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CASE REPORT

Using water consumption smart metering for water loss assessment in a DMA: a case study

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ABSTRACT
In this study we analyse the benefits that may be gained from using a smart metering system to assess water losses at a district level with reference to a real case. Consumptions of all the users of this district metered area (DMA) were monitored at an hourly time step by means of electromagnetic meters. Assuming that information on water consumption was available for only a portion of users, we then estimated the water consumption of the entire DMA and calculated the error committed in this estimation as the number of available users varied. Finally, as the simultaneous hourly pattern of inflow into the DMA was also available, we used the water balance method to assess water losses. The results obtained show that monitoring even only 60% of users makes it possible to achieve an error of less than 2% in the estimation of daily consumption across the entire DMA.

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Smart metering; consumption; losses; water balance

1. Introduction

In recent years, sustainable management of water resources has become a topic of foremost importance, since though water is a renewable resource, various concomitant factors, including climate changes and population increases, considerably reduce its availability (Boyle et al. 2013). Furthermore, individual users' lack of awareness about the need to save water and the profound structural and management deficiencies affecting water distribution systems give rise to pointless waste (Willis et al. 2011; Buchberger and Nadimpalli 2004). Therefore, estimating and monitoring real water losses take on a role of fundamental importance for a sustainable management of water resources, also taking into account their energy impact (Mamade et al. 2017). In recent decades, various approaches for assessing real losses have been proposed in the technical-scientific literature. They can be divided into two main types: bottom-up and top-down (Puust et al. 2010; Mutikanga, Sharma, and Vairavamoorthy 2013; Mazzolani et al. 2016). The bottom-down approaches include an analysis of the minimum night flow (MNF) entering precisely delimited portions of the distribution network, or district metered areas (Farley and Trow 2003). This approach is based on the measurement of inflow into a DMA during the night, typically between 2:00 a.m. and 4:00 a.m., when user demand is minimal, pressure in the network is high and the portion of flow due to real losses is dominant. This portion is determined by subtracting the estimated acceptable night consumption from the night flow entering the DMA. Therefore, the accuracy of the estimate of losses depends directly on the accuracy with which the acceptable night consumption of users can be estimated. Among the top-down approaches, it is worth mentioning the water balance (WB) method, which, unlike the MNF method, enables a long-term estimation of water losses, calculated as the difference between inflow, i.e. the volume fed into the monitored area, and outflow, given by the sum of apparent or commercial losses and authorised consumption (IWA, Water Loss Task Force 2005; Kanakoudis and Tsitsifli 2010). Knowledge of authorised consumption clearly depends on the planning of water meter readings; this service is usually performed by the utility every four or six months, mainly for billing purposes (Fontanazza et al. 2012; Fortunato, Arena, and Mazzola 2015). Consequently, under such conditions, it is possible to arrive at an estimate of the degree of loss in the DMA only over long time horizons, and not in real time (Kanakoudis and Tsitsifli 2014).

However, thanks to recent developments in Information Communication Technology (ICT) related to integrated urban water management (IUWM), smart metering systems are being increasingly adopted to monitor water consumption. These systems can indeed provide a number of operating advantages to the utility responsible for the IUWM system (Cole and Stewart 2013), including real-time monitoring of water losses both within a DMA and at the point of use of individual users. In fact, smart metering infrastructures taken as a whole enable a simplification of administrative procedures such as, for example, billing of consumption and at the same time a reduction in operating costs tied to periodic meter readings. This is possible since information regarding the volume of water consumed by each user is constantly available through GSM or wireless network infrastructures. Moreover, continuous monitoring of water consumption makes it possible for utilities that implement IUWM to improve the quality of the service offered to users by enabling them to acquire full awareness of their consumption patterns and to reduce pointless waste due to water losses within buildings, the ultimate objective being a more sustainable management of water resources (Cominola et al. 2015; Koutiva et al. 2017; Liu et al.

