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A fully adaptive forecasting model for short-term drinking water demand

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ABSTRACT

For the optimal control of a water supply system, a short-term water demand forecast is necessary. We developed a model that forecasts the water demand for the next 48 h with 15-min time steps. The model uses measured water demands and static calendar data as single input. Based on this input, the model fully adaptively derives day factors and daily demand patterns for the seven days of the week, and for a configurable number of deviant day types. Although not using weather data as input, the model is able to identify occasional extra water demand in the evening during fair weather periods, and to adjust the forecast accordingly.

The model was tested on datasets containing six years of water demand data in six different areas in the central and Southern part of Netherlands. The areas have all the same moderate weather conditions, and vary in size from very large (950,000 inhabitants) to small (2400 inhabitants). The mean absolute percentage error (MAPE) for the 24-h forecasts varied between 1.44 and 5.12%, and for the 15-min time step forecasts between 3.35 and 10.44%. The model is easy to implement, fully adaptive and accurate, which makes it suitable for application in real time control.

1. Introduction

The goal for a water supply utility is to constantly supply water of good quality and under sufficient pressure. To achieve this, regular adjustments of pumps, valves and other controls of the water supply system are needed in order to balance supply and demand. The balancing of supply and demand is the normal daily operation of a water supply system. Initially the daily operation was done manually by operators, who intuitively made forecasts of the water demand. They made this forecasts based on their experience, taking information into account such as day of the week, hour of the day, water demand in previous days, weather, and special events like holidays.

Around the mid 1970's water utilities started automating their water supply systems by installing and operating telemetry and supervisory control and data acquisition (SCADA) systems (Bunn and Reynolds, 2009). The control loops of the first automated water supply systems were rather straightforward, resulting in inefficient operations with respect to energy consumption and costs, and fluctuations in the production flow. The operation of a system can be optimized by using forecasts in the control, which is effectively applied in different areas, like in the control of electricity grids (Manera and Marzullo, 2005), the control of open channels (Xu et al., 2013), and the control of the water quality reservoirs (Chen et al., 2012). Forecasts are also applied to increase the efficiency of the automatic control of water supply systems. Bakker et al. (2013) showed that application of such optimal control software at water supply systems in the Netherlands, led to 3.1% reduction of energy consumption and 5.2% reduction of energy costs. Bunn and Reynolds (2009) reported 6%–9% reduction of energy consumption and 12% reduction of energy cost at water supply systems in the United States. Simulations with optimal control software showed that savings of 25% may be expected when applied at a real water supply system in Israel (Salomons et al., 2007), and saving of 17.6% when applied at a real system in Spain (Martínez et al., 2007).

All software applications for the optimal control of water supply systems contain a model that forecasts the water demand for the

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next 24–48 h. This necessity for forecasting models has been one of the dominant reasons for researchers to develop such models. Both House-Peters and Chang (2011) and Donkor et al. (2012) present extensive overviews of water demand forecasting models. Though many researchers addressed water demand modelling and developed water demand forecasting models, still we found that the existing models can be improved with respect to adaptive functionality, forecasting time step and daily demand patterns.

We developed a model which forecasts the water demand for the next 48 h with 15-min time steps. The model we present in this paper has enhanced functionalities compared to existing models, with respect to the abovementioned topics: The model is fully adaptive, and can as a result be implemented and operated without manual (off-line) initial and interim data analysis for (re-)calibration; The model forecasts the water demand in 15-min time steps for the next 48 h; And the model discerns different demand patterns for the days of the week and a configurable number of deviant days (typically some 10 deviant day types are used). The forecasting model is an integral part of the advanced control software for water supply systems called OPIR (Optimal Production by Intelligent contRol). OPIR is capable of generating optimal set-points for both production flow control of treatment plants, and detailed pump control in the water distribution network. The software was first implemented in 2006, and now forecasts and controls the water demand in 80 areas in the Netherlands, and in 20 areas in other countries (Belgium, Poland, Portugal and Canada). In these real water supply systems, the forecasting model has proved its effectiveness and its easy and reliable implementation.

In Section 2 of this paper, we describe some important issues in water demand forecasting, and where existing forecasting models can be improved. In Section 3 we present the formulation of our model for forecasting the water demand, as well as for adaptively building up the database with water the demand characteristics. Section 4 presents the forecasting accuracy the model on six different datasets of water demand over a period of six years. In Section 5 we present the conclusions of this paper.

2. Water demand forecasting issues

2.1. Inputs water demand forecasting models

A number of one hour time step water demand forecasting models found in literature use measured water demand as single input (Jowitt and Chengchao, 1992; Shvartser et al., 1993; Homwongs et al., 1994; Alvisi et al., 2007). The papers show that it is possible to generate fairly accurate forecasts with measured water demand as single input. Other models also use, beside measured water demand, weather information as input: The model of Zhou et al. (2002) uses the daily maximum temperature, the daily precipitation, the number of days since the last rainfall and the pan evaporation; The ANN model of Ghiassi et al. (2008) uses hourly values of temperature, and; the ANN model of Herrera et al. (2010) uses daily values of temperature, wind velocity, atmospheric pressure and rain.

A potential drawback of using weather information is that the model needs an extra input. It is often difficult to make this extra input available in a production environment, because most automation networks are not connected to internet for ICT security reasons. And if weather input can be made available, it typically has a lower availability and reliability than measured water demand input, because it depends on a number of external systems. For this reason, the implementation of water demand forecasting models which use weather information is less easy and reliable, than the implementation of models that do not use weather information. So even though, there is relation between the weather conditions and the water demand (as will be shown in the next section), there is an advantage from an implementation point of view not to use weather data as input.

2.2. Time scales

Water demand forecasting can be done at different time scales. The time scale for any water demand forecasting model is dictated by the purpose for which the model is to be used (Bakker et al., 2003). For the daily operation of treatment plants and pumping stations, a short-term forecasting model for the next 24–48 h is needed. The output of the model can either be one day forecast for general production flow control of water treatment plants, or hourly forecasts for detailed distribution pump scheduling and operation of clear water reservoirs. Extensive research has been done to the forecast of the daily demand. To generate the daily demand forecast, various techniques can be used: Univariate Time Series Models, which generate forecasts using observations as single input (Msiza and Nelwamondo, 2011); Time Series Regression Models, which generate forecasts based on the relation between water demand and its determinants (Maidment and Miaou, 1986); Artificial Neural Network (ANN) models (Lertpalangsunti et al., 1999; Jain et al., 2001; Jentgen et al., 2007; Babel and Shinde, 2011); Composite or hybrid models in which two or more forecasting techniques are combined (Zhou et al., 2000; Aly and Wanakule, 2004; Gato et al., 2007; Alvisi et al., 2007; Bárdossy et al., 2009). In Ghiassi et al. (2008) and Adamowski et al. (2012) comparisons between several of the abovementioned techniques are presented.

The forecast of water demand on an hourly basis has been studied by a smaller number of researchers. The applied techniques to generate hourly forecasts are identical to used techniques to generate daily forecasts: Time Series Models (Jowitt and Chengchao, 1992; Shvartser et al., 1993; Homwongs et al., 1994), Time Series Regression Models (Zhou et al., 2002) ANN models (Ghiassi et al., 2008; Herrera et al., 2010; Jentgen et al., 2007) and Composite models (Alvisi et al., 2007). The smallest time step of forecasting models found in literature is one hour. However, we observed that a one hour time step is too large to describe all the variations in water demand. We found that the dynamics in the water demand in the morning peak around 8:00 h, are not described properly with a one hour time step, see also the normal Monday demand pattern in Fig. 1. The 15-min time step describes the water demand dynamics in more detail, which makes a 15-min time step more suitable for application in water distribution control. Note that the more detailed 15-min forecast has only added value when applied for detailed control, where the exact point in time to switch pumps is essential for the optimization. Application of the smaller time step in a less critical time domain will be less valuable, and application in an area with a highly variable demand might result in less stable forecasts.

