THE USE OF AN ADAPTIVE WATER DEMAND PREDICTION MODEL

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ABSTRACT

Water demand is a result of human behaviour. Human behaviour is characterized by daily and weekly cycles, and therefore water demand also shows daily and weekly cycles. The human behaviour and the short term water demand deviates from the normal cycles in 2 types of situations: 1: at special days or periods (like national holidays, or vacation periods): 2 at changes in the weather. In both situations not only the daily water consumption deviates from the normal patterns, but also the distribution of the quarter of an hourly demands over the day. The knowledge of the water demand was used to construct a water demand forecasting model. The model has been made adaptive, enabling to cope with fast variations in the water demand caused by weather conditions, slower seasonal variations in the water demand and even slower changes in the water demand caused by socio-economic changes.

INTRODUCTION

Demand prediction for control of water supply systems

The general goal for any water supply utility is to constantly supply water to all customers of good quality and under sufficient pressure (Zhou *et al.*, 2002, Herrera *et al.*, 2010). To achieve this, frequent adjustments of pumps, valves and other controls of the water supply system are needed in order to balance supply and demand (Zhou *et al.*, 2002). 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 predictions of the water demand. They made this prediction based on their experience, taking information into account such as day of the week, hour of the day, water demand in previous days, weather, special events like holidays, et cetera.

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 in respect to energy consumption and costs, and fluctuations in the production flow. In order to increase the efficiency of the automatic control more sophisticated algorithms were developed and implemented, resulting in significant savings. Bakker, *et al.*, 2011, reported energy efficiency improvements of 3%, and energy cost saving of 5% at optimally controlled systems in the Netherlands. Bunn and Reynolds, 2009, report energy efficiency improvements of 6%-9%, and the energy cost savings of around 12% at systems in the United States.

All algorithms for (near) optimal control contain a model for the prediction of the water demand for the next 24 to 48 hours (like Bunn and Reynolds, 2009, and Cembrano *et al.*, 2011). The necessity of a water demand prediction model for (near) optimal control, has been one of the dominant reasons for researchers to develop water demand prediction models (Alvisi *et al.*, 2007, Bárdossy *et al.*, 2009, Ghiassi *et al.*, 2008, Homwongs *et al.*, 1994, Herrera *et al.*, 2010, Jain *et al.*, 2001, Jowitt and Xu 1992, Shvartser and Shamir, 1993, Zhou *et al.*, 2000, Zhou *et al.*, 2002).

Time scales demand prediction

The prediction of water demand can be done on different time scales. Qi and Chang, 2011, and House-Peters and Chang, 2011, present an overview of water demand prediction models on various time scales. The time scale for any prediction model is dictated by the purpose for which the prediction model is to be used (Bakker *et al.*, 2003). Planning issues for constructing water supply infrastructure demand a long term prediction model for the next 5-25 years (unit m^3/year, or maximum daily demand m^3/day). Issues for the use of raw water sources (e.g. river, reservoir, ground water) or for planning large scale maintenance activities require a medium term prediction model for 1-2 years (unit m^3/day). For the daily operation of treatments plants and pumping stations a short-term prediction model for the next 24-48 hours is needed. The unit can be either 1 or 2 values in m^3/day for general production flow control of water treatment plants, or (quarter of an) hourly values in m^3/h in a pattern for detailed distribution pump scheduling and operation of clear water reservoirs.

Extensive research has been done to the prediction of the daily demand, like Maidment and Miaou 1986, Lertpalangsunti *et al.*, 1999, Zhou *et al.*, 2000, Jain *et al.*, 2001, Joo *et al.*, 2002, Aly and Wanakule, 2004, Wong *et al.*, 2010, Msiza and Nelwamondo, 2011. Other researchers also studied water demand at a smaller time scale. Prediction of water demand on an hourly basis is described by Jowitt and Xu, 1992, Shvartser *et al.*, 1993, Homwongs *et al.*, 1994, Zhou *et al.*, 2002, Bunn *et al.*, 2006, Alvisi *et al.*, 2007, Ghiassi *et al.*, 2008, Herrera *et al.*, 2010. Jowitt and Xu use for three different templates for the day types Weekdays, Saturdays and Sundays to predict the diurnal demand pattern.

Development of an adaptive pattern-based demand prediction model

A difficulty in implementing a water demand prediction model is that in general an extensive analysis of historical water demand data of the supply area is necessary. This process is time consuming and costly, and sometimes impossible in no complete data set is available. In order to overcome this problem, an adaptive water demand forecasting model was developed, which is presented in this paper. The adaptive pattern-based demand prediction model, predicts the water demand for the next 48 hour, on an quarter of hourly basis. The model has been implemented since 1996 and now predicts the water demand in 75 different supply areas in the Netherlands (see Figure 1).

Figure 1: User interface water demand prediction model

METHODOLOGY/ PROCESS

Analysis of different water demands

In most water supply systems the major part of the water demand consists of domestic demand. When analysing water demand trends of such areas, daily and weekly patterns will be observed. The people living in the areas have a highly repetitive life pattern: waking up, showering, go to work, come home, prepare dinner, showering, and go to bed. This results in a highly repetitive water demand pattern, for normal working days, Saturdays and Sundays. In order to get a better understanding of water demand, the water demands of 9 different supply areas in different parts of the Netherlands over a period of 5 years (2007-2011) were analysed. For each area all water flows flowing into the area (from treatment plants, pumping stations and reservoirs) were summed (and reduced with the flows flowing out of the area) in order to derive the water demands. 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. The total water losses in the Netherlands are relatively low (3%-7% for all water companies, Beuken *et al.*, 2007), and relatively constant because of limited variations in pressure. The influence of water losses on the water demands is therefore small. Each dataset consist of the water demand per 15 minutes in m^3/h over a period of 5 years (175,296 values). The characteristics of the areas are shown in Table 1.

Table 1: Characteristics of the investigated water demand data sets

Area	Company	Average demand	Type	Orientation
1. Amsterdam	Waternet	7,540 m^3/h	urban	Central West
2. Rijnregio	Dunea	2,295 m^3/h	urban / (rural)	West
3. Tilburg	Brabant Water	1,523 m^3/h	urban / (rural)	South
4. Almere	Vitens	1,160 m^3/h	urban	Central
5. Helden	WML	291 m^3/h	rural	South East
6. Drachten	Vitens	256 m^3/h	rural	North
7. Wassenaar	Dunea	211 m^3/h	urban / (rural)	West
8. Valkenburg	WML	73 m^3/h	rural	South East
9. Hulsberg	WML	18 m^3/h	rural	South East

Quarter of an hourly water demand patterns

By analysing the quarter of an hourly water demand patterns, it was observed that during large parts of the year the demand patterns are highly repetitive in a weekly pattern. The water demand pattern at each day (Monday, Tuesday, et cetera) in an area, shows similarity with the water demand pattern on the same day the week before. This observation is illustrated in Figure 2, where the water demands of 5 subsequent Mondays are shown in the 9 areas. Although the patterns in the different areas can differ largely from each other, the patterns within each area have a high similarity. Note that the demand patterns in the bigger and more urban areas (1. Amsterdam and 4. Almere) have a higher similarity than the demand patterns in the smaller and more rural areas. The repetitive character of the water demand patterns is not only observed for "normal" days, but also for incidentally occurring special days like national holidays. This observation is illustrated in Figure 3, where the water demands of New Years Day of 5 subsequent years are shown in the 9 areas. In Figure 3 the higher similarity of the demand pattern in bigger and more urban areas can be observed as well.