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2017; Luciani et al. 2018). Finally, by monitoring the real consumption of all users belonging to a given DMA in real time and comparing the sum with the inflow into the same area (Loureiro et al. 2016), the utility can optimise the planning of maintenance on the water distribution system thanks to the possibility of closing the water balance on a daily or even hourly basis with a high degree of accuracy and thus of assessing the level of losses in the network using the same time step. However, with reference to the latter aspect, it must be taken into account that, from an operational standpoint, situations may occur in which the water balance in a DMA cannot be perfectly closed because of a temporary lack of consumption information about some users, due, for example, to a communication failure in the smart metering infrastructure or more simply a malfunction at the point of use. In these circumstances it will be necessary to estimate consumption within a DMA correctly based on the water consumption monitoring data of only a part of the users in the DMA itself. Furthermore, it is worth observing that even though smart water metering systems are being developed and increasingly implemented, utilities must address the practical problem of replacing thousands of meters, an operation that entails the involvement of field technicians, lengthy time frames and high costs. Therefore, a utility managing a large water distribution system serving thousands of users and made up of dozens or hundreds of DMAs cannot think of replacing all meters of all users simultaneously, but must rather establish meter replacement plans. In such circumstances, a generic utility might be interested in assessing whether – given the same investment and number of meters to be replaced – it is better, for example, to replace all the meters in one DMA or replace half of them, but in two DMAs. In the former case, it would be possible to close the balance of the single DMA perfectly, in the latter to close it only partially but with reference to two DMAs. Essentially, the problem is to determine whether it is possible to estimate the total consumption of a DMA with sufficient precision and with a fraction of meters monitored in real time.

The aim of this study was thus to assess the accuracy of the water balance that can be determined through smart meter-based real-time monitoring of only a fraction of users belonging to a DMA. Below we analyse the results obtained with reference to a real case, that of Gorino Ferrarese (Ferrara province), monitored as part of a research project funded by the European Community, Green-Smart Technology for the sustainable use of water resources in buildings and urban environments (GST4Water).

2. Case study

The case study considered relates to the water distribution system managed by the utility company CADF S.p.A. and serving the town of Gorino Ferrarese (Ferrara province). The town in question, situated in northern Italy and specifically in the easternmost extremity of the province of Ferrara, occupies a surface area of about 3 Km^2 and has a resident population of about 650 inhabitants. The number of users is 293; 276 are residential users and the remaining 17 are ascribable to public services and commercial or tourist activities. From a hydraulic standpoint, the water distribution system, extending for a total of about 9 Km, constitutes a district metered area (see Figure 1); there is a single supply point at which the local hydraulic conditions (flow rate and pressure) are measured. There are no storage tank systems within the area.

In June 2016, the traditional mechanical meter at each point of use was replaced with an electromagnetic meter also capable of performing a data logging function and a data collection campaign was undertaken, which made it possible to obtain hourly water consumption time series for all users starting from July 2016. In particular, in the present study we considered the historical series of the cumulative volume demanded by users, recorded on an hourly basis, and the series of inflows into the DMA, likewise recorded on an hourly basis in the period between 7 August 2016 and 7 January 2017. In the period considered, total user water demand was about 20,000 m^3, with residential users accounting for 90%. It worth noting that within the set of residential users, the water demand pattern changes from user to user, according to their habits, as shown in Figure 2(a,b) where the patterns of hourly flow coefficients ('mean hourly flow'/'mean daily flow') of a couple of residential users are presented. In any case, residential users' patterns are generally characterised by periods of greater consumption, mainly during the daytime, alternating with periods of lower demand during the

Figure 1. Water distribution network of Gorino Ferrarese (Ferrara province).