2.3. Water demand patterns

Most water demand forecasting models found in literature use a limited number of demand patterns. The first models (Jowitt and Chengchao, 1992; Homwongs et al., 1994) use three different water demand patterns: one for weekdays, one for Saturdays and one for Sundays. The model described by Zhou et al. (2002) uses only two different patterns: one for weekdays and one for weekend days, including national holidays. A more recent model (Alvisi et al., 2007) uses demand patterns for each individual day of the week. In all four papers, it was observed that the patterns change with the seasons, and therefore the forecasting models use different patterns for each season. The models described by Ghiassi et al. (2008) and Herrera

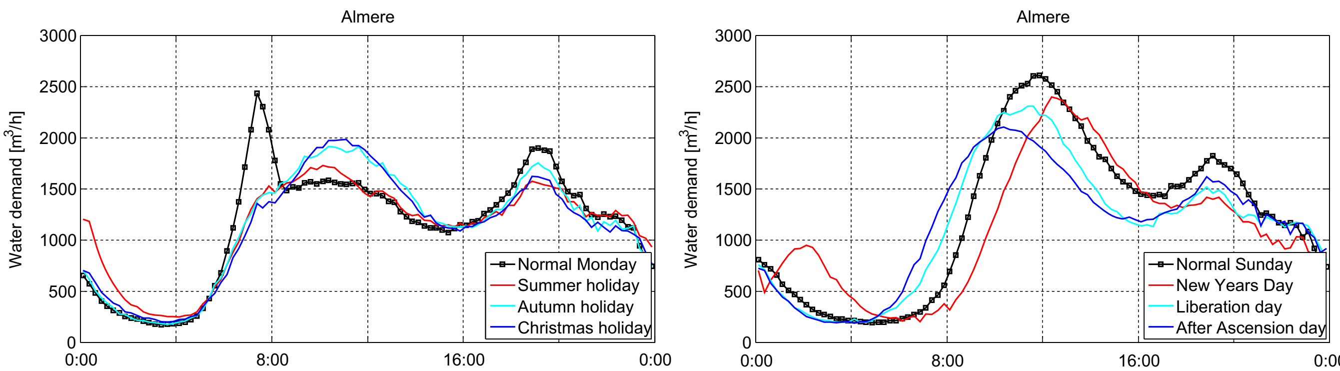

Fig. 1. Deviant water demand patterns during primary school holiday periods (left graph) and during individual deviant days (right graph).

et al. (2010) use advanced mathematical modelling techniques (like Artificial Neural Networks), where the number of demand patterns is not explicitly discerned. To generate hourly forecasts, both models use information about the day of the week combined with weather information (Ghiassi et al. (2008) use hourly temperature readings at the end of each hour; Herrera et al. (2010) use daily values of temperature, wind velocity, rainfall and atmospheric pressure). These approaches imply that many different water demand patterns may be forecasted, depending on the combination of inputs in the mathematical models.

Observations of water demands in the Netherlands show that more deviant water demand patterns can be discerned. The first type of days with a deviant water demand pattern, as mentioned by Zhou et al. (2002), is national holidays (like Easter, Labour Day, Christmas, et cetera). On those days, the vast majority of the people and industries behave as on Sundays. The second type of days is the weekdays (Monday till Friday) in primary school holiday periods. In those periods, a substantial part of the population is not working and behaves differently than on normal weekdays. Typically the water demand peak in the morning is lower and smoothed out, compared to non holiday water demand. For each holiday period (in the Netherlands: Summer holiday, Autumn holiday, Christmas holiday, Spring holiday, May holiday) a different pattern can be discerned, see the left graph in Fig. 1.

The third type of days is individual annual occurring days with a deviant demand pattern. Examples are, see the right graph in Fig. 1: New Year's Day (very specific demand pattern), the day after Ascension Day (this is a Friday after a national holiday; many but not all people take an extra day off), Liberation Day (this is not a national holiday, but still many people take a day off to attend the

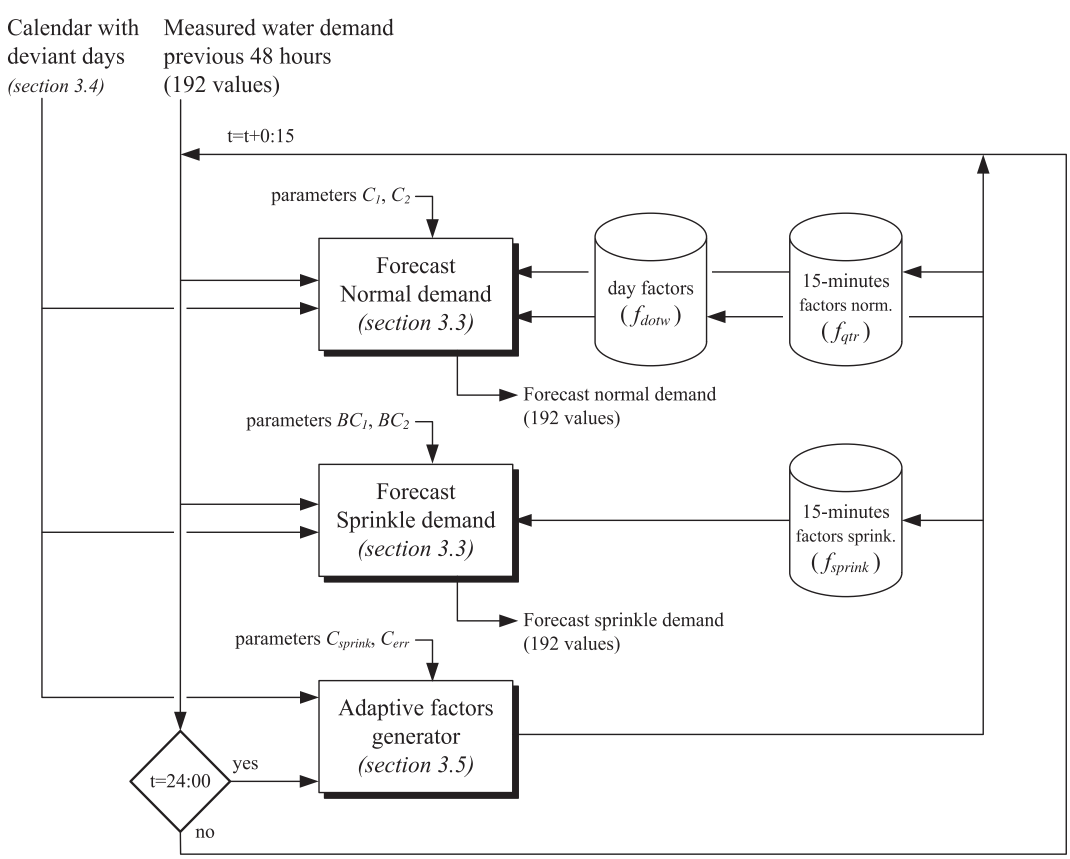

Fig. 2. Setup of the water demand forecasting model.

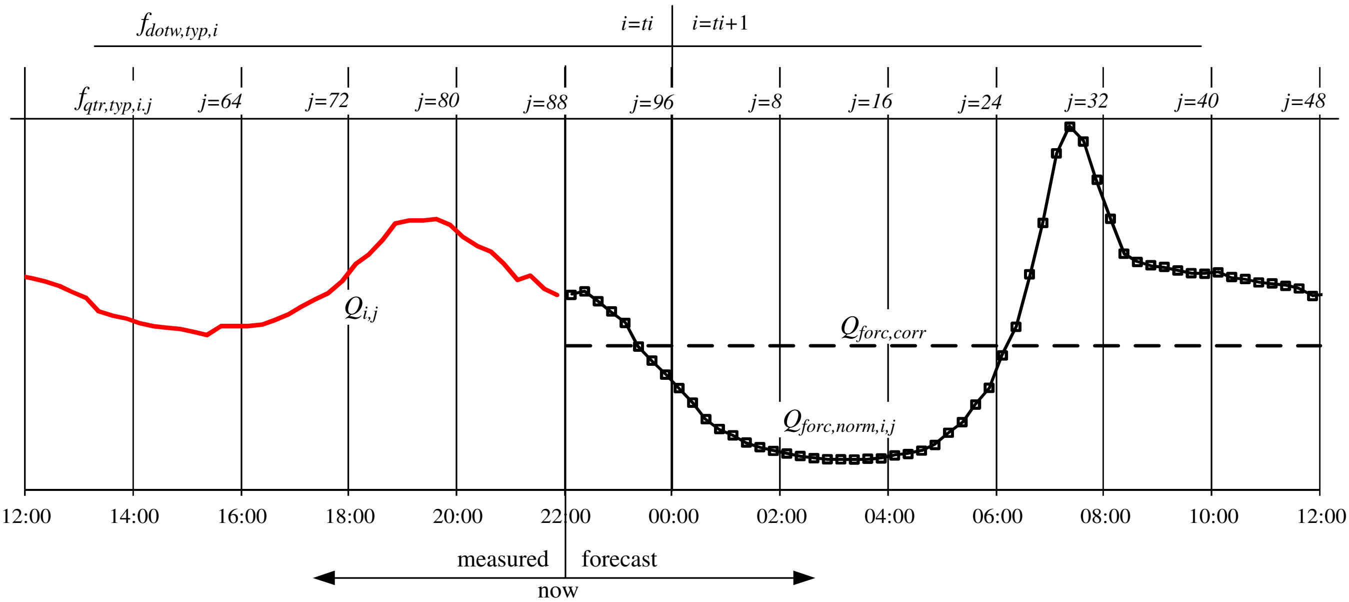

Fig. 3. Selection of i and j in $f_{dotw,typ,i}$ and $f_{qtr,typ,i,j}$. Example of a forecast at 22:00 h: for the first 8 forecasted values $i = ti$, and $j = 89$ to 96; for the next 96 forecasted values $i = ti + 1$ and $j = 1$ to 96; for the remaining 88 forecasted values $i = ti + 2$ and $j = 1$–88.

festivities). The dates on which the three abovementioned types of deviant water demand patterns occur are known in advance. This information can be made available to a water demand forecasting model.