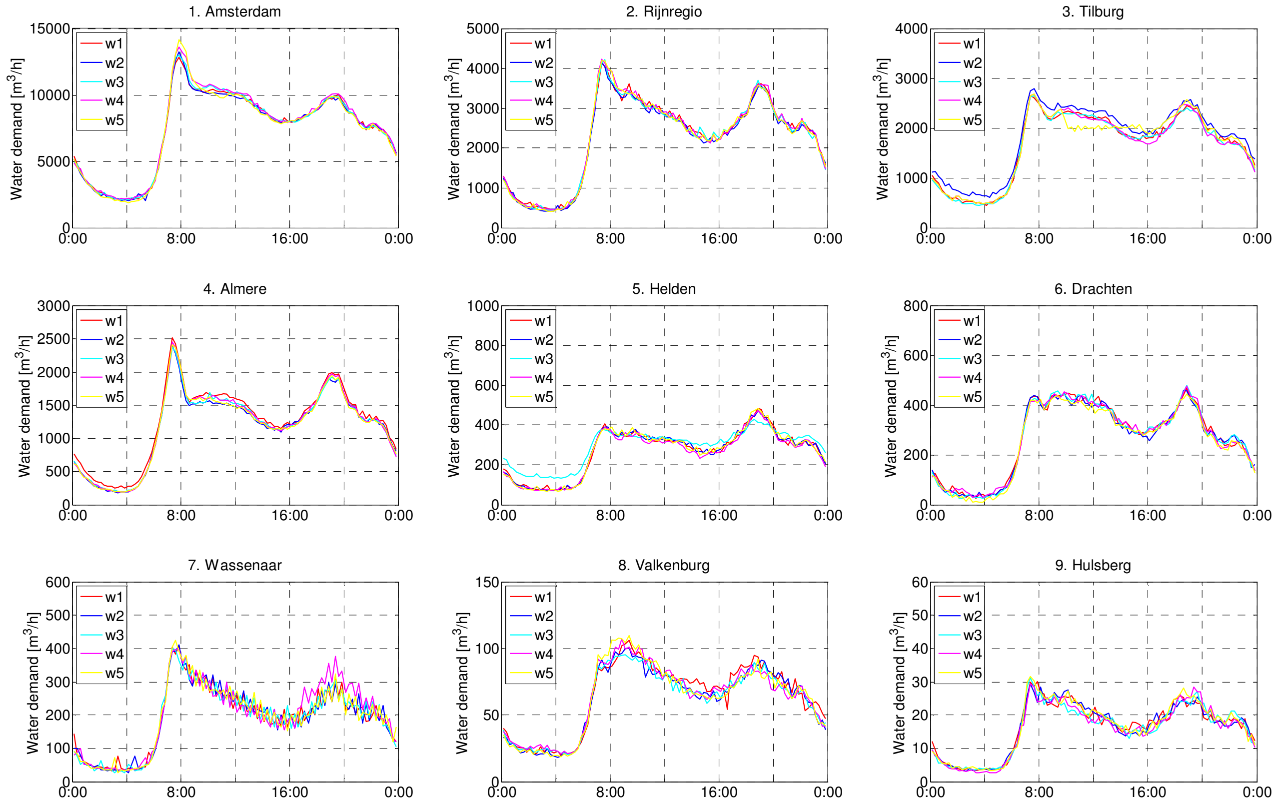

Figure 2: Uniformity of water demand patterns on subsequent Mondays (10 January 2011-7 February 2011). The graphs are ordered by water demand (1. Amsterdam has highest water demand; 9. Hulsberg has lowest water demand)

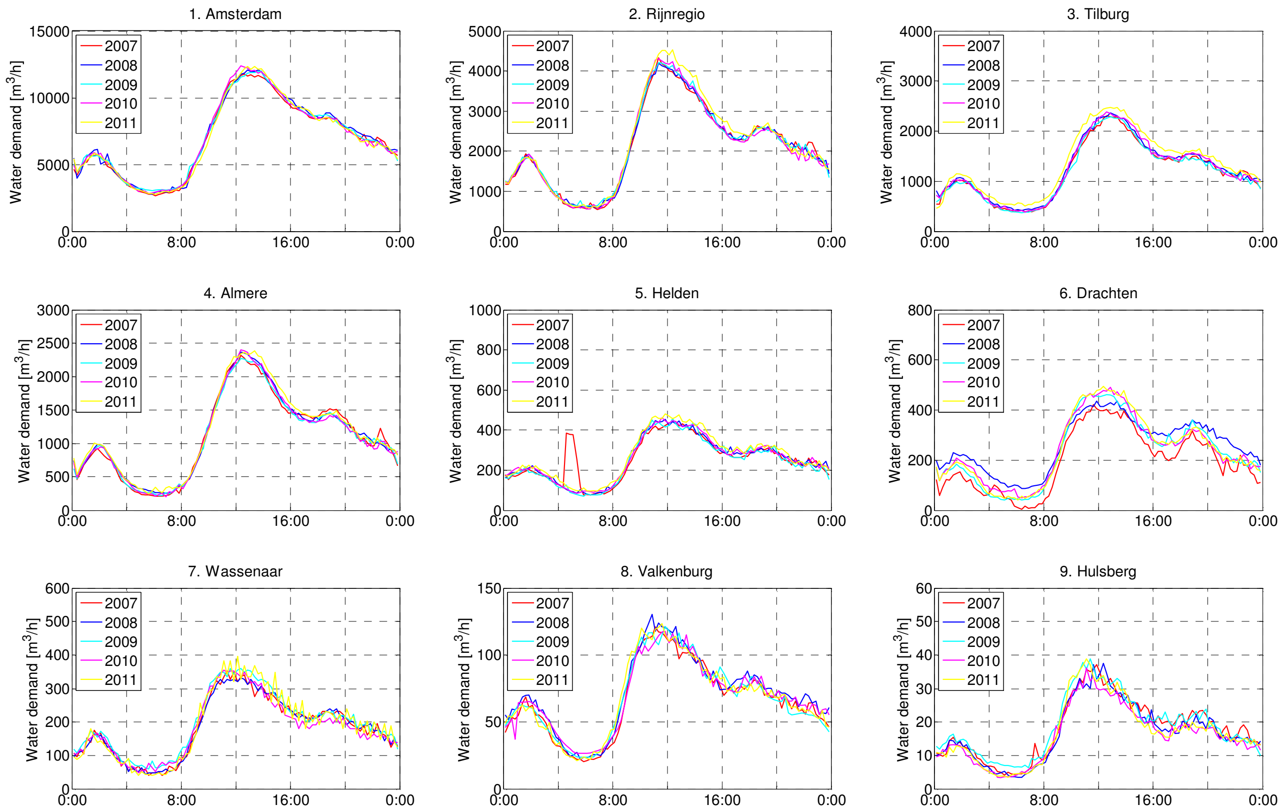

Figure 3: Uniformity of water demand patterns on subsequent New Years Days (2007-2011). Note that in the Helden area in 2007 a pipe burst occurred around 4:00.