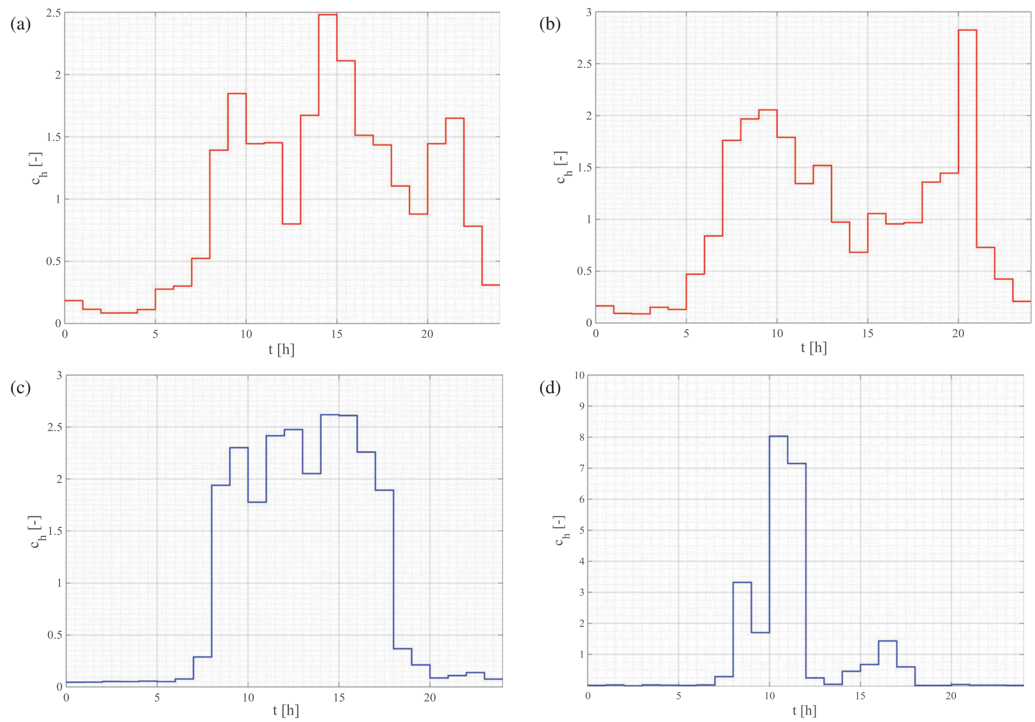

Figure 2. Pattern of hourly consumption coefficients: (a) and (b) residential users, (c) and (d) commercial users (the harbour and an aquaculture cooperative, respectively).

night-time hours. The other users, by contrast, contributed a lower amount (about 10%) to the water demand of the DMA and the water demand patterns were clearly different from those of residential users and varied significantly according to the type of user considered (Figure 2(c,d)). Data related to the billed volumes of each user in the year before the year of observation (2015) were also available. The utility company collected this information throughout the whole network for billing purposes, even before installing smart meters. In particular, in 2015 as well, commercial users and/or public services accounted for a limited amount (9.28%) of total user water demand and 82% was attributable essentially to 3 specific users (a sports facility, restaurant/hotel and bar/hostel).

3. Methodology

Below we discuss some methods aimed at evaluating the possibility for a utility company to monitor only a fraction of users and at the same time get an accurate estimate of total consumption within the DMA. Each of these methods comprises two steps: the first step is to select the users to be monitored, whereas the second step consists in estimating the total water consumption of the DMA based on knowledge solely of the consumption of the selected users, measured on a real-time basis. It is worth noting that the methods for selecting the users to be monitored (first step) are defined on the basis of information that the utility typically possesses before replacing traditional meters with smart meters, i.e. the type of user in question and the volumes billed in the previous year(s).

The error that would be committed by estimating the consumption of the totality of users with each of the methods developed is assessed in relation to variations in the number of selected users. In particular, the mean absolute percentage error (MAPE) is evaluated in relation both to the estimation of the hourly flow pattern associated with the whole set of users, and the estimation of the daily demand pattern of the same users.

More specifically, as regards the selection step, after establishing the percentage of users to be monitored P, that is, after assuming the selection of a given number of users n_P, we considered three different methods. The first method, indicated hereinafter as SM1 (Selection Method 1), provides for a random choice within the entire pool of users. The second method, indicated hereinafter as SM2, envisages choosing the users who, irrespective of type, showed the highest consumption in the previous year; these users were judged to be most representative of overall consumption within the DMA, even though they are characterized by different patterns. Finally, the third method, indicated hereinafter as SM3, provides for the selection of all commercial users and public services, considered to have distinctive consumption patterns, while the target percentage of users to be monitored is reached by selecting within the residential pool, the ones for whom the highest consumption was recorded in the previous year.

