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, based on a stochastic analysis of the system, was proposed by Van Zyl et al (2008). They recommended that tanks are sized for a minimum reliability of one failure in ten years at the most critical time of the year, typically being 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 source capacity over 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 through 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

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concluded that the optimal combination of source capacity and tank size should be determined based on economical factors, and that it is likely to be system specific.

Keywords: Water distribution systems, Storage tanks, Reliability, Stochastic models, Water demand

INTRODUCTION

Municipal storage tanks are normally sized for three functions: to balance user demand (balancing storage), provide water for fire fighting (fire storage), and maintain the water supply when source interruptions occur (emergency storage). Design guidelines that specify these storage requirements have to cater for 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 US, standards are generally based on GLUMRB (1992). These state “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 are sized for a risk of one failure in ten years at the most critical time of the year, typically being 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 impact on 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 impact on 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. While 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.

Since 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 and the relative importance of the different demand parameters on tank reliability is discussed, before 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 control of a municipality and can be done at low risk periods in the year. Disasters, such as earthquakes, tornados and terrorist attacks are specific to a supply system, and are thus 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 simulation days before the logged data is 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, as well as 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 Figure 1.

Ideal position for Figure 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 parameters values. They concluded the following based on 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 ten 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 roughly 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 for 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 2000. 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 one failure in 137 years) are based on fewer than 2000 data points. To determine the failure duration distribution of a tank, the first 2000 failures were analyzed.

EXAMPLE SYSTEM

The study was based on the simple, but frequently used system configuration consisting of a source, tank and a user node (Figure 2a). 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 where the users are placed between the source and tank (Figure 2b), and thus the results of the study can be applied to both configurations.

Ideal position for Figure 2 Equivalent system layouts considered in this study.

STOCHASTIC DEMAND MODEL

User demand was modeled using a generic demand model consisting of an average demand, patterns (e.g. day-of-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 basis for calculating the hourly demands. In each step the cyclical patterns are modeled using a multiplicative model and the remainder as an auto-correlated random process. The model for daily demand is as follows:

$$D_d = D_{ave} \cdot C_{DOW} \cdot \upsilon_d \qquad (1)$$

Where D_d is the simulated average demand in day d, D_{ave} is the average demand for the period studied, C_{DOW} is a day-of-week demand factor and υ_d is the daily demand residual function, described by:

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

Were i is a lag counter, m the number of daily autocorrelation lags, ϕ_i the daily auto regression coefficient for lag i and $\ln\varepsilon_d$ a white-noise process. The notation

$\ln \varepsilon_d \sim \mathrm{IN}\left(0, \sigma_D^2\right)$ indicates that the natural logarithms of the residuals are normally and independently distributed with mean 0 and variance σ_D^2.

Auto-correlation 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 is the average demand for hour h, D_d is the average demand for the current day, C_h is the hourly demand factor and υ_h is the hourly demand residual function, described with a similar equation as 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 based on available data or published results.
- When a parameter is bounded, the lower or upper bound was often used as the *very low* or *very high* value.

- When little is known about the range of a parameter, the *typical* value was estimated, and the *low*, *high* and *very high* parameters determined by multiplying this value by 0.5, 2 and 4 respectively. The *very low* value was typically taken as zero.

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 the east of 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 (say 1.50), this represents an average annual demand of 4.6 ML/ day, which is equivalent to a low density (suburban) residential area of 3 to 5 thousand 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

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

Day-of-the-week (DOW) demand fluctuations are typically small compared to seasonal and diurnal patterns. Our demand data had a maximum DOW factor of 1.14, which occurred on a Saturday. This pattern is shown as the *typical* pattern in Figure 3. The *very low* demand pattern was taken 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 Figure 3. The peak DOW factor for the *low*, *high* and *very high* patterns were assumed to be 1.07, 1.3 and 1.5 respectively.

Ideal position for Figure 3 Day-of-the-week demand patterns

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 was re-arranged as oscillating, declining, bulging and increasing as shown in Figure 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 was thus taken as the *very low* pattern. The declining, bulging and rising patterns were taken as *low*, *high* and *very high* values respectively.

Ideal position for Figure 4 Demand pattern shapes: (a) oscillating, (b) declining, (c) bulging, (d) rising.

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 Figure 5.

The coefficients starts with a positive coefficient at lag one, and then remain negative for the remainder of the lags. It was decided to only use the lag-one autocorrelation coefficient with a value 0.12 for the *typical* case. Alvisi et al. (2007) also used a lag-one auto correlated process to model daily water demand. An advantage of this approach is that, when testing the sensitivity of the auto-correlation 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.

Ideal position for Figure 5 Significant daily auto-correlation coefficients in the demand data

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 have values 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 our demand data (0.12) was assumed to be the *typical* value. Due to the relatively low value in the measured data, it was decided not to use the upper bound of the lag-1 auto correlated 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 our data was confirmed using the chi-square test. The Kolmogorov-Smirnov test rejected normality of natural logs of the residuals, probably due to 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).

The base value of the standard deviation was assumed to be that determined from our 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 our 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 (1981) 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.

Figure 6 shows our measured pattern, which was taken as the *typical* pattern, as well as 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 zero, and the shape of the morning peak adjusted to return the average to one.

Ideal position for Figure 6 Hourly demand patterns used

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

Hourly persistence

The hourly persistence for our demand data was analyzed, and the statistically significant coefficients are shown in Figure 7. The series start with a high lag-1 coefficient of 0.70, and the other coefficients are all substantially smaller.

Ideal position for Figure 7 Significant hourly auto-correlation coefficients in the demand data

In a previous study, Homwongs et al (1994) modeled hourly water demand using a lag-2 auto-correlated process. However, since the demand data has such a dominating lag-1 coefficient and no significant lag-2 coefficient, it was 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 hours respectively were used. No *low* value was modeled.

The lag-1 daily autocorrelation coefficient was assumed to be our 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 taken as 0.90, close to the upper bound of one, and the *high* coefficient as 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 our 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.

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

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 Figure 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 to one failure in 100 years.

Ideal position for Figure 8 Failure frequency as a function of tank capacity for the typical system

Van Zyl et al (2008) proposed that tanks are sized for a probability of one failure in ten years at the most critical time of the year. Thus a tank capacity of 10 hours 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 Figure 9. The median failure duration is 1.8 h, and 95 % of failures are shorter than 5.4 h.

Ideal position for Figure 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 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 Figure 10. The failure frequency increases exponentially with decreasing supply ratio, even as the supply ratio gets close to a value of one. It is interesting to note that a failure rate of 2.3 failures per day is predicted for the example system at a supply ratio of one. This seems reasonable, since two failures per day can be expected due to the morning and afternoon peaks, and further failures will result as a result of random demand fluctuations.

