Impact of Water Demand Parameters on the Reliability of Municipal Storage Tanks

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Abstract: Municipal storage tanks are normally sized according to inherently conservative design guidelines. An alternative way to determine the required size of a tank, on the basis of a stochastic analysis of the system, was proposed in a previous study, in which it was recommended that tanks should be sized for a minimum reliability of one failure in 10 years at the most critical time of the year, typically under seasonal peak demand conditions. In this study, the same method is used to investigate the impact of different user demand parameters on tank reliability. It was concluded that the supply ratio, defined as the ratio of the source capacity to the average demand in the week considered, is the most important demand-related factor affecting tank reliability. It is shown that the reliability of tanks varies greatly throughout the year, and it is recommended that municipalities do everything possible to ensure that their system runs smoothly over the seasonal peak demand period. Several other important demand factors affecting tank reliability are also identified. It is concluded that the optimal combination of source capacity and tank size should be determined on the basis of economic factors, and that it is likely to be system specific. **DOI:** 10.1061/(ASCE)WR.1943-5452.0000200. © *2012 American Society of Civil Engineers.*

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Introduction

Municipal storage tanks are normally sized for three functions: to balance user demand (balancing storage), provide water for firefighting (fire storage), and maintain the water supply when source interruptions occur (emergency storage). Design guidelines that specify these storage requirements have to cater to a large range of systems and thus need to follow a conservative approach. As a result, it is likely that many storage tanks are larger than they need to be.

Tank-sizing criteria vary widely between different countries and regulatory agencies. In the United States, standards are generally based on those of the Great Lake and Upper Mississippi River Board of State Public Health and Enviornmental Managers (GLUMRB) (1992). These standards state that "storage facilities should have sufficient capacity, as determined from engineering studies, to meet domestic, and where fire protection is provided, fire flow demands." They do not address the issue of risk. Walski (2000) provides an overview of tank-sizing considerations.

Nel and Haarhoff (1996) proposed a stochastic analysis technique for evaluating tank reliability, which employs a Monte Carlo simulation of a system using stochastic models for user demand, fire demand, and pipe failures. Van Zyl et al. (2008) refined this technique and proposed that tanks should be sized for a risk of one failure in 10 years at the most critical time of the year, typically during the seasonal peak demand.

In this study, the stochastic analysis method is used to investigate the reliability of storage tanks for user demand only (i.e., without any fires or source failures). The aim of the study was to determine the impact of different demand parameters on tank reliability and how these parameters affect the required tank capacity. This information may be useful to engineers to identify water demand parameters to include in future tank reliability analyses, inform data measurement and collection strategies, and provide guidance on planning routine maintenance and other interventions that may affect tank reliability. The results are particularly important for systems with reliable water source systems and where fire flows are small compared with normal demands.

A tank failure is simply defined as any period when the tank runs dry. The reliability of a tank is defined in terms of the frequencies and durations of its failures, with more reliable tanks failing less often and for shorter periods. Although failure frequency is likely to be the most critical parameter, the duration of a failure may be more critical in certain circumstances, for instance when important users have a limited capacity of on-site storage available. In this study, tank reliability was based on two parameters: failure frequency and the 95% quantile failure duration.

Because stochastic analysis can only be performed on a specific system, it was necessary to base this work on an example system. The next section provides an overview of the stochastic analysis methodology, followed by a description of the example system used. The stochastic user demand model and its parameters are then discussed, and typical *low*, *very low*, *high*, and *very high* values are estimated for each parameter. The sensitivity analysis results are then presented, followed by a discussion about the relative

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importance of the different demand parameters for tank reliability. Finally, the conclusions of the study are summarized.

Methodology

This study applied the stochastic analysis methodology proposed by van Zyl et al. (2008) to analyze the reliability of a municipal storage tank in a water supply system. The method was implemented using the public domain software EPANET (Rossman 2000) and OOTEN (van Zyl et al. 2003), an object-oriented programmers toolkit for EPANET. The key assumptions of the method can be summarized as follows:

- Only operational factors, consisting of user demands, fire demands, and pipe failures, are considered. Scheduled maintenance events are excluded from the analysis on the basis that these are under the control of a municipality and can be done at low-risk periods during the year. Disasters, such as earthquakes, tornadoes, and terrorist attacks, are specific to a supply system and thus are also excluded. Tank-size requirements for disasters are assumed to form part of the emergency preparedness plans.
- The analysis is done at a particular time, typically a week long, in the year and design horizon. Thus, long-term and seasonal variations in parameters are not included in a simulation run. To consider these, simulations are repeated at different times in the year and design horizon.

The method consists of calculating the stochastic demand parameters for the next day, implementing these parameters in EPANET and then performing an EPANET simulation of the day while logging results and updating tank levels. This process is repeated for a large number of simulation days before the logged data are statistically analyzed and the results presented.

The node in the system at which the tank reliability analysis is to be conducted is specified by the user and the tank sizes to be evaluated. A reservoir node is placed at this position, and the water levels in the different tank sizes are monitored throughout the simulation to identify and log failures for each size. A simplified flow chart of the simulation procedure is presented in Fig. 1.

