Simulating Residential Water Demand with a Stochastic End-Use Model

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Abstract: A water demand end-use model was developed to predict water demand patterns with a small time scale (1 s) and small spatial scale (residence level). The end-use model is based on statistical information of users and end-uses: census data such as the number of people per household and their ages; the frequency of use; duration and flow per water-use event; occurrence over the day for different end-uses such as flushing the toilet, doing the laundry, washing hands, etc. With this approach, water demand patterns can be simulated. The simulation results were compared to measured water demand patterns on attributes such as peak flow and daily total water use, as well as on the shape of the pattern and the frequency distribution of flows and accelerations in flow. The simulation results show a good correspondence to measured water demands. Because the end-use model is based on statistical information rather than flow measurements, the model is transferable to diverse residential areas in different countries. The model can be applied in the design stage (prebuild), in scenario studies, and in water quality distribution network models.

Introduction

Water quality changes during transport and distribution. There is a requirement for more knowledge on the behavior of both particulate and dissolved substances throughout drinking water distribution systems (Powell et al. 2004). The key element of a water quality model for a drinking water distribution system is a detailed hydraulic model (Slaats et al. 2003; Vreeburg 2007), which not only takes into account the maximum flows but also the flows on all preceding time steps (Powell et al. 2004; Slaats et al. 2003; Vreeburg and Boxall 2007). For that reason, knowledge of water demands is essential. For a water quality network model of drinking water distribution systems, a hydraulic model with an accurate probability of turbulent and laminar flow and of stagnant water is needed, and thus a detailed stochastic water demand model per (household) connection on a per second or per minute basis is required (Blokker et al. 2008).

Buchberger and Wu (1995) have shown that residential water demand develops from rectangular pulses; the pulses are described by their arrival time over the day, their intensity (flow) and duration. The parameters and probability distributions to constitute a Poisson rectangular pulse (PRP) model are derived from measurements (Buchberger and Wells 1996). The PRP model was applied in the United States (Buchberger et al. 2003), Italy (Guercio et al. 2001), Spain (García et al. 2004) and Mexico (Alcocer-Yamanaka et al. 2006). Different probability distributions for intensity and duration were found for different data sets, such as lognormal, exponential and Weibull distributions. Alvisi et al. (2003) use a model analogous to the PRP model based on a Neyman-Scott stochastic process (NSRP model), for which the parameters are also found by analyzing the measurements.

Obtaining the PRP parameters requires many (expensive) flow measurements. The parameters for Milford, Ohio (Buchberger et al. 2003), for example, were obtained from 30 days of measurements from 21 homes on a per second basis. The retrieved PRP parameters led to mainly short pulses of 1 min or less. This means that showering, for example (circa 5 to 15 min), is almost never simulated as a single coherent event. Another issue is that it is difficult to determine how well the simulation performs compared to the actual measurements, since the simulation parameters were derived from the same or similar measurements. Also, it is difficult to correlate the parameters retrieved from these measurements with such data as population size, age and installed water-using appliances. As a consequence, the parameters for the PRP model are not easily transferable to other networks. The PRP model is a descriptive model, rather than a predictive one. The PRP model, thus, has a lot of potential to provide insight into some basic elements of water use, such as peak demands (Buchberger et al. 2008), travel times (Buchberger et al. 2003) and cross correlations (Li et al. 2007).

Within the KWR Watercycle Research Institute, an approach based on end-uses was developed to prevent large measurement campaigns. Within this approach each end-use is simulated as a rectangular pulse from end-use specific PDFs for the intensity, duration and frequency of use, and a given probability of use over the day (related to the residents' activities). Changes in appliances

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Table 1. Penetration Rate or Occurrence per End-Use in The Netherlands (Blokker 2006)

End-use type	Penetration rate (%)	End-use subtype	Penetration rate (%) within end-use
Bathtub	36	120 L	100
Bathroom tap	100	Washing and shaving	33
		Brushing teeth	67
Dishwasher	45	Different brands and types	100
Kitchen tap	100	Consumption (drinking water, water for coffee and tea, water for cooking)	37.5
		Dishes (and cleaning)	25
		Washing hands	25
		Other (e.g., watering plants)	12.5
Outside tap	58	Garden	75
		Other	25
Shower	100	Different water heaters without water-saving shower head	50
		Different water heaters with water-saving shower head	50
Washing machine	98	Different brands and types	100
WC	100	High cistern (9 L)	11.1
		Low cistern (9 L)	22.2
		Low cistern (9 L) with water-saving option	22.2
		Low cistern, new (6 L)	11.1
		Low cistern, new (6 L), with water saving option	33.3

and water-use behavior lead to different water demand patterns. An end-use model, therefore, acts as a predictive model and can be utilized in the design stage and in existing networks where no household water meters are installed.

