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Stochastic model applied to water demand management in Brazil

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ABSTRACT

The increasing scarcity of water sources near urban areas, coupled with urbanization and population growth, necessitates the development of solutions that optimize water demand management, which entails a more accurate estimation of consumption patterns and implementing measures that promote the rational use of water. A stochastic residential water demand model was built based on the superposition of pulses of constant intensity and variable arrival time and duration applied to the microcomponent consumption at a 1-minute resolution, reflecting the aggregate system contributions to the total instantaneous demand. The model can support the planning of water supply systems (WSSs) and was calibrated using data from Brazilian institutes combined with a literature review of statistical data on users and end uses of water in Brazilian dwellings. Innovatively, it proposes using water demand forecasting to apply demand management measures evaluating the replacement of conventional devices for water-saving ones by analyzing hydrographs of 50–50,000 households, in addition to detailing the influence of the K2 peak factor. The results demonstrated a new water consumption profile with about a 40% reduction in water demand. A new equation for K2 is proposed as an alternative to estimate the demand for small populations fittingly.

Key words: computational model, demand management, efficient appliance, end uses

HIGHLIGHTS

- The model can support the planning of water supply systems (WSS).
- From its use, it is possible to obtain essential characteristics for the dimensioning and operation of supply networks, such as maximum, average, and minimum flows, peak hours, per capita consumption, and consumption per appliance, among others.
- A new formulation for the peak coefficient is available from the data used in the model.

1. INTRODUCTION

One of the main obstacles to achieving urban sustainability is the management of resources, especially water. Providing sufficient water is crucial for maintaining the well-being of urban populations, yet many people worldwide still lack access to safe water sources (WHO & UNICEF 2021). To address these challenges, effective management methods for water supply systems (WSSs) are needed to ensure equilibrium between supply and demand. This equilibrium is attained through operational measures, some of which involve using prediction instruments (Groppo *et al.* 2019).

Furthermore, the limitation of water supply in urban areas necessitates a more comprehensive examination of water demand, which goes beyond per capita consumption and more accurately assesses the effects produced by applying demand management strategies.

Understanding where and when people use water in their homes, gathering information on the contribution of various appliances to total water use, the relative split between indoor and outdoor use, or seasonal and geographic variations in water consumption is essential to determine the likely future demands for water supply, detecting leaks in the system, designing demand management programs and their interventions, such as replacing appliances and offering alternative sources of water (Giurco *et al.* 2008).

The domestic water supply's primary function is to supply its residents' basic needs (Stec 2019). In Brazil, per capita consumption varies from around 100–150 L, and some studies specify consumption by end-use in different study regions, as shown in Table 1.

From the analysis of Table 1, it can be observed that, regardless of the region, bathrooms represent the highest point of water consumption, accounting for more than half of domestic water consumption. In some places, the consumption of toilets and showers is relatively similar, justifying the need to invest energy and resources in research on reuse practices.

The variability of consumption in different study regions, as shown in Table 1, also highlights the need to consider other intervening consumption factors, such as demographic, geographic, and cultural characteristics. Abu-Bakar *et al.* (2021) proposed a classification for the determinants of residential water demand between exogenous (environmental), behavioral (psychosocial), and endogenous (contextual) so that each one can influence both final consumption and the consumption of each hydro-sanitary device in each dwelling, as shown in Figure 1.

Furthermore, it is necessary to understand the daily consumption profiles for different populations and building models. It is known that the size of the population strongly influences the coefficient of maximum hourly flow and may assume values greater than those recommended in ABNT NBR 9649 (1986), as evidenced by the equations of Babbitt & Baumann (1958), Gifft (1945), Johnson (1942) and Harmon (1918). At the same time, van Duuren *et al.* (2019) argue that the coefficient can also undergo variations influenced by adopting measures aimed at the rational use and implementing more efficient hydro-sanitary devices.

Implementing water-saving appliances is also one of the water benchmarking strategies in buildings. Although essential, that is not easy to know, only through measures that require high investment and operating costs, such as using smart meters at each point of consumption in homes. Due to this, there is significant variability in methodologies applied and models created to characterize the water demand and its future projections (Ghalehkhondabi *et al.* 2017).

Software with a stochastic methodology meets the need to obtain this information at a much lower cost. A stochastic process occurs through a variable that behaves over time, where at least part is considered random; therefore, evaluating several different and independent scenarios from stochastic modeling is possible.

Based on the stochastic method, there are two main ways of obtaining residential consumption: obtaining demand without characterizing the microcomponents or by summing the demand pulses for each end-use. Some models and applications are referenced in Table 2.

Buchberger & Wu (1995) presented the first stochastic model for residential water demands. This approach assumes that Poisson Rectangular Pulses (PRP) can simulate the intensity, duration, and frequency of water consumption in a home. The model conceives the household, so PRP parameters and probability functions can be adjusted based on flow measurements in monitored households (Buchberger & Wells 1996). This method established a foundation for the analysis, upon which several other pulse models were presented (see Creaco *et al.* 2017 for a literature review). Later, an alternative to the available methods emerged, the so-called: '*Simulation of Water Demand and End-Use Model*' (SIMDEUM) (Blokker *et al.* 2010). SIMDEUM is a model that obtains the overall water demand in a household by aggregating the microcomponent demand pulses for each inhabitant (i.e., end-user) at an installation level (e.g., faucet, shower, washing machine) (Creaco *et al.* 2017). The end-use approach is fed with survey-based parameters rather than relying on flow measurements like the first model type. It implies dealing with more input parameters, which are easier to obtain (i.e., surveys rather than experimental campaigns).

Table 1 | Water demand in Brazilian households per use

	Per capita consumption (L.P./D)							
Author/city	**Shower**	**Sanitary bowl**	**Lavatory**	**Kitchen sink**	**Tank**	**Washing machine**	**Others**	**Total**
Botelho (2013)[a]/Salvador (BR)	21.1	24.1	4.0	16.6	20.1	33.8	3.4	123.1
Barreto (2008)/São Paulo (BR)	35.3	14	10.8	30.3	13.6	27.7	77.4	209.1
Cohim *et al.* (2008)[b]/Salvador (BR)	31.43	18.8	8.7	25.0	14.6	–	–	80.16
Sant'Ana & Mazzega (2018)[c]/Brasília (BR)	33	27	10	29	14	25	6.5	144.5

[a]Analysis carried out by Botelho (2013) in residences with income of up to two minimum wages without the intervention of demand management measures.
[b]Research carried out with low-income families in Salvador.
[c]Per capita consumption values for households earning up to two minimum wages.

