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Minimum Night Flow Estimation in District Metered Areas

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Abstract: The residential minimum water demand characterisation is of fundamental importance for water distribution system management. During the minimum consumption, indeed, maximum pressures are on network pipes, and at the same time, tank levels rise. The water consumption analysis during the period of low demand and high pressure is thus of great interest for leakage estimation due to the increase in water loss with pressure. In order to contribute to the study of and forecast the daily minimum residential water demand, some probability distributions were tested by means of statistical inferences on a data set collected from different District Metering Areas (DMAs), showing that the stochastic minimum flow demand is defined by the Log-Normal (*LN*), Gumbel (*Gu*) and Log-Logistic (*LL*) distributions, as an extreme minimum value. With reference to the analysed DMAs, the parameters of such statistical distributions were estimated and the relationships are provided as a function only of the supplied users for different DMAs. The data were analysed with 1 h intervals of discretisation, with the aim of providing a useful guide to water utilities, which usually manage water distribution system data with such a resolution time. Indeed, once the minimum residential flow consumption at a 1 h interval was estimated as a function of the user number, by subtracting it to the inflow measured, it is possible to estimate the leakages rate at the DMA.

Keywords: minimum residential water demand; minimum night flow; leakages; probabilistic analysis; logistic distribution; water distribution system; district metering area

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1. Introduction

Minimum water demand characterisation is of fundamental importance for water distribution system (WDS) management, being the lower residential consumption responsible for higher pressures on the system pipes (and then for increased leakages) and for the increase in tank levels.

Several methodologies (e.g., [1–3]) are available in the literature to support WDS management in estimating leakage quantities.

A usual approach for leakages assessment is the minimum night flow (MNF) method (e.g., [4–6]). It is based on detecting leakages in a network by subtracting the inflow data—usually known from water companies—from the user night consumption. Usually, in residential areas, this balance refers to the nighttime—between 02:00 and 04:00 a.m. (e.g., [7])—being the period of the day in which residential water consumption is minimum and high leakages occur.

However, the accuracy in leakage estimation strongly depends on the accuracy of the night flow consumption. Indeed, while the inflow data are generally measured by water companies, the MNF is dependent on the needs of the users and, due to its random nature, it is very difficult to be estimated.

Because of this interest, the aim of this work was to contribute to the characterisation of the random MNF by means of a probabilistic approach.

Several approaches in the literature are aimed at estimating the MNF, usually assuming the residential consumption as a given percentage of the total flow. Most of them analyse the possible consumption from users by summing the amount of L/h used by a single apparatus (i.e., flushing toilets, etc.) and estimating the sum of them as a function of the number of possible taps opened at nighttime (e.g., [8–11]). The so-detected MNF value, however, not considering its random nature, resulted in some cases too low with respect to the real night flow consumption (e.g., [11]) even when the contributions were based on measurements carried out with high temporal frequency, minutes respect to hours, leading to an overestimation of leakages.

Some other approaches (e.g., [12]) highlight the importance of analysing high-resolution data, even at 1 s sampling intervals, for a more realistic characterisation of water losses. This assumption is also more necessary with an increase in user numbers.

The analysis of the water demand for aggregate users, as proposed in this study for the MNF, requires a trade-off between the need to characterise the water requirement as close as possible to the real consumption by considering the shortest interval time and the water companies' need to record and collect a big amount of data. Numerous contributions (i.e., [13–16]) underly the incidence of the discretisation interval time (ΔT) on the water demand estimation. In reference to the maximum peak condition, Tricarico et al. [17] observed an underestimation of 20% in considering the time step equal to 1 h with respect to ΔT = 1 min. Gargano et al. [14] determined a corrective coefficient for estimating the peak value at varying time intervals. The importance of assuming an interval time ranging from 1 to 10 min in the study of the probability of null water demand (F_0) has been highlighted by Tricarico et al. [18] and Gargano et al. [19], in which for an interval time greater than 10 min and a number of users ranging between 500 and 1250, the F_0 was almost null. Indeed, Buchberger and Nadimpally [12] demonstrated that the probability of a null request decreases exponentially with an increasing ΔT.

However, achieving this accuracy in reality is a very difficult task. Water utilities are not equipped with flow and pressure measurement instruments able to constantly reach this level of accurateness. Indeed, water companies have the necessity to manage a big amount of data and usually achieve a sampling interval time of 1 h, in particular due to problems related to data transmission. To model water demand for practical applications, it is essential to estimate and characterise water demand on an hourly basis. In this context, it becomes nearly impossible—even for the lower end of the user range examined—to identify an hour of the day when there is a probability that no user requires water. This challenge becomes even greater as the number of users increases.