The fourth type of days with a deviant water demand pattern is related to the weather conditions, and is therefore not known in advance. On days with dry and sunny weather, the water demand resembles the normal pattern for the first part of the day, albeit somewhat higher than normal. In the (late) afternoon and evening the water demand is higher than the normal demand. This extra demand is presumably caused by people sprinkling their gardens. In Section 3.3 (Fig. 4) an example is shown of the water demand on a day with dry and sunny weather.

2.4. Requirements for model (re-)calibration

All water demand forecasting models need a substantial initial dataset with historic water demands to calibrate the model. And when implemented in a practical situation, the models also need temporal re-calibration with new datasets, in order to keep up with the gradually changing water demand patterns. In the first models, this off-line data was used to derive the static seasonal demand curves and factors (Jowitt and Chengchao, 1992; Homwongs et al., 1994). The adaptive models described by Zhou et al. (2002) and Alvisi et al. (2007) also need a dataset with historic demands to derive initial seasonal curves and factors. Data driven (ANN) models need data to train the mathematical model (Ghiassi et al., 2008; Homwongs et al., 1994), which is necessary for generating a forecast.

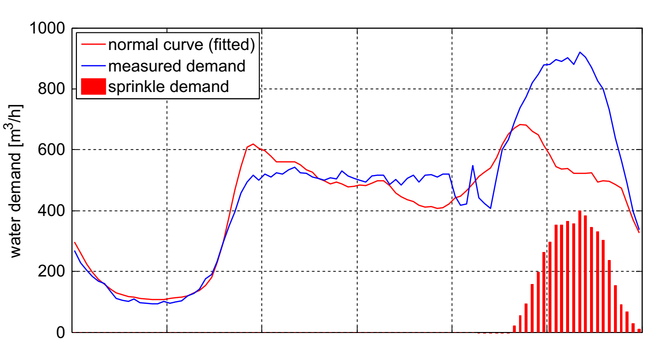

Fig. 4. Identifying sprinkle demand by comparing measured demand with the normal expected demand according to the fitted normal demand curve.

3. Materials and methods

3.1. Data and locations

We collected datasets of water demand in six different areas in the Netherlands in the period 2006–2011. We used the data we collected as input in simulations to assess the accuracy of the water demand forecasting model we developed. The weather conditions in the Netherlands in the whole country are more or less the same, and can be characterised as moderate with an average daily maximum temperature in summer of around 19 °C and in winter of around 3 °C. For each area, all water flows supplied to the area (from treatment plants, pumping stations and reservoirs) were summed in order to derive the net water demand in the area. Each number in the datasets represents the water consumption by all customers in the area, plus all (occasional and planned) water losses in the area. Each dataset consisted of the water demand per 15-min time step in m^3/h over a period of six years (210,336 values). The characteristics of the areas are shown in Table 1.

3.2. Setup of the model

Considering the implementation of the model in real water supply systems, we focussed on three issues in the setup of the model: 1. easy and reliable implementation; 2. low maintenance costs, and; 3. high accuracy. For easy and reliable implementation of the model, we chose to use measured water demands and static

Table 1
Characteristics of the six investigated areas.

Area	Water utility	Average demand	# Consumers	Type
1. Amsterdam	Waternet	7540 m^3/h	950,000	Urban
2. Rijnregio	Dunea	2295 m^3/h	305,000	Urban/ (rural)
3. Almere	Vitens	1160 m^3/h	193,000	Urban
4. Helden	WML	291 m^3/h	39,000	Rural
5. Valkenburg	WML	73 m^3/h	9200	Rural
6. Hulsberg	WML	18 m^3/h	2400	Rural

calendar data as single input, and to use no other inputs like weather information. Though the relation between water demand and weather conditions seems evident, the model does not use weather input. Instead, the model uses a specific functionality to identify deviant weather related water demand, and to adjust the forecast accordingly (see Section 3.3 of this paper). To achieve low maintenance costs, we made the model fully adaptive. Fully adaptive means that the model automatically builds up a database with demand curves and patterns using its input (measured water demand), and while running, the model constantly renews these curves and factors (this process is described in Section 3.5 of this paper). In this way, the model automatically adapts to gradually changing water demand characteristics. This functionality makes manual (off-line) initial data analysis and temporal manual re-calibration unnecessary. It also enables to model to use one setup throughout the year, and not to use different setups for each season. For a high accuracy, the model forecasts the water demand with 15-min time steps, using a relatively large number of demand patterns: The model discerns not only demand patterns for the seven days of the week, but also for other deviant day types like primary school holiday periods and individual deviant days (see Section 3.5 of this paper). National holidays are treated as Sundays. The setup of the model is shown in Fig. 2.

3.3. Description of the water demand forecasting model

The model forecasts the water demand for the next 48 h with 15-min time steps (192 forecasted values). Each time step, a new 48 h forecast is calculated moving forward the vector with forecasted water demands. The model forecasts the water demand in three main phases: in phase one, the average water demand for the next 48 h is forecasted; in phase two, the normal water demands for the individual 15-min time steps are forecasted; in phase three, if applicable, extra sprinkle water demands for the individual 15-min time steps are forecasted.

The forecast of the average water demand for the next 48 h in phase one is based on the measured water demand in the previous 48 h. In order to filter out the influence of the day of the week, the measured water demand on day i at 15-min time step j ($Q_{i,j}$) is corrected by dividing the value with the typical day of the week factor ($f_{dotw,typ,i}$, which is adaptively determined by the model, see Section 3.5) of day i:

$$Q_{i,j,corr} = \frac{Q_{i,j}}{f_{dotw,typ,i}} \quad \left[\mathrm{m^3/h}\right] \tag{1}$$

The forecasted average water demand ($Q_{forc,corr}$) for the next 48 h is based on the average of the corrected water demands in the previous 48 h ($Q_{t\,=\,-1\ to\ -96,corr}$ and $Q_{t\,=\,-97\ to\ -192,corr}$):

$$Q_{forc,corr} = C_1 \cdot \left(\sum\nolimits_{t=-96}^{t=-1} Q_{t,corr}\right) + C_2 \cdot \left(\sum_{t=-192}^{t=-97} Q_{t,corr}\right) \quad \left[\mathrm{m^3/h}\right] \tag{2}$$

The weighing constants C_1 and C_2 are by default set at 0.8 and 0.2 respectively, making the more recent measured water demands weigh heavier than the older demands. In Section 5.1 of this paper, a sensitivity analysis of these model parameters is presented. By using Equation (2) the forecasted average water demand is based on a relative short period of measured demands (previous 48 h, with emphasis on the previous 24 h). This results in a rapid adjustment of the forecasted water demand, after a change of the measured water demand.

In phase two, the normal water demands for the individual 15-min time steps on day i, time step j ($Q_{forc,norm,i,j}$) for the next 48 h are calculated. This is done by multiplying the forecasted average demand ($Q_{forc,corr}$), by the typical day of the week factor and the typical 15-min time step factor ($f_{dotw,typ,i}$ and $f_{qtr,typ,i,j}$ which are adaptively determined by the model, see Section 3.5):

$$Q_{forc,norm,i,j} = Q_{forc,corr} \cdot f_{dotw,typ,i} \cdot f_{qtr,typ,i,j} \quad \left[m^3/h\right] \tag{3}$$

Note that the model selects the proper factors ($f_{dotw,typ,i}$ and $f_{qtr,typ,i,j}$) that match with the period which is being forecasted. An example is shown in Fig. 3.