Methods and Materials

Basic Model

Buchberger and Wells (1996) have shown that the water demand pattern can be described by a PRP model. The end-use model is based on the same principle of rectangular pulses. The probability distributions describing the arrival time over the day, intensity (flow) and duration of the pulses in the end-use model are specified per end-use. Furthermore, the parameters of the probability distributions are not retrieved from flow measurements but from statistical data from surveys. The end-use model produces a water demand pattern which can be described by the following equations:

$$Q = \sum_{k=1}^{M} \sum_{j=1}^{N} \sum_{i=1}^{F_{jk}} B(I_{ijk}, D_{ijk}, \tau_{ijk}) \tag{1}$$

$$B(I_{ijk}, D_{ijk}, \tau_{ijk}) = \begin{cases} I_{ijk} & \tau_{ijk} < T < \tau_{ijk} + D_{ijk} \\ 0 & \text{elsewhere} \end{cases} \tag{2}$$

Here, i, j, and k=indices; k=all end-uses from 1 to M; j=all users from 1 to N; and i=all busy times per end-use from 1 to F_{jk} (the frequency of use for user j and end-use k). D=pulse duration (in seconds); I=pulse intensity (flow in L/s); and τ=time at which the tap is opened. Thus, D_{ijk}=duration for end-use type k for user j and occurrence i. $B(I, D, \tau)$=block function, which equals I at time τ to $\tau+D$ and 0 during the rest of the day. The summation is done for all (M) available end-uses, all (N) users and per end-use for the frequency of use (F); this leads to the total water demand pattern Q (L/s) over the day.

All parameters are described by PDFs which are different for each end-use.

End-Uses (k)

Eight main types of end-uses are defined at the fixture or appliance level, viz. water closet (WC), shower, washing machine, dishwasher, kitchen tap, bathroom tap, bathtub, and outside tap. In The Netherlands, most of these main types have a penetration rate (number of households that possess a specific appliance) of 100% (Table 1). Dishwashers and bathtubs have a penetration rate that positively relates to the household size; the penetration rate of the bathtub also relates to a wealth class (defined by education level and income) and thus it relates to the type of house (price). The penetration rate of dishwashers is increasing (45% of about 3200 surveyed households in 2001, 54% in 2007) and the penetration rate of the bathtub is decreasing (Foekema and Engelsma 2001; Foekema et al. 2008).

For each type of end-use there are different subtypes which constitute the end-use (Table 1). For a WC, this can be an old-fashioned toilet with a large cistern of 9 to 12 L or a new one of only 6 L with a water-saving possibility of flushing only 3 L. The subtypes of washing machines and dishwashers are different brands and types of machines with a specific water inlet pattern. A front-load washing machine (as mainly used in Europe) has a different inlet pattern and a considerably smaller total water use than a top-load washing machine (as mainly used in the Unite States). For the kitchen tap, a subtype is defined by its use, e.g., doing the dishes, consumption (water for meals and tea or coffee), washing hands and other uses. The penetration rate of the subtypes in Table 1 is the number of households that possess the subtype (e.g., type of toilet) or it is the distribution of use per subtype (e.g., for kitchen tap).

Users (j)

Users are the key in an end-use model because they choose the end-uses. Users are divided into groups based on household size,

Table 2. Household Statistics in The Netherlands (Blokker 2006)

		One person households	Two person households	Families with children
Number of people per household		1	2	3.75[a]
Number of households (%)		34	30	36
Gender division: male/female (%)		46/54	50/50	50/50
Age division (%)	Children (0–12 years old)	0	0	25
	Teens (13–18 years old)	0	0	16.5
	Adults (19–64 years old)	70	70	58.5
	Subdivision: % of adults with job away from home	Male: 67.5	Both persons: 49	Both parents: 39
			Only male: 26	Only father: 52
		Female: 52.4	Only female: 6	Only mother: 3
			Neither person: 18	Neither parent: 5
	Seniors (>65 years old)	30	30	0

[a]On average.

age, gender, and occupation. Since the frequency of use is given per person, the number of people per household is of importance. A residential water-use survey in The Netherlands (Foekema and Engelsma 2001) showed several relationships: between age and frequency of use (e.g., older people flush the toilet more often and young children more often take a bath), between age and shower duration (teenagers take the longest showers), and between penetration rate and household size (e.g., possession of a dishwasher and a bathtub correlate positively with household size). It is possible to take these relationships into account and use an age-dependent frequency of use (F_{jk}) and duration (D_{ijk}). The time of water use (τ_{ijk}) is strongly related to the users' diurnal patterns (presence at home and sleep-wake rhythms). Consequently, the ages and occupations of users are important in the model as children (elementary school) and teens (secondary school or college) have different diurnal patterns from adults with jobs away from home or from senior citizens.