Ideal position for Figure 10 Tank failure frequency as a function of the supply ratio.

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

Ideal position for Figure 11 Tank failure duration as a function of the supply ratio.

The relationship between the required tank capacity and the supply ratio is shown in Figure 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 due to 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 towards one.

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.

Ideal position for Figure 12 Required tank capacity as a function of the supply ratio.

Seasonal Variations in Tank Reliability

The very high sensitivity of tank reliability to the supply ratio means that the reliability of storage tanks will vary greatly with seasonal variations in demand. The relationship between tank failure frequency and the supply ratio (Figure 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 Figure 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 mean 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 non-critical repairs without compromising tank reliability.

Ideal position for Figure 13 Seasonal variations in tank failure frequency for a demand only system.

Major Demand Parameters

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

- Supply ratio
- DOW peak factor

- Hourly peak factor
- Daily random component (white noise standard deviation)
- Hourly persistence (lag-1 autocorrelation coefficient)
- Hourly random component (white noise standard deviation)

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

Although the hourly random component showed the greatest impact on failure frequency, this finding is not considered reliable since 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 this 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 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 roughly 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, means 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 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 here. In particular, the hourly autocorrelation factor gets close to its maximum possible value of one, and it is unlikely that such a high autocorrelation will occur in practice. It is recommended that persistence and random fluctuations in demands are verified for a system before stochastic analyses is applied to it.

Ideal position for Figure 14 Impact of major demand parameters on tank failure frequency.

A larger variation in the effects of the major parameters was found for the *low* and *very low* cases. Besides 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.

Ideal position for Figure 15 Impact of major demand parameters on failure duration.

It has been shown that tank reliability is very sensitive to the tank capacity (Figure 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 Figure 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 hours of seasonal peak demand will be sufficient for all values of the demand parameters, with the exception of the *very high* values for daily random component, 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 since 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.

Ideal position for Figure 16 Required tank capacity for the major demand parameters.

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
- Number of hourly autocorrelation coefficients

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 based on an allowable failure frequency of one failure in ten years under seasonal peak conditions, which resulted in a *typical* tank size of 10 hours 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:

- The supply ratio (source capacity over 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.

- Due to the very high sensitivity of tank reliability to the supply ratio, a tank will undergo profound changes in its reliability through the year as the seasonal demand (and thus the supply ratio) varies. This means 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 non-critical 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 are 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 are likely to be system dependent.

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Figure 1 Simplified flow diagram of stochastic analysis procedure

Figure 2 Equivalent system layouts considered in this study.

Figure 3 Day-of-the-week demand patterns

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

Figure 5 Significant daily auto-correlation coefficients in the demand data

Figure 6 Hourly demand patterns used

Figure 7 Significant hourly auto-correlation coefficients in the demand data

Figure 8 Failure frequency as a function of tank capacity for the *typical* system

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

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

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

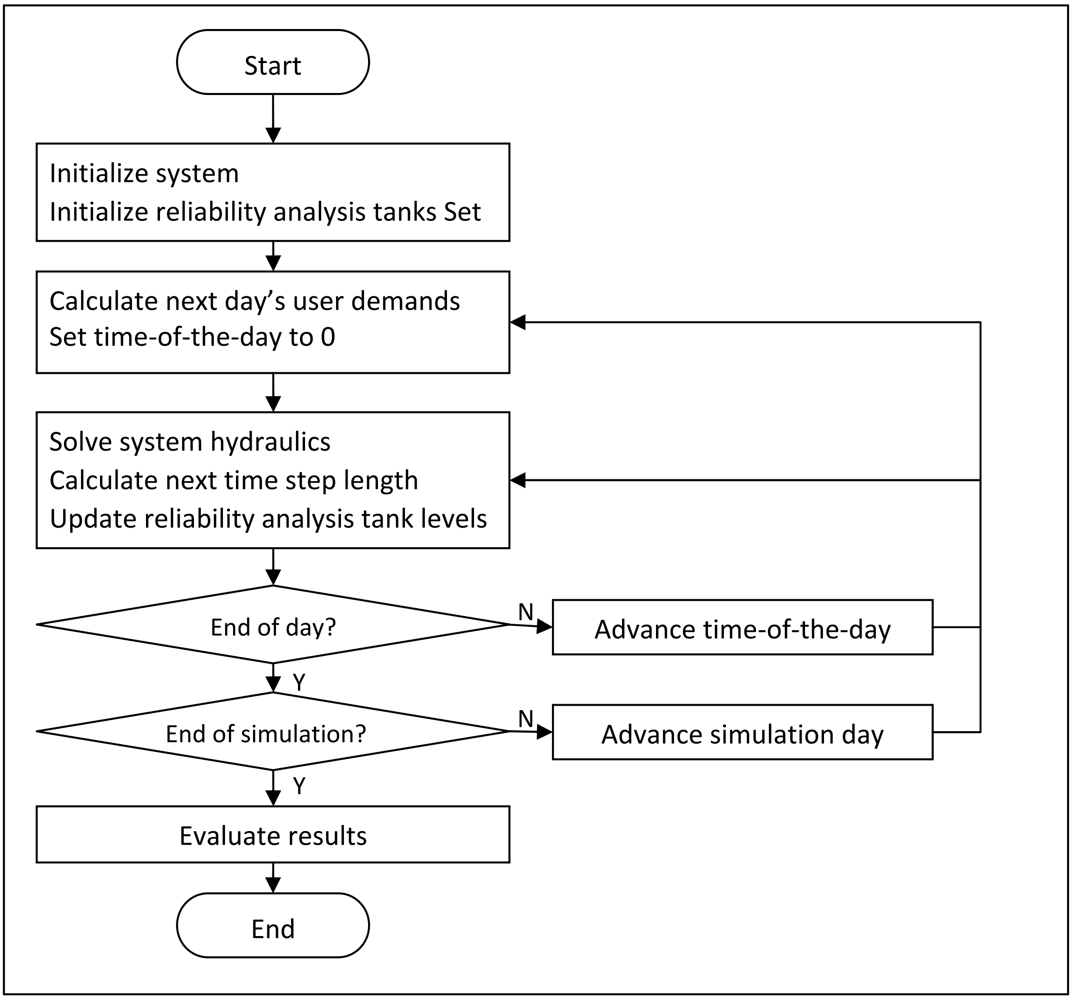
Figure 12 Required tank capacity as a function of the supply ratio.

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

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

Figure 15 Impact of major demand parameters on failure duration.

Figure 16 Required tank capacity for the major demand parameters.