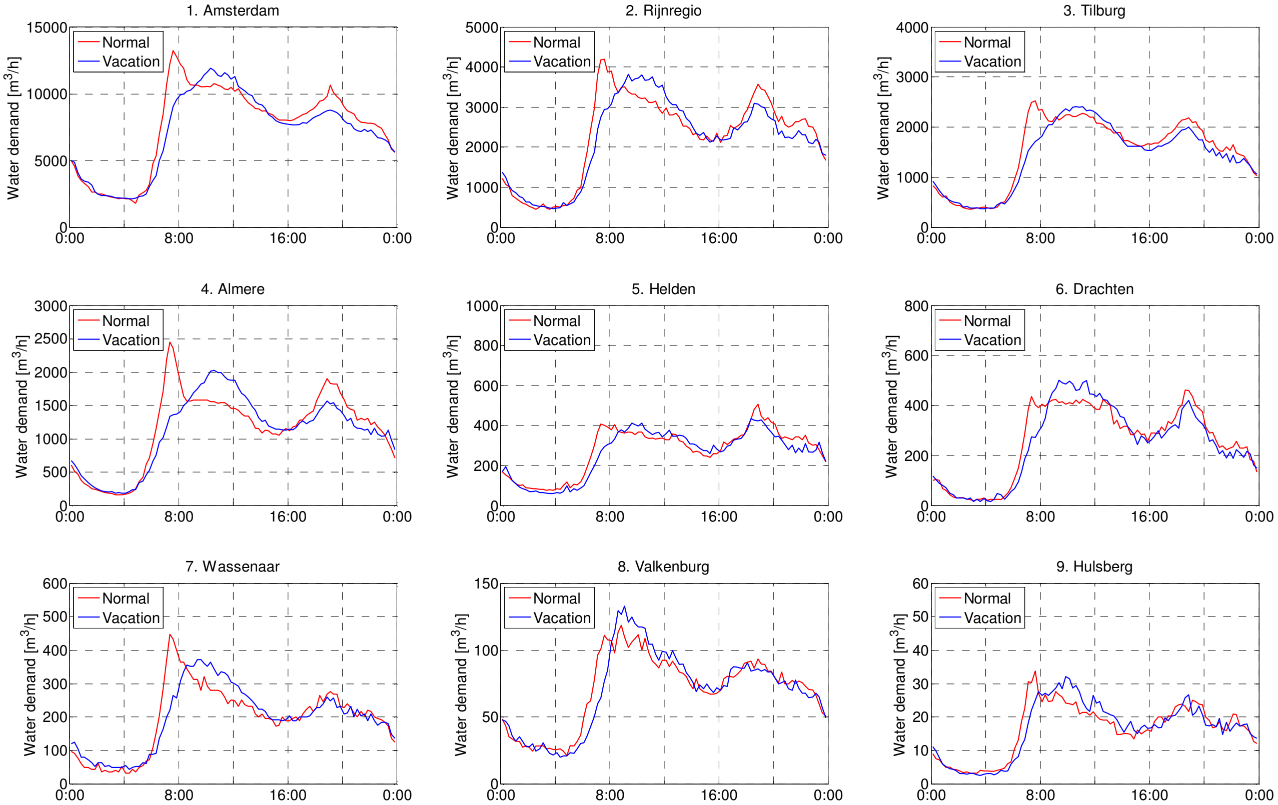

Figure 4: Difference in water demand pattern on a "normal" Monday (1 December 2008) and on a Monday in a vacation period (22 December 2008, Christmas Holidays)

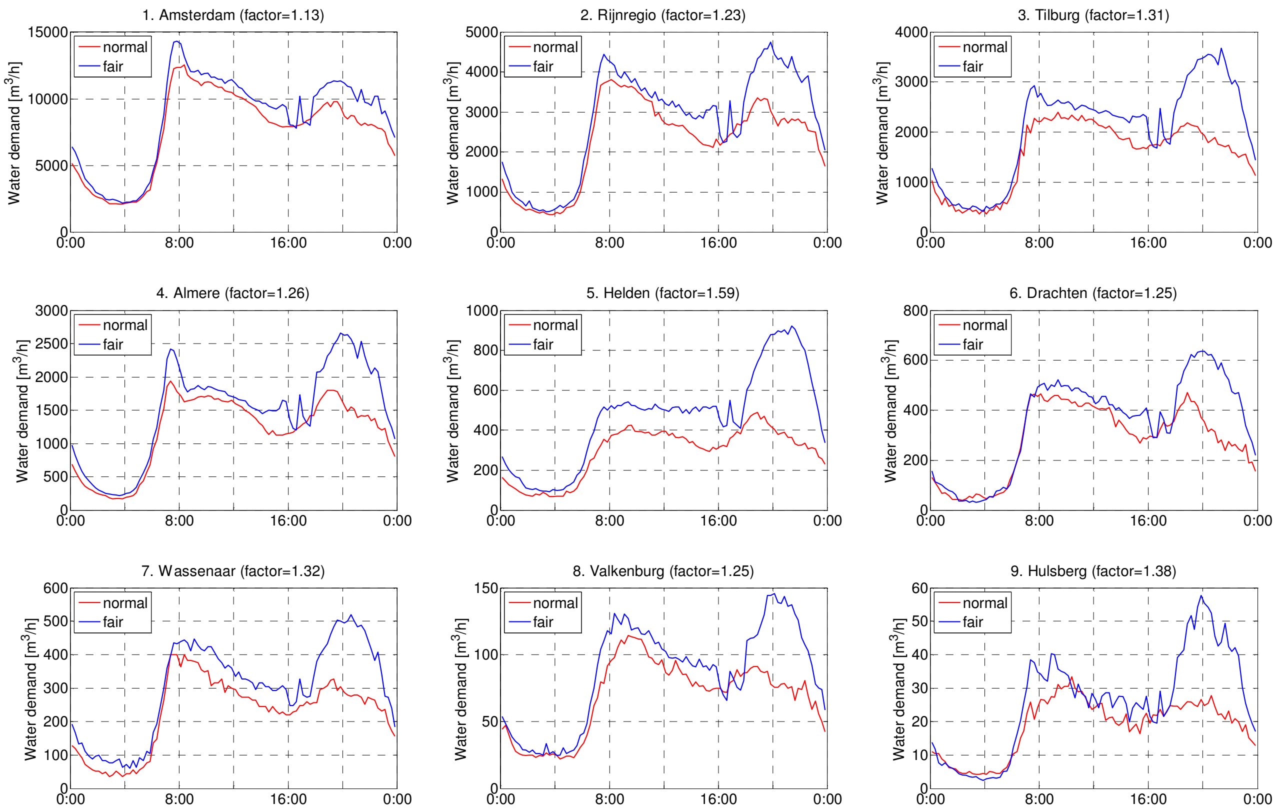

Figure 5: Difference in water demand pattern on a "normal" Monday (5 May 2010, Tmax = 12.4 °C) and on a Monday with fair weather (28 June 2010, Tmax = 26.8 °C). The factor indicates the difference in daily water demand between both demands. Note that on 28 June 2010 at 16:00 an important soccer match started, which is visible in the water demands at all areas

During several periods or at certain days in each year, the water demand patterns divert from the normally observed patterns. Figure 4 illustrates the deviation of the water demand pattern during vacation periods of primary schools. In all supply areas a delayed rise of the demand in the morning can be observed, probably caused by many people having vacation and not going to work, despite the fact that it is normal working day. This diversion from the normal pattern in vacation periods is –like the diversion from the pattern on New Years Day shown in Figure 3– repetitive for each vacation period. Figure 5 illustrates the deviation of the water demand pattern during days with fair weather. On average the weather conditions in the summer in the Netherlands are moderate, but occasionally periods of 1-2 weeks with higher temperatures and more sunshine occur. Those weather conditions result in higher water demands, especially in the evenings between 17:00 and 23:00. The extra demand is the result of people sprinkling their gardens (Bakker *et al.*, 2000).