Statistics Netherlands (CBS 2007) gives information on the number of households per city (or even per district) and the number of people, and their ages, within a household. Three major household types are discerned, viz. one-person households, two or more people without children (98.6% of these households consist of only two people; for the model, 100% of this household type is assumed to consist of two people), and two or more people with children (with an average occupancy of 3.75 people). The average household size in The Netherlands is 2.3 people. For every household type, the number of people, the fraction of men and women, and the division over the different age groups is given (Table 2).

Frequency of Use (*F*)

For each end-use, the frequency was retrieved from the residential water-use survey (Foekema and Engelsma 2001). The frequency is the number of uses per person per day; for the kitchen tap, however, it is the number of uses per household per day. The kitchen tap is often used for family purposes, such as cleaning, cooking and doing the dishes. Therefore, the frequency of use for the kitchen tap is less strongly related to individual users.

The frequency of use is described by a discrete statistical distribution, preferably the Poisson distribution because it has only one parameter that is easy to determine (i.e., the average). For six of the end-uses, the frequency fits a Poisson distribution. For the kitchen tap, this is not the case because the high number of uses comes with a sample variance that exceeds the sample mean.

Instead, a negative binomial distribution (an alternative to the Poisson distribution, where the sample variance is an explicit input parameter) is fitted on the data. For the shower, a binomial distribution is used, which means the number of showers is either zero or one. Table 3 summarizes for all end-uses how *F* can be described.

Pulse Intensity (*I*)

For each end-use, the flow (in L/s) was determined (Table 3), partly from the water-use survey (Foekema and Engelsma 2001) and partly from technical information on water-using appliances as collected from installation guides (ISSO-kontaktgroep 62 2003). For the shower, the intensity depends on the type of shower head as well as on the type of water heater. For the kitchen and bathroom taps, the maximum flow is determined by the pressure and the internal resistance of the indoor plumbing. The average flow during normal operation was equal to half the maximum flow from the technical data. Because faucets are not always operated at the same flow, a uniform distribution is assumed. The flow was not measured for all end-uses, so this could not be verified.

Pulse Duration (*D*)

For each end-use, the duration was determined (Table 3), partly from the water-use survey (Foekema and Engelsma 2001) and partly from technical information on water-using appliances. The duration of taking a shower is typically determined by the user, while the duration of filling the toilet bowl is determined by the volume of the bowl and the inlet flow which is related to the installation. The duration of taking water from a bathroom or kitchen tap, which is determined by the user, can be described using a lognormal distribution function.

For the kitchen tap, a lognormal distribution fits the data, with the variance equal to 130% of the mean value. For the durations of the bathroom tap and outside tap, the averages are known, but the standard deviations are not. A lognormal distribution with a variance equal to 130% of the mean is assumed. For the duration of showering, a lognormal distribution with the variance equal to 50% of the mean value or a χ^2 distribution can be used. However, the χ^2 distribution is only valid when the duration is expressed in minutes because this frequency distribution is not linearly scalable.

Table 3. Frequency, Duration, and Intensity for Several Types and Subtypes of End-Uses in The Netherlands (Blokker 2006)

End-use type/subtype		Frequency (day^{-1}) Average	Frequency Distribution	Duration Average	Duration Distribution	Intensity (L/s) Average	Intensity Distribution
Bathtub	120 L	0.044	Poisson	10 min	N.A. (fixed)	0.2	N.A. (fixed)
Bathroom tap	Washing and shaving	4.1	Poisson	40 s	Lognormal	0.042	Uniform distribution
	Brushing teeth			15 s			
Dishwasher	Brand and type	0.3	Poisson	Specific dishwashing pattern (4 cycles of water entering, total 84 seconds, 0.167 L/sec=14 L)			
Kitchen tap	Consumption	12.6[a]	Negative binomial distribution (r=3, p=0.192)	16 s	Lognormal	0.083	Uniform
	Doing dishes			48 s		0.125	
	Washing hands			15 s		0.083	
	Other			37 s		0.083	
Outside tap	Garden	0.44	Poisson	300 s	Lognormal	0.1	Uniform
	Other			15 s			
Shower	Normal	0.7	Binomial	8.5min[b]	χ^2 distribution	0.142[c]	N.A. (fixed)
	Water saving type					0.123[c]	
Washing machine	Brand and type	0.3	Poisson	Specific washing pattern (4 cycles of water entering, total 5 minutes, 0.167 L/sec=50 L)			
WC	6-L cistern	6	Poisson	2.4min[d]	N.A. (fixed)	0.042	N.A. (fixed)
	9-L cistern	3.6 min[d]					

[a]Frequency for the kitchen tap is per household per day.

