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Short-Term Variability Effect on Peak Demand: Assessment Based on a Microcomponent Stochastic Demand Model

Sarai Díaz[1] and **Javier González**[1,2]

[1]Department of Civil Engineering, University of Castilla-La Mancha, Ciudad Real, Spain, [2]Hidralab Ingeniería y Desarrollos S.L., Spin-off UCLM, Hydraulics Laboratory, University of Castilla-La Mancha, Ciudad Real, Spain

Key Points:

- A novel analytical approach for assessing short-term variability effect on peak demand at different temporal and spatial scales is presented
- Peak demands are computed probabilistically, based on a microcomponent stochastic demand model that enables short-term variability analysis
- The method eases the understanding of peak demands thanks to the physically based (rather than empirical) approach

Correspondence to:

S. Díaz,
sarai.diaz@uclm.es

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Abstract

Peak demand plays a major role in water distribution system design. Peak demand assessment is currently facing a double challenge: shifting toward a probabilistic approach, and considering the effect of different spatial and temporal resolutions. Most probabilistic approaches so far have focused on inferring scaling laws by analyzing measurement time series for different spatial and temporal resolutions. The aim of this paper is two-fold: (a) to present a novel analytical approach that enables to assess the short-term variability effect on probabilistic peak demands for different spatial and temporal scales, and (b) to ease the understanding of peak demand factors thanks to a physically based (rather than an empirical) approach. This is possible by combining the principles of peak demand analysis with a microcomponent-based (i.e., end-use oriented) demand model that enables assessment of short-term variability. The methodology here proposed is applied to two case studies with the purpose of validating the approach and showing its full potential. Results prove that stochastic demand models can be a powerful tool for peak demand assessment.

1. Introduction

Peak demand has an important role in water distribution system design because it is associated with one of the most burdensome operating scenarios in a network. For this reason, peak demand has been widely discussed over the last century. Traditionally, peak demand assessment has focused on determining the peak demand coefficient or peak factor, which is defined as the ratio between the maximum and the mean daily flow. Authors like Harmon (1918), Babbitt (1928), Metcalf and Eddy (1935), or Johnson (1942) (among others) proposed expressions that provide the peak factor at sewer systems based on the size of the population. These empirical equations set up the basis for peak demand analysis at water supply systems, although they address the problem from a deterministic point of view.

Water demand is nowadays recognized as one of the main random factors that condition flow variability (Magini et al., 2008). The development of stochastic demand models that simulate the complex pulsed nature of water demands has motivated the shift toward probabilistic (rather than deterministic) demand analysis (Vertommen et al., 2015), also for peak demand assessment. According to the literature review presented by Creaco, Blokker, and Buchberger (2017), stochastic demand models can be broadly classified as: (a) household-based models, which adjust statistical models based on flow measurements at monitored households, like the Poisson Rectangular Pulse (PRP) model originally presented by Buchberger and Wu (1995), and (b) end-use models, which compute household consumption by aggregating the contribution of each end-use or microcomponent (e.g., taps, showers, washing machines) according to survey-based data. Zhang et al. (2005) and Creaco et al. (2018) have already applied PRP-like models to assess peak demands. Zhang et al. (2005) proposed a theoretical explanation for peaking factors by combining a PRP model with extreme value theory. Balacco et al. (2017) adapted this approach to a case study in Italy, comparing it with traditional formulas and real measurements. On the other hand, SIMDEUM (SIMulation of water Demands, an End-Use Model) is the reference microcomponent model at present (Creaco, Blokker, & Buchberger, 2017), and it has also been used to compute accurate estimates of peak demands (Blokker et al., 2012).

Addressing peak demand assessment probabilistically is not the only current challenge. The temporal and spatial resolution effect on peak factors is being discussed as well. As pointed out by Tricarico et al. (2007), assuming a time interval of one hour (traditional temporal framework for peak assessment) may result in an underestimation of peak demand, because major peaks could take place within the hour. On the contrary, using very fine time scales (e.g., 1 s) is excessive considering that per second variations are not expected to be decisive in order to guarantee the supply service. Moreover, using fine temporal scales would require adopting unsteady flow models rather than the conventional extended period simulation approach (Creaco, Pezzinga, & Savic, 2017). De Marinis et al. (2003), Tricarico et al. (2007), and Gato-Trinidad and Gan (2012) analyzed peak values in real networks and demonstrated that 1 to 5 min interval data can be a good compromise solution. Furthermore, Gargano et al. (2017) assumed different probabilistic distributions (Lognormal, Gumbel, and Log-logistic) for the peak factor and proposed empirical formulas to estimate the mean and coefficient of variation of the peak factor for different spatial (239–1,220 users) and temporal (60–3,600 s time step) resolution levels. Del Giudice et al. (2020) go one step further and propose a methodological framework to estimate the expected value of hourly peak demand factors considering its dependence on the spatial aggregation level. Creaco et al. (2021) have also recently worked in developing a two-step methodology for the generation of snapshot peak demand scenarios, each of which is based on a single combination of demand values at nodes.

Deriving empirical formulas to assess the effect of spatial and temporal resolution on peak demands has a limitation: it is usually site-specific. This work intends to provide a conceptual framework to analyze the effect of short-term variability (i.e., variability below the hour, as it will be explained in Section 2) on probabilistic peak demand analysis. The aim of this paper is two fold: (a) to present a novel analytical approach that enables to assess the effect of short-term variability on probabilistic peak demands for different spatial and temporal resolutions, and (b) to ease the understanding of peak demand factors thanks to a physically based (rather than an empirical) approach. This is possible by combining peak demand analysis with a stochastic demand model that accounts for short-term variability. As mentioned before, other authors have already applied stochastic demand models to assess peak demands (e.g., Blokker et al., 2010; Creaco et al., 2018; Zhang et al., 2005), but their focus (to the best of the authors' knowledge) was not on specifically assessing scale effects. The novelty of this work lies in combining peak analysis with a microcomponent-based (i.e., end-use oriented) demand model to assess the effect of short-term variability on peak demands. Instead of using the original SIMDEUM model, which runs Monte Carlo simulations to provide high-resolution demand patterns based on survey-data, the analytical approach to SIMDEUM model presented by Díaz and González (2021) is adopted to characterize water demands. As it will be discussed later, this offers some advantages for the statistical characterization of water demand and enables to focus on short-term variability effects.

The rest of this work is organized as follows. First, the concept of variability and the implications of assessing short-term variability are presented in order to clearly define the scope of this paper. This explanation will help to clarify the interest of adopting an analytical microcomponent based demand model to analyze peak demands. The analytical methodology to assess the effect of short-term variability on peak demand values and peak demand coefficients is later presented. Then, the methodology is applied to two case studies. The first application is intended to validate the analytical approach and the second case study is proposed in order to enhance the understanding of peak values at a particular example. Finally, practical implications and conclusions are duly drawn.

2. Short-Term Variability Conceptualization: Using a Microcomponent Stochastic Demand Model to Assess Peak Demands

Water demand variability conditions the peak values expected within a water system. "Variability" is understood all along this work as the variation of water demands when all possible realizations are considered, that is, variance is a measure of variability. In order to explain the effect of demand variability on peak demands, it is important to first understand the different types of water demand temporal variability that may exist for a particular spatial scale. They can be inferred by analyzing human interaction with supplied drinking water in a populated area.

Every day, each inhabitant (here called end-user) carries out his/her daily activities (e.g., waking up, going to work, working). Along the day, each person uses the water provided by the supply system whenever he/she needs. Therefore, end-users behave randomly and independently, although they are all subjected to behavior temporal patterns according to frequency of use distribution functions. These functions come determined by the culture of the populated area (e.g., village, town, city), timetables (e.g., business, study, and leisure hours), weather conditions (e.g., temperature, rainfall), particular events (e.g., multitudinary sports events, television programming), festivities, etc. These external factors apply similarly to a significant amount of the population, conditioning the aggregated water consumption. This leads to apparent correlation of aggregated water use between different population groups (Díaz & González, 2021).