With regard to the second step – estimation of the hourly consumption of the entire district metered area based on the consumption solely of the monitored users – two approaches were considered, independently of how the selection was made. With the first approach, indicated hereinafter as CF1 (Correction Factor 1), the hourly flow (m^3/h) of the entire DMA

Q_h is estimated on the basis of the hourly flow of the monitored users q_{h_i} with $i = 1 : n_p$, in the following manner:

$$Q_h = F_a \cdot \sum_{i=1}^{n_p} q_{h_i}$$

F_a being an amplifying correction factor (CF) defined as:

$$F_a = \frac{\sum_{j=1}^{n_{tot}} \overline{V_{y_j}}}{\sum_{i=1}^{n_p} \overline{V_{y_i}}}$$

where $\sum_{j=1}^{n_{tot}} \overline{V_{y_j}}$ represents the yearly water demand of the n_{tot} users within the DMA calculated taking into account the billed volumes of the previous year, whilst $\sum_{i=1}^{n_p} \overline{V_{y_i}}$ represents the yearly water demand solely of the selected n_p users, again calculated taking into account the billed volumes of the previous year.

With the second approach, indicated hereinafter as CF2, the hourly flow of the entire DMA Q_h is estimated in the following manner:

$$Q_h = \sum_{i=1}^{n_p} q_{h_i} + k_h \cdot \sum_{k=1}^{n_{tot}-n_p} \overline{Q_{y_k}}$$

i.e. by adding to the hourly flow of the set of monitored users $\sum_{i=1}^{n_p} q_{h_i}$ the mean hourly flow of the set of unselected users $\sum_{k=1}^{n_{tot}-n_p} \overline{Q_{y_k}}$, calculated on the basis of the billed volumes of the previous year (the yearly volumes being divided by 365 × 24). In particular, in order to also take into account variations in the consumption of the unselected users over the course of the day, the constant contribution given by the mean hourly flow of the set of unselected users was adjusted by means of the hourly coefficient k_h, variable from one hour to another, defined as:

$$k_h = \frac{\sum_{i=1}^{n_p} q_{h_{i,t-24\times21}} + \sum_{i=1}^{n_p} q_{h_{i,t-24\times14}} + \sum_{i=1}^{n_p} q_{h_{i,t-24\times7}} + \sum_{i=1}^{n_p} q_{h_{i,t}}}{4 \cdot \sum_{i=1}^{n_p} \overline{Q_{y_i}}}$$

In practical terms, the hourly coefficient was estimated on the basis of the water consumption of the monitored users observed in the current hour and in the same hour of the same day during the previous three weeks, so as to take account of variations in daily periodic patterns. This hourly coefficient is assumed representative also of the unmonitored users even though demand pattern changes from user to user. This approach, borrowed from recently proposed short-term water demand forecasting models (Bakker et al. 2013; Pacchin, Alvisi, and Franchini 2017), is operatively applicable only starting from a month after the installation of the smart meters.

Finally, the goodness of fit of the reconstructions obtained, both in terms of the pattern in the times series data of hourly flow across the entire district metered area, and in terms of the volume of daily demand, as previously illustrated, was assessed using the mean absolute percentage error defined as:

$$MAPE = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| \frac{x_i^{obs} - x_i^{eval}}{x_i^{obs}} \right| \cdot 100$$

where n represents the number of observed data (i.e. the number of hours or the number of days elapsing between 7 August 2016 and 7 January 2017), x_i^{obs} represents the observed parameter (hourly flow or volume of daily demand of all users in the DMA) and x_i^{eval} represents the corresponding parameter (hourly flow or volume of daily demand) estimated with the previously described methods.

4. Analysis and discussion of the results

The user selection methods (SM1, SM2 and SM3), combined with the two approaches CF1 and CF2 for estimating the overall consumption of all users in the district metered area, were applied for percentages of monitored users varying from 10% to 90%, with steps of 10%. Figure 3 shows the results obtained in terms of the trend in the MAPE with respect to the hourly flow estimates derived with the different methods and percentages of users monitored. In particular, with reference to the selection method SM1 (random selection), Figure 3 shows the trend in the average value of the MAPE obtained when the random selection (and hence the estimation step) was repeated 100 times, as well as the trend in the minimum and maximum values. In this manner it was possible to verify to what extent the error committed in the estimation of the hourly flow for the entire set of users varied with variations in the random choice. For example, where 30% of users are randomly selected, the MAPE associated with the hourly flow estimate obtained applying the correction factor CF1 amounts to 17.5% and ranges from a minimum value of 14.5% to a maximum value of 23.5%. In general, irrespective of the user selection and hourly flow estimation methods adopted, it was observed that, as expected, the MAPE decreases with increases in the number of users monitored. However, with specific reference to the selection methods adopted, SM2 and SM3 furnish distinctly better results than SM1. It is interesting to note, in particular, that although for very mall number of monitored users the percentage errors are fairly high in all cases, even selecting only 60% of users with the methods SM2 and SM3 results in an MAPE lower than 5%, less than the one obtained with a random selection of users. This result underscores the fact that it is better to select the users on the basis of known information closely connected to them in order to obtain a more accurate water balance. It may be further observed that once the percentage of users to be monitored has been determined, irrespective of the method then used to estimate the hourly flow of the totality of users, the selection methods SM2 and SM3 furnish wholly comparable results. This observation may be explained by the fact that the commercial users which consume most are in any event included in the selection made with the method SM2. Indeed, the 3 commercial users that consumed most in 2015 (82% of the total consumption of all commercial users combined) are also the 3 users that consumed most within the entire pool in 2015. If,

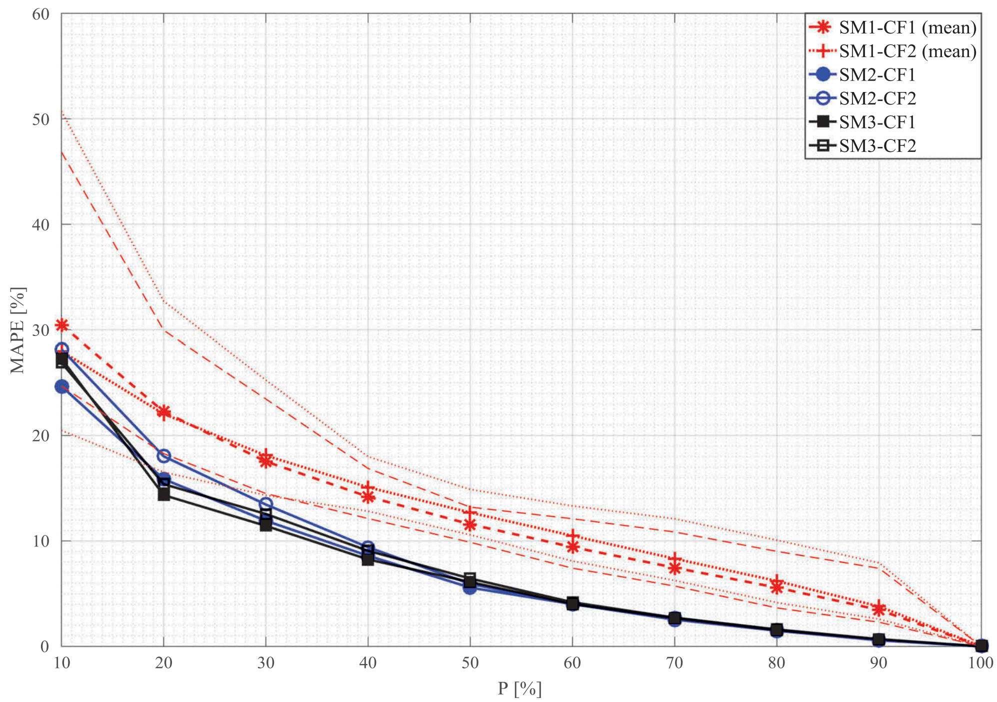

Figure 3. Trend in MAPE in the estimation of hourly flow for the totality of users according to the different methods and percentages of users monitored.

on the other hand, the users to be monitored had been selected exclusively among residential users, the error in the hourly flow estimate for the totality of users would have been distinctly greater (MAPE of around 9.5% with a percentage of users monitored equal to 60%). Finally, irrespective of the selection method (SM2 or SM3), it may be noted that the two approaches considered (CF1 and CF2) to estimate the hourly consumption of the entire district metered area based solely on the monitored users provide substantially equivalent results.