The latter is the reason for which it is of fundamental importance the WDS division into district metering areas (DMAs) (e.g., [20–22]). This methodology, originally developed in the UK (e.g., [23]) and already implemented in many countries, consists of partitioning a water system into subsystems ('districts') delimited by control valves (physical district) or by flow meters (virtual district), in which the water balance calculation is simplified and referred to a lower number of users with respect to the whole WDS.

Under this assumption, this work aims to contribute to the characterisation of the minimum flow consumption by analysing with a probabilistic approach real water consumption data recorded and remotely transmitted with a mean interval time of 1 h in 14 DMAs, realised on a real WDS in the Campania region, Italy. The measurements were obtained using electromagnetic flow meters with an accuracy of $\pm$2% on a water velocity V greater than 0.4 m/s or otherwise $\pm$0,8/V%. In the following section (Section 2), the case studies examined and a demand analysis on the collected data are reported.

Three different probabilistic distributions were examined, Log-Normal (LN), Gumbel (Gu), and Log-Logistic (LL), for studying and forecasting the MNF (Sections 3 and 4).

With reference to the analysed DMAs, the parameters of such statistical distributions were estimated, and the relationship is provided as a function only of the supplied users for different DMAs (Section 5). The generalisation of the obtained relationships can improve the capability of estimating water losses in a DMAs by means of the MNF method, and then one can perform strategies for water loss reduction.

2. Case Studies and Demand Data Analysis

The DMAs analysed in this study (Figure 1) are defined by the number of users (N_{users}), ranging from approximately 600 to 17,000. Data were recorded continuously with an average time interval of 1 h, focusing on the winter period from September to February and limited to weekdays only. This choice was made because of the need of analysing the minimum effective night consumption at the residential level, or else it could be influenced by seasonal temperature variability or by the different residential behaviours during the weekends or holidays periods. However, because of leakage variability with time, only 30–35 continuous days for each DMA were examined for the MNF estimation, due to the absence of variation in leakages due to structural works performed by water utilities.

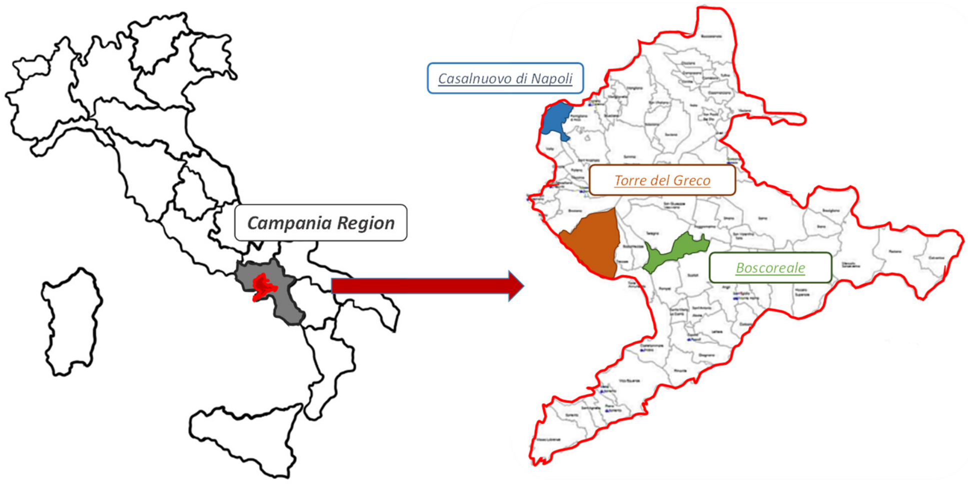

Figure 1. Location of the analysed DMAs in the Campania region (Italy).

The analysed DMAs exhibited a high level of leakage, partly attributed to the elevated pressures within the systems. Because of this, the water utility companies introduced in some districts Pressure Reduction Valves (PRVs) and carried out a water leak search and reduction campaign. In the DMAs analysed, flow and pressure measurements were simultaneously performed, and this allowed the estimation of the time variation of the water loss. An in-depth analysis of flow pressure data was conducted to estimate leakage levels during the analysed period and to identify their daily patterns, which varied depending on the pressure regulation settings. The PRV adjusted pressure levels throughout the day, reducing them during the nighttime hours. This effect is clearly illustrated in the plots of Figure 2, where the leakage flow was lower at nighttime compared to the daytime levels.