Table 1
Water Demand Temporal Variability for a Particular Spatial Scale

	Temporal framework	Sources of variability	Spatial implications	Predictability
Short-term variability	$\Delta t \leq 1$ hr	Random processes	None (independent users)	Unpredictable
Medium-term variability	1 hr $< \Delta t \leq 1$ week	Business, study, and leisure hours	Correlation among users (external factor influence)	Partially predictable
		Working and nonworking days		
		Social events and weekend activities		
		Weather		
Long-term variability	1 week $< \Delta t \leq 1$ year	Holiday periods	Correlation among users (external factor influence)	Partially predictable
		Climatic season		
		Second residence use		
Very long-term variability	$\Delta t > 1$ year	Consumption pattern changes	Correlation among users (external factor influence)	Partially predictable
		Electric tariff changes	Demographic changes (number and/or type of end-user)	
		Cultural changes		

In other words, there is a short-term variability that refers to the random processes carried out by independent users, each one involved in different activities that make more or less probable their use of water. Users can be classified based on their consumption pattern, which is at the same time linked to the influence of external factors. For example, it can be assumed that five different types of end-user exist (children, teenagers, working adults, nonworking adults and seniors). These types correspond to groups of people that are influenced by similar external factors (Díaz & González, 2021). Within a short temporal framework (e.g., $\Delta t \leq 1$ hr), it can be assumed that the same conditions apply to all users of the same type, but their behavior is inherently random, that is, they respond independently to similar water use probability distributions associated with their consumer type. Note that one hour is the typical temporal unit adopted to define demand patterns (i.e., demand multipliers, which correspond to water use probability distributions under a microcomponent approach), so it is reasonable to believe that within that period consumption probability distributions are set and water use is a random independent process. Also, a medium-term variability that accounts for daily and weekly routines (derived from timetables, festivities, social events, weather conditions, etc.) can be identified. Because users of the same type may be subjected to higher or lower probabilities of water use during specific periods of time, apparent correlation occurs within this temporal scale. Long-term variability should accommodate changes over the year (holidays, climatic season, second residence use etc.), and even a very long-term variability could be distinguished to consider changing consumption patterns, electricity tariff updates or population trends. Interannual changes of the population itself (change in the number and type of inhabitants) could be considered as very long-term variability as well. As discussed by Ruiz et al. (2022), the thresholds between short, medium and long-term variability are not clearly stablished, but 1 hr, 1 week, and 1 year will be considered in this work as a reference. Table 1 summarizes the different levels of temporal variability adopted in this work and their practical implications.

Note that very long, long, and mid-term variability are naturally periodic or semi-periodic: they are partially predictable. They are associated with high correlation among inhabitants, so they can be simulated by considering external factors that condition the behavior of the population. In other words, long and mid-term variance can be characterized or even forecasted (e.g., Zhou et al., 2002; Xenochristou & Kapelan, 2020) based on time series analysis because they are subjected to inertia. By contrast, the here called short-term variability is random and unpredictable: it is associated with low correlation among inhabitants. Short-term variability is not typically completely known, unless captured by telemetry devices. Ruiz et al. (2022) have recently proposed that short-term variability can alternatively be characterized with stochastic demand models, because pulse demand models represent the complexity of water demands on a low spatial aggregation level (Buchberger & Wu, 1995). As mentioned in the Introduction, there are different types of stochastic demand models, and the end-use approach seems especially suitable to account for short-term variability. The original SIMDEUM model uses frequency, duration and intensity information from surveys in order to simulate water demand with Monte Carlo simulations (Díaz et al., 2021). This requires multiple simulation runs in order to assess variability (Blokker et al., 2011). Rather than working with the conventional SIMDEUM model, the analytical approach presented by Díaz and

González (2021) is here adopted. This approach analytically provides the temporally averaged statistical properties (mean and variance) of water demands over a time interval Δt thanks to the assumption of independent behavior among inhabitants, which is reasonable for short-term variability estimations. Note that as long as per-hour daily patterns are assumed for different types of end-user (Díaz & González, 2020), short-term variability can be quantified. The short-term variability threshold, which is referred to in this work as $\Delta t_{short} = 1$ h = 3,600 s, could be further reduced below the hour if more detailed patterns were available. The model presented by Díaz and González (2021) assumes steady conditions for the time interval under analysis, so in order to simulate the effect of medium, long or very-long term variability, it should be combined with convenient models that update the daily distribution of frequency of use over time.

It is reasonable to believe that when analyzing peak demands, these types of variability (very long, long, medium, and short-term) must be considered. However, long and very long-term variability are very difficult to distinguish in practice, as population is in continuous change. When peak demands are to be assessed, it is usual to assume a fixed population size (N number of inhabitants). This implies that very-long term variability is not usually considered, that is, variability is bounded for a fixed value of N. Long and medium-term variability characterization is site-specific, and thus it is not straightforward to develop a general model for its quantification. However, short-term variability has already been deeply analyzed under the microconsumption conceptual framework. Díaz and González (2021) highlight the importance of the sampling rate (i.e., temporal framework) and the spatial scale to characterize water demand variability. This offers an opportunity to extend the assessment of short-term variability to peak demand assessment under different temporal and spatial scales. For this reason, this paper focuses on assessing the effect of short-term variability on peak demand analysis. This implies that addressing peak assessment with this stochastic demand model will enable to understand and compute the changes of peak demands over the temporal scale below the hour ($\Delta t \leq \Delta t_{short}$). This is reasonable given that peak demand assessment based on measurement series analysis is the procedure that has been traditionally adopted to characterize peak demand or peak demand coefficient values between the minute and the hour (Gargano et al., 2017; Gato-Trinidad & Gan, 2012; Tricarico et al., 2007). The added value of the approach presented in this paper is that it provides a conceptual framework to analyze results rather than being measurement series specific.

Note that in the temporal domain, as long as $\Delta t \leq \Delta t_{short}$, it can be guaranteed that peak demand differences are only due to short-term variability. On the other hand, too low Δt values cannot be used for snapshot simulation, as Δt must be large enough to dampen transients (Creaco, Pezzinga, & Savic, 2017). Therefore, this conceptual framework assumes that peak demand differences for any Δt below the hour would be related to short-term variability, considering average conditions during a sufficiently long Δt to avoid network transient effects. In the spatial domain, this cannot be generally guaranteed. But if changes in the population (from N_1 to N_2) are small and the pattern distribution across end-users is homogeneous over the populated area (i.e., similar distribution of end-users and frequency patterns), changes will foreseeably be mainly associated with short-term variability. In this scenario, the methodology presented in this work is sufficient to assess peak demands over different spatial scales. If there are significant changes across the population, they must be accounted for with a convenient long/medium-term variability model. This is out of the scope of this paper. The method that will now be presented is suitable to assess short-term variability effect on peak demands at different temporal and spatial scales.

3. Peak Demand Assessment

3.1. Peak Demand Values

Water demands present a random behavior, which must be statistically characterized. Individual water consumption is not expected to behave according to a normal distribution. However, when a sufficient amount of population is assessed, the aggregated water consumption can be assumed to follow a normal distribution with mean μ_Q and standard deviation σ_Q. Other authors have proved that skewness is non negligible for low aggregation levels based on measurement series (Creaco et al., 2021), but the normal assumption is here adopted as a conceptual simplification and will be validated in the Results section. The mean and standard deviation statistical properties are not constant: they vary with the spatial aggregation level being considered (N number of inhabitants) and they depend on the temporal framework adopted for demand analysis. In this work, only the effect of short-term variability is assessed. Its theoretical threshold has been previously defined as $\Delta t_{short} = 3{,}600$ s (see Table 1), so one hour is here adopted as the time step for frequency of use definition in the microcomponent demand model and as the longest time-interval possible for peak demand assessment.

