be optimized using the available data through the use of a trial-and-error procedure. In addition, optimal values for the learning coefficients have to be determined for certain types of ANNs.

In this study, ANN networks consisting of an input layer with 2–7 input nodes, one single hidden layer composed of 15 nodes, and one output layer consisting of 1 node denoting the predicted peak weekly water demand were developed. Each ANN model was tested on a trial-and-error basis for the optimum number of neurons in the hidden layer (found to be 15 neurons for all models). For the RP ANNs the optimum learning coefficient was found to be 0.01. The LM ANNs and CGPB ANNs do not have a learning coefficient.

Ten LM ANN models, ten RP ANN models, and ten CGPB ANN models were developed using Matlab for the Athalassa region of Nicosia and ten LM ANN models, ten RP ANN models, and ten CGPB models were developed for the Public Garden region of Nicosia. The neurons in the input layer of each of these different ANN models represented different combinations of the various physical variables considered, and were chosen based on the correlation coefficients between each variable (at different time steps from t to t-3) and the original peak weekly waterdemand data. These can be seen in Tables 2-5. Based on the results of the cross-correlation analysis, the ANN models were developed using a combination of the following variables: peak water demand for the previous week WD(t-1), maximum temperature for the current week T(t), maximum temperature for the previous week T(t-1), maximum temperature from 2 weeks ago T(t-2), total rainfall for the current week R(t), total rainfall for the previous week R(t-1), total rainfall from 2 weeks ago R(t-2), occurrence or nonoccurrence of rainfall for the current week CR(t), and occurrence or nonoccurrence of rainfall for the previous week CR(t-1).

For both the Athalassa region and the Public Garden region, all of the ANN models were first trained using the data in the training sets (using the first 70% of the data) to obtain the optimized set of connection strengths, then validated (using the next 10% of the

Table 3. Performance Statistics for ANN Models 6–10 for Athalassa, 1	Nicosia
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Model	Parameters	R^2 training	R^2 validation	R^2 testing	RMSE (ML/d)	AARE	Max ARE
LM-6(A)	WD(t-1), T(t), CR(t)	0.9485	0.8875	0.9536	0.1605	2.1262	13.9639
RP-6(A)	WD(t-1), T(t), CR(t)	0.9391	0.8860	0.9502	0.1748	2.2464	13.3371
CGPB-6(A)	WD(t-1), T(t), CR(t)	0.9339	0.8876	0.9577	0.1765	2.2954	13.3131
LM-7(A)	WD(t-1), T(t), T(t-1), CR(t)	0.9391	0.8868	0.8683	0.1358	2.4924	11.6271
RP-7(A)	WD(t-1), T(t), T(t-1), CR(t)	0.9220	0.8876	0.8844	0.1837	2.6127	12.6338
CGPB-7(A)	WD(t-1), T(t), T(t-1), CR(t)	0.9299	0.8991	0.9128	0.1826	2.5186	12.4840
LM-8(A)	WD(t-1), T(t), T(t-1), R(t-1)	0.9503	0.8523	0.9337	0.1461	2.0800	21.5706
RP-8(A)	WD(t-1), T(t), T(t-1), R(t-1)	0.9390	0.8854	0.8778	0.1684	2.2929	12.8536
CGPB-8(A)	WD(t-1), T(t), T(t-1), R(t-1)	0.9393	0.8997	0.8886	0.1696	2.2308	13.1382
LM-9(A)	WD(t-1), T(t), T(t-1), R(t-2)	0.9523	0.9042	0.9218	0.1473	2.0604	10.9234
RP-9(A)	WD(t-1), T(t), T(t-1), R(t-2)	0.8923	0.8547	0.8859	0.2061	3.1349	13.5761
CGPB-9(A)	WD(t-1), T(t), T(t-1), R(t-2)	0.9075	0.8821	0.9034	0.1877	2.7841	12.5440
LM-10(A)	WD(t-1), T(t), T(t-1), T(t-2)	0.9612	0.9276	0.8873	0.1311	1.9488	12.9935
RP-10(A)	WD(t-1), T(t), T(t-1), T(t-2)	0.9401	0.9063	0.9007	0.1678	2.2311	12.1537
CGPB-10(A)	WD(t-1), T(t), T(t-1), T(t-2)	0.9339	0.9036	0.9326	0.1738	2.3097	11.0284

Note: A=Athalassa, LM=Levenberg-Marquardt, RP=resilient back-propagation, CGB=conjugate gradient Powell-Beale, R^2 =coefficient of determination, RMSE=root-mean-square error, AARE=average absolute relative error, Max ARE=maximum absolute relative error, WD(t)=demand at time t, T(t)=temperature at time t, R(t)=rainfall at time t, and CR(t)=occurrence or nonoccurrence of rainfall at time t.

data), and then tested (using the last 20% of the data). The models were then compared using the four statistical measures of goodness of fit.

Model Performance Comparison

The performance of developed models can be evaluated using several statistical tests that describe the errors associated with the model. After each of the model structures is calibrated using the calibration/testing data set, the performance can then be evaluated in terms of these statistical measures of goodness of fit. In order to provide an indication of goodness of fit between the observed and forecasted values the coefficient of determination (R^2), the root-mean-square error (RMSE), the average absolute relative error (Max

ARE) can be used. In addition, the persistence index (PI) can be used to compare the performance of a model with that of a "naïve" model, which always gives as a forecast the previous observation.

The coefficient of determination (R^2) measures the degree of correlation among the observed and predicted values. It is a measure of the strength of the model in developing a relationship among input and output variables. The higher the R^2 value (with 1 being the maximum value), the better is the performance of the model. R^2 is given by

$$R^{2} = \frac{\sum_{i=1}^{N} (\hat{y}_{i} - \overline{y}_{i})^{2}}{\sum_{i=1}^{N} (y_{i} - \overline{y}_{i})^{2}}$$
(2)

with

 Table 4. Performance Statistics for ANN Models 1–5 for Public Garden, Nicosia

Model	Parameters	R^2 training	R^2 validation	R^2 testing	RMSE (ML/d)	AARE	Max ARE
LM-1(PG)	WD(t-1), T, T(t-1), R, R(t-1), CR, CR(t-1)	0.9271	0.8583	0.9063	0.1430	2.5925	14.4620
RP-1(PG)	WD(t-1), T, T(t-1), R, R(t-1), CR, CR(t-1)	0.9075	0.8278	0.8873	0.2041	2.9152	13.8981
CGPB-1(PG)	WD(t-1), T, T(t-1), R, R(t-1), CR, CR(t-1)	0.9181	0.8812	0.8843	0.1874	2.4896	12.2139
LM-2(PG)	WD(t-1), T(t)	0.9357	0.8776	0.9319	0.1790	2.2967	10.8208
RP-2(PG)	WD(t-1), T(t)	0.9007	0.8781	0.9445	0.2184	2.7308	18.5083
CGPB-2(PG)	WD(t-1), T(t)	0.9130	0.8699	0.9306	0.1938	2.6485	17.3165
LM-3(PG)	WD(t-1), T(t), T(t-1)	0.9445	0.8660	0.9404	0.1531	2.4113	13.2683
RP-3(PG)	WD(t-1), T(t), T(t-1)	0.9421	0.8792	0.9432	0.1698	2.2686	13.1499
CGPB-3(PG)	WD(t-1), T(t), T(t-1)	0.9301	0.8666	0.9322	0.1809	2.4538	13.7948
LM-4(PG)	WD(t-1), T(t), R(t)	0.9388	0.8721	0.9496	0.1634	2.3514	14.8739
RP-4(PG)	WD(t-1), T(t), R(t)	0.9046	0.8260	0.8938	0.2100	3.0256	13.1829
CGPB-4(PG)	WD(t-1), T(t), R(t)	0.9288	0.8685	0.9446	0.1877	2.4713	14.5310
LM-5(PG)	WD(t-1), T(t), T(t-1), R(t)	0.946	0.9145	0.8642	0.1550	2.248	10.8404
RP-5(PG)	WD(t-1), T(t), T(t-1), R(t)	0.9027	0.8922	0.8898	0.2057	2.8156	11.8469
CGPB-5(PG)	WD(t-1), T(t), T(t-1), R(t)	0.9140	0.8901	0.8884	0.1883	2.6698	12.6940

Note: A=Athalassa, LM=Levenberg-Marquardt, RP=resilient back-propagation, CGB=conjugate gradient Powell-Beale, R^2 =coefficient of determination, RMSE=root-mean-square error, AARE=average absolute relative error, Max ARE=maximum absolute relative error, WD(t)=demand at time t, T(t)=temperature at time t, R(t)=rainfall at time t, and CR(t)=occurrence or nonoccurrence of rainfall at time t.

734 / JOURNAL OF HYDROLOGIC ENGINEERING © ASCE / OCTOBER 2010

					RMSE		
Model	Parameters	R^2 training	R^2 validation	R^2 testing	(ML/d)	AARE	Max ARE
LM-6(PG)	WD(t-1), T(t), CR(t)	0.9471	0.8936	0.9447	0.1600	2.1432	14.5859
RP-6(PG)	WD(t-1), T(t), CR(t)	0.9320	0.8835	0.9314	0.1813	2.3726	13.0461
CGPB-6(PG)	WD(t-1), T(t), CR(t)	0.9342	0.8850	0.9513	0.1775	2.3125	13.1695
LM-7(PG)	WD(t-1), T(t), T(t-1), CR(t)	0.9471	0.9139	0.9372	0.1525	2.0182	10.8899
RP-7(PG)	WD(t-1), T(t), T(t-1), CR(t)	0.9272	0.9080	0.9055	0.1837	2.3779	10.2757
CGPB-7(PG)	WD(t-1), T(t), T(t-1), CR(t)	0.9350	0.9074	0.9053	0.1743	2.2086	11.2556
LM-8(PG)	WD(t-1), T(t), T(t-1), R(t-1)	0.9435	0.9161	0.9239	0.1601	2.1168	11.4054
RP-8(PG)	WD(t-1), T(t), T(t-1), R(t-1)	0.9279	0.9051	0.9335	0.1824	2.3456	12.6191
CGPB-8(PG)	WD(t-1), T(t), T(t-1), R(t-1)	0.9322	0.8990	0.9207	0.1784	2.3002	12.7193
LM-9(PG)	WD(t-1), T(t), T(t-1), R(t-2)	0.9473	0.9042	0.8856	0.1543	2.1334	10.9598
RP-9(PG)	WD(t-1), T(t), T(t-1), R(t-2)	0.9072	0.8712	0.9076	0.2060	2.7951	12.9751
CGPB-9(PG)	WD(t-1), T(t), T(t-1), R(t-2)	0.9305	0.9021	0.9078	0.1802	2.3335	12.7975
LM-10(PG)	WD(t-1), T(t), T(t-1), T(t-2)	0.9567	0.9327	0.9174	0.1366	1.9727	9.7623
RP-10(PG)	WD(t-1), T(t), T(t-1), T(t-2)	0.9423	0.9052	0.9001	0.1655	2.2712	10.4138
CGPB-10(PG)	WD(t-1), T(t), T(t-1), T(t-2)	0.9305	0.9005	0.9274	0.1783	2.3778	11.2030

Note: A=Athalassa, LM=Levenberg-Marquardt, RP=resilient back-propagation, CGB=conjugate gradient Powell-Beale, R^2 =coefficient of determination, RMSE=root-mean-square error, AARE=average absolute relative error, Max ARE=maximum absolute relative error, WD(t)=demand at time t, T(t)=temperature at time t, R(t)=rainfall at time t, and CR(t)=occurrence or nonoccurrence of rainfall at time t.

$$\overline{y}_i = \frac{1}{N} \sum_{i=1}^{N} y_i \tag{3}$$

where \bar{y}_i =mean value taken over *N*, *N*=number of data points used, y_i =observed peak weekly water demand, and \hat{y}_i =forecasted peak weekly water demand from the model.

The RMSE evaluates the variance of errors independently of the sample size, and is given by

$$RMSE = \sqrt{\frac{SEE}{N}}$$
(4)

where SEE = sum of squared errors and N = number of data points used. *SEE* is given by

$$SEE = \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$
(5)

with the variables having already been defined. The smaller the RMSE, the better is the performance of the model.