By way of example, Figure 4 shows the pattern of the total hourly flow estimated with the method SM3 – CF2 (in green), considering 60% of users selected for monitoring. It may be observed that the aforesaid method provides a very good approximation of the observed total hourly flow (in blue). This implies that, assuming that the utility monitored 60% of the entire pool of users, it could achieve a very accurate hourly district-level water balance, with an error of about 4%.

Similar considerations apply with respect to the MAPE in the estimation of the volume of daily demand of the set of users shown in Table 1. More specifically, if we look at the values taken on by the MAPE, we note that monitoring 60% of users – selected on the basis of selection criteria that take into account the yearly volumes billed in the year 2015 (SM2 and SM3) – results in MAPEs of less than 2%. In particular, it may be observed that the selection method SM3 furnishes slightly better results than SM2. Moreover, as regards the correction factor for estimating the daily consumption across the entire DMA based on the consumption of the monitored users alone, it may be noted that, irrespective of the selection method adopted (SM2 or SM3), the approach CF2 provides slightly higher accuracy than the approach CF1. Therefore, the method SM3-CF2 is the one that provides the greatest accuracy overall in the estimation of daily consumption across the entire DMA based on the consumption of only the 60% of users selected for monitoring, with a mean absolute percentage error of 1.2%.

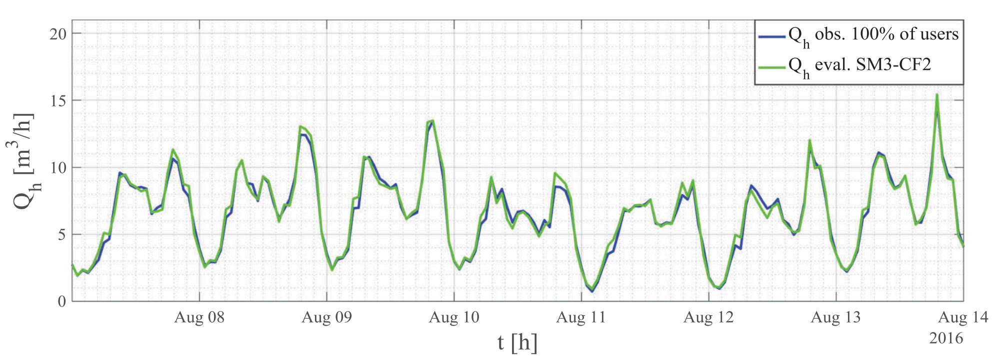

Figure 4. Hourly consumption for all of the users as observed (in blue) and estimated with the SM3 – CF2 method (in green).

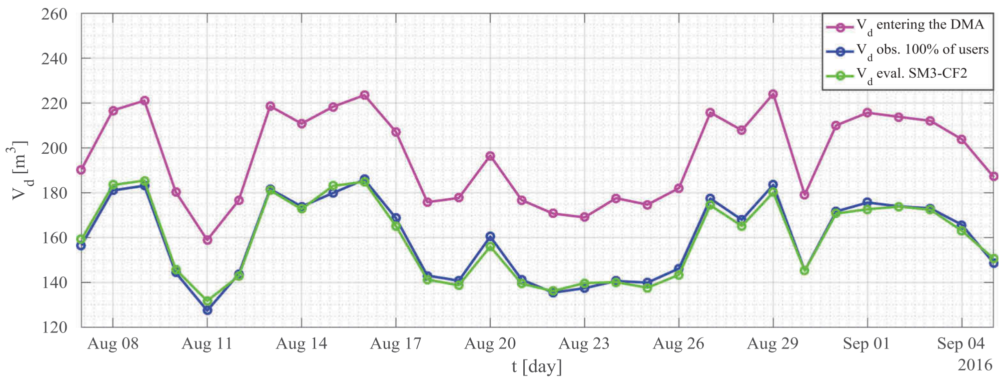

Figure 5. Daily observed volume of inflow into the DMA (in magenta) and of the volume of daily demand of users, observed (in blue), and estimated with the SM3 – CF2 method (in green).