[b]Shower duration has an age dependency; children and teens take longer showers.

[c]Shower intensity depends on the type of water heater.

[d]With a water saving option the duration is reduced to 50% of the original value.

Diurnal Pattern, Time of Water Use (τ)

There is no survey available that addresses for all end-uses the time of the day when a water-use event is likely to take place. For the washing machine and dishwasher, a question was included in the residential water-use survey (Foekema and Engelsma 2001) about when these appliances were mainly used: morning, afternoon, evening, or night. For doing the dishes by hand, a much more accurate pattern can be constructed based on the time-budget survey of 1995 across 3227 individuals (Van der Broek and Breedveld 1995). This pattern correlates to the pattern of preparing a meal and dining. For these activities a (rough) pattern can be constructed to estimate τ (Blokker 2006).

For the other types of end-uses, it is assumed that the start of water use is strongly related to whether people are at home or not and if they are asleep, getting up or preparing for bed. From the time-budget survey (Van der Broek and Breedveld 1995), the duration of sleep and being away and the time of getting up and leaving home (in the morning) can be fitted to a normal distribution (Table 4). For all four parameters, a chi-square test failed to confirm on a 5% significance level that the data are normally distributed. As an alternative to using the data from the time-budget survey directly, the end-use model uses the normal probability distributions to draw random numbers because it simplifies the model, and the difference between the two approaches is small (Blokker 2006). A diurnal pattern for the probability of water use is thus constructed from the diurnal pattern of users, i.e., their sleep-wake rhythm and their being at home. For weekdays, this pattern is strongly related to people's ages and occupations; for weekend days, this correlation is not very strong.

A diurnal pattern for a user can be constructed with random picks from the normal distribution. This pattern is converted to a probability distribution function (PDF) of water-use events in the following way:

- During the sleeping hours, the total volume of water use is estimated at 1.5% of the total daily demand, based on the analysis of Dutch water use measurements between 1:00 AM and 5:00 AM (Blokker 2006).

Table 4. Statistics for Diurnal Patterns in The Netherlands (Blokker 2006)

		Weekday Child	Teen	Adult with job away from home	Adult without job away from home	Senior	Total	Weekend day
Time of getting up	μ	7:00	7:00	7:00	8:00	8:00	7:00	9:00
	σ	1:00	1:00	1:00	1:00	1:00	1:00	1:30
Time of leaving the house	μ	8:30	8:15	8:00	13:00	13:00	8:00	13:00
	σ	0:30	0:30	0:45	3:00	3:00	1:00	3:00
Duration of being away	μ	7 h	8 h	9.5 h	10 h	10 h	8.5 h	10 h
	σ	2 h	2 h	3.25 h	4.5 h	4.5 h	1 h	4.5 h
Duration of sleep	μ	10 h	9 h	7 h	8 h	8 h	8 h	9 h
	σ	1 h	1 h	1 h	1 h	1 h	1 h	1.5 h

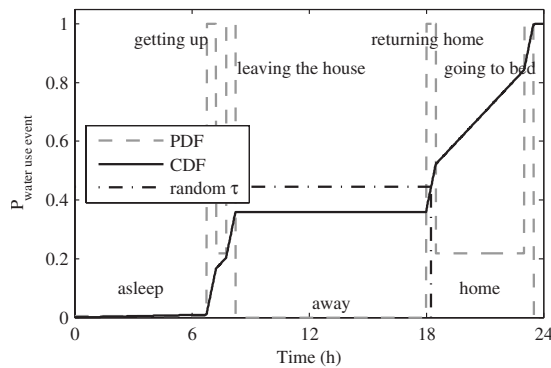**Fig. 1.** Example of drawing a random time (τ) from the PDF and CDF of water use for a working adult

- During absence, the probability of (the start of) water use is set to zero.
- During the half hour after getting up and returning home and the half hour before leaving home and going to bed, peak hours are assumed and the fraction of the total demand occurring in this period is estimated at 65%. The 65% is based on the assumption that, during the peak hours, 100% of washing (use of shower, bathtub and bathroom tap) takes place (which is 50% of the average Dutch water use), 50% of flushing the toilet and 10% of all other water uses take place.
- The rest of the water use then corresponds to 33.5% of the daily water use.