In phase three, if applicable, extra sprinkle water demand is forecasted. We observed in water demand patterns in the Netherlands, that on a number of days the water demand in the late afternoon and evening (between 18:00 and 0:00 h) is much higher (Fig. 4). In order to forecast this extra demand, the model identifies sprinkle demand in the measured demand. This identification is done by "fitting" the normal demand curve (consisting of 96 factors $f_{qtr,typ,i,j}$) on the measured water demand during the time frame between 0:00 and 18:00 h. This is the time frame where (in the Netherlands) no sprinkle water demand occurs. The fitting of the demand curve is done by multiplying the factors $f_{qtr,typ,i,j}$ with a factor D, where:

$$\sum_{j=1}^{j=72} Q_{i,j} = D \cdot \sum_{j=1}^{j=72} f_{qtr,typ,i,j} \tag{4}$$

The factor D is calculated at the end of 15-min time step number 72 (at 18:00 h) and remains constant for the rest of the day. The model calculates the sprinkle demand ($Q_{sprink,i,j}$) by taking the difference between the measured water demand and the normal water demand according to the fitted demand curve, as shown in Fig. 4.

The sprinkle demand is calculated with:

$$Q_{sprink,i,j} = Q_{i,j} - \left(D \cdot f_{qtr,typ,i,j}\right) \quad \left[\mathrm{m^3/h}\right] \tag{5}$$

Sprinkle demand is only calculated in the time frame between 18:00 and 0:00 h ($j = 73$–96), at the end of each 15-min time step j ($j = 73$ at 18:15; $j = 74$ at 18:30; to $j = 96$ at 0:00 h). In the other time frames ($j = 1$–72) the sprinkle demand is set at 0. The forecasted average sprinkle demand ($Q_{forc,sprink}$) for the next 48 h is based on the average of the observed sprinkle demands in the previous 48 h ($Q_{t\,=\,-96\ to\ -1,sprink}$ and $Q_{t\,=\,-192\ to\ -97,sprink}$):

$$Q_{forc,sprink} = BC_1 \cdot \left(\sum_{t=-96}^{t=-1} Q_{t,sprink}\right) + BC_2 \cdot \left(\sum_{t=-192}^{t=-97} Q_{t,sprink}\right) \quad \left[\mathrm{m^3/h}\right] \tag{6}$$

Note that by using Equation (6) the forecasted sprinkle demand does not change between 0:00 and 18:00 h (because $Q_{t\,=\,-96\ to\ -1,sprink}$ and $Q_{t\,=\,-192\ to\ -97,sprink}$ do not change). The water demand until 18:00 h has no predictive value for the sprinkle demand, and therefore does not affect the forecast. The weighing constants BC_1 and BC_2 are by default set at 1.10 and 0.10 making the more recent observed sprinkle demands weigh heavier than the older demands. In Section 5.1 of this paper, a sensitivity analysis of these model parameters is presented. By using Equation (6) the forecasted sprinkle water demand is rapidly adjusted once sprinkle water demand has been identified. Moreover, Equation (6) implies that the forecasted sprinkle demand will be higher than the observed sprinkle demand: the sum of BC_1 and $BC_2 = 1.20$, which means that the forecast will be 20% higher than the observation. This is necessary because sprinkle water demand can increase rather quickly, quicker than the change in the normal water demand. In this way, the model performs well in a period with increasing sprinkle demand. However, in a period with constant or (sudden) decreasing sprinkle demand, the model will overestimate the sprinkle demand. We chose to design the model in this way, because an overestimate of the sprinkle demand is preferred over an underestimate when using the forecast for control. Fig. 5 shows an example of the observed and forecasted sprinkle demand per day as a percentage of the normal demand in a summer period. The figure shows that the sprinkle demand does not change from zero to its maximum value (around 12%) in one day, but that this takes some 5–7 days to rise to this maximum value. Although not using weather information as input, the model is still fairly able to forecast the sprinkle demand. The model is not able to forecast sudden changes in the sprinkle demand.

Like the forecast of the normal demand, the forecasted average sprinkle demand must be transferred to the individual 15-min time steps ($Q_{forc,sprink,i,j}$) for the next 48 h. This is done by multiplying the forecasted average sprinkle demand ($Q_{forc,sprink}$), by the typical 15-min time step sprinkle factor ($f_{sprink,typ,i,j}$, which is adaptively determined by the model, see Section 3.5):

$$Q_{forc,sprink,i,j} = Q_{forc,sprink} \cdot f_{sprink,typ,i,j} \quad \left[\mathrm{m^3/h}\right] \tag{7}$$

Finally, the model derives the total water demand forecast ($Q_{forc,tot,i,j}$) by summing the forecasts of the normal and the sprinkle demand:

$$Q_{forc,tot,i,j} = Q_{forc,norm,i,j} + Q_{forc,sprink,i,j} \quad \left[\mathrm{m^3/h}\right] \tag{8}$$

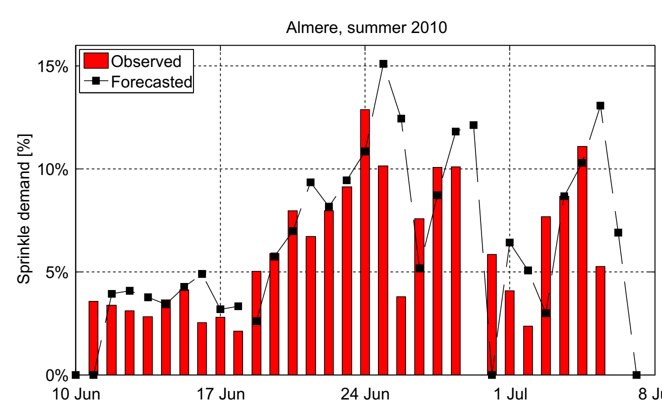

Fig. 5. Observed and forecasted sprinkle demand in the summer of 2010 in the Almere area. Note that the sprinkle demand is underestimated when it (largely) increases (2, 19, 30 June, 4 July) and overestimated when it (largely) decreases (25, 26, 29 June, 7, 8 July).

3.4. Day types

The model discerns the following different day types: seven types for the normal Monday till Sunday (including national holidays which are forecasted as if they were Sundays); five types for configured primary school holiday periods (Summer break, Autumn break, Christmas break, Spring break and May break); and four types for individual deviant days (New Year's Day, Good Friday, day after Ascension Day, and Liberation Day). For each day type, a day of the week factor ($f_{dotw,typ,i}$), and two arrays containing 96 factors for the normal demand pattern ($f_{qtr,typ,i,1-96}$) and for the sprinkle demand pattern ($f_{sprink,typ,i,1-96}$) are available. The dates when the nonnormal day types occur, need to be selected in the calendar menu of the model. This enables the model to determine which day types have occurred in previous 48 h and which will occur in the next 48 h, in order to select the proper factors. The model uses the factors to correct the observed demand (Equation (1)), to forecast the normal water demand (Equation (3)), to identify sprinkle demand (Equations (4) and (5)), and to forecast the sprinkle demand (Equation (7)). In contrast to the models of Zhou et al. (2002) and Alvisi et al. (2007), our model does not explicitly discern different demand patterns for each season. However, the adaptive functionality of our model will result in different seasonal patterns, as will be explained in the next section.

3.5. Adaptive factors and curves

The model uses different factors in transforming measured water demand in a forecast (see Equations (1) and (3)–(5) and (7)). Each water supply area has its own characteristic water demand, and therefore these factors are unique for each area. The factors are adaptively learned by the model based on the measured demand. In this way, the model re-calibrates continuously and automatically all the factors, normally using recent observations of water demand for the day type. Initially the model starts with default values for all factors, and once the model is running, it starts updating the factors. Each day at 0:00 h the model stores the water demand information of the previous day. Along with the type of day, the average water demand ($Q_{avg,i}$) [m^3/h], as well as an array of 96 dimensionless 15-min time step demand factors ($f_{qtr,i,j}$ or $f_{sprink,i,j}$) are stored. The model stores either the factors for the normal demand or the factors for the sprinkle demand, depending on whether a substantial amount of sprinkle demand was identified. The model uses the following filter to store the factors for normal demand:

$$\frac{\sum_{j=1}^{j=96} Q_{sprink,i,j}}{\sum_{j=1}^{j=96} Q_{i,j}} < C_{sprink} \tag{9}$$

Where C_{sprink} has a default value of 0.02. This means that if the identified sprinkle demand is less than 2% of the total measured demand, the normal demand factors will be stored; if the sprinkle demand is more than 2%, the sprinkle factors will be stored. The dimensionless factors for the normal demand ($f_{qtr,i,j}$) are calculated by:

$$f_{qtr,i,j} = \frac{Q_{i,j}}{\frac{1}{96}\sum_{j=1}^{j=96} Q_{i,j}} \quad [-] \tag{10}$$