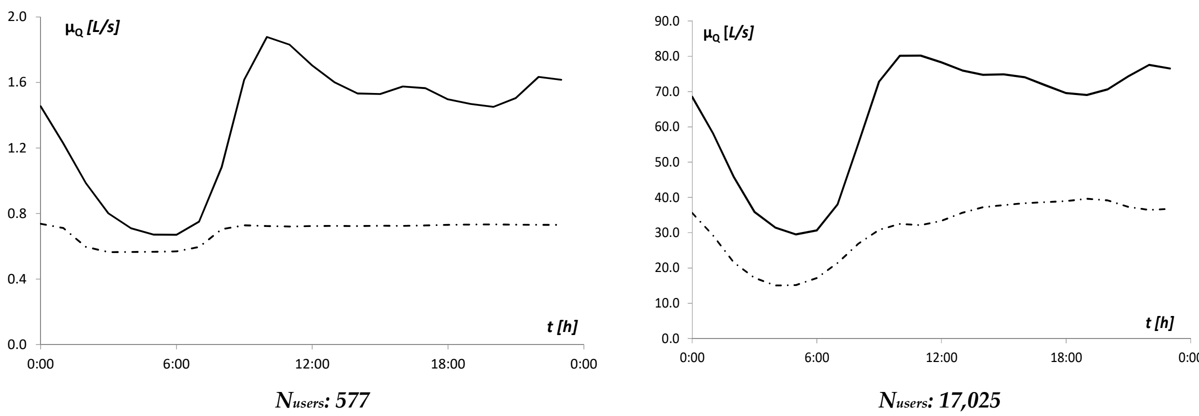

Figure 2. Example of average measured daily flow (μQ) pattern (-) and leakage flow pattern (-·-) for two DMAs with differing user numbers.

The same procedure was applied to DMAs without a PRV, where pressure measurements were available at each time interval [h] (Figure 3). In these cases, as expected, the leakage flows during nighttime hours was higher than those during the day, as the pressures were not regulated by a PRV.

In the examined case studies, accounting for variations in leakages as a function of pressure proved particularly important for accurately detecting water losses. Assuming water losses to be constant and equal to the average leakage value is not appropriate, especially in systems with PRV regulation, where nighttime losses are reduced. Similarly, in DMAs without pressure regulation (as shown in Figure 3), this assumption could result in underestimating nighttime leakages and overestimating daytime leakages.

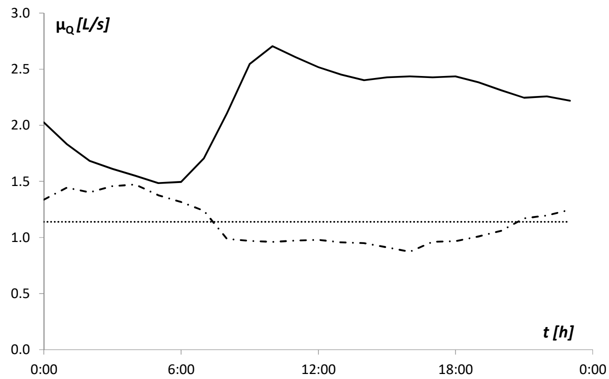

Figure 3. Example of mean measured daily flow (μQ) pattern (-) and leakage flow pattern (-··-) for a DMA without pressure regulation (702 users). Comparison of the flow pattern (-··-) with the constant leakage estimation (····).

The recorded data were adjusted to exclude physical leakages, allowing for the estimation of actual user water demand.

Water demand was then represented in a dimensionless form using the demand coefficient C_D (t):

$$C_D(t) = \frac{Q(t)}{\mu_Q} \tag{1}$$

where μ_Q is the averaged water demand of the examined period and Q(t) the value of water demand at time t.

Hence, in Section 3, the statistics of the residential minimum consumption refer to the dimensionless random variable of Equation (1).

In particular, the night consumption, as different from leakages, could be considered as a random variable, changing as a function of the needs of the residential users and not solely with the pressure. Under this assumption, a probabilistic approach was undertaken.

3. Methodology: MNF Probabilistic Distributions

The extreme events, as the minimum night consumption, are effectively described by the means of asymmetric distributions (e.g., [24]), as for instance the Log-Normal distribution (*LN*) that has the following f_x—probability density function (pdf):

$$f_x^{LN} = \frac{1}{x\sigma_y\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{\ln x - \mu_y}{\sigma_y}\right)^2\right] \tag{2}$$

or the pdf of the Gumbel distribution (*Gu*):

$$f_x^{Gu} = \alpha \exp[-\alpha(x-\varepsilon) - \exp[-\alpha(x-\varepsilon)]] \tag{3}$$

where x is the random variable and $y = lnx$; the symbols μ and σ represent the mean and the standard deviation, respectively. The parameters α and ε of *Gu* are defined by the following relations:

$$\frac{1}{\alpha} = \frac{\sqrt{6}}{\pi}\sigma_x \qquad \varepsilon = \mu_x - 0.45\sigma_x \tag{4}$$

and the Log-Logistic (*LL*) model exhibits a trend similar to that of the *LN*. However, unlike the Gaussian model, its probability density function can be analytically integrated [25,26]. The CDF of the *LL* distribution is expressed as follows:

$$\mathrm{F_x^{LL}} = \left[\left(\frac{\mathrm{e}^{\mu_y}}{\mathrm{x}}\right)^{\frac{\pi}{\sigma_y\sqrt{3}}} + 1\right]^{-1} \tag{5}$$

If $x = \mathrm{C_{dmin}}$ (dimensionless minimum demand Equation (1)), y is $\mathrm{lnC_{dmin}}$.