In order to investigate the variability of the quarter of an hourly water demand patterns, the observed patterns were transformed to dimensionless patterns, where the average of each daily curve equals 1 (by definition). The transformation to this dimensionless quarter of an hour factor on day *i,* at quarter of an hour *j* ($f_{qoh,i,j}$) is done for each observed quarter of an hourly water demand $H_{i,j}$ by:

$$f_{qoh,i,j} = \frac{H_{i,j}}{\frac{1}{m}\sum_{j=i}^{m} H_{i,j}} \quad [-] \qquad (1)$$

For 8 different types of days (1-6 = normal Monday – Saturday; 7 = Sundays + national Holidays; 8 = weekdays in primary school vacation periods), all dimensionless patterns were selected, and an average pattern per type of day was calculated. Next, for all quarter of an hourly dimensionless factors the absolute value of the deviation between the observed pattern and the average pattern for the concerning day type was calculated for all observed patterns. An example of an average pattern, an observed individual pattern and the absolute value of the deviation is shown in Figure 6.

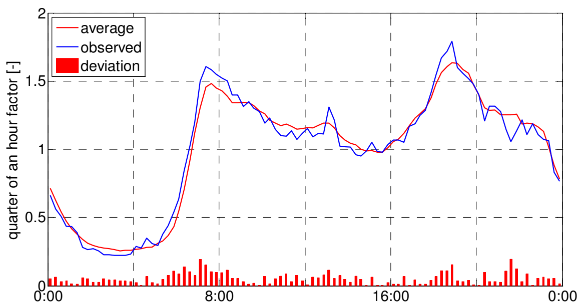

Figure 6: Dimensionless average and individual observed demand pattern of a Monday in the Helden area, including the absolute values of the deviation between both curves

Finally, the average absolute deviation for the 96 quarter of an hourly factors per day was calculated. The relative frequency distribution of the deviations is shown in Figure 7. The figure shows that for most areas the absolute average deviation is around 5-10%. The deviation in large areas (1. Amsterdam, 4.78% on average) is smaller than in small areas (9. Hulsberg, 10.47% in average). This differences show that the variability of the water demand patterns in small areas is higher than in large areas. Though the average deviations are rather limited, in all areas days were observed where the deviation exceeds 30%. This indicates that at a number of days the observed water demand pattern differs largely from the normal pattern for that type of day.

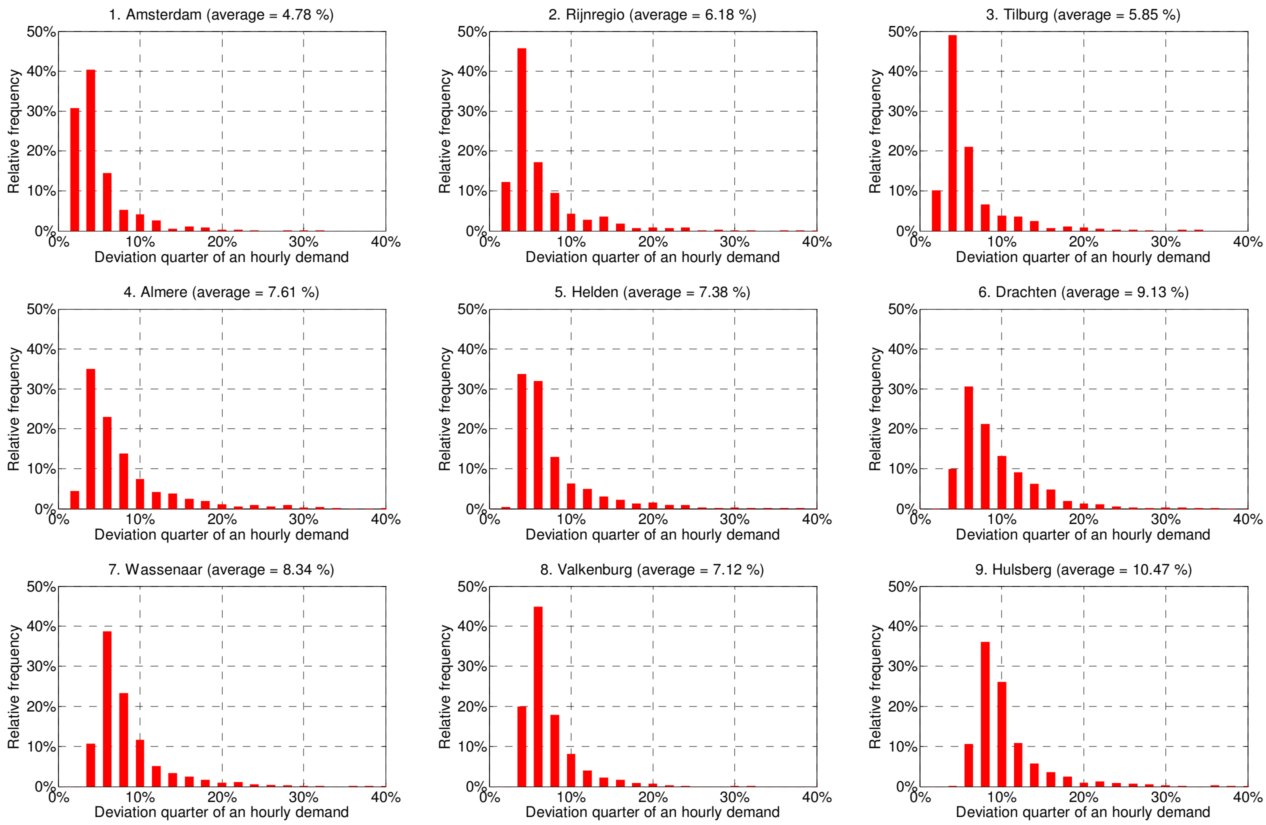

Figure 7: Relative frequency distribution of the deviation between the observed demand patterns and the average demand pattern for the concerning day type (the diagrams show average absolute deviation values per day)

Daily demand figures

When the daily water demand figures were analyzed, the same observations were made as in the analysis of the quarter of an hourly water demand patterns: During large parts of the year the water demand shows a repetitive a weekly pattern. The day to day increase or decrease of the daily demand shows a weekly pattern. By “correcting” the observed daily water demand for the weekly pattern, the changes in the water demand which can *not* be explained by the weekly pattern become visible. The corrected daily demand at day i ($D_{i,corr}$) is derived by dividing the observed water demand of day type t at day i ($D_{t,i}$), by the typical “day of the week factor” of day type t ($f_{dotw,typ,t}$):

$$D_{i,corr} = \frac{D_{t,i}}{f_{dotw,typ,t}} \qquad [{}^{m^3}\!/_{d}] \qquad (2)$$

For each day of the week, Monday, Tuesday, et cetera, the $f_{dotw,typ,t}$ is derived by dividing the average daily demand of day type t, by the average daily demand of all days, over a period of n weeks:

$$f_{dotw,typ,t} = \frac{\frac{1}{n}\sum_{i=i}^{n} D_{t,i}}{\frac{1}{n\cdot 7}\sum_{i=i}^{n\cdot 7} D_{all,i}} \qquad [-] \qquad (3)$$

Figure 8 shows the average day of the week factors for the period 2007-2011 for all areas. For some areas the day of the week factors are all close to 1, meaning that the daily demand on average differs little for the different day types (areas 1. Amsterdam, 2. Rijnregio and 4. Almere). In other areas larger differences between the day of the week factors occur, especially for the weekend days (areas 5. Helden, 8. Valkenburg, 9. Hulsberg).