The dimensionless factors for the sprinkle demand ($f_{sprink,i,j}$) are calculated by:

$$f_{sprink,i,j} = \frac{Q_{sprink,i,j}}{\frac{1}{24}\sum_{j=73}^{j=96} Q_{sprink,i,j}} \quad [-] \tag{11}$$

After calculating and storing the new array with dimensionless factors, the model validates this array. This validation is necessary to avoid that an error in the measured demand or very deviant demand, disturbs the typical factors which are used in the forecast. An array of demand factors of a day is disapproved if any of the factors differs more than the maximum allowed error (C_{err}, default value = 0.50):

$$\text{Any}_{j=1 \text{ to } 96}\left|f_{i,j} - f_{typ,i,j}\right| > C_{err} \tag{12}$$

The model uses the stored data to derive the typical factors which are used in the forecast. The array of 15-min time step factors for the normal demand ($f_{qtr,typ,i,j}$) and for the sprinkle demand ($f_{sprink,typ,i,j}$) for day type ti are calculated by using Equation (13) and (14). In both formulae n is the number of previous stored arrays of factors, which are used to calculate the typical factors:

$$f_{qtr,typ,ti,j} = \frac{1}{n}\sum_{i=1}^{i=n} f_{qtr,\{typ=ti\},j} \quad [-] \tag{13}$$

$$f_{sprink,typ,ti,j} = \frac{1}{n}\sum_{i=1}^{i=n} f_{sprink,\{typ=ti\},j} \quad [-] \tag{14}$$

The model selects only the approved arrays of curves when applying Equation (13) and (14). When less than n (approved) arrays of factors are available, which is typically the situation if the model has just been implemented with only default factors, n is temporarily set to the number of available arrays. With this functionality, the model can forecast the water demand using proper arrays of normal demand factors, already one week after implementation.

The typical day of the week factors ($f_{dotw,typ,i}$) for each day type ti are calculated by using Equation (15) over a time frame of m previous observations of that type of water demand.

$$f_{dotw,typ,ti} = \frac{\frac{1}{m}\sum_{i=1}^{i=m} Q_{avg,\{typ=ti\},i}}{\frac{1}{m\cdot 7}\sum_{i=1}^{i=m\cdot 7} Q_{avg,all,i}} \quad [-] \tag{15}$$

The number of previous observations n and m from which the model calculates the demand factors is 5 and 10 respectively by default. In Section 5.1 of this paper, a sensitivity analysis of these model parameters is presented. By default, the number is chosen small enough to rapidly adjust the factors during the seasons, but large enough to average out random variations in the water demand. By continuously updating the factors, it is not necessary to discern different patterns for the seasons. Moreover, the functionality to forecast the sprinkle demand, results in a very quick adjustment of the forecasted demand pattern when applicable in the summer. With this functionality, the model will forecast the water demand in the summer more accurately, than when using a (static) summer demand pattern. A (static) summer demand pattern will be an averaged pattern of both days with and without substantial sprinkle demand. With such average demand pattern, the model will not be able to describe the dynamics in the water demand in summer properly.

3.6. Simulations with the water demand forecasting model

The datasets with water demands in the years 2006–2011 in six different areas were used as input in simulations to test the water demand forecasting model. The first year (2006) of the datasets was used by the forecasting model to adapt the typical demand factors to the demand characteristics of the simulated area; the other years (2007–2011) were used to evaluate the accuracy of the model. When evaluating the accuracy, the forecasted values were compared to the measured values. In Bennett et al. (2013) a wide range of measures is suggested to characterise the performance of environmental models. We selected four of those measures (generating dimensionless outputs), which are also commonly used by other researchers addressing water demand forecasting (e.g. Alvisi et al. (2007) and Adamowski et al. (2012)): The Relative Error for each individual value (RE$_i$); The Mean Absolute Percentage Error (MAPE, noted as Relative Volume Error RVE in Bennett et al. (2013); The Relative Root Mean Square Error (RRMSE); The Nash–Sutcliffe Model Efficiency (R^2, noted as NSE in Bennett et al. (2013)):

$$\text{RE}_i = \frac{(\hat{y} - y_i)}{\overline{y}}\cdot 100\% \tag{16}$$

$$\text{MAPE} = \frac{\frac{1}{n}\sum_{i=1}^{i=n}|y_i - \hat{y}_i|}{\overline{y}}\cdot 100\% \tag{17}$$

$$\text{RRMSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{i=n}(y_i - \hat{y}_i)^2}}{\overline{y}}\cdot 100\% \tag{18}$$

$$R^2 = 1 - \frac{\frac{1}{n}\sum_{i=1}^{i=n}(y_i - \hat{y}_i)^2}{\frac{1}{n}\sum_{i=1}^{i=n}(y_i - \overline{y}_i)^2}\cdot 100\% \tag{19}$$

Where y_i is the measured value, $\hat{y}_i$ is the forecasted value, and $\overline{y}$ is mean of the measured values. The accuracy of the forecast of both the water demand per 24-h and per 15-min time step were investigated. For the 24-h evaluation, the 15-min time step values of each 24 h period (96 values) were transformed to 24-h averages. For the 15-min time step evaluation, each measured value is compared to 96 forecasted values corresponding to forecasted values of the first 24-h period (note that the model produces a moving forecast for the next 48 h, where each observed value is forecasted 192 times, of which only the first 96 values are considered in the evaluation).

The simulations were executed on a 64-bit Windows7 HP EliteBook 8470p, with a Intel® Core™ i5-320M 2.60 GHz processor and 8 GB installed memory. The model was built in a Matlab R2012b simulation environment. The simulation time to generate the forecasts for one area for six years amounted 43.1 s.

4. Results

4.1. Overall accuracy of the model

Table 2 shows the MAPE, the RRMSE, the R^2, and the 0.5%, 25%, 75% and 95.5% confidence intervals of RE for the 24-h forecast, and Table 3 shows the values for the 15-min time step forecasts.

Table 2
Performance of the model per 24-h in the period 2007–2011.

	$\bar{y}$ [m^3/h]	MAPE [%]	RRMSE [%]	R^2 [−]	Confidence intervals RE [%]			
					0.5%	25%	75%	95.5%
1. Amsterdam	7540	1.44	2.01	0.785	−6.5	−0.9	1.2	7.2
2. Rijnregio	2295	1.86	2.78	0.710	−8.2	−1.0	1.4	11.2
3. Almere	1160	2.12	3.12	0.740	−9.7	−1.3	1.6	12.7
4. Helden	291	3.40	5.17	0.803	−16.8	−1.8	2.4	21.7
5. Valkenburg	73	3.49	4.83	0.802	−15.0	−2.3	2.8	17.5
6. Hulsberg	18	5.12	8.21	0.658	−26.5	−2.9	3.6	29.0

For the 24-h forecast, the values of the MAPE, the RRMSE, and the R^2 varied between 1.44% and 5.12%, 2.01–8.21, and 0.658–0.803 respectively. The errors expressed as MAPE and RRMSE were smallest in the largest areas and increased where the size of the areas decreased. However, the R^2 values were smallest for the relative smaller areas Helden and Valkenburg. For the 15-min time step forecast, the values of the MAPE, the RRMSE, and the R^2 varied between 3.35% and 10.44%, 4.85–16.71, and 0.905–0.987 respectively. The errors expressed as MAPE and RRMSE were smallest in the largest areas and increased where the size of the areas decreased. The MAPE and RRMSE of the 15-min time step were on average a factor 2.2 larger than the MAPE of 24-h forecast. For both the 24-h forecast and the 15-min time step forecast, the largest forecast errors which occur during 1% of the time (the 0.5% and 95.5% intervals of RE) were on average a factor 7.7 larger than the errors which occur during 50% of the time (the 25% and 75% intervals of RE).

Fig. 6 shows the MAPE for the individual years. The figure shows the accuracy in both the years that were evaluated (2007–2011), and the initial year (2006) that was used to adapt the typical demand factors of the area. The graph shows that the MAPE varied in the years. This indicates that the unexplained variability of the water demand is not constant in all years. A possible explanation is that the variability in water demand is related to the weather conditions which vary among years. However, we cannot prove this assumption for not having weather data available. Fig. 6 does not show a gradual increasing or decreasing MAPE over the years. This indicates that (after adapting the typical factors in the initial year) the MAPE was rather constant, and the accuracy is not improving further after the first year. This can be explained by the fact that the model derives the typical factors from the last five measured demand patterns per day type (for the normal days this implies a “memory” of five weeks). It also indicates that the adaptive functionality was able to keep up with changes in the water demand.

