

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

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Abstract

Over the last two decades, water smart metering programs have been launched in a number of medium to large cities worldwide to nearly continuously monitor water consumption at the single household level. The availability of data at such very high spatial and temporal resolution advanced the ability in characterizing, modeling, and, ultimately, designing user-oriented residential water demand management strategies. Research to date has been focusing on one or more of these aspects but with limited integration between the specialized methodologies developed so far. This manuscript is the first comprehensive review of the literature in this quickly evolving water research domain. The paper contributes a general framework for the classification of residential water demand modeling studies, which allows revising consolidated approaches, describing emerging trends, and identifying potential future developments. In particular, the future challenges posed by growing population demands, constrained sources of water supply and climate change impacts are expected to require more and more integrated procedures for effectively supporting residential water demand modeling and management in several countries across the world.

Keywords: Smart meter, Residential water management, Water demand

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1 **1. Introduction**

2 World's urban population is expected to raise from current 54% to 66% in
3 2050 and to further increase as a consequence of the unlikely stabilization of
4 human population by the end of the century (Gerland et al., 2014). By 2030
5 the number of mega-cities, namely cities with more than 10 million inhabitants,
6 will grow over 40 (UNDESA, 2010). This will boost residential water demand
7 (Cosgrove and Cosgrove, 2012), which nowadays covers a large portion of the
8 public drinking water supply worldwide (e.g., 60-80% in Europe (Collins et al.,
9 2009), 58% in the United States (Kenny et al., 2009)).

10 The concentration of the water demands of thousands or millions of people
11 into small areas will considerