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TEMPORAL SCALE SIGMOID CURVE (TESIC): A TOOL TO CHARACTERIZE SHORT-TERM DEMAND VARIABILITY AT WATER SUPPLY SYSTEMS

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Abstract

Water demand is the main random factor that conditions flow variability across water supply systems. Water demand measurements or pseudomeasurements (i.e. estimations based on historical data) are associated with a time interval (sampling rate), which affects the variability of water demands. Considering a long time interval implies losing information about water consumption within that temporal window. The variance (i.e. quantification of variability) computed from demand records is thus only "apparent", because the variability within the time interval is averaged and lost (i.e. "missed"). The relationship between missed and apparent variability can be assessed through the so-called TEmporal scale SIgmoid Curve (TESIC), which is here presented as a tool to characterize short-term demand variability. TESIC is used in this work to compute demand uncertainty for a given time resolution level and to estimate peak demands for different temporal resolutions in a realistic water supply case study. These applications show that TESIC provides a conceptual framework to explain and quantify the temporal resolution effect in hydraulic modelling applications.

Keywords
Water supply systems, smart meters, water consumption, uncertainty analysis, peak demand, high resolution.

1 INTRODUCTION

Water demands are stochastic in nature and constitute the main source of variability in water supply systems [1]. Consumption drives flow through the network, so it is paramount to have a good characterization of water demands to accurately simulate the hydraulic behaviour and associated water quality [2]. At a transport level, through the main arteries that supply water to District Metered Areas (DMAs), it may be enough to spatially and temporally average water demands [3]. This means that several users can be aggregated into a demand node (spatial averaging) and instantaneous variations in demand can be smoothed (temporal averaging). However, this approach is not suitable in the distribution mains that provide water to final users. Stochastic demand models were conceived to simulate the pulsating nature of water demand in these final pipelines (see [4] for references). Since these models particularly focus on what happens within a household (high spatial resolution), they are also associated with a very high temporal resolution, typically in the order of seconds (e.g. [5], [6]). This means that there is a large gap between the temporal resolutions typically adopted to model the macro network behaviour (15-60 minutes [7]) and the resolutions required to understand what happens on a micro household/fixture scale.

Temporal scale effects have been discussed in water supply systems for decades [8] and they are known for affecting the variability of water demands: considering longer time intervals (i.e. sampling rates) is associated with a loss of information from the consumption signal, leading to lower variance values [9]. Note that variance is here understood as a metric for demand variability. Several authors have worked on analysing the statistical properties of water consumption at different scales [1, 7, 10], but few have delved into how the sampling rate affects the ability to explain network behaviour and performance at different spatial aggregation levels. Note that the variance computed from demand/flow records is only the “apparent” variance, because the variability within the time interval is averaged and lost. This variability can therefore be accounted for as a “missed” variance. As presented by [11], the addition of the Apparent Variance (AV) and the Missed Variance (MV) provides the Total or instantaneous Variance (TV) for that time and spatial aggregation level, and both components are complementary. As a matter of fact, AV and MV describe a sigmoid curve when represented against the time interval. This S-shaped curved is called TESIC (TEmporal scale SIgmoid Curve) and can be computed either by progressively averaging measurement records with a very small time interval or by relying on a suitable stochastic demand model [12].

The aim of this work is to present the fundamentals of TESIC, as well as some related applications where this tool proves to be useful. More specifically, TESIC will be here used (1) to quantify the additional uncertainty derived from using larger time intervals than the monitoring time resolution [12], and (2) to compute peak demands considering different time intervals [13]. These application examples will show that TESIC provides a conceptual framework to explain short-term demand variability and combine information associated with different temporal scales. Therefore, it is relevant to bridge the gap between the micro and macro scales that coexist in water supply systems.

2 METHODOLOGY

2.1 TESIC conceptual framework and short-term variability scope

The relationship between AV, MV and TV was first explored in [11]. In this publication, an analytical approach to the end-use stochastic demand model SIMDEUM (SIMulation of water Demand, an End-Use Model) [6] was used to quantify not only the variance associated with a specific sampling rate (AV), but also the variability that is lost within the time interval (MV). This approach enables to compute AV, MV and TV at different times and for different sampling rates, proving that AV and MV are complementary. Figure 1 shows that AV is maximum for small time intervals (a high frequency sampling rate enables to capture most of the variability), keeping MV low. For long time intervals, there is a lot of variability not captured by the sampling rate (high MV), and AV is at its minimum. It is important to highlight that the curve presented in Figure 1 has two asymptotes at 0 and TV. This happens because TESIC focuses in “short-term” variability, which is unpredictable (i.e. fully random) and happens mostly within the 1-hour threshold.

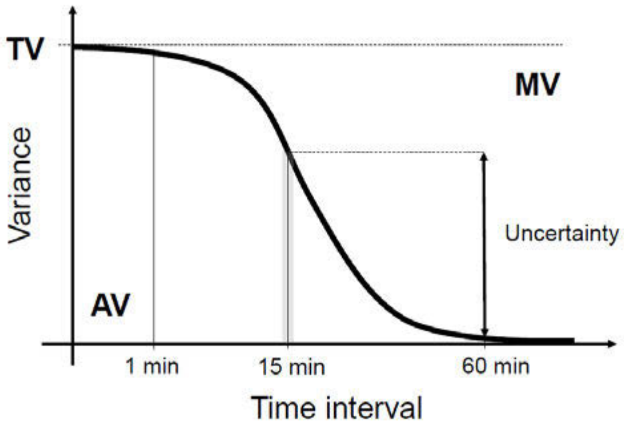

Figure 1. TESIC conceptualisation: Apparent (AV), Missed (MV) and Total (TV) Variances

Note that any water demand or flow time series can be decomposed into seasonality and noise. These components come determined by their period, so they can be associated with long and short-term variability. Short-term behaviour is here considered to take place with time periods below 1 hour, and periods above this threshold determine the mid and long-term behaviour [12]. Long-term variability is mainly associated with tendency, and it is more predictable because it comes mostly determined by the external factors that condition the population behaviour (e.g. working schedules, temperature, rainfall) [13]. Therefore, it is captured with usual demand sampling rates (above the hour) and/or it can be estimated with a predictive demand model (e.g. [14, 15, 16]). On the other hand, short-term variability is mostly random and associated with low correlation, i.e. it is poorly captured with usual sampling rates (above the hour) and more difficult to forecast. However, it can be estimated with a suitable stochastic demand model. Due to the limitations of the current models available to compute TESIC, these curves can only be applied to assess random short-term variability effects. TESIC definition is however universal, so it could be extended to cope with long and medium-term variability if micro demand models were combined with a suitable predictive model. This is a subject for further research.

TESIC has been presented up until now as a curve that can be derived from a stochastic demand model to characterize how short-term demand/flow variability changes with the temporal resolution. When computed like this, TESIC enables quantification of pseudomeasurement uncertainty [17], which may need to be additionally complemented with the medium/long-term component provided by a forecast model. However, TESIC can also be computed from available high-resolution measurement series. Infinitesimal time intervals are required to ensure that the original AV is representative of TV, but then the rest of the curve can be obtained by averaging AV over larger time intervals. Since flow metering devices with short time intervals are expensive and uncommon [2], TESIC estimation from a stochastic demand model is a good alternative to explore short-term variability. Note that if a model-based TESIC is to be compared with a measurement-based TESIC, the measurement series should be first treated to filter seasonality out [12], so that they both focus on short-term variability.

2.2 Demand time resolution uncertainty computation

TESIC provides the TV, AV and MV associated with a measured or pseudomeasured demand/flow at a specific time for different time intervals. Therefore, it can be useful to compute the uncertainty that would be induced in a hydraulic model by considering one sampling rate and not another. To explain this, it is important to highlight that, depending on the origin of the input, possible sources of uncertainty coexist [12]:

- Measurement uncertainty (for measured data): from the device metrological error

- Pseudomeasurement uncertainty (for pseudomeasured data): from the inaccuracy of the considered estimation model
- Time resolution uncertainty (for either measured or pseudomeasured data): it appears when an input has a higher time interval than the time resolution required for modelling. This requires the input to be temporally disaggregated, introducing an additional uncertainty to the demand variable

Time resolution uncertainty can be quantified by making use of TESIC. Let us assume that a time resolution of 15 minutes is required for a specific hydraulic modelling application, but only demand measurements/pseudomeasurements with a 1-hour (i.e. 60 minutes) time interval are available. Time resolution uncertainty could be computed as the difference between the apparent variance associated with 15 minutes and the apparent variance for the 1-hour interval measurements/pseudomeasurements (see Figure 1). This uncertainty should be added to the measurement or pseudomeasurement uncertainty, and this total should be considered the input uncertainty for the modelling application. If measurements/pseudomeasurements with a time interval of 1 minute were available instead, averaging would be needed to adapt to the required time resolution, leading to a reduction in the perceived variability (AV).

It could be argued that in this case the best thing to do is to limit the temporal resolution of the model to 1 hour. However, this is simply not affordable for some applications. For example, this tool could be crucial to expand the scope of hydraulic state estimation from water transport networks to water distribution networks, where different sources of information with very different sampling rates coexist [12]. Since redundancy if of utmost importance for state estimation [18], TESIC is a necessary tool to maximize the number of measurements while coping with uncertainty correctly.

2.3 Peak demand computation

Peak demand has traditionally been defined as the maximum hourly consumption that takes place at a given spatial aggregation level (i.e. for a number of inhabitants N). Different empirical formulas are available to estimate the peak factor (ratio between the hourly maximum and the mean daily flow) based on the size of the population (see [19] for references), but such a deterministic approach is not in compliance with the now well-known stochastic nature of water demands. This explains why some authors have started to address peak demand analysis from a stochastic/probabilistic perspective (e.g. [20, 21]). The temporal and spatial resolution effect on peak factors is also a subject of ongoing research. Lower temporal scales are associated with greater peak demands, and 1-5 minute interval data have been found to be a good compromise solution to characterize maximum consumption [22, 23, 24].

Since the short-term variability of demand is characterized by TESIC, this curve can be used as a tool to explore the variability of peak demands for time intervals below 1 hour. Note that the demand/flow variance associated with a time resolution Δt and a number of inhabitants N (i.e. position of the network that provides water to N inhabitants) can be computed from the so called AV, i.e. $\sigma_Q(N, \Delta t) = AV$. This population size is also associated with a water demand mean value $\mu_Q(N)$, which remains constant regardless of the temporal framework adopted for the analysis and can be estimated according to [10] and [11]. Individual water consumption is not expected to follow a normal distribution, but this works assumes (and Section 3.3 shows) that when a sufficient number of inhabitants is considered, the aggregated water consumption can be assumed to follow a normal distribution with $\mu_Q(N)$ and $\sigma_Q(N, \Delta t)$. Therefore, the probability P of not exceeding a specific peak demand $Q_P(N, \Delta t)$ over a short time period where temporal homogeneity can be assumed [13] is:

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

Where Φ corresponds to the cumulative distribution function of the normal distribution. In order to analyse if peak demand values remain below $Q_P(N, \Delta t)$ not only for a time interval but over the whole temporal window (1 hour), and assuming that water demands behave independently, this probability should be modified as:

$$P = \Phi[Q_p(N, \Delta t), \mu_Q(N), \sigma_Q(N, \Delta t)]^{\frac{3600}{\Delta t}}; \forall N, \forall \Delta t \tag{2}$$

Note that $\mu_Q(N)$ and $\sigma_Q(N, \Delta t)$ refer to the statistical properties of the original normal distribution at peak hour. Both can be computed according to the microcomponent stochastic demand model presented in [10] and [11]. More specifically, the variance corresponds to the AV of the corresponding TESIC curve (position that supplies water to N inhabitants) at peak hour and for a Δt time interval.