The parameters of Equation (5) can be estimated either through a statistical analysis of the logarithm of the original sample, or using μ and σ of the original random variable, as given by the following equations [25]:

$$\mu_y = \ln\left[\frac{\mu_x}{\sigma_y\sqrt{3}}\sin\left(\sigma_y\sqrt{3}\right)\right] \qquad \mathrm{CV_x} = \sqrt{\frac{1}{\sigma_y\sqrt{3}}\tan\left(\sigma_y\sqrt{3}\right) - 1} \tag{6}$$

where $\mathrm{CV_x} = \sigma_x/\mu_x$ is the coefficient of variation.

All the suggested distributions are defined for $\mathrm{C_{dmin}} > 0$. The decision to consider bi-parametric models was driven by the need to identify models that offer the reliable estimation of a few parameters, making them suitable for practical application.

4. Results and Discussion

The *LN*, *Gu*, and *LL* distributions were tested using the observed data from the different DMAs, with a time aggregation of $\Delta T = 1$ h.

The diagrams in Figure 4 are the Quantile–Quantile (Q-Q) plots for the monitored number of users. These plots compare the observed and the theoretical $\mathrm{C_{dmin}}$ quantiles, each with the same probability of occurrence. The theoretical values were estimated using the integral of Equations (2) and (3)—the numerical integration for *LN* distribution—and Equation (5). The quantiles for the minimum demand of Figure 4 closely align with the bisector line, which represents the condition where the observed and the theoretical quantiles are equal.

The effectiveness of the three distributions was assessed using the Kolmogorov–Smirnov (KS) test. Figure 5 summarises the threshold values for a 1% confidence level (D1%—reported with the dot line) and the relative KS parameters (D) for the *LN* ($\mathrm{D_{LN}}$), *Gu* ($\mathrm{D_{Gu}}$), and *LL* ($\mathrm{D_{LL}}$) CDFs. The fit tests were satisfied (D < D1%) for all monitored users.

In Table 1, the statistics of the data sample (μ_{Cdmin} and σ_{Cdmin}) for different DMAs with varying user numbers are reported.

As it is of evidence, all the examined distributions proved to be equally effective in modelling the night flow demand.

Equations (2) and (3) allow one to determine the minimum demand coefficient $[\mathrm{C_{dmin}}]_\mathrm{F}$ for a predefined probability Pr [*S*] of not exceedance or (1−Pr [*S*]) of exceedance. Therefore, the MNF coefficient with a specified probability of not exceedance, following an *LL* distribution, is given by the following:

$$[\mathrm{C_{dmin}}]_\mathrm{F} = e^{\mu_y}\left[\frac{\Pr[S]}{1-\Pr[S]}\right]^{\frac{\sigma_y\sqrt{3}}{\pi}} \tag{7}$$

While, for a *Gu* distribution, $[\mathrm{C_{dmin}}]_\mathrm{F}$ is expressed by the following relation:

$$[\mathrm{C_{dmin}}]_\mathrm{F} = \sigma_x \left[\frac{1}{\mathrm{CV}_x} - 0.45 - \frac{\sqrt{6}}{\pi} \ln\left(\ln \frac{1}{\Pr[S]} \right) \right] \tag{8}$$

The quantile $[\mathrm{C_{dmin}}]_\mathrm{F}$ for an *LN* model can be estimated only by means of a numerical approximation.