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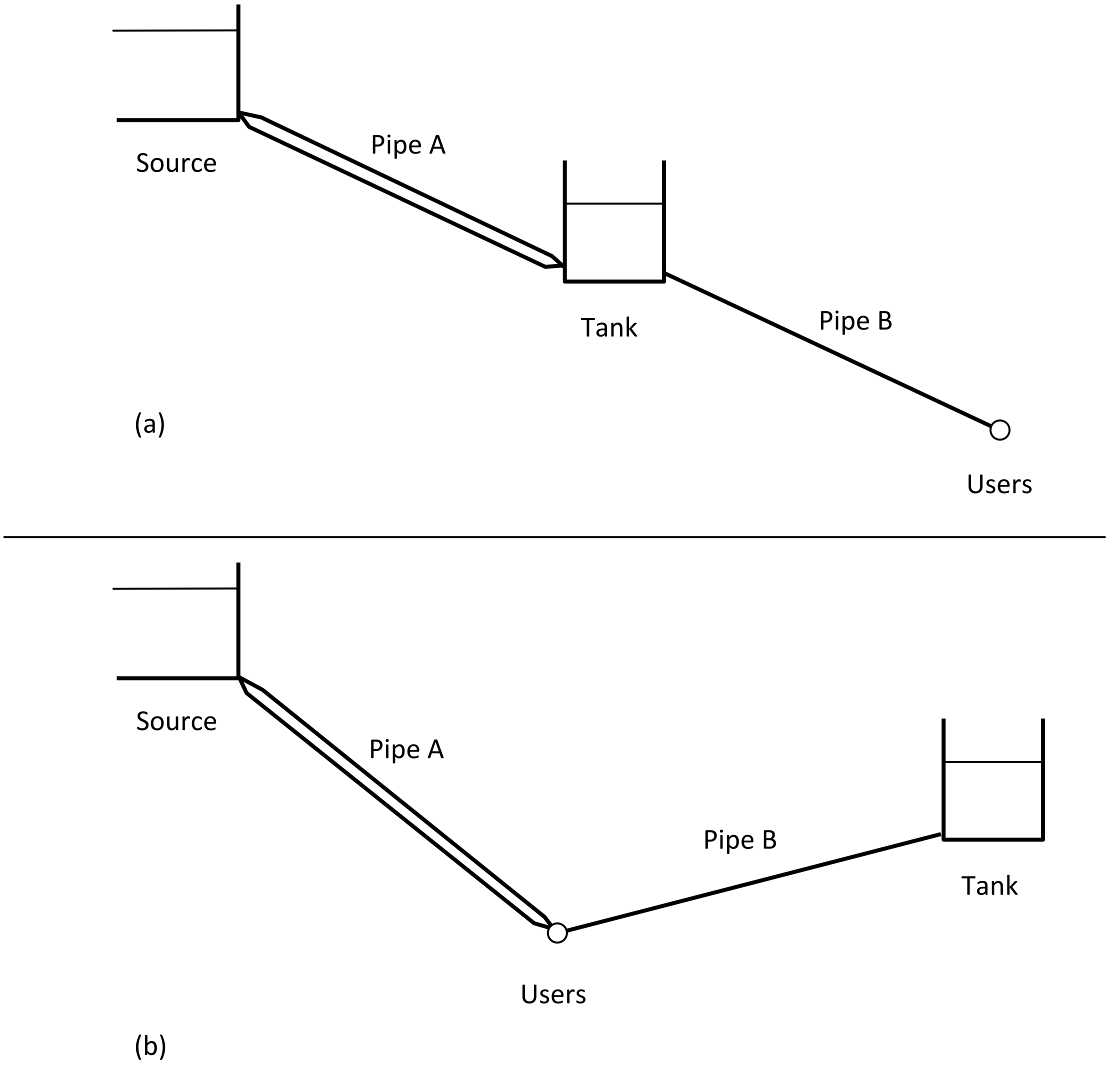

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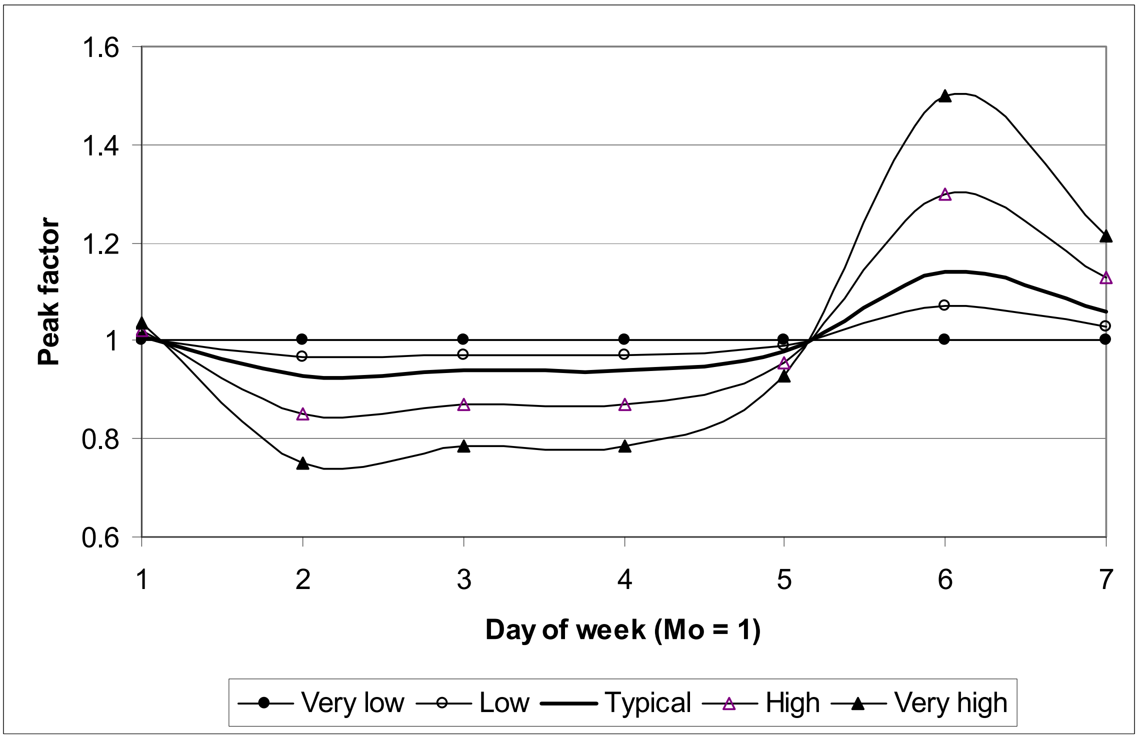
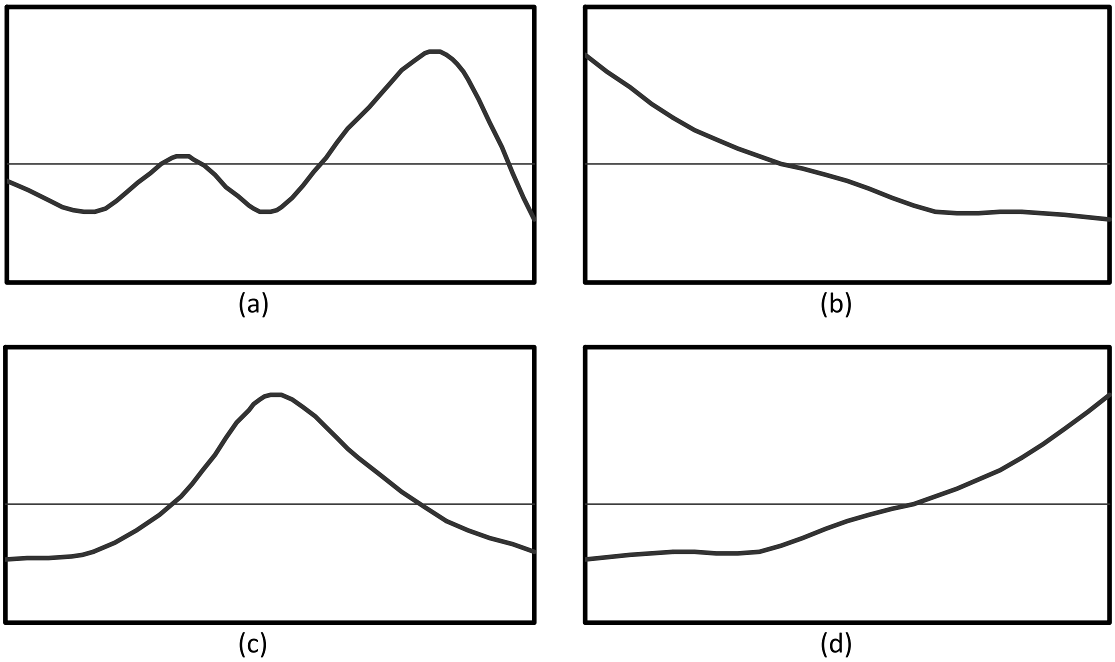