As explained before, the subjacent stochastic model assumes steady conditions around each time, which is reasonable below the hour. This hypothesis enables to assume that water demand mean value $\mu_Q(N)$ remains constant regardless of Δt for a N number of inhabitants, always considering $\Delta t \le \Delta t_{\text{short}}$. On the contrary, water demand variance also depends on the temporal framework adopted for the analysis: we must talk about $\sigma_Q(N, \Delta t)$ rather than $\sigma_Q(N)$. The variance registered by a metering device depends on its sampling rate: considering longer Δt implies losing information about consumption behavior, leading to lower variance values (Buchberger & Nadimpalli, 2004). Apparent variance is defined as the variance associated with the recorded behavior. This is a relevant concept for peak demand characterization under different temporal scales. The smaller the temporal scale, the larger the apparent variability, and thus the larger the peak demand over the interval. Note that in this work apparent variance (the variance associated with the recorded behavior) is discussed all along. Previous studies have focused in explaining the difference between apparent and missed variance (i.e., variance of the unrecorded behavior), but missed variance is out of the scope of this paper. The reader may refer to Díaz and González (2021) or Ruiz et al. (2022) for a more detailed explanation about their differences.

Considering that water demands follow a normal distribution with $\mu_Q(N)$ and $\sigma_Q(N, \Delta t)$, the probability P of not exceeding a specific $Q_p(N, \Delta t)$ value over a short time period where temporal homogeneity can be assumed is given by:

$$P = \Pr[Q \le Q_p(N, \Delta t)] = \Phi[Q_p(N, \Delta t), \mu_Q(N), \sigma_Q(N, \Delta t)], \tag{1}$$

where Φ represents the cumulative distribution function of the normal distribution. In order to analyze peak demand values over a temporal framework, it is not enough to assess if demand values will remain below the threshold value at one Δt time interval. All demand values at each interval within the Δt_{short} temporal framework must keep below $Q_p(N, \Delta t)$. Assuming that water demands behave independently, the probability of not exceeding $Q_p(N, \Delta t)$ at any point within Δt can generally be written as:

$$P = \Phi[Q_p(N, \Delta t), \mu_Q(N), \sigma_Q(N, \Delta t)]^n; \forall N, \forall \Delta t \tag{2}$$

where n refers to the number of Δt intervals within the temporal framework $n = \frac{\Delta t_{short}}{\Delta t}$. According to extreme value theory, it can be proved that the maxima of a n-sequence of independent normally distributed samples follows a Gumbel distribution (David & Nagaraja, 2003). This holds when considering a large number of n intervals (very fine Δt to maximize the number of intervals within the hour), which are of low interest for modeling purposes (Creaco, Pezzinga, & Savic, 2017), but this idea will be useful for discussion of results in Section 4.1.

It is important to highlight that $\mu_Q(N)$ and $\sigma_Q(N, \Delta t)$ refer to the mean and standard deviation of the original normal distribution assumed for water demands at peak hour. These values could be computed from the measurement series of a metering device with a Δt sampling rate located at a position that supplies water to N inhabitants. Alternatively, they can be obtained with the microcomponent stochastic demand model proposed by Díaz and González (2021). The reader may refer to Díaz and González (2020) and Díaz and González (2021) for details.

3.2. Peak Demand Coefficients

Peak demand analysis has traditionally focused on computing peak demand coefficients (relative values) rather than peak demand absolute values. The peak demand coefficient C_p has traditionally been defined in the literature (e.g. Gargano et al., 2017) as:

$$C_p = \frac{Q_p}{Q_d} \tag{3}$$

where Q_p represents the peak flow during the day and Q_d corresponds to the average daily mean water demand. As mentioned in the Introduction, several authors have already highlighted that C_p depends on N and Δt. To be consistent, it will be here assumed that:

$$C_p(N, \Delta t) = \frac{Q_p(N, \Delta t)}{Q_d(N)}; \forall N, \forall \Delta t \tag{4}$$

with $Q_p(N, \Delta t)$ and $C_p(N, \Delta t)$ referring, respectively, to the peak demand value and peak demand coefficient associated with the N spatial and Δt temporal scales under analysis.

Equation 2 can be written in relative terms as:

$$P = \Phi\left[\frac{Q_p(N,\Delta t)}{Q_d(N)}, \mu_{\frac{Q}{Q_d}}(N), \sigma_{\frac{Q}{Q_d}}(N,\Delta t)\right]^n; \forall N, \forall \Delta t \quad (5)$$

where $\mu_{\frac{Q}{Q_d}}$ and $\sigma_{\frac{Q}{Q_d}}$ represent the mean and the standard deviation of relative demand with respect to the daily mean water demand. According to Equation 4, Equation 5 can be written as:

$$P = \Phi\left[C_p(N,\Delta t), \mu_{\frac{Q}{Q_d}}(N), \sigma_{\frac{Q}{Q_d}}(N,\Delta t)\right]^n; \forall N, \forall \Delta t \quad (6)$$

The standard deviation can be computed from the corresponding mean and coefficient of variation (CV):

$$\sigma_{\frac{Q}{Q_d}}(N,\Delta t) = CV_{\frac{Q}{Q_d}}(N,\Delta t) \cdot \mu_{\frac{Q}{Q_d}}(N); \forall N, \forall \Delta t \quad (7)$$

So Equation 6 can be rewritten as:

$$P = \Phi\left[C_p(N,\Delta t), \mu_{\frac{Q}{Q_d}}(N), CV_{\frac{Q}{Q_d}}(N,\Delta t) \cdot \mu_{\frac{Q}{Q_d}}(N)\right]^n; \forall N, \forall \Delta t \quad (8)$$

Note that $\mu_{\frac{Q}{Q_d}}(N)$, $\sigma_{\frac{Q}{Q_d}}(N,\Delta t)$ and $CV_{\frac{Q}{Q_d}}(N,\Delta t)$ all refer to the statistical properties of water demands (or rather the ratio of water demands over daily values) and not to the statistical properties of peak water demands. In order to assess peak demands, the statistical properties of the ratio should focus on the hour where maximum values are expected. Within this time window, different Δt values are possible. We here assume that the mean ratio of water flows over daily flows at peak hour is equal to the mean of the peak demand coefficient over one hour $[\mu_{\frac{Q}{Q_d}}(N) = \mu_{C_p}(N, \Delta t_{short})]$. This implies approximating the mean of relative demands over the peak period as the mean of the peak coefficient for the longest Δt possible within the short-term variability domain (i.e., $\Delta t \approx \Delta t_{\text{short}}$). Under this assumption, Equation 8 can be simplified as:

$$P = \Phi\left[C_p(N,\Delta t), \mu_{C_p}(N,\Delta t_{short}), CV_{\frac{Q}{Q_d}}(N,\Delta t) \cdot \mu_{C_p}(N,\Delta t_{short})\right]^n; \forall N, \forall \Delta t \quad (9)$$

4. Results

Two case studies are here adopted to explain the full potential of using a microcomponent-based demand model to assess the effect of short-term variability on peak demand. The first case study corresponds to the network presented by Ruiz (2020). Note that a stochastic water demand microcomponent model has already been adjusted for this case study in the literature before (Ruiz, 2020; Ruiz et al., 2022). This means that the demand engine can be considered a well-fitted model to reality. The purpose of this example is to check if the analytical approach here proposed to compute probabilities of not exceedance for flow threshold values (Section 3.1) is consistent with equivalent Monte Carlo simulations. The assumption of considering water demands as normally distributed is also checked.

The second case study involves the real water distribution network of the small town Piedimonte San Germano (Italy), as presented in Gargano et al. (2017). This publication provides information about measured peak coefficients in the system, and these values will be used to infer the statistical properties of water demand. Moreover, it will be shown that using a microcomponent-based approach enables to explain the short-term variability of peak coefficients with a physically based model. This is advantageous with respect to deriving empirical formulas, as it will be discussed later.