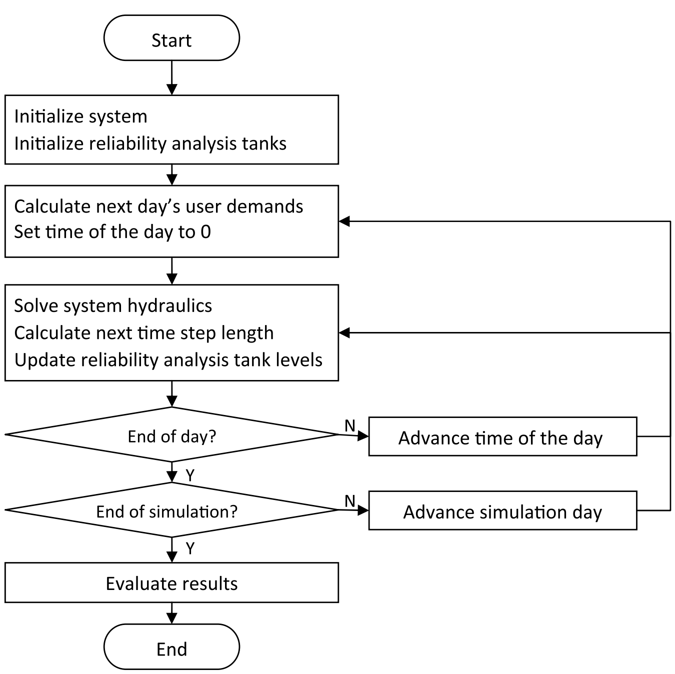

Fig. 1. Simplified flow diagram of stochastic analysis procedure

In their 2008 paper, Van Zyl et al. applied the stochastic analysis method to evaluate the reliability of tanks in an example system consisting of a simple configuration with typical parameter values. They concluded the following on the basis of this system:

- The tank failure rate is very sensitive to the tank size and can be described with an exponential function.
- The average failure duration is not greatly affected by the tank size, and the failure duration distribution of a given tank size follows a Weibull distribution.
- A criterion of one failure in 10 years under seasonal peak conditions was proposed as an acceptable level of reliability for municipal storage tanks. The required tank size for the example system was approximately half that specified by international design guidelines.
- The power of the proposed method lies in its ability to analyze site-specific conditions to determine an appropriate tank size, rather than rely on design guidelines that have to cater to all types of systems and may result in overly conservative tank sizes.

Any given tank size that is analyzed requires a certain minimum number of failures to ensure that its failure statistics are reliable. This number can be determined theoretically or through a sensitivity analysis (van Zyl et al. 2008). In this study, enough simulations were run to ensure that the minimum number of failures of any tank size reported was 2,000. A simulation duration of 10 million days (27,000 years) was used as the default value but was increased when this did not produce enough failures in the tank sizes required. However, a maximum simulation duration of 100 million days (270,000 years) was used, and thus a few results (with fail frequencies lower than 1 failure in 137 years) are based on fewer than 2,000 data points. To determine the failure duration distribution of a tank, the first 2,000 failures were analyzed.

Example System

The study was based on the simple, but frequently used system configuration consisting of a source, tank, and user node [Fig. 2(a)]. The link between the source and tank (Pipe A) consists of two parallel pipes, each of which was subjected to failures independently of the other. Failures of the source itself were not considered, and thus the tank is effectively supplied from two sources.

To ensure the maximum demand load on the tank, Pipe B was not subjected to failures and had negligible hydraulic resistance. Under these conditions, the behavior of the example system will be identical to one in which the users are placed between the source and tank [Fig. 2(b)], and thus the results of the study can be applied to both configurations.

Stochastic Demand Model

User demand was modeled using a generic demand model consisting of an average demand, patterns (e.g., day of the week and hourly), persistence, and a random component. The demand is calculated in two steps: first the average daily demand is calculated, and this is then used as the basis for calculating the hourly demands. In each step, the cyclical patterns are modeled using a multiplicative model and the remainder as an autocorrelated random process. The model for daily demand is as follows:

$$D_d = D_{\text{ave}} \cdot C_{\text{DOW}} \cdot \upsilon_d \tag{1}$$

where D_d = simulated average demand in day d; D_{ave} = average demand for the period studied; C_{DOW} = day-of-the-week (DOW)

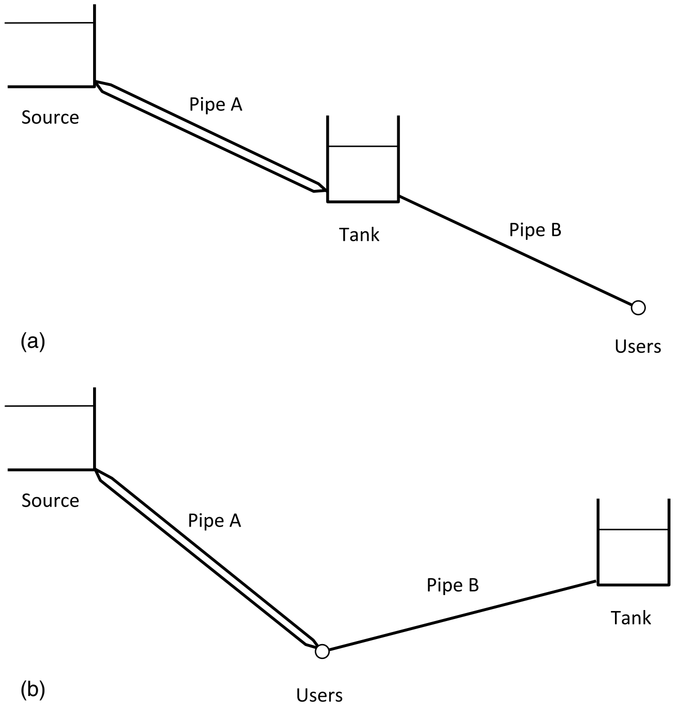

Fig. 2. Equivalent system layouts considered in this study: (a) configuration consisting of source, tank, and users; (b) configuration in which the users are placed between the source and tank

demand factor; and υ_d = daily demand residual function, described by

$$\ln\,\upsilon_d = \sum_{i=1}^{m} \phi_i \ln\,\upsilon_{d-i} + \ln\,\varepsilon_d; \ln\,\varepsilon_d \sim \mathrm{IN}(0, \sigma_D^2) \tag{2}$$

where i = lag counter; m = number of daily autocorrelation lags; ϕ_i = daily autoregression coefficient for lag i; and $\ln\,\varepsilon_d$ = white-noise process. The notation $\ln\,\varepsilon_d \sim \mathrm{IN}(0, \sigma_D^2)$ indicates that the natural logarithms of the residuals are normally and independently distributed with mean 0 and variance σ_D^2.