Figure 3 Day-of-the-week demand patterns



(a) (b) (c) (d)

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

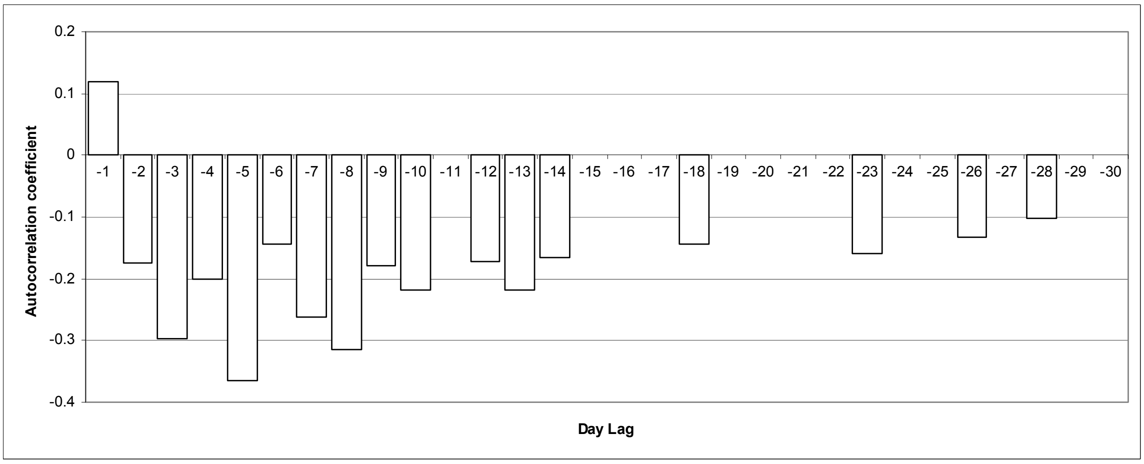


Figure 5 Significant daily auto-correlation coefficients in the demand data

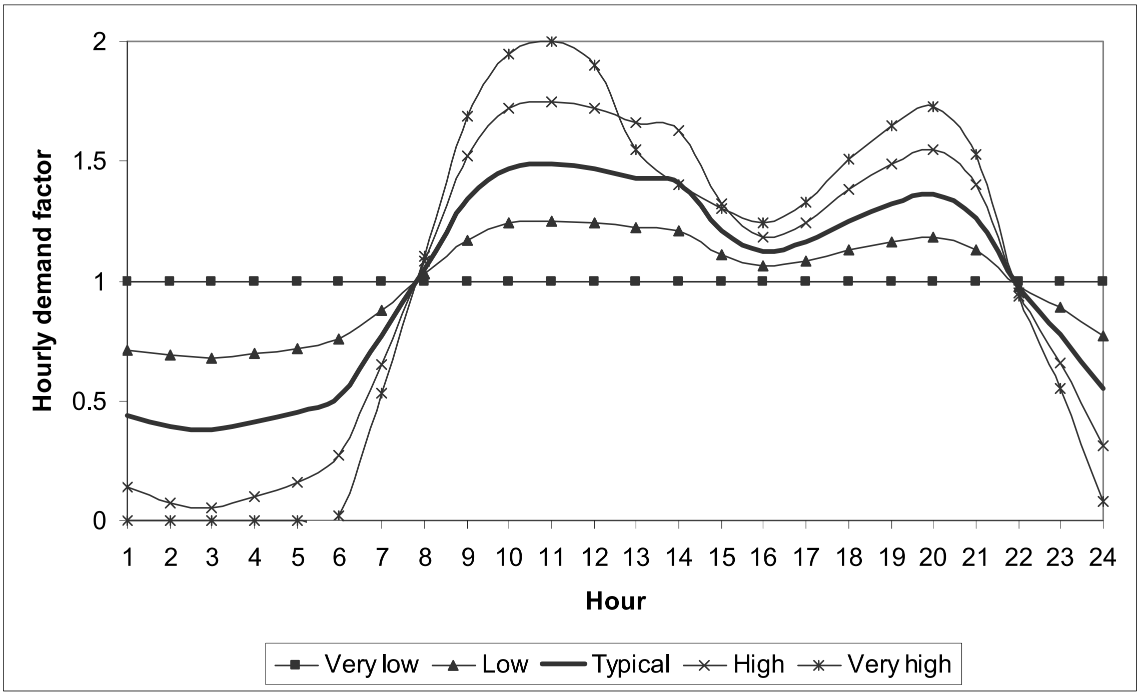