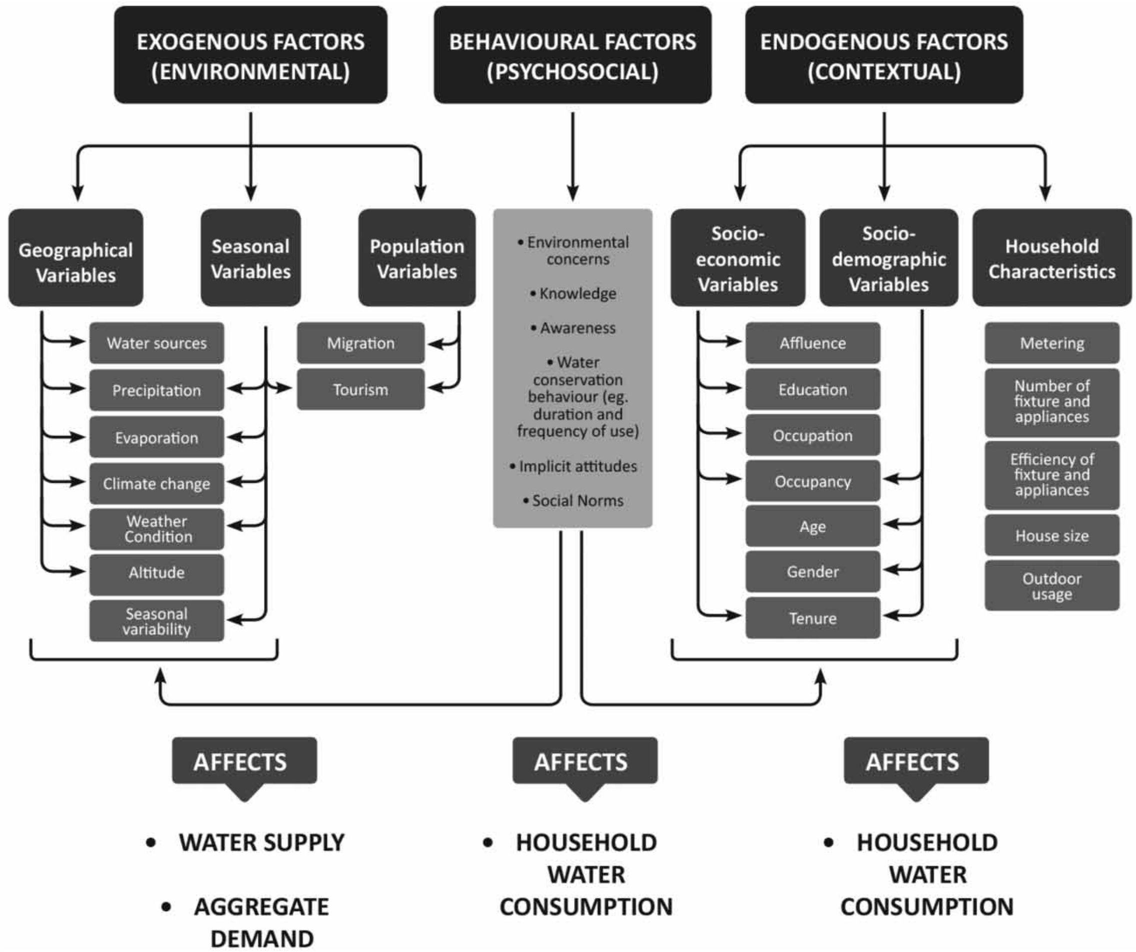

Figure 1 | Consumption determining factors. *Source:* Abu-Bakar *et al.* (2021).

The original SIMDEUM model is based on Monte Carlo simulations. Each simulation provides a high-resolution water demand pattern. The spatial resolution can be adjusted by aggregating the pulse demands as needed, and a small-time scale (1 s) is used (Blokker *et al.* 2010). PRP-like and SIMDEUM models gave similar results for different spatial and temporal scales (Creaco *et al.* 2017). Gargano *et al.* (2015) and Creaco *et al.* (2020) proposed more simplified stochastic models with less detail and easier computational processing. Both represent the total instantaneous demand, proving the model's effectiveness based on comparing results in different regions, based on Milford, in the USA, and the Italian cities of San Germano and Naples.

The main difference between the models by Blokker *et al.* (2010) and Ferreira & Gonçalves (2019), which inspired the model developed in this work, is that both models associate the characteristics of each end-user with the residents of the households. In these models, the demand is generated by each fixture, from each family unit, from each final use, and each one associated with a probability distribution. Probability distributions are used to describe the habits of the occupants of the housing units in order to identify the moments with the most significant probability of using the system components.

In this paper, a new methodology is proposed to generate, at any time step, synthetic demand time series for different populations, combining literature data with regional demographic statistics. Compared to the work of Ferreira & Gonçalves (2019) and Blokker *et al.* (2010), the novel methodology has the following features:

- The model can estimate the peak demand factor for different populational group sizes and proposes a new formulation for its determination in Brazil, in contrast to the Brazilian resolution ABNT NBR 9649 (1986), avoiding undersizing events in projects for populations of less than 200,000 inhabitants.

