Short-term forecasting of hourly water demands — a Portuguese case-study

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ABSTRACT

Predicting future water demands is becoming fundamental in the efficient management of Water Supply Systems (WSS). To improve the operations of a Portuguese network, short-term water demand forecasting models are applied to four data sets collected from distinct locations in the network. Traditional forecasting models, based on exponential smoothing and naïve models, and artificial neural network (ANN) based models are developed and compared. Additionally, the influence of anthropic and weather variables in the ANN-based models is also analysed. Results demonstrate that ANN-based models outperform the traditional models when external predictors such as anthropic and weather variables are included in the models. However, inappropriate choice of such variables may lead to worse forecasting performances.

Keywords: Water demand forecasting, Artificial Neural Networks, Data analysis, Exponential Smoothing, Naïve methods, Portuguese water network.

INTRODUCTION

Water demand have been predicted for a variety of purposes, such as understanding spatial and temporal patterns of water use, optimise system operations, plan for future system expansion or even prepare for future revenue and expenditures. According to the purpose, distinct scales for the forecasting methods are defined, from short-term to long-term scales. Medium- to long-term forecasts (months to decades) are mostly used in strategic planning and to determine future resource requirements (Hyndman and Athanasopoulos 2013). Sizing system capacity, staging system im-

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provements and assessing future environmental and economic conditions that likely change water supply and demand are the main purposes of this forecast scale.

There are a number of recent works dealing with monthly water demand forecasting, applying from ARIMA models (Ghiassi et al. 2008) to ANN models (Ghiassi et al. 2008; Babel and Shinde 2011) and also hybrid ANN models (Tiwari and Adamowski 2013; Tiwari and Adamowski 2014), where the ANN-based models commonly outperform the traditional ones.

Short-term scales, in turn, are mostly used in scheduling processes (Hyndman and Athanasopoulos 2013), including optimisation and management of systems operations. Hourly, daily and weekly forecasts are commonly included in this scale. Comparatively to the medium/long-term forecasts, a lot more studies can be found related to (i) hourly forecasts (Salomons et al. 2007; Martinez et al. 2007; Romano and Kapelan 2014; Santos and Pereira Filho 2014; Odan and Reis 2012; Herrera et al. 2010; Alvisi et al. 2007; Ghiassi et al. 2008; Kang et al. 2015), (ii) daily forecasts (Alvisi et al. 2007; Ghiassi et al. 2008; Msiza et al. 2008; Adamowski 2008; Tabesh and Dini 2009; Babel and Shinde 2011; Adamowski et al. 2012; Bakker et al. 2014) and (iii) weekly forecasts (Jain et al. 2001; Bougadis et al. 2005; Ghiassi et al. 2008; Adamowski and Karapataki 2010; Tiwari and Adamowski 2013; Adamowski et al. 2014; Tiwari and Adamowski 2014).

A literature review on water demand forecasting published from 200 to 2010 can be found in the work of Donkor et al. (2014). Their analysis shows that the application of methods and models differ and are dependent on the forecasting variable, periodicity and horizon. This fact is also supported by an updated review work, as can be seen concisely in tables 1 to 4.

The use of bootstrap data re-sampling techniques and wavelet analysis for the series decomposition applied to ANN models for water demand forecasting was introduced by Tiwari and Adamowski (2013). The authors tested such techniques for daily and weekly water demand forecast for the city of Montreal (Canada). Four distinct ANN methods were developed and compared to ARIMA models: (i) a simple ANN, (ii) a bootstrap artificial neural network (BANN), using bootstrap data samples from 100 ANN outputs, (iii) a wavelet ANN (WANN), using, as input, 4 distinct components of the series (water demand, temperature and precipitation) and (iv) a wavelet bootstrap ANN (WBANN), using 100 data samples of the wavelet series components (100 WANN). Results demonstrated that the WANN outperform the other methods in the daily forecast, however, the WBANN provided better results in the weekly forecast scale.

Later, Tiwari and Adamowski (2014) and Adamowski et al. (2014) tested the previously mentioned bootstrap and wavelet-based ANN models for weekly water demand forecasting in the city of Calgary (Canada) considering limited data availability (around 2 years and 9 months). Similar to the previous case-study, the WBANN provided the best results, with the wavelet analysis improving the model performance and the bootstrap technique increasing the reliability of forecasts by producing ensemble forecasts.

Odan and Reis (2012) applied the same dynamic ANN proposed by Ghiassi et al. (2008) in Araraqua city (Brazil) for the hourly water demand forecasting and compared their results with the ones of a ANN (testing distinct numbers of hidden layers), a hybrid ANN and a hybrid dynamic ANN, consisting in the additional use of Fourier Series as input of the networks. The best results (both for 1h and 24h time horizon) were obtained with the dynamic ANN model using past demand observations and Fourier Series as input (not requiring weather information).

Babel and Shinde (2011) evaluated the effect of weather variables as ANN inputs for daily and monthly water demand forecast in the city of Bangkok (Thailand). In the daily forecasts, no significant differences were found in the forecast accuracy including weather variables (rainfall, average temperature and relative humidity) are taken into account. However, in the monthly forecasts, other variables, such as population, per capita Gross Provincial Product, education status and household connections, have significant influence.

To face the problem of water scarcity in the South Africa's Gauteng Province, Msiza et al. (2008) developed a work on the daily water demand forecast using ANN and Support Vector Machines (SVM). These authors tested distinct training algorithms and distinct activation functions for Multilayer Perceptron and Radial Basis Function ANNs (ANN-MLP and ANN-RBF) and, in the case of the SVM, distinct kernel functions. The best results were obtained with an ANN-RBF using a linear activation function and a scaled conjugate gradient algorithm for training the model. This ANN-RBF model also outperformed the best SVM model.

Fuzzy and Neural-fuzzy forecasting techniques for daily water demand forecasting were proposed by Tabesh and Dini (2009) and compared with ANN using a case-study in Tehran (Iran). In order to face an expected water crisis and for the development of a water conservation programme, a short-term forecast of water demand in this city is necessary. These later authors found that fuzzy models, in general, do not produce good results for this case-study. However, the Neural-fuzzy models reveal to be comparable to ANN models, with similar forecast accuracy. In the work of Tabesh and Dini (2009), the use of random input variables was also tested, demonstrating, in general, slightly improvements in the neural-fuzzy model's performance. The best results were obtained with the models considering only past water demand variables as input.

Candelieri and Archetti (2014) decided to use a support Vector model (SVM) for the hourly water demand forecast in the city of Milano (Italy), one of the case-studies of the ICeWater project (ICT Solutions for efficient Water Resources Management). The novelty introduced in this work is the use of daily time clusters that characterise the water demand patterns and their training as separate SVM models. For the tested case-study, six typical daily patterns (and thus, six clusters) were identified. The MAPE obtained for each cluster range from 0.79% to 14.33%, with an average of 5.29%.

Recently, Santos and Pereira Filho (2014) published a work on the hourly water demand forecast in São Paulo Metropolitan area (Brazil). These authors decided to investigate the influence of distinct input variables (demand, anthropic and weather) with several lag times (up to 24 hours) and distinct output lead times (forecast of 1, 6, 12, 18 and 24 hours) in ANN models. The forecasting performance is also compared with a MLR model, which demonstrated to be less accurate than the best ANN. The drawbacks observed in this study are that no ANN model is tested using only previous water demand (excluding anthropic and/or weather variables) and the definition of the MLR model variables.

Romano and Kapelan (2014) evaluated hourly ANN forecasting models (1 to 24 hours horizon) using data measured at distinct zones in the Yorkshire WSS (United Kingdom): at 3 distinct District Metered Areas (DMA), each one supplying different population sizes, and at 1 reservoir outlet. According to the provided results (see table 1), no significant differences are found in the forecast accuracy for the distinct model scales tested. The authors tested the use of an Evolutionary Algorithm to automatically find the best parameters and structure of the ANN (EA-ANN) instead of using fixed user-defined structures. This approach provided significant improvements in the model's performance.

Another approach proposed by Romano and Kapelan (2014) for the 24h forecast horizon is the use of multiple parallel ANN instead of a single ANN. Results showed slight improvements using such approach for both the EA-ANN and the fixed-structure ANN, however with increased computational effort.

For the optimal control and to detect pipe bursts in water distribution networks, Bakker (2014) (following (Bakker et al. 2013)) proposed the use of 15-min time-steps to better describe the water demand variations instead of the typical 1-hour time-steps. Since the models to detect pipe bursts typically use small time-steps, Bakker (2014) decided to use such time scales for water demand forecasting and pumps control. This approach was used to predict the future 48 hours of water demand in six different cities in the Netherlands. In order to implement the forecasting model in real WSS, this author developed a pattern-based model that only uses past water demand and anthropic variables. To assess the developed forecast model, the authors computed the accuracy measures considering 15 minutes and 24-hour forecast intervals (obtained from the the 15-min steps averages). Although the RMSE and the MAPE presented significantly better values for the

24-hour forecast, the 15-min forecast demonstrated a better fit, providing higher values for the NSE. The case-studies of larger cities demonstrate to be easier to predict (Bakker et al. 2013; Bakker 2014), showing again the dependence of the forecasting models on their scales.

The previously mentioned case-studies from the Netherlands were also used to analyse the performance of the forecasting models using weather variables (particularly the average daily temperature) as input (Bakker et al. 2014; Bakker 2014). Results obtained using the adaptive pattern-based method were compared with a MLR model and a transfer-/noise method (combination of an ARIMA model with a linear transfer model). Using the weather variables, the largest forecasting errors were reduced by 9.4 % and the average by 6.3 % (Bakker et al. 2014; Bakker 2014) in case-studies with low variability in weather conditions, which means that differences can be larger for other case-studies presenting higher weather influences. Concerning the distinct applied methods, although the introduced tranfer-/noise model provided slightly better results than the adaptive pattern-based model, it was mention that the later may be better accepted for real implementations since it is easier to understand by the control operators.

In other recent works for the hourly water demand forecast, instead of applying innovative machine learning techniques that demonstrated good performances in previous works, Wang et al. (2014) and Kang et al. (2015) have decided to use combinations of classic ARIMA and Exponential Smoothing methods in order to improve the model's performance. Wang et al. (2014) proposed a Double-Seasonal multiplicative Holt-Winters model combined with a Gaussian Process regression with uncertainty propagation for multiple-step ahead forecasts. This approach was applied to the WSS of Barcelona.

Kang et al. (2015) combined an ARIMA model with Exponential Smoothing to forecast the hourly water demand in a WSS in the Gallella region (a rural area in Sri Lanka). While the ARIMA method failed to predict the lower water demands, the combination with the Exponential Smoothing method with the smoothing parameter α set to 0.9 allowed to overcome such drawback, improving the forecast accuracy. Although no comparison was made, it is possible to compare this case-study (with an average demand of 450 m^3/day) with another rural area in Netherlands, the city of Hulsber (440 m^3/day) presented by Bakker (2014). Comparing the values of the accuracy measures (see table 1), it is observed that the models used by Bakker (2014) provided more accurate results.

From the analysis of the previously mentioned works, it is possible to conclude that the data analysis and pre-processing represents an important role in the forecasting process with influence in the models accuracy.

Although distinct amounts of data have been used to develop forecasting models, the work of Herrera et al. (2010) demonstrated that, for hourly forecasts, the use of large historical data for training the models does not provide significant models improvements. The use of data of the most recent weeks of available data should be enough to train hourly water demand forecasting models. The only problem on following this approach is the possible occurrence of data failures due to measurement and/or communication faults, which can significantly reduce the amount of existent data for training the model. Thus, the use of a larger amount of data is recommended.

The development of a forecasting model involves several steps that go from the knowledge of the problem to the implementation of the developed model. The main stages of the process can be described as (Montgomery et al. 2008) (i) problem definition; (ii) data collection and selection; (iii) data analysis and pre-processing; (iv) model selection, fitting/training and validation and (v) model forecasting and evaluation. For more details concerning these steps see, for instance, Coelho (2016).

The aim of this work is to evaluate distinct forecasting models for several delivery points of the presented case-study considering each particular input data (including historical demands, anthropic and weather variables). Hourly time-scales and forecasting horizons of 1 hour and 24 hours are considered.

CASE STUDY

The aim of the forecasting studies presented in this work is to contribute for the improvement of the operational control of a Portuguese water network. Fig. 1 provides a simplified scheme of such network, including the data measurement points. Due to confidentiality reasons, the water utility and the details concerning the system analysed are not revealed.

Data, from August 2012 to July 2013, was taken from selected delivery points. V6 to V15 are gravity points, V1, V3 and V17 are tanks inlet and V2, V4, V5 and V16 are tanks outlet. Data from tank D is not available since it is managed by a distinct water utility. The collected data were provided in the format of accumulated volumes of water measured in time intervals of 10 minutes. The water consumers of this case-study belong to the class of domestic, agriculture and industrial consumers.

Besides the historical data of delivered water, hourly meteorological data, such as temperature, relative humidity and rainfall occurrence, was obtained from the nearest meteorological station in the area (Freemeteo 2015) during the same period (Aug 2012 to Jul 2013).

Taking into account that none information from experts, such as explanations for failures or unexpected occurrences, is available, all the analyses of water demands are based on interpretations of the available historical data and meteorological effects.

DATA SELECTION

In this case study, enough historical data for both tanks A and B is available to predict future supply needs (points V2, V4 and V5).

Considering that data from points V6 to V15 presented large inconsistencies and gaps, in this work, it was decided to analyse and present the data from V2, V4, V5 and V16. V5 represents the sum of the delivery points V6 to V15, V16 and the outlet water of tank D.

DATA ANALYSIS AND PRE-PROCESSING

Historical demands

After plotting the time series of the raw data as provided by the water utility it became clear that several measurement failures occurred over the year, *i.e.* the measurements of accumulated water volume were not always increasing over time as expected. Additionally, some data presented observations set to zero, pointing out extreme outliers. This data may be related to interruptions in data collection or communication and must be discarded.

In order to clean the data, the detection and removal of outliers was made using the method based on the interquartile range of each data set (see, for example, outliers detection in Natrella (2010)), rejecting values inferior to the lower quartile (lower outlier boundary) and superior to the upper quartile (upper outlier boundary).

Other types of data failures resulting from the counting re-initialisation of the measurement device were also identified. Fig. 2 provides a representation of this type of occurrence. All data sets presenting this type of occurrence were corrected by adding the value of the last measure (device limit) to the initialised values.

An analysis of the amount of missing data was also performed. For all data sets, it was verified that in the first two months of data (August and September of 2012), more than 40 % of data were missing. For this reason, it was only considered the data from 21/09/2012 to 31/07/2013. All the other missing data identified represented only 0.4, 0.5 and 0.8 % for V2, V4 and V16, and V5 data sets, respectively.

After correcting the 10-minutes intervals measurement failures, the hourly values were computed using linear interpolation.

In order to obtain the hourly water demands (WD, in m^3/h), the differences between each measured hour were computed, transforming the initial time series (V2, V4, V5 and V16) that present a linear trend (water volume increasing linearly with time) into stationary series (WD2, WD4, WD5 and WD16).

Anthropic variables

After analysing the patterns of the time series, it was verified that different patterns were observed for different months, as well as for different days of the week. Thus, an analysis to the influence of anthropic variables was performed.

In a first step, the Pearson correlation coefficients between the water demand data sets and the selected anthropic variables were computed. Results of such coefficients are provided in Table 5. The Pearson correlation (a quantitative sensitivity parameter) is often used by researchers for the choice of the variables to include in their forecasting models. However, such measure provides only information concerning the linear relationship between variables (Hamby 1994). This means that, other type of relationship may be undetected with this approach. For this reason, it was decided to analyse the scatter plots for all variables in order to reveal other possible relationships. According to Fig. 3, the correlation between the water demands and the anthropic variables are not linear. The variable *Day of week* (D) presents the weakest correlation with the water demand. However, analysing, for instance, the correlation of this variable with WD5, it is possible to observe that higher water demands occur during the weekends. Analysing the variable *Month* (M), it is also notorious the higher water demands for the summer months. However, it should be noticed that data from August to mid-September is missing, which may hide additional information concerning the summer months. By adjusting a polynomial trend line, the correlation coefficients between the variable *Hour* and the water demand significantly increases compared to the linear correlation coefficients. All the correlation coefficients obtained from these scatter plots are presented in Fig. 4 for a faster analysis. The anthropic variables with higher correlations, marked in the figure with dashed lines, were selected for the forecasting models of this work.

Historical demands in neighbour sites

From the results presented in Table 5, it is also worth to mention the strong correlation between the water demand series and the water demand in the neighbouring measurement points. WD2 has a strong correlation with both WD4 and WD16 and WD4 present a high correlation with WD16. The scatter plot matrix provided in Fig. 5 clearly shows these linear relationships. Such observations mean that the water demand pattern is similar for these demand points. Although this fact is expected considering that the consumers are similar for these points, the inclusion of these variables (past water demands observed in neighbouring areas) in the forecasting models can be beneficial. Although the use of such variables was not found in the literature, in this work, these variables are included in some forecasting models.

Weather variables

Although no outliers were identified in the weather data (temperature, relative humidity and rainfall occurrence), a large amount of the available data was missing. In the period considered for the water demand data (09/2012 to 07/2013), around 30 % of data were missing. Considering only the data from 12/2012 to 07/2013 (last 5761 observations) the amount of missing data is around 10 % for the variables *Temperature* (T) and *Relative Humidity* (RH) and around 11 % for the *Rainfall Occurrence* (RO) variable. For the T and RH data sets, the 10 % of missing data was approximated using the Kriging interpolation method. Since the *Rainfall Occurrence* is a binary variable, the nearest-neighbour interpolation method was used. Both interpolation methods were implemented using the XonGrid interpolation Add-in for Excel (SourceForge 2015).

In order to access the influence of the weather variables in the water demand, the Pearson correlation was analysed (see Fig. 6). Although the strongest correlations are from the temperature and relative humidity, the strength of all relationships is moderate or weak.

From the trend lines of the scatter plots provided in Fig. 7, a symmetric relationship of both *Temperature* and *Relative Humidity* with the water demands is observed. The highest demands occur typically for higher temperatures and lower relative humidity.

Lagged demand time series

The analysis to the water demand time series lags allows to verify which demands in previous hours present higher correlation with the current demands. Results of the correlation coefficients between the current time data and the time data for lags 1 to 168 (previous one hour to one week) are provided in Fig. 8, showing the more significant lags.

For all data sets, the hours that demonstrate higher correlation with the current hour are the previous 1, 24 and 168 hours. However, while the highest correlation for the datasets WD2 and WD4 was obtained for the 168-hours lag, for the data sets WD5 and WD16, the 1-hour lag has a higher correlation. Thus, the three lags were taken into account in the forecasting models.

FORECASTING MODELS

Naïve models

Naïve models are the simplest models for time series forecasting. In these models, the forecast is given by the last observation (Naïve model) or the last seasonal observation (Seasonal Naïve model) (Montgomery et al. 2008; Hyndman and Athanasopoulos 2013).

Exponential Smoothing models

Smoothing models use a function obtained from previous observations to predict future ones (Montgomery et al. 2008). This technique of obtaining a smooth function (exponential smoother) from the data can be attractive to deal with noisy data.

The Holt-Winters Seasonal models use three smoother functions that represents three components of a time series: (i) the level component, L_t^s, (ii) the trend component, T_t^s, and (iii) the seasonal component, S_t^s. The difference between the two proposed models is related with the nature of the seasonal component. While the additive seasonal model is preferred when seasonal variations are roughly constant through the series, the multiplicative seasonal model works better when the seasonal variations change proportionally to the level of the series (Hyndman and Athanasopoulos 2013).

The equation for modelling the series using the **Holt-Winters Additive Seasonal model** is:

$$y_t = L_t^s + T_t^s + S_t^s + \varepsilon_t. \tag{1}$$

The level, trend and seasonal smoothers can be respectively written as:

$$L_t^s = \alpha_1^s (y_t - L_{t-m}^s) + (1 - \alpha_1^s)(L_{t-1}^s + T_{t-1}^s), \tag{2}$$

$$T_t^s = \alpha_2^s (L_t^s - L_{t-1}^s) + (1 - \alpha_2^s) T_{t-1}^s \quad \text{and} \tag{3}$$

$$S_t^s = \alpha_3^s (y_t - L_{t-1}^s) + (1 - \alpha_3^s) S_{t-m}^s, \tag{4}$$

where m represents the period of seasonality and α_1^s, α_2^s and α_3^s are smoother parameters with ranges between 0 and 1. The estimation of these parameters can be seen in the work of Hyndman and Athanasopoulos (2013).

The **Holt-Winters Multiplicative Seasonal model** is given as

$$y_t = (L_t^{\mathrm{s}} + T_t^{\mathrm{s}}) S_t^{\mathrm{s}} + \varepsilon_t. \tag{5}$$

In this case, the level, trend and seasonal smoothers are respectively written as (Hyndman and Athanasopoulos 2013):

$$L_t^{\mathrm{s}} = \alpha_1^{\mathrm{s}} \left(\frac{y_t}{S_{t-m}^{\mathrm{s}}} \right) + (1 - \alpha_1^{\mathrm{s}})(L_{t-1}^{\mathrm{s}} + T_{t-1}^{\mathrm{s}}), \tag{6}$$

$$T_t^{\mathrm{s}} = \alpha_2^{\mathrm{s}}(L_t^{\mathrm{s}} - L_{t-1}^{\mathrm{s}}) + (1 - \alpha_2^{\mathrm{s}}) T_{t-1}^{\mathrm{s}} \quad \text{and} \tag{7}$$

$$S_t^{\mathrm{s}} = \alpha_3^{\mathrm{s}} \left(\frac{y_t}{L_{t-1}^{\mathrm{s}}} \right) + (1 - \alpha_3^{\mathrm{s}}) S_{t-m}^{\mathrm{s}}. \tag{8}$$

Artificial Intelligence-based models

Traditional statistical methods can be limited with non-linear relationships and very noisy data. For this reason, models based on artificial intelligence, capable of identifying complex and non-linear phenomena/behaviours, have been largely applied.

Applied to time series forecasting, machine learning techniques operate by processing historical data and/or another type of input data and building a data-driven model capable of solve prediction problems. Such data-driven models are trained on a set of input and target output describing the phenomena in question (Solomatine and Siek 2006).

Artificial Neural Networks (ANN) are based on mathematical models inspired in the way the human brain process information. An ANN-based forecasting model consists of two or more layers: (i) an input layer, (ii) an output layer and, optionally, (iii) one or more intermediary layers called hidden layers. Each layer consists of multiple nodes (also called neurons or elements) that represent the variables of the model. In feed-forward neural networks, such as the one represented in Fig.9, each node of the network receives information from the previous layer as a linear combination of each node output, according to the connection weights u^{c} and w^{c} (parameters to be estimated) defined in each connection and then returns an output that is represented by a transformation of such combined information through an activation function. This output is used for the next layers (and the feed-forward process is repeated) or as the model output.

Each node output $\hat{y}_k$ of a 2-layer ANN model (2 layers of connections) with n_{in} input nodes, n_{hidden} hidden nodes and n_{out} output nodes can be represented as:

$$\hat{y}_k = f_1^{\text{A}} \left(\sum_{j=1}^{n_{\text{hidden}}} u_{j,k}^{\text{c}} f_2^{\text{A}} \left(\sum_{i=1}^{n_{\text{in}}} w_{i,j}^{\text{c}} z_i + \theta_j^{\text{b}} \right) + \theta_k^{\text{b}} \right), \tag{9}$$

where $i = 1, \ldots, n_{\text{in}}$, $j = 1, \ldots, n_{\text{hidden}}$ and $k = 1, \ldots, n_{\text{out}}$. z_i and $\hat{y}_k$ represents, respectively, the i^{th} model input and the k^{th} model output, θ^{b} is a parameter that represents an intercept in linear regression (the bias node) and f_1^{A} and f_2^{A} are activation functions. The activation functions are usually sigmoidal (S shaped) or linear (Montgomery et al. 2008). Considering, f_1^{A} as a log-sigmoid function, $f_1^{\text{A}}(z) = \frac{1}{1+e^{-z}}$, and f_2^{A} as a linear function, $f_2^{\text{A}}(z) = z$, then equation 9 would take the following form:

$$\hat{y}_k = \sum_{j=1}^{n_{\text{hidden}}} \left(u_{j,k}^{\text{c}} \frac{1}{1 + exp\left(\sum_{i=1}^{n_{\text{in}}} w_{i,j}^{\text{c}} x_i + \theta_j^{\text{b}} \right)} \right) + \theta_k^{\text{b}}. \tag{10}$$

The use of non-linear activation functions (such as sigmoid or hyperbolic tangent functions) in the hidden layers is commonly preferable since they tend to reduce the effect of extreme input values, thus making the network somewhat robust to outliers (Hyndman and Athanasopoulos 2013). Recently, Radial Basis functions (RBF), where $f^{\text{A}}(z) = e^{-z^2}$, have also been used.