Figure 6 Hourly demand patterns used

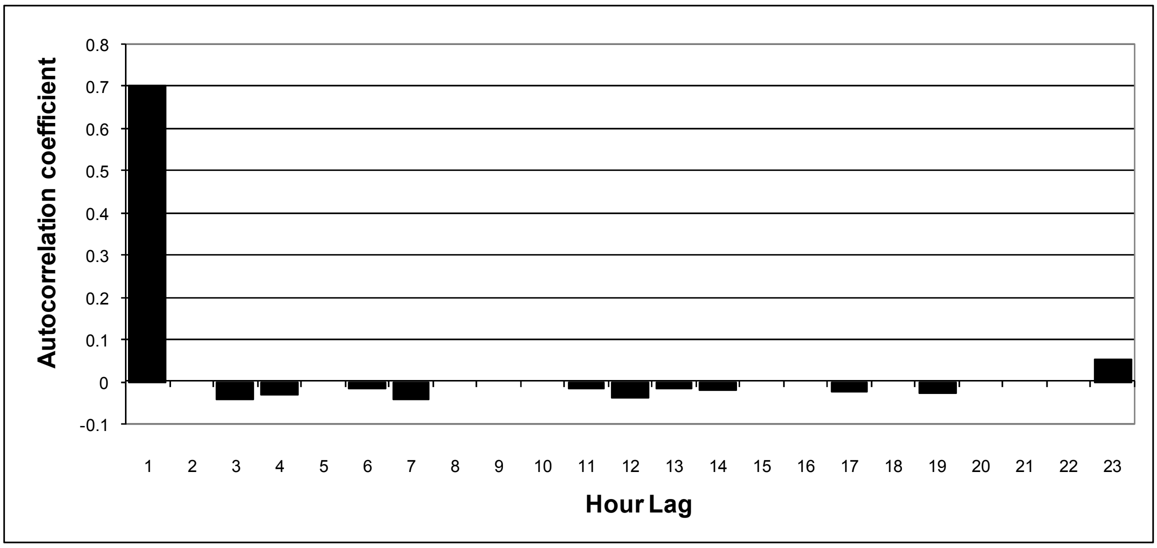
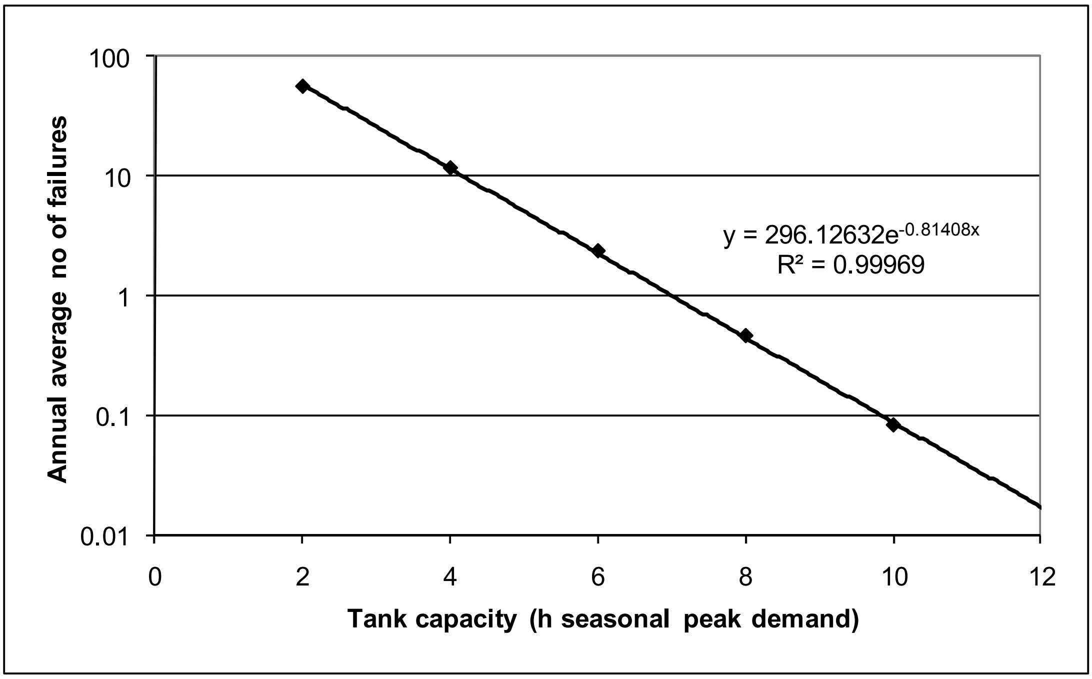


Figure 7 Significant hourly auto-correlation coefficients in the demand data



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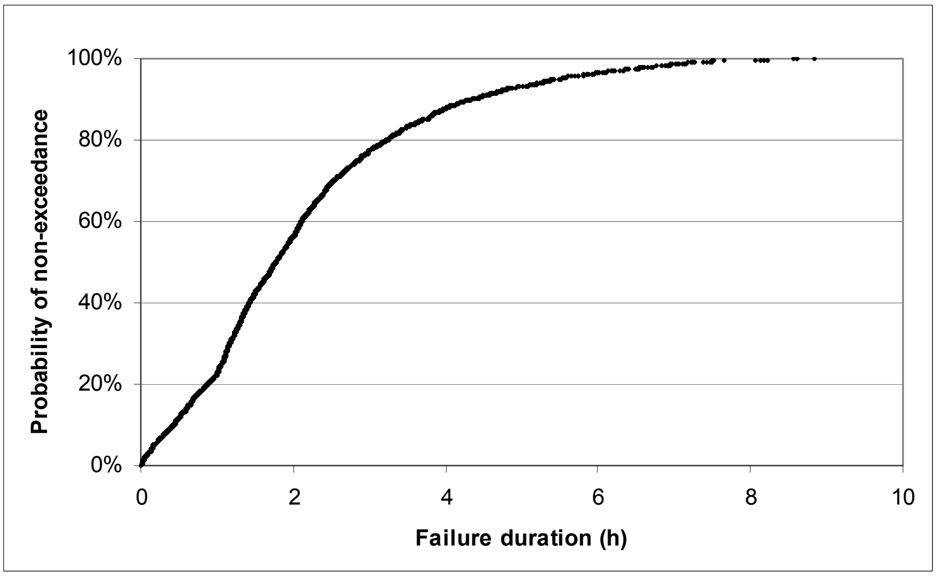