Table 2 | Stochastic models applied to household water demand estimation

Author	Model	City	Applications
Buchberger & Wu (1995)	PRP (hourly pulses generated through the Poisson process, with pulses of duration and intensity generated by monovarietal probability distributions).	Cincinnati (USA)	Determination of the flow Q as the sum of all pulses, without distinction of devices, and determination of the Reynolds number of the system.
Creaco *et al.* (2017)	Cor-PRP (hourly pulses generated through the Poisson process, with duration and intensity pulses generated by bivariate probability distributions).	Milford (USA)	Determination of the Q flow as the sum of all pulses, regardless of device.
Blokker *et al.* (2010)	SIMDEUM (time pulses dependent on the frequency of use and users' routine, with duration and frequency associated with each pulse).	Milford (USA), Holand	Determining the Q flow as the sum of all pulses for each usage event per resident and appliance.
Gargano *et al.* (2015)	Overall Pulse (OP), where the water requests at each time step in the OP have been directly modeled as the sum of several demand pulses at the faucets in a resolution of 1 minute.	Piedimonte San Germano (Italy) and Milford (USA)	The Monte Carlo method displays the generation of the overall domestic demand at the house water meter.
Ferreira & Gonçalves (2019)	Hourly pulses depend on the frequency of use and users' routine, with duration and frequency associated with each pulse.	São Paulo (Brazil)	Determination of the Q flow as the sum of all pulses of each use event per resident and appliance; analysis of replacement of higher-pressure devices in the hydraulic system.
Creaco *et al.* (2020)	Aggregates the water demand per user in a magnitude of 1 h using a beta probability distribution with tunable bounds or a gamma distribution with shift parameter. The refinement is made by ranking cross-correlations between users and at all temporal lags through a single Copula-based resort.	Milford (USA) and Naples (Italy)	Generates demand time series of the first attempt for each user and time step of the day, which is consistent with the measured time series in terms of mean, standard deviation, and skewness.

- The model substitutes some sanitary appliances for more efficient ones, preserving residents' behavioral patterns and use in other devices, helping evaluate measures that encourage the reduction of water consumption.
- It can establish, from the analysis of synthetic data, factors that most impact the residential consumption profile, such as occupancy rate and behavioral patterns.

2. METHODS

In this work, using SIMDEUM as a reference, a rectangular pulse of demand was simulated for each user in each sanitary appliance, which occurs at a particular time, with a specific duration and intensity. As shown in Figure 2, a rectangular pulse is defined as a usage event that starts at a specific time, '*t*', with the constant flow '*q*' until the end of its duration, '*d*':

$$Q = \sum_{r=1}^{R} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{f=1}^{F_{m;n}} (q_f; d_f)_t \tag{1}$$

The other indexes of the equation are as follows: q_f indicates the flow rate of use of a sanitary appliance, associated with frequency; d_f indicates the duration of use of a sanitary appliance, associated with frequency; f indicates the frequency of use index associated with each device and each resident; t indicates the instantaneous activation of a sanitary appliance; $F_{m;n}$ indicates the total number of uses of sanitary appliance 'n' by resident 'm'; N indicates the total number of sanitary appliances; n indicates the index of the number of devices; M indicates the total number of residents of a given residence; m indicates the

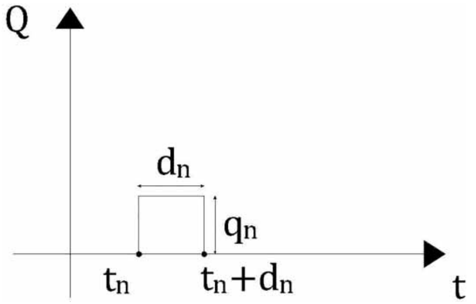

Figure 2 | Schematization of a rectangular demand pulse.

index of the number of residents of a given residence; R indicates the total number of households; r indicates the index of the number of simulated residences; Q indicates the total flow.

Concerning the components of the residential hydro-sanitary system, all end uses are identified, and for each use, a probability distribution is defined to characterize the pulses of frequency of use, duration, and intensity so we can separate the system parameters dependent on the characteristics of users and device characteristics which behave like random variables that have the probability of each value associated with a probability function. The model was parameterized based on data collection from Brazilian literature for the parameters of Equation (1), combined with demographic data also from Brazil to define the occupancy rate and age per household, corresponding to the variables 'R', 'M', and 'N'.

The best-fitting probability distributions are determined by analyzing the results of the normality tests and the adjustment error using the Kolmogorov–Smirnov (KS) test and Standard Mean Error verification. The KS test is a nonparametric goodness-of-fit test used to determine if an underlying probability distribution differs from sample, while the Standard Mean Error measures the accuracy with which a sample distribution represents a population

2.1. Generation of residents of each household

When building the model and defining the household, it is necessary to define the number of residents and the age of each one by type of housing. In order to guarantee the stochasticity of the model, the number and age of residents can be randomly projected by defining probability distributions associated with demographic data. In the case of the generation of residents for the urban population living in apartments and their ages, the adjustment according to Table 3 was used.

2.2. Parameters associated with the characteristics of the associated devices

The model is built in the MATLAB programming language. The parameterization takes place by reviewing the bibliography of statistical data related to the types of existing hydro-sanitary devices, their use and consumption patterns, and information associated with demographic data.

Based on an empirical literature review, Table 4 shows the probability distributions defined by some authors for the metropolitan region of São Paulo.

The frequency of use of each device is associated with the classification between collective or individual use, as established by each author. Individual uses will have frequency distributions associated with each resident's use, while collective uses will have distributions associated with the use of all household residents.

Table 3 | Weibull and Gamma fitting distribution parameters to the urban population according to the household occupancy rate

	Probability function	Parameters	Kolmogorov–Smirnov (KS)
Residents per household	Weibull	$\lambda = 1,584$ $k = 35.831$	$KS_{p} = 0.7821$ $KS_{stats} = 0.064$
Age of residents	Gamma	$k = 4.096$ $\theta = 0.637$	$KS_{p} = 0.8284$ $KS_{stats} = 0.157$

Source: Data extracted and adapted from IBGE (2011) and IBGE (2018).