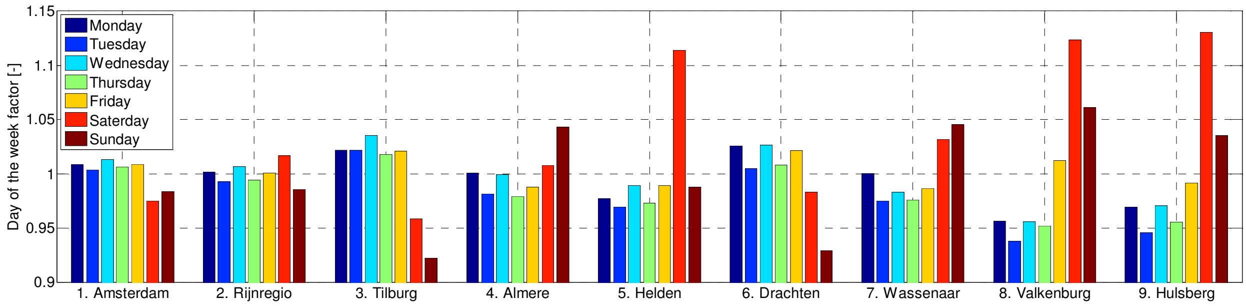

Figure 8: Average “day of the week” factors 2007-2011

Figure 9 shows the relative frequency distribution of the change (increase / decrease) of the daily water demand, for both the observed daily water demands and for the daily water demands corrected for the day of the week. Table 2 shows the 0.5%, 25%, 75% en 95.5% confidence intervals of the graphs of Figure 9. The figure and table show large differences between the investigated areas: the day to day change of the daily water demand in the Hulsberg area is 3-4 times larger than in the Amsterdam area, which shows the higher variability in the water demand in the Hulsberg area. The figure and table also show that the mean change (the “25% and 75%” values of Table 2) are some 40% lower for the corrected data than for the observed data. This means that the changes in the daily water demand can be explained for 40% by the repetitive weekly pattern, as captured by the day of week factors. The other 60% are *not* the result of repetitive human behaviour, but of other phenomena. The mean change (the “25% and 75%” columns) of the corrected data, show values between 1% and 3.5%. This means that on average the changes in the daily water demand (*not* caused by a weekly pattern) is limited to 1% (Amsterdam, large area) to 3.5% (Hulsberg, small area).

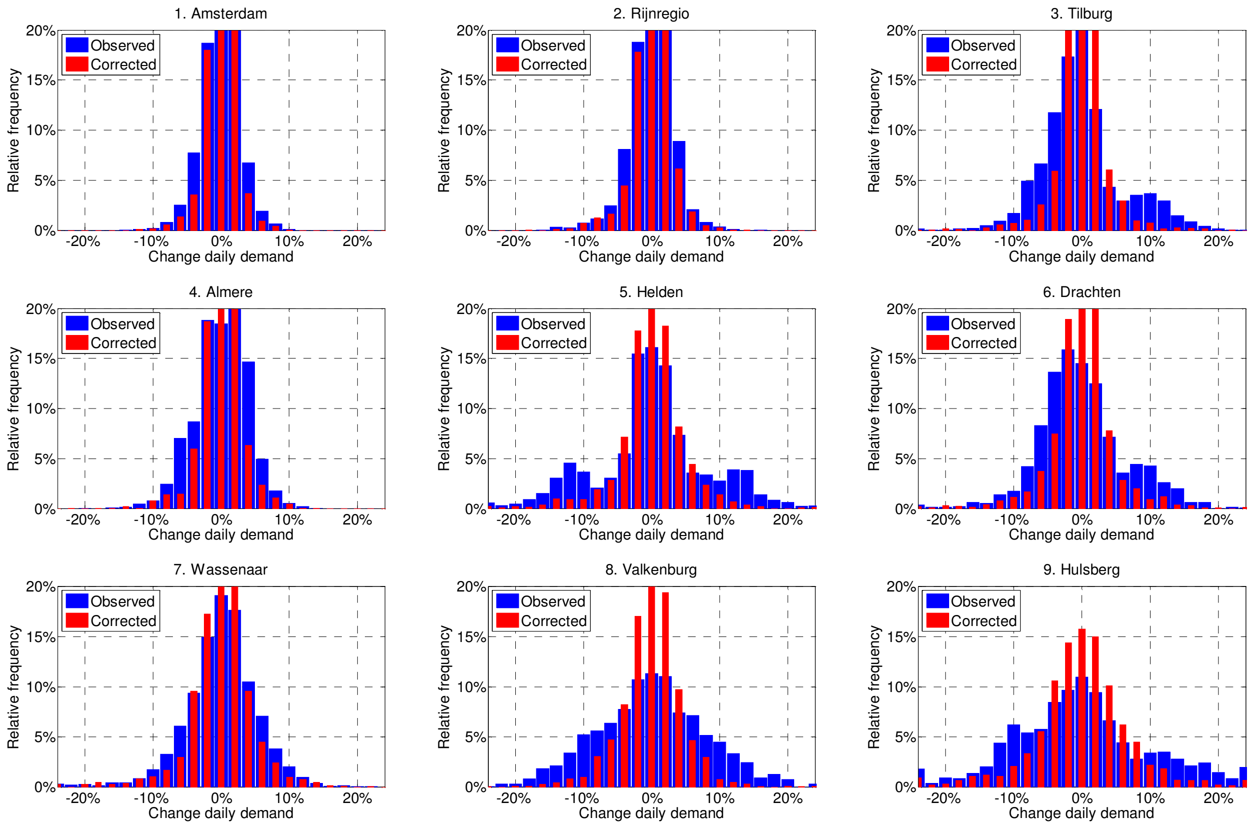

Figure 9: Relative frequency distribution of the change of the daily water demand for the observed data and for data corrected for the day of the week

For the largest changes of the daily water demand (“0.5%” and “95.5% column of Table 2) the differences between observed and corrected data are smaller: some 15%. This means that large changes in the daily water demand are for 85% caused by random or unexplained phenomena. The largest changes of the daily water demand (of the corrected data), show values between 8% and 25%. This means that occasionally (0.5% of time, which equals some 2 days per year) the water demand changes largely from one day to the next. This “unexplained” change of the water demand (“0.5%” and “95.5% columns), is 5 to 8 times larger than the average change of the daily demand (“25%” and “75% columns).

Table 2: Confidence intervals of the frequency distribution of the change of the daily water demand

	Observed data				**Corrected data**			
interval	*0.5%*	*25%*	*75%*	*95.5%*	*0.5%*	*25%*	*75%*	*95.5%*
1. Amsterdam	-8.5%	-1.4%	1.5%	7.6%	-8.3%	-1.0%	1.0%	7.0%
2. Rijnregio	-11.9%	-1.5%	1.9%	9.4%	-10.2%	-1.1%	1.2%	8.8%
3. Tilburg	-16.9%	-3.3%	2.0%	17.6%	-13.4%	-1.4%	1.6%	13.6%
4. Almere	-12.7%	-2.3%	2.8%	9.8%	-11.0%	-1.3%	1.4%	9.2%
5. Helden	-25.5%	-3.3%	3.7%	21.8%	-20.5%	-1.7%	2.1%	14.9%
6. Drachten	-22.2%	-3.8%	3.2%	18.1%	-19.7%	-1.9%	2.1%	15.7%
7. Wassenaar	-21.5%	-2.7%	3.0%	13.8%	-19.1%	-1.9%	2.2%	13.8%
8. Valkenburg	-19.9%	-5.3%	5.2%	20.4%	-15.7%	-2.1%	2.3%	14.1%
9. Hulsberg	-34.5%	-6.4%	5.3%	30.7%	-25.9%	-3.4%	3.5%	24.1%

Gradual changing day of the week factors and demand patterns

The repeating water demand factors and water demand patterns are not fixed in time. Within the year and over a longer period of a number of years the day of the week factors and the typical demand patterns for each day of week gradually change. For one of the investigated areas older data was available going back 20 years. From this data the gradual changes are illustrated in Figure 10. The figure shows that the traditional lower demand on Sundays (9% lower than the average demand in 1991) has almost disappeared in 2011. And the demand patterns show that in the water demand on Mondays a shift has taken place from day hours (between 8:00 and 18:00) to evening hours (between 18:00 and 0:00).