Autocorrelation is used to describe the persistence inherent in the data (i.e., how much the demand of a current period is affected by previous periods). Persistence may be observed on different temporal scales (Alvisi et al. 2003; Homwongs et al. 1994), and Aly and Wanakule (2004) concluded that persistence is more pronounced in water demand than correlations with weather parameters. Persistence can be identified on a daily or hourly level, and both were included in this study.

The hourly demand variation is modeled with a similar model

$$D_h = D_d \cdot C_h \cdot \upsilon_h \tag{3}$$

where D_h = average demand for hour h; D_d = average demand for the current day; C_h = hourly demand factor; and υ_h = hourly demand residual function, described with an equation similar to the one used to calculate the daily demand residuals.

User Demand Sensitivity Parameters

In this section, the water demand model parameters are discussed with the aim of determining a *typical* value and a realistic range for each parameter. The range is defined by the values that would be described as very low, low, high, and very high. The following rules were used to estimate the parameter ranges:

- Where possible, values were estimated on the basis of available data or published results.
- When a parameter was bounded, the lower or upper bound was often used as the very low or very high value, respectively.
- When little was known about the range of a parameter, the typical value was estimated, and the low, high, and very high parameters were determined by multiplying this value by 0.5, 2, and 4, respectively. The very low value was typically assumed to be 0.

In all cases, the judgment of the authors and the advice of various professionals in the water distribution systems field played a large role. Most typical demand parameter values were based on the measured demands of three small residential towns located in the Moselle area in eastern France as described in van Zyl et al. (2008). A seasonal peak (maximum week) demand of 80 L/s was used. Given the measured seasonal peak factor of 1.49 (rounded to 1.50), this represents an average annual demand of 4.6 ML/day,

Table 1. Sensitivity Analysis Parameters for Water Demand

Parameter	Very low	Low	Typical	High	Very high
Supply ratio					
Supply ratio at seasonal peak	2	1.75	1.5	1.3	1.1
Seasonal peak demand (L/s)	60.0	68.6	80	92.3	109.1
Day-of-the-week pattern					
Peak factor	1.0	1.07	1.14	1.3	1.5
Pattern shape	Oscillating	Declining	Measured	Bulging	Increasing
Daily autocorrelation					
Number of lags	0	—	1	7	28
Lag-1 coefficient	0	0.06	0.12	0.25	0.50
Daily white noise					
Standard deviation	0	0.034	0.068	0.125	0.25
Hourly pattern					
Peak factor	1.00	1.25	1.49	1.75	2.00
Pattern shape	Oscillating	Declining	Measured	Bulging	Increasing
Hourly autocorrelation					
Number of lags	0	—	1	11	23
Lag-1 coefficient	0	0.35	0.70	0.80	0.90
Hourly white noise					
Standard deviation	0	0.065	0.13	0.25	0.50

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which is equivalent to a low-density (suburban) residential area of 3,000–5,000 homes.

The values selected for each demand model parameter are discussed in the following sections, and are summarized in Table 1.

Long-Term and Seasonal Variations

The water demand of an area often displays long-term growth because of increasing income levels, densification, and so forth. In addition, water demand has a strong seasonal pattern because of climatic variations and annual events such as holiday periods. A storage tank will thus experience the greatest stress during the seasonal peak demand in any year, and this stress will be increased every year because of long-term growth.

The critical parameter for long-term demand growth and seasonal variations is likely to be the supply ratio, which is defined as the ratio between the available source capacity (including the source itself and the supply system serving the tank) and the average demand in the week under consideration (called the seasonal demand). The supply system will typically be designed for a certain minimum supply ratio, which is projected to occur during the seasonal peak demand at the end of the design horizon. When the minimum supply ratio is reached, the system has to be upgraded to increase the source and/or tank storage capacities.

It was assumed that the example system has a typical supply ratio of 1.50 during the seasonal peak demand period, which translates to a supply capacity of 120 L/s. The very low, low, high, and very high seasonal peak values were chosen to correspond to supply ratios of 2.0, 1.75, 1.3, and 1.1, respectively.

Day-of-the-Week Pattern

The DOW demand fluctuations are typically small compared with seasonal and diurnal patterns. The authors' demand data had a maximum DOW factor of 1.14, which occurred on a Saturday. This pattern is shown as the typical pattern in Fig. 3. The very low demand pattern was assumed to have no DOW variations. The other patterns were found by pushing this demand pattern closer to 1 or stretching it away from 1 as also shown in Fig. 3. The peak DOW factor for the low, high, and very high, patterns was assumed to be 1.07, 1.3, and 1.5, respectively.

The shape of the DOW curve may also have an effect on tank reliability. To investigate this, the demand factors of the typical DOW curve were rearranged as oscillating, declining, bulging, and increasing as shown in Fig. 4. The oscillating pattern was found by starting with the median value and then alternating higher and lower factors. It was assumed to put the least stress on the tank and