Table 1. MAPE related to the estimated daily water demand of the totality of users.

% Users Monitored		10	20	30	40	50	60	70	80	90	100
SM1 – CF1	mean	12.2	9.8	8.1	6.7	5.4	4.4	3.7	2.5	1.3	0.0
	min.	6.3	5.4	5.0	4.6	4.1	2.9	2.0	1.1	0.6	0.0
	Max.	33.2	21.2	13.1	10.4	8.4	6.9	7.1	6.4	5.6	0.0
SM1 – CF2	mean	11.7	9.9	8.4	7.2	6.0	4.9	4.1	2.7	1.4	0.0
	min.	6.4	5.8	5.9	5.2	4.1	3.0	2.0	1.3	0.6	0.0
	Max.	31.3	20.8	13.5	10.3	9.3	7.5	7.6	6.8	5.9	0.0
SM2 – CF1		15.4	10.3	7.6	4.6	2.6	1.7	0.9	0.6	0.4	0.0
SM2 – CF2		13.8	9.3	7.1	4.3	2.2	1.4	0.8	0.6	0.4	0.0
SM3 – CF1		9.0	4.6	5.3	3.6	2.0	1.3	0.8	0.6	0.4	0.0
SM3 – CF2		7.5	3.8	4.7	3.4	1.9	1.2	0.8	0.6	0.4	0.0

Again by way of example, Figure 5 shows the daily pattern of the volume of inflow into the DMA (in magenta), as well as the pattern of the observed volume of daily water demand of the totality of users (in blue) and the pattern of the volume of daily water demand of all users estimated with the method SM3 – CF2, considering 60% of users selected for monitoring (in green). It is evident that by monitoring 60% of users it would be possible to obtain a highly accurate estimate of the total consumption within the DMA, and thus of water losses, using the water balance method. In fact, in the period of time falling between 7 August and 4 September 2014, the observed rate of water loss in the network was 1.54 m^3/h, a value wholly in line with the one that would be obtained by estimating the consumption of the set of users with the method SM3 – CF2, namely, 1.52 m^3/h.

5. Conclusion

In this paper, with reference to the case study on Gorino Ferrarese (FE), we assessed the error that would be committed in estimating the hourly and daily water balance if only a percentage of users belonging to a district metered area were monitored on a real-time basis. Specifically, on the basis of recorded hourly time series of the volume of water demanded by the 293 users belonging to the selected DMA and the yearly volumes billed in the year 2015, we developed different methods for estimating the consumption of the set of users. Each method includes a step of selecting users to be monitored, followed by a step of estimating the consumption of the entire pool of users based on knowledge of the consumption solely of the selected users. The results show that making a selection on the basis of the users that consume most enables a significant reduction in the error that would be committed if a random selection were made. Moreover, even though each user is characterized by a different pattern, not taking into account this different kind of pattern seems not to make difference, at least in the case considered, provided that the users who consume most are selected. The analysis of the values taken on by the MAPE in the estimation of hourly flow (or the daily volume of demand) shows that, given a fixed percentage of users to be monitored and irrespective of the criterion adopted in the selection step, the estimation methods enable substantially comparable results to be achieved. Finally, it is possible to estimate the consumption of the totality of users with an accuracy that increases with the number of users monitored. It follows that a good estimate of the water balance, and thus of losses, may be obtained through real-time monitoring of only part of the users within a DMA. Accordingly, the utility company can obtain useful information for optimal planning of the replacement of traditional meters with smart meters.

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Disclosure statement

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