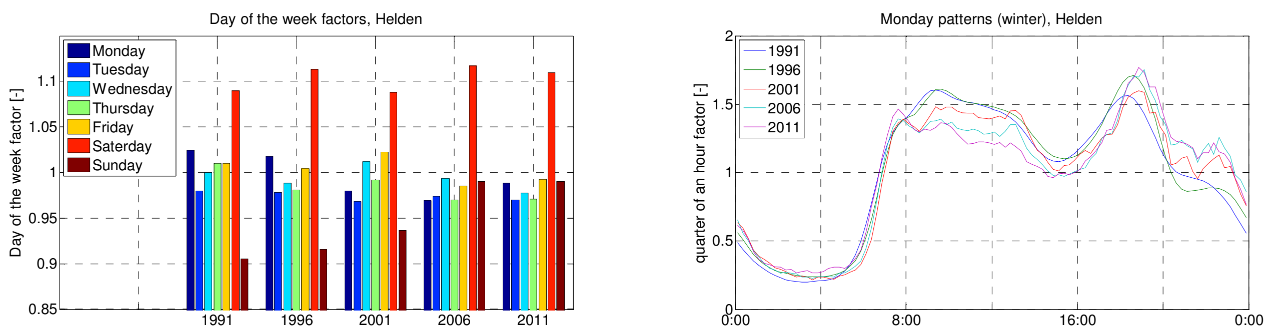

Figure 10: Gradual change in demand factors (day of the week factor, left graph) and demand patterns (winter Monday pattern, right graph) in a period of 20 years in the Helden area

Summary observed water demands

Based on the observations of water demand figures of different water supply areas, a number of conclusions were drawn about water demands. The water demand, both for the demand pattern on a day as well as the total daily amount, in large parts of the year is characterized by weekly repeating patterns. This is observed for all investigated areas, though the demand factors and demand patterns can be quite different between different areas. Also the variability (deviations from the normal patterns) differs between areas: larger / urban areas have a lower variability than smaller / rural areas. In 2 types of situations the water demand diverts from the normal patterns. The first type of situation is at special days or periods (like national holidays, or vacation periods). At those days people divert from their normal living / working pattern, which results in aberrant water demand. At national holidays people don't work and shops and factories are closed, and the water demand resembles the water demand on Sundays. In primary school vacation periods, (part of) the people get up later in the morning, because there is no need to bring the children to school or because they are on holiday. This behaviour results in a delayed and smoothed morning water demand peak, compared to the normal water demand. Typical for this type of deviations from the normal water demand, is that the dates are known in advance and the demand patterns and factors are similar to the patterns and factors of previous national holidays and vacation periods. Although the demand patterns at those types of days differ from the *normal* pattern, the patterns themselves are typical for the type of day (as is illustrated in Figure 3 for the water demand on New Years days).

The second type of situation where the water demand differs from the normal water demand is at days with unusual weather conditions, like exceptional warm and dry weather. In the investigated areas was observed that the water demand can change largely due to changing weather conditions (see Figure 5). Typical for this type of deviations from the normal water demand, is that the dates are *not* known in advance, and the deviations in the water demand can occur at any day between early spring and late autumn. Also the increase of the daily water demand and the deviation from the normal demand pattern show a large variability.

Description of the water demand prediction model

Based on the observations of water demand, a fully adaptive water demand prediction model was constructed. The model predicts the water demand for the next 48 hours on a quarter of an hourly basis. Each quarter of an hour the prediction is calculated anew, moving forward the vector with predicted water demands for the next 48 hours. The main input of the model is the actual (real time) measured water demand in the area. The other input of the model is a calendar with (future) dates of national holidays and primary school vacation days. Currently, no other inputs are used in the model. The model predicts the water demand in three main steps. In step 1 the average water demand for the next 48 hours is predicted; In step 2 the normal water demand for the individual quarters of an hour is predicted; In step 3 the extra sprinkle water demand in the evening for the individual quarters of an hour is predicted, if applicable.

The prediction of the average water demand for the next 48 hours in step 1 is based on the measured water demand of the previous 48 hours. In order to filter out the influence of the day of the week, the measured quarter of an hourly previous water demands on day i at quarter of an hour j ($H_{i,j}$) are corrected by dividing the value with the typical day of the week factor ($f_{dotw,typ,t}$) of the concerning day type t:

$$H_{i,j,corr} = \frac{H_{i,j}}{f_{dotw,typ,(t=i)}} \quad [m^3/h] \qquad (4)$$

The predicted average water demand ($H_{pred,corr}$) for the next 48 hours is based on the average corrected water demand of the previous 96 quarters of an hour ($H_{q=\{0:-95\},corr}$) and the 96 quarters of hour before ($H_{q=\{-96:-191\},corr}$):

$$H_{pred,corr} = C_1 \cdot \left(\tfrac{1}{96} \sum_{q=\{0:-95\}} H_{q,corr} \right) + C_2 \cdot \left(\tfrac{1}{96} \sum_{q=\{-96:-191\}} H_{q,corr} \right) \qquad [m^3/h] \qquad (5)$$

The constants C_1 and C_2 are set at 0.8 and 0.2 making the more recent previous water demands weigh heavier than the older demands. By using this formula the predicted average water demand is based on a relative short period of previous demands (previous 48 hours, with emphasis on the previous 24 hours) . This results in a quick adjustment of the predicted water demand, after a change of the observed water demand. As observed in the water demands of 9 areas, the average change in the daily water demand is smaller than 1%-3.5% on half of all days. This means that by using this formula, the prediction will have an error on everage of 1%-3.5% on daily values.

In step 2 the normal water demand for the individual quarters of an hour on day i at quarter of an hour j ($H_{pred,norm,i,j}$) for the next 48 hours is predicted. This is done by multiplying the predicted average demand, by the concerning typical day of the week factor for day type i ($f_{dotw,typ,i}$) and the typical quarter of an hour factor for day type i and quarter of an hour j ($f_{qoh,typ,i,j}$):

$$H_{pred,norm,i,j} = H_{pred,corr} \cdot f_{dotw,typ,i} \cdot f_{qoh,typ,i,j} \qquad [m^3/h] \qquad (6)$$

In step 3 the extra sprinkle water demand in the evening (which occurs during fair weather periods) is predicted, if applicable. The prediction of this sprinkle demand, is based on the identification of sprinkle demand in the previous 48 hour. The prediction model identifies sprinkle demand by "fitting" the demand curve (which consists of 96 factors $f_{qoh,typ,i,j}$) on the first 68 quarters of an hour of water demands on a day. The first 68 quarters of hour corresponds to the time frame between midnight and 5 PM, which is the time frame where no sprinkle water demand occurs, as can be seen in Figure 5. The fitting of the demand curve is done by multiplying the factors $f_{qoh,typ,i,j}$ with a factor D, where:

$$\sum_{i=1:68} H_{i,j} = D \cdot \sum_{i=1:68} f_{qoh,typ,i,j} \qquad [m^3] \qquad (7)$$