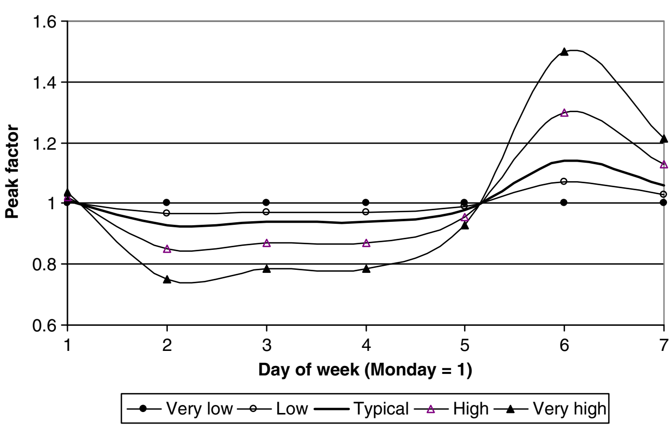

Fig. 3. Day-of-the-week demand patterns

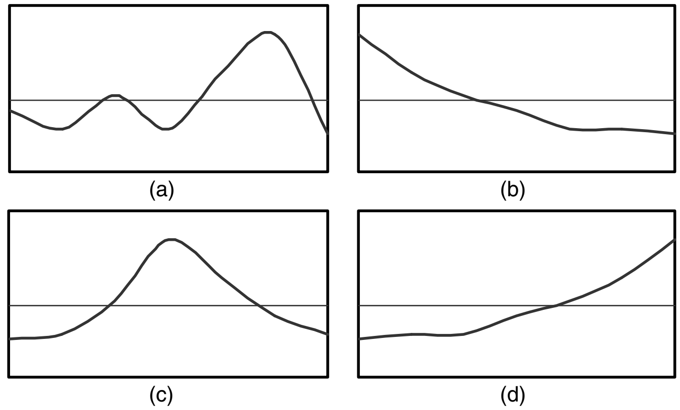

Fig. 4. Demand pattern shapes: (a) oscillating; (b) declining; (c) bulging; (d) rising

was thus assumed to be the very low pattern. The declining, bulging, and rising patterns were assumed to be the low, high, and very high values, respectively.

Daily Persistence

Daily persistence is defined by the number of elements in the autocorrelation series and their values. The daily autocorrelation coefficients in the measured demand data were analyzed up to a lag of 30 days, and the statistically significant daily coefficients are shown in Fig. 5.

The coefficients start with a positive coefficient at lag 1, and then remain negative for the remainder of the lags. The authors decided to only use the lag-1 autocorrelation coefficient with a value 0.12 for the typical case. Alvisi et al. (2007) also used a lag-1 autocorrelated process to model daily water demand. An advantage of this approach is that when testing the sensitivity of the autocorrelation coefficient value, only one positive coefficient is varied. This removes the possible negating effect that further negative coefficients might have on the impact of this parameter.

For the very low value, no autocorrelation coefficient (i.e., no daily persistence) was assumed. For the high and very high values, the measured lags of 7 and 28 days, respectively, were used. No low value was modeled.

Autocorrelation coefficient values can be between -1 and 1. A negative lag-1 coefficient is highly unlikely for a water demand process, and thus the very low value was assumed to be 0 (no daily persistence). The lag-1 autocorrelation coefficient value in the authors' demand data (0.12) was assumed to be the typical value. Because of the relatively low value in the measured data, it was decided not to use the upper bound of the lag-1 autocorrelated process as the very high value, but rather a value of 0.5. The low and high values were assumed to be 0.06 and 0.25, respectively.

Daily Random Component

In a good model, the remaining random component should have a zero mean and constant variance (Homwongs et al. 1994). The zero mean of the daily residuals in the " data was confirmed using the chi-square test. The Kolmogorov-Smirnov test rejected normality of natural logs of the residuals, probably because of a high kurtosis and some skewness in the data. However, the natural logs of the residuals were judged to be close enough to a normal distribution to assume normality. In addition, normal distributions were used by several others, including Xu et al. (1998) and Aly and Wanakule (2004).

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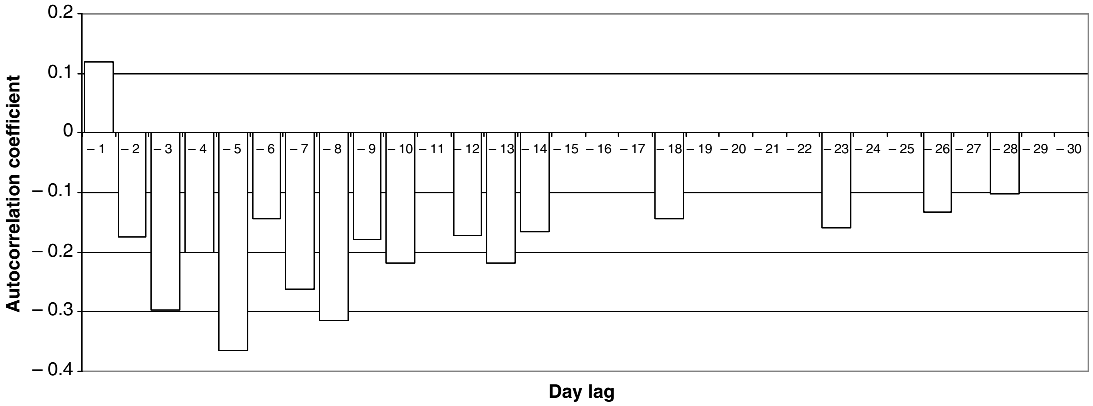

Fig. 5. Significant daily autocorrelation coefficients in the demand data

The base value of the standard deviation was assumed to be that determined from the authors' data (i.e., 0.068). Values for the very low, low, high, and very high standard deviations were assumed to be 0 (no random component), 0.034, 0.125, and 0.25, respectively.

Hourly Pattern

The hourly pattern in the authors' demand data follows a classical residential demand pattern with factors varying between 0.38 and 1.49. No distinction was made between the behavior of week and weekend days as these displayed similar hourly patterns.

Barnes et al. (1986) published ranges of peak factors at different temporal scales and climatic zones. These values were used to estimate the range of hourly peak factors to be between 1.4 and 2.0.

Fig. 6 shows the author' measured pattern, which was assumed to be the typical pattern, and the other patterns used in the sensitivity analysis. The very low pattern was assumed to have no hourly variations. The high and low patterns were obtained by scaling the typical pattern to obtain peak factors of 1.25 and 1.75, respectively. The very high pattern was assumed to have an hourly peak factor of 2, but when the typical pattern was scaled to this peak, the lowest factors became negative. To correct this, these negative factors were set equal to 0, and the shape of the morning peak adjusted to return the average to 1.