Table 4 | Statistical pattern of use by sanitary appliance

	Frequency		Duration (s)		Flow (l/s)	
	Distribution	Parameter	Distribution	Parameter	Distribution	Parameter
Lavatory[a]	Poisson	$\lambda = 5.93$	Lognormal	$\sigma = 0.845$ $\mu = 3.355$	Lognormal	$\sigma = 0.328$ $\mu = -2.668$
Sink[b]	Poisson	$\lambda = 24.88$	Lognormal	$\sigma = 0.785$ $\mu = 3.176$	Weibull	$\lambda = 0.569$ $k = 1.587$
Shower[a]	Poisson	$\lambda = 1.08$	Gama	$k = 6.522$ $\theta = 0.767$	Lognormal	$\mu = -2.421$ $\sigma = 0.201$
Washing machine[c]	GEV	$k = 0.249$ $\sigma = 0.134$ $\mu = 0.185$	6 Min/Cycle		Uniform	0.1
Toilet flush[d]	Poisson	$\lambda = 2.75$	Fixed	60s	Fixed	0.25 L/s
Tank[a]	Poisson	$\lambda = 1.15$	Lognormal	$\sigma = 0.892$ $\mu = 3.291$	Lognormal	$\sigma = 0.328$ $\mu = -0.349$

[a]Distribution according to data from de Oliveira *et al.* (2013).
[b]Distribution according to data from Ilha & Gonçalves (1991).
[c]Distribution according to PROCEL INFO data for defining frequency of use and duration and flow according to data from de Oliveira *et al.* (2013).
[d]Distribution according to data from de Oliveira *et al.* (2013), considering a sanitary basin with a 12-L box.

2.3. Demand event time (τ)

The definition of the time for each event is determined based on the behavior pattern of each household resident, depending on the type of use. First, the behavior pattern is defined randomly according to the resident's age group. An example is given in Table 4 with the definition of five types of behavioral patterns that may vary according to the σ parameter of the normal distribution. Therefore, the construction of Table 5 is carried out based on the following works and research:

- Santos-Silva *et al.* (2010) carried out a probabilistic and comparative study in the Metropolitan Region of São Paulo on sleep characteristics, such as duration and sleeping time of the population by age group.
- According to the IBGE census (2010), commuting working time is, on average, 6 min–1 h in Brazil.
- The study carried out by Silva *et al.* (2005) about sleep habits and school hours of Brazilian children.
- The average workday of 8 h a day.
- The Brazilian unemployment rate according to the Continuous National Household Sample Survey (PNAD) data.

Therefore, five types of behavioral patterns were defined, which may vary according to the σ parameter of the standard normal distribution (Table 5).

Table 5 | User behavioral time pattern applied to a standard normal distribution by age group

Age group		Wake-up	Leave home	Return to home	Sleep
Up to 17 years old: morning shift [60%]	μ	6:00:00	07:30:00	12:30:00	22:30:00
	σ	01:00:00	00:30:00	00:30:00	01:00:00
Up to 17 years old: afternoon shift [40%]	μ	09:30:00	13:00:00	18:00:00	01:00:00
	σ	01:00:00	00:30:00	00:30:00	01:30:00
18–65 years: employed [75%]	μ	5:30:00	07:30:00	19:30:00	22:30:00
	σ	01:00:00	00:30:00	00:45:00	01:30:00
18–65 years: non-employed [25%]	μ	8:00:00	10:00:00	14:00:00	23:30:00
	σ	01:00:00	03:00:00	04:00:00	01:00:00
From 65 years	μ	05:30:00	10:00:00	14:00:00	21:30:00
	σ	01:00:00	03:00:00	04:00:00	00:30:00

The probability of the time of occurrence of an event of use is associated with the behavioral pattern of its resident through the establishment of peak demand time bands, in which the use of certain appliances has a greater tendency to occur.

In the absence of data in the Brazilian literature that estimates peak hours of use of sanitary equipment, this work adopted peak hour parameters similar to those adopted by Blokker *et al.* (2010) so that the authors defined *peak time* as 30 min after waking up, 30 min before leaving home, 30 min after returning, and 30 min before going to sleep.

Within the developed model, each device has a probability of time of occurrence, and for the shower, kitchen sink, wash-basin, and toilet, the probabilities of use correspond to:

- Shower: 15% probability 30 min after waking up and before leaving; 50% probability up to 30 min after returning; and 20% up to 30 min before going to sleep.
- Kitchen sink: 5% probability at dawn; 25% probability between wake-up time and the leave-home time; 70% probability between the return time and sleep time.
- Lavatory: 10% probability of use at dawn; 15% probability of use within 30 min of waking up and 20% probability of use within 30 min of leaving; 40% probability of use after returning home and 15% up to 30 min before going to sleep.
- Sanitary basin: 5% probability of use during the night; 13% probability of use in each time range included in the morning and evening peak hours; 10% probability in the off-peak interval in the morning time slot; 35% in the off-peak period between returning home and the time the resident goes to sleep.

This pattern of peak use of specific devices is in line with the usage database by Mazzoni *et al.* (2023) for households in Amsterdam and in the consumption profiles of Botelho (2013) for Salvador, Brazil. Their time series shows peak demand for devices associated with when residents wake-up or go to sleep and when they leave and return home.

In the case of the washing machine and the tank, the probability of use is adjusted according to the PROCEL INFO (2020) data for using the washing machine, as shown in Figure 3.

For the frequency of washing machine cycles in Brazil, the Generalized Probability Distribution of Extreme Values (GEV) and Gamma were adjusted according to the PROCEL INFO database, as shown in Table 6.

2.4. Efficient appliance substitution

For the insertion of efficient devices, the devices most used at peak times were chosen, such as the shower and the toilet. For the duration of the baths, a triangular distribution was used with a minimum of 2 and a maximum of 5 min/bath, taking into

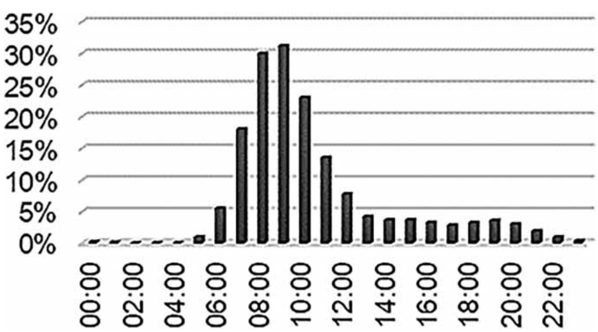

Figure 3 | Probability of time of use of the washing machine and the tank. *Source:* PROCEL INFO (2020).