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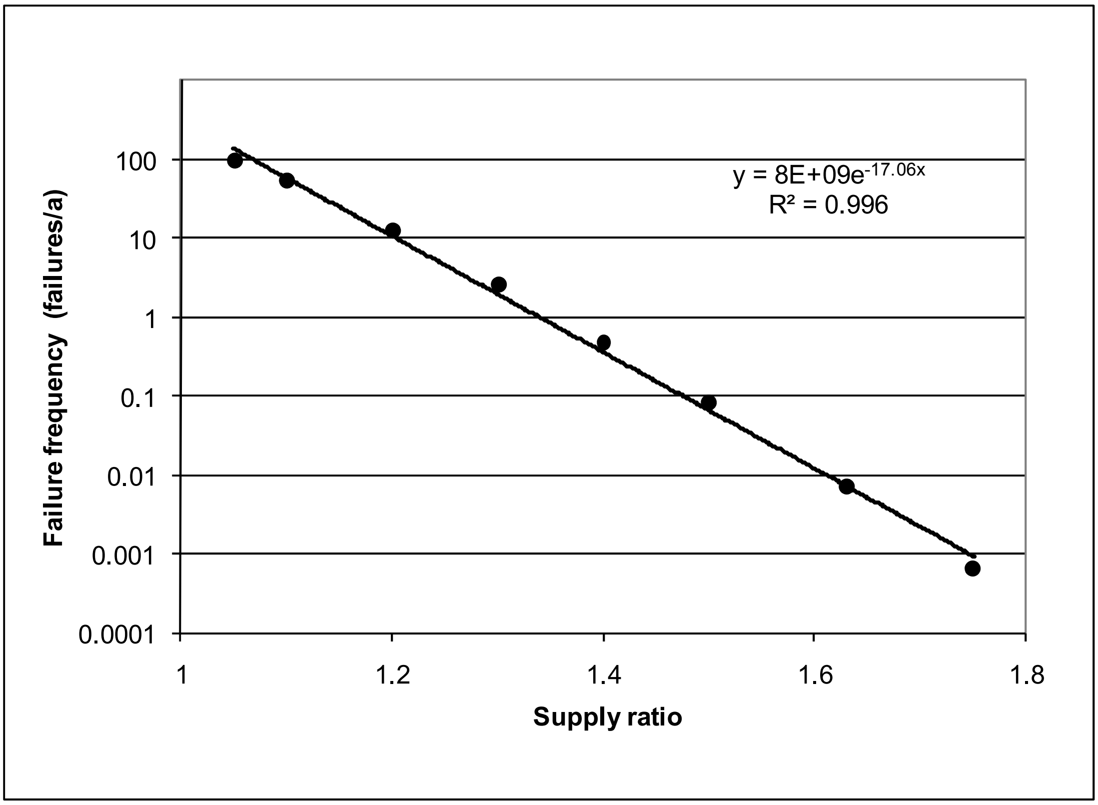

Figure 10 Tank failure frequency as a function of the supply ratio.

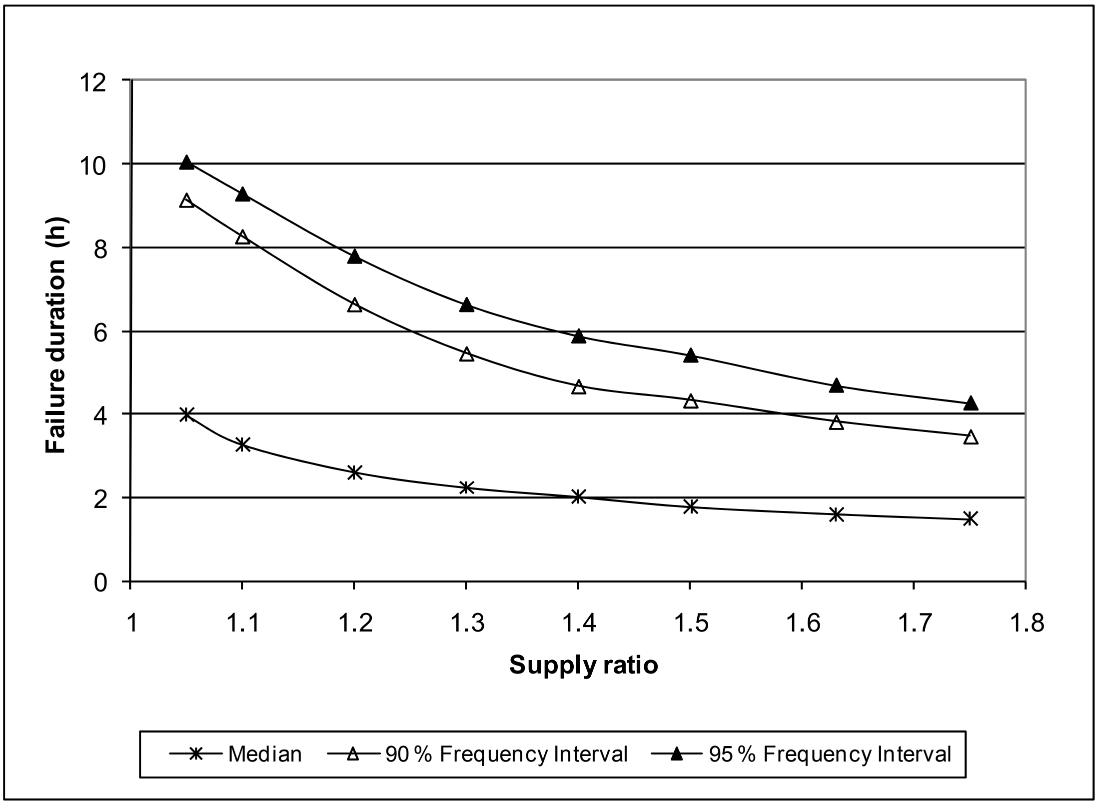

Figure 11 Tank failure duration as a function of the supply ratio.