In order to estimate the model parameters (weights and bias) that fit the data, a set of inputs and target outputs are initially provided to the model (supervised learning). Thus, the training/learning process (parameter estimation) begins typically by minimising the overall residual sum of squares taking into account all responses (target outputs) and observations (inputs). This is a non-linear Least Squares problem (Montgomery et al. 2008; Hyndman and Athanasopoulos 2013).

A popular learning method is the Back-Propagation, which looks for the minimum of the error function in weight space using gradient-based optimisation methods (Rojas 1996; Atiya 1991). Although the steepest descent algorithm is typically associated with the Back-propagation method, other derivative-based optimisation algorithms, such as the Levenberg-Marquardt (LM) or the Conjugate Gradient (CG), can also be employed to find the minimum of the error function.

The initial values for the model parameters are commonly defined randomly and then are updated/adjusted through the iterative learning process using the observed data. In ANNs, each iteration of weights update is called epoch. It is common to set a maximum number of epochs to stop the training process in case of non-convergence.

For the choice of the most adequate network architecture (number of layers, number of nodes and activation functions form), *trial and error* procedures or optimisation methods can be used.

Models performance evaluation

The performance of a forecasting model can be defined according to (i) how well the model fits the sample data (in training/fitting process) or (ii) the capability of the forecasting technique to predict future observations (Montgomery et al. 2008).

The performance measures mostly used for the models evaluation are the Nash-Sutcliffe Model Efficiency (NSE), the Pearson Product Moment Correlation (PPMC), the Mean Absolute Error (MAE) , the Root Mean Square Error (RMSE), the Maximum Absolute Error (MAE), the Root Mean Square Error (RMSE), the MEAN Absolute Percentage Error (MAPE) and the Mean Square Error (MSE). For more details, see the works of Bennett et al. (2013), Hyndman and Athanasopoulos (2013), Donkor et al. (2014) and Coelho (2016), where the performance measures are discussed.

Developed forecasting models

Models selection

Seasonal Naïve models, Additive Seasonal Holt-Winters and the Multiplicative Seasonal Holt-Winters with a seasonality of one week (168 hours) were developed. Since the data sets demonstrated high correlations with the 1-hour lagged series, simple Naïve models were also developed.

ANN-based models with distinct additional input variables were developed in order to analyse the influence of each input variable and obtain better forecasting models using the most influential variables. Table 6 lists the ANN analysed models.

All ANN-based models were developed using Matlab R2012a and the narnet and narxnet libraries (MathWorks 2015) for single and multiple predictors, respectively.

The first developed models (WD_hist) use the historical data as single input. The WD_1lag models consider as additional input the lagged data that presented the highest correlation coefficient (according to Fig. 8). The WD_3lags models consider the addition of the three lagged data that presented the highest correlation coefficients (1, 24 and 168 hours for all data sets). The WD_anthrop models include the selected anthropic variables for each data set (according to Fig. 4).

For all data sets (except WD5), models considering the water demand series of the neighbouring areas as additional input were also developed and analysed.

The weather variables that presented the higher correlation coefficients with each data set were included in the WD_meteo models. However, since it was verified that the variable *Rainfall Occurrence* could present some influence in the water demand, a separate model (WD_rain) was also developed in order to analyse the performance of including such variable.

WD_all and WD_selection are the forecasting models with all variables and the two more influential input variables, respectively.

Normalised accuracy measures are used as results in order to compare between distinct data sets.

Data sets division

For the development of the Naïve and exponential smoothing forecasting models, each water demand data set was divided into two subsets. The first 80 % of data (6036 observations) was used for fitting the model while the 20 % remaining data (1500 observations) was left to validate the developed model.

Concerning the ANN-based forecasting models, the same amount of data was left for the final validation of each model. However, only the remaining data with associated weather data was used to develop the neural network. Here, 70 % for training, 15 % for cross-validation and 15 % for testing, corresponding to 2867, 613 and 613 data points, respectively, were used.

Neural networks architecture

The most appropriate architecture for each ANN-based model was found through an automatic methodology developed and implemented in Matlab. Considering a single hidden layer for all cases, varying only the number of nodes, the developed methodology performs sequentially (i) the networks architecture selection, (ii) the networks development and (iii) the forecast. The main implemented steps of the proposed methodology are:

1. Computation of the Water Demand series autocorrelation (ACF) and partial autocorrelation (PACF) functions.
2. Definition of the number of input delays and feed-back delays: ID $= \max(\text{ACF})$ and FD $= \max(\text{PACF})$.
3. For 1 to 10 hidden nodes (HN), considering always the same random variables for the weights initialisation:
   (a) Generation of the nonlinear autoregression neural networks using HN hidden nodes, ID input delays and FD feedback delays;
   (b) Network training, cross-validation and testing with WD series feedback (open-loop network);
   (c) Open-loop network performance computation (MSE).
4. Selection of the number of hidden nodes according to the best open-loop network performance obtained.
5. Close the network loop for forecasts without target feedback (only output feedback).
6. For 1 to 10 runs, considering distinct random variables initialisation:
   (a) Predict missing values using the closed-loop trained network;
   (b) Compute the forecast accuracy using the validation data;
7. Save the network with the best performance.

FORECASTING RESULTS

The forecasting accuracy was computed for (i) the first hour predicted, (ii) the first 24 hours predicted and (iii) all the validation data set period (last 1500 observations $\approx$ 9 weeks) predicted. Similarly with the procedure followed for the traditional forecasting methods, the validation accuracy measures for each ANN-based model were computed for (i) the first predicted hour, (ii) the first 24 hours predicted and (iii) the entire validation set dimension prediction.

Tables 7 to 10 provide the forecasting accuracy results for the traditional methods developed for each demand data set. Observing table 7, it is possible to see that the Exponential Smoothing methods better fit the data than both the Naïve models for all data series. However, analysing the validation forecast accuracy for the first 24 hours (table 9), the Exponential Smoothing methods do not perform better. For the WD2 data set, the Seasonal Naïve model revealed to be better than any of the other traditional methods.

Results demonstrated that, for Exponential Smoothing methods, perfect fitting does not imply a good forecast accuracy. At the same time, comparing tables 8 and 9, it can be concluded that the method that best predicts the first hour, may not be the best method to predict the first 24 hours.

The Seasonal Naïve model presented good performance when predicting 24-hours or even the $\approx$ 9 weeks ahead.

Given the analysed results, both Seasonal Holt-Winters methods may not be the most appropriate to predict the water demands. This is probably because the serial dependence in the observations may not be appropriately captured by these approaches.

Table 11 provides the best ANN-based models results as well as the correspondent automatically selected architecture for the water demand forecast. Such results are compared with the ones obtained with the Seasonal Naïve in Table 11 and in Fig. 10.

From Table 11, it can be observed that the input variables that provided the best forecast results for the four tested data sets are distinct, although these data sets correspond to water demand from regions close to each other. Therefore, the influence of each input variable in the models performance is notorious.

Starting from the WD2 and WD4 time series, that presented the highest autocorrelation with the 168h-lagged series, both demonstrated better results when including such lagged series as model input. However, while the anthropic variables allowed to achieve one of the best results with ANN-based models for the WD2 series, this does not occur in the case of the WD4 series. In turn, for this last time series data set, the inclusion of historical water demands of neighbour sites (WD2(t) and WD16(t)) significantly improved the forecasting models performance. As represented in Fig. 10, while the model for predicting the WD4 series including the 168-hour lag (WD4_1lag) presented predicted values quite below to the targets, the model considering the neighbourhood past demands (WD4_neighb) was able to provide a better fitting.

Observing the best ANN-based models obtained for WD5 and WD16, in both cases the inclusion of the 3 most correlated lagged series allows to improve the forecasting results (see Table 11). However, the other variables that also improved the series prediction are not coincident. Models to predict WD5 perform better when including the variable *Rainfall Occurrence*, while models to predict WD16 perform significantly better with the simultaneous use of the three more significant lagged series (WD16(t-1), WD16(t-168) and WD16(t-1)) and the anthropic variable *Hour* (*i.e.* the WD16_selection model). From Fig. 10 it is observed that the model WD5_1lag is capable of detecting variations in demand while the model WD5_rain, despite resulting in slightly better accuracies, presents predicted values almost constant during the day (similar to the average of the observations). Concerning the charts of the WD16 time series results, the WD16_anthrop and the WD16_selection models are clearly the ones that best fit the targets.

The ANN-based models did not provide significantly better performances than the seasonal Naïve for predicting the WD2 and WD5 series. However, for the WD4 and WD16 series, the ANN-based models outperformed the traditional Naïve.

It is important to mention that the use of all variables that apparently demonstrated to have influence on the water demands (from the preliminary correlation and scatter plots analysis) as model input, does not necessarily improve the forecasts performance. In fact, in almost all cases, the use of all variables as input decreased the forecast model performance when compared with the simple ANN-model that only uses the historical demands. This occurs possibly due to the increase of the neural networks complexity.

CONCLUSIONS

From the extensive literature review performed on the water demand forecasting topic, it is possible to conclude that the data analysis and pre-processing represents a very important role in the forecasting process with influence in the models' accuracy. This part of the process represents also the most time-consuming since a large amount of data is usually needed. At the same time, the collected data from the networks often presents a large number of occurrences and missing data that, if not treated properly, can significantly influence the real data trends, reducing the accuracy of the models and, consequently, influencing the efficiency of the networks operational control.

The traditional forecasting models (Naïve and Exponential Smoothing) demonstrated variable performances for different data sets when predicting only one hour ahead. However, in the prediction of 24 hours ahead, the seasonal Naïve forecasting models were more adequate. Even using a smaller data set, the models based on artificial neural networks can improve such results if external input variables are introduced in the models. However, the influence of each additional input variable (both anthropic and meteorological) is dissimilar for each data set. Therefore, the wrong choice of the input variables may lead to a decrease in the forecasting model accuracy. It should then be concluded that a preliminary analysis to the input variables and their selection is of the most importance in the development of a forecasting model.

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APPENDIX II. NOTATION

The following symbols are used in this paper:

AME	=	Absolute Maximum Error
f^{A}	=	Activation function
$\bar{y}$	=	Arithmetic mean of observed variables
ANN	=	Artificial Neural Networks
ACF	=	Autocorrelation Function
ARIMA	=	Autoregressive Integrated Moving Average
ARMA	=	Autoregressive Moving Average
AR	=	Autoregressive
θ^{b}	=	Bias node
BANN	=	Bootstrap Artificial Neural Network
R^2	=	Coefficient of Determination
CGPB	=	Conjugate Gradient Powell Beale
CG	=	Conjugate Gradient
u^{c}, w^{c}	=	connection weights
D	=	Day of week
DMA	=	District Metered Areas
ε	=	Error/residual
EA-ANN	=	Evolutionary Algorithms Artificial Neural Network
FD	=	Feed-back Delay
$\hat{y}$	=	Forecasted variable
HN	=	Hidden Neurons - vector of the number of neurons in the hidden layer(s)
H	=	Hour
ID	=	Input Delay of the external time series

z = Input variable

h = Lag (h-step ahead)

L^{s} = Level component/smoother

S^{s} = Level component/smoother

LM = Levenberg-Marquardt

MAE = Mean Absolute Error

MAPE = Mean Absolute Percent Error

MARE = Mean Absolute Relative Error

MASE = Mean Absolute Scaled Error

M = Month

ANN-MLP = Multilayer Perceptron Artificial Neural Network

MLR = Multiple Linear Regression

603 MNLR = Multiple Non-Linear Regression

MARS = Multivariate Adaptive Regression Splines

NSE = Nash-Sutcliff Efficiency (or Coefficient of Determination)

f^{NL} = Non-linear function

n_{hidden} = Number of hidden nodes

n_{in} = Number of input nodes

O_{t} = Number of observations used for training

O = Number of observations

n_{out} = Number of output nodes

y = Observed variable

PACF = Partial Autocorrelation Function

PPMC = Pearson Product Moment Correlation

m = Period of seasonality (season)

PPR = Projection Pursuit Regression

ANN-RBF = Radial Basis Function Artificial Neural Network

RO = Rainfall Occurrence

RH = Relative Humidity

RMSE = Root Mean Square Error

α^{s} = Smoother parameter

SEE = Sum of Square Errors

SVM = Support Vector Machines

T = Temperature

t = Time instant

T^{s} = Trend component/smoother

WD = Water Demand

WSS = Water Supply System

WANN = Wavelet Artificial Neural Network

WBANN = Wavelet Bootstrap Artificial Neural Network

List of Tables

TABLE 1. Comparison of the performances of short-term water demand forecasting methods applied to distinct case-studies.