Table 6 | GEV and log logistic distribution parameters for washing machine

	GEV		Log logistic	
	Frequency	**Mean error**	**Time**	**Mean error**
Parameters	$k = 0.249$	$7{,}686 \times 10^{-3}$	$\sigma = 0.186$	$1{,}238 \times 10^{-3}$
	$\sigma = 0.134$	$1{,}112 \times 10^{-3}$		
	$\mu = 0.185$	$1{,}355 \times 10^{-3}$	$\mu = 10{,}453$	$2{,}480 \times 10^{-3}$

Source: PROCEL INFO (2020).

account that, according to Moon (2015), the minimum amount of water needed for a bath varies between 1 and 3 min while for SAPESB (2002), the necessary duration of baths is 5 min. The flow of the showers and the most efficient models of showers on the market vary between 3 and 5 L/min, according to the United States Environmental Protection Agency (US EPA 2022) database, so a triangular distribution with these data is also used in the model. To replace the toilet, for this study, the replacement of the conventional 12 L basin by de Oliveira *et al.* (2013) for the Acquamantic do Brasil sanitary basin model Karoll, with 2.0 L/discharge activation, as it is a more compatible sanitary basin for Brazil, both for acquisition and installation.

2.5. The maximum hourly flow rate

The maximum hourly flow coefficient analysis is performed by obtaining each simulation's maximum and average flows. Then, a correlation is made with the empirical equations used in other study regions using mathematical adjustment methods, such as the method of least squares.

3. RESULTS AND DISCUSSION

The average of the simulations ranged from 115.21 to 127.68 L/p.day, with the data set represented in Figure 4 by box diagrams for each simulated population size. In it, it is observed that the per capita consumption values are of the same order of magnitude as the values found by other authors for apartments, such as 148.06 L/inhab.day by Cominato *et al.* (2022), 140.3 L/p.day by Costa & Mota (2022), 150.8 L/p.day by Cohim *et al.* (2012), 123.1 L/p.day by Botelho (2013), 144.5 L/p.day by Sant'Ana & Mazzega (2018) and other authors in Table 1. Notably, these results found by other authors were obtained from small samples. At the same time, the Brazilian National Sanitation Information System (SNIS) values represent the reading of the macro-measured hydrometer once it considers other uses such as irrigation of plants and car washing, among other external uses, undetermined and leaks.

Based on each household's demographic characteristics and consumption, it is possible to establish a relationship between per capita consumption and the occupancy rate and a relationship between the occupancy rate and the monthly consumption of each household. The data allowed us to conclude that as the occupancy rate increases (Figure 5(b)), there is also an increase in average residential consumption. However, per capita consumption follows an inverse order concerning the occupancy rate, and an adjustment can be made to an exponential function (Figure 5(a)). Furthermore, other authors, such as Cohim *et al.* (2012) and Botelho (2013), reported the reduction pattern of consumption related to the number of residents. That is a consequence of the more significant number of residents; the consumption made for collective use in the residence, such as washing clothes, cooking, and washing dishes, is divided among the number of residents, reducing per capita consumption outcomes do not provide new significant insights, as also evidenced by the comments of the results.

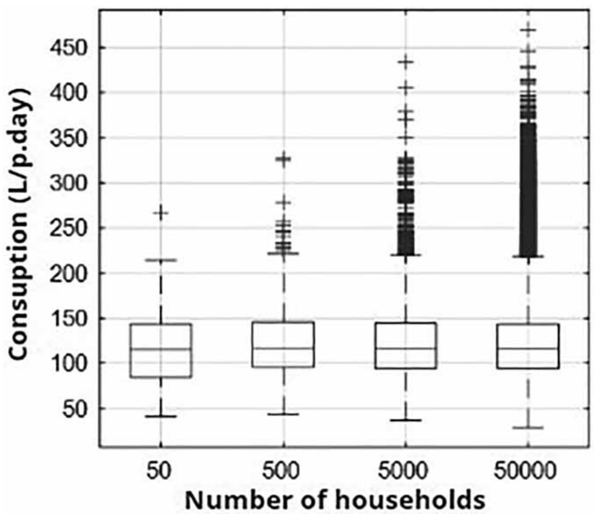

Figure 4 | *Per capita* consumption in different population groups. *Source*: PROCEL INFO (2020).