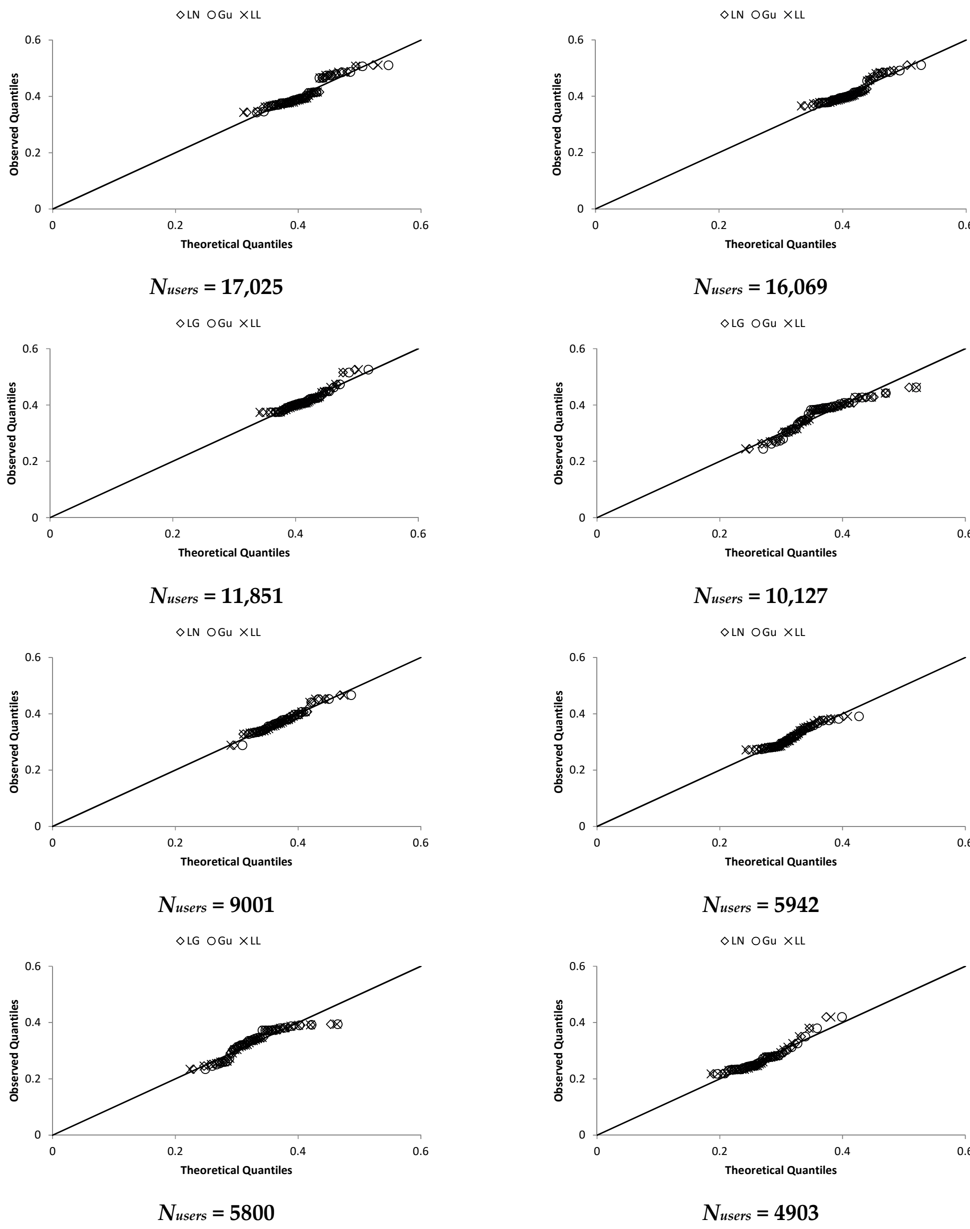

Figure 4. *Cont.*

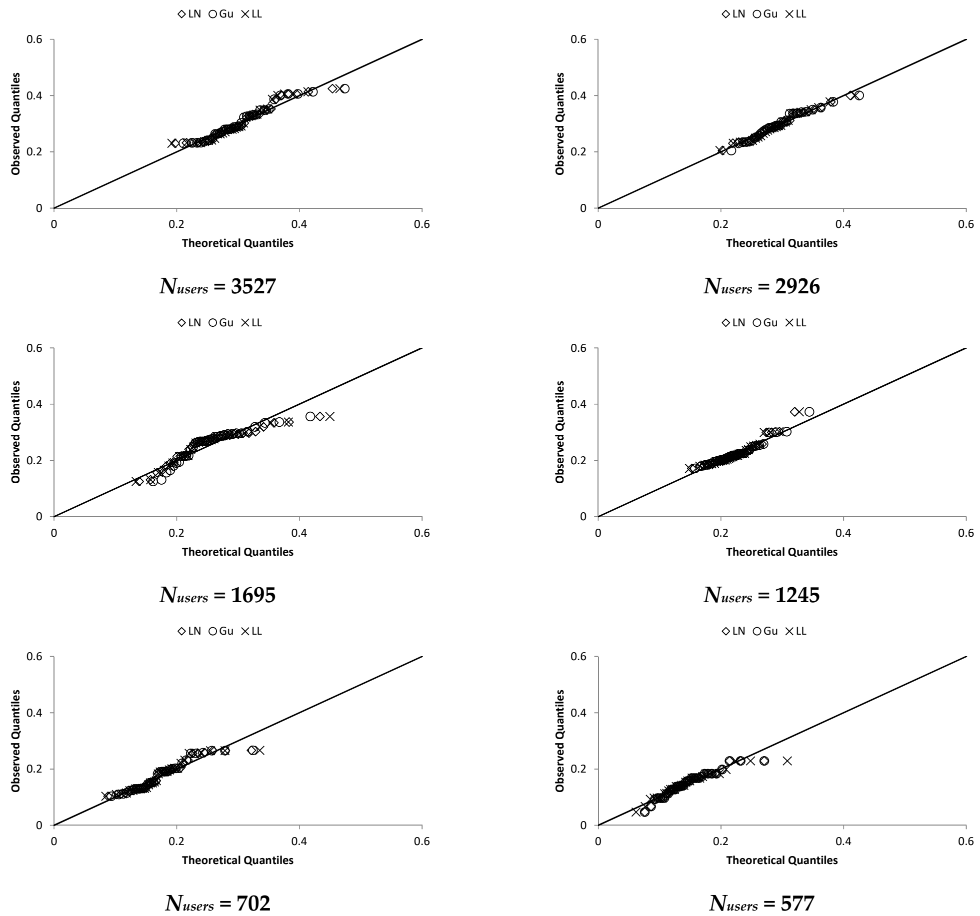

Figure 4. Q-Q plots of the C_{dmin} for the different distributions considered and for ΔT = 1 h, at varying user numbers, i.e., DMAs.

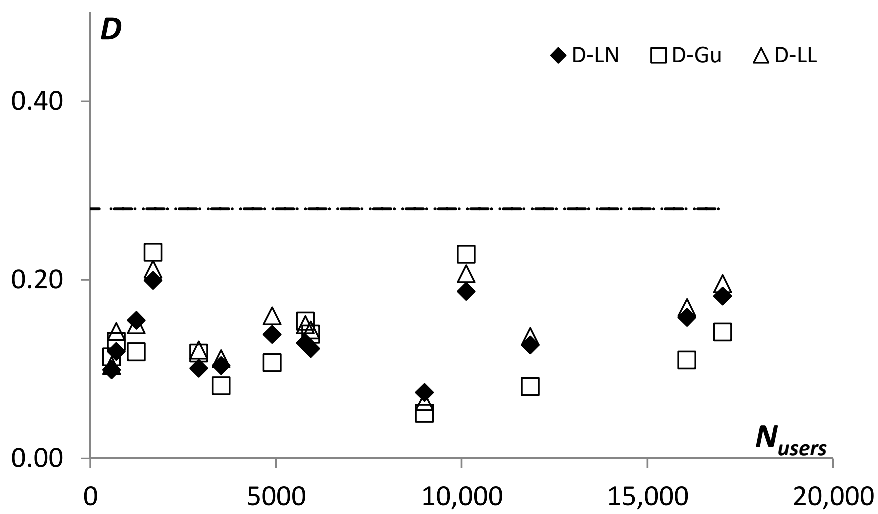

Figure 5. KS test results with a confidence level of 1% for the analysed samples referring to the three probabilistic distributions examined, *LN*, *Gu*, and *LL*.

Table 1. Statistics for the analysed samples and goodness of fit with D K-S.

N_{users}	μ_{Cdmin}	σ_{Cdmin}	D_{LN}	D_{Gu}	D_{LL}	$D_{1\%}$
17,025	0.409	0.049	0.181	0.141	0.195	0.280
16,069	0.415	0.040	0.157	0.110	0.169	0.280
11,851	0.416	0.036	0.126	0.080	0.136	0.280
10,127	0.360	0.056	0.187	0.229	0.206	0.280
9001	0.374	0.042	0.073	0.050	0.063	0.303
5942	0.319	0.038	0.122	0.139	0.143	0.280
5800	0.326	0.049	0.129	0.153	0.149	0.280
4903	0.270	0.047	0.138	0.107	0.159	0.288
3527	0.305	0.060	0.103	0.081	0.111	0.280
2926	0.292	0.049	0.101	0.118	0.121	0.298
1695	0.253	0.058	0.199	0.231	0.211	0.280
1245	0.225	0.042	0.154	0.119	0.149	0.280
702	0.176	0.052	0.119	0.131	0.142	0.280
577	0.145	0.044	0.099	0.114	0.103	0.280

5. Estimation of Parameters

All the proposed distributions (*LN*, *Gu*, and *LL*) are bi-parametric models; hence, they require the estimation of two parameters as the mean and coefficient of variation (CV).

The mean value of the minimum C_D recorded each day during the examined period (μ_{Cdmin}) was plotted against the number of users (N_{users}), i.e., corresponding to the different DMAs analysed, as shown in Figure 6.