The shape of the hourly curve was also investigated by arranging the demand factors as shown in Fig. 4.

Hourly Persistence

The hourly persistence for the authors' demand data was analyzed, and the statistically significant coefficients are shown in Fig. 7.

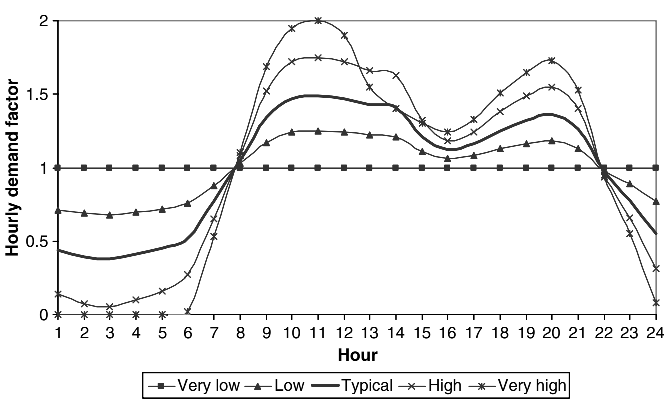

Fig. 6. Hourly demand patterns used

The series starts with a high lag-1 coefficient of 0.70, and the other coefficients are all substantially smaller.

In a previous study, Homwongs et al. (1994) modeled hourly water demand using a lag-2 autocorrelated process. However, because the demand data have such a dominating lag-1 coefficient and no significant lag-2 coefficient, the authors decided to use a lag-1 model for the typical case. For the very low value, autocorrelation was removed to represent a system without any persistence on an hourly level. For the high and very high values, lags up to 11 and 23 h, respectively, were used. No low value was modeled.

The lag-1 daily autocorrelation coefficient was assumed to be the authors' measured value of 0.7. Values for the very low and low values were assumed to be 0 (no hourly persistence) and 0.35, respectively. The very high coefficient was assumed to be 0.90, close to the upper bound of 1, and the high coefficient was assumed to be 0.80.

Hourly Random Component

As in the case of the daily residual data, normality of the natural logarithms was assumed after the zero mean of the hourly residuals was confirmed by the chi-square test, and the Kolmogorov-Smirnov test rejected normality.

The base value of the standard deviation was assumed to be that determined from the authors' data (i.e., 0.13). Values for the very low, low, high, and very high values were assumed to be 0 (no white noise), 0.065, 0.25, and 0.5, respectively.

Results

The system was first analyzed with all parameters set to their typical values. The results show that the tank fail frequency reduces exponentially with increasing capacity as shown in Fig. 8. Tank capacity is expressed as hours of the seasonal peak demand.

The results show that a tank capacity of 7 h of demand will result in an average failure rate of one failure per year. Increasing the tank by 2.8 h (40%) will reduce the failure rate to one failure in 10 years, and another 2.8 h capacity increase will reduce the rate to one failure in 100 years.

Van Zyl et al. (2008) proposed that tanks are sized for a probability of one failure in 10 years at the most critical time of the year. Thus, a tank capacity of 10 h of seasonal peak demand (or 15 h of annual average demand) was selected for the example system.

The distribution of failure durations for the 10 h tank is shown in Fig. 9. The median failure duration is 1.8 h, and 95% of failures are shorter than 5.4 h.

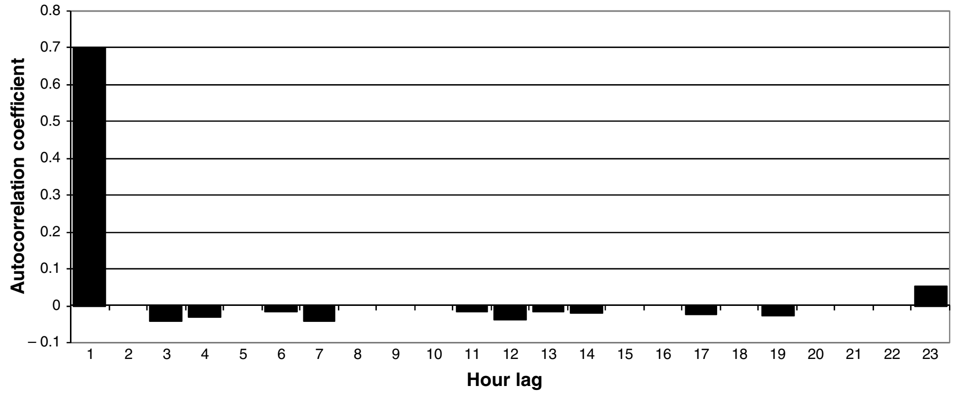

Fig. 7. Significant hourly autocorrelation coefficients in the demand data

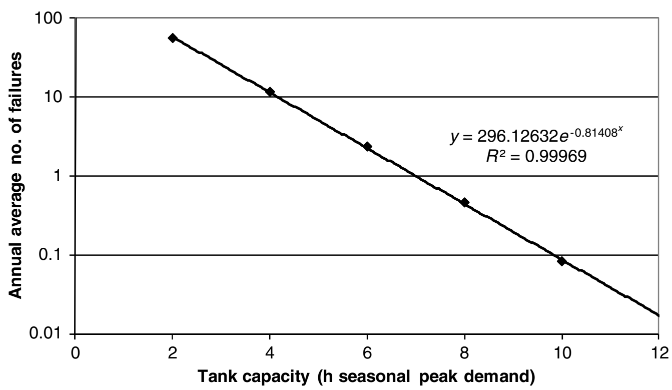

Fig. 8. Failure frequency as a function of tank capacity for the typical system

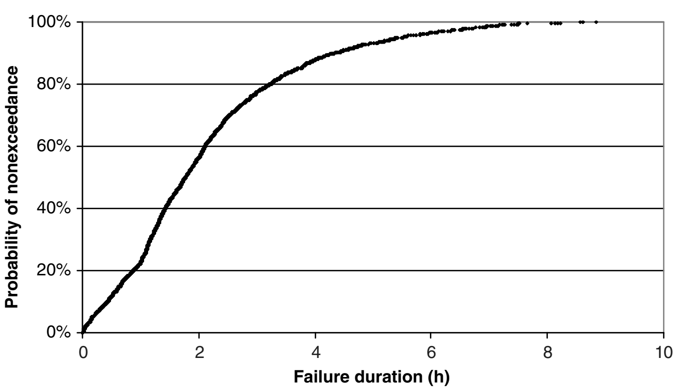

Fig. 9. Failure duration distribution for a tank in the typical system with a capacity of 10 h of seasonal peak demand