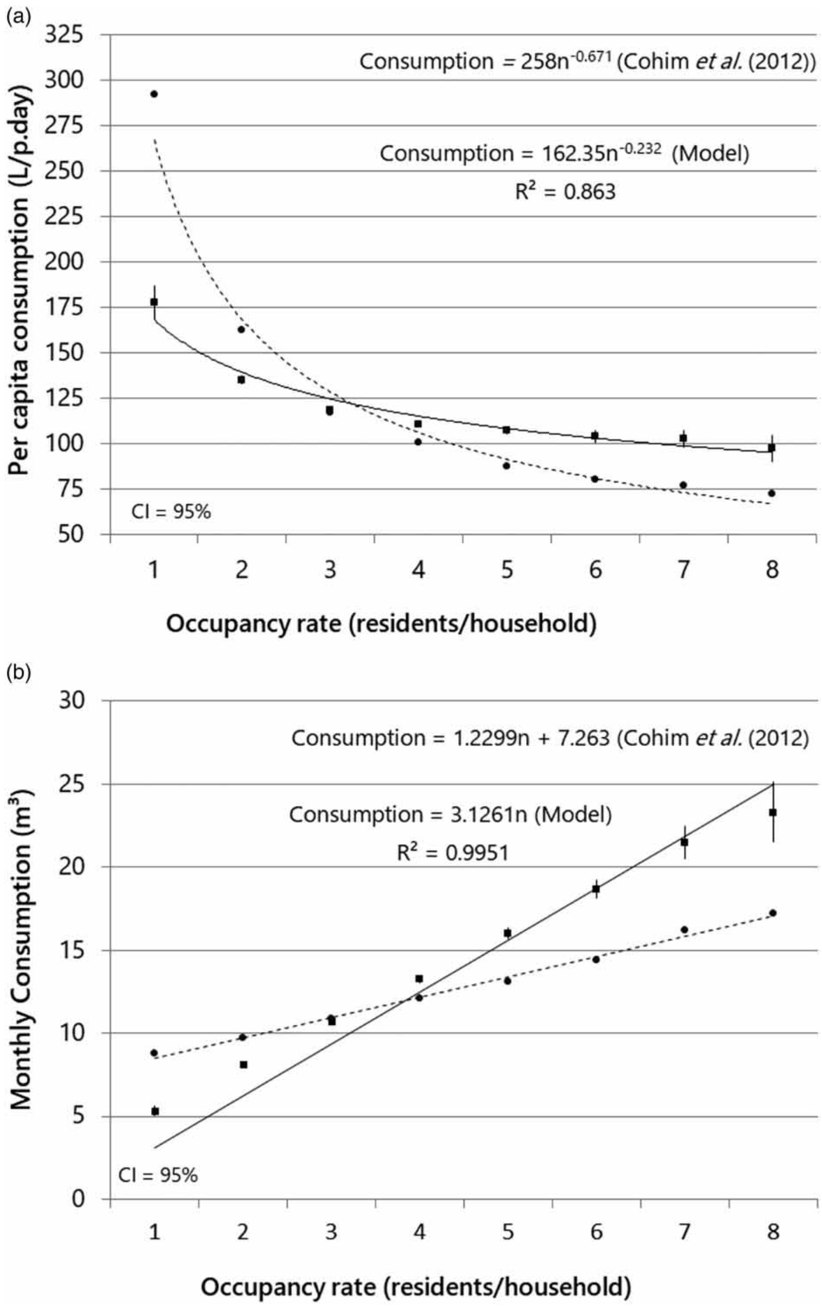

Figure 5 | (a) Average per capita consumption per home occupancy rate and (b) mensal residential consumption per home occupancy rate.

When analyzing the hydrographs in Figure 6, important considerations can be made about their format concerning the size of the population analyzed, which smoothes out as the number of simulated households increases, and the insertion of efficient appliances also results in attenuation demand spikes. This observation of the reduction of demand peaks through the observation of the hydrographs emphasizes that replacing devices with a great tendency to use at times when there are many simultaneous uses due to the concentration of people in residence is an excellent strategy to reduce water stress and supply failures.

An important consideration can be made regarding demand peaks, the model's reliability, and other data sets. As in the data set analyzed by Mazzoni *et al.* (2023) for residences in Holland, there is a tendency for a concentration of uses in

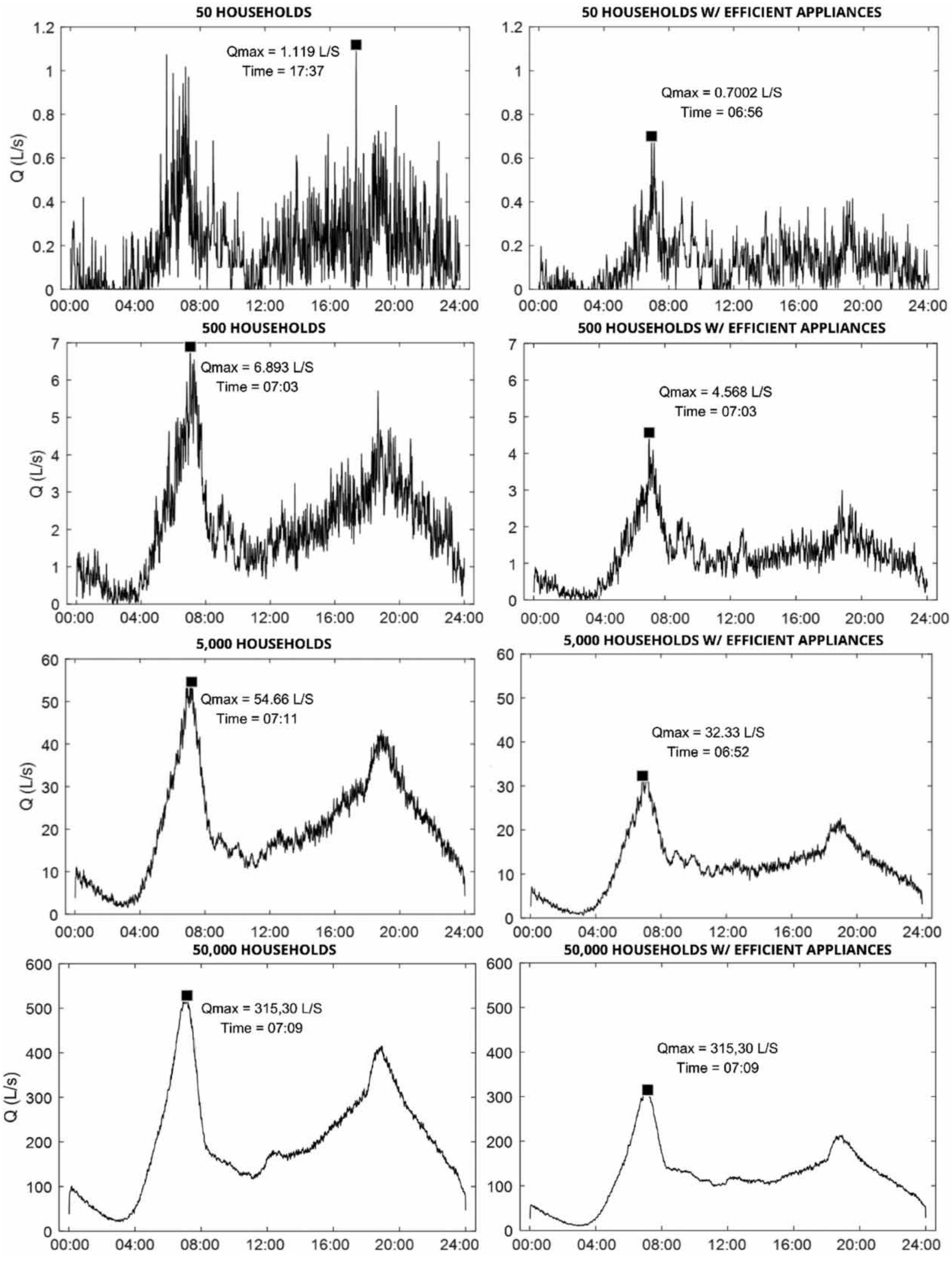

Figure 6 | Flow Q (L/s) by household sample.

the morning, between 07:00 and 09:00, and another in the evening, of lower intensity, which is associated with the behavioral pattern of residents.

