Benefits and challenges of using smart meters for advancing residential water demand modeling and management: A review

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1. Introduction

World's urban population is expected to raise from current 54%–66% in 2050 and to further increase as a consequence of the unlikely stabilization of human population by the end of the century (Gerland et al., 2014). By 2030 the number of mega-cities, namely cities with more than 10 million inhabitants, will grow over 40 (UNDESA, 2010). This will boost residential water demand (Cosgrove and Cosgrove, 2012), which nowadays covers a large portion of the public drinking water supply worldwide (e.g., 60–80% in Europe (Collins et al., 2009), 58% in the United States (Kenny et al., 2009)).

The concentration of the water demands of thousands or millions of people into small areas will considerably raise the stress on finite supplies of available freshwater (McDonald et al., 2011a). Besides, climate and land use change will further increase the number of people facing water shortage (McDonald et al., 2011b). In such context, water supply expansion through the construction of new infrastructures might be an option to escape water stress in some situations. Yet, geographical or financial limitations largely restrict such options in most countries (McDonald et al., 2014). Here, acting on the water demand management side through the promotion of cost-effective water-saving technologies, revised economic policies, appropriate national and local regulations, and education represents an alternative strategy for securing reliable water supply and reduce water utilities' costs (Gleick et al., 2003). In recent years, a variety of water demand management stra-tegies (WDMS) has been applied (for a review, see Inman and Jeffrey, 2006, and references therein). However, the effectiveness of these WDMS is often context-specific and strongly depends on our understanding of the drivers inducing people to consume or save water (Jorgensen et al., 2009). Models that quantitatively describe how water demand is influenced and varies in relation to exogenous uncontrolled drivers (e.g., seasonality, climatic conditions) and demand management actions (e.g., water restrictions, pricing schemes, education campaigns) are essential to explore water users' response to alternative WDMS, ultimately supporting

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strategic planning and policy design.

Traditionally, water demand models focus on different temporal and spatial scales. At the lowest resolution, studies have been carried out, mostly in the 1990s, to model water demand at the urban or block group scale, using low time resolution (i.e., above daily) consumption data retrieved through billing databases or experimental measurement campaigns on a quarterly or monthly basis. The main goal of these works is to inform regional water systems planning and management on the basis of estimated relationships between water consumption patterns and socio-economic or climatic drivers (e.g., House-Peters and Chang, 2011).

The advent of smart meters (Mayer and DeOreo, 1999) in the late 1990s made available new water consumption data at very high spatial (household) and temporal (from several minutes up to few seconds) resolution, enabling the application of data analytics tools to develop accurate characterizations of end-use water consump-tion profiles. Similarly to the recent developments in integrated smart solutions (Hilty et al., 2014; Laniak et al., 2013), the use of smart meters provides essential information to construct models of the individual consumers behaviors, which can be employed for designing and evaluating consumer-tailored WDMS that can more effectively modify the users' attitude favoring water saving be-haviors. In particular, smart meters themselves constitute tech-nologies that promote behavioral changes and water saving attitudes via tailored feedbacks (Fielding et al., 2013).

A general procedure to study residential water demand management relying on the high-resolution data nowadays available can be structured in the following four phases (see Fig. 1): (*i*) data gathering, (*ii*) water end-uses characterization, (*iii*) user modeling, (*iv*) design and implementation of personalized WDMS. In the literature, a number of tools and techniques have been proposed for each of these steps, with many works focused either on the data gathering process (e.g., Cordell et al., 2003; Boyle et al., 2013) or on the analysis of WDMS (e.g., Inman and Jeffrey, 2006). Yet, to the authors' knowledge, a systematic and comprehensive review of residential water demand modeling and management is still missing. This review contributes the first effort of classification and critical analysis of 134 studies that in the last 25 years (Fig. 2) contributed new methodologies and tools in one or more of the steps of the above procedure (see Table 1).

The review is structured according to the procedure shown in Fig. 1: the current status, research challenges, and future directions associated to each phase are discussed in Sections 2–5, while the last section reports final remarks and directions for follow up research.

2. Data gathering

Residential water consumption data gathering (box 1 in Fig. 1) represents the first step needed to built the baseline upon which the water demand is estimated and management strategies are designed. Depending on the sampling frequency, we distinguish two main classes, namely *low-resolution* and *high-resolution* data, which delimit the type of the analysis that can be performed.

2.1. Low resolution data

Periodically billed data are characterized by a low level of resolution and recording frequency. Although water consumption is detected with the precision of kilolitres, readings are generally recorded with the frequency of the quarter of year at most (Britton et al., 2008). This low resolution restricts the use of these data to regional planning, where statistical analysis estimating the amount of domestic water consumption can be used to forecast the aggregated water demand at the municipal or district level. In particular, such data have been widely used to study the effect of economic variables and seasonality on the water use at the regional scale since the seminal works by Howe and Linaweaver (1967); Young (1973); Berk et al. (1980); Howe (1982); Maidment and Parzen (1984); Thomas and Syme (1988) (for a review see House-Peters and Chang, 2011, and references therein). Those ap-proaches relied on simple econometric models and time series models based on multivariate regression, and required limited datasets and low computational resources. Their main drawback is related to their limited capability of representing the spatial and temporal heterogeneity of residential water demand, which can be understood and modeled using higher resolution data. While data

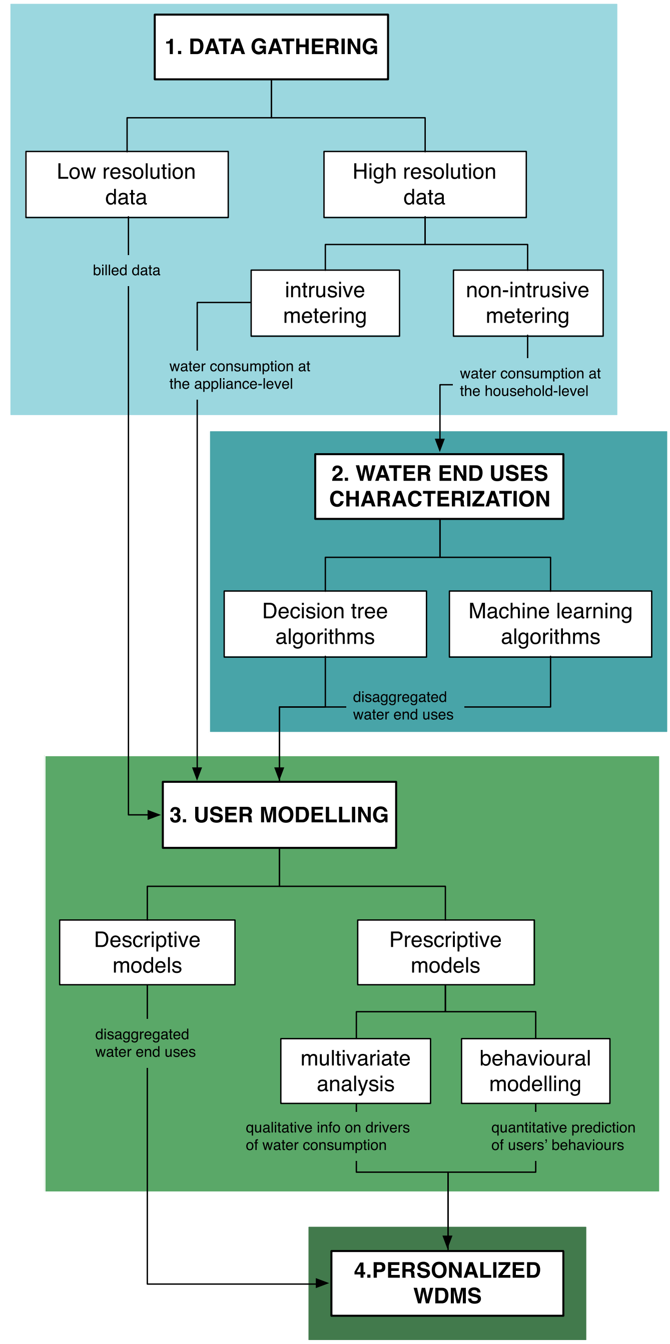

Fig. 1. Flowchart of the general procedure for studying residential water demand management.