4.1. Validation Case Study

Ruiz (2020) presented this case study with the aim of better understanding residential water demand variability according to different sources of information and its implications on state estimation (Díaz et al., 2018). This archetypical example comprises 79,106 inhabitants (in 30,203 households), and its microcomponent stochastic demand model has already been adjusted in Ruiz et al. (2022) based on metered data and statistical information.

Table 2
Mean Water Demand Values $\mu_Q(N)$ at 10:00 in the Validation Case Study

	$N = 1$	$N = 100$	$N = 1{,}000$	$N = 10{,}000$	$N = 40{,}000$	$N = 79{,}106$
μ_Q (L/s)	0.0025	0.2099	2.0163	19.7142	78.1249	154.5292

Thus, it can be assumed that the demand model is valid and consistently provides the temporally averaged mean $[\mu_Q(N)]$ and apparent variance $[\sigma_Q(N, \Delta t)]$ of water consumption, which quantifies short-term variability.

Table 2 provides the mean water demand at peak hour (10:00) for six different spatial aggregation levels: $N = 1$, $N = 100$, $N = 1{,}000$, $N = 10{,}000$, $N = 40{,}000$ (approximately half of the population) and $N = 79{,}106$ inhabitants (total population). These values illustrate that mean water demand is directly related to the number of inhabitants considered, provided that the end-use distribution is homogeneous at different spatial aggregation levels. Figure 1a shows the water demand variance values obtained with the model for different spatial aggregation levels and temporal scales at peak hour. Variance (i.e., quantification of apparent variability) has a S-shaped curve that represents the evolution of the short-term variance with Δt: the greater the temporal scale, the smaller the associated variance. These curves were named by Ruiz et al. (2022) as TESIC (which stands for Temporal scale Effect Sigmoid Curve). Figure 1a proves that TESIC (i.e., variance) rises as the population increases, with maximum values of nearly 20 L^2/s^2 for its maximum population. Figure 1b shows the equivalent coefficients of variation, which also decrease as Δt increases for a particular N value. However, coefficients of variation increase as the number of inhabitants reduces. This figure proves that short-term variance gains relative importance as N reduces.

Probabilities of not exceedance are analytically computed according to Equation 2. In this theoretical example, four threshold values are considered:

1. $Q_p(N, \Delta t) = \mu_Q(N)$
2. $Q_p(N, \Delta t) = \mu_Q(N) + \sigma_Q(N, \Delta t)$
3. $Q_p(N, \Delta t) = \mu_Q(N) + 2 \cdot \sigma_Q(N, \Delta t)$
4. $Q_p(N, \Delta t) = \mu_Q(N) + 3 \cdot \sigma_Q(N, \Delta t)$

Because $n = \Delta t_{short}/\Delta t$ is assumed in this work, it is expected that the first threshold value will be associated with $P = 0.5$ (50% probability) for $\Delta t = \Delta t_{short} = 3{,}600$ s and smaller values as the number of intervals increases (0.5^n).

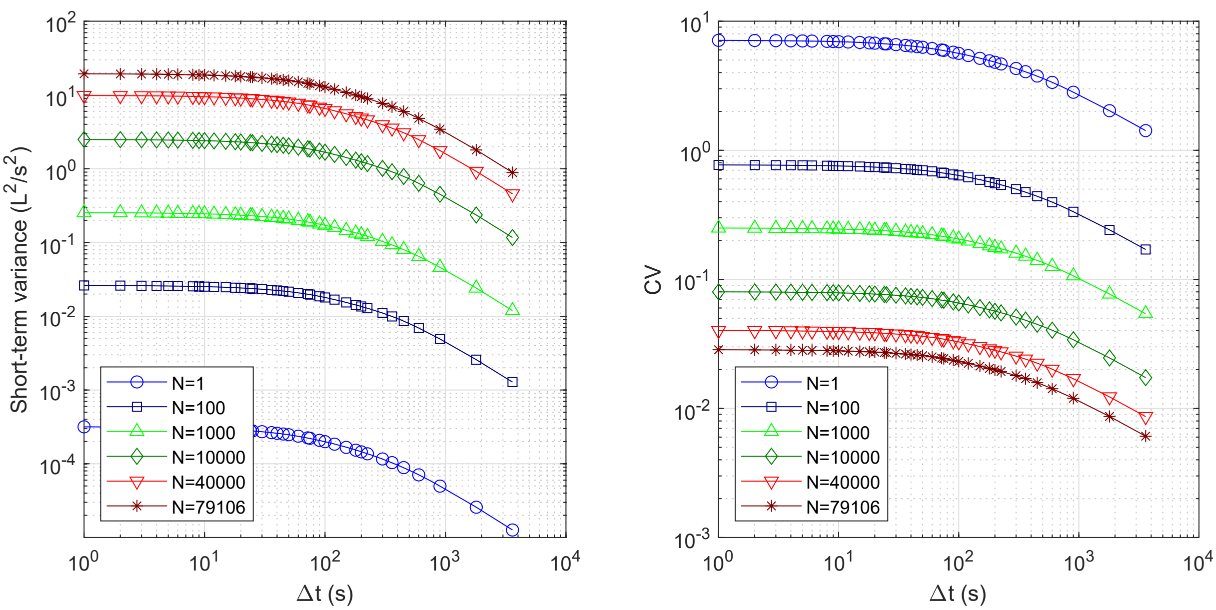

Figure 1. Water demand (a) short-term variance (TESIC) and (b) coefficient of variation at 10:00 for different number of inhabitants (N) and temporal scales (Δt) in the validation case study.