From the simulations created, obtaining the maximum hourly flow coefficient, K_2, is also possible. The K_2 coefficient, which is the ratio between the maximum hourly flow and the average flow of the maximum day of consumption, used to

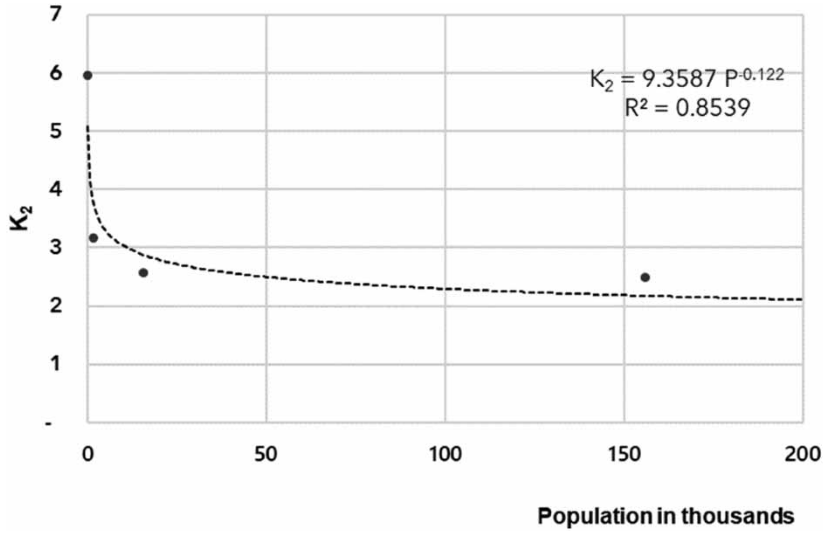

Figure 7 | Relationship between the K_2 coefficient and the number of residents.

determine the water demand for sizing the WSS, varied according to the size of the samples, different from the provisions of NBR 9649 (ABNT 1986) where the value is fixed at 1.5. As shown in Figure 7, in both scenarios, the coefficient shows an inverse relationship to the size of the samples but with a tendency to stabilize in large population groups, such that with an adjustment of an exponential function, from 3.2 million inhabitants, the value of K_2 would equal 1.5.

The variation of the peak factor, which represents the multiplication between K_1 and K_2, and its decrease with population size have also been pointed out by some authors (Figure 8) when investigating the effects of population size on water demand. When comparing the value obtained for the K_2 coefficient with the other empirical equations in the literature for population samples of the same size, as shown in Figure 8, we see that the simulation results, although different from the literature, decrease following the same pattern.

Another way of analyzing the relationship between the results obtained from K_2 and the other empirical equations is through a regression method to adjust the simulated values to the empirical equations in the literature. Thus, Table 7 was constructed through regression using the least squares method between simulated data and considering $K_1 = 1.2$ (NBR

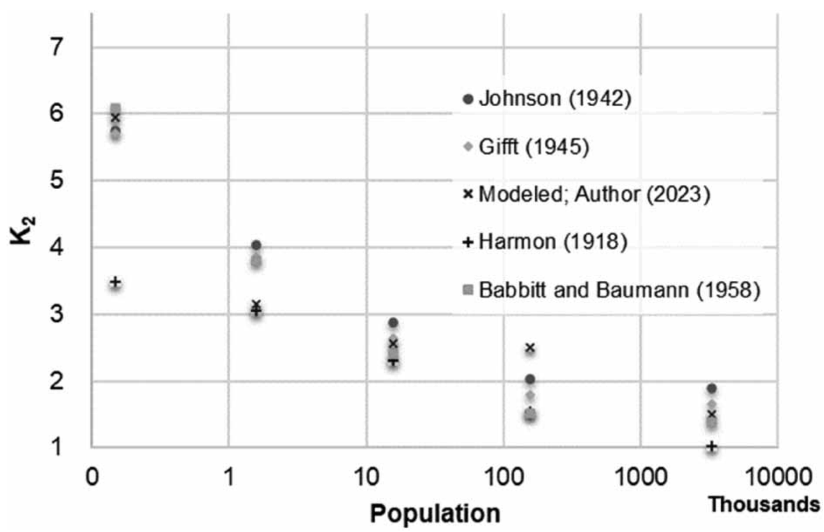

Figure 8 | Comparison between the K_2 value extracted from the model and that determined by empirical equations for the same populations.

Table 7 | Adjustment of simulated peak factors to the Babbit and Baumann equation

	Original equation	Adjustment with simulated data (assuming $K_1 = 1{,}2$)	$E = (K_2' - K_2'')^2$
Babbitt & Baumann (1958)	$K_1 \times K_2 = \frac{5}{(p/1,000)^{0.2}}$	$K_1 \times K_2 = \frac{5.54}{(p/1,000)^{0.19}}$	1.08
Harmon (1918)	$K_1 \times K_2 = 1 + \frac{14}{4 + \sqrt{p}}$	$K_1 \times K_2 = 2.27 + \frac{2.87}{0.09 + \sqrt{p}}$	0.53
Gifft (1945)	$K_1 \times K_2 = \frac{14}{p^{0.1667}}$	$K_1 \times K_2 = \frac{20.36}{p^{0.1885}}$	1.08
Johnson (1942)	$K_1 \times K_2 = \frac{5.2}{p^{0.15}}$	$K_1 \times K_2 = \frac{20.36}{p^{0.1885}}$	1.08

9646). Thus, it is notorious that it approximates the simulated data to the empirical equations, mainly the equation of Babbitt & Baumann (1958), with a low margin of error.

Disregarding the variation of the K_2 factor for small populations, as provided for in NBR 9646 (1986), also affects the definition of the supply flow and, consequently, the sizing of the supply network. Using a K_2 of 1.5, as recommended by NBR 9646, in the simulated population would lead to an undersizing of the supply flow, as shown in Table 8, which could result in failures in the supply network of the study population.

On the other hand, Josey *et al.* (2023) and Ferreira & Gonçalves (2019) analyzed consumption in buildings and stated a peak demand overestimation in the data generated and analyzed by them in Australia and New Zealand, and Brazil, where the design flow would be primarily part of the time, lower than the designed flow rate. However, Josey *et al.* (2023) also states that '*the period of peak water use is not synchronized among apartments in small buildings*' and the magnitude of measured peak flow increases as the sampling interval decreases. Therefore, more studies should be conducted for smaller and larger populations, and analyzing the influence of regional and behavioral factors to define the peak factor better to avoid both overestimations and underestimations.