The cumulative distribution function (CDF) is the cumulative sum of the PDF and is scaled to be between zero and one. Because the times of waking up, leaving the home, returning home and going to bed vary (Table 4), the probability of water-use events varies as well. A random time of water use (τ) can be retrieved from the CDF. An example is shown in Fig. 1 where a random number equal to 0.45 means that τ for the water-use event is 18:15.

For *Bathtub*, *Bathroom tap*, *Outside tap*, *Shower* and WC, the CDF over the day is constructed from Table 4 as described above. For *Kitchen tap*, *Dishwasher* and *Washing machine*, the CDF is constructed by multiplying the pattern from Table 4 by the respective patterns for dishwashing by hand or machine and washing machine use (Blokker 2006).

Simulation

Once the statistical information on users and water outlets per house are put into the model, the simulation can be run. First, for each simulated house, the occupancy and the age and gender (Table 2) and diurnal patterns of the occupants (Table 4) are determined. The input statistics can be specific for certain types of houses. For example, small apartments hardly ever house more than two people; special apartments for elderly people will not be inhabited by families with children.

Next, it is determined what end-uses ($k = 1$ to 8) and subtypes are present in each simulated house (Table 1; for the human operated taps the subtype is determined per occurrence). Then, per end-use k (in random order), for all users ($j = 1$ to N) in the house, the frequency of use (F_{jk}) is determined from the appropriate PDF (often a Poisson distribution, Table 3). After that, for all occurrences ($i = 1$ to F_{jk}), the duration and intensity are determined from the appropriate PDF (often a lognormal distribution for the duration and a uniform distribution or fixed value for the inten-

sity, Table 3) and when during the day (τ) the water-use event occurs (from the probability function per person, Fig. 1). When for end-use k, user j and occurrence i the time τ_{ijk} is established, the time $\tau_{ijk} - D_{ijk} < T < \tau_{ijk} + D_{ijk}$ is blocked for end-use k, user $j+1$ to N and occurrence $i+1$ to F_{jk}. This ensures that there is no overlapping use by multiple users of one end-use, e.g., when only a single shower is present, the use of it by one person cannot coincide with its use by a second person. However, user j could potentially draw water from multiple end-uses (k and $k+1$) at the same time. This is not actively blocked, but seems to occur seldom. The sum of all water demands is the water demand pattern of the home.

The output of one simulation run is one water demand pattern. By doing more simulations, either multiple patterns (days) of a specific house are found or a water demand pattern of a street with several houses on it could be constructed. Due to the stochastic nature of water demand patterns, this single simulated water demand pattern is only one possible outcome. With a Monte Carlo simulation, many simulation results are obtained and a statistical analysis can be made on the results.

Parameters to Compare Simulation Results and Measurements

To establish the performance of the water demand model, the results need to be compared to water demand measurements. Since the output of the model is stochastic in nature, several statistical parameters are used to validate the simulation by comparing it to measured water demands. García et al. (2004) suggest Q_{max} (the maximum flow on different time scales), V (the volume per day), the number of pulses per day and the number of clock hours of water use per day. For all these parameters, both the average and probability distributions are considered. Furthermore, the mean and variance of water demands over the day (Q_{day}) on different time scales can be used. Q_{day} can also be converted to a dimensionless water demand multiplier pattern (C_d). The cumulative frequency distribution of water demands (Q_{CFD}) and the cumulative frequency distribution of the change in water demands (ΔQ_{CFD}) are introduced as extra parameters. These parameters, and the time and spatial scales that they are valid for, are summarized in Table 5.

Validation on different time scales (from 1 second to 1 hour) and different spatial scales needs to be considered (from an individual house to a street of 5–50 homes to an isolated section of 100–500 homes). The reason is that water demand models are applied on different scales, not only in a network model, but also in design and scenario studies. A good match between measurement and simulation on a small time (or spatial) scale does not automatically lead to a good match on longer time (or larger spatial) scales.

