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Automated Household Water End-Use Disaggregation through Rule-Based Methodology

Filippo Mazzoni[1]; Stefano Alvisi[2]; Marco Franchini[3]; Marco Ferraris[4]; and Zoran Kapelan[5]

Abstract: Application of smart meters to the residential sector can provide insight into where and when water is used, thereby enabling utilities to achieve an efficient management of water distribution systems. Moreover, detailed information about domestic water use can be obtained by disaggregating smart meter data collected at the household inlet point. In this paper, a rule-based, automated methodology for disaggregating household water-use data into end uses is presented. The methodology is applicable to 1-min temporal resolution data, whose granularity is slightly lower than the one generally used in other methodologies, potentially allowing it to be applied to several contexts in the field of water-use monitoring. The methodology was set up and validated with data collected for 2 months through intrusive monitoring of four households in Bologna, Italy, and represents a pioneering case in which disaggregation performance is directly assessed by the comparison against data collected at each end use. The results obtained showed that the methodology enables household water use to be efficiently disaggregated even if detailed information about end-use features is not available. **DOI: 10.1061/(ASCE)WR.1943-5452.0001379.**

Introduction

Owing to population growth and urbanization, cities require continuously increasing supplies of freshwater (Suero et al. 2012; Cosgrove and Loucks 2015). Where new development is not possible (given limitations in the availability of water resources) or economically infeasible, better management of the currently available water resources is the only way to cope with rising demand. This goal can be achieved through several measures (Gleick et al. 2003): new water-saving technologies; smarter water policies, regulations, and incentives; proper water pricing; and information and education. However, to adequately and effectively manage water infrastructure, it is essential to accurately estimate water demand (Aksela and Aksela 2011) based on an understanding of how water resources are used across space and time (Sanchez et al. 2018).

Water demand characterization typically starts from household water meter readings. In most cases, readings are still taken manually by water utility employees at a monthly or lower frequency for the purpose of recording consumption data for the billing system (Sønderlund et al. 2016). In recent years, several advantages have been brought by smart meters, which allow high-frequency data recording, logging, and transmitting. In this way, sparse, approximate water-use information can be replaced by data obtained through an automated and nearly continuous reading system, which provides a more accurate and detailed overview of householders' behavior in terms of water consumption.

Smart-metering technology can lead to multiple benefits for both water utilities and their customers. It enables water utilities to continuously monitor their customers' water consumption without the need for manual readings, enabling them to gain a better understanding of how water is used at the household level and detecting any anomalous consumption patterns (e.g., leaks) (Luciani et al. 2019). This in turn can help the development of improved demand forecasts (both short and long term) and, hence, improve the operation and long-term planning of water supply and distribution systems (Stewart et al. 2018). In addition, smart meters can be used by utilities to implement different tariff models for billing. At the same time, receiving information about the water consumed may increase householders' awareness of their own (and other people's) water use and is likely to encourage them to save water and money, as demonstrated by several empirical studies (e.g., Davies et al. 2014).

Detailed knowledge about water consumption at the household level can also aid water-saving technologies. For example, it can support the development of systems for graywater reuse (e.g., Dixon et al. 1999), bringing benefits to both utilities and customers: on the one hand, demand for water from the water mains could decrease, leading to a reduced network load, and, on the other hand, water savings would translate into money savings for householders. However, the aforementioned improvements depend on information about individual end uses. Where this information is not available (e.g., Agudelo-Vera et al. 2013), stochastic demand models (e.g., Blokker et al. 2010) can be used to simulate residential water demand; however, even these models need to be calibrated using realistic water end-use data.

Information about water demand at the end-use level could be obtained through direct measurements via intrusive monitoring, i.e., by installing smart meters at all domestic end uses.

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Note. This manuscript was submitted on October 8, 2019; approved on December 20, 2020; published online on March 17, 2021. Discussion period open until August 17, 2021; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Water Resources Planning and Management***, © ASCE, ISSN 0733-9496.

However, this is often time-consuming and expensive. In addition, the installation of smart meters at end uses may sometimes be practically unfeasible, since some of these could have inaccessible inlet points (e.g., wall-mounted toilet tanks), and it could also be rejected by the householders because of the intrusiveness of smart meters.

Limits to directly collecting water-use data at the domestic end uses has led to the development of several nonintrusive techniques, which have the advantage of allowing the decomposition (i.e., disaggregation) of a signal measured at the household level (i.e., aggregate water use) into the individual contribution of each end use (Cominola et al. 2017). Generally, these techniques are applied on flow (or volume) smart meter data collected at the household water inlet point, but techniques also exploiting other sensor data (e.g., pressure data) have been proposed as well (e.g., Kim et al. 2008; Froehlich et al. 2009, 2011; Srinivasan et al. 2011; Ellert et al. 2015; Vitter and Webber 2018).

Focusing on techniques using only flow (or volume) smart meter data collected at the household water inlet point, these can be classified according to the temporal resolution of smart meter data (Clifford et al. 2018) distinguishing between data at a high temporal resolution (e.g., 1–10 s) and data at a medium temporal resolution (e.g., on the order of a minute). As suggested by Cominola et al. (2015) and Yang et al. (2018), in the case of smart meter data at a high temporal resolution (e.g., 1–10 s), two main approaches have been introduced: (1) decision tree algorithms; and (2) machine learning algorithms. Decision tree algorithms include rule-based tools such as Trace Wizard (Mayer et al. 1999) and Identiflow (Kowalski and Marshallsay 2003), which disaggregate flow data based on the observation of water-use volume, duration, and flow rate. Both tools provide results with an average classification accuracy of around 70% (Cominola et al. 2015). However, Trace Wizard parameters must be "fine-tuned" by the analyst to fit the end uses (Cominola et al. 2015), requiring approximately 1 h per week of data to complete flow trace analysis when working for the first time with data from a household (Mayer et al. 1999). On the other hand, Identiflow performance can be significantly affected by water end-use physical features input into the software (Yang et al. 2018). Machine learning and data mining methods include tools such as Autoflow software (Nguyen et al. 2013, 2015; Yang et al. 2018), which is able to achieve considerably higher accuracy in end-use recognition (i.e., above 94%). However, such data-driven tools require consistent training data sets. Considering techniques using smart meter data collected at a medium temporal resolution (e.g., on the order of a minute), it is first of all worth noting that they can represent a more widely applicable tool than methods using high temporal resolution data, since in practice a water utility may not be in possession of data at such fine temporal resolution. In fact, even though several commercial smart meters with a sampling frequency higher than 1 min (e.g., 15 s) exist (e.g., Sensus iPerl) data logging is often limited to 1-min frequency so as not to saturate the device's memory and to increase the battery life. Again in this context (i.e., medium temporal resolution data), some machine learning methods (Cominola et al. 2017) or optimization algorithms (Piga et al. 2015) have been developed to disaggregate data into end uses. However, to the authors' best knowledge, the aforementioned approaches have been tested for disaggregating water consumption only by using a set of synthetic data. Finally, as demonstrated by Cominola et al. (2018), a complete end-use disaggregation cannot generally be performed efficiently in the case of water-use data at lower resolutions, although some results in terms of indoor-outdoor disaggregation (Cole and Stewart 2013) can still be obtained.

Given the aforementioned limitations in disaggregating water-use data at medium or low temporal resolutions, the current research aimed at developing a new methodology that would enable water end-use disaggregation to be performed for granular smart meter data, i.e., data at 1-min resolution. Specifically, a rule-based, automated disaggregation methodology is presented here that allows for the disaggregation of water-use data collected at 1-min frequency at the household inlet point. Like rule-based tools, such as Trace Wizard and Identiflow, the methodology developed was based on deterministic rules relying on water-use physical parameters (e.g., duration, flow rate, consumed volume) to perform water end-use disaggregation. However, accurate results were achieved with data whose resolution was close to that of the most widespread commercial smart meters (i.e., 1 min instead of 1–10 s), thus making the methodology potentially applicable to several contexts in the field of water demand monitoring. Moreover, unlike in the case of some of the aforementioned tools, performance was not dependent on the experience of the analyst. The methodology was applied to a real 2-month water-use data set collected at both the inlet point of four households and their end-use points. Although the sample of monitored households was limited, it is worth noting that, to the authors' knowledge, this represented the first case reported in the literature in which disaggregation performance was directly assessed through a comparison against water-use data collected at each domestic end-use point.

In the following sections, the phases of the monitoring operation for the collection of smart meter data and the new, automated, and rule-based methodology for water end-use disaggregation are presented. The methodology developed was then tested and validated with different groups of parameter values, and its performance was assessed by means of metrics defined in similar studies. Finally, the outcomes provided by the application of the automated methodology and the related key findings, as well as limitations and future work recommendations, are discussed in the conclusions.

Methods

Data Collection

To develop and test the disaggregation methodology, a preliminary water-use monitoring operation was conducted to obtain household aggregate water-use time series and household end-use time series (i.e., water-use time series for each domestic end use). The monitoring took place in early 2018, in four households (denoted here as H1, H2, H3, and H4) located in the city of Bologna, Italy. Although they represent a relatively small sample of water-use data (coming from the same geographic region as well), the selected households were different in terms of number of inhabitants, consumption, and end uses, as reported in Table 1. Therefore, and as will be demonstrated later on in the paper, the limited data acquired still presented a (sufficiently) complex challenge when it came to the task of automated water-use disaggregation.

The intrusive submetering phase was initiated by installing smart meters at the domestic water inlet point and at each end-use point. All the (mechanical) smart meters, provided by Itron, were equipped with an optical reader and a radio transmitter (EquaScan wMIU-RF, making use of the Wireless M-Bus communication protocol). Data collected were transmitted to a receiver kit, logged at 1-min resolution (as cumulative volume information) and sent to a digital platform once a day by means of a domestic Wi-Fi connection. Based on the available technology, and taking into account the intrusiveness of the end-use monitoring system and users' readiness to cooperate, it was possible to record water-use data for 8 weeks (i.e., 56 days, from January 1 to February 25, 2018) at 1-min resolution and with 1-L accuracy.

Table 1. Main features of monitored households

Household	Type	N (person)	Age (years)	T (days)	Q (L/person/day)	End uses Indoor	End uses Outdoor
H1	Flat	1	40–45	56/56	108	6	—
H2	Flat	1	40–45	56/56	83	7	—
H3	Flat	2	50–60	53/56	121	12	3
H4	Flat	3	30–65[a]	42/56	122	12	—

Note: N = number of inhabitants; Age = inhabitants age range; T = period of available water-use data; and Q = per capita water consumption.
[a]Two inhabitants of age 60–65, one inhabitant of age 25–30.

In addition, surveys and interviews of householders were conducted in order to collect information both about the householders themselves and their habits (e.g., daily use frequency for each end use) and characteristics of the end uses (e.g., manufacturer and model). However, apart from data about the householders' age and number (Table 1), the information collected via surveys was omitted from consideration in this study. This was done intentionally to develop a methodology that could be used even when such information is not available.

Although the households were different in terms of the number and characteristics of the end uses, it was possible to distinguish six main end-use categories: dishwasher, kitchen sink, washing machine, shower, bathroom taps (i.e., washbasin and bidet), and toilet. Some of the selected households also included outdoor end uses (e.g., irrigation systems or outdoor sinks), but the lack of use thereof during the monitored period did not enable them to be considered in the study.