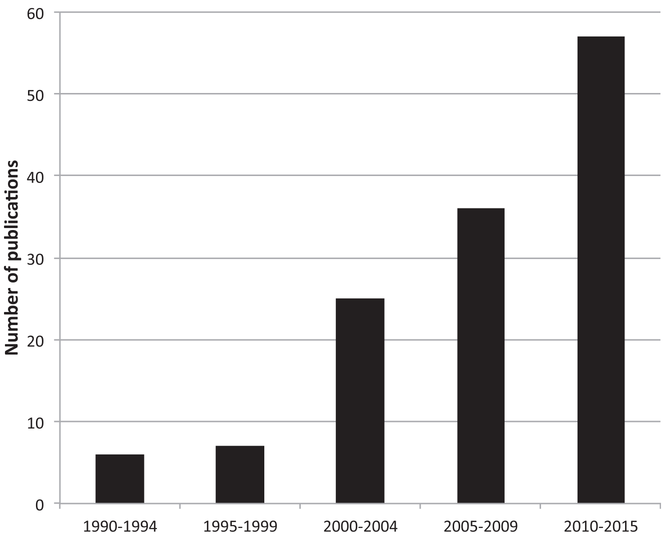

Fig. 2. Five-years count of the 134 publications reviewed in this study.

resolution depends on the installed meter, the logging time can be shortened without installation of smart meters but simply increasing the traditional reading frequency by the users. However, so far only ad-hoc studies systematically collected and analyzed data at daily resolution (e.g., Olmstead et al., 2007; Wong et al., 2010) and few water companies (e.g., Water Corporation in Western Australia and Thames Water in London) started increasing their reading frequency by direct involvement of their customers, who are invited to self-read their consumption and communicate it online to the water company (e.g., Anda et al., 2013).

2.2. High resolution data

The advent of high resolution sensors, with their ability of sampling water consumption on sub-daily basis, opened up a new potential to better characterize domestic water consumption. Two distinctive metering approaches can be distinguished: *intrusive metering*, which ensures direct estimates of the residential water end-uses by installing high resolution sensors on-device, namely one sensor for each water consuming appliance (e.g., washing machine, toilet flush, shower-head); *non-intrusive metering*, which registers the total water flow at the household level over one single detection point for the whole house.

Intrusive metering (see Rowlands et al., 2014, and references therein) is generally considered inapplicable in real-world, large-scale analysis as the number of sensors to be installed makes this approach resource intensive, costly, and hardly accepted by household occupants (Cordell et al., 2003; Kim et al., 2008). On the contrary, non-intrusive metering represents a more acceptable, though less accurate, alternative (Mayer and DeOreo, 1999). However, this approach requires disaggregation algorithms to breakdown the total consumption data at the household level into the different end-use categories (see Section 3).

Several types of sensors have been developed (Table 2) by exploiting different technologies and physical properties of the water flow (for a review see Arregui et al., 2006, and references therein):

- Accelerometers (e.g., Evans et al., 2004), which analyze vibrations in a pipe induced by the turbulence of the water flow. A sampling frequency of 100 Hz of the pipe vibrations allows reconstructing the average flow within the pipe with a resolution of 0.015 L (Kim et al., 2008).
- Ultrasonic sensors (Mori et al., 2004), which estimate the flow velocity, and then determine the flow rate knowing the pipe section, by measuring the difference in time between ultrasonic beams generated by piezoelectric devices and transmitted within the water flow. The transducers are generally operated in the range 0.5–2 MHz and allow attaining an average resolution around 0.0018 L (e.g., Sanderson and Yeung, 2002).
- Pressure sensors (Froehlich et al., 2009, 2011), which consist in steel devices, equipped with an analog-digital converter and a micro-controller, continuously sampling pressure with a theoretical maximum resolution of 2 kHZ. Flow rate is related to the pressure change generated by the opening/close of the water devices valves via Poiseuille's Law.
- Flow meters (Mayer and DeOreo, 1999), which exploit the water flow to spin either pistons (mechanic flow meters) or magnets (magnetic meters) and correlate the number of revolutions or pulse to the water volume passing through the pipe. Sensing resolution spans between 34.2 and 72 pulses per liter (i.e., 1 pulse every 0.029 and 0.014 L, respectively) associated to a logging frequency in the range of 1–10 s (Kowalski and Marshallsay, 2005; Heinrich, 2007; Willis et al., 2013).

So far, only flow meters and pressure sensors have been employed in *smart meters* applications because ultrasonic sensors are too costly and the use of accelerometers requires an intrusive calibration phase with the placement of multiple meters distributed on the pipe network for each single device of interest (Kim et al., 2008). It is worth noting that the “smartness” of these sen-sors is related both to their high sampling resolution and to their integration in efficient systems combining data collection, transfer, storage, and analysis. Although sensors can be equipped with data loggers requiring human intervention to retrieve the data directly from the sensors (Mayer et al., 2004), bluetooth and wireless connections have been recently exploited for improving data management. For example, Froehlich et al. (2009) installed a network of pressure sensors communicating via bluetooth with a laptop deployed at each household, which runs a custom data logger to receive, compress, and archive data. These latter are then uploaded to a web server at 30-min intervals.

2.3. Research challenges and future directions

While smart meters are becoming easily available, we identified a list of open research and technical challenges that need to be addressed to promote the coherent use of this wide range of technologies:

1. The first open research question relates to the management of the metered high resolution flow data. In particular, the development of robust, automated processes to transfer the generated big data requires further elaborations, both in terms of hardware and software performance due to existing issues with respect to wireless network reliability, black spots, power source and battery life (Stewart et al., 2010; Little and Flynn, 2012). All these aspects appear key also because the possibility of inte-grating water and energy meters and using the same data log-gers and transmission systems is expected to enhance the diffusion of high resolution water sensors (Benzi et al., 2011; Froes Lima and Portillo Navas, 2012).
2. The second open challenge concerns the design of centralized or distributed information systems to store the data collected by the smart meters (Oracle, 2009). A centralized system would allow checking the accuracy of the collected data, which can

Table 1
Details of the papers reviewed.

Reference	Location	Data gathering	Water end-uses	User modeling	Personalized WDMS
Anda et al. (2013)	Australia	x			
Boyle et al. (2013)	N/A	x			
Willis et al. (2013)	Australia	x		x	
Froehlich et al. (2011)	N/A	x	x		
Wong et al. (2010)	Hong Kong	x			
Froehlich et al. (2009)	N/A	x			
Kim et al. (2008)	N/A	x			
Heinrich (2007)	New Zealand	x	x		
Olmstead et al. (2007)	USA	x		x	
Kowalski and Marshallsay (2005)	UK	x	x		
Evans et al. (2004)	N/A	x			
Mayer et al. (2004)	USA	x	x		x
Mori et al. (2004)	N/A	x			
Cordell et al. (2003)	Australia	x			
Sanderson and Yeung (2002)	N/A	x			
Mayer and DeOreo (1999)	USA	x			x
Nguyen et al. (2014)	Australia		x		
Nguyen et al. (2013a)	Australia		x		
Nguyen et al. (2013b)	Australia		x		
Cardell-Oliver (2013a)	Australia		x		
Cardell-Oliver (2013b)	Australia		x		
Aquacraft Inc. (2011)	USA		x		
Beal et al. (2011a)	Australia		x		
DeOreo et al. (2011)	USA		x		
Mead and Aravinthan (2009)	Australia		x		
Willis et al. (2009a)	Australia		x		
Willis et al. (2009b)	Australia		x		
Roberts (2005)	Australia		x		x
Kowalski and Marshallsay (2003)	UK		x		
Loh et al. (2003)	Australia		x	x	
DeOreo and Mayer (2000)	USA		x		
DeOreo et al. (1996)	USA		x		
Mayer and DeOreo (1995)	USA		x		
DeOreo and Mayer (1994)	USA		x		
Makki et al. (2015)	Australia			x	
Beal et al. (2014)	Australia			x	
Kanta and Zechman (2014)	N/A			x	
Beal and Stewart (2014)	Australia			x	
Matos et al. (2014)	Portugal			x	
Talebpour et al. (2014)	Australia			x	
Romano et al. (2014)	Italy			x	
Cardell-Oliver and Peach (2013)	Australia			x	
Beal et al. (2013)	Australia			x	
Bennett et al. (2013)	Australia			x	
Cahill et al. (2013)	USA			x	
Cole and Stewart (2013)	Australia			x	
Makki et al. (2013)	Australia			x	
Beal et al. (2011b)	Australia			x	
Gato-Trinidad et al. (2011)	Australia			x	
Grafton et al. (2011)	10 OECD countries			x	
House-Peters and Chang (2011)	N/A			x	
Lee et al. (2011)	USA			x	
Nasseri et al. (2011)	Iran			x	
Qi and Chang (2011)	USA			x	
SDU (2011)	USA			x	
SJESD (2011)	USA			x	
Willis et al. (2011)	Australia			x	
Blokker et al. (2010)	Nederland			x	
Chang et al. (2010)	USA			x	
Lee and Wentz (2010)	USA			x	
Polebitski and Palmer (2010)	USA			x	
Rosenberg (2010)	Jordan			x	
Russell and Fielding (2010)	N/A			x	
Chu et al. (2009)	China			x	
Corbella and Pujol (2009)	N/A			x	
Fox et al. (2009)	UK			x	
Galán et al. (2009)	Spain			x	
Jorgensen et al. (2009)	N/A			x	
Olmstead and Stavins (2009)	N/A			x	
Praskievicz and Chang (2009)	Korea			x	
Balling et al. (2008)	USA			x	
Lee and Wentz (2008)	USA			x	
Alvisi et al. (2007)	Italy			x	
Balling and Gober (2007)	USA			x	