10.1029/2021WR030532

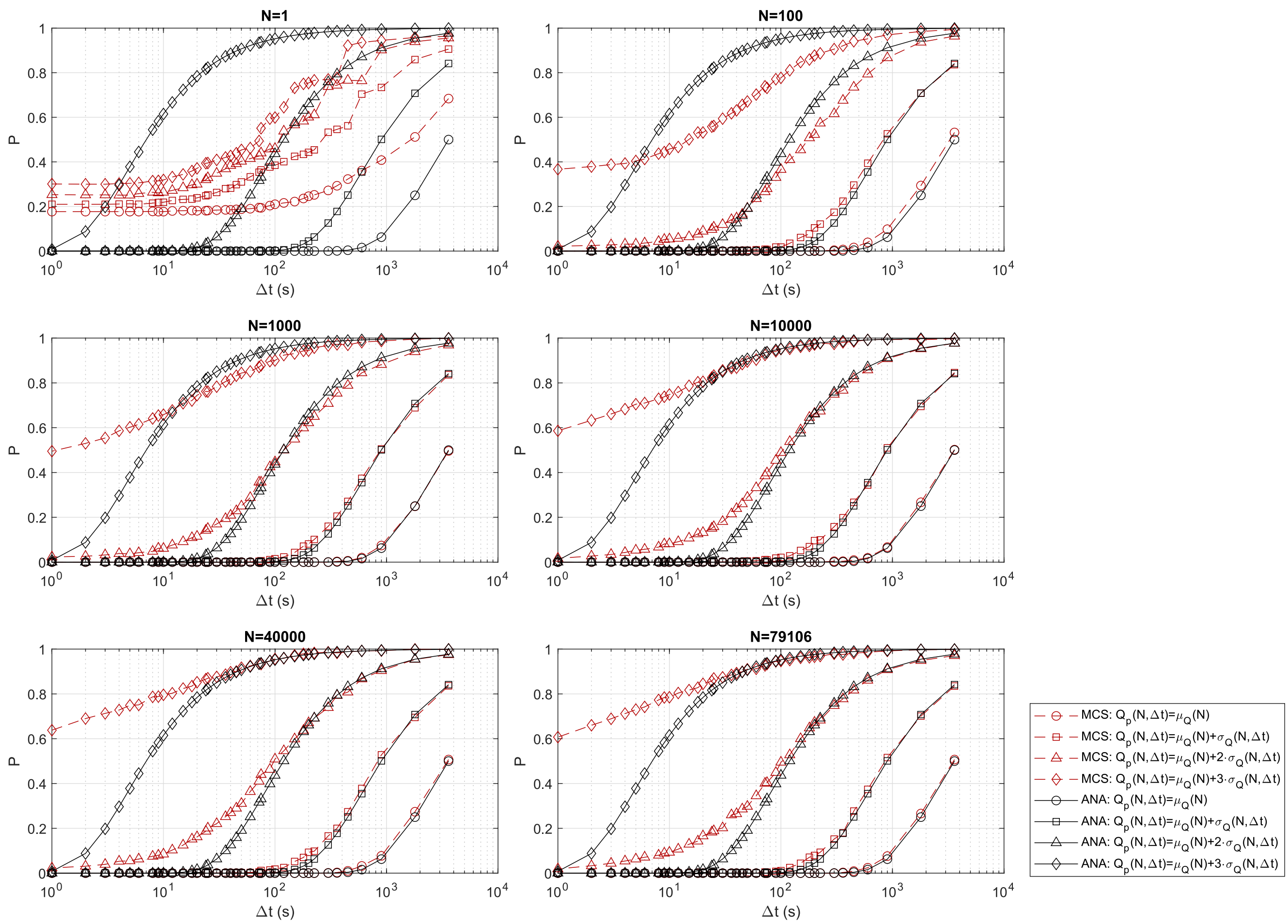

Figure 2. Probability of not exceedance for different peak demand values $Q_p(N, \Delta t)$: analytical approach (ANA) versus Monte Carlo simulation (MCS).

The rest of $Q_p(N, \Delta t)$ values will exceed the mean value, and thus enable a variety of probabilities in this example network. Figure 2 provides the analytically computed probabilities of not exceedance and their equivalent values according to 1,000 Monte Carlo simulations. For Monte Carlo simulations, 1,000 per-second demand series have been generated over 1 h for each N value. Then, water demands have been averaged over each Δt time interval, and the maximum value has been selected. The numerical probability of not exceedance has been computed by counting the number of times that the maximum average value remains below the four threshold $Q_p(N, \Delta t)$ values.

Figure 2 shows good correspondence between analytical and numerical results for $N \geq 100$. This proves that water demands can be considered normal for a sufficient number of aggregated users. The upper row of Figure 3 includes the normal probability plot of the maximum averaged water demands according to Monte Carlo simulations for $N = 1$, 100, and 79,106 inhabitants when $\Delta t = \Delta t_{short}$. Note that for $\Delta t = \Delta t_{short}$, the exponent in Equation 2 is $n = 1$ and so maximum averaged water demand values should correspond to a normal distribution. This starts to happen for $N \geq 100$, but not for a lower number of inhabitants. For $N = 1$, data is far from fitting to a normal probability plot. This is because averaged water demands are predominantly zero, and so a normal distribution cannot be assumed for water demands. For $N = 100$ there is some skewness, which is consistent with the findings of Creaco et al. (2021), but data starts to resemble a normal probability plot. Data fits a normal probability plot for the total population ($N = 79{,}106$). The lower row in Figure 3 shows the analogous for $\Delta t = 1$ s. In this case, the exponent in Equation 2 is $n = \Delta t_{short}/\Delta t = 3{,}600$. This explains the curvature at the extremes of the normal probability plot for $N \geq 100$, which calls for a Gumbel distribution rather than a normal distribution as the number of intervals within the hour increases.

In the overall, Figure 2 proves that the analytical approach is a good approximation for $\Delta t > 60$–120 s as long as normality can be assumed for water demands, that is, a sufficient amount of inhabitants is considered. If this

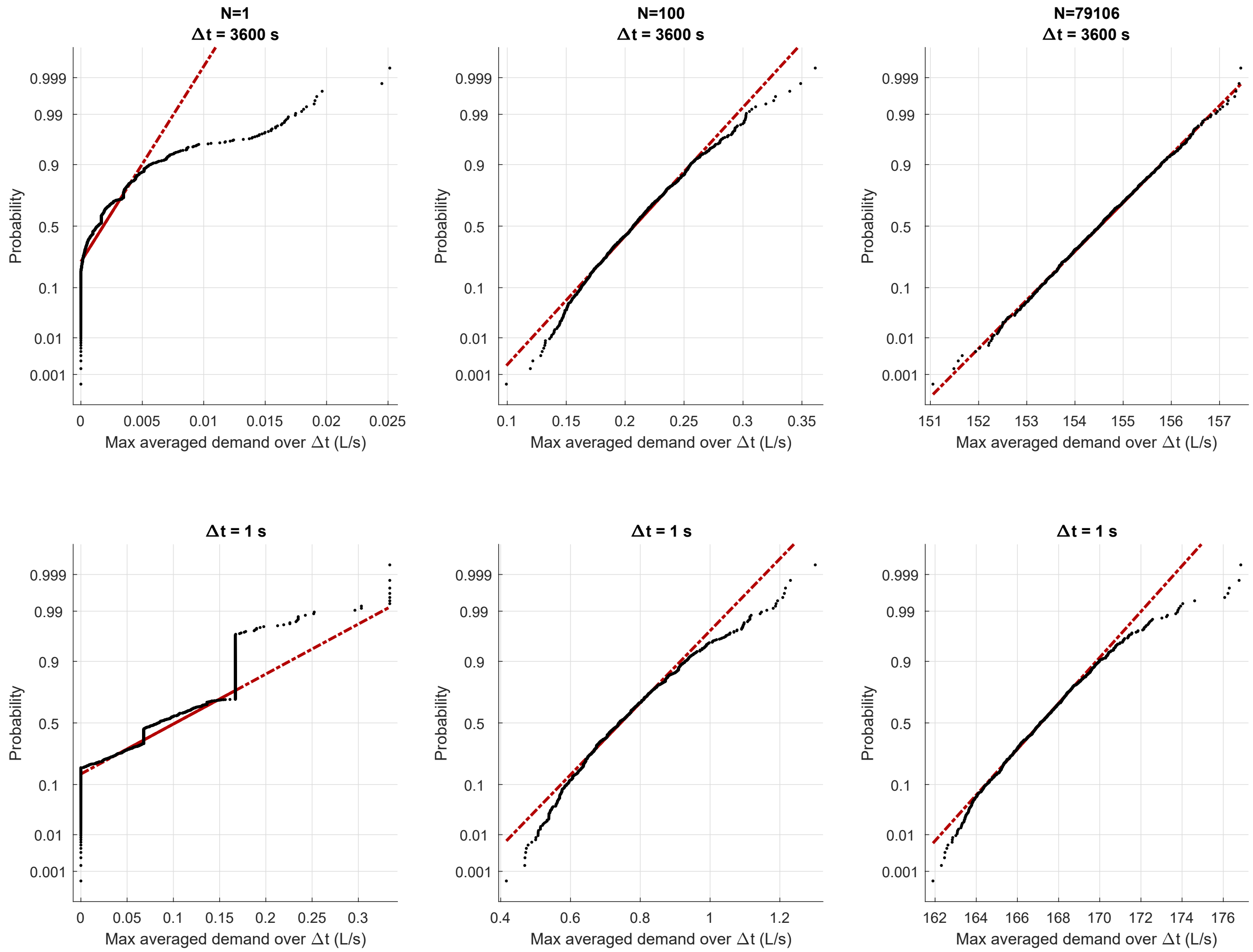

Figure 3. Normal probability plot of maximum averaged water demand values according to Monte Carlo simulations for $N = 1$, 100, and 79,106 inhabitants for $\Delta t = \Delta t_{\text{short}}$ and $\Delta t = 1$ s: testing the normality hypothesis and the importance of N and Δt.

condition is met, the analytical approach is reasonable for temporal scales above the order of one or two minutes. According to De Marinis et al. (2003) and Tricarico et al. (2007) 1-min intervals provide a good compromise for peak demand characterization, and the analytical approach here presented can be validated for that range of application. This means that the effect of short-term variability on peak demand values or peak coefficients for time intervals 60 s $\leq \Delta t \leq \Delta t_{\text{short}}$ can be explored with the methodology presented in Section 3 as long as a reliable stochastic demand model exists.