Authors, year	Time scale [amount of data]	Model scale [population]	Forecasting model	training/testing R^2 (-)	RMSE (m^3/h)	MAE (m^3/h)	MARE/ MAPE (%)	maxARE (%)	NSE (-)	Observations
Jain et al., 2001	Weekly [98weeks]	Indian institute [12k]	MLR	0.684 / 0.642	-	-	5.16	10.39	-	-
			MNLR	0.667 / 0.602	-	-	5.59	10.52	-	
			AR	0.826 / 0.624	-	-	17.68	24.07	-	
			ANN (1HL) âĂŞ FFBP	0.963 / 0.640	-	-	3.74	12.08	-	
			ANN (2HL) - FFBP	0.992 / 0.872	-	-	2.41	6.49	-	
Bougadis et al., 2005	Peak weekly [4 months]	City of Otawa, Canada [0.75M]	MLR	0.620 / 0.445	-	-	19.25	43.18	-	-
			ARIMA(2,1,0)	0.300 / 0.352	-	-	14.31	36.28	-	
			ANN (1HL) âĂŞ FFBP - sigmoid	0.708 / 0.810	-	-	12.26	30.05	-	
Alvisi et al., 2007 [POWADIMA]	Hourly [1year]	Castelfranco Emilia, Italy [23k]	Pattern-based model with periodic and persistence components (1h/24h lead time)	- / -	16.2-28.8	-	5.0-9.0	-	-	The distinct case-studies show the scale effect in the models performance
Salomons et al., 2007 [POWADIMA]	Hourly [1year]	Haifa-A, Israel [60k]		- / -	131.0-155.5	-	8.6 / 10.3	-	-	
Martinez et al., 2007 [POWADIMA]	Hourly [1year]	Valencia, Spain [1.2M]		- / -	784.8-860.4	-	4.7 / 5.1	-	-	
Adamowski, 2008	Peak daily summer [10 years - May to Aug]	City of Ottawa, Canada [0.75M]	MLR	0.610 / 0.590	-	-	14.00	56.00	-	-
			ARIMA(2,1,0)	0.530 / 0.460	-	-	15.00	62.00	-	
			ANN (1HL) - FFBP	0.660 / 0.690	-	-	12.00	41.00	-	
Ghiassi et al., 2008	Hourly [1 month - Sep/Apr]	City of San Jose & surroundings, California [0.9 M]	ARIMA	- / -	-	-	3.38 / 4.51	-	-	-
			ANN - FFBP	- / -	-	-	3.41 / 4.52	-	-	
			dynamic ANN	- / -	-	-	2.04 / 3.26	-	-	
	Daily [1 year - 366 days]		ARIMA	- / -	-	-	2.35	-	-	
			ANN - FFBP	- / -	-	-	2.32	-	-	
			dynamic ANN	- / -	-	-	0.84	-	-	
	Weekly [4 years - 208 weeks]		ARIMA	- / -	-	-	1.17	-	-	
			ANN - FFBP	- / -	-	-	0.92	-	-	
			dynamic ANN	- / -	-	-	0.80	-	-	
Msiza et al., 2008	Daily [9 years & 5 months - 3473 days]	Gauteng Province, South Africa [9M]	ANN - RBF	- / -	-	-	2.96	-	-	-
			SVM	- / -	-	-	5.47	-	-	
Tabesh & Dini, 2009	Daily [13years]	Tehran, Iran [8/12M, night/day]	ANN (3HL)	- / 0.943	0.28	-	2.74	-	-	-
			ANN-RBF	- / 0.932	0.30	-	2.94	-	-	
			Fuzzy	- / 0.760	0.74	-	7.62	-	-	
			Neural-Fuzzy (non-random input data)	- / 0.801	0.32	-	2.77	-	-	
			Neural-Fuzzy (random input data)	- / 0.936	0.30	-	2.86	-		
Adamowski & Karapataki, 2010	Peak weekly [6years]	Athalassa, Nicosia, Cyprus [0.2M in the city]	MLR	0.838 / 0.820	8.13	-	2.51	11.99	-	-
			ANN(1HL, 15HN) - Resilient BP	0.940 / 0.901	6.99	-	2.23	12.15	-	
			ANN(1HL, 15HN) - CGPB	0.947 / 0.942	6.77	-	2.09	11.93	-	
			ANN(1HL, 15HN) - LM	0.953 / 0.946	5.23	-	2.15	11.18	-	
		Public Garden, Nicosia, Cyprus [0.2M in the city]	MLR	0.839 / 0.813	8.05	-	2.48	12.59	-	
			ANN(1HL, 15HN) - Resilient BP	0.942 / 0.900	6.90	-	2.27	10.41		
			ANN(1HL, 15HN) - CGPB	0.935 / 0.905	7.26	-	2.21	11.26	-	
			ANN(1HL, 15HN) - LM	0.957 / 0.917	5.69	-	1.97	9.76	-	
Herrera et al., 2010	Hourly [4months]	WSS in a city, Spain [5k]	ANN(1HL) - FFBP (grow/slide data update)	- / -	-	6.23 / 6.30	-	-	-	No significant difference when updating data by accumulating (grow) or considering only last observations (slide).
			Project Pursuite Regression	- / -	-	4.36 / 4.36	-	-	-	
			Multivariate Adaptive Regression Splines	- / -	-	4.36 / 4.36	-	-	-	
			Random Forests (regression trees)	- / -	-	4.36 / 4.36	-	-	-	
			Pattern-based	- / -	-	9.32 / 9.61	-	-	-	
			SVR	- / -	-	4.32 / 4.32	-	-	-	
			SVR (best model with other data)	- / -	4.38	3.24	-	-	0.445	

TABLE 2. Comparison of the performances of short-term water demand forecasting methods applied to distinct case-studies (cont.).

Authors, year	Time scale [amount of data]	Model scale [population]	Forecasting model	training/testing R^2 (-)	RMSE (m^3/h)	MAE (m^3/h)	MARE/ MAPE (%)	maxARE (%)	NSE (-)	Observations
Babel & Shinde, 2011	Daily [1066days]	Bangkok, Thailand [7.91M]	ANN (3HL) - FF - Momentum (gradient-descent) âĂŞ tanh	- / -	2083.32	-	1.12	-	-	Meteorological variables have more influence on monthly forecasts
Odan & Reis, 2012	Hourly [10 months]	Araraquara city, Brazil [224k]	ANN (MLP) - BP	0.846 / 0.740	-	16.20	-	-	-	-
			dynamic ANN	0.757 / 0.810	-	12.60	-	-	-	
			Hybrid ANN (MLP) - BP (Fourier Series as input)	0.792 / 0.740	-	16.20	-	-	-	
			Hybrid dynamic ANN (FS input)	0.846 / 0.865	-	10.44	-	-	-	
Adamowski et al., 2012	Daily summer [8 years & 3 months - May to Aug]	City of Montreal, Canada [1.8M]	MLR	0.76 / 0.786	-	-	-	-	0.629	-
			MNLR	0.848 / 0.838	-	-	-	-	0.633	
			ARIMA	0.758 / 0.782	-	-	-	-	0.778	
			ANN	0.792 / 0.865	-	-	-	-	0.864	
			WANN (wavelets as input)	0.896 / 0.919	-	-	-	-	0.919	
Tiwari & Adamowski, 2013	Daily [4179 days]	City of Montreal, Canada [1.8M]	ARIMA	0.900 / -	271.26	202.07	-	-	-	-
			ARIMA with exogenous input (maxT and totP)	0.910 / -	272.92	196.67	-	-	-	
			ANN (13HN)	0.920 / -	245.02	173.74	-	-	-	
			BANN (bootstrap)	0.900 / -	253.76	183.74	-	-	-	
			WANN	0.980 / -	129.56	92.09	-	-	-	
			WBANN	0.980 / -	170.42	124.60	-	-	-	
	Weekly [138months]		ARIMA	0.680 / -	489.17	312.08	-	-	-	-
			ARIMA with exogenous input (maxT and totP)	0.680 / -	495.43	366.66	-	-	-	
			ANN (5HN)	0.670 / -	492.91	357.91	-	-	-	
			BANN	0.680 / -	513.76	382.07	-	-	-	
			WANN	0.760 / -	502.92	370.84	-	-	-	
			WBANN	0.780 / -	419.18	312.08	-	-	-	
Adamowski et al., 2014; Tiwari & Adamowski, 2014	Weekly [2 years & 9 months]	City of Calgary, Canada [1.1M]	ANN (6HN)	0.590 / -	2502.07	1849.57	-	-	-	-
			BANN (6HN) - bootstrap of 100ANN	0.560 / -	2442.92	1772.10	-	-	-	
			WANN (4HN)	0.730 / -	1899.58	1424.16	-	-	-	
			WBANN (4HN) - bootstrap of 100WANN	0.800 / -	1666.66	1218.35	-	-	-	
Santos & Filho, 2014	Hourly (1 to 24h forecast) [1 year]	Cantareira WSS, SÃčo Paulo, Brazil [6.5M**]	MLR	0.442 / -	4853	3715.20	-	-	-	Best model obtained for predicting 12h ahead using anthropic, weather and past demand variables*
			ANN(1HL)	0.481 / 0.454	7380	5634.00	-	-	-	
			FFBP	0.679 / 0.5	3722	2761.00	-	-	-	
Romano & Kapelan, 201	Hourly (24h ahead), [6 months]	DMA1 of Yorkshire WSS, UK	EA-ANN (with / without data update)	- / -	86.08 / 207.94	-	6.39 / 8.47	-	0.96 / 0.94	
			fixed-structure ANN	- / -	561.60 / 786.41	-	9.83 / 11.93	-	0.91 / 0.89	
			ensemble EA-ANN	- / -	82.94 / 128.30	-	6.30 / 7.73	-	0.96 / 0.96	
			ensemble fixed-structure ANN	- / -	370.15 / 370.88	-	9.07 /10.54	-	0.93 / 0.93	
		DMA3 (less consumers) of Yorkshire WSS, UK	EA-ANN (with/without data update)	- / -	0.13 / 0.14	-	5.64 / 5.51	-	0.98 / 0.97	
			fixed-structure ANN	- / -	1.05 / 0.86	-	9.24 / 9.72	-	0.93 /0.94	
			ensemble EA-ANN	- / -	0.13 / 0.14	-	5.68 / 5.51	-	0.98 / 0.98	
			ensemble fixed-structure ANN	- / -	0.76 / 0.86	-	8.68 / 9.72	-	0.94 / 0.94	
		Reservoir outlet of Yorkshire WSS, UK [70k]	EA-ANN (with/without data update)	- / -	-	-	6.23 / 7.36	-	0.94 / 0.93	
			fixed-structure ANN	- / -	-	-	8.84 / 9.37	-	0.91 / 0.91	
			ensemble EA-ANN	- / -	-	-	5.68 / 6.26	-	0.95 / 0.95	
			ensemble fixed-structure ANN	- / -	-	-	7.75 / 8.63	-	0.93 / 0.92	

Do not provide RMSE nor MAE units. In order to convert for l/s units, it was considered that the authors used the same units of water consumption; **Value retrieved from http://site.sabesp.com.br/

TABLE 3. Comparison of the performances of short-term water demand forecasting methods applied to distinct case-studies (cont.).