(*continued on next page*)

Table 1 (*continued*)

Reference	Location	Data gathering	Water end-uses	User modeling	Personalized WDMS
Gato et al. (2007)	Australia			x	
Rosenberg et al. (2007)	Jordan			x	
Wentz and Gober (2007)	USA			x	
Gato (2006)	Australia			x	
Altunkaynak et al. (2005)	Turkey			x	
Fullerton and Elias (2004)	USA			x	
Aly and Wanakule (2004)	USA			x	
Syme et al. (2004)	Australia			x	
Brookshire et al. (2002)	N/A			x	
Zhou et al. (2000)	Australia			x	
Zhou et al. (2002)	Australia			x	
Espey et al. (1997)	N/A			x	
Molino et al. (1996)	Italy			x	
Homwongs et al. (1994)	USA			x	
Lyman (1992)	USA			x	
Griffin and Chang (1991)	USA			x	
Rixon et al. (2007)	Australia			x	
Schneider and Whitlatch (1991)	USA			x	
Miaou (1990)	USA			x	
Maggioni (2015)	USA				x
Sonderlund et al. (2014)	N/A				x
Molinos-Senante (2014)	Spain				x
Britton et al. (2013)	Australia				x
Fielding et al. (2013)	Australia				x
Stewart et al. (2013)	Australia				x
Carragher et al. (2012)	Australia				x
Cole et al. (2012)	Australia				x
Froehlich et al. (2012)	USA				x
Froes Lima and Portillo Navas (2012)	Brazil				x
DeOreo (2011)	USA				x
Willis et al. (2010)	Australia				x
Mead and Aravinthan (2009)	Australia				x
Steg and Vlek (2009)	N/A				x
Britton et al. (2008)	Australia				x
Grafton and Ward (2008)	Australia				x
Worthington and Hoffman (2008)	N/A				x
Brennan et al. (2007)	Australia				x
Brooks (2006)	N/A				x
Hensher et al. (2006)	Australia				x
Inman and Jeffrey (2006)	N/A				x
Howarth and Butler (2004)	UK				x
Arbués et al. (2003)	N/A				x
Duke et al. (2002)	USA				x
Geller (2002)	N/A				x
Garcia and Thomas (2001)	France				x
Kanakoudis (2002)	Greece				x
Renwick and Green (2000) Renwick	USA				x
and Archibald (1998) Dandy et al.	USA				x
(1997)	Australia				x
Gurung et al. (2015)	Australia			x	x
Gurung et al. (2014)	Australia			x	
Suero et al. (2012)	USA			x	x
Giacomoni and Berglund (2015)	USA			x	x
Escriva-Bou et al. (2015a)	USA			x	x
Escriva-Bou et al. (2015b)	USA			x	x
Kenney et al. (2008)	USA			x	x
Kenney et al. (2004)	USA				x
Dalhuisen et al. (2003)	N/A			x	x
Mayer et al. (2003)	USA	x	x		x
Mayer et al. (2000)	USA	x	x		x

then be made easily available for data processing and analysis. On the contrary, a distributed solution would reduce transmission costs and facilitate providing immediate feedbacks to customers, who can use this information to make decisions about their water use.

3. A third open question is how householder privacy is impacted by collection and communication of detailed water-use information. Although such issues are currently underestimated as in many communities (e.g., in Australia) severe water shortages have led to a permissive attitude to conserve water (Giurco et al., 2010), it is likely that the collection of information on both water use and behavior change over time implies increased privacy risks (McIntyre, 2008; Chen et al., 2014).

4. Finally, a challenge is posed by the actual deployment of large-scale high-resolution metering network in the real world. While literature presents a number of trials (e.g., Mayer et al.(2004); Heinrich (2007); Froehlich et al. (2009)) that exploit smart sensors with extremely fine resolutions (sub-minute), cost, privacy, and regulations may limit their scalability to large-scale continuous operative smart meter installations. For example, data protection and data security issues are being seriously considered by the European Union, which is imposing

Table 2
Studies contributing in the data gathering step. Studies gathering data with a sub-daily resolution are considered as *high-resolution*, *low-resolution* otherwise.

Reference	Location	Resolution	Sensor type	Resolution [liters]
Olmstead et al. (2007)	USA	Low	–	–
Wong et al. (2010)	Hong Kong	Low	–	–
Anda et al. (2013)	Australia	Low	–	–
Boyle et al. (2013)	N/A	High	–	–
Cordell et al. (2003)	Australia	High	–	–
Kim et al. (2008)	N/A	High	Accelerometer	0.0150
Mayer and DeOreo (1999) Evans	USA	High	Flow meter	0.014–0.029
et al. (2004)	N/A	High	Accelerometer	0.0150
Mori et al. (2004)	N/A	High	Ultrasonic	0.0018
Sanderson and Yeung (2002)	N/A	High	Ultrasonic	0.0018
Froehlich et al. (2009) Froehlich	N/A	High	Pressure	0.0600
et al. (2011)	N/A	High	Pressure	0.0600
Kowalski and Marshallsay (2005)	UK	High	Flow meter	0.014–0.029
Heinrich (2007)	New Zealand	High	Flow meter	0.014–0.029
Willis et al. (2013)	Australia	High	Flow meter	0.014–0.029
Mayer et al. (2004)	USA	High	Flow meter	0.014–0.029
Mayer et al. (2000)	USA	High	Flow meter	0.014–0.029
Mayer et al. (2003)	USA	High	Flow meter	0.014–0.029

some strict guidelines to utilities willing to deploy smart meter solutions for their customers and many water utilities collect data at lower resolution than the minute (e.g., Thames Water in London reads data at 15-min resolution, EMIVASA in Valencia and SES in Switzerland at 1-h resolution). This implies that the theoretical capabilities of smart metering technologies may not be fully exploited, potentially limiting the accuracy in characterizing the residential water consumption as studies relying on medium/low resolution data. Large-scale smart-meters application would therefore benefit from a better understanding of the consequences of different time resolutions on the models accuracy and on the effectiveness of WDMS.