4.2. Piedimonte San Germano (PSG)

Piedimonte San Germano is a monitored network in Italy. As presented by Gargano et al. (2017), the monitoring system consists of four measurement points that measure supplied flow (i.e., aggregated demands) to $N = 239$, 777, 981, and 1,220 inhabitants. The analysis presented by these authors assumes an initial time resolution of $\Delta t = 60$ s, although measurements are then aggregated to assess the mean and the coefficient of variation of peak demands up until $\Delta t = \Delta t_{\text{short}} = 3{,}600$ s. This publication provides values of $\mu_{C_p}(N, \Delta t)$ and $CV_{C_p}(N, \Delta t)$. This implies that instead of having information about water demand statistical properties [$\mu_Q(N)$ and $\sigma_Q(N, \Delta t)$] like in the previous case study, statistical properties of peak demand coefficients are available. Therefore, this case study is analyzed according to the formulation in Section 3.2.

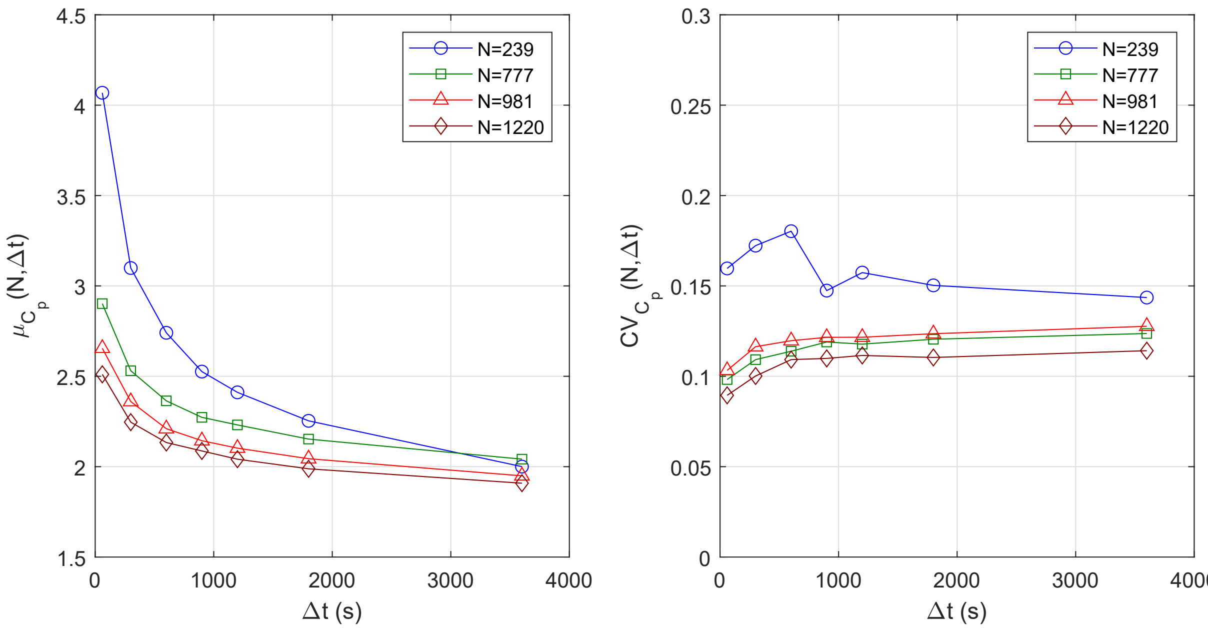

Figure 4. Peak demand coefficient statistical properties: (a) mean $\mu_{C_p}(N, \Delta t)$, (b) coefficient of variation $CV_{C_p}(N, \Delta t)$. From Gargano et al. (2017).

Figure 4 gathers the mean (4a) and the coefficient of variation (4b) of peak demand coefficients for different N and Δt values. These values have been obtained by digitalizing the original figures in Gargano et al. (2017), which correspond to measured data. The authors also propose empirical formulas, but they have not been used in this work to avoid possible deviations from original values. Figure 4a shows that the mean peak demand coefficient reduces as the number of inhabitants increases. This implies that the greater the population size, the smaller the peak coefficient, and it is consistent with prior observations in the literature (see Balacco et al., 2017 for references). It also shows that the peak demand coefficient reduces as the temporal scale increases, highlighting the importance of assessing the temporal scale effect on peak demands. Figure 4b shows the coefficient of variation for peak demand coefficients, which also reduces as the number of inhabitants increases. This is reasonable given that the smaller the population, the greater the variability. The coefficient of variation for relative peak demands reduces with the temporal scale: the smaller Δt, the smaller $CV_{C_p}(N, \Delta t)$. Note that points for $N = 239$ have a less clear trend in terms of coefficient of variation. This behavior can already be seen in Gargano et al. (2017), and its assessment is out of the scope of this paper.

Because $\mu_{C_p}(N, \Delta t)$ is known (Figure 4a), it is important to determine $CV_{\frac{Q}{Q_d}}(N, \Delta t)$ so that the probability of no exceedance can be determined for any peak demand coefficient according to Equation 9. With this purpose, probability has been sampled (P_{sample}) between 0 and 1 with 1,000 values. According to Equation 9, it can be written that:

$$P_{sample} = \Phi\left[C_{p,sample}(N, \Delta t), \mu_{C_p}(N, \Delta t_{short}), CV_{\frac{Q}{Q_d}}(N, \Delta t) \cdot \mu_{C_p}(N, \Delta t_{short})\right]^n ; \forall N, \forall \Delta t \quad (10)$$

So:

$$C_{p,sample}(N, \Delta t) = \Phi^{-1}\left[P_{sample}^{\frac{1}{n}}, \mu_{C_p}(N, \Delta t_{short}), CV_{\frac{Q}{Q_d}}(N, \Delta t) \cdot \mu_{C_p}(N, \Delta t_{short})\right] ; \forall N, \forall \Delta t \quad (11)$$

At the same time, $\mu_{C_{p,sample}}(N, \Delta t)$ and $CV_{C_{p,sample}}(N, \Delta t)$ can be estimated by computing the mean and coefficient of variation of $C_{p,sample}(N, \Delta t)$. The unknown $CV_{\frac{Q}{Q_d}}(N, \Delta t)$ can be determined by minimizing the sum of relative quadratic errors for the mean and coefficient of variation of $C_{p,sample}(N, \Delta t)$ and those published by Gargano et al. (2017):