A preliminary phase was aimed at detecting smart meter data gaps, i.e., periods of time when data were not recorded due to disturbances affecting the equipment (e.g., blackouts) or data transmission (e.g., Wi-Fi connection drops). All water-use data for each of the four households were analyzed using a Microsoft Excel spreadsheet, in order to detect data gaps. Specifically, Households H1 and H2 showed no data gaps across the monitoring period (i.e., 56/56 days of available data), whereas the other two revealed some gaps (specifically, Households H3 and H4 included 53/56 and 42/56 days of available data, respectively).

Moreover, the water-use data collected was checked for consistency to avoid considering long periods without any water-use in the analyzed households (e.g., due to occupants' absence). This was done using a threshold time period of 3 days without any water use. The aggregate volume of water used was calculated for each day and for each household and no periods without water use longer than 3 days were observed in any household.

In addition, the following aspects regarding the available data set were observed: (1) per capita daily water use for each household in the monitoring period (Table 1) was in line with—and actually slightly lower than—the Bologna average domestic water use for the year 2017, i.e., 154 L/person/day (Comune di Bologna 2019); (2) the households were not affected by leakages since the volume of water used in every household over the monitored period equalled the sum of domestic end-use volumes; and (3) only 9.4% of the monitored water uses were combined uses (i.e., simultaneous water uses) and the majority of those (i.e., 6.1% out of 9.4%) were a combined use of a toilet and a tap.

The aggregate water-use and end-use time series for Households H1, H2, and H3 were split into two subsets as follows: (1) a calibration data set (for the development and calibration of the automated methodology) including water-use time series from January 1 to 31, 2018; and (2) a validation data set (for testing the methodology) including water-use time series from February 1 to 25, 2018. Household H4 end-use time series, although available, were not considered for the development of the methodology, i.e., the method was not calibrated on the basis of Household H4 information. Hence, the aforementioned household was kept exclusively as a test sample and used for validation of the methodology.

Disaggregation Methodology

The methodology for automated water-use disaggregation is based on a set of rules. This methodology detects, disaggregates, and classifies individual water uses one end-use category at a time. Specifically, the disaggregation of the aggregate water-use time series collected at the domestic water inlet point is performed by means of a set of *functions*. Such functions are applied in a specific order, starting with functions aimed at detecting end uses that, given their very nature, are generally more regular in terms of water use, and ending with the most irregular ones.

The main structure of the automated methodology is shown in Fig. 1. First, the use of electronic appliances is investigated through the *dishwasher* function (F_DW) and *washing machine* function (F_WM). Then, shower uses are assessed through the *shower* function (F_S). Lastly, toilet and tap uses (which are generally less recognisable at 1-min resolution or often overlap in time with other uses) are detected and classified by means of the *tap and toilet* function (F_TT). On completion of the process, the water-use time series for each end-use category is available.

From an operational standpoint, the automated methodology for water-use disaggregation was developed using MATLAB version R2019a programming software and consists of a main code, where

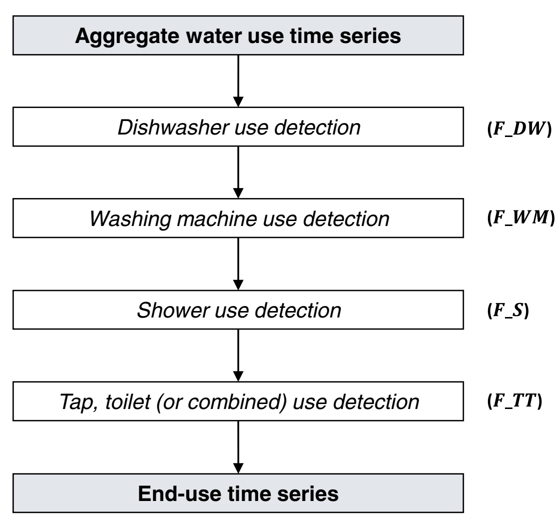

Fig. 1. Structure of automated methodology for water end-use disaggregation.

the Microsoft Excel spreadsheet including the collected aggregate water use is loaded and the functions for water-use disaggregation are applied in turn. The developed MATLAB code is available online (more details are provided in the "Data Availability" section), whereas the underlying ideas and main characteristics of the functions for water-use disaggregation and their parameters are described in the following paragraphs:

- **Dishwasher.** Dishwasher water uses (*cycles*) are typically discontinuous and include long periods of time during which the appliance works without taking water from the network. Such intervals are separated by short periods of continuous inflow (*withdrawals*). Cycles can be different from each other based on the overall volume of water used and duration. However, they all include a group of water withdrawals whose number, volume, duration, and time of occurrence depend on appliance manufacturer, model, and selected program. The function for dishwasher water-use detection and classification (F_DW) makes use of a moving window to first identify all the possible daily water withdrawals, according to their typical duration and volume. Then a group of possible withdrawals is classified as a dishwasher cycle if the number of possible withdrawals and the time of occurrence of each of them fall within the acceptance parameter values (and if, additionally, the number of already detected dishwasher uses is lower than a given daily threshold). Overlapping or excessively long cycles are not allowed. The function flow chart is shown in Fig. S1.
- **Washing machine.** Washing machine water use is similar to dishwasher water use (i.e., based on a number of water inflows) but withdrawal volumes and durations are considerably different. Therefore, the function for washing machine use detection and classification (F_WM) is the same as the one for dishwashers (F_DW) but with different parameter values. As in the case of the *dishwasher* function, it is assumed that two (or more) simultaneous washing machine water uses cannot occur.
- **Shower.** Shower uses are harder to detect by means of rule-based functions because of the way in which people use showers: some might be used to having a shower of near constant intensity (i.e., water flow), while others may be used to turning the water on and off, sometimes several times during shower use. Given this fact, the function for shower use detection (F_S) includes a moving window approach aimed at first identifying every possible shower use. Deterministic rules are then applied to remove all those uses whose features are not compatible with shower use in terms of duration, volume of water used and shape of the water-use trace. A maximum flow interruption lasting $p_S^{\max}$ is allowed during shower water use (more details about the value of this parameter are provided in the following subsections). The function flow chart is shown in Fig. S2.
- **Tap and toilet.** On the one hand, toilet uses are fairly homogeneous in terms of volume of water used and duration, although sometimes dual-flush systems are included. On the other hand, kitchen sink and bathroom tap use is much more heterogeneous since the duration and volume of water used are totally dependent on householders' habits and needs. However, both toilet and tap uses are hard to detect and disaggregate at 1-min resolution because such uses are often simultaneous (e.g., use of toilet and consequent handwashing in a same minute). This difficulty led to the development of a single function (F_TT) that disaggregates between toilet uses, tap uses, and combined uses (i.e., toilet and tap uses). The main rules of the preceding function are as follows: (1) water uses are classified as short duration (1-min) or longer duration (multiple-minute) uses and analyzed in turn, (2) a maximum number of toilet flushes is imposed for longer-duration (multiple-min) uses, and (3) disaggregation between kitchen sink and bathroom tap uses is based on the time of day (i.e., water uses occurring at meal times are more likely to be associated with a kitchen sink). The function flow chart is shown in Fig. S3.