3. Water end-uses characterization

Non-intrusive metering requires disaggregation algorithms to breakdown the total consumption data registered at the household level into the different end-use categories (second block of Fig. 1). In the water research literature, several studies have been conducted in the last two decades using a variety of single or mixed disag-gregation methods, such as household auditing, diaries, high res-olution flow meters and pressure sensors (see Table 3). According to the methodology adopted, we can identify two main approaches for disaggregating smart metered water data at very high temporal resolution: *decision tree algorithms*, namely Trace Wizard® (DeOreo et al., 1996) and Identiflow® (Kowalski and Marshallsay, 2003), and *machine learning algorithms*, namely HydroSense (Froehlich et al., 2011) and SEQREUS (Beal et al., 2011a). Recently, the disaggrega-tion of medium resolution water data (i.e., hourly data) has been explored by means of water use signature patterns method (Cardell-Oliver, 2013a, b), namely a combination of feature selec-tion, unsupervised learning, and cluster evaluation.

3.1. Trace Wizard

Trace Wizard (DeOreo et al., 1996) is a commercial software (recently replaced by an on-demand service developed and managed by Aquacraft Inc) which applies a decision tree algorithm to interpret magnetic metered flow data based on some basic flow boundary conditions (e.g., minimum/maximum volume, peak flow rate, duration range, etc.). The disaggregation process is structured in the following steps:

1. Conduct a detailed water device stock inventory audit for each household to determine the efficiency rating of each household appliance/fixture;
2. Household occupants should complete a diary of water use events over a one-week period to gain information on their water use habits;
3. Analysts use water audits, diaries, and sample flow trace data for each household to create specific templates that serve to match water end-use patterns depending on some basic flow boundary conditions.
4. Based on the developed templates, stock survey audit, diary information and analysts' experience, the individual water end-uses are disaggregated.

It is worth noting that the human resource effort required by Trace Wizard makes the overall process extremely time and resource intensive, with the quality of the results that is strongly dependent on the experience of the analyst in understanding flow signatures. It has been estimated that the classification of two weeks of data approximatively requires two hours of works by the analyst and attains an average classification accuracy of 70% (Nguyen et al., 2013a). In addition, the prediction accuracy of Trace Wizard is significantly reduced when more than two events occur concurrently (Mayer and DeOreo, 1999). However, Trace Wizard still has an edge on disaggregation techniques and has been used in several research works and projects (DeOreo and Mayer, 1994; Mayer and DeOreo, 1995; DeOreo et al., 1996; Mayer and DeOreo, 1999; DeOreo and Mayer, 2000; Loh et al., 2003; Mayer et al., 2004; Roberts, 2005; Heinrich, 2007; Mead and Aravinthan, 2009; Willis et al., 2009a, b; Aquacraft Inc, 2011; DeOreo et al., 2011).

3.2. Identiflow

Similar to Trace Wizard, Identiflow (Kowalski and Marshallsay, 2003) relies on a decision tree algorithm to perform a semi-automatic disaggregation of the total water consumption at the household level. Identiflow uses fixed physical features of various water-use devices (e.g., volume, flow rate, duration, etc.) to classify the different end-use events. Although Identiflow has shown better performance than Trace Wizard (i.e., 74.8% accuracy in terms of the correctly classified volume over 3870 events (Nguyen et al., 2013a)), its classification accuracy strongly depends on the physical features used to describe each fixture/appliance. Two different

Table 3
Studies contributing in the water end-uses characterization step.

Reference	Location	Disaggregation algorithm	Number of households
Froehlich et al. (2011)	N/A	HydoSense	5
Heinrich (2007)	New Zealand	Trace Wizard	12
Mayer et al. (2004)	USA	Trace Wizard	33
DeOreo et al. (1996)	USA	Trace Wizard	N/A
Kowalski and Marshallsay (2003)	UK	Identiflow	250
Kowalski and Marshallsay (2005)	UK	Identiflow	N/A
Beal et al. (2011a)	Australia	SEQREUS	1500
DeOreo and Mayer (1994) Mayer	USA	Trace Wizard	16
and DeOreo (1995) DeOreo and	USA	Trace Wizard	16
Mayer (2000)	USA	Trace Wizard	10
Loh et al. (2003)	Australia	Trace Wizard	720
Roberts (2005)	Australia	Trace Wizard	100
Mead and Aravinthan (2009)	Australia	Trace Wizard	10
Willis et al. (2009a)	Australia	Trace Wizard	200
Willis et al. (2009b)	Australia	Trace Wizard	151
Aquacraft Inc. (2011)	USA	Trace Wizard	209
Nguyen et al. (2014)	Australia	SEQREUS	3
Nguyen et al. (2013a)	Australia	SEQREUS	252
Nguyen et al. (2013b)	Australia	SEQREUS	3 (out of 252)
Mayer et al. (2000)	USA	Trace Wizard	37 (out of 1188)
Mayer et al. (2003)	USA	Trace Wizard	33
DeOreo (2011)	USA	Trace Wizard	1000
Cardell-Oliver (2013a)	Australia	Water Use Signature Patterns	11,000
Cardell-Oliver (2013b)	Australia	Water Use Signature Patterns	187

water events are likely classified into the same category if they exhibit similar physical characteristics. Moreover, it fails to classify events when old devices are replaced by modern ones, since the physical characteristics of these latter might be completely different compared to the old ones.

3.3. HydroSense

HydroSense (Froehlich et al., 2011) is a probabilistic-based classification approach which relies on data collected through pressure sensors. Water end-use events are classified with respect to the unique pressure waves that propagate to the sensors when valves are opened or closed. Specifically, when a valve is opened or closed, a pressure change occurs and a pressure wave is generated in the plumbing system. Based on the pressure wave (which depends on the valve type and its location), water end-use events are classified by using advanced pattern matching algorithms and Bayesian probabilistic models. HydroSense has been demonstrated to attain very high levels of classification accuracy, namely 90% and 94% with one or two pressure sensors, respectively (Froehlich et al., 2011). However, the calibration of the algorithm requires an intrusive monitoring period with the installation of a much larger number of pressure sensors connected to each water device (i.e., Froehlich et al. (2011) used 33 sensors in a single household). This requirement significantly constrains the portability of this approach to a wide urban context as it would entail large costs and privacy issues.

3.4. SEQREUS

The SEQREUS approach (Beal et al., 2011a) proposes a combination of Hidden Markov Models (HMMs), Dynamic Time Warping (DTW), and time-of-day probability to automatically categorize the collected data at the household level into particular water end-use categories. To minimize the intrusiveness of the approach, the ground truth for the calibration (i.e., a set of disaggregated end-use events) is obtained using Trace Wizard. Then, the SEQREUS approach works as follows:

1. The disaggregated data are used for training multiple HMMs, one for each end-use category (excluding the inconclusive event);
2. The physical characteristics of each end-use category are used to refine the estimate given by the HHMs (e.g., any shower event with a volume less than 7 L or any bathtub event with duration less than 4 min is placed in the inconclusive event for future analysis);
3. A DTW algorithm determines if any event in the inconclusive dataset is similar to an event in categories having clearly defined consumption patterns, namely the washing machine and dishwasher cycles;
4. Time of day probability is used to assign inconclusive events to an end-use category.

Testing on three independent households located in Melbourne (Australia) demonstrated a high prediction accuracy, namely between 80% and 90% for the major end-use categories (Nguyen et al., 2014). However, the method still requires human input to achieve such levels of recognition accuracy (e.g., for the classification of inconclusive events supported by DTW and for manually classifying combine events) (Nguyen et al., 2013a, b).

3.5. Research challenges and future directions

Given the small number of algorithms for disaggregating water flow data, there is still a large room for developing new methods addressing the major limitations of the existing approaches:

1. First, most of the approaches used in the water sector requires time consuming expert manual processing and intensive human interactions via surveys, audits and water event diaries, while the development of automatic procedures is fundamental to further extend the application of these methods beyond experimental trials and research projects (Stewart et al., 2010). Moreover, the existing methods have limited accuracy in identifying overlapping events.

The disaggregation problem has been addressed in other research fields as a general problem of *blind identification*, or output-only system identification (Reynders, 2012). The real state of the system (i.e., the set of the working states and water consumption of each single fixture in the household) is unknown and only observations of the system output (i.e., the total water consumption) are available. Starting from the 1990s, several techniques have been proposed to address blind identification problems in different research field, such as signal processing, data communication, speech recognition, image restoration, seismic signal processing (see Abed-Meraim et al., 1997, and references therein).