In the quarters of an hour between 5 PM and midnight extra sprinkle demand can be observed. The model calculates the sprinkle demand ($H_{sprink,i,j}$) by taking the difference between the measured water demand and the normal water demand according to the fitted demand curve in the indicated time frame (j = 69 to 92, on the other hours j=1 to 68 the sprinkle demand is 0):

$$H_{sprink,i,j} = H_{i,j} - (D \cdot f_{qoh,i,j}) \quad [m^3/h] \qquad (8)$$

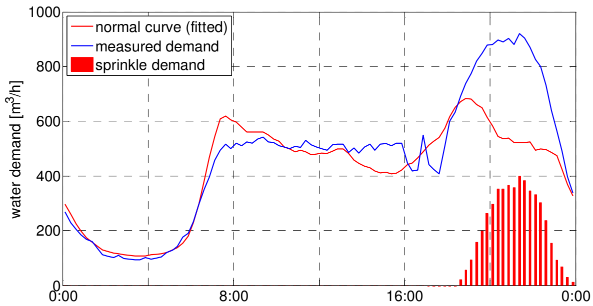

Figure 11: Identifying sprinkle demand by comparing measured demand with the normal expected demand according to the fitted normal demand curve

The predicted average sprinkle demand ($H_{pred,sprink}$) for the next 48 hours is based on the average sprinkle demand of the previous 96 quarters of an hour ($H_{q=\{0:-95\},sprink}$) and the 96 quarters of hour before ($H_{q=\{-96:-191\},sprink}$):

$$H_{pred,sprink} = BC_1 \cdot \left(\tfrac{1}{96} \sum_{q=\{0:-95\}} H_{q,sprink} \right) + BC_2 \cdot \left(\tfrac{1}{96} \sum_{q=\{-96:-191\}} H_{q,sprink} \right) \qquad [{}^{m^3}\!/\!_{h}] \qquad (9)$$

The constants BC_1 and BC_2 are set at 1.1 and 0.1 making the more recent previous observed sprinkle demands weigh heavier than the older demands. By using this formula the predicted sprinkle water demand is quickly adjusted once sprinkle water demand is identified. This is necessary because sprinkle water demand can develop rather quickly, quicker than the change in the normal water demand.

Like the prediction of the normal demand, the predicted average sprinkle demand must be transferred to the individual quarters of an hour on day i at quarter of an hour j ($H_{pred,sprink,i,j}$) for the next 48 hours. This is done by multiplying the predicted average sprinkle demand, by the concerning quarter of an hourly sprinkle factor for day type i and quarter of an hour j ($f_{sprink,i,j}$):

$$H_{pred,sprink,i,j} = H_{pred,sprink} \cdot f_{sprink,i,j} \qquad [{}^{m^3}\!/\!_{h}] \qquad (10)$$

The total water prediction ($H_{pred,tot,i,j}$) is derived by summing the predicted normal demand and the predicted sprinkle demand:

$$H_{pred,tot,i,j} = H_{pred,norm,i,j} + H_{pred,sprink,i,j} \qquad [{}^{m^3}\!/\!_{h}] \qquad (11)$$

Adaptive factors and curves

As can be seen from formulas above, the model uses different factors which are typical for the characteristics of the water demand in the area: the typical day of the week factors ($f_{dotw,typ,i}$), the typical quarter of an hour factors ($f_{qoh,typ,i,j}$) and the typical sprinkle factors ($f_{sprink,typ,i,j}$) for day type i and quarter of an hour j. All these factors are adapted by the model based on the measured demand, which is the main input of the model. Initially the model starts with standard default values for all factors, and once the model is running, it starts updating the factors based on the observed demands of the area. Each day at midnight the model stores the water demand information of the previous day: along with the type of day, the daily water consumption is stored (D_i), the dimensionless quarter of an hourly demand factors ($f_{qoh,i,j}$, according to formula 1.) and the dimensionless quarter of an hourly sprinkle factors ($f_{sprink,i,j}$, also according to formula 1., but with observed sprinkle demand $H_{sprink,i,j}$, rather than with observed normal demand $H_{i,j}$). The sprinkle demand factors are only stored if extra sprinkle demand has actually occurred (in the prediction model this is the case if the average sprinkle demand exceeds 10% of the average normal demand). The prediction model uses the stored data to derive the typical factors which are used in the prediction. The typical day of the week factors ($f_{dotw,typ,i}$) are calculated by using formula 2, over a time frame of 7 weeks (n = 7). The typical quarter of an hour demand factors ($f_{qoh,typ,i,j}$) are calculated by taking the average of the stored previous 7 factors for day type i and quarter of an hour j. In the same manner the typical quarter of an hour sprinkle factors ($f_{sprink,typ,i,j}$) are calculated.

The model distinguishes a number of different day types for which the factors are determined separately: 7 types for the normal Monday till Sunday, 3-5 types for weekdays in vacation periods (depending on how many different vacation periods occur in the area), and 2-5 types for individual aberrant days (like New years day, Good Friday, Liberation day). For each distinguished day type, the dates in the future when the type of day will occur, have to be filled in the calendar menu. This is necessary for the correct prediction (taking the proper typical factors), as well as for storing the water demand information (assign the demand information to the proper type of day).

RESULTS

Analysis of the demand prediction in 10 areas in 2007-2011

To assess the reliability of the prediction model, simulations with 9 different historic datasets of the period 2007-2011 were carried out. In the simulations the model was used to predict the water demand. Of all investigated areas, also data of (a part of) 2006 was available. With this data the simulations could be started in 2006, enabling the prediction model to adapt the typical demand factors to the demand characteristics of the simulated area.

Prediction accuracy

In order to asses the accuracy of the model the predicted values were compared with the measured values. Both the accuracy of the prediction of the daily water demands as well as the accuracy of the prediction of the water demand per quarter of an hour was investigated. For each simulated day *i* of the dataset from 2007 until 2011 (1,826 days) the relative prediction error per day ($E_{D,i}$) and the (daily average of the) absolute relative prediction error per quarter of hour ($E_{H,i}$) were calculated:

$$E_{D,i} = \frac{D_{meas,i} - D_{pred,i}}{\frac{1}{1826}\sum_{i=1}^{1826} D_{meas,i}} \cdot 100\% \qquad (12)$$

$$E_{H,i} = \frac{\frac{1}{96}\sum_{j=1}^{96}\left|H_{meas,i,j} - H_{pred,i,j}\right|}{\frac{1}{1826}\sum_{i=1}^{1826}\frac{1}{96}\sum_{j=1}^{96} H_{meas,i,j}} \cdot 100\% \qquad (13)$$

Where $D_{meas,i}$ and $D_{pred,i}$ the measured and predicted daily water demand at day *i* represent, and $H_{meas,i,j}$ and $H_{pred,i,j}$ the measured and predicted quarter of hourly water demand at day *i* and quarter of an hour *j*. Table 3 shows the 0.5%, 25%, 75% en 95.5% confidence intervals of the prediction errors per day, and the average, and 95.5% confidence interval of the (absolute average per day) prediction error per quarter of an hour. Figure 12 shows the average values for the individual years 2007 to 2011.