An illustrative application of the methodology is included in Fig. 2 and discussed in what follows. More specifically, the aggregate water use shown in Fig. 2 was taken from the water-use time series of Household H1. The disaggregation parameters given here by way of example refer specifically to Household H1 and were obtained by analyzing the end-use time series of this household for the calibration period. Additional details can be found in the subsection "Parameters and Their Calibration." The main steps of the automated methodology are as follows:

1. Aggregate water use and disaggregation parameter values are loaded [Fig. 2(a)].
2. All possible daily dishwasher withdrawals are selected, i.e., water uses whose duration is in the range $d_{\mathrm{DW}}^{\min} - d_{\mathrm{DW}}^{\max}$ (e.g., 2–5 min) and whose volume is in the range $V_{\mathrm{DW}}^{\min} - V_{\mathrm{DW}}^{\max}$ (e.g., 2–5 L), without interruptions of flow. If some of these uses are in a number $\left(x_{\mathrm{DW}}^{\min} - x_{\mathrm{DW}}^{\max}\right)$ (e.g., 3–5) and time intervals between them are in the allowed range $p_{\mathrm{DW}}^{\min} - p_{\mathrm{DW}}^{\max}$ (e.g., 10–110 min), such uses would be classified as a dishwasher cycle. In this example, owing to the lack of those conditions, no dishwasher cycles are found [Fig. 2(b)].
3. All possible daily washing machine withdrawals are selected, i.e., water uses whose duration is in the range $d_{\mathrm{WM}}^{\min} - d_{\mathrm{WM}}^{\max}$ (e.g., 2–4 min) and whose volume is in the range $V_{\mathrm{WM}}^{\min} - V_{\mathrm{WM}}^{\max}$ (e.g., 8–15 L), without interruptions of flow. Then the number of possible withdrawals and time intervals between them are analyzed. In this example, some of the selected withdrawals are in the range $x_{\mathrm{WM}}^{\min} - x_{\mathrm{WM}}^{\max}$ (e.g., 3–5), and time intervals between them are in the allowed range $p_{\mathrm{WM}}^{\min} - p_{\mathrm{WM}}^{\max}$ (e.g., 15–95 min), so the aforementioned water uses are classified as a washing machine cycle and removed from the aggregate trace [Fig. 2(c)].
4. All daily shower uses are selected, i.e., water uses whose duration is in the range $D_S^{\min} - D_S^{\max}$ (e.g., 8–16 min) and whose volume of water used is in the range $V_S^{\min} - V_S^{\max}$ (e.g., 20–90 L), with a maximum flow interruption of $p_S^{\max}$ (e.g., 3 min). These uses are then removed from the aggregate trace [Fig. 2(d)].
5. Residual water uses are analyzed in turn. Each use is classified as toilet use, tap use (kitchen sink, bathroom taps), or combined use (toilet and tap uses) based on the following considerations: (1) the duration of the selected water use; (2) toilet parameter values, i.e., half-flush volume $\left(V_{\mathrm{TH}}^{\min} - V_{\mathrm{TH}}^{\max}\right)$ (e.g., 3–4 L), and full-flush volume $\left(V_{\mathrm{TF}}^{\min} - V_{\mathrm{TF}}^{\max}\right)$ (e.g., 8–9 L); (3) the number of already occurring toilet flushes in the selected water use; and (4) time of day. All the residual water uses are classified and removed from the aggregate trace, as shown in Fig. 2(e).

Parameters and Their Calibration

The automated methodology requires a set of parameters to be defined in order to disaggregate water use. These parameters can be classified into two main groups: (1) parameters related to householders' habits, i.e., the time of day when householders are likely to have lunch or dinner; and (2) parameters related to end-use features, e.g., volume of water used, duration, time of day. Parameters are listed and described in Table 2. Clearly, the values of each parameter vary from one household to another because of different habits or end-use features.