The AARE is a quantitative measure of the average error in one step ahead forecasts from a particular model and is defined by

AARE =
$$\frac{1}{N} \sum_{i=1}^{N} \left| \frac{O_i - D_i}{O_i} \right| \times 100\%$$
 (6)

where O_i =observed peak weekly water demand and D_i =forecasted peak weekly water demand. The smaller the value of AARE, the better is the performance of the model.

The Max ARE is the maximum of the absolute relative error (AARE) among all of the forecasted data points and is a measure of the robustness of the model. The smaller the value of the Max ARE, the better is the performance of the model.

The PI compares the performance of a model with that of a naïve model and is given by

$$PI = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - y_{i-L})^2}$$
(7)

where y_{i-L} =observed water demand at the time step i-L and L=lead time (52 weeks). A PI value of 1 reflects perfect adjustment between forecasted and observed values. A PI value of zero is equivalent to saying that the model is no better than a naïve model, which always gives as a forecast the previous observation. A negative PI value means that the model degrades the original information, thus exhibiting a performance worse than the one given by the naïve model (Pulido-Calvo and Portela 2007).

Results

Pls

The performance indices were calculated for the best model of each forecasting method over the last 52-week seasonal cycle (i.e., a comparison was made between 2006 and 2007). This was done only for the Athalassa region. The PI for MLR-10(A) was 0.5742, the PI for LM-1(A) was 0.6654, the PI for RP-10(A) was 0.6873, and the PI for CGPB-1(A) was 0.6318. For each of these models, the PI is greater than zero, indicating that all forecasts are better than the naïve model, which gives as a forecast the previous observation at all times. As expected, there is a noticeable improvement shown by the ANN models compared to the MLR model. It can also be seen from Figs. 1-4 [which compare the forecasted water demand with the observed water demand for the last 52-week seasonal cycle for the MLR-10(A), LM-1(A), RP-10(A), and CGPB-1(A) models, respectively] that there is no systematic displacement between the observed and forecasted waterdemand time series.

MLR Analysis

Table 1 shows the performance statistics for the testing of all ten of the Athalassa MLR models and all ten of the Public Garden

Athalassa Multiple Linear Regression best model results - MLR-10 (A) 2007 (52-week period)



MLR models while Table 8 shows the performance statistics for the best Athalassa and Public Garden MLR models. For the Athalassa region, the best MLR model was MLR-10(A), which had a testing R^2 of 0.8196, a RMSE of 0.1952, an AARE of 2.5143, and a Max ARE of 11.9900. MLR-10(A) had the following param-

eters: WD(t-1), T(t), T(t-1), and T(t-2). Fig. 5 compares the actual water demand for the Athalassa region with the water demand forecasted using model MLR-10(A). It can be seen that both the peaks and troughs are relatively well forecasted.

For the Public Garden region, the best MLR model was MLR-









1(PG), which had a testing R^2 of 0.8133, a RMSE of 0.1932, an AARE of 2.4806, and a Max ARE of 12.5852. MLR-1(PG) had the following parameters: WD(t-1), T(t), T(t-1), R(t), R(t-1), CR(t), and CR(t-1).

Artificial Neural Network Analysis

Tables 2–5 show the individual model performance statistics for the 60 ANN models developed in this study for both the Athalassa



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Table 6. Average Performance Statistics for Each Type of Method for Athalassa, Nicosia

Method	R^2 training	R^2 validation	R^2 testing	RMSE (ML/d)	AARE	Max ARE
LM ANN	0.9516	0.8937	0.9233	0.1437	2.0987	13.7500
RP ANN	0.9265	0.8855	0.9150	0.1822	2.4761	13.0845
CGPB ANN	0.9284	0.8920	0.9274	0.1773	2.4208	13.1621
MLR	0.8288		0.8034	0.2012	2.6342	12.7960

and Public Garden regions. Table 6 shows the performance statistics for the best model for each type of method for the Athalassa and Public Garden regions. Tables 7 and 8 show the average performance statistics for each type of method (LM, RP, CGPB, and MLR) for both the Athalassa and Public Garden regions.

For all of the ANN models, it was determined that 15 neurons in the hidden layer produced the highest coefficients of determination and as such each of the 60 models used 15 neurons in the hidden layer.