Authors, year	Time scale [amount of data]	Model scale [population]	Forecasting model	training/testing R^2 (-)	RMSE (m^3/h)	MAE (m^3/h)	MARE/ MAPE (%)	maxARE (%)	NSE (-)	Observations
Bakker et al., 2013 & Bakker, 2014	48h forecast with 15-min time steps [6 years - 210336 values]	Amsterdam, Netherlands [950k]	adaptive pattern-based, 24-h	- / -	151.55	-	1.44	-	0.785	Better accuracy for larger areas / higher NSE (better fit) when using 15-min time steps
			adaptive pattern-based, 15-min	- / -	365.69	-	3.35	-	0.987	
		Rijnregio, Netherlands [305k]	adaptive pattern-based, 24-h	- / -	63.80	-	1.86	-	0.710	
			adaptive pattern-based, 15-min	- / -	165.70	-	4.64	-	0.978	
		Almere, Netherlands [193k]	adaptive pattern-based, 24-h	- / -	36.19	-	2.12	-	0.740	
			adaptive pattern-based, 15-min	- / -	100.69	-	5.28	-	0.972	
		Helden, Netherlands [39k]	adaptive pattern-based, 24-h	- / -	15.04	-	3.4	-	0.803	
			adaptive pattern-based, 15-min	- / -	30.03	-	6.55	-	0.952	
		Valkenburg, Netherlands [9.2k]	adaptive pattern-based, 24-h	- / -	3.53	-	3.49	-	0.802	
			adaptive pattern-based, 15-min	- / -	7.30	-	6.90	-	0.949	
		Hulsberg, Netherlands [2.4k]	adaptive pattern-based, 24-h	- / -	1.48	-	5.12	-	0.658	
			adaptive pattern-based, 15-min	- / -	3.01	-	10.44	-	0.905	
Bakker et al., 2014 & Bakker, 2014	Daily [6 years - 2192 days]	Amsterdam (urban), Netherlands	MLR (without/with weather input)	- / -	-	-	1.54/1.47	-	0.709 / 0.738	Rural areas more difficult to predict. The input of weather variables improves the models performance in all cases
			adaptive pattern-based, 1day	- / -	-	-	1.39/1.32	-	0.756 / 0.790	
			transfer-/noise (transfer model with ARIMA(0,8,3))	- / -	-	-	1.36/1.25	-	0.766 / 0.812	
		Rijnregio (mix), Netherlands	MLR	- / -	-	-	1.99/1.87	-	0.681 / 0.731	
			adaptive pattern-based, 1day	- / -	-	-	1.88/1.73	-	0.694 / 0.751	
			transfer-/noise	- / -	-	-	1.77/1.65	-	0.740 / 0.777	
		Almere (urban), Netherlands	MLR	- / -	-	-	2.37/2.26	-	0.681 / 0.731	
			adaptive pattern-based, 1day	- / -	-	-	2.08/1.97	-	0.718 / 0.764	
			transfer-/noise	- / -	-	-	2.03/1.87	-	0.733 / 0.793	
		Helden (rural), Netherlands	MLR	- / -	-	-	4.25/4.01	-	0.747 / 0.780	
			adaptive pattern-based, 1day	- / -	-	-	3.72/3.33	-	0.794 / 0.848	
			transfer-/noise	- / -	-	-	3.74/3.47	-	0.791 / 0.832	
		Valkenburg (rural), Netherlands	MLR	- / -	-	-	3.97/3.81	-	0.756 / 0.772	
			adaptive pattern-based, 1day	- / -	-	-	3.55/3.38	-	0.788 / 0.808	
			transfer-/noise	- / -	-	-	3.44/3.32	-	0.807 / 0.818	
		Hulsberg (rural), Netherlands	MLR	- / -	-	-	5.97/5.73	-	0.619 / 0.643	
			adaptive pattern-based, 1day	- / -	-	-	5.08/4.48	-	0.688 / 0.755	
			transfer-/noise	- / -	-	-	5.04/4.77	-	0.696 / 0.727	
Wang et al., 2014	Hourly [1 year]	Barcelona, Spain [3M]	Double-Season multiplicative Holt-Winters + Gaussian Process regression	- / -	3.99-5.47	3.06-4.32	-	-	-	-
Candelieri & Archetti, 2014	Hourly [13 months]	Milan, Italy [1M]	data clustering + SVM	- / -	-	-	0.79-14.33	-	-	-
Kang et al., 2015	Hourly [6 months]	WSS in Gallella (rural), Sri Lanka [3k]	ARIMA(1,1,2)	- / 0.83	6.21	-	-	-	0.80	-
			ARIMA(1,1,2)+ Exponential Smoothing	- / 0.90	5.26	-	-	-	0.88	

ANN - Artificial Neural Networks; AR - Autoregression; ARIMA - Auto Regressive Integrated Moving Average; ARMA - Auto Regressive Moving Average; BP - Back-Propagation; CG - Conjugate Gradient; FF - Feed Forward; HL - Hidden Layer; LM - Levenberg-Marquardt; MLR - Multiple Linear Regression; MNLR - Multiple Non-Linear Regression; RBF - Radial Basis Function; SVM - Support Vector Machine; SVR - Support Vector Regression; WBANN - Wavelet Bootstrap ANN.

TABLE 4. Comparison of the influence of several variables as input for distinct short-term water demand forecasting models.

Authors, year	Time scale	Model scale	Tested input variables	Best forecasting model / other observations
Jain et al., 2001	Weekly	Indian institute	WD(t-2,t-1), maxT(t-1,t), R(t-1, t), RO(t-1,t)	ANN(1HL) / ANN(2HL): WD(t-1), maxT(t), RO(t) AR: WD(t-2, t-1) MLR: WD(t-1), maxT(t), RO(t) MNLR: WD(t-1), maxT(t-1, t), R(t-1, t)
Bougadis et al., 2005	Peak weekly	City of Otawa, Canada	WD(t-3 to t), maxT(t-1, t), WD(t-3 to t), maxT(t-1, t), R(t-1, t), RO(t-1, t)	ANN(1HL): WD(t-1), maxT(t), R(t) ARIMA(2,1,0): WD(t-3 to t-1) MLR: WD(t-1), maxT(t-1,t), R(t-1,t)
Adamowski, 2008	Peak daily	City of Otawa, Canada	WD(t-3 to t), maxT(t-1, t), R(t-5 to t), RO(t-5 to t)	ANN(1HL) / MLR: WD(t-1), maxT(t-1,t), RO(t-5) ARIMA(2,1,0): WD(t-3 to t-1)
Msiza et al., 2008	Daily	Gauteng province, South Africa	WD(t-5 to t), annual Pop.	ANN: WD(t-3 to t) and annual Pop.
Tabesh & Dini, 2009	Daily	Tehran, Iran	WD(t-7 to t), previous week and previous year total WD, avgT, RH	ANN/Neuro-fuzzy: WD(t-7 to t), previous week and previous year total WD
Adamowski & Karapataki, 2010	Peak weekly	Athalassa, Nicosia Public Garden, Nicosia	WD, maxT, R, RO	MLR: WD(t-1), maxT(t-2 to t) ANN-LM(1HL, 15HN): WD(t-1), maxT(t-1, t), R(t-1, t), RO(t-1, t) MLR: WD(t-1), maxT(t-1, t), R(t-1, t), RO(t-1, t) ANN-LM(1HL, 15HN): WD(t-1), maxT(t-2 to t)
Herrera et al., 2010	Hourly	Spain WSS	WD(t-168+1, t-1, t), R, T, windS, Press	-
Babel & Shinde, 2011	Daily	Bangkok, Thailand	WD(t-6 to t), R(t), Evap(t), RH(t), maxT(t), minT(t), avgT(t)	WD(t), R(t), avgT(t), RH(t)
Odan & Reis, 2012	Hourly	WSS subsector, Sao Paulo, Brazil	WD(t-168, t-24, t-3 to t), T(t), RH(t) and FS	ANN(MLP)-BP (8HN): WD(t-168, t-3 to t), RH(t) dynamic ANN (15HN): WD(t-168, t-2 to t) hybrid ANN (8HN): WD(t-168, t-3 to t), FS(t-168, t-3 to t), RH(t) hybrid dynamic ANN (15HN): WD(t-168, t-2 to t), FS(t-168, t-2 to t)
Adamowski et al., 2012	Daily	City of Montreal, Canada	maxT, totP & WD (t-3 to t)	MLR: WD(t-1, t) & maxT(t-1, t) MNLR: WD(t-3 to t) & maxT(t-3 to t) ANN: WD(t-2 to t) & maxT(t-1, t) WANN: WD(t-3 to t) & maxT(t-1, t)
Tiwari & Adamowski, 2013	Daily Weekly	City of Montreal, Canada	WD(t-6 to t), maxT(t-6 to t), totP(t-6 to t) + 4 wavelet components of each	WANN: all 4 wavelet components of WD(t) WBANN: all 4 wavelet components of WD(t), 2 wavelet components of maxT(t-3 to t-1) and of totP(t-3 to t-1)
Adamowski et al., 2014	Weekly	Calgary city, Canada	WD(t-3 to t), maxT(t-3 to t), totP(t-3 to t) + 4 wavelet components for each series	WBANN:all 4 wavelet components of WD(t), 2 wavelet components of maxT(t-3 to t-1) and 1 wavelet component of totP(t-3 to t-1)
Santos & Filho, 2014	Hourly	39 cities in São Paulo, Brazil	demand(t-1,t-6,t-12, t-18,t-24):WD / anthropic (t,t+6,t+12,t+18,t+24):Hour, Day, Seas, typeDay / weather(t,t-1,t-6,t-12,t-18,t-24): T, RH, R, P, windDir, windS	Output: WD(t+12) / Input: anthropic(t+12), weather(t,t-12), WD(t,t-12) [best model] Output: WD(t) / Input: anthropic(t), weather(t, t-1), WD(t-1) [worst than MLR]

WD - Water Demand; maxT - maximum Temperature; R - Rainfall amount; RO - Rainfall occurrence (binary); Pop - Population; windS - Wind Speed; Evap - Evaporation; minT - minimum Temperature; totP - total precipitation (not only rain); P - Pressure; Vc - climatic variables; HL - hidden layers; HN - hidden neurons; FS - Fourier Series;

TABLE 5. Pearson correlation coefficients between the distinct water demand sets (WD) and the considered anthropic variables *Day of the week* (D), *Month* (M) and *Hour of the day* (H).

	D	M	H	WD2	WD4	WD5	WD16
D	1.000						
M	0.005	1.000					
H	0.000	0.000	1.000				
WD2	0.000	0.120	**0.605**	1.000			
WD4	0.047	0.116	**0.650**	**0.915**	1.000		
WD5	0.094	-0.057	0.130	0.107	0.120	1.000	
WD16	0.075	-0.008	**0.650**	**0.836**	**0.894**	0.069	1.000

TABLE 6. Input variables for each ANN-based model developed.

Data set	ANN model	Input variables	Data set	ANN model	Input variables
	WD2_hist	WD2(t)		WD16_hist	WD16(t)
	WD2_1lag	WD2(t, t-168)		WD16_1lag	WD16(t, t-1)
	WD2_3lags	WD2(t, t-1, t-24, t-168)		WD16_3lags	WD16(t, t-1, t-24, t-168)
WD2	WD2_anthrop	WD2(t), Hour, Month	WD16	WD16_anthrop	WD16(t), Hour
	WD2_neighb	WD2(t), WD4(t), WD16(t)		WD16_neighb	WD16(t), WD2(t), WD4(t)
	WD2_meteo	WD2(t), T(t), RH(t)		WD16_meteo	WD16(t), T(t), RH(t)
	WD2_rain	WD2(t), RO(t)		WD16_rain	WD16(t), RO(t)
	WD2_selection	selected variables		WD16_selection	selected variables
	WD2_all	all variables		WD16_all	all variables
	WD4_hist	WD4(t)		WD5_hist	WD5(t)
	WD4_1lag	WD4(t, t-168)		WD5_1lag	WD5(t, t-1)
	WD4_3lags	WD4(t, t-1, t-24, t-168)		WD5_3lags	WD5(t, t-1, t-24, t-168)
WD4	WD4_anthrop	WD4(t), Hour, Month	WD5	WD5_anthrop	WD5(t), Hour, Month
	WD4_neighb	WD4(t), WD2(t), WD16(t)		WD5_meteo	WD5(t), T(t)
	WD4_meteo	WD4(t), T(t), RH(t)		WD5_rain	WD5(t), RO(t)
	WD4_rain	WD4(t), RO(t)		WD5_selection	selected variables
	WD4_selection	selected variables		WD5_all	all variables
	WD4_all	all variables			

TABLE 7. Forecasting accuracy obtained for each data set with the Naïve, Seasonal Naïve, Additive Seasonal Holt-Winters and Multiplicative Seasonal Holt-Winters models. Fitting stage.