Impact of the Supply Ratio

The supply ratio has to be a critical factor for tank reliability, and it is also the only factor that the designer can control. Thus, it was investigated first by varying the source capacity to obtain supply ratios between 1.05 and 2. It was found that a 10 h capacity tank did not fail at all with a supply ratio of 2, even after the simulation duration was extended to 100 million days. A supply ratio of 1.75 produced 175 failures in the extend simulation run.

The effect of the supply ratio on the tank failure frequency of a 10 h capacity tank is shown in Fig. 10. The failure frequency

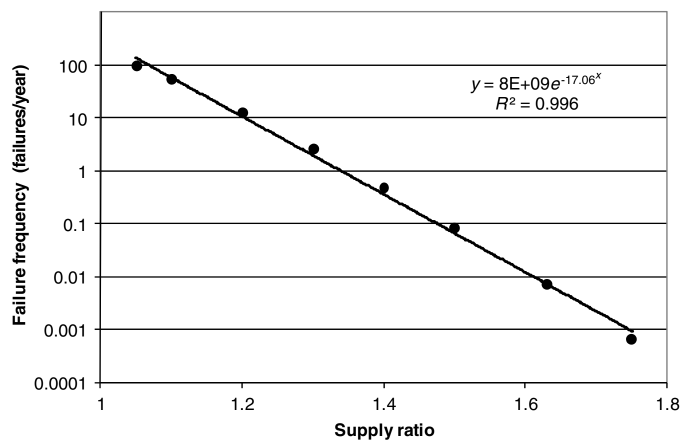

Fig. 10. Tank failure frequency as a function of the supply ratio

increases exponentially with decreasing supply ratio, even as the supply ratio gets close to a value of 1. A failure rate of 2.3 failures per day is predicted for the example system at a supply ratio of 1. This seems reasonable because 2 failures per day can be expected due to the morning and afternoon peaks, and further failures will occur as a result of random demand fluctuations.

The supply ratio also significantly affects the failure duration distribution as shown in Fig. 11 for the 50% (median), 90%, and 95% quantiles of the failure duration.

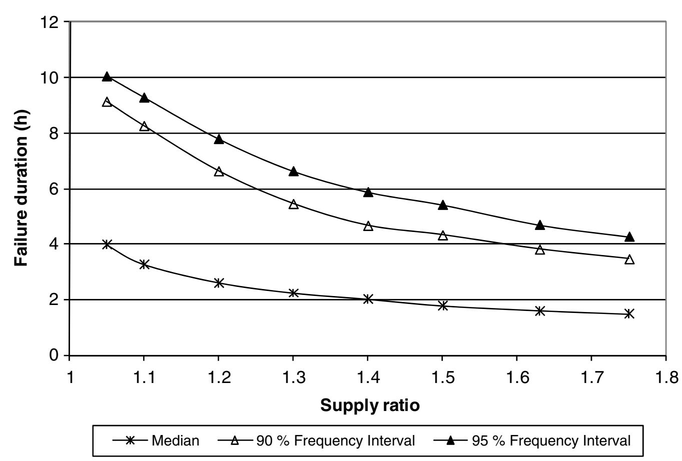

Fig. 11. Tank failure duration as a function of the supply ratio

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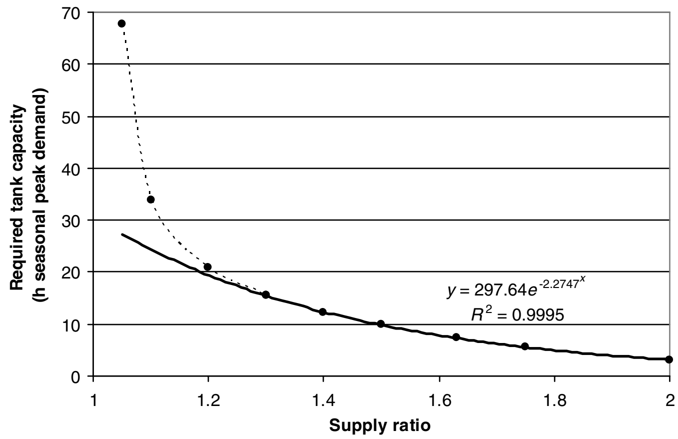

Fig. 12. Required tank capacity as a function of the supply ratio

The relationship between the required tank capacity and the supply ratio is shown in Fig. 12. Conceptually, it is possible to determine upper and lower extremes for this relationship: at one extreme, no storage tank is required if the source capacity is adequate for the instantaneous peak demand. This is reflected in the exponential reduction in the required tank capacity with increasing supply ratio. The function never reaches zero because of the stochastic nature of the demand.

At the other extreme, an infinitely large tank would be required if the source capacity is below the annual average demand. This is evident from the way that the required tank capacity moves away from the otherwise exponential function at a supply ratio of 1.3, and increases asymptotically when the supply ratio reduces toward 1.

A supply ratio of 1.3 may look like a potential design value. However, the result will be a source capacity that has almost twice the capacity of the annual average demand and may not be the most economical solution for all systems. It is likely that economic factors will be the overriding consideration in determining the optimal supply ratio.