ANN Results for the Athalassa Region

For the Athalassa region, it can be seen from Table 6 that the best ANN model overall was LM-1(A), which had a testing R^2 of 0.9462, a RMSE of 0.1255, an AARE of 2.1467, and a Max ARE of 11.1821. LM-1(A) had the following parameters: WD(t-1), T(t), T(t-1), R(t), R(t-1), CR(t), and CR(t-1). The best RP ANN model for the Athalassa region was RP-10(A), which had a testing R^2 of 0.9007, a RMSE of 0.1678, an AARE of 2.2311, and a Max ARE of 12.1537. And finally, the best CGPB ANN model for the Athalassa region was CGPB-1(A), which had a testing R^2 of 0.9418, a RMSE of 0.1626, an AARE of 2.0949, and a Max ARE of 11.9275. Figs. 6–8 compare the actual water demand for the Athalassa region with the water demand forecasted using LM-1(A), RP-10(A), and CGPB-1(A), respectively. It can be seen that the LM-1(A) model is slightly better than the best MLR, RP, and CGPB models at forecasting sharp increases in water demand as well as forecasting low water demand, compared to LM-1(A), MLR-10(A), RP-10(A), and CGPB-1(A) under forecast low water demand.

For the Athalassa region, it can be seen from Table 7 that the LM ANN method had the highest average training R^2 (0.9516), the second highest average testing R^2 (0.9233), the lowest average RMSE (0.1437), the lowest average AARE (2.0987), but that it also had the highest average Max Are (13.7500).

When comparing the best ANN model for the Athalassa region [LM-1(A)] with the best CGPB model for the Athalassa region [CGPB-1(A)], it was found that the LM model had a testing R^2 that was 0.46% more accurate, a RMSE that was 29.6% more accurate, an AARE that was 2.4% less accurate, and a Max ARE that was 6.7% more accurate. When comparing LM-1(A) with the best RP model [RP-10(A)] for the Athalassa region, it was found that the LM model had a testing R^2 that was 4.8% more accurate, a RMSE that was 33.7% more accurate, an AARE that was 8.7% more accurate. When comparing LM-1(A) with the best MLR model [MLR-10(A)] for the Athalassa region, it was found that the LM model a testing R^2 that was 8.7% more accurate. When comparing LM-1(A) with the best MLR model [MLR-10(A)] for the Athalassa region, it was found that the LM model had a testing R^2 that was 13.38% more accurate, a RMSE that was 13.38% more accurate, a RMSE that was 13.38% more accurate.





Fig. 5. Athalassa MLR best model result—MLR-10(A)

Table 7. Average Performance Statistics for Each Type of Method for Public Garden, Nicosia

Method	R^2 training	R^2 validation	R^2 testing	RMSE (ML/d)	AARE	Max ARE
LM ANN	0.9434	0.8949	0.9201	0.1557	2.2284	12.1869
RP ANN	0.9194	0.8776	0.9137	0.1927	2.5918	12.9916
CGPB ANN	0.9266	0.8870	0.9193	0.1827	2.4266	13.1695
MLR	0.8211		0.8011	0.2031	2.6342	13.9830

Table 8. Performance Statistics for the Best Model for Each Type of Method for Athalassa and Public Garden, Nicosia

			RMSE		
Model	R^2 training	R^2 testing	(ML/d)	AARE	Max ARE
		Athalassa	ı		
MLR-10(A)	0.8383	0.8196	0.1892	2.5143	11.9900
LM-1(A)	0.9526	0.9462	0.1255	2.1467	11.1821
RP-10(A)	0.9401	0.9007	0.1678	2.2311	12.1537
CGPB-1(A)	0.9473	0.9418	0.1626	2.0949	11.9275
		Public Gard	len		
MLR-1(PG)	0.8385	0.8133	0.1872	2.4806	12.5852
LM-10(PG)	0.9567	0.9174	0.1366	1.9727	9.7623
RP-10(PG)	0.9423	0.9001	0.1655	2.2712	10.4138
CGPB-7(PG)	0.9350	0.9074	0.1743	2.2086	11.2556

Note: A=Athalassa, PG=Public Garden, MLR=multiple linear regression, LM=Levenberg-Marquardt, RP=resilient back-propagation, CGB = conjugate gradient Powell-Beale, R^2 =coefficient of determination, RMSE=root-mean-square error, AARE=average absolute relative error, and Max ARE=maximum absolute relative error.