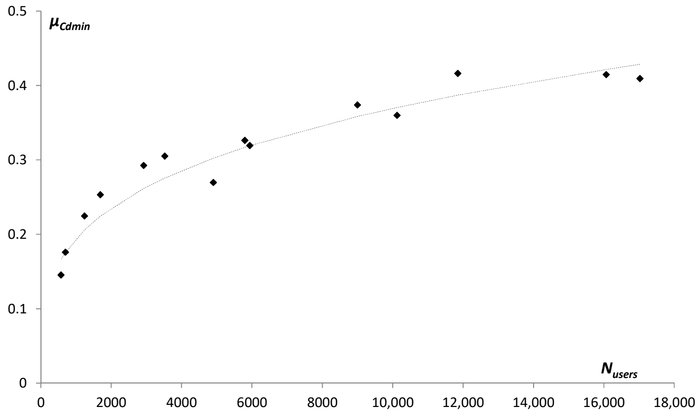

Figure 6. DMA mean C_d minimum (μ_{Cdmin}) at varying numbers of users and relative trend (- - -) reported in (9).

The minimum demand coefficient increases with the number of users, as expected. For the analysed DMAs, the experimental data follow the trend described in Relation (9) with R^2 = 0.94:

$$\mu_{Cdmin} = 0.028\, N_{users}^{0.28} \tag{9}$$

The proposed relationship enables the estimation of the user night flow consumption by knowing only the mean inflow at the DMA and the number of users.

The CV of the minimum night data, CV_{Cdmin}, can also be estimated as a function of the number of users:

$$CV_{Cdmin} = 0.1 + \frac{3.9}{(0.039 \cdot N_{users})^{0.9}} \tag{10}$$

The CV experimental points reported in Figure 7 are well-fitted by the proposed (10) relationship with R^2 = 0.83, which shows, as expected, a decreasing trend in the CV with the user number. It needs to be highlighted that CV experimental points tend to 0.1 with an increase in the user number, as evidenced also in other residential water demand analyses (e.g., [14,17,19]). The spread of the CV data with respect to the trend could be due to the different pressure regulations operated by the PRV during the night.

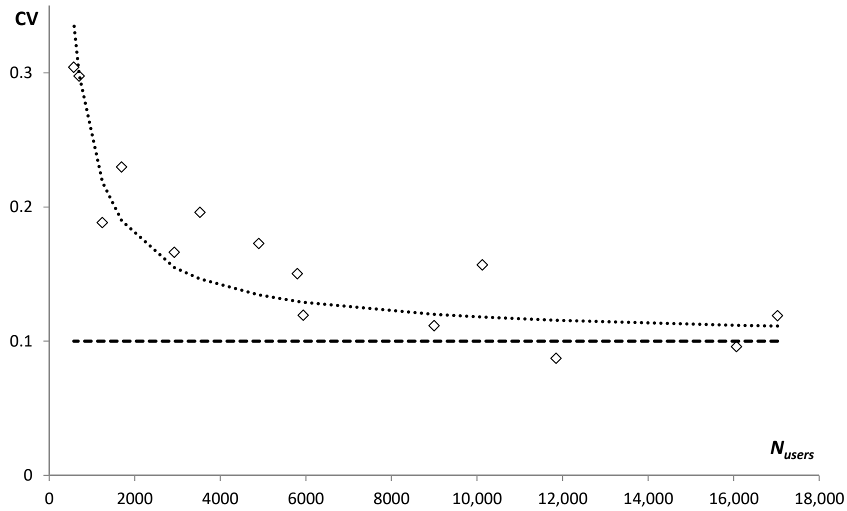

Figure 7. CV of C_{dmin} at varying numbers of users and relative trend (. . .) reported in (10).

By means of Equations (9) and (10), the parameters of μ_{Cdmin} and CV_{Cdmin} were estimated solely as a function of the DMA number of users.

By the application of Equations (7) and (8), however, it is possible to define the MNF with an assigned probability of success/failure. In Figure 8, the confidence intervals for the μ_{Cdmin} are reported for predefined probabilities.

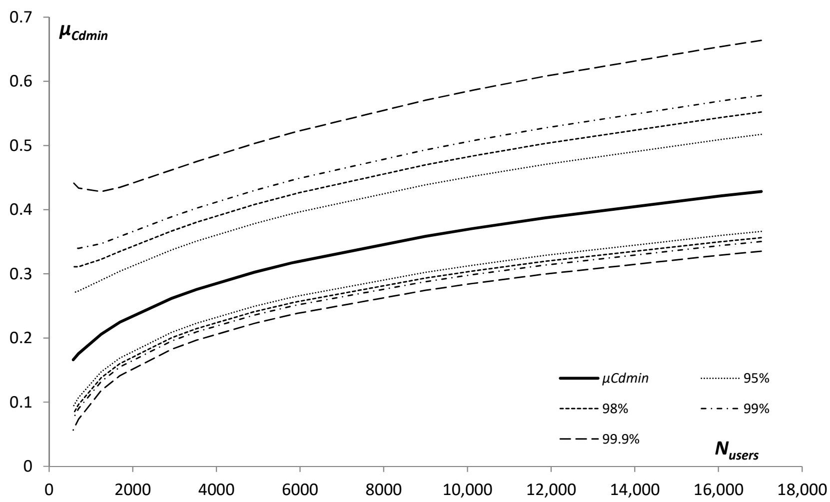

Figure 8. Mean C_{dmin} variation with the number of users for the predefined confidence interval estimated with the CDF of the Gumbel distribution.