Data set	Forecasting method	R^2 (-)	NSE (-)	MAE (m^3/h)	RMSE (m^3/h)	MAPE (%)	maxAE (m^3/h)
WD2	Naïve	0.73	0.71	1.90	2.74	1.67E+12	21.61
	Seas. Naïve	**0.79**	0.78	1.54	2.38	8.85E+12	20.35
	Add H-W	0.01	**1.00**	**0.01**	**0.01**	1.67E+10	**0.01**
	Mult H-W	0.01	**1.00**	**0.01**	**0.01**	9.43E+09	**0.01**
WD4	Naïve	0.78	0.77	5.54	7.46	1.19E+12	61.08
	Seas. Naïve	**0.88**	0.87	3.57	5.55	3.31E+12	42.83
	Add H-W	0.01	**1.00**	**0.00**	**0.01**	2.19E+09	**0.03**
	Mult H-W	0.01	**1.00**	**0.01**	**0.02**	7.49E+09	**0.09**
WD5	Naïve	**0.33**	0.15	106.29	139.87	5.61E+10	934.13
	Seas. Naïve	0.26	0.03	113.45	149.97	4.07E+12	709.43
	Add H-W	0.01	**1.00**	**0.09**	**0.09**	5.10E+08	**0.16**
	Mult H-W	0.01	**1.00**	**0.09**	**0.09**	4.99E+08	**0.19**
WD16	Naïve	0.71	0.68	0.69	0.98	6.21E+10	11.50
	Seas. Naïve	**0.74**	0.72	0.57	0.93	3.40E+11	12.05
	Add H-W	0.00	**1.00**	**0.00**	**0.00**	1.25E+08	**0.00**
	Mult H-W	0.00	**1.00**	**0.00**	**0.00**	4.71E+07	**0.00**

TABLE 8. Forecasting accuracy obtained for each data set with the Naïve, Seasonal Naïve, Additive Seasonal Holt-Winters and Multiplicative Seasonal Holt-Winters models. First hour validation.

Data set	Forecasting method	R^2 (-)	NSE (-)	MAE (m^3/h)	RMSE (m^3/h)	MAPE (%)	maxAE (m^3/h)
WD2	Naïve	_	_	4.18	4.18	35.86	4.18
	Seas. Naïve	_	_	**1.86**	**1.86**	**15.95**	**1.86**
	Add H-W	_	_	5.09	5.09	43.64	5.09
	Mult H-W	_	_	5.23	5.23	44.85	5.23
WD4	Naïve	_	_	3.99	3.99	9.21	3.99
	Seas. Naïve	_	_	12.07	12.07	27.84	12.07
	Add H-W	_	_	**0.86**	**0.86**	**1.98**	**0.86**
	Mult H-W	_	_	1.09	1.09	2.51	1.09
WD5	Naïve	_	_	**97.15**	**97.15**	**43.73**	**97.15**
	Seas. Naïve	_	_	111.92	111.92	50.38	111.92
	Add H-W	_	_	169.36	169.36	76.23	169.36
	Mult H-W	_	_	218.90	218.90	98.53	218.90
WD16	Naïve	_	_	0.45	0.45	18.84	0.45
	Seas. Naïve	_	_	2.65	2.65	110.23	2.65
	Add H-W	_	_	**0.35**	**0.35**	**14.62**	**0.35**
	Mult H-W	_	_	**0.35**	**0.35**	14.63	**0.35**

TABLE 9. Forecasting accuracy obtained for each data set with the Naïve, Seasonal Naïve, Additive Seasonal Holt-Winters and Multiplicative Seasonal Holt-Winters models. First 24 hours validation.

Data set	Forecasting method	R^2 (-)	NSE (-)	MAE (m^3/h)	RMSE (m^3/h)	MAPE (%)	maxAE (m^3/h)
WD2	Naïve	0.00	-1.07	5.02	6.66	94.01	12.41
	Seas. Naïve	**0.86**	**0.81**	**1.33**	**2.01**	**10.35**	**5.12**
	Add H-W	0.33	0.34	5.15	5.45	64.52	9.57
	Mult H-W	0.26	0.31	5.19	5.58	60.22	9.27
WD4	Naïve	0.00	-0.07	13.11	16.14	73.95	30.36
	Seas. Naïve	**0.80**	**0.70**	**6.08**	8.62	**16.49**	27.15
	Add H-W	0.00	-0.41	6.46	**7.98**	22.10	20.56
	Mult H-W	0.01	-0.34	6.50	**7.76**	24.69	**19.75**
WD5	Naïve	0.01	-0.89	110.35	129.40	28.80	292.61
	Seas. Naïve	0.33	**-0.32**	**96.86**	**108.10**	**26.47**	**201.05**
	Add H-W	0.54	-1195.96	206.95	232.19	60.18	361.13
	Mult H-W	**0.62**	-4119.31	395.20	430.80	108.25	643.13
WD16	Naïve	0.00	-0.04	1.40	1.68	418.31	2.75
	Seas. Naïve	**0.79**	0.70	**0.59**	**0.90**	**37.88**	2.65
	Add H-W	0.03	**0.98**	0.82	1.03	48.73	**2.38**
	Mult H-W	0.03	**0.98**	0.82	1.03	48.49	**2.38**

TABLE 10. Forecasting accuracy obtained for each data set with the Naïve, Seasonal Naïve, Additive Seasonal Holt-Winters and Multiplicative Seasonal Holt-Winters models. All data validation.

Data set	Forecasting method	R^2 (-)	NSE (-)	MAE (m^3/h)	RMSE (m^3/h)	MAPE (%)	maxAE (m^3/h)
WD2	Naïve	0.09	-0.10	5.03	6.41	69.09	17.85
	Seas. Naïve	**0.73**	0.73	**2.21**	**3.16**	**16.25**	**17.67**
	Add H-W	0.00	**1.00**	3.36	4.23	31.99	18.46
	Mult H-W	0.00	**1.00**	3.40	4.29	31.83	18.43
WD4	Naïve	0.10	0.07	16.75	20.24	54.41	58.35
	Seas. Naïve	**0.68**	0.68	9.33	11.92	21.52	**41.54**
	Add H-W	0.03	**1.00**	9.40	12.78	21.18	46.89
	Mult H-W	0.00	**1.00**	**8.66**	**11.87**	**20.23**	44.89
WD5	Naïve	0.31	-1.08	224.65	256.55	41.02	630.02
	Seas. Naïve	0.26	0.21	**124.55**	**157.84**	**26.03**	**517.76**
	Add H-W	**0.39**	**0.80**	159.38	194.80	38.82	598.67
	Mult H-W	0.48	0.24	324.53	376.91	72.09	996.23
WD16	Naïve	0.02	0.02	1.66	2.07	361.07	11.56
	Seas. Naïve	**0.55**	0.46	**0.86**	1.53	**35.18**	13.66
	Add H-W	0.04	**1.00**	1.05	1.51	47.07	12.71
	Mult H-W	0.00	**1.00**	1.04	**1.47**	51.30	**12.39**

TABLE 11. Forecasting accuracy measures for the best ANN-based models obtained in each data. Results of the 24 hours forecasting.

Best models	Network architecture	R^2 (-)	NSE (-)	MAE (m^3/h)	RMSE (m^3/h)	MAPE (%)	maxAE (m^3/h)
WD2_1lag	narxnet(1:168,1:1,6)	0.77	0.77	1.72	2.16	16.16	**4.67**
WD2_anthrop	narxnet(1:168,1:1,3)	0.74	0.73	1.59	2.33	12.96	6.24
WD2 Seas. Naïve	_	0.86	0.81	1.33	2.01	10.35	5.12
WD4_1lag	narxnet(1:168,1:1,8)	0.88	0.87	3.91	5.49	11.33	12.96
WD4_neighb	narxnet(1:168,1:1,2)	**0.94**	**0.93**	**3.09**	**3.88**	**10.81**	**8.84**
WD4 Seas. Naïve	_	0.80	0.70	6.08	8.62	16.49	27.15
WD5_3lags	narxnet(1:1,1:1,8)	0.25	0.01	79.79	95.58	25.47	209.81
WD5_rain	narxnet(1:1,1:1,7)	0.08	0.00	68.78	95.96	23.36	282.76
WD5 Seas. Naïve	_	0.33	-0.32	96.86	108.10	26.47	201.05
WD16_3lags	narxnet(1:1,1:1,6)	0.40	0.39	1.00	1.23	275.25	2.70
WD16_anthrop	narxnet(1:1,1:1,5)	0.87	0.87	0.45	0.57	38.81	1.11
WD16_selection	narxnet(1:1,1:1,10)	**0.92**	**0.91**	**0.38**	**0.47**	**24.12**	**0.87**
WD16 Seas. Naïve	_	0.79	0.70	0.59	0.90	37.88	2.65

List of Figures

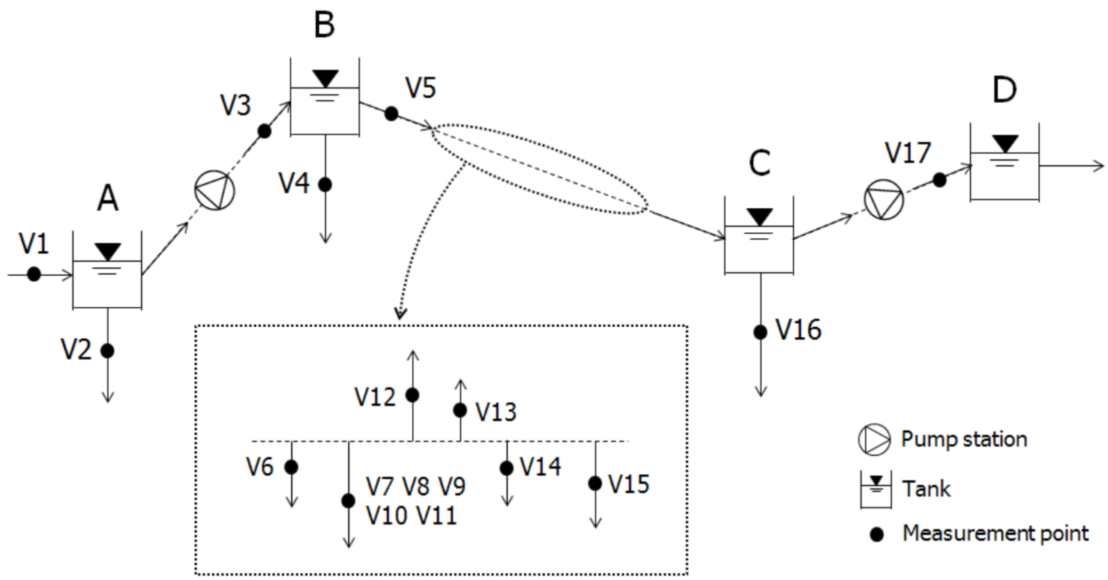

FIG. 1. Simplified representation of the Portuguese water network showing the available measurement points.

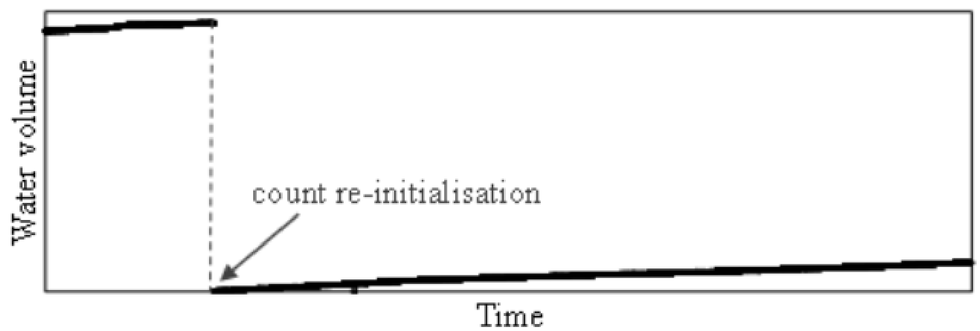

FIG. 2. Representation of an occurrence in collected data. After reaching the limit of the measurement device, the counting starts again from zero.