Fig. 6. Athalassa LM ANN best model result—LM-1(A)

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Fig. 7. Athalassa RP ANN best model result—RP-10(A)

was 55.5% more accurate, an AARE that was 17.12% more accurate, and a Max ARE that was 68.3% more accurate.

For the Athalassa region, it can be seen that overall the best models were the LM ANN models, followed by the CGPB ANN models, followed by the RP ANN models, followed by the MLR models.

ANN Results for the Public Garden Region

For the Public Garden region, it can be seen from Table 6 that the best ANN model overall was LM-10(PG), which had a testing R^2 of 0.9174, a RMSE of 0.1366, an AARE of 1.9727, and a Max ARE of 9.7623. LM-10(PG) had the following parameters:



Athalassa Conjugate Gradient Powell-Beale best model results - CGPB-1 (A)

WD(t-1), T(t), T(t-1), and T(t-2). The best RP ANN model for the Public Garden region was RP-10(PG), which had a testing R^2 of 0.9001, a RMSE of 0.1655, an AARE of 2.2712, and a Max ARE of 10.4138. And finally, the best CGPB ANN model for the Public Garden region was CGPB-7(PG), which had a testing R^2 of 0.9053, a RMSE of 0.1743, an AARE of 2.2086, and a Max ARE of 11.2556.

For the Public Garden region, it can be seen from Table 8 that the LM ANN method had the highest average training R^2 (0.9434), the highest average testing R^2 (0.9201), the lowest average RMSE (0.1557), the lowest average AARE (2.2284), and the lowest average Max Are (12.1869).

When comparing the best ANN model for the Public Garden region [LM-10(PG)] with the best CGPB model for the Public Garden region [CGPB-7(PG)], it was found that the LM model had a testing R^2 that was 1.3% more accurate, a RMSE that was 27.6% more accurate, an AARE that was 11.9% more accurate, and a Max ARE that was 15.3% more accurate. When comparing LM-10(PG) with the best RP model [RP-10(PG)] for the Public Garden region, it was found that the LM model had a testing R^2 that was 1.9% more accurate, a RMSE that was 27.6% more accurate, an AARE that was 15.1% more accurate, and a Max ARE that was 6.7% more accurate. When comparing LM-10(PG) with the best MLR model [MLR-10(PG)] for the Public Garden region, it was found that the LM model had a testing R^2 that was 11.3% more accurate, a RMSE that was 41.4% more accurate, an AARE that was 28.5% more accurate, and a Max ARE that was 42.5% more accurate.

For the Public Garden region, as with the Athalassa region, it can be seen that overall the best models were the LM ANN models, followed by the CGPB ANN models, followed by the RP ANN models, followed by the MLR models.

Use of Occurrence of Rainfall versus Actual Amount of Rainfall in Models

For both the Athalassa and Public Garden regions and for all three different types of ANNs (LM, RP, and CGPB), Models 4, 5, 8, and 9 demonstrate that the weekly peak water-demand series in both regions is better described with the use of the occurrence or nonoccurrence of rainfall rather than the actual rainfall amount. ANN models using the rainfall amount (LM-4/5/8/9, RP-4/5/8/9, and CGPB-4/5/8/9 for both Athalassa and Public Garden) produced an average testing R^2 of 0.9180, an average RMSE of 0.1506, an average AARE of 2.0971, and an average Max ARE of 13.6272. ANN models including the occurrence or nonoccurrence of rainfall (LM-1/6/7, RP-1/6/7, and CGPB-1/6/7) produced an average testing R^2 of 0.9261, an average RMSE of 0.1462, an average AARE of 2.2532, and an average Max ARE of 12.7852. This suggests that the peak weekly water-demand process in Nicosia is better correlated with the occurrence or nonoccurrence of rainfall rather than the amount of rainfall.