With the development of smart electricity grids (Kramers et al., 2014; Niesse et al., 2014), this problem has been largely studied in the energy sector to develop automatic disaggregation methods, also known as Non Intrusive Load Monitoring (NILM) algorithms, which aim at decomposing the aggregate household energy con-sumption data collected from a single measurement point into device-level consumption data (for a review, see Zeifman and Roth, 2011; Zoha et al., 2012; Carrie Armel et al., 2013, and references therein). These methods show promising results and seem effective also up to 6—10 appliances (Figueiredo et al., 2014; Makonin et al., 2013). Yet, the portability of such techniques in the water field has not been assessed. Some additional challenges in characterizing water end-use events might be introduced by the larger human dependency than the one of electric appliances, which are more automatic. These concerns primarily involve manually controlled fixtures (e.g., bathtubs, showers, faucets), which might be used not at the maximum capacity (Froehlich et al., 2009).

2. The second main open question relates to the acquisition of the ground truth for initial calibration. All the algorithms used for disaggregating water data, but also the majority of the ones used for energy data, need an intrusive period to collect a dataset of disaggregated end-use events, which incurs extra cost and human effort, ultimately challenging their large-scale application. Researchers are actively looking to devise completely unsupervised or semi-supervised methods that avoid the effort of acquiring the calibration ground truth data (e.g., Gonçalves et al., 2011; Parson et al., 2014).
3. Finally, most of the approaches developed in the energy sector are currently focused on correctly characterizing the on/off status of the devices and, possibly, the fraction of total energy assigned correctly, while their performance in reproducing the timings and frequencies of each device are lower (Batra et al., 2014). Yet, timings and frequencies represent key information to understand consumers behaviors and design personalized demand management strategies (e.g., deferring the use of some appliances to peak-off hours). Accordingly, knowledge about use frequencies, timing and peak-hours in the water sector would constitute crucial information for identifying both typical consumption behaviors and patterns, as well as consumption anomalies (e.g., leakages (Loureiro et al., 2014; Ponce et al., 2014; Pérez et al., 2014; Perez et al., 2014)). This knowledge would aid the activities of water utilities at different levels: demand management, network maintenance, and strategic planning.

4. User modeling

The user modeling phase (third block in Fig. 1) aims at representing the water demand at the household level, thus preserving the heterogeneity of the individual users in the modeled community, possibly as determined by natural and socio-psychographic factors as well as by the users' response to different WDMS. In the literature, two distinctive approaches exist (see Table 4): *descriptive models*, which limit their extent to the analysis of water consumption patterns, and *predictive models*, which provide estimate of the water consumption at the individual (household) level as determined by natural and socio-psychographic factors, and in response to different WDMS.

4.1. Descriptive models

The first class of models, namely descriptive models, aims at analyzing the observed water consumption behaviors of water users. Depending on the resolution of the data available, the analysis can focus on identifying aggregated consumption patterns or on defining users' profiles on the basis of the disaggregated end-uses (e.g., Loh et al., 2003; SDU, 2011; SJESD, 2011; Gato-Trinidad et al., 2011; Willis et al., 2011; Beal et al., 2011b, 2013; Cardell-Oliver and Peach, 2013; Cole and Stewart, 2013; Beal and Stewart, 2014; Beal et al., 2014; Gurung et al., 2014, 2015).

The construction of descriptive models allows studying historical trends (Agudelo-Vera et al., 2014; Kofinas et al., 2014) to build a user consumption profile that constitutes the baseline for identifying the most promising areas where conservation efforts may be polarized (e.g., restriction on irrigation practices in case gardening represents the dominant end-use). However, the majority of these models cannot be used to predict the water savings potential of alternative WDMS, unless combined with control group experiments to observe user responses (Cahill et al., 2013).

4.2. Predictive models

The second class of models, namely predictive models, aims at estimating the water demand at the individual (household) level. Some works developed predictive models that mostly provide short-term forecast of the water demand on the basis of time series analyses (e.g., Homwongs et al., 1994; Molino et al., 1996; Altunkaynak et al., 2005; Alvisi et al., 2007; Nasseri et al., 2011). Yet, these approaches are ineffective in supporting the design and implementation of WDMS as the predicted water consumption of a user is not related to his socio-psychographic factors or his response to different WDMS. An alternative approach can be structured in the following two sub-steps: (*i*) *multivariate analysis*, which consists in the identification and selection of the most relevant inputs to explain the preselected output, and (*ii*) *behavioral modeling*, which means model structure identification, parameter calibration and validation.

The multivariate analysis phase (i.e., variable selection as called in data-driven modeling (George, 2000)) is a fundamental step to build predictive models of urban water demand variability in space and time. In most of the works, the identification of the most relevant drivers relies on the results of data mining techniques (e.g., correlation analysis) between a pre-defined set of variables (candidate drivers) and the water consumption data. This approach is also referred to as *inductive* modeling (Cahill et al., 2013). An alternative to this data-driven approach is the *deductive* construction of models according to empirical or theoretical causality (Cahill et al., 2013). Depending on the specific domains from which the candidate drivers are extracted, which is often delimited by data availability (Arbués et al., 2003), we can distinguish the following three main approaches:

- *economic-driven studies*, which focus on studying the correlation between water consumption and purely economic drivers, such as water tariff structures or water price elasticity (e.g., Schneider and Whitlatch, 1991; Espey et al., 1997; Brookshire et al., 2002; Dalhuisen et al., 2003; Olmstead et al., 2007; Olmstead and Stavins, 2009; Rosenberg, 2010; Qi and Chang, 2011);

Table 4
Studies contributing in the user modeling step. Legend for multi-variate analysis approaches: E = economic-driven; GS = geo-spatial; P = psychographic driven; AR = autoregressive. Legend for behavioral models approach: single = single user model; multi = multi-user model.