Seasonal Variations in Tank Reliability

The very high sensitivity of tank reliability to the supply ratio indicates that the reliability of storage tanks will vary greatly with seasonal variations in demand. The relationship between tank failure frequency and the supply ratio (Fig. 10) was used to estimate the seasonal variations in tank reliability. The seasonal demand pattern was assumed to vary smoothly between a minimum demand factor of 0.65 in January and a maximum demand factor of 1.5 in August.

The resulting variation in tank reliability is profound as shown in Fig. 13, varying by 15 orders of magnitude between the winter and summer peaks. These results do not consider fire and pipe failures and thus are likely to vary less in a real system.

The results indicate that a municipality should make every effort during the few weeks of seasonal peak demand to ensure that the bulk supply system runs smoothly at total capacity, and that all tanks are kept as full as possible. During the off-peak period, the municipality has considerable opportunity to do preventative maintenance and noncritical repairs without compromising tank reliability.

Major Demand Parameters

The sensitivity analysis as described previously and in Table 1 identified the following six parameters that have major impacts on tank reliability:

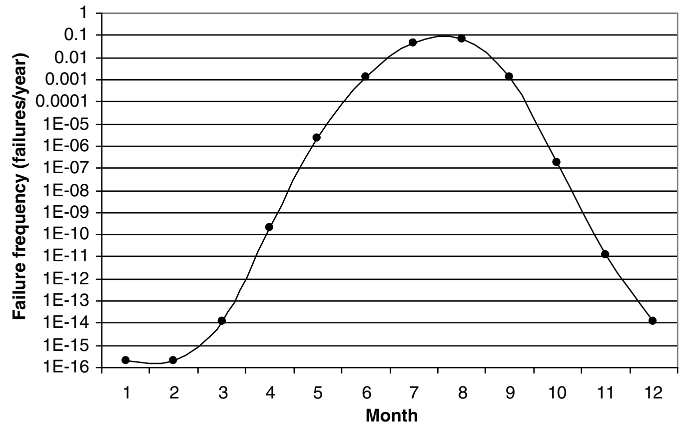

Fig. 13. Seasonal variations in tank failure frequency for a demand-only system

- Supply ratio,
- DOW peak factor,
- Hourly peak factor,
- Daily random component (white-noise standard deviation),
- Hourly persistence (lag-1 autocorrelation coefficient), and
- Hourly random component (white-noise standard deviation).

The impact of these factors on the tank failure frequency is shown in Fig. 14, and their impact on the 95% quantile of failure duration is shown in Fig. 15.

Although the hourly random component showed the greatest impact on failure frequency, this finding is not considered reliable because the values used in the sensitivity analysis were not based on measured data, but estimated by doubling and redoubling the typical value. These values are likely to be unrealistic, especially when considered with the very high autocorrelation coefficient of 0.7.

The supply ratio is considered to be the dominant factor for failure frequency and is also very important for the failure duration behavior. This, coupled with the fact that it is the only factor that can be controlled by the water supplier, identifies it as the most important parameter affecting tank reliability. It is critical that the designer selects the optimal combination of tank size and source capacity to ensure a reliable supply at minimum cost.

The other major parameters have very similar effects on the tank fail frequency for the high and very high cases, increasing the fail frequency by one order of magnitude in each step. The only

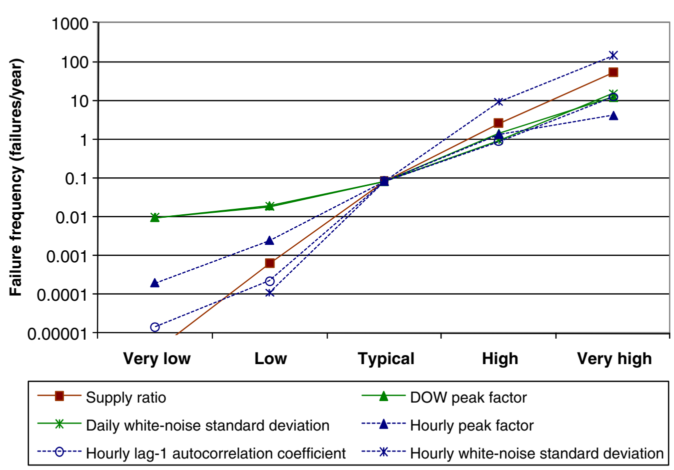

Fig. 14. Impact of major demand parameters on tank failure frequency

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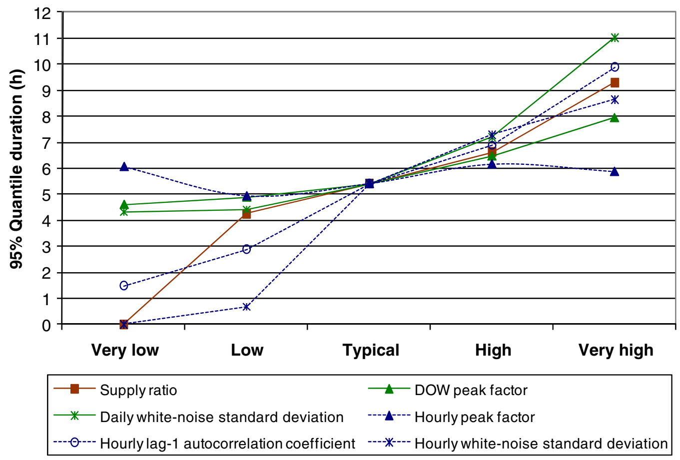

Fig. 15. Impact of major demand parameters on failure duration

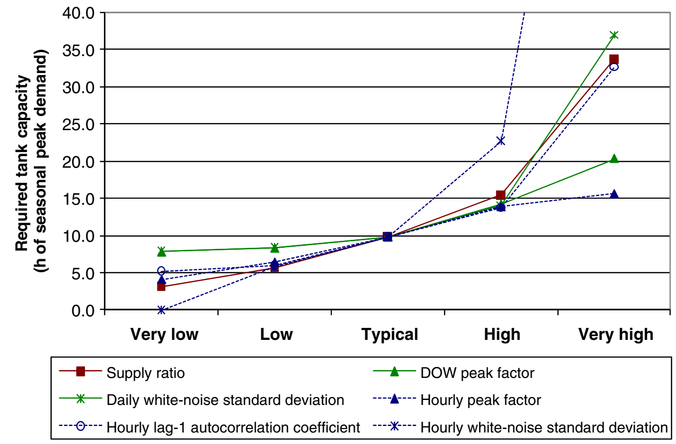

Fig. 16. Required tank capacity for the major demand parameters

exception is the hourly peak factor, which has a lower impact than the others for the very high case.