Accordingly, the value for each parameter can be defined in, first, a *specific* or a *general* way. Specific parameter values relate

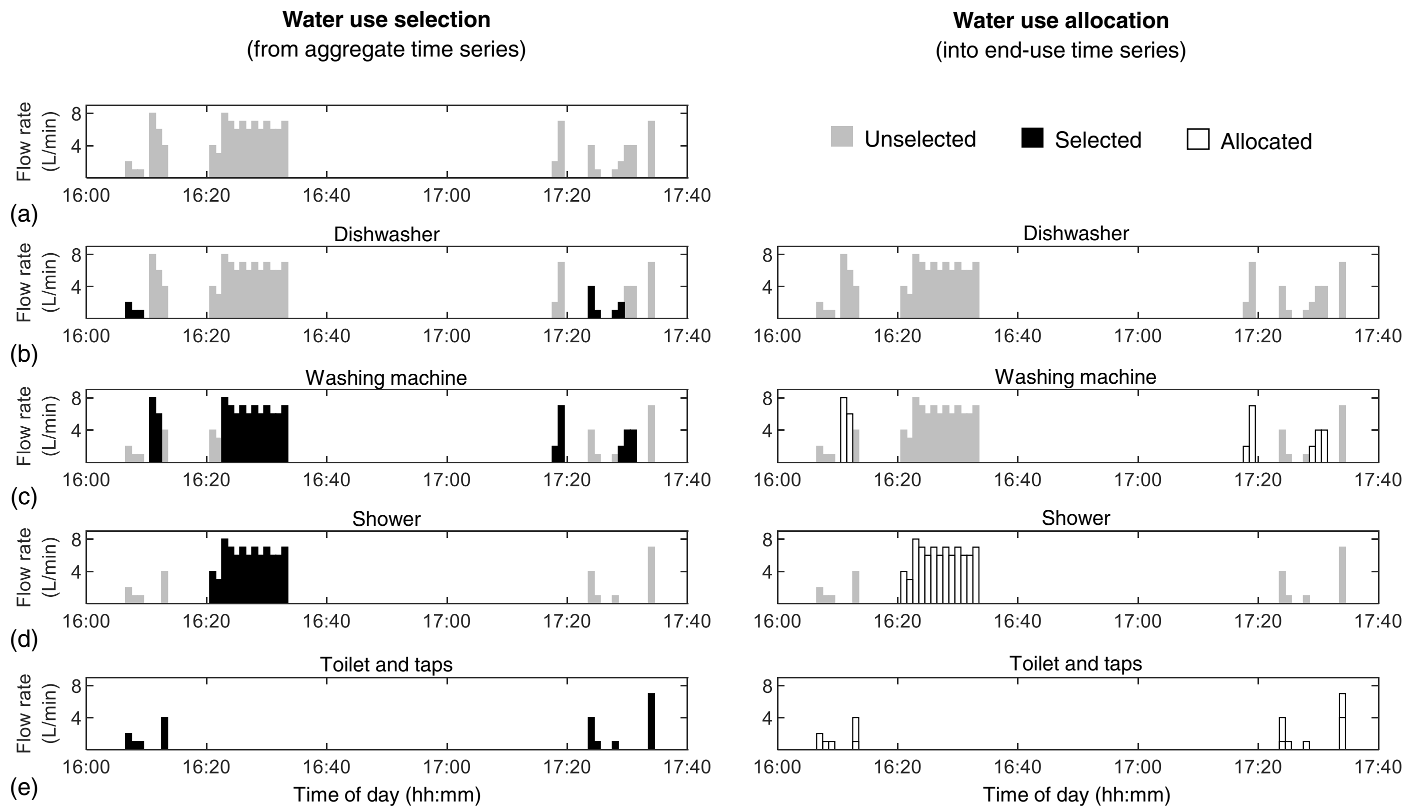

Fig. 2. Example of application of automated methodology. Each panel (a–e) in the figure corresponds to Steps 1–5 described in the "Methods" section ("Disaggregation Methodology" subsection).

Table 2. Automated methodology parameters

Category	Parameter description	Symbol	General values
Habits	Lunch time	$t_L^{\min} - t_L^{\max}$	11:00–14:00
	Dinner time	$t_D^{\min} - t_D^{\max}$	19:00–22:00
Dishwasher	Time of day of dishwasher use	$t_{\mathrm{DW}}^{\min} - t_{\mathrm{DW}}^{\max}$	0:00–24:00
	Daily maximum frequency of use	$n_{\mathrm{DW}}^{\max}$	3
	Maximum cycle duration	$D_{\mathrm{DW}}^{\max}$	180 min
	Number of water withdrawals per cycle	$x_{\mathrm{DW}}^{\min} - x_{\mathrm{DW}}^{\max}$	3–5
	Single withdrawal volume	$V_{\mathrm{DW}}^{\min} - V_{\mathrm{DW}}^{\max}$	1–5 L
	Single withdrawal duration	$d_{\mathrm{DW}}^{\min} - d_D^{\max}$	1–5 min
	Time from a withdrawal to the next	$p_{\mathrm{DW}}^{\min} - p_{\mathrm{DW}}^{\max}$	10–120 min
Washing machine	Time of day of washing machine use	$t_{\mathrm{WM}}^{\min} - t_{\mathrm{WM}}^{\max}$	0:00–24:00
	Daily maximum frequency of use	$n_{\mathrm{WM}}^{\max}$	5
	Maximum cycle duration	$D_{\mathrm{WM}}^{\max}$	180 min
	Number of water withdrawals per cycle	$x_{\mathrm{WM}}^{\min} - x_{\mathrm{WM}}^{\max}$	3–5
	Single withdrawal volume	$V_{\mathrm{WM}}^{\min} - V_{\mathrm{WM}}^{\max}$	5–20 L
	Single withdrawal duration	$d_{\mathrm{WM}}^{\min} - d_{\mathrm{WM}}^{\max}$	1–5 min
	Time from a withdrawal to the next	$p_{\mathrm{WM}}^{\min} - p_{\mathrm{WM}}^{\max}$	10–120 min
Shower	Time of day of shower use	$t_S^{\min} - t_S^{\max}$	0:00–24:00
	Volume	$V_S^{\min} - V_S^{\max}$	20–150 L
	Duration	$D_S^{\min} - D_S^{\max}$	3–30 min
	Maximum duration of flow interruption during a shower	$p_S^{\max}$	3 min
Toilet	Maximum number of flushes per multiple-minute water use	$x_T^{\max}$	3
	Full-flush volume	$V_{\mathrm{TF}}^{\min} - V_{\mathrm{TF}}^{\max}$	4–12 L
	Half-flush volume	$V_{\mathrm{TH}}^{\min} - V_{\mathrm{TH}}^{\max}$	3 L
Kitchen sink	Manual dishwashing or meal preparation water-use duration	$D_{\mathrm{KS}}^{\min} - D_{\mathrm{KS}}^{\max}$	2–15 min