In the intervention of water-saving appliances, it is essential to note that there was no change in consumption habits or the routine of users, which gives greater reliability in predicting the impact of their use. We also see that the toilet and shower have a greater weight in household consumption, as shown in Figure 9(a) and as already demonstrated by other researchers in Table 1. Therefore, the model shows that replacing the toilet and shower with more efficient devices results in a new distribution of consumption percentages per appliance (Figure 9(b) and 9(c)) and savings of up to 40% of the total consumption in these homes.

4. CONCLUSIONS

The model created acts as a tool with good potential for dimensioning the WSSs, capable of characterizing the demand for microcomponents in different population groups and creating historical series according to the population characteristics of entry into the model.

Thus, from its use, it is possible to obtain essential characteristics for the dimensioning and operation of supply networks, such as maximum, average, and minimum flows, peak hours, per capita consumption, and consumption per appliance, among others.

Table 8 | Comparison of the supply flow with simulated and theoretical K_2

	ABNT NBR 9649	Model
K_2	1.50	2.52
Q (L/s)	487.50	1,023.75

$Q = K_1 \times K_2 \times \frac{p \times q}{86,400}$.

Note 1: So that (per capita consumption) = 150 L/p.day.

Note 2: Sample with 50,000 households and occupancy rate of 3.12.

Note 3: $K_1 = 1.2$ (NBR 9649).

Note 4: 'q' represents the per capita water consumption and 'p' represents the population.

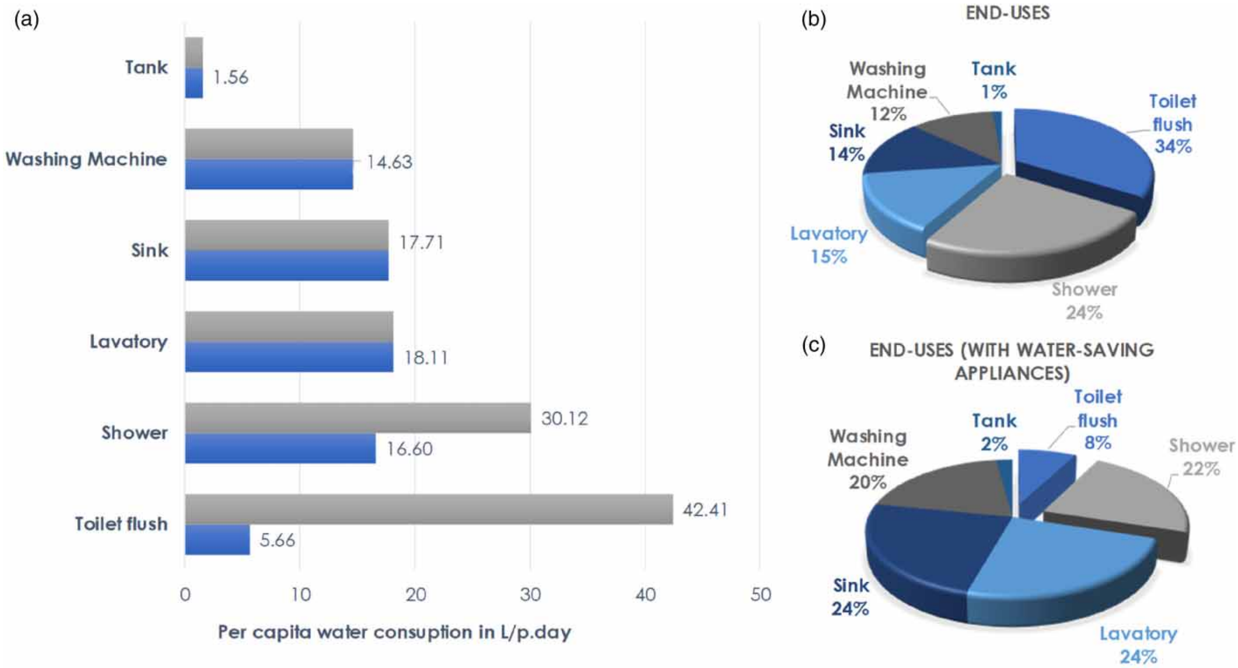

Figure 9 | (a) Consumption in L/p.day by final use for 5,000 homes simulating conventional use and rational use in the basin and shower; (b) and (c) percentage of consumption per sanitary appliance in the simulation of 5,000 households with and without the intervention of energy-saving appliances and rational use, respectively.

The results presented by the model are within the margin already presented in the literature for the same study region and not inconsistent with those presented in other Brazilian regions. It is noted that the application of demand management measures in a hierarchical way in the devices with the greatest potential for use at peak times, which would be the devices inside the bathroom, such as the washbasin, toilet flush, and shower, standardize the demand and, therefore, they attenuate overload events in the WSS, such that efficient use of the shower and toilet reduced about 40% of the total consumption.

From the comparison with the results of different samples collected by the authors cited here, it is inferred that the quality of the analysis products generated by the model proves to be useful not only in the management of WSSs but also as a tool with great potential for assessing the impact of these releases on the sanitary sewage system and assessing demand management as a whole.

The simulations carried out by the program reinforce that the dimensioning of supply networks and sanitary sewage with the value fixed in NBR 9646 (ABNT 1986) in small populations induces the undersizing of networks and the design flow, as a solution, a new equation for defining K_2 can be applied to populations of up to 200,000 inhabitants.

From the data analysis, factors such as occupancy rate and the resident's time pattern have strongly influenced the consumption profile. On the one hand, there is an inverse exponential relationship between per capita consumption and occupancy rate. On the other hand, the definition of the wake/sleep and leave-home/return-home time plays a crucial role in demand peaks.

The model can be replicated in different scenarios and regions to analyze more parameters; however, its parameterization would still require monitoring each domestic appliance, which may be impractical, and householders are unlikely to provide permission to install this intrusive instrumentation.

In future work, more iterations, extended periods, uses, and different scenarios should be considered, as well as the influence of gender on consumption variables and the influence of the variance of the water demand profile on the sewage system and the cooling of pipes and reservoirs.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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