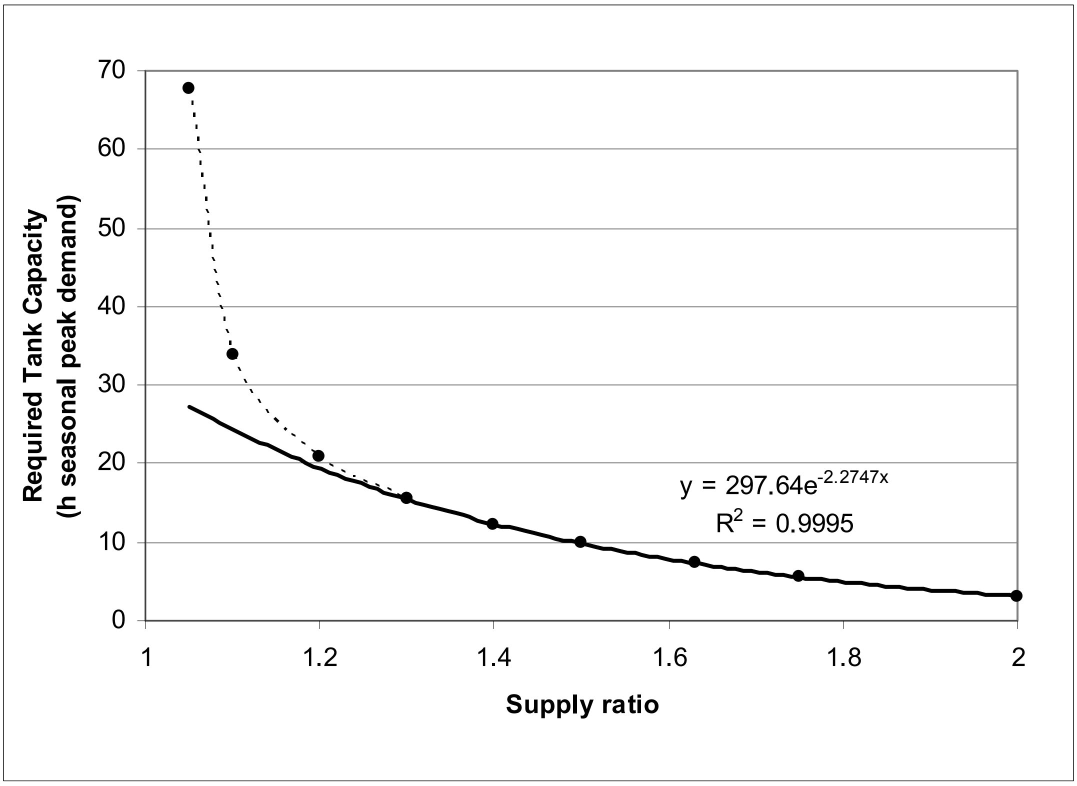

Figure 12 Required tank capacity as a function of the supply ratio.

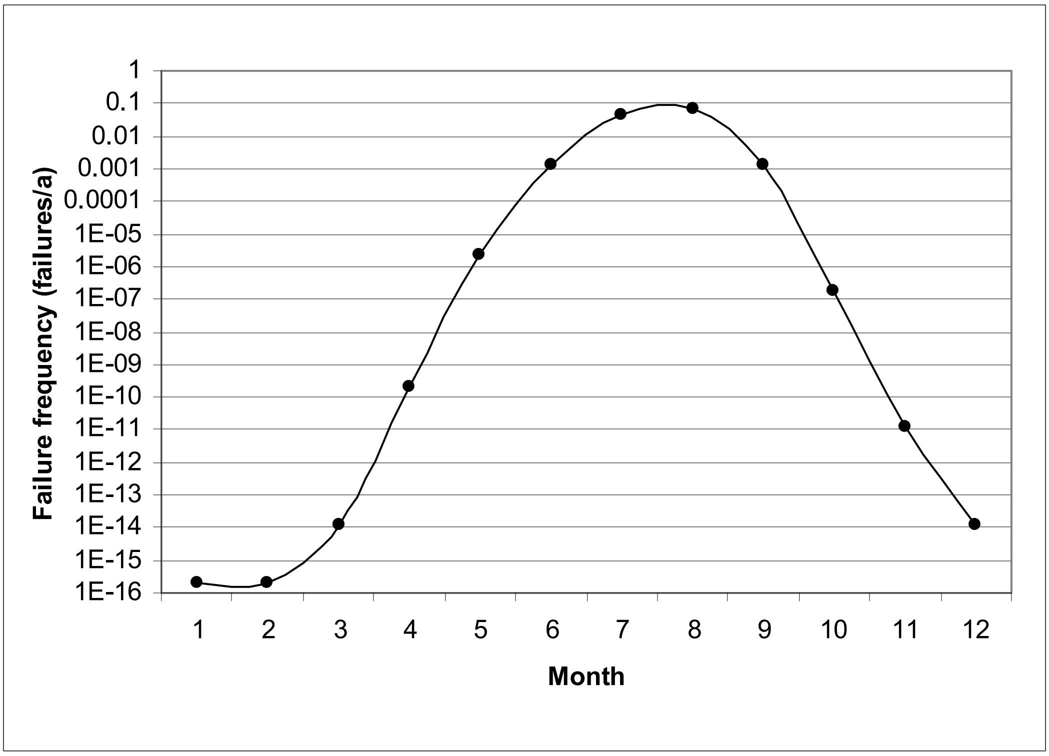

Figure 13 Seasonal variations in tank failure frequency for a demand only system.

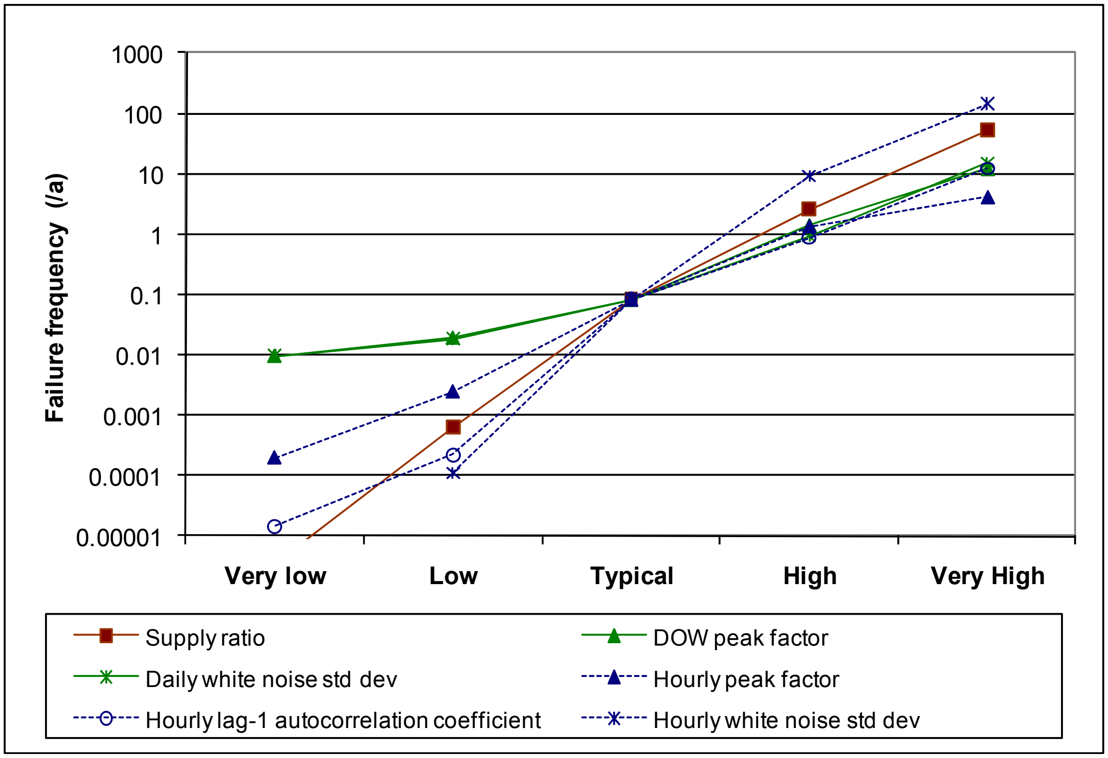

Figure 14 Impact of major demand parameters on tank failure frequency.