to individual household features and can be obtained through knowledge about the householders' habits and the characteristics of the end uses concerned. Obtaining such information often requires direct, intrusive monitoring, single household investigations, a detailed specification of electrical appliances, and interaction with householders (e.g., surveys), which may be infeasible given both the cost and time required. General parameter values describe the average end-use features and householders' habits in terms of water use. Such values can be obtained based on commonsense observations or by referring to information available in the literature.

The automated methodology developed was applied considering both specific and general parameter values. Specific values were defined for each household by considering individual end-use time series. In particular, specific parameter values were defined by considering only Households H1, H2, and H3 over the calibration period (i.e., using data from January 1 to 31, 2018). In addition, a set of general parameter values valid for all the households (i.e., H1, H2, H3, and H4) was defined by grouping the previously obtained sets of specific parameter values and enlarging their ranges by a few units (e.g., 1 L for volumes, 1 min for durations) in order to obtain a data set covering as many cases as possible. All the general values of water-use parameters are shown in Table 2.

The automated methodology was thus tested using the validation part of the water-use data set first considering Households H1, H2, and H3 with specific parameter values and with general parameter values; then the methodology with general parameter values was applied to the test household (i.e., H4) with the aim of demonstrating its effectiveness. To summarize, three analyses were conducted

1. Automated disaggregation (with specific parameter values) of water use in Households H1, H2, and H3;
2. Automated disaggregation (with general parameter values) of water use in Households H1, H2, and H3; and
3. Automated disaggregation (with general parameter values) of Test Household H4 water use.

Evaluation of Disaggregation Methodology Performance

The results of the automated methodology for water-use disaggregation were assessed through a comparison against observed data. Thus, the collected water-use data at the end-use level for each of the selected households were used as a benchmark against which to evaluate the performance of disaggregation. Following the approach adopted by Cominola et al. (2018), two evaluation metrics were used: (1) *water contribution accuracy* (WCA), involving an assessment of end-use accuracy at the level of aggregate end-use combination, and (2) *normalized root-mean-square error* (NRMSE), which quantifies the over- and underestimation of water-use time series. The aforementioned metrics were applied for each end use k of household i, as shown in Eqs. (1) and (2)

$$\mathrm{WCA}_i^k = 1 - \frac{|\sum_{t=1}^{T} v_{i,t}^k - \sum_{t=1}^{T} \hat{v}_{i,t}^k|}{\sum_{t=1}^{T} V_{i,t}} \tag{1}$$

$$\mathrm{NRMSE}_i^k = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T} (v_{i,t}^k - \hat{v}_{i,t}^k)^2}}{\max(v_{i,t}^k) - \min(v_{i,t}^k)} \tag{2}$$

where T = length of monitoring period; $V_{i,t}$ = aggregate water use in household i at time t; $v_{i,t}^k$ = observed water use of appliance k in household i at time t; and $\hat{v}_{i,t}^k$ = water use disaggregated and classified as use of appliance k in household i at time t. As reported by Cominola et al. (2018), since WCA is an aggregate metric that could lead to inaccuracies, especially in the case of occasionally used appliances, a combined analysis of WCA and other less aggregated metrics (such as NRMSE) was useful to achieve a better interpretation of the results.

The overall performance of the methodology with respect to a group of households was assessed through the *appliance contribution accuracy* (ACA) and *appliance root-mean-square error* (ARMSE), formulated as the average of the metrics WCA_i^k and NRMSE_i^k across all household i and end uses k. Given the number n of monitored households and the number m_i of end uses in each household i, the aforementioned metrics were as expressed in Eqs. (3) and (4)

$$\mathrm{ACA} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\sum_{k=1}^{m_i} \mathrm{WCA}_i^k}{m_i}\right) \tag{3}$$

$$\mathrm{ARMSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\sum_{k=1}^{m_i} \mathrm{NRMSE}_i^k}{m_i}\right) \tag{4}$$

It is worth noting that, given the nature of Eqs. (1) and (3), the metrics WCA and ACA can take on a value between 0 and 1, with an accurate end-use disaggregation resulting in WCA and ACA values close to 1. Given this fact, these metrics will henceforth be expressed as a percentage. In contrast, the metrics NRMSE and ARMSE can take on any positive value, and an accurate end-use disaggregation would lead to values close to 0.

Results and Discussion

The results obtained for the validation period are presented in Figs. 3 and 4. Specifically, Fig. 3 includes results in terms of WCA and ACA. As can be seen from this figure, the automated methodology had an ACA of at least 90%, which was noteworthy given the difficulties and complexities associated with the disaggregation of water end use in households. Furthermore, between Cases *a* and *b*, the most accurate case of automated disaggregation (ACA = 95.7%) was the one related to the use of specific parameter values (i.e., Case *a*), which are typically more representative of domestic end-use features than general ones. In fact, a lower accuracy (ACA = 90.4%) was achieved through automated disaggregation with general parameter values (i.e., Case *b*). However, the relatively small loss of accuracy resulting from the use of general rather than specific parameter values may be acceptable given the considerable time and effort needed to obtain specific parameter values for each household through, for example, surveys or intrusive monitoring.