Reference	Location	Modeling approach	Multivariate analysis	Behavioral model	Spatial scale
Loh et al. (2003)	Australia	Descriptive	–	–	Household
Gato-Trinidad et al. (2011) SDU	Australia	Descriptive	–	–	Household
(2011)	USA	Descriptive	–	–	Household
SJESD (2011)	USA	Descriptive	–	–	Household
Cardell-Oliver and Peach	Australia	Descriptive	–	–	Household
(2013) Beal et al. (2013)	Australia	Descriptive	–	–	Household
Beal and Stewart (2014)	Australia	Descriptive	–	–	Household
Gurung et al. (2015)	Australia	Descriptive	–	–	Household
Gurung et al. (2014)	Australia	Descriptive	–	–	Household
Beal et al. (2014)	Australia	Descriptive	–	–	Household
Cole and Stewart (2013) Willis	Australia	Descriptive	–	–	Household
et al. (2011)	Australia	Descriptive	–	–	Household
Beal et al. (2011b)	Australia	Descriptive	–	–	Household
Maggioni (2015)	USA	Predictive	E + GS + P	Single	Household
Makki et al. (2015)	Australia	Predictive	E + P	Single	Household
House-Peters and Chang	N/A	Predictive	E + GS + P	Single + multi	N/A
(2011) Schneider and	USA	Predictive	E	–	District
Whitlatch (1991) Lyman (1992)	USA	Predictive	E + GS + P	single	Household
Espey et al. (1997)	N/A	Predictive	E	–	N/A
Dalhuisen et al. (2003)	N/A	Predictive	E	–	N/A
Miaou (1990)	USA	Predictive	GS	–	Urban
Polebitski and Palmer (2010)	USA	Predictive	GS	–	Census tracts
Lee et al. (2011)	USA	Predictive	GS	–	Household
Olmstead et al. (2007)	USA	Predictive	E	–	Household
Willis et al. (2013)	Australia	Predictive	P	–	Household
Homwongs et al. (1994) Molino	USA	Predictive	AR	–	Urban
et al. (1996) Altunkaynak et al.	Italy	Predictive	AR	–	Urban
(2005) Alvisi et al. (2007)	Turkey	Predictive	AR	–	Urban
Nasseri et al. (2011) Brookshire	Italy	Predictive	AR	–	Household
et al. (2002) Olmstead and	Iran	Predictive	AR	–	Urban
Stavins (2009) Rosenberg	N/A	Predictive	E	–	N/A
(2010)	N/A	Predictive	E	–	N/A
Qi and Chang (2011)	Jordan	Predictive	E	–	Household
Griffin and Chang (1991)	USA	Predictive	E	–	Urban
Zhou et al. (2000)	USA	Predictive	GS	–	District
Zhou et al. (2002)	Australia	Predictive	GS	–	Urban
Fullerton and Elias (2004)	Australia	Predictive	GS	–	District
Aly and Wanakule (2004) Gato	USA	Predictive	GS	–	Urban
et al. (2007)	USA	Predictive	GS	–	Urban
Balling and Gober (2007)	Australia	Predictive	GS	–	Urban
Balling et al. (2008)	USA	Predictive	GS	–	Urban
Lee and Wentz (2008)	USA	Predictive	GS	–	Census tracts
Praskievicz and Chang (2009)	USA	Predictive	GS	–	Census tracts
Corbella and Pujol (2009)	Korea	Predictive	GS	–	urban
Chang et al. (2010)	N/A	Predictive	GS	–	N/A
Lee and Wentz (2010)	USA	Predictive	GS	–	Household
Syme et al. (2004)	USA	Predictive	GS	–	Urban
Wentz and Gober (2007)	Australia	Predictive	P	–	Household
Fox et al. (2009)	USA	Predictive	P	–	Household
Russell and Fielding (2010)	UK	Predictive	P	–	Household
Grafton et al. (2011)	N/A	Predictive	P	–	N/A
Suero et al. (2012)	10 OECD countries	Predictive	P	–	Household
Matos et al. (2014)	USA	Predictive	P	–	Household
Talebpour et al. (2014) Romano	Portugal	Predictive	P	–	Household
et al. (2014)	Australia	Predictive	P	–	Household
Gato (2006)	Italy	Predictive	P	–	Water utility
Rosenberg et al. (2007) Blokker	Australia	Predictive	GS	Single	Urban
et al. (2010)	Jordan	Predictive	GS + P	Single	Household
Cahill et al. (2013)	Nederland	Predictive	P	Single	Household
Bennett et al. (2013)	USA	Predictive	P	Single	Household
Rixon et al. (2007)	Australia	Predictive	GS + E + P	Single	Household
Gal´an et al. (2009)	Australia	Predictive	E + P	Multi	Household
Chu et al. (2009)	Spain	Predictive	P	Multi	Household
Kanta and Zechman (2014)	China	Predictive	E + P	Multi	Household
Jorgensen et al. (2009) Kenney	N/A	Predictive	GS + P	Multi	Household
et al. (2008)	N/A	Predictive	P	–	Household
Makki et al. (2013)	USA	Predictive	E + GS + P	Single	Household
Giacomoni and Berglund	Australia	Predictive	E + P	Single	Household
(2015) Escriva-Bou et al.	USA	Predictive	GS	Multi	Urban
(2015a)	USA	Predictive	P	Single	Household
?	USA	Predictive	P	Single	Household

- *geo-spatial studies*, which assess the correlation between hydro-climatic variables and seasonality with water consumption (e.g., Miaou, 1990; Griffin and Chang, 1991; Zhou et al., 2000, 2002; Fullerton and Elias, 2004; Aly and Wanakule, 2004; Gato et al., 2007; Balling and Gober, 2007; Balling et al., 2008; Lee and Wentz, 2008; Praskievicz and Chang, 2009; Corbella and Pujol, 2009; Chang et al., 2010; Polebitski and Palmer, 2010; Lee and Wentz, 2010; Lee et al., 2011);
- *psycographic-driven studies*, which infer the influence of users' personal attributes on their water consumption, including income, family composition, lifestyle, and households physical characteristics (e.g., number of rooms, type, presence of garden) (e.g., Syme et al., 2004; Wentz and Gober, 2007; Fox et al., 2009; Jorgensen et al., 2009; Russell and Fielding, 2010; Grafton et al., 2011; Willis et al., 2013; Suero et al., 2012; Matos et al., 2014; Talebpour et al., 2014; Romano et al., 2014).

Note that this classification is not stringent, in the sense that hybrid approaches dealing with more than one of the mentioned domains have already been developed (e.g., Makki et al., 2015). Similarly to the descriptive models discussed in the previous section, the development of predictive models could significantly benefit from smart metering technologies and high-resolution water consumption data. Indeed, the availability of high-resolution and end-use characterization of the water consump-tion allows predicting the effects of customized WDMS focused on specific end-uses (e.g., Makki et al. (2013)). In most of the literature, the user modeling is limited to the multivariate analysis, which however provides only qualitative information to water managers, water utilities, and decision makers. Only few works completed the second phase (i.e., behavioral modeling) and provide a quantitative prediction of the water demand at the household level, thus representing better decision-aiding tools as they can use these models to develop what-if analysis as well as scenario simulation and analysis.

The construction of behavioral models aims at the identification, calibration, and validation of mathematical models, which describe the water demand (i.e., output variable) as a function of the drivers identified in the multivariate analysis. In the behavioral modeling literature, we can identify a first class of models, named *single-user models*, which describe the consumption behavior of individual users considered as isolated entities. These works (e.g., Lyman, 1992; Gato, 2006; Kenney et al., 2008; Maggioni, 2015) generally rely on dynamic models based on sampling of statistical distributions describing average users and end-uses (e.g., number of people per household and their ages, the frequency of use, flow duration and event occurrence likelihood). Water demand patterns can be then estimated via model simulation and comparison of the results with the observed data. Yet, this approach often reduces the heterogeneity of the water users, which can be preserved by running Monte Carlo simulations that sample also the extreme values of the associated statistical distributions (Rosenberg et al., 2007; Blokker et al., 2010; Cahill et al., 2013). Recently, different approaches (Bennett et al., 2013; Makki et al., 2013, 2015) combining non-parametric statistical tests and advanced regression models to identify key water consumption drivers and forecast urban water consumption have been demonstrated to successfully identify the main drivers of water consumption and to attain good forecast accuracy levels.

A second class of behavioral models, named *multi-user models*, instead focus on studying the social interactions and influence/mimicking mechanisms among the users. The majority of these works relies on multiagent systems (Shoham and Leyton-Brown, 2009), where each water user (agent) is defined as a computer system situated in some environment and capable of autonomous actions to meet its design objectives, but also able to exchange information with the neighbor agents and change its behavior accordingly (Wooldridge, 2009). The adoption of agent-based modeling offers several advantages with respect to other approaches (Bonabeau, 2002; Bousquet and Le Page, 2004): (1) it provides a more natural description of a system, especially when it is composed of multiple, distributed, and autonomous agents, (2) it relaxes the hypothesis of homogeneity in a population of actually heterogeneous individuals, (3) it allows an explicit representation of spatial variability, and (4) it captures emergent global behaviors resulting from local interactions. As a consequence, multiagent systems can be employed to study the role of social network structures and mechanisms of mutual interaction and mimicking on the behaviors of water users (e.g., Rixon et al., 2007; Galán et al., 2009), to estimate market penetration of water-saving technologies (e.g., Chu et al., 2009), and to simulate the feedbacks between water consumers and policy makers (e.g., Kanta and Zechman, 2014).