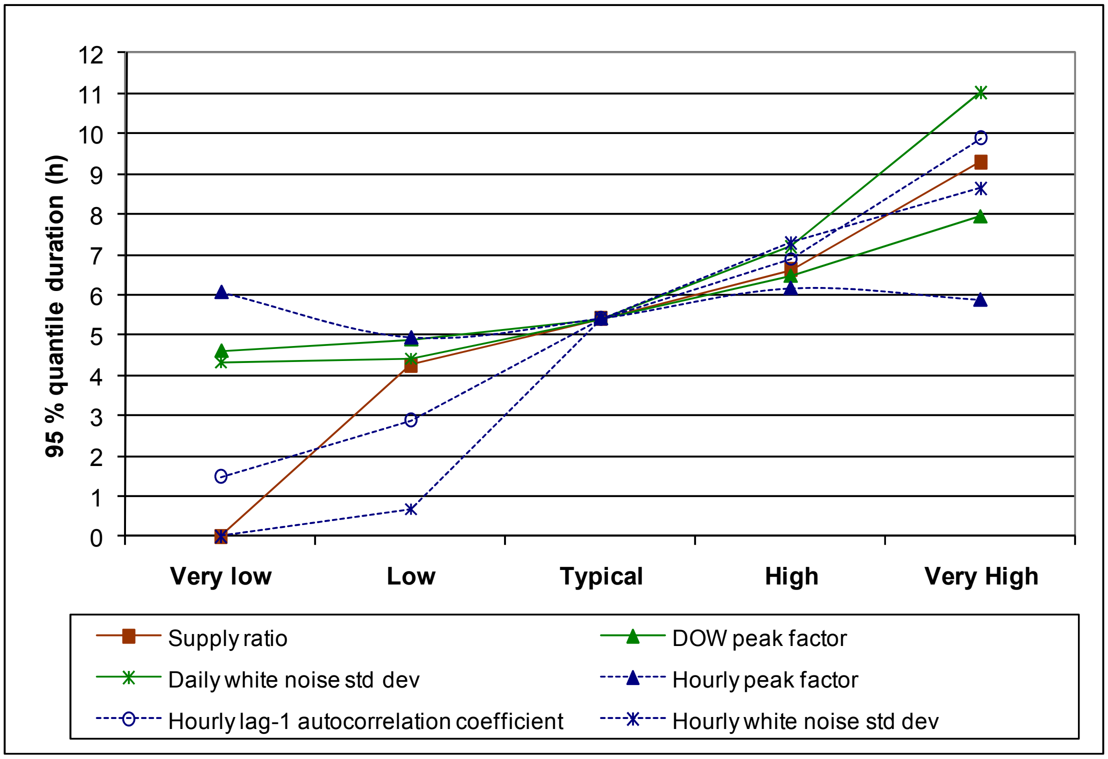

Figure 15 Impact of major demand parameters on failure duration.

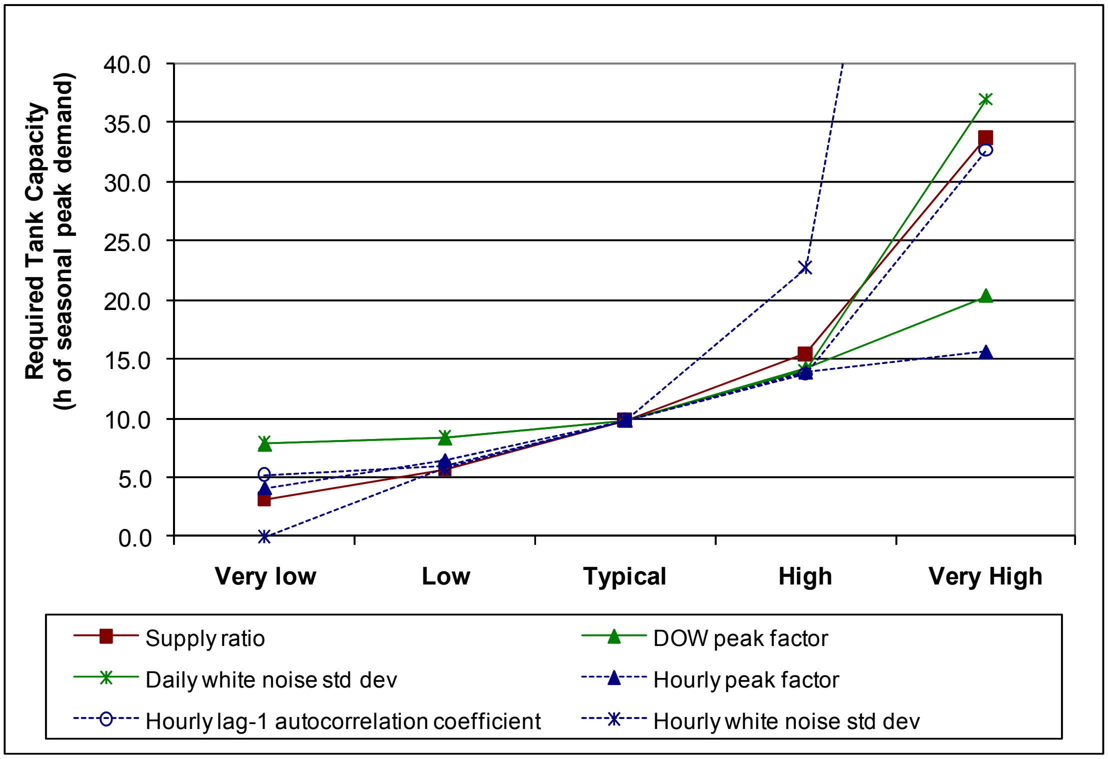

Figure 16 Required tank capacity for the major demand parameters.

Figure Caption List