Discussion

Overall, it was found that for both the Athalassa and Public Garden regions of Nicosia, the LM ANN models were more accurate than all the other types of models for forecasting peak weekly water demand, followed by the CGPB ANN models, followed by the RP ANN models, followed by the MLR models. The MLR models most likely did not perform as well as the ANN models because MLR equations can only capture relationships of a prespecified functional form, and as such they may not always be sufficient to accurately predict the nonlinear nature of the variables involved. In this study, the best peak weekly water-demand forecasting ANN model (which had as inputs the previous weekly peak water demand, the maximum temperature of the current and previous week, the maximum temperature of the previous week, the total rainfall of the current week, the total rainfall of the previous week, the occurrence/nonoccurrence of rainfall from the current week, and the occurrence/nonoccurrence of rainfall from the previous week) had a coefficient of determination of 0.95 in testing for the Athalassa region of the city of Nicosia, Cyprus. As mentioned earlier, this ANN model was trained with a LM training algorithm. In Bougadis et al. (2005), the best ANN model (which had as inputs the previous weekly peak water demand, the temperature of the current week, and the total rainfall of the current week) had a coefficient of determination of 0.81 in testing for the city of Ottawa, Canada. This ANN model was trained with a gradient-descent training algorithm. In Jain et al. (2001), the best ANN model (which had as inputs the previous total weekly water demand, the temperature of the current week, and the occurrence/ nonoccurrence of rainfall of the current week) had a coefficient of determination of 0.87 for the city of Kanpur, India. This ANN model (which had two hidden layers) was trained with a gradientdescent training algorithm. It can be seen that the accuracy of the weekly water-demand ANN forecasting model developed in this study was high when compared to similar studies.

It was found that the peak weekly water demand in Nicosia is better described with the use of the occurrence or nonoccurrence of rainfall rather than the actual rainfall amount. This supports the findings of Jain et al. (2001) and Adamowski (2008), but is opposite to the findings of Bougadis et al. (2005).

The present study focused on the modeling of peak waterdemand forecasts using climatic variables in addition to past water demands. The work could potentially be improved if other variables, which affect water demand, were to be examined. Examples of socioeconomic variables that could be investigated include housing characteristics (number of bathrooms, number of rooms, size of garden, household size, and the number of people in the house), property values, land use (residential, commercial, or industrial), economic status (house income), day of the week (including weekday, weekend, and holidays), and water price. Of these variables, it is most likely that the day of the week (weekday, weekend, or holiday) and water price could potentially improve the short-term water-demand forecasts. Examples of climatic variables not used in this research that could be investigated in future studies include evaporation, evapotranspiration, wind speed, relative humidity, cloud amount, and sunshine amount. Unfortunately, not all of the above data are readily available, and often do not exist at all. Nevertheless, if the aforementioned socioeconomic and climatic variables are available, it is possible that different combinations of driving variables could potentially improve the forecasting ability of the various methods explored in this study.

In future short-term urban water-demand forecasting studies, it would also be useful to compare the use of LM, RP, and CGPB ANNs with RBF ANNs, Elman network ANNs, or coupled wavelet ANNs.

Conclusions

The motivation for this study was to investigate two important issues that have not been investigated in literature concerning short-term peak water-demand forecasting. Based on the results of this study, the following can be concluded: (1) LM ANNs are more accurate than CGPB and RP ANNs, as well as MLR, for urban weekly peak water-demand forecasting in Nicosia; and (2) rainfall occurrence or nonoccurrence is more significant than the amount of rainfall in determining the peak weekly water demand in Nicosia.

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Notation

The following symbols are used in this paper:

- B = regression coefficient;
- CR = occurrence or nonoccurrence of rainfall;
- L = lead time for PI calculation;
- N = number of data points used;
- R = amount of rainfall;
- T = maximum temperature;
- WD = water demand;
 - \overline{y}_i = mean value taken over N;
 - y_i = observed peak weekly water demand in coefficient of determination calculation;
 - \hat{y}_i = forecasted peak weekly water demand in coefficient of determination calculation;
- y_{i-l} = observed peak weekly water demand at time step *i*-*L* in PI calculation;
- O_i = observed peak weekly water demand in AARE calculation; and
- D_i = forecasted peak weekly water demand in AARE calculation.

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