4.3. Research challenges and future directions

Given the current status of user modeling studies and the room for improvement given by the use of high resolution, smart metered data, several research challenges and future directions emerge:

1. The first open question in terms of descriptive models concerns matching the analysis of the water consumption patterns with the potential drivers generating the observed users' behaviors. This would allow validating the results of the classification of the users on the basis of their consumption and understanding if this latter is a good proxy representing different characteristics of the users.
2. The use of spatially explicit models to take advantage of the high temporal and spatial resolution of smart metered data is often hindered by the aggregation of individual household data to a larger spatial scale to protect customers' privacy as well as by the difficulties in collecting and sharing data coming across multiple water authorities and administrative institutions (House-Peters and Chang, 2011).
3. The third major challenge relates to the validation of the agent-based behavioral models. As in the construction of complex process-based models, accurately describing the single user (agent) behavior and connecting multiple users within an agent-based model does not ensure the validity of the results, although these latter are contrasted with observed data. In addition, given the large number of assumption and parameters, the problem of equifinality (i.e., the potential existence of multiple, alternative parameterization leading to same simulation outcomes) has to be addressed (Ligtenberg et al., 2010).
4. It is worth noting that the type of candidate drivers considered in the user modeling phase impacts the statistical representativeness of the results. The construction of sufficiently large datasets to estimate the relationships between water consumption data and the uncontrolled drivers (i.e., hydro-climatic and psychographic variables) is generally easy, provided that the time period is long enough and the number of involved users is sufficiently high. On the contrary, in most of the cases there is a single historical realization of the controllable drivers, namely the ones subject to human decisions (e.g., the existing pricing scheme). In such cases, the response of the users to different options is generally estimated via economics principles or sur-veys. Yet, economic principles introduce a priori general rules that might be inaccurate in characterizing the specific users under study, and the surveys provide only a static snapshot of the system conditions. The potential for using experimental

trials (e.g., Gilg and Barr, 2006; Borisova and Useche, 2013; Fielding et al., 2013) and gamification platforms (e.g., Mühlhäuser et al., 2008) to validate behavioral models results by retrieving information to the real users in large-scale applications has not been tested yet.

5. Finally, a major opportunity is represented by the development of integrated models that cross-analyze water and water-related energy consumption data to improve residential water demand models (Abdallah and Rosenberg, 2014; Escriva-Bou et al., 2015b, a).

5. Personalized water demand management strategies

Literature reports of a variety of management policies acting on the demand side of residential water consumption, designed with the purpose of improving water conservation and safeguarding water security in urban contexts. According to Inman and Jeffrey (2006), they can be classified in the following five categories (Table 5): *technological*, *financial*, *legislative*, *maintenance*, and *educational*. These strategies differ in the time scales they act on: price and prescriptive (i.e., command-and-control) approaches have been shown to achieve significant reductions of water de-mand in the short-period, but also have some drawbacks (such as equity issues and limits in consumers' price elasticity) that may limit the effectiveness of such strategies in the long term, if not integrated with other water conservation interventions (Fielding et al., 2013; Renwick and Green, 2000). In contrast, users' awareness and educational approaches allow for smaller reductions in the short period, but appear to be crucial to pursue reductions on the long run, as they require a change in users' behaviors (Geller, 2002).

Technological strategies involve the installation of water efficient household appliances (e.g., Mead and Aravinthan, 2009; Suero et al., 2012; Carragher et al., 2012; Froes Lima and Portillo Navas, 2012; Gurung et al., 2015). This option offers great potential for reducing indoor and outdoor water consumption (Mayer et al., 2000, 2003, 2004; DeOreo, 2011). Yet, the benefits associ-ated to these advanced systems are inconstant (Maggioni, 2015). For example, an incorrect use of automatic sprinkler may consume more water than manually operated irrigation systems (Syme et al., 2004), thus requiring educational programs to ensure an appropriate use.

Financial strategies, (also called market-based or price approaches (Olmstead and Stavins, 2009)), consist in water tariffs control associated to analysis of water demand elasticity (e.g., Dandy et al., 1997; Dalhuisen et al., 2003; Arbués et al., 2003;

Table 5
Studies contributing in the personalized WDMS step. Different WDMS are considered: E = educational; F = financial; L = legislative; M = maintenance; T = technological.

Reference	Location	Type of WDMS	Personalized
Maggioni (2015)	USA	L + T + F	x
Inman and Jeffrey (2006)	N/A	T + F + L + M + E	
Britton et al. (2008)	Australia	M	x
Dalhuisen et al. (2003)	N/A	E	
Mayer and DeOreo (1999)	USA	M	x
Mayer et al. (2004)	USA	T + M	x
Roberts (2005)	Australia	M	x
Suero et al. (2012)	USA	T	x
Mayer et al. (2000)	USA	T	x
Mayer et al. (2003)	USA	T	x
DeOreo (2011)	USA	T	x
Dandy et al. (1997)	Australia	F	
Arbués et al. (2003)	N/A	F	
Molinos-Senante (2014)	Spain	F	
Worthington and Hoffman (2008)	N/A	F	
Kanakoudis (2002)	Greece	F	
Duke et al. (2002)	USA	F	
Hensher et al. (2006)	Australia	L	x
Brennan et al. (2007)	Australia	L	
Grafton and Ward (2008)	Australia	L	
Renwick and Archibald (1998)	USA	L	x
Steg and Vlek (2009)	N/A	L-E	x
Britton et al. (2013)	Australia	M	x
Garcia and Thomas (2001)	France	M	
Brooks (2006)	N/A	M	
Fielding et al. (2013)	Australia	E	x
Renwick and Green (2000) Howarth	USA	E	
and Butler (2004)	UK	E	x
Geller (2002)	N/A	E	x
Willis et al. (2010)	Australia	E	x
Froehlich et al. (2012)	USA	E	x
Sonderlund et al. (2014)	N/A	E	x
Kenney et al. (2004)	USA	L	
Kenney et al. (2008)	USA	L + F + E	x
Mead and Aravinthan (2009)	Australia	T	x
Froes Lima and Portillo Navas (2012)	Brazil	T + E	x
Carragher et al. (2012)	Australia	T	x
Cole et al. (2012)	Australia	F	x
Stewart et al. (2013)	Australia	E	x
Gurung et al. (2015)	Australia	T	x
Giacomoni and Berglund (2015)	USA	L + T	
Escriva-Bou et al. (2015a)	USA	T + E	
Escriva-Bou et al. (2015b)	USA	T + E	

Kenney et al., 2008; Cole et al., 2012; Molinos-Senante, 2014; Maggioni, 2015). Even though some authors claim that price-based strategies are more cost effective than other conservation programs (Olmstead and Stavins, 2009), the effectiveness of this strategies seems uncertain as water demand has been shown to be relatively price inelastic (Worthington and Hoffman, 2008) and to rebound to the same or even higher levels after an initial decrease (Kanakoudis, 2002). Yet, a careful assessment of the effectiveness of these stra-tegies would benefit from longer dataset gathered in multiple ju-risdictions and contexts (Worthington and Hoffman, 2008). In addition, the are also concerns about the equity of raising prices (Duke et al., 2002).

Legislative strategies correspond to mandatory regulations and restrictions on water use, particularly in case of drought (e.g., Kenney et al., 2004; Hensher et al., 2006; Brennan et al., 2007; Kenney et al., 2008; Grafton and Ward, 2008). Restrictions applied to specific water uses, such as car washing or irrigation, have been demonstrated to reduce water consumption up to 30%(Renwick and Archibald, 1998; Kanakoudis, 2002). However, they require policy intervention to be implemented (Maggioni, 2015) and may be resisted by the community (Steg and Vlek, 2009).

Maintenance strategies consist in operations aiming at reducing or eliminating leakages in the water supply networks (e.g., Britton et al., 2008, 2013), which generally account for a significant fraction of the water consumption (e.g., EEA (2001) estimated losses due to leakage equal to 30% in Italy and 50% in Bulgaria). The identification and repair of leakages, which are often associated to a small number of households (Roberts, 2005; Mayer and DeOreo, 1999; Mayer et al., 2004), allows substantial increase in the efficiency of the water supply systems at lower costs with respect to augmenting the water supplied without repairing the network (Garcia and Thomas, 2001; Brooks, 2006).

Educational strategies aim at engaging the water users by means of public awareness and education campaigns (e.g., Geller, 2002; Steg and Vlek, 2009; Froes Lima and Portillo Navas, 2012; Anda et al., 2013; Fielding et al., 2013; Stewart et al., 2013). The effec-tiveness of these approaches is case-dependent: for example, it is estimated that information campaigns successfully led to a reduc-tion of water demand equal to 8% in the period 1989−1996 in California (Renwick and Green, 2000), while no impact was observed in UK, where, although a large campaign involving direct mailing as well as newspaper and radio advertisements, only 5% of the 8000 residences involved noticed the campaign (Howarth and Butler, 2004). Recent studies however suggest that a relevant water saving potential can be obtained by providing feedbacks to the users about their water consumption or suggestions on customized water savings practices (e.g., Kenney et al., 2008; Willis et al., 2010; Froehlich et al., 2012; Sonderlund et al., 2014).