With an increase in the probability of not exceedance, the μ_{Cdmin} value increases, leading to a greater MNF coefficient, and this is more evident with a decreasing number of users. The choice of which probability to consider is usually made by the decision maker as a function of the problem and as a consequence of a cost–benefit analysis.

The proposed relationships for the model's parameters estimation (Equations (9) and (10)) were then used as a test for evaluating the CDF of the data by only knowing the number of users. In Figure 9, the CDF estimated by means of the Gumbel distribution application is compared with the observed one, obtaining a good fit in the data representation.

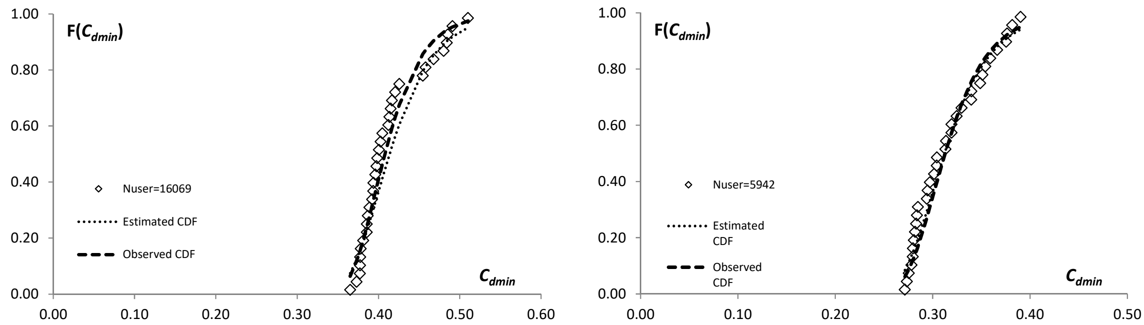

Figure 9. Observed and estimated CDF for different user numbers, i.e., different DMAs.

6. Conclusions

The study of the residential minimum water demand is crucial for WDS management and in leakage estimation. Understanding minimum residential consumption is also valuable for quantifying leaks, usually known from the water companies solely by the total volume supplied to the urban area during a specific period of time. This study investigated the MNF characterisation 14 different DMAs in the Campania region, Italy, with the number of users ranging between 600 and 17,000. Winter weekly water demand data at hourly time steps were analysed, and the hourly minimum consumption with varying user numbers was probabilistically modelled. The decision to represent the results with an interval time of 1 h was due to the aim of providing a practical application for the proposed methodology, as data are usually collected from the water companies at an hourly time step.

By means of statistical inferences on the data set collected from different district metering areas (DMAs), the effectiveness of the Log-Normal (*LN*), Gumbel (*Gu*) and Log-Logistic (*LL*) distributions was demonstrated. The latter is of particular interest, being the *LL* probability density function analytically integrated. For the DMAs and the number of users investigated, the relationship of the model parameters were proposed as functions of the number of users supplied. The advantage of using the proposed relationships undoubtedly lies in their simplicity, even if they are probabilistically based. Indeed, in order to estimate the random minimum water consumption from residential users, it is necessary to know solely the number of users supplied and the daily mean value of flow requested by the DMA.

The results should be considered valid for the range of users examined in this research, with a residential characteristic and indoor water use. In future works, it would be desirable to extend the analysis to a greater number of DMAs.

The generalisation of the obtained relationships can enhance the ability to estimate water losses in a DMA using the MNF method, thereby facilitating the implementation of strategies for reducing water losses.

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Abbreviations

$CV_{C_{dmin}}$	Coefficient of variation of minimum demand coefficient
C_D (t)	Demand coefficient at time t
CDF	(acronym) Cumulative distribution function
C_{dmin}	Minimum demand coefficient
CV	Variation coefficient
CV_x	Coefficient of variation of random variable
DMA	(acronym) District monitoring area
f_x	Probability density function
F_x	CDF of random variable
Gu	(acronym) Gumbel distribution
KS	(acronym) Kolmogorov–Smirnov test
LL	(acronym) Log-Logistic
LN	(acronym) Log-Normal distribution
MNF	Minimum night flow
N_{users}	Number of users
pdf	Probability density function
PRV	Pressure reducing valve
WDS	(acronym) Water distribution system
x	[depending on variable] Random variable
y	[depending on variable] lnx
α	Gumbel parameter
ΔT [T]	Time step
ε	Gumbel parameter, mode
μ	Mean
$\mu_{C_{dmin}}$	Mean minimum demand coefficient
μ_Q [L/s]	Mean daily water demand
σ	[depending on variable] standard deviation

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