Fig. 6 also shows that on average the MAPE in the initial year was 20% higher than in the other years. The reason for this is that the model needs to observe each day type a number of times, before it is able to generate an accurate forecast. We observed that after approximately 30 days the MAPE for the 15-min time step in the first year had the same magnitude as in subsequent years, and each time a day type occurred for the first time, we observed a peak in the error.

Table 3
Performance of the model per 15-min time step in the period 2007–2011.

	$\bar{y}$ [m^3/h]	MAPE [%]	RRMSE [%]	R^2 [−]	Confidence intervals RE [%]			
					0.5%	25%	75%	95.5%
1. Amsterdam	7540	3.35	4.85	0.987	−16.4	−2.1	2.5	16.8
2. Rijnregio	2295	4.64	7.22	0.978	−24.1	−2.8	3.2	28.9
3. Almere	1160	5.28	8.68	0.972	−29.9	−2.9	3.4	35.6
4. Helden	291	6.55	10.32	0.952	−35.8	−3.8	4.5	40.2
5. Valkenburg	73	6.90	10.00	0.949	−33.0	−4.5	5.3	31.9
6. Hulsberg	18	10.44	16.71	0.905	−57.9	−6.0	7.5	53.1

4.2. Accuracy in relation to the water demand in the area

The forecast errors showed a relation with the average demand in the area (see Tables 2 and 3 and Fig. 6): The MAPE was smaller when the average demand in the area was higher. The relation between the water demand and the forecast error was further investigated by plotting the relation in logX–Y diagram (Fig. 7).

Fig. 7 shows a correlation between the MAPE and the log value of the water demand (H_{avg}):

$$\mathrm{MAPE}_{day} = 6.5 - 0.59\ln(H_{avg}) \quad R^2 = 0.92$$

$$\mathrm{MAPE}_{qtr} = 12.6 - 1.05\ \ln(H_{avg}) \quad R^2 = 0.90$$

The correlation (R^2) between the forecast error and the average demand in the array is rather good. Based on this correlation, we can estimate the average accuracy of the model when implementing it in a new area.

4.3. Accuracy in relation to the hour of forecast and the number of hours ahead

The accuracy of the model was not constant for each point in time on a day. In order to assess the differences in accuracy, the errors were calculated and plotted in Fig. 8. The figure shows that in all areas the errors were smaller during the night, especially between 1:00 and 5:00 h. This indicates that the water demand in the night varied little over time, and that the predictability was high. The patterns of the errors somewhat resembled the patterns of the water demand, albeit that the amplitude of the error patterns was smaller. This indicates that the MAPE was related to forecasted water demand: the MAPE increased as the forecasted water demand increased.

The model forecasts the water demand for 48 h ahead (192 15-min time step values). The first forecasted value is mainly based on the measured water demand right before this time step, as can observed in Equation (2). The last forecasted value (for 48 h ahead) is mainly based on the same information, but this information is measured some 48 h before the time step actually occurs. This implies that a lower accuracy may be expected as the number of time steps ahead forecast increases. Fig. 8 shows the MAPE as a function of the number of 15-min time steps ahead for the 192 forecasted values. The figure shows that the MAPE gradually increased as the number of time steps ahead increased. Compared to the first forecasted value, the MAPE of the 96th value (24 h ahead) was on average 15.7% higher, and of the 192th value (48 h ahead) 23.7% higher.

5. Discussion and conclusions

5.1. Discussion

5.1.1. Influence model parameters

When assessing the accuracy of the model at different datasets, the model parameters were kept the same and were not optimized for the specific data set. By doing this, the results resemble most the case when the model is implemented in a practical situation. However, the model parameters will affect the performance. In order to assess the influence of the model parameters, a sensitivity analysis was carried out. The model parameters which influence the forecast per 24 h are: the weighing factors C_1 and C_2 (Equation (2)) for forecasting the total demand per 24 h; and the number of m previous observations to determine the day of the week factors, $f_{dotw,typ,i}$ (Equation (15)). Fig. 9 shows the sensitivity analysis for the

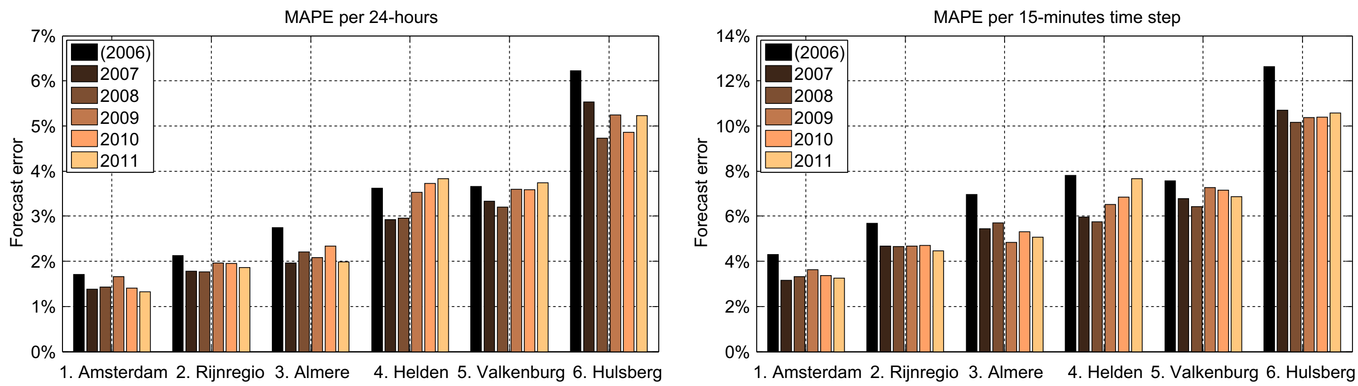

Fig. 6. MAPE for the 24-h forecast and the 15-min time step forecast.

C_1/C_2 parameters, where C_1 was varied between 0.6 and 1.0, and $C_2 = 1 - C_1$. The graph shows optimal values for C_1 between 0.75 and 0.85. The graph also shows little variation in MAPE (per 24 h) value when changing the values of C_1/C_2: for values of C_1 between 0.75 and 0.85 the variation was on average 0.014%. In the sensitivity analysis, we varied the m parameter between 2 and 22, and found minimal errors for m between 8 and 12. Like the C_1/C_2 parameters, we found little variation in the MAPE (per 24 h) value when changing the values of m: for values of m between 8 and 12 the variation was on average 0.011%.

The parameters which influence the forecast per 15-min time step are: the number of n previous observations to determine the 15-min time step factors, $f_{qtr,typ,i,j}$ and $f_{sprink,typ,i,j}$ (Equations (13) and (14)); and the weighing factors BC_1 and BC_2 (Equation (6)) for forecasting extra sprinkle demand. In the sensitivity analysis, we varied the n parameter between 1 and 7 and found minimal errors for n between 2.5 and 6.5. Like the parameters influencing the demand per 24-h, we found little variation in MAPE value when changing the values of n: for values of n between 4 and 6 the variation was on average 0.07%. Fig. 10 shows the sensitivity analysis for the BC_1 and BC_2 parameters. In order to illustrate the differences, the figure shows the frequency distribution of the MAPE (in summer of the period between 18:00 and 0:00 h) of one area for three different sets of BC_1 and BC_2. The figure shows that large underestimates occur when BC_1 and BC_2 are 0. This illustrates that sprinkle demand forecast mechanism is able to improve the forecast. The differences between the other sets of BC_1 and BC_2 are small. The largest underestimates are smaller when the sum of BC_1 and BC_2 exceeds 1. Because large underestimates need to be avoided when using the forecast for control, the default values for BC_1 and BC_2 were chosen at 1.1 and 0.1.

The sensitivity analysis showed that the model performance is affected only to a small degree by the model parameters. Therefore we conclude that calibrating the model parameters for a specific data set instead of using the default values, will result in a relatively small improvement of the performance of the model. In most implementations the better performance will not justify the extra effort for calibrating the model. This justifies using the default parameters in most situations.

5.1.2. Weather conditions

This paper shows that the model we developed is able to generate fairly accurate forecasts without using weather data as input, in the researched areas. All researched areas are situated in the Netherlands and have an equal moderate climate. The average daily maximum temperature in summer is around 19 °C and in winter around 3 °C. The moderate climate probably induces moderately changing water demands. The maximum daily water demand is around 30–50% higher than average and the minimum 20–30% lower than average. The moderately changing water demand might be the reason for the good performance of the model without using weather data as input. The model has not been tested in areas with more variation in the weather conditions. Implementing the model in such areas may show a limitation of the model's performance.