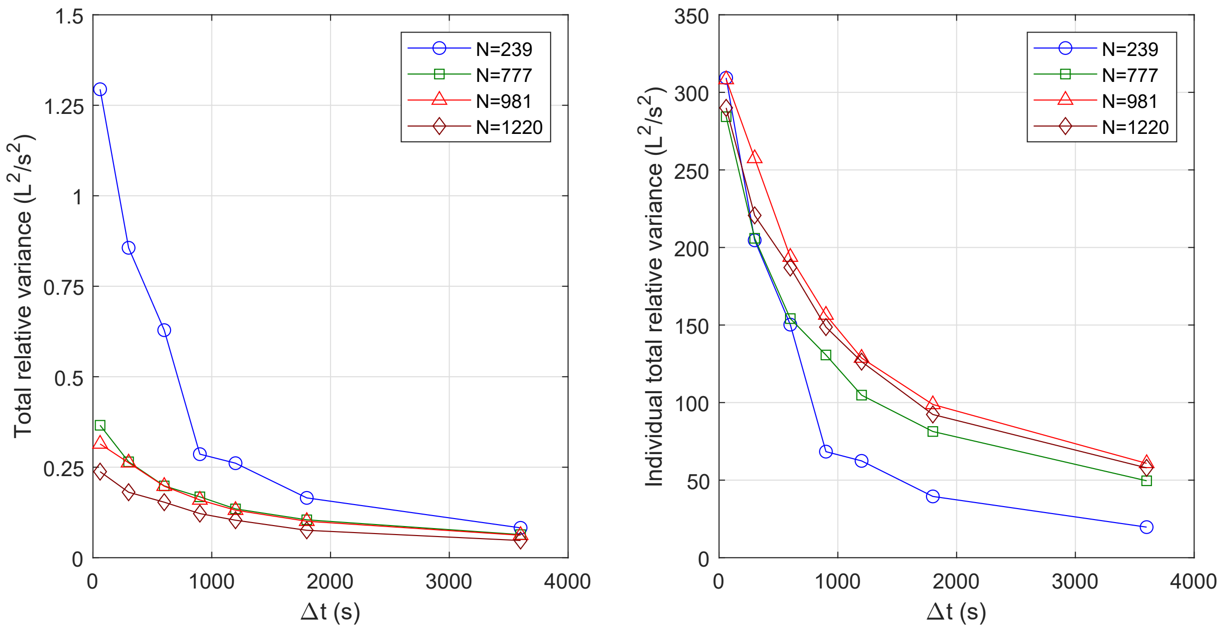

Figure 5. Total variance for different number of inhabitants (N) and temporal scales (Δt) at Piedimonte San Germano (PSG) case study: (a) relative variance, (b) individual relative variance.

$$\min_{CV_{\frac{Q}{Q_d}}(N,\Delta t)\in\mathbb{R}} \left[\left(\frac{\mu_{C_{p,sample}}(N,\Delta t)-\mu_{C_p}(N,\Delta t)}{\mu_{C_p}(N,\Delta t)}\right)^2+\left(\frac{CV_{C_{p,sample}}(N,\Delta t)-CV_{C_p}(N,\Delta t)}{CV_{C_p}(N,\Delta t)}\right)^2\right];\forall N,\forall\Delta t \quad (12)$$

Optimization function (Equation 12) is here solved with the simplex search method (Lagarias et al., 1998) to compute $CV_{\frac{Q}{Q_d}}(N,\Delta t)$ for all N and Δt according to the relationship established by Equation 11.

Once $CV_{\frac{Q}{Q_d}}(N,\Delta t)$ is computed, the associated variance can be obtained as:

$$\sigma^2_{\frac{Q}{Q_d}}(N,\Delta t)=\left[CV_{\frac{Q}{Q_d}}(N,\Delta t)\cdot\mu_{C_p}(N,\Delta t_{short})\right]^2;\forall N,\forall\Delta t \quad (13)$$

Note that $\mu_{C_p}(N,\Delta t)$ and $CV_{C_p}(N,\Delta t)$ were originally computed from a measurement time series (where long, medium and short-term variability is present), so this variance represents the "total" relative variance of water demands. Figure 5a shows that the total relative variance diminishes in general as Δt increases, and greater values are obtained for smaller N. This is because variance is expressed in relative terms, so the less inhabitants, the greater the expected variance. A relationship can be found between the relative total variance for N inhabitants $[\sigma^2_{\frac{Q}{Q_d}}(N,\Delta t)]$ and the individual total relative variance for one inhabitant $[\sigma^2_{\frac{Q}{Q_d}}(N=1,\Delta t)]$. By considering $Q_d(N)$ much less variable than the peak flow, it can be written that:

$$\sigma^2_{\frac{Q}{Q_d}}(N,\Delta t)=\frac{\sigma^2_Q(N,\Delta t)}{Q_d^2(N)}=\frac{N\cdot\sigma^2_{\frac{Q}{Q_d}}(N=1,\Delta t)}{N^2\cdot Q_d^2(N=1)}=\frac{1}{N}\cdot\sigma^2_{\frac{Q}{Q_d}}(N=1,\Delta t);\forall N,\forall\Delta t \quad (14)$$

So the individual total relative variance can be obtained by multiplying the relative total variance by N:

$$\sigma^2_{\frac{Q}{Q_d}}(N=1;\Delta t)=N\cdot\sigma^2_{\frac{Q}{Q_d}}(N,\Delta t);\forall N,\forall\Delta t \quad (15)$$

Figure 5b shows the resulting individual total relative variance. This figure proves that the individual relative variance evolves similarly no matter the reference number of inhabitants (N) considered for its computation. Remember that $N = 239$ is not to be fully trusted.

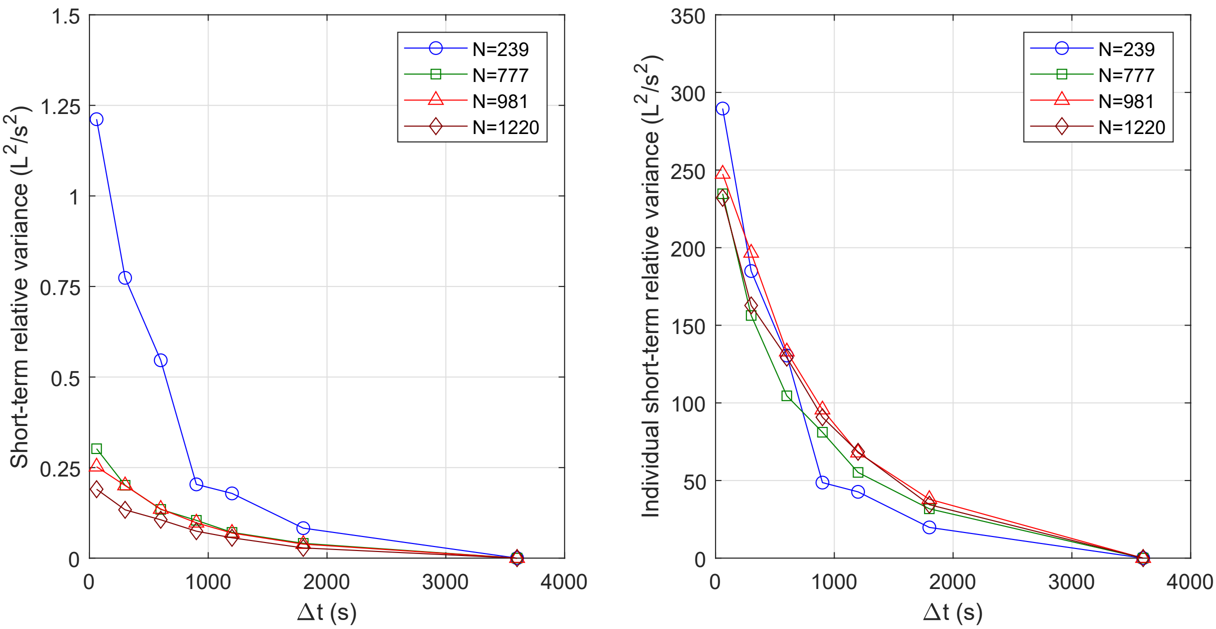

Figure 6. Short-term variance for different number of inhabitants (N) and temporal scales (Δt) at Piedimonte San Germano (PSG) case study: (a) relative variance, (b) individual relative variance.