Table 3: Confidence intervals of the prediction error of the daily water demand, and the absolute prediction error of the quarter of an hourly water demand (average per day), 2007-2011

	Day prediction				**Quarter of an hourly prediction**	
interval	*0.5%*	*25%*	*75%*	*95.5%*	*average*	*95.5%*
1. Amsterdam	-4,4%	-0,7%	0,6%	4,2%	3,2%	8,9%
2. Rijnregio	-6,6%	-0,8%	0,6%	4,7%	4,1%	11,7%
3. Tilburg	-6,8%	-1,0%	0,8%	7,0%	4,4%	13,3%
4. Almere	-6,3%	-1,0%	1,0%	5,8%	4,5%	14,2%
5. Helden	-12,9%	-1,4%	1,1%	10,3%	6,1%	20,9%
6. Drachten	-12,7%	-1,6%	1,2%	9,6%	7,1%	23,7%
7. Wassenaar	-11,6%	-1,6%	1,2%	8,6%	7,3%	17,5%
8. Valkenburg	-9,6%	-1,7%	1,2%	8,5%	6,3%	17,1%
9. Hulsberg	-16,2%	-2,5%	1,9%	13,8%	9,8%	35,6%

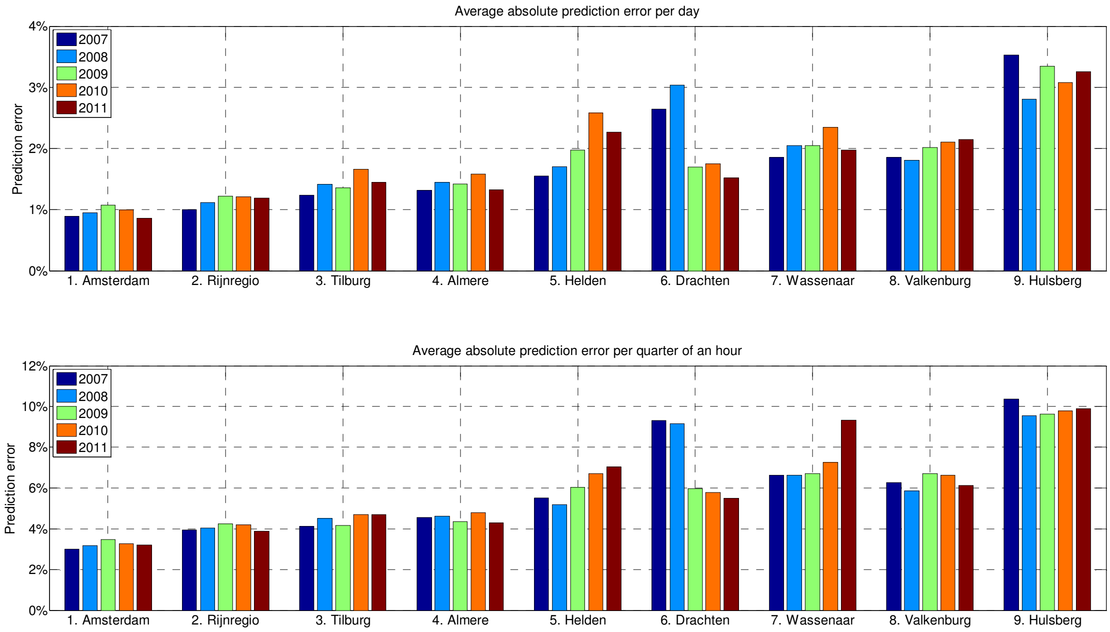

Figure 12: Average prediction errors per year of different areas

The results of the water demand prediction model are in line with the observations from the water demand data sets (Figure 7and Table 2). As observed in the data sets, the variability of the demands is smaller in larger / more urban areas (1. Amsterdam, 2. Rijnregio, 4. Almere) than in smaller / more rural areas (5. Helden, 8. Valkenburg, 9. Hulsberg). The smaller variability in the water demand results in smaller prediction errors by the water prediction model. This indicates that accuracy of the prediction model is largely determined by the variability of the water demand in the area. Figure 12 shows the prediction errors of the individual years. The figure shows that the accuracy from one year to another is not constant but varies (the variation in accuracy is some 20-40%). Despite the fact that the same model is used for the demand prediction in one area, the performance of the model in term accuracy varies from one year to another. This is another indication that the performance of the water prediction model is determined by the variability of the water demand in the area.

The observed prediction errors of the water prediction model (Table 3) are smaller than the observed variability in the water demand of the datasets (Figure 7and Table 2). This indicates that the prediction model achieves a higher accuracy than can be expected based on the variability of the water demand. This higher accuracy can be explained by the fact that the adaptive functionality of the prediction model continuously updates its used demand factors, based on the history of the previous 7 weeks). This gradual change of the used factors results in smaller deviations, than using the average factors of the complete dataset of 5 years. Another difference is that the prediction model distinguishes more different day types (14 types) than were used in the analysis of the variability of demand (8 types). Finally the functionality for the prediction of sprinkle demand in the prediction model, results in smaller deviations in periods with large volumes of sprinkle demand.

The results show that the (relative) prediction errors are smaller when the average demand in the area is bigger. The relation between the water demand and the prediction error was further investigated by plotting the relation in a diagram. Because of the large range of the water demands, plotting the relation in a normal X-Y diagram proved to be not informative. Therefore the relation was plotted in a logX-Y diagram, see Figure 13.

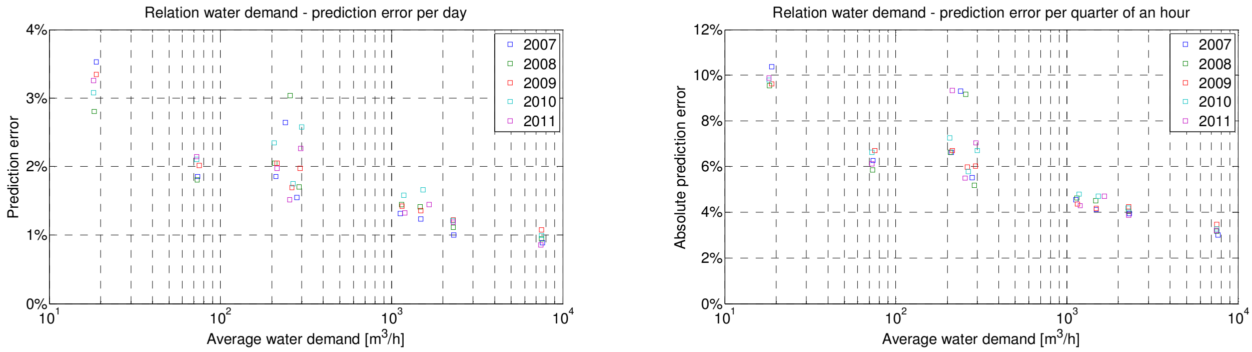

Figure 13: Relation between the water demand in the area and average absolute prediction error (left=prediction error per day, right=prediction error per quarter of an hour)

Figure 13 shows a correlation between the average prediction error and log value of the water demand (U_{avg}), which is estimated at:

$$E_D = 3.9 - 0.35\ ln(U_{avg})\ [\%], \qquad R^2=0.77$$

$$E_H = 12.3 - 1.05\ ln(U_{avg})\ [\%], \qquad R^2=0.78$$

A strong correlation was not expected, because some of the systems with comparable water demands (5. Helden, 6. Drachten and 7. Wassenaar, water demand around 250 m^3/h) showed considerable variation in prediction accuracy. This indicates that the water demand is not the only factor influencing the predictability of the water demand, but that local characteristics (urban / rural, touristic / non-touristic) also influence the prediction accuracy. However, the correlation is sufficiently strong to make a first estimate of the expected prediction accuracy when the prediction model is applied.

CONCLUSION

Each water supply area has its own characteristic weekly repeating water demand pattern. In large parts of the year the water demand occurs according to this pattern. During some periods or some days, the water demand deviates from this pattern. On the one hand this deviation is related to special days or periods which are known in advance (like national holidays and vacation periods), on the other hand this deviation is related to special weather conditions. The variability of the water demand during normal periods, and the degree to which the water demand deviates during special periods or days, is different for each area. In general, the variability of the water demand decreases at in increasing average water demand in the area.

Based on the observations of water demands, an adaptive demand prediction model was constructed en tested on 9 datasets with 5 years of data. The tests were done with identical parameters and initial demand factors in the prediction model for all 9 different data sets of water demand. The results showed that the prediction model was capable of predicting the water with a higher accuracy than the average variability of the water demand in the areas. This higher accuracy could be achieved by the model, because the model automatically adjusts demand factors (which are used in the prediction) based on the observed demand in the previous weeks. The adaptive functionality enables the model to be implemented without any prior data analysis.

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