5.1.3. Model accuracy in smaller areas

Tables 2 and 3 show that the forecast errors expressed as MAPE and RRMSE increase as the size of the area decreases. This is the result of the fact that in larger areas random deviant water uses by individual consumers (or groups of consumers) are levelled out by a large group of consumers who consume water "normally". This

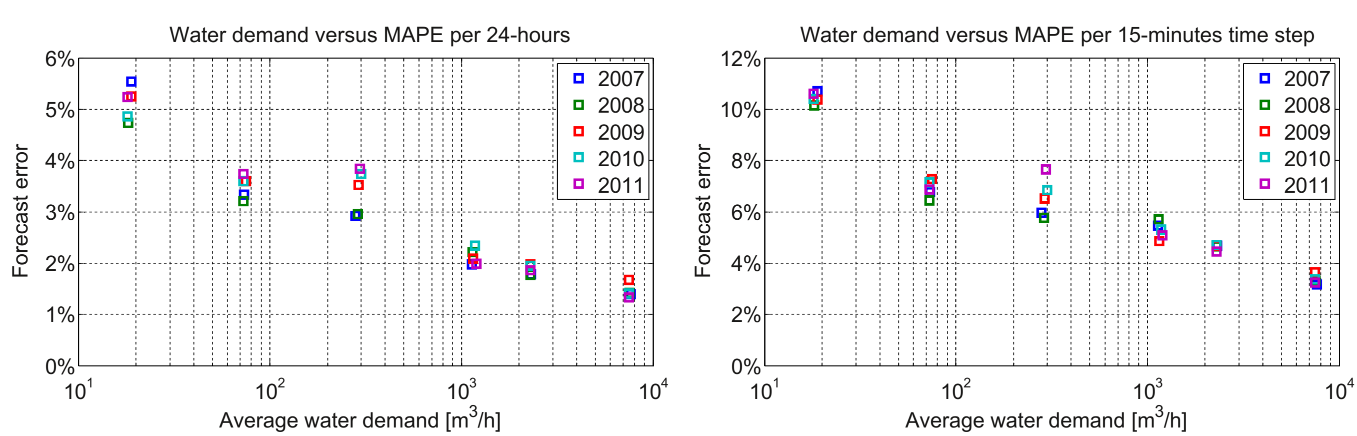

Fig. 7. Relation between the water demand in the area and MAPE (left = 24-h forecast, right = 15-min time step forecast).

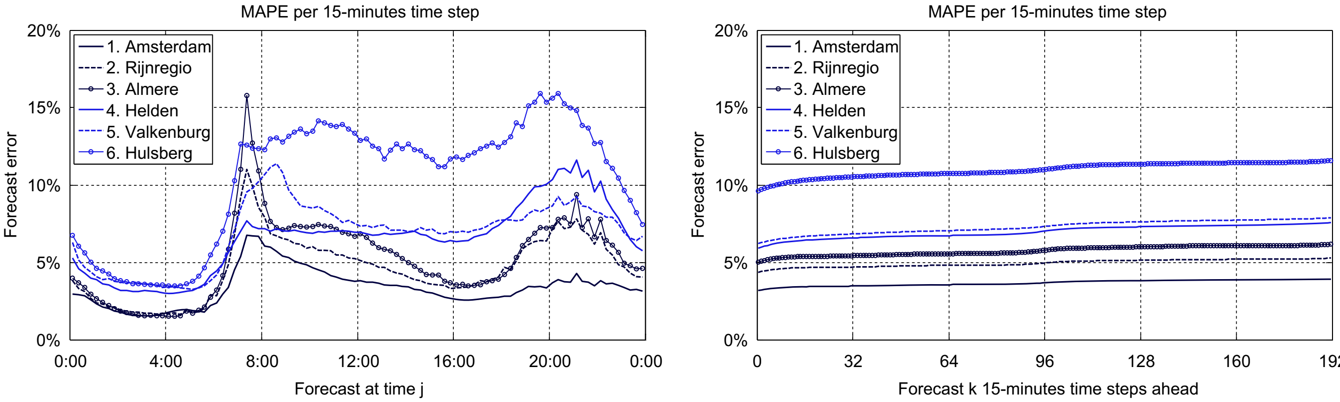

Fig. 8. MAPE in relation to the forecasted point in time on the day (left graph), and in relation to the number of 15-min time steps ahead forecast (right graph).

results in an increasing unexplained variability in the water demand, which cannot be forecasted by the forecasting model. This is especially true for the smallest area ("Hulsberg"), which does not only have the highest values for MAPE and RRMSE, but also a considerable lower value for R^2 compared to all other areas. This limits the applicability of the model, and when implementing the model in small areas, the expected errors need to be considered in relation to the purpose of using the forecasting model.

5.1.4. Comparison to other water demand forecasting models

When comparing the performance of our model wit other models, we observed comparable results with the models of Alvisi et al. (2007) and Ghiassi et al. (2008), and seemingly better performance than the model of Herrera et al. (2010). However, it is very difficult to compare forecast accuracies of different models, because the forecast accuracy highly depends on the variability (or rather the forecastibility) of the water demand in the datasets. As can be seen in Tables 2 and 3, the MAPE and the RRMSE can vary by a factor 3 and the R^2-values can vary by 0.15 when using one model on different datasets. This indicates that the accuracy of forecasting models obtained by simulations on different datasets cannot be compared objectively. Therefore we cannot draw conclusions about the performance of different models found in literature.

5.1.5. Influence of water loss on the demand forecast

The model forecasts the water demand based on the measured water flow supplied to the area. This flow consists of the water consumption by all customers in the area plus all water losses in the area. Water loss can be divided in: 1. background leakage and; 2. water loss as a result of pipe bursts. Background leakage (1.) is rather constant and makes up a constant value in the measured flow. Therefore, it forms a consistent part of the water demand pattern in the area which will be captured by the water demand forecasting model in the adaptive typical demand curves. As a result, background leakage will not disturb the performance of the model. Only in case when new (small) leaks arise or when existing leaks are repaired, a subtle change in the demand pattern will occur. The model will gradually adapt the demand curves to this new situation, and after some five weeks the curves are fully adapted. The effect of background leakage on the forecast accuracy is therefore rather small.

A pipe burst results in a sudden, rather large, but temporal change in the water supplied to an area. In contrast to background leakage, the effect of a pipe burst to the forecast accuracy can be large. The sudden extra water flow is completely random, and cannot be forecasted by the model. And also the point in time that the pipe is repaired or the leak is isolated (which results in a sudden decrease of the flow) cannot be forecasted. The forecast error on a day with (large) pipe burst is likely to be one of the largest errors in a year. However, large pipe burst do not occur very frequently, which limits the effect of pipe bursts on the average forecast accuracy.

The total water losses in the Netherlands are relatively low (3%–7% for all water utilities (Beuken et al., 2007)) and therefore, the influence of water losses on the water demand is small on average in the researched datasets. However, the datasets will most likely contain measured flows during pipe burst events. We expect that some of the largest forecast errors (see Tables 2 and 3) are the result of pipe burst events. Because we had no information about burst events, we were not able to confirm this presumption.

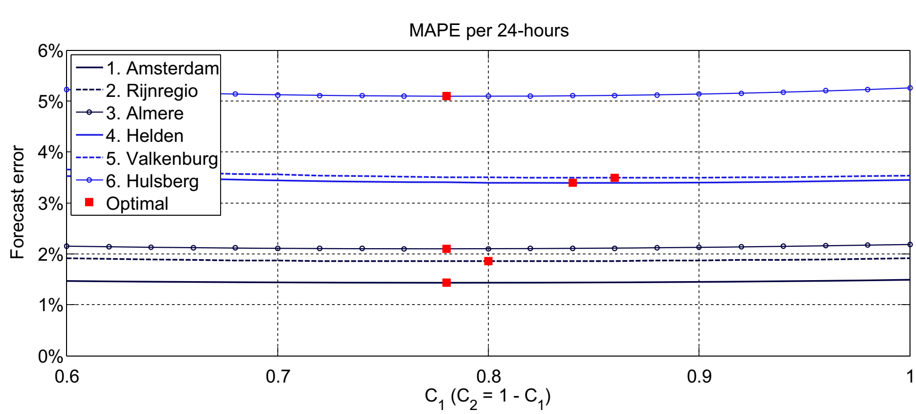

Fig. 9. MAPE in relation to values of C_1 and C_2 (default 0.8 and 0.2).