Not all parameters are suitable for all time scales and all spatial scales. The number of pulses per day is only of interest with small time scales; measurements on a five-minute basis will give no information about how many times a tap was opened within that time. To compare the actual patterns, Q_{day} is most suitable for larger time and spatial scales (about 10 minutes or longer and the spatial scale is at least the sum of 15 houses); for smaller time scales (1 second to circa 15 min) and smaller spatial scales (e.g., a single house), Q_{CFD} and ΔQ_{CFD} can be used. Furthermore, the minimum applicable time scale depends mainly on the accuracy of the measurements.

To get an accurate statistical overview, the number of measurements is important. The parameters Q_{day}, C_d, Q_{CFD}, and ΔQ_{CFD}

Table 5. Overview of Parameters Used for Validating Simulation Results; the Temporal and Spatial Scales Are Independent

Parameter	Description	Temporal scale	Spatial scale
Q_{max}	Maximum flow per day	1 s, 1 min, 1 h	House, street, isolated section
V	Total water use per day	1 day	House, street, isolated section
n_{pulse}	Number of pulses per day	1 s	House
n_{hours}	Number of hours of water use/busy hours	1 h	House
Q_{day}	The water demand over the day	10 min, 1 h	Street, isolated section
C_d	Dimensionless water demand multiplier pattern over the day (daily water demand coefficient)		
Q_{CFD}	Cumulative frequency distribution of water demand over the day (CFD of flows)	1 s, 1 min, 15 min	House, street
ΔQ_{CFD}	Cumulative frequency distribution of change in water demand over the day (CFD of flow accelerations).		

are based on all measurements over the day and, thus, an accurate overview is already acquired with a few measurement days. The other parameters are based on one number per day (e.g., maximum daily flow) and, therefore, at least 25 days' worth of measurements are required.

The parameters Q_{max}, V, n_{pulse}, n_{hours}, Q_{CFD}, and ΔQ_{CFD} are presented as cumulative frequency distributions. The goodness-of-fit for the cumulative frequency distributions is expressed with two measures for the error between empirical and modeled distributions [mean error (ME); and root mean square error, (RMSE)] and a measure for the similarity in shape between empirical and modeled distributions (*Fraction Declaring Variance* or R^2). Q_{day} and C_d are patterns; the goodness-of-fit is expressed as ME and RMSE of Q_{day} and R^2 of C_d. In this paper the number of pulses per day and C_d are not used, due to the lack of detailed data.

Results

The results that are presented here are comparisons of available measurements and simulations that were done specifically for this purpose. The end-use model was programmed in MATLAB (The MathWorks, Natick, MA) to run the simulations. The software model was named SIMDEUM: Simulation of water demand; an end-use model.

In 2004, Waternet (the water company of Amsterdam) logged the water use of 46 homes dispersed over the city; each home was measured over seven days. A standard water meter with a nominal flow of 1.5 m³/h and an external pulse was used. The logging frequency was one minute; the logging precision was 1 L per pulse. This resulted in errors due to rounding. Therefore, the time scale of the water demand patterns was converted to five minutes. One of the homes had a 0.2 L/min leak; this house was not considered in the validation because SIMDEUM does not simulate leakage. The measurements of two other homes were excluded because they had extremely high water uses which casted doubt on the accuracy of the measurements. The measurements were not all done on the same days. Water demand patterns for the sum of the remaining 43 homes were constructed by adding the measured patterns of equal weekdays.

At the original 46 homes, a residential water-use survey was conducted (Kanne 2005). This led to accurate knowledge of the number of people per home and specific information on water use at the measured homes. Compared to the data of Table 1 that looked at locations throughout The Netherlands, the 46 "measured" houses in Amsterdam had fewer water-saving options on toilets (48% instead of 56%), fewer water-saving shower heads

(20% instead of 50%), different hot water devices (35% kitchen geyser, 53% combi or miniboilers and 12% collective hot water supply), and fewer outside taps (23% instead of 58%). Compared to Table 2, the household composition in Amsterdam is also different. There are more one-person households (55% instead of 34%), fewer two-person households (21% instead of 30%), fewer families with children (24% instead of 36%), and the average household size is smaller (1.8 instead of 2.3). The average age is younger, only 11% (instead of 19%) of the population is over 65 years old (CBS 2007).

Simulations were done using SIMDEUM, with the default input parameters plus the specific information on households and in-home installations. Only weekday patterns were considered; no specific weekend patterns were taken into account. The statistical results were retrieved from 1,000 simulated patterns over 10 days at 100 different houses. The simulations were done on a 1 second time scale and time-averaged over five minutes.