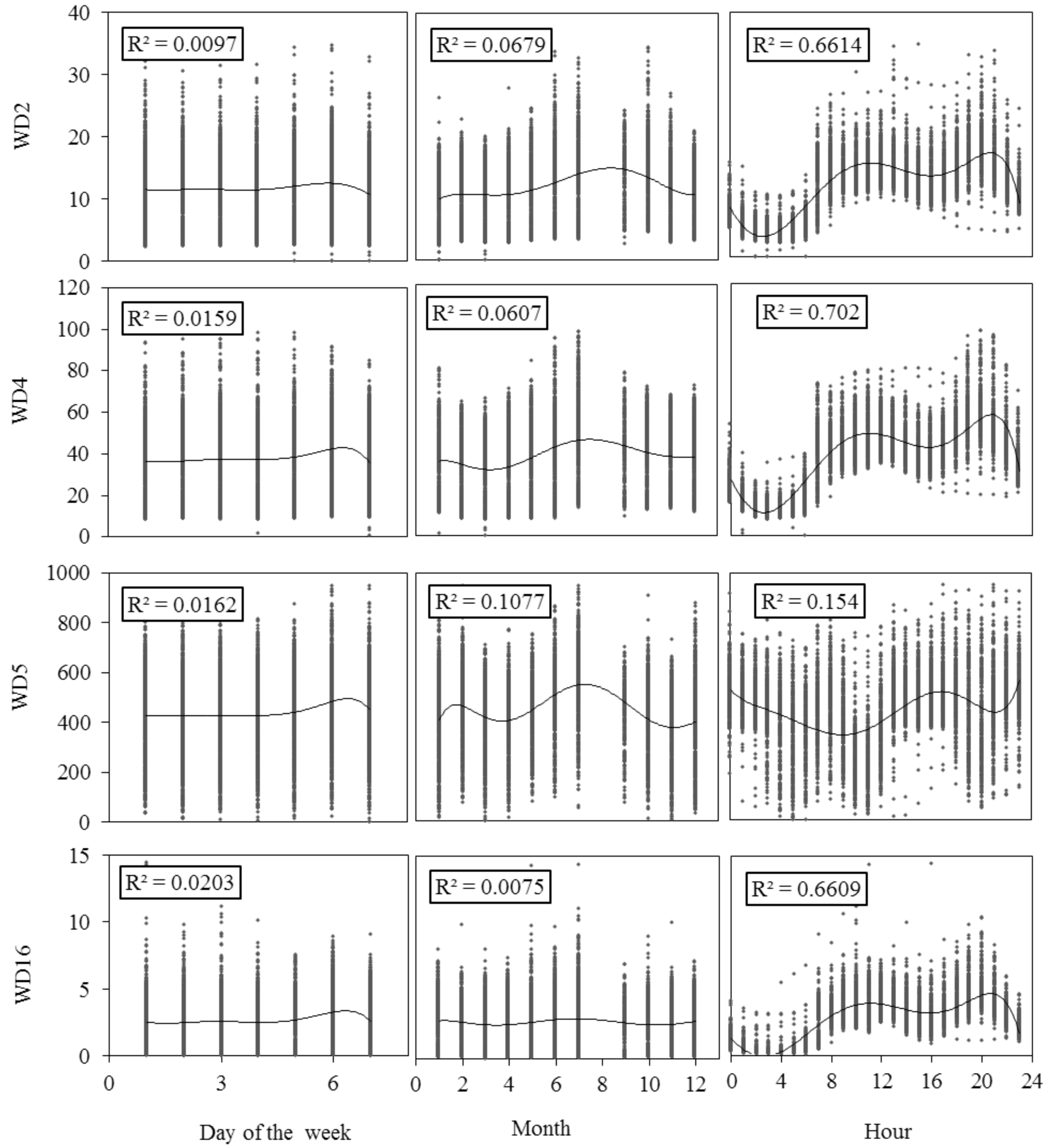

FIG. 3. Scatter plots showing the relationship between the water demand time series (in m^3/h) and the anthropic variables *Hour* (H), *Day of the week* (D) and *Month* (M). Adjusted 6^{th}-order polynomial trend lines and the squared correlation coefficients are also represented.

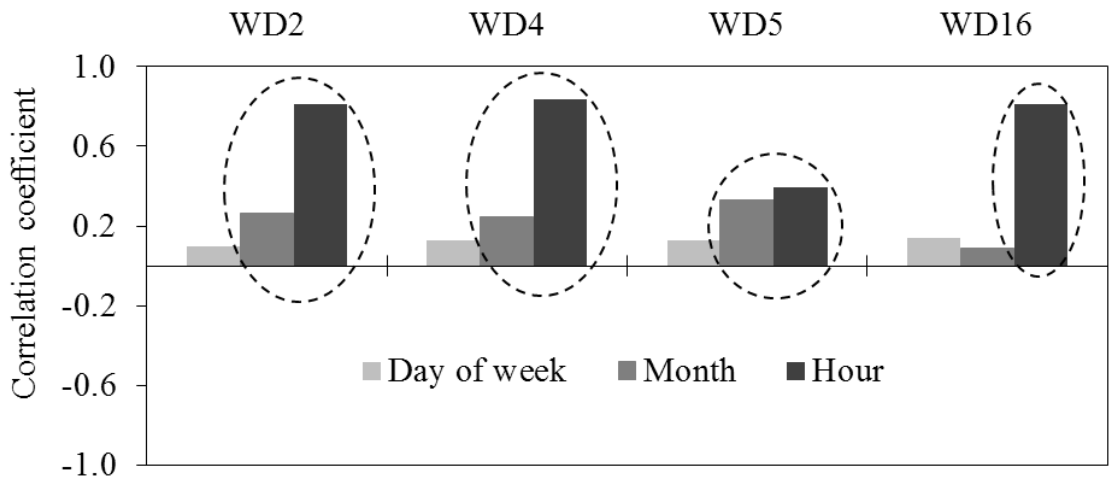

FIG. 4. Correlation coefficients (from a polynomial trend) between the water demand in each data set and the anthropic variables. The variables signed with the dashed lines were selected for the forecasting models.

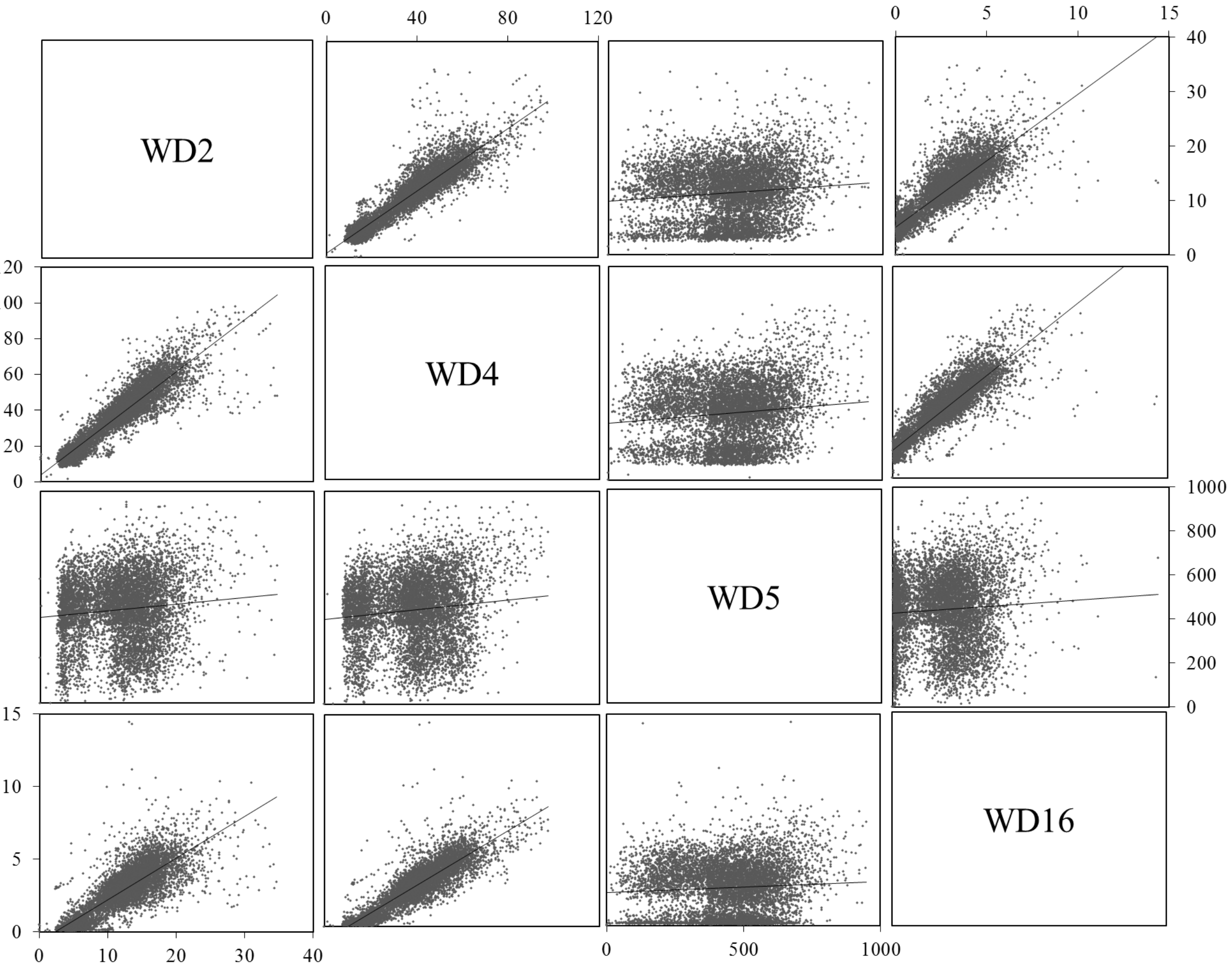

FIG. 5. Scatter plot matrix showing the relationships between the water demand data sets and their neighbour delivery points.

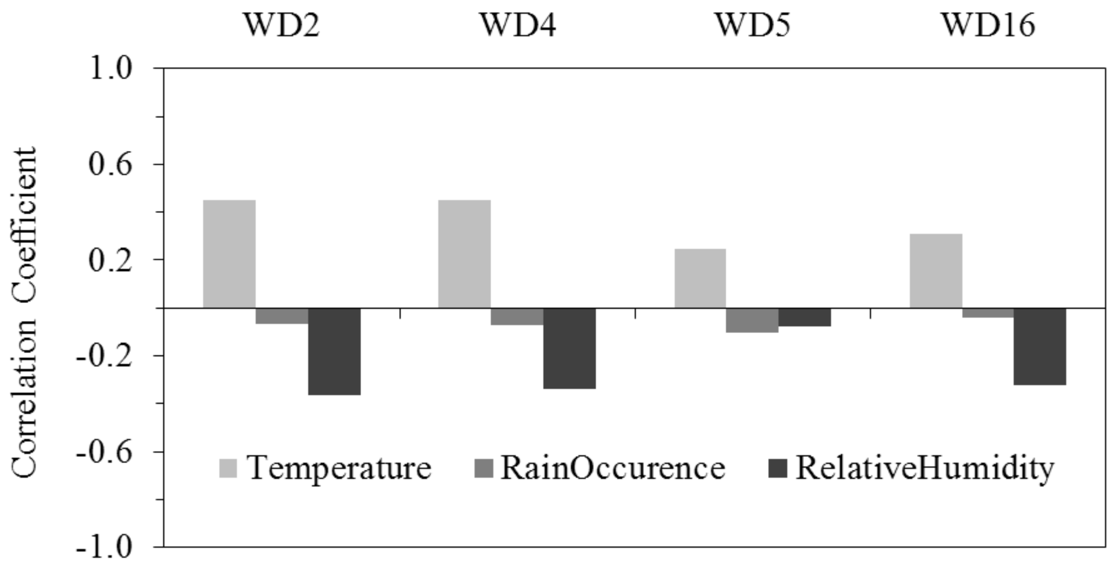

FIG. 6. Pearson correlation coefficients between the water demand in each data set and the weather variables.