Regardless the type of demand-side management strategy implemented, the availability of high-resolution data appears crucial both for the design and for an accurate evaluation of the effects of such interventions. Studies like Mayer et al. (2000) and Mayer et al. (2003), for instance, demonstrate that smart metered data and end-use characterization are crucial tools for evaluating the effects of retrofitting interventions both in terms of consumption reduction for particular end-uses and changes in consumption patterns (i.e., use frequencies and volumes). The same stands for price-based approaches, as smart metered data can be exploited to differentiate the price elasticity in relation to different uses (e.g., outdoor and indoor water consumption), allowing for the design of new price schemes, such as *Time of Use Tariffs* (Cole et al., 2012). In turn, if we consider educational campaigns, there is evidence of the potential of high-resolution metering in supporting the design of effective feedbacks and assess behavioral changes (Froehlich et al., 2012; Stewart et al., 2013; Sonderlund et al., 2014).

5.1. Research challenges and future directions

Given the recent improvements in characterizing water users' behaviors, a list of open research challenges exists to improve the designed of personalized WDMS:

1. The first challenge is the identification of more effective strategies for influencing the users behaviors. Technological strategies mostly impact on a limited number of end-uses (e.g., clothes or dish washers), whereas are less effective in inducing water savings in more human-controlled end-uses, such as showering or tap water. Moreover, investment inefficiencies can limit the effectiveness of these strategies causing the *Efficiency Gap* that is well-known in the energy field (Allcott and Greenstone, 2012). Educational intervention and programs can be more effective in controlling these latter, for example by providing feedbacks to the users as already applied in the energy sector (e.g., Abrahamse et al., 2007; Costanza et al., 2012). Yet, there are still open questions on the use of feedbacks to reduce water (or energy) consumption, particularly with respect to the most effective feedback format, whether the effect persists over time, as well as assessments of costs and benefits of feedback (Strengers, 2011; Desley et al., 2013).
2. The second main open question relates to the long-term effect of WDMS, especially for educational programs and awareness campaigns (e.g., Peschiera et al., 2010; Pereira et al., 2013). Although they showed promising results during the program and some months afterwards, their effect eventually dissipated and water consumption returned to pre-intervention levels after approximately 12 months (Fielding et al., 2013).
3. Finally, further effort should be devoted to examine the role of social norms and social influence in promoting water conservation (Rixon et al., 2007; Van Der Linden, 2013; Schultz et al., 2014). In particular, the potential for using gamification platforms and social applications to allow users monitoring their consumption coupled with normative information about similar households in their neighborhood should be assessed (Bogost, 2007; Rizzoli et al., 2014; Harou et al., 2014; Clifford et al., 2014; Curry et al., 2014; Savić et al., 2014; Vieira et al., 2014; Kossieris et al., 2014; Magiera and Froelich, 2014; Laspidou, 2014). Water utilities can indeed take advantage of people's tendency to mimic the behavior of their neighbors in order to target their efforts to “early adopters” and encourage technology diffusion (Janmaat, 2013).

6. Discussion and conclusions

Designing and implementing effective water demand management strategies is becoming more and more important to secure reliable water supply and reduce water utilities' costs over the next years. The advent of smart meters made available new water consumption data at very high spatial and temporal resolution, enabling a more detailed description of the drivers inducing people to consume or save water. A better understanding of water users' behaviors is indeed fundamental to promote water savings actions as it allows (*i*) selecting the specific behaviors to be changed, (*ii*) examining the factors causing those behaviors, (*iii*) applying well-tuned interventions, and (*iv*) systematically evaluating the effects of these interventions on the resulting behaviors (Geller, 2002).

In this paper, we reviewed 134 papers (Table 1) that contributed new methodologies and tools in one or more of the blocks underlying the general 4-step procedure represented in Fig. 1. A “road-map” of the main research challenges that need to be addressed in order to move the application of smart meters forward over the next decade is shown in Table 6 and summarized below:

Table 6
Main research challenges for the use of smart meters in residential water demand modeling and management.

1) Data gathering	2) Water end-uses characterization	3) User modeling	4) Personalized WDMS
1.1) Management of big data	2.1) Automatic disaggregation procedures (i.e., no manual processing)	3.1) Matching observed water consumption profiles with potential drivers of users' behaviors	4.1) More effective behavioral influence via customized feedbacks
1.2) Centralized or distributed information system	2.2) Unsupervised disaggregation algorithms (i.e., no ground truth)	3.2) Identification of spatial patterns across geographical areas	4.2) Long-term effect of WDMS
1.3) Impacts on household privacy	2.3) Higher accuracy in reproducing timings and frequencies	3.3) Validation of the agent- based behavioral models	4.3) Social norms and social influence
1.4) Real world scalability of high-resolution networks		3.4) Testing experimental trials and gamification platforms	
		3.5) Developing integrated models for water and water-related energy	

1. Data gathering: (*i*) how to efficiently and reliably manage the big data generated by the acquisition of high resolution smart metered flow data; (*ii*) understanding the best information system architecture (i.e., centralized or distributed) to store the data collected by the smart meters; (*iii*) how householder privacy is impacted by collection and communication of detailed water-use information;
2. Water End-uses characterization: (*i*) development of automatic procedures for disaggregating water consumption data at the household level to reduce the manual processing and intensive human interactions required by current methods; (*ii*) development of unsupervised methods that avoid the effort of acquiring the ground truth for training the algorithms; (*iii*) enhancing the accuracy of the methods in reproducing the timings and frequencies of each device usage.
3. User modeling: (*i*) matching the analysis of the observed water consumption profiles identified in the descriptive models with the potential drivers generating the observed users' behaviors; (*ii*) better exploit the high spatial resolution of smart metered data to identify water use patterns across geographic areas; (*iii*) validation of the agent-based behavioral models' simulation against observed data; (*iv*) testing of experimental trials and gamification platforms to support the validation of the behavioral models as well as to retrieve information from the water users; (*v*) developing integrated models for water and water-related energy.
4. Personalized water demand management strategies: (*i*) identification of more effective strategies for influencing the users behaviors, particularly by means of customized feedbacks to the water users providing information about their water consumption or suggestions on water savings practices; (*ii*) how to ensure a long-term effect of the implemented water demand management strategies, especially for educational programs and awareness campaigns; (*iii*) a better understanding of the role of social norms and social influence in promoting water conservation;

Despite the large number of papers published over the last years, the analysis of the studies discussed in this review highlights a clear need to shift research efforts from the development of specialized methodologies within each step of the procedure toward a more integrated approach that covers all the four phases. Indeed, the majority of the studies reviewed (i.e., 89% over 134 papers) provides contribution to a single step, whereas only few works go across multiple steps.

Moreover, we can observe that the case study locations are not homogeneously distributed: 79% of the papers reviewed are applied in the United States (36%) or Australia (43%), while the remaining studies were developed in Europe (13%) or Asia (6%) and a single application found in South America and no one in Africa. However, we expect that the challenges posed by climate change impacts, growing population demands, and constrained sources of water supply will call for the application of integrated residential water demand modeling and management in several countries across the world. Finally, we foresee that the investments for smart technologies in fields other than urban water management (e.g., Fernndez et al., 2014; Niesse et al., 2014; Kramers et al., 2014; Rezgui et al., 2014; Zarli et al., 2014) will create opportunities for collaborations and common actions among different spheres. Residential water demand modeling and management can benefit from these collaborations because smart technologies and networks have already been deployed in other fields, like domestic energy, thus representing a benchmark for learning and integration. Moreover, the existing nexus between energy and water is expected to foster synergies and cross-influences for addressing future demands (WWAP, 2014; Escriva-Bou et al., 2015b). Integrated, interdisciplinary science will thus support policy makers and planners addressing the major sustainability challenges placed by modern urban contexts and their evolution towards smart cities (Hilty et al., 2006; Laniak et al., 2013; Kelly et al., 2013).

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