The automated disaggregation performance was also in line with that of the method in the study by Cominola et al. (2018) for water end-use disaggregation with 1-min resolution. Indeed, in view of the fact that the case study and the disaggregation data set considered by Cominola et al. (2018) were different from those used here (the cited authors used synthetically generated water-use time series for a sample of 500 households and a period of 1 year), it can in any case be observed that the ACA reported by Cominola et. al (2018) was around 89%. That is in line with or slightly lower than the ACA obtained by applying the methodology proposed here to the collected data set.

Regarding end uses (Fig. 3), in the case of automated disaggregation with specific parameter values (Case *a*), the metric WCA was generally the highest for electrical appliances and showers, the WCA in these cases being always above 97%. Lower WCA values were obtained for toilet and tap water uses, but this is understandable given that, at 1-min resolution, tap uses often overlap in time with other uses—especially toilet use—and are rather

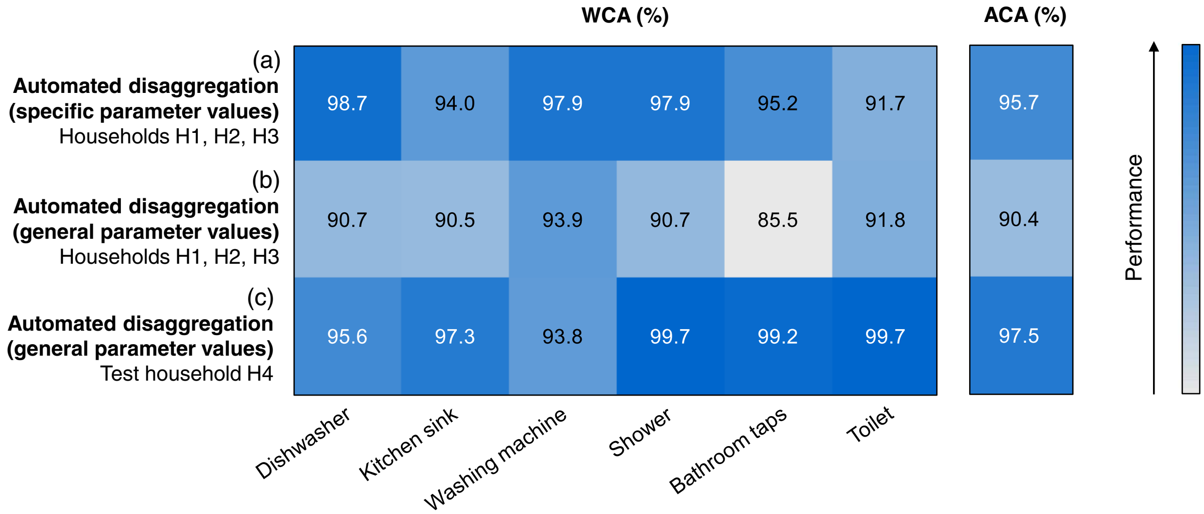

Fig. 3. Disaggregation results in terms of water contribution accuracy (WCA) and appliance contribution accuracy (ACA).

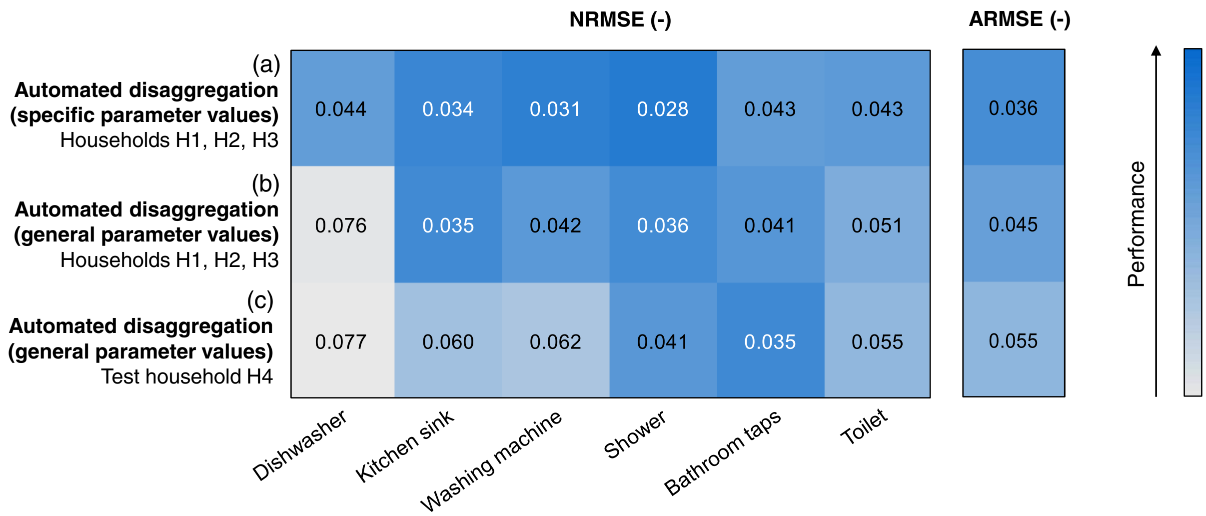

Fig. 4. Disaggregation results in terms of normalized root-mean-square error (NRMSE) and appliance root-mean-square error (ARMSE).

heterogeneous. A decrease in WCA occurred in the case of automated disaggregation with general parameter values (Case *b*), especially for electrical appliances, showers, and bathroom taps, with WCA being around 94% for washing machines, around 90% for dishwashers and showers, and around 85% for bathroom taps.