The key interest of using TESIC rather than an empirical formula derived for a particular set of measurements is that this approach provides a conceptual framework, i.e. it is not site specific. Note that there are different ways of benefiting from TESIC depending on the available information [13]. If a consistent end-use model is available, $\mu_Q(N)$ and $\sigma_Q(N, \Delta t)$ can be computed at peak hour, and TESIC can be inferred. If there is no access to a microcomponent demand model, but a TESIC curve is available at peak hour (e.g. shape extrapolated from other similarly populated areas), the effect of short-term variability on peak demands can still be assessed. This is especially interesting when only low-resolution (i.e. per hour) measurements are available, because it enables to pre-evaluate the effect of adopting higher resolutions (e.g. installing new high resolution meters). If there is no access to a microcomponent demand model or a TESIC curve at all, TESIC (or a partial TESIC) could still be inferred from measurements. Extrapolation to other population sizes would be possible if the population is homogeneous (i.e. short-term effects predominate).

3 RESULTS

The archetypical network presented by [25] is here adopted (see Figure 2) to show the different TESIC curves (and so the order of magnitude of demand uncertainty) that would be obtained for different spatial aggregation levels in a realistic case study. A microcomponent demand model has already been adjusted at this network according to metered data and statistical information [12], so TESIC is computed directly from the demand model. The same case study is later on used to show the interest of the peak demand assessment strategy here presented.

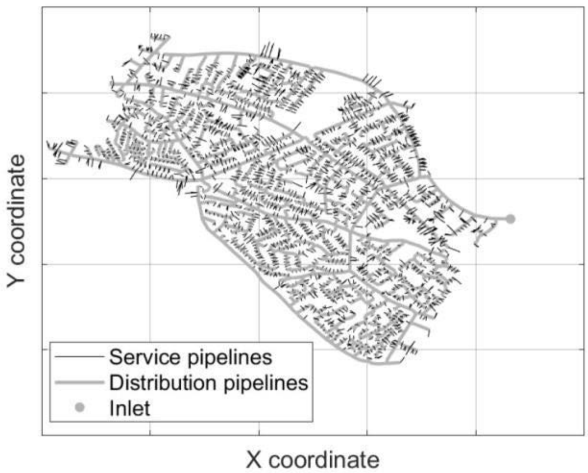

Figure 2. Case study layout

3.1 TESIC

TESIC have been computed in this work at peak hour (10:00) for different spatial aggregation levels (N=100, 1000, 10000 and 79106 – total population). Figure 3a shows that the short-term variance lowers as the time interval increases, reaching the zero value for 1 hour (short-term threshold). Moreover, TV increases with the number of inhabitants, and so does AV for the different scales here considered. Figure 3b shows that the tendency is opposite in terms of Coefficient of Variation (CV): coefficients of variation are maximum for the minimum number of inhabitants here considered (N=100) and reduce as N increases. Results show that relative variability is bound to reduce when aggregating end-users. This highlights the importance of quantifying uncertainty when dealing with low spatial aggregation scales.