Figure 5 shows that the total relative variance and the individual total relative variance do not tend to zero for $\Delta t_{short} = 3{,}600$ s. This is because adjusted values represent the total variance of water demands according to measured data. As explained in Section 2, variability when assessing peak demands includes not only short, but also medium and long-term components. These unpredictable (short-term) and predictable (long/medium-term) terms can be separated based on previous observations. It has already been proven that the short-term variance tends to zero for $\Delta t_{\mathrm{short}}$ (see Section 4.1 or Díaz & González, 2021). For this reason, the long/medium-term variance is here considered equal to $\sigma^2_{\frac{Q}{Q_d}}(N, \Delta t_{short})$ and short-term variability can be computed as:

$$\sigma^2_{\frac{Q}{Q_d},short}(N, \Delta t) = \sigma^2_{\frac{Q}{Q_d}}(N, \Delta t) - \sigma^2_{\frac{Q}{Q_d}}(N, \Delta t_{short}); \forall N, \forall t \tag{16}$$

Figure 6 summarizes the behavior of short-term relative variance in this case study. Figure 6a provides the short-term relative variance for different N and Δt values, and Figure 6b shows the corresponding individual short-term relative variance, obtained by multiplying Equation 16 by N. Figure 6a shows that the short-term relative variance is greater for smaller N, but Figure 6b illustrates that the individual relative TESIC curve remains constant no matter the spatial aggregation level used to derive its values. This implies that once an individual TESIC curve is obtained, it can be used to extrapolate short-term variability for other scales. Additionally, Table 3 gives the relative importance (in %) of the individual short-term relative variance (Figure 6b) with respect to individual total relative variance (Figure 5b). It shows that short-term variance has a greater influence for small Δt and N values. This implies that long/medium-term variance loses importance for time intervals in the order of minutes, where short-term variability is crucial.

Table 3
Relative Importance (in %) of Individual Short-Term Relative Variance With Respect to Individual Total Relative Variance

	$\Delta t = 60$ s	$\Delta t = 300$ s	$\Delta t = 600$ s	$\Delta t = 900$ s	$\Delta t = 1{,}200$ s	$\Delta t = 1{,}800$ s	$\Delta t = 3{,}600$ s
$N = 239$	93.6292	90.3700	86.8841	71.1751	68.4238	50.1012	0
$N = 777$	82.5610	75.9209	67.8348	62.0611	52.6877	39.0581	0
$N = 981$	80.2737	76.3741	68.6208	61.1309	52.7570	38.4335	0
$N = 1{,}220$	80.0311	73.7580	69.0417	61.0459	54.1811	37.2727	0

4.3. Practical Implications

These examples enable to conclude that microcomponent stochastic demand models can be a useful tool to assess the effect of short-term variability on peak demands. Note that the most important equations for the analysis here presented correspond to Equation 2 for peak demand value assessment (more general), Equation 9 for peak demand coefficient analysis, and Equation 16 to understand how TESIC curves are incorporated in the formulation. Depending on the available information, there are different ways of benefiting from the conceptual framework presented in this paper:

1. If a consistent microcomponent demand model is available, both $\mu_Q(N)$ and $\sigma_Q(N, \Delta t)$ can be computed at peak hour. Note that the so called TESIC curve is a representation of $\sigma_Q(N, \Delta t)$ over different time intervals for a specific N and at a specific time: the peak hour. Having a reliable stochastic model enables to compute the TESIC curve and the mean consumption value for N at peak hour. With this input, peak values for different $\Delta t \leq \Delta t_{\text{short}}$ can be probabilistically computed according to Equation 2 in order to asess the short-term variability effect on peak demands. This procedure was applied in the validation case study presented in Section 4.1.
2. If there is no access to a full stochastic demand model, but a TESIC curve is available at peak hour, the effect of short-term variability on peak demands can still be analyzed. Note that TESIC at peak hour is an isolated result from the stochastic demand model (i.e., $\sigma_Q(N, \Delta t)$; $\forall\ \Delta t \leq \Delta t_{\text{short}}$ at peak hour). A measurement series for that N and a Δt sampling rate would still be needed to apply Equation 2. The conceptual framework here presented would enable to extrapolate peak demands from a measurement series with a specific Δt to other $\Delta t \leq \Delta t_{\text{short}}$ thanks to the TESIC curve. This may seem unimportant when high-resolution (e.g., per minute) measurements are available, but it becomes of utmost importance when conventional low-resolution (i.e., per hour) measurements are available. Note that it is easy to aggregate measurements for ascending Δt values, but it is not straightforward to decompose averaged values over long Δt into smaller time intervals. The TESIC curve is therefore an asset to analyze and better understand the effect of short-term variability on peak demands. Moreover, the shape of the TESIC curve could be extrapolated from results at other populated areas that are similar to a particular case study. In purely empirical approaches (like the one presented by Gargano et al., 2017), extrapolations are not possible.
3. If there is no access to a microcomponent demand model or a TESIC curve at all, the conceptual framework here presented can still be used to assess the effect of short-term variability on peak demands. Note that Gargano et al. (2017) (like other authors that work with measurement series) start from a per-minute measurement series and progressively aggregate the metered values in order to analyze the temporal scale effect on peak demands, proposing empirical formulas to compute peak coefficients for different N and Δt. In Section 4.2 of this work, the individual short-term relative variance TESIC curve is inferred from the statistical properties of peak demand coefficients published by Gargano et al. (2017). Once this curve is known, Equation 9 is used to assess the short-term variability effect on peak demands. In other words, TESIC curve is an alternative to the empirical formulas originally proposed to interpolate peak coefficients over different Δt. The difference is that this expression is physically based and supported by a microcomponent-based stochastic demand model. In Section 4.2, the TESIC curve has been obtained from the statistical properties of peak demands for seven Δt values. If the information at only one Δt was available (e.g., per-hour sampling rate) and population characteristics were similar, the equivalent TESIC curve could still be inferred by assuming the characteristic shape of the curve here obtained (Figure 6b) or from other similar case studies.

To finish with, note that in these three hypotheses of available information, only the extrapolation or interpolation to other $60\ \text{s} \leq \Delta t \leq \Delta t_{\text{short}}$ has been discussed. Extrapolation to other N would be possible if it can be guaranteed that short-term effects predominate, that is, population is homogeneous. This implies that the approach here presented would be suitable on its own to assess the variability of peak demands on a short-term basis, with direct implications on simulation and/or water quality applications. The approach could be further extended by combining short-term variability curves with suitable models that explain long/medium-term variability. Their combination would provide a fully operative methodology to compute peak demands over any N and Δt. This would be crucial to design or test new supply areas within a water system based on available information in the pre-existing network. Therefore, this paper is presenting a methodological approach that could be systematically extended to account for demand variability across all temporal horizons.

5. Conclusions

In this work, an analytical methodology to probabilistically assess the effect of short-term variability on peak demand values and/or peak demand coefficients is presented. This is possible by combining peak demand assessment principles with the analytical approach to SIMDEUM model proposed by Díaz and González (2021). This analytical approach is here adopted to quantify and/or explain the short-term variability of water demands. Note that short-term variability (below one hour) is random and unpredictable, so it can only be estimated either with stochastic demand models or analyzing measurement series. Long and medium-term variability effects on peak demands are out of the scope of this paper, but they could be incorporated if a suitable variability model was available.

The interest of using an analytical approach to assess peak demands lies in avoiding the site-specific empirical formulas that can be derived from measurement series. This physically based perspective enables not only to compute, but also to better understand, the meaning of peak demand variations over different temporal resolutions within the short-term threshold. Results in both case studies have proved that a short-term variance curve for different time intervals can either be built (with a stochastic demand model) or inferred (from measurement series analysis) to assess peak demands. This curve can then be used to characterize short-term variability for any number of inhabitants as long as end-uses are similarly distributed. This paper proves that short-term variability has a significant effect on peak demand assessment. Moreover, it has been here identified as crucial when dealing with small populations and small time intervals. This contribution highlights the importance of developing strategies that enable bottom-up peak demand assignment, as applying a single peak coefficient to the whole network results in an overly simplified top-down approach given the variability of water demands.

Data Availability Statement

The data and code that support this work are available at https://doi.org/10.5281/zenodo.5834352

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