Fig. 4 depicts the automated disaggregation results in terms of NRMSE and ARMSE. The use of such metrics confirmed what had been observed with the metrics WCA and ACA: in fact, as can be seen from Fig. 4, the lowest error was still related to automated disaggregation with specific parameter values (Case *a*; ARMSE = 0.036), while increasing in the case of general parameter values (Case *b*; ARMSE = 0.045). Therefore, it was again shown that general parameter values lead to worse results than specific parameter values, but with a rather limited decrease in performance. The results in terms of ARMSE were likewise consistent with those reported by Cominola et al. (2018) for disaggregation at 1-min resolution (ARMSE = 0.04).

Regarding NRMSE for different end uses, the automated disaggregation methodology generally resulted in the lowest errors for shower and washing machine uses, as expected. On the other hand, contrary to what one might expect, a rather large NRMSE was related to dishwasher use, when both specific (NRMSE = 0.044) and general (NRMSE = 0.076) parameter values were considered. However, this result might be explained by the limited range of dishwasher flow rates (i.e., from 1 to 3 L/min) appearing in the denominator of NRMSE Eq. (2), which influenced its value.

Figs. 3 and 4 also include the results of Case *c* where the automated disaggregation methodology using general parameter values was applied to Test Household H4. As can be seen from these two figures, the automated disaggregation results for this case were similar to those obtained for the automated disaggregation of Households H1, H2, and H3 with general values (Case *b*): the WCA ranged between 93.8% (washing machine) and 99.7% (shower, toilet), with an average rate (ACA) of 97.5%, while the NRMSE was between 0.035 (bathroom taps) and 0.077 (dishwasher), with an average rate (ARMSE) of 0.055. Thus, the results for Case *d* were in line with the results of the other two cases and those reported in the literature despite the fact that Household H4 end-use traces were not taken into account when calibrating the automated methodology parameters.

Limitations of Study

The application of the automated methodology for water end-use disaggregation to the available water-use data set led to noteworthy results, i.e., an ACA generally higher than 90% and NRMSE typically around 0.05, as shown in the previous section. Despite this, the methodology developed has some limitations.

First, the method was calibrated and validated by considering only four households in the same geographical area and, even though the households differed in terms of end-use features, the automated disaggregation methodology calibration and validation were nonetheless limited by the small data set. In addition, the sample of selected households included a limited number of inhabitants (i.e., 1–3, as shown in Table 1), which decreased the likelihood of overlapping water uses. Accordingly, different results in terms of accuracy may be obtained when the automated methodology for water end-use disaggregation is applied to households having a larger number of inhabitants.

Furthermore, the automated methodology was calibrated and validated over a rather limited (winter) period, i.e., 8 weeks. This was mainly due to the fact that the calibration and validation data were smart meter data, i.e., data collected at each end use through a complex and time-consuming intrusive monitoring procedure. The method's application to real water-use data led to promising outcomes, but it would be of interest to extend the aforementioned water-use data set to test the methodology on new households and for longer periods. Moreover, the availability of a larger data set may enable new rules to be defined for the disaggregation of some end uses that were not included in the current study (such as leakages) or prior rules to be adapted to different and more heterogeneous behaviors in terms of water use (such as unusually frequent or simultaneous use of washing machines). Extending the data set would also allow the methodology to be calibrated and verified in other seasons (when different habits and outdoor end uses are likely to be observed).

Furthermore, as noted, the version of the methodology described here was able to detect only combined uses of toilet and taps. Such combined water uses were the most common in the available data set, but they are generally not the only ones (e.g., combined uses of other appliances could also be observed). As a result, the methodology did not cover all possible water-use combinations, and, though the authors are aware that the task of disaggregating water uses may be efficiently addressed only using higher resolution data than the ones used here, future development of the proposed methodology will focus on this aspect.

Conclusions

This paper has introduced a novel, automated, and rule-based methodology for water end-use disaggregation of smart meter data at 1-min resolution. The methodology was applied to a sample of four households in Italy where detailed water-use data were collected at the inlet point and at each end use over a period of 2 months. The performance of the method was evaluated using metrics already introduced in the literature (Cominola et al. 2018) that quantify the success of detection by comparing disaggregated and observed water uses.

Based on the results obtained, the proposed methodology was able to perform the task of household water end-use disaggregation both effectively and efficiently. The effectiveness was evidenced in the obtained values of the metrics (ACA generally higher than 90% and NRMSE typically around 0.05, also when using a set of general parameter values based on typical water use and its most common features). Moreover, the results were consistent with those obtained in similar studies making use of synthetic data with 1-min resolution (i.e., Cominola et al. 2018). The efficiency of the proposed methodology was evidenced by the fact that it took only a few seconds to disaggregate 1 month of 1-min-resolution aggregate water-use data for a single household.

In addition—and consistently with the aim of the present study—the methodology as developed was able to perform end-use disaggregation of water-use data collected at 1-min resolution, i.e., at a temporal resolution that is closer to the resolutions of commercial smart water meters than those used in most other existing methods. In fact, most approaches described in the literature made use of data collected at a higher resolution (e.g., 1 s or slightly lower), which may not be available to water utilities. Thus, the methodology proposed here might be extendable to broader and further contexts in the field of residential demand monitoring.

The automated methodology is also transparent and easy to implement and use since it includes deterministic rules based on the analysis of physical features for each individual water use (i.e., duration, volume, shape of the flow trace, and daily period). No black box models, such as stochastic models or machine learning methods, were used here.

In conclusion, future studies will mainly focus on enlarging the water-use data set and addressing the challenge of overlapping water uses in order to test the methodology on a larger sample of households and make the method more versatile.

Data Availability Statement

The data and code generated and used during the study are available in an online repository in accordance with funder data retention policies. Specifically, anonymized water-use data and the developed code are available on the Zenodo repository (Mazzoni et al. 2020).

Supplemental Materials

Figs. S1–S3 are available online in the ASCE Library (www.ascelibrary.org).

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