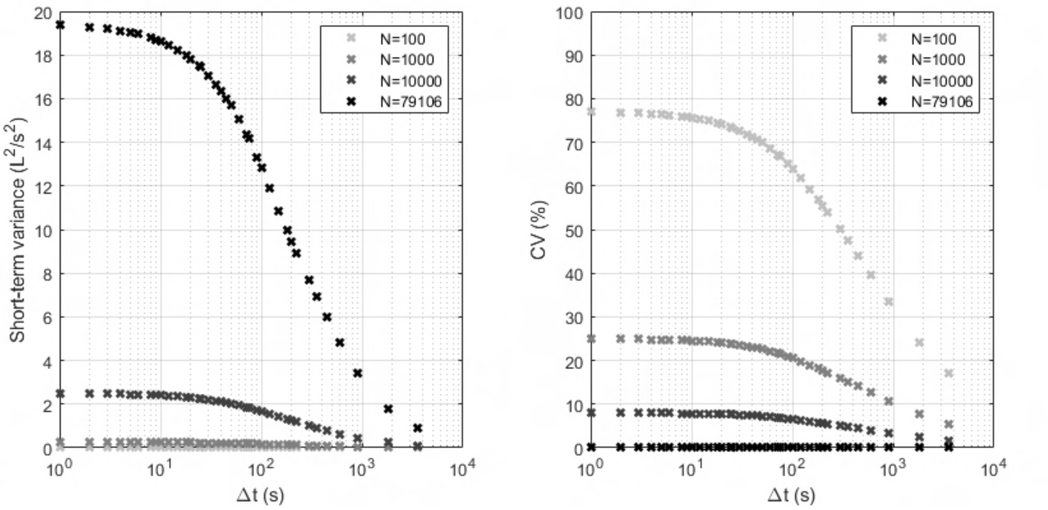

Figure 3. TESIC at peak hour for different spatial aggregation levels: a) original short-term variance curve and b) associated coefficient of variation

3.2 Demand time resolution uncertainty computation

In order to estimate how much uncertainty would be induced in a hydraulic model by changing the time resolution of aggregated water demands, Figure 4 presents a normalized version of the TESIC curve. Note that this curve remains approximately the same no matter the spatial aggregation level because population characteristics have been assumed homogeneous in the full network area in this example case study [10, 11]. This enables to estimate how much uncertainty should be added as a result of a change in temporal resolution. Note that if 1-hour (3600 s) time interval measurements were available and a 1-hour time resolution was required, the associated time resolution uncertainty would be null. However, if a 15-minute (900 s) time resolution was required, about 20% of the total variance for that spatial aggregation scale should be incorporated as uncertainty to the hydraulic model. If a 5-minute (300 s) time resolution was the target, this value would increase up until 36%, reaching 80% for 1 minute (60 s) and 100% if an instantaneous resolution was required. This figure shows the importance of having measurements with a sampling rate similar to the required time resolution (note that measurement or pseudomeasurement uncertainty should be added to compute the total uncertainty as explained in Section 2.2), and should serve a motivation to install convenient smart meters through the system. This conclusion is relatively intuitive and could have been anticipated, but the interest of TESIC lies in being able to quantify how much uncertainty should be included if there is no option to reduce the time interval of the available measurements/pseudomeasurements and/or if different sources of information with different sampling rates coexist.

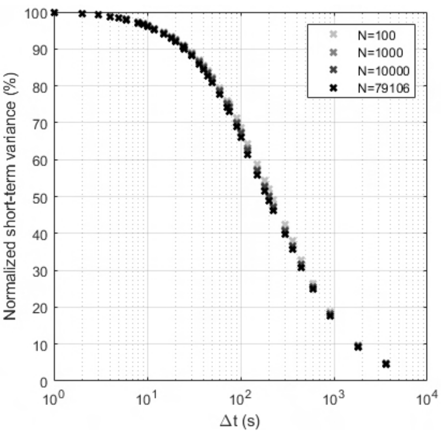

Figure 4. Normalized TESIC for different spatial aggregation levels

3.3 Peak demand computation

Probabilities of not exceedance have been computed for different threshold values $Q_P(N, \Delta t)$ in this case study: $\mu_Q(N)$; $\mu_Q(N) + \sigma_Q(N, \Delta t)$; $\mu_Q(N) + 2\sigma_Q(N, \Delta t)$ and $\mu_Q(N) + 3\sigma_Q(N, \Delta t)$. Figure 5 shows the analytically computed probabilities of not exceedance according to Eq (2) and 1000 Monte Carlo simulations. The probability of not exceedance has been computed in the numerical case by: 1) generating 1000 per-second demand series over the peak hour for each spatial aggregation level, 2) averaging these demand series over each Δt time interval and 3) counting the number of times that the maximum average value stays below each threshold value. Figure 5 shows similar results for the analytical and numerical simulations for time intervals above 1-2 minutes. Therefore, the analytical approach is adequate to quantify the temporal scale effect of peak demands in the range of time intervals that have been identified as a good compromise for maximum consumption assessment (1-5 minutes [20, 21, 22]). Note that the numerical and the analytical approach have a better correspondence as the number of inhabitants increases. Since this approach assumes that flows behave as a normal distribution and this is only true when a sufficient number of inhabitants is aggregated, the minimum number of inhabitants analysed in this work is 100 (equivalent to a few residential buildings).