Figs. 2 and 3 and Table 6 show that there is good agreement between simulations and measurements. The maximum flow on
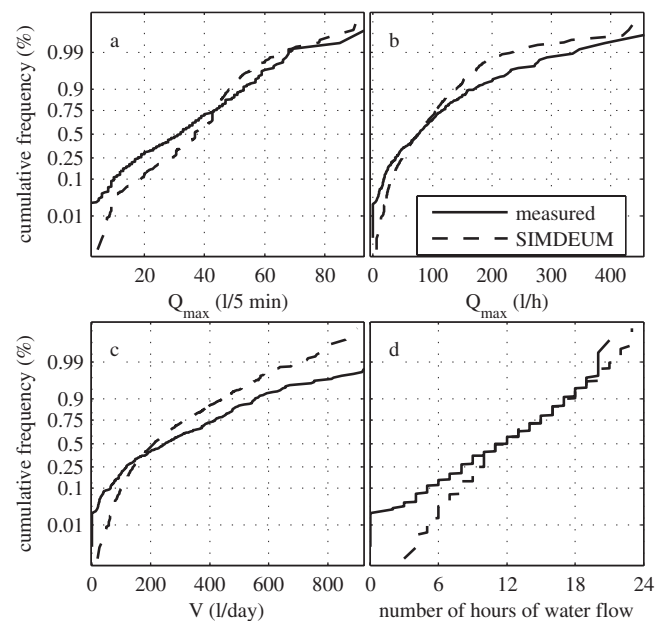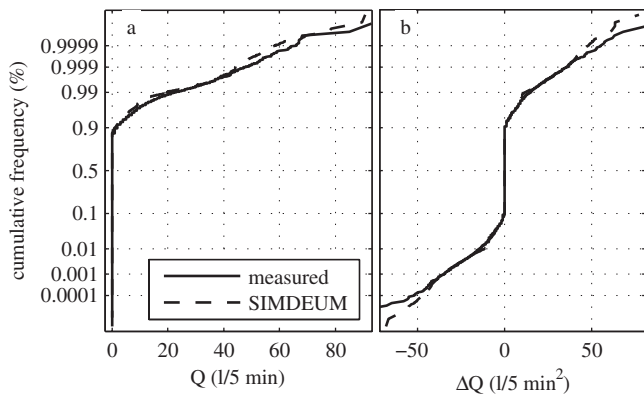

Fig. 2. Comparing, at a time scale of 5 min and spatial scale of 1 home, measurements (43 houses, 7 days each) and simulations (100 houses, 10 weekdays at 1 s time scale time-averaged over 5 min); (a) Q_{max} per 5 min; (b) Q_{max} per h; (c) V; and (d) n_{hours}

Fig. 3. Comparing, at a time scale of 5 min and spatial scale of 1 home, measurements (43 houses, 7 days each) and simulations (100 houses, 10 weekdays at a 1 s time scale time-averaged over 5 min); (a) Q_{CDF}; (b) ΔQ_{CDF}
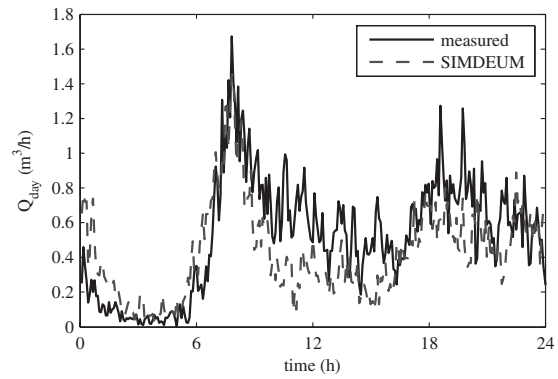

Fig. 4. Comparing average Q_{day}, at a time scale of 5 min and spatial scale of 43 homes, of measurements (sum of 43 houses, 5 weekdays each) and simulations (sum of 43 houses, 10 weekdays at a 1 s time scale time-averaged over 5 min)

different time scales and volume per day are predicted well by the end-use model. The pattern is defined by the parameters n_{hours}, Q_{CDF} and ΔQ_{CDF}; these parameters are predicted well by the end-use model. Fig. 4 shows that Q_{day} is well predicted for the sum of 43 homes; the peaks in the morning coincide in time and maximum flow, the minimum values are also predicted well. The average water use in the simulation, however, is about 17% too low and relates mainly to afternoon consumption. The reason for the lower simulated average is that in Amsterdam more people are at home than the end-use model assumes; in Amsterdam people work fewer hours than the overall Dutch average (CBS 2007).