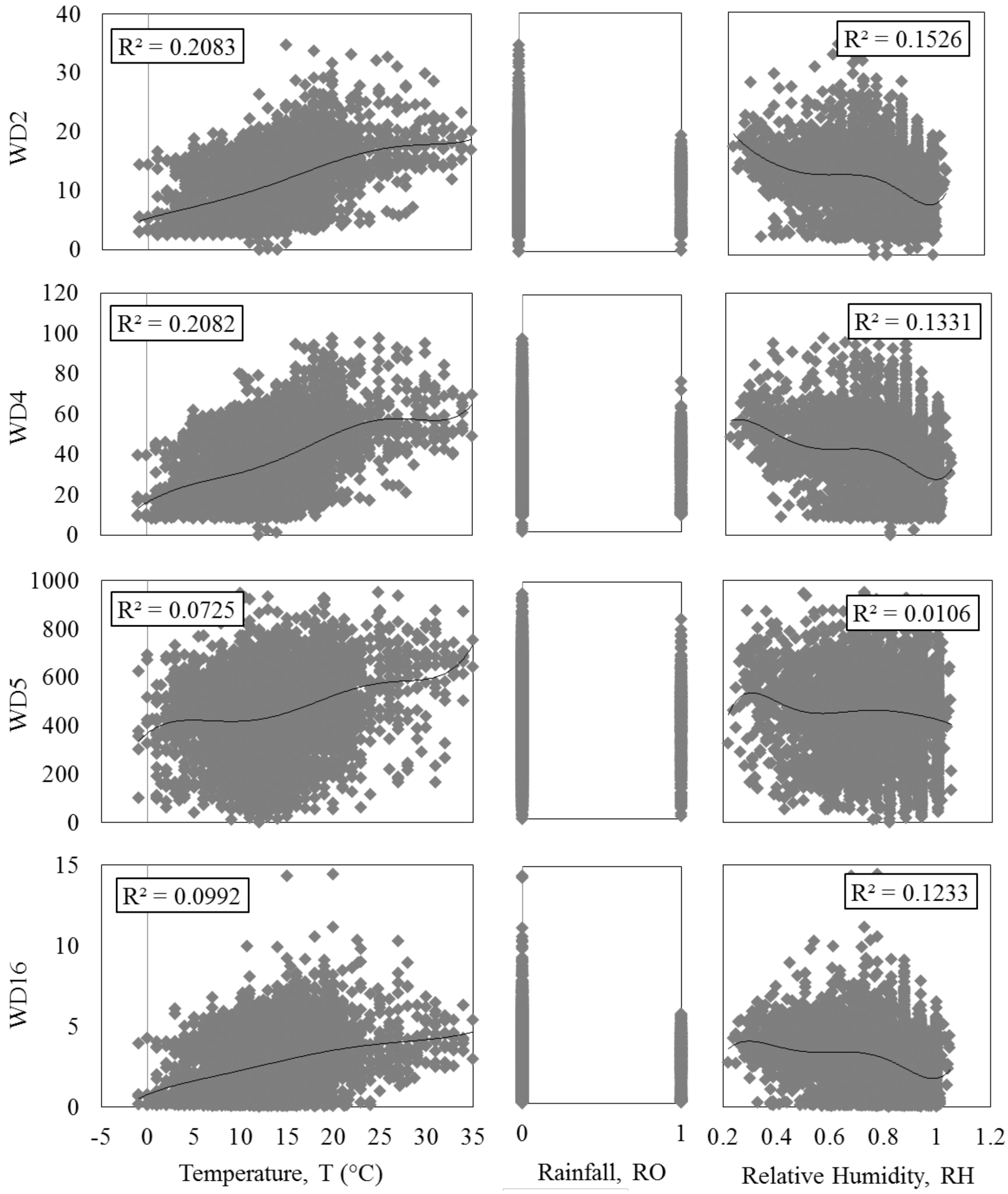

FIG. 7. Scatter plots showing the relationship between the water demand (in m^3/h) and the weather variables. Adjusted 6^{th}-order polynomial trend lines and the corresponding squared correlation coefficients.

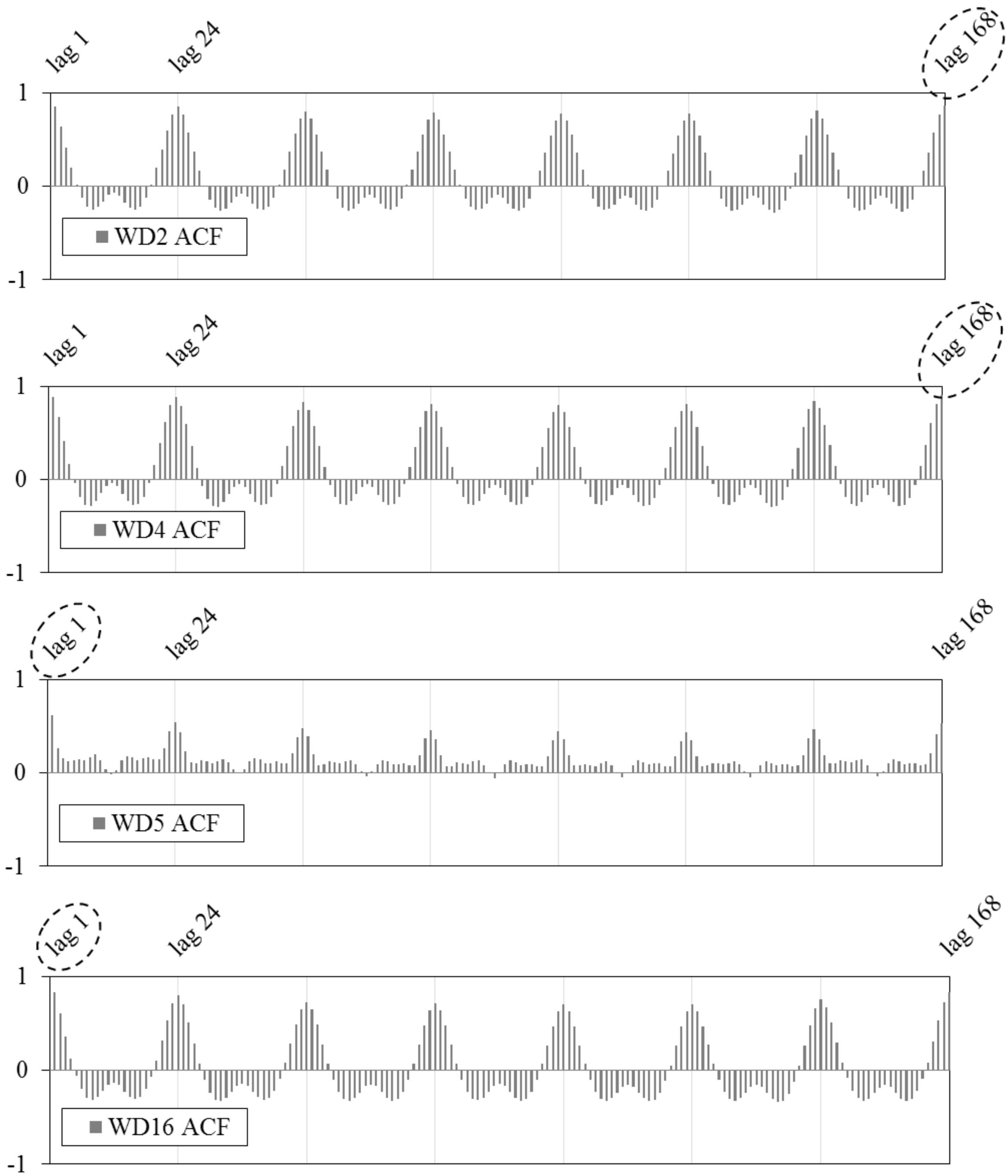

FIG. 8. Autocorrelation Functions (ACF) for the distinct water demand time series considered in this work. The black dashed lines mark the lag that presents the highest correlation in each case.

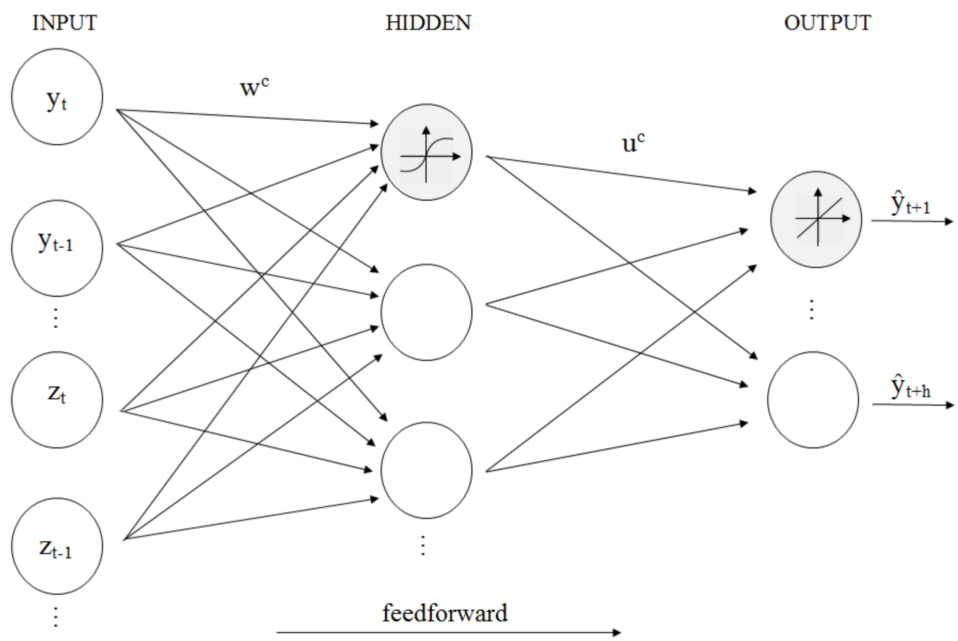

FIG. 9. Scheme representing an example of a 2-layer feed-forward artificial neural network for time series forecasting. The input layer may contain the lags of the variable to predict ($y_t, y_{t-1}, \ldots$) as well as other predictors ($z_t, z_{t-1}, \ldots$) and the output can have a single or multiple neurons according to the defined time horizon (1 to h steps ahead).

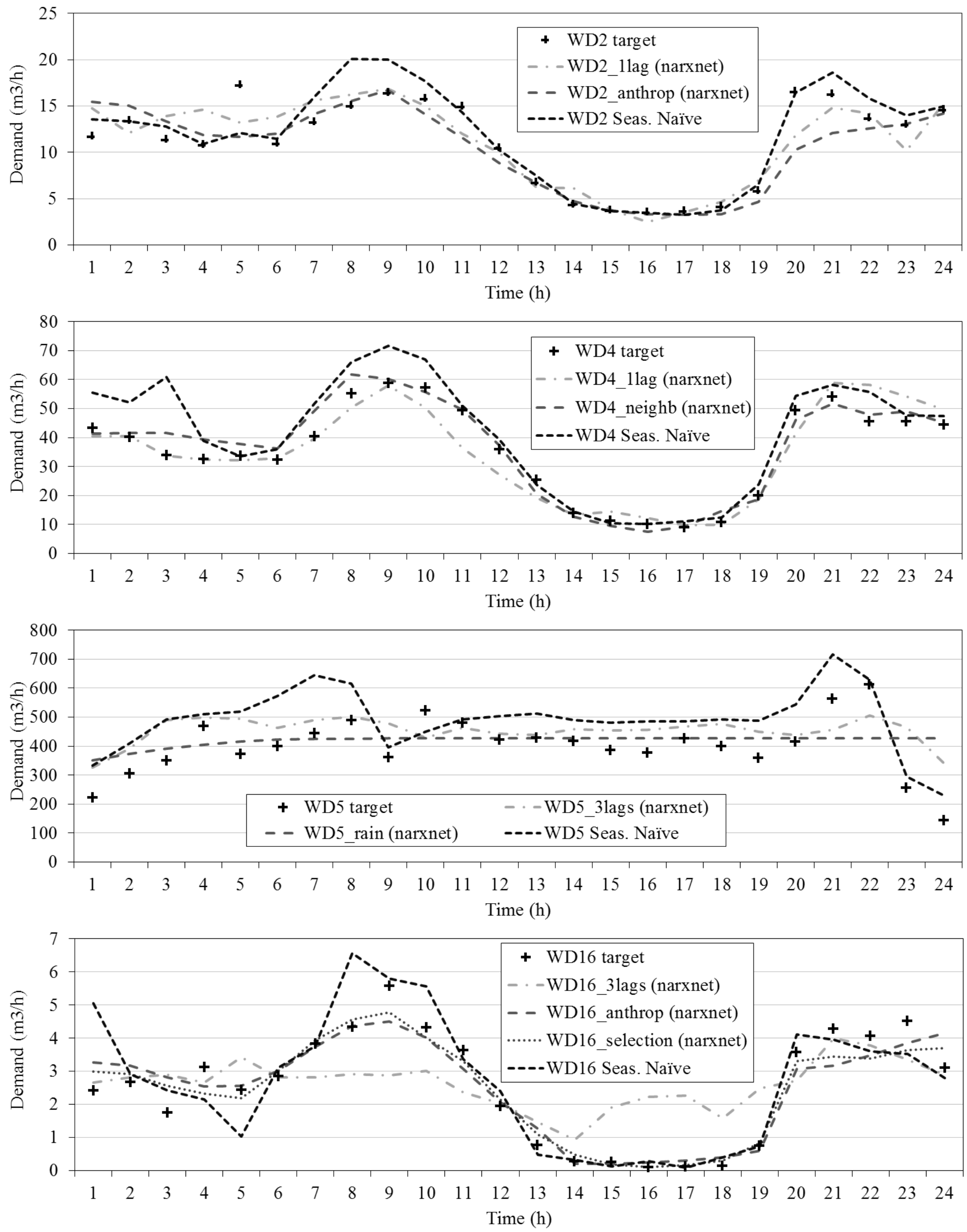

FIG. 10. 24 hours predictions of the water demand models that provided the best results for each distinct dataset compared with the expected values (target).