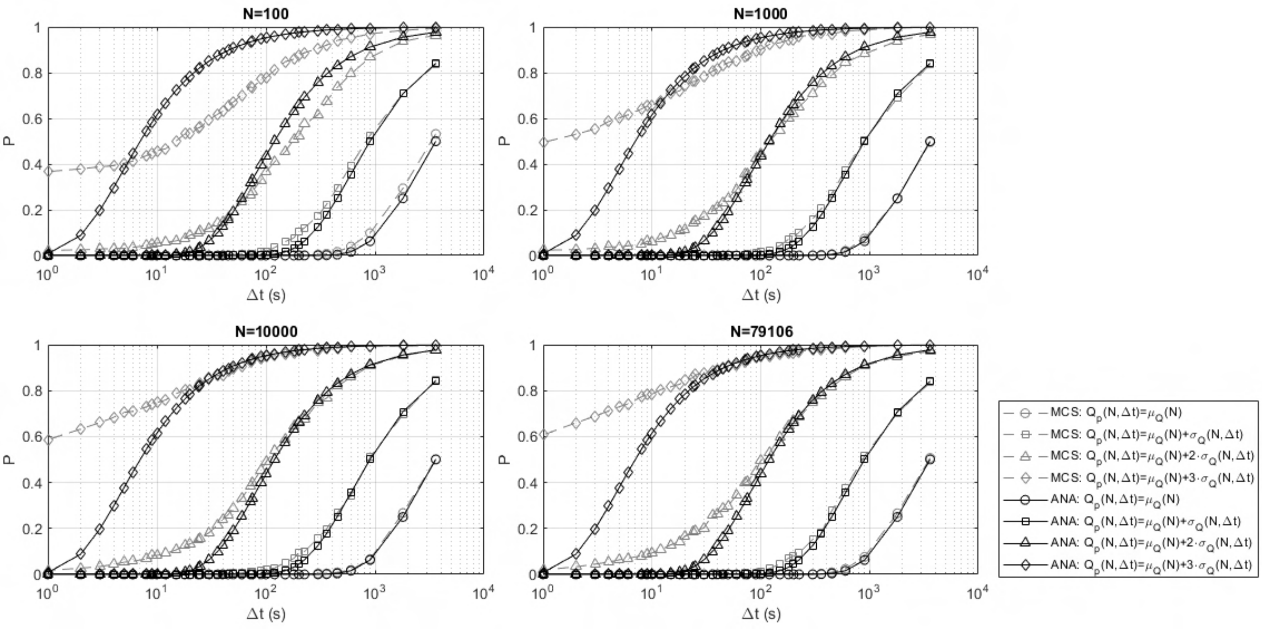

Figure 5. Probability of not exceedance for different peak demand values and spatial aggregation levels: analytical approach vs Monte Carlo simulation

4 CONCLUSIONS

TESIC has been here presented as a conceptual framework to explain and quantify the effect of adopting different time intervals/temporal resolutions to account for the variability of water demands. More specifically, it has been applied to quantify the uncertainty stemming from using measurements/pseudomeasurements with time intervals greater than the required temporal resolution in a hydraulic modelling application and to explore the temporal variability effect of peak demands. These applications show that now that smart meters are gaining importance, but technology is still limited to provide high spatial and temporal resolution measurements through entire systems continuously, TESIC could be a powerful tool to maximise the available information, because it allows to combine different sources of information by properly quantifying uncertainty.

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