Discussion

Building a water demand model from statistical information on users, end-uses, frequency of use, intensity and duration per use, and time of water use leads to realistic water demand patterns that compare well to measured water demand patterns. The assumption of a strong correlation between time of water use and the users' sleep-wake rhythm and their being at home appears to be valid.

The end-use model could be improved or extended in several ways, which can be related to the parameters of Eq. (1)

- Other kinds of water use (k), such as leaks, could be incorporated. Dripping taps or other types of leakage could form a substantial part of the total water demand (Cobacho et al. 2004). The 2007 residential water-use survey (Foekema et al. 2008) showed that, in The Netherlands, about 5% of the

households have dripping taps, 2% have leaking toilets and fewer than 1% have leaking pipes.
- The intensity (I) of most end-uses is assumed to be deterministic, rather than random. From measurements (e.g., Buchberger et al. 2003), a lognormal probability would be more likely.
- The duration (D) of the end-uses is mainly assessed as a lognormal probability with equal mean and variance. This is not necessarily true for all cases. Improving the model with better estimates of duration would require measurements of microcomponents.
- The probability of a water-use event over the day (τ) is based on many assumptions. For example, occurrences of taking a shower during the day are not explicit in the model due to a lack of information. In the water-use survey of 2007 (Foekema et al. 2008), an extra question was included to determine when, over the day, the shower was being used. Most people indicated taking a shower after getting up in the morning (65%), 42% take a shower before going to bed and 17% take a shower at other times (e.g., after physical exercise). This specific information may improve the model.
- Demand could be a function of network pressure, i.e., with lower pressure I decreases and D may increase. It would be interesting to further investigate how this can be modeled.

A thorough sensitivity analysis is required to determine how accurately parameters must be known. This will provide insight into the applicability of the end-use model and into what improvements will be most effective.

Another expansion of the model can be towards its application outside of The Netherlands. An end-use model can easily be constructed for various neighborhoods in different countries, even in the design stage, provided the statistics are available. Centre for Time Use Research (2007) has links to data from time-use surveys all over the world. Literature on water use, often aimed at coarse water demand management, is available for many countries (e.g. Jacobs and Haarhoff 2004; Memon et al. 2007; Vieira et al. 2007; White et al. 2004). With the information on averages and frequency distributions of the frequency of use, duration and intensity per end-use from the Dutch data and some country specific information, input into the end-use model for other regions can be determined.

The model is based on statistical information about in-home installations and residents; therefore, the influence of an aging population on the total and peak water demand, of the decrease in

Table 6. Statistics of Comparison between Measured and Simulated Frequency Distributions from Figs. 2 and 4; All Values Are Statistically Significant

	ME	RMSE	R^2
Q_{max}(l/5 min)	0.0421 (6%)	0.0886 (13%)	93.8%
Q_{max}(l/h)	−0.0120 (−2%)	0.0440 (6%)	97.8%
V(l/day)	−0.0355 (−5%)	0.0719 (9%)	94.1%
Busy hours	0.0358 (7%)	0.0587 (11%)	97.7%
Q_{CDF}(l/5 min)	−0.0016 (<1%)	0.0038 (<1%)	97.1%
ΔQ_{CDF}(l/5 min^2)	6.3e-6 (<1%)	0.0016 (<1%)	100%

household size, or of the replacement of old appliances with new ones can be easily determined. The end-use model thus enables quantitative scenario studies. Because no flow measurements are needed as an input, the model can be employed before a drinking water distribution system is built and can then be utilized in the design stage and in existing networks where no household water meters are installed.

With the end-use model, a realistic consumption estimation is available and new applications, therefore, come into sight. Water-demand allocation in a water distribution network model can be done without using measured water demand patterns and without the calibration of water demands.

Conclusions

A stochastic end-use model for the simulation of residential water demand was developed. The end-use model is based on statistical information of water-using appliances and (residential) users instead of water demand measurements. The frequency of water use is mainly determined by a Poisson distribution; a negative binomial distribution is applicable to the frequency of use for the kitchen tap. The intensity of water use depends on the type of end-use and was described by a constant or a uniform probability distribution. The duration of water use is either determined by the user and can be described by a lognormal distribution, or by a water-using appliance and can then be described by a constant. The diurnal water use was estimated by using statistical information of users' activities, such as their time of going to bed and getting up, leaving the house and returning home. With limited input information, a pattern was predicted for a fraction of the costs involved in the conventional measuring approach.

First results show that the simulation results are in good agreement with measured water demand patterns. This is true for a range of time scales (from 1 min to 1 h) and a spatial scale of a single home and the sum of 43 homes.

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