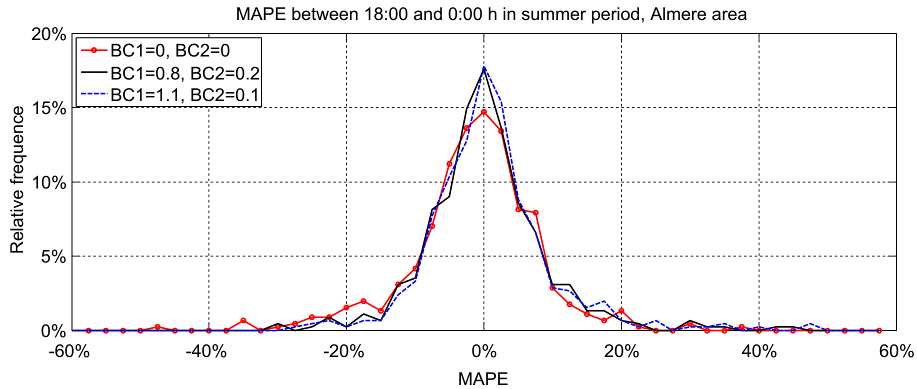

Fig. 10. MAPE in the hours between 18:00 and 0:00 h (sprinkle period) in the summer period in the Almere area, in relation to parameters BC_1 and BC_2.

5.2. Conclusions

The model presented in this paper, forecasts the drinking water demand for the next 48 h with 15-min time steps. The model uses measured water demand and static calendar data as single input to calculate the forecast. For six water distribution areas, the performance of the model was examined. The results showed that MAPE of the model varied between 1.44 and 5.12% for the 24-h forecast, and between 3.35 and 10.44% for the 15-min time step forecasts. The error had a strong relation with the average water demand in the area: The error increased as the average water demand in the area decreased.

The model has enhanced functionality compared to existing models with respect to the small time step (15-min), the fully adaptive functionality, the number of discerned water demand patterns, and the mechanism to detect and forecast sprinkle demand without using weather input. The 15-min time step is especially valuable, when the forecast is used for detailed optimization where one hour time steps are too coarse. Because the model does not need weather input, it can be implemented reliably and easily. Still, with the mechanism to detect and forecast sprinkle demand, the model is able to generate fairly accurate forecast under different weather conditions. However, under highly changing weather conditions, the forecast errors increase. Inclusion of weather input in the model will likely reduce the errors under such circumstances.

The setup of the model is such, that it can be implemented and operated at low cost, and still generate accurate forecast. The characteristics make the model very suitable for implementation in practical situations. Experiences with implementations, showed that the model performs well, and that its forecast can be used for optimal control of the water supply systems.

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References

Adamowski, J., Fung Chan, H., Prasher, S.O., Ozga-Zielinski, B., Sliusarieva, A., 2012. Comparison of multiple linear and nonlinear regression, autoregressive integrated moving average, artificial neural network, and wavelet artificial neural network methods for urban water demand forecasting in Montreal, Canada. Water Resources Research 48 (1).
Alvisi, S., Franchini, M., Marinelli, A., 2007. A short-term, pattern-based model for water-demand forecasting. Journal of Hydroinformatics 9 (1), 39–50.
Aly, A.H., Wanakule, N., 2004. Short-term forecasting for urban water consumption. Journal of Water Resources Planning and Management 130 (5), 405–410.
Babel, M.S., Shinde, V.R., 2011. Identifying prominent explanatory variables for water demand prediction using artificial neural networks: a case study of Bangkok. Water Resources Management 25 (6), 1653–1676.
Bakker, M., Van Schagen, K., Timmer, J., 2003. Flow control by prediction of water demand. Journal of Water Supply: Research and Technology – AQUA 52 (6), 417–424.
Bakker, M., Vreeburg, J.H.G., Palmen, L.J., Sperber, V., Bakker, G., Rietveld, L.C., 2013. Better water quality and higher energy efficiency by using model predictive flow control at water supply systems. Journal of Water Supply: Research and Technology – AQUA 62 (1), 1–13.
Bárdossy, G., Halász, G., Winter, J., 2009. Prognosis of urban water consumption using hybrid fuzzy algorithms. Journal of Water Supply: Research and Technology – AQUA 58 (3), 203–211.
Bennett, N.D., Croke, B.F.W., Guariso, G., Guillaume, J.H.A., Hamilton, S.H., Jakeman, A.J., Marsili-Libelli, S., Newham, L.T.H., Norton, J.P., Perrin, C., Pierce, S.A., Robson, B., Seppelt, R., Voinov, A.A., Fath, B.D., Andreassian, V., 2013. Characterising performance of environmental models. Environmental Modelling and Software 40, 1–20.
Beuken, R.H.S., Lavooij, C.S.W., Bosch, A., Schaap, P.G., 2007. Low leakage in the Netherlands confirmed. In: Proceedings, Cincinnati, OH.
Bunn, S.M., Reynolds, L., 2009. The energy-efficiency benefits of pumps-scheduling optimization for potable water supplies. IBM Journal of Research and Development 53 (3).
Chen, L., Kao, S.J., Traore, S., 2012. Predicting and managing reservoir total phosphorus by using modified grammatical evolution coupled with a macro-genetic algorithm. Environmental Modelling and Software 38, 89–100.
Donkor, E., Mazzuchi, T., Soyer, R., Roberson, J., 2012. Urban water demand forecasting: a review of methods and models. Journal of Water Resources Planning and Management. http://dx.doi.org/10.1061/(ASCE)WR.1943-5452.0000314.
Gato, S., Jayasuriya, N., Roberts, P., 2007. Forecasting residential water demand: case study. Journal of Water Resources Planning and Management 133 (4), 309–319.
Ghiassi, G., Zimbra, D.K., Saidane, H., 2008. Urban water demand forecasting with a dynamic artificial neural network model. Journal of Water Resources Planning and Management 134 (2), 138–146.
Herrera, M., Torgo, L., Izquierdo, J., Pérez-García, R., 2010. Predictive models for forecasting hourly urban water demand. Journal of Hydrology 387 (1–2), 141–150.
Homwongs, C., Sastri, T., Foster, J.W., 1994. Adaptive forecasting of hourly municipal water consumption. Journal of Water Resources Planning & Management – ASCE 120 (6), 888–905.
House-Peters, L.A., Chang, H., 2011. Urban water demand modeling: review of concepts, methods, and organizing principles. Water Resources Research 47 (5).
Jain, A., Varshney, A.K., Joshi, U.C., 2001. Short-term water demand forecast modelling at IIT Kanpur using artificial neural networks. Water Resources Management 15 (5), 299–321.
Jentgen, L., Kiddler, H., Hill, R., Conrad, S., 2007. Energy management strategies use short-term water consumption forecasting to minimize cost of pumping operations. Journal American Water Works Association 99 (6), 86–94.
Jowitt, P.W., Chengchao, X., 1992. Demand forecasting for water distribution systems. Civil Engineering Systems 9 (2), 105–121.
Lertpalangsunti, N., Chan, C.W., Mason, R., Tontiwachwuthikul, P., 1999. Toolset for construction of hybrid intelligent forecasting systems: application for water demand prediction. Artificial Intelligence in Engineering 13 (1), 21–42.
Maidment, D.R., Miaou, S.-P., 1986. Daily water use in nine cities. Water Resources Research 22 (6), 845–851.

Manera, M., Marzullo, A., 2005. Modelling the load curve of aggregate electricity consumption using principal components. Environmental Modelling and Software 20 (11), 1389–1400.
Martínez, F., Hernández, V., Alonso, J.M., Rao, Z., Alvisi, S., 2007. Optimizing the operation of the Valencia water-distribution network. Journal of Hydroinformatics 9 (1), 65–78.
Msiza, I.S., Nelwamondo, F.V., 2011. Predictive analysis of a water demand time series using a numerical method. In: Proceedings, Shah Alam.
Salomons, E., Goryashko, A., Shamir, U., Rao, Z., Alvisi, S., 2007. Optimizing the operation of the Haifa-A water-distribution network. Journal of Hydroinformatics 9 (1), 51–64.
Shvartser, L., Shamir, U., Feldman, M., 1993. Forecasting hourly water demands by pattern recognition approach. Journal of Water Resources Planning & Management –ASCE 119 (6), 611–627.
Xu, M., van Overloop, P.J., van de Giesen, N.C., 2013. Model reduction in model predictive control of combined water quantity and quality in open channels. Environmental Modelling and Software 42, 72–87.
Zhou, S.L., McMahon, T.A., Walton, A., Lewis, J., 2000. Forecasting daily urban water demand: a case study of Melbourne. Journal of Hydrology 236 (3–4), 153–164.
Zhou, S.L., McMahon, T.A., Walton, A., Lewis, J., 2002. Forecasting operational demand for an urban water supply zone. Journal of Hydrology 259 (1–4), 189–202.