The impact of the major parameters on the failure duration was substantially lower than on the failure frequency: in the worst cases (daily random component and hourly persistence), the 95% quantile failure duration was approximately doubled. In comparison, the increases in the failure frequency were as much as two orders of magnitude. The lower sensitivity of failure duration, in combination with a finding by Kwietniewski and Roman (1997) that failure frequency is more important to consumers that failure duration, indicates that the failure frequency is a more appropriate tank reliability measure than the failure duration, although the latter may be important in certain cases (e.g., when the emergency storage capacity of hospitals and other critical infrastructure are exceeded).

An important factor to consider is the uncertainty in the sensitivity parameter values: the supply ratio is controlled by the designer, and quite a lot is known about DOW and hourly peak factors in distribution systems. In contrast, relatively little is known about the range of values that persistence and random demand components can take on. It is likely that the large ranges selected for these parameters in the study are conservative, and that their true impacts are lower than shown in this paper. In particular, the hourly autocorrelation factor gets close to its maximum possible value of 1, and it is unlikely that such a high autocorrelation will occur in practice. It is recommended that persistence and random fluctuations in demands be verified for a system before stochastic analyses are applied to it.

A larger variation in the effects of the major parameters was found for the low and very low cases. Beside the supply ratio, the hourly lag-1 coefficient showed the greatest reduction in failure frequency, followed by the hourly peak factor. The other parameters had comparatively little or no impact on the lower side of the typical parameters.

It has been shown that tank reliability is very sensitive to the tank capacity (Fig. 8), and thus the large impact of the major demand parameters may well be countered by increasing the tank size and/or increasing the supply ratio. The required tank capacities were determined for all major sensitivity parameters and are shown in Fig. 16.

It is evident from the figure that tank size can be used effectively to counteract the effects of most demand parameters. A tank with a capacity of 24 h of seasonal peak demand will be sufficient for all values of the demand parameters, with the exception of the very high values for the daily random component, the hourly persistence, and the supply ratio. As discussed, the sensitivity analysis values for the random demand components could not be based on data, and thus these results may not be significant. The supply ratio is less of a problem because it can be controlled by the designer.

Finally, the simulation of the typical system was repeated after removing all model parameters except the major parameters: the results were within 2.5% of the all-parameter model for both the failure frequency and duration parameters. It may thus be concluded that only the major demand parameters have to be estimated accurately (or at least conservatively) to obtain reliable results from the stochastic analysis model.

Minor Demand Parameters

The results showed that the following parameters have little or no impact on tank reliability and will be referred to as "minor" demand parameters:

- The number of daily autocorrelation coefficients,
- Daily persistence (lag-1 autocorrelation coefficient),
- DOW demand pattern shape,
- Hourly demand pattern shape, and
- Number of hourly autocorrelation coefficients.

The most significant of the minor factors is the number of daily autocorrelation coefficients, which increased the failure frequency to one failure every 3.6 years in the very high case.

Conclusions

In this study, the stochastic analysis method proposed by van Zyl et al. (2008) was used to investigate the impact of different demand parameters on the reliability of municipal storage tanks. The method was applied to two hydraulically equivalent example systems with typical stochastic parameters for low-density residential settlements. The tank size for this system was determined on the basis of an allowable failure frequency of one failure in 10 years under seasonal peak conditions, which resulted in a typical tank size of 10 h of seasonal peak demand.

A sensitivity analysis of user demand parameters on tank reliability was then conducted. A typical value was estimated for each demand parameter, as well as very low, low, high, and very high values. The demand parameters were varied one at a time to determine the impact of each on the tank reliability. Fires and pipe failures were not considered.

The main conclusions of the study can be summarized as follows:

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- The supply ratio (the ratio of the source capacity to the average demand in the week considered) is the most important demand-related factor that affects tank reliability, especially in terms of failure frequency, but also failure duration. It is the only parameter in this study that can be influenced by the water supplier, and thus provides an important tool for managing tank reliability.
- Because of the very high sensitivity of tank reliability to the supply ratio, a tank will undergo profound changes in its reliability throughout the year as the seasonal demand (and thus the supply ratio) varies. This indicates that everything possible should be done to ensure that the system functions effectively during the few weeks of seasonal peak demand, and that maintenance and noncritical repairs should be done during off-peak periods.
- Failure frequency is not only much more sensitive to changes in demand parameters than failure duration, but according to Kwietniewski and Roman (1997), users are also more sensitive to failure frequency than failure duration. Failure frequency is thus a more appropriate measure of tank reliability than failure duration, although the latter may be important in certain cases (e.g., when the emergency storage capacity of hospitals and other critical infrastructure is exceeded).
- Besides the supply ratio, the most important demand parameters for tank reliability are the DOW and hourly peak factors, the daily and hourly random components, and the hourly persistence. The results showed that only the major demand parameters have to be estimated accurately (or at least conservatively) to obtain reliable results. Further research is required to confirm that the range of values for the daily and hourly random components and hourly persistence used in the sensitivity analyses are realistic and not overly conservative.
- The optimal combination of source and tank capacities to ensure the required level of reliability at minimum cost would likely be determined by economic factors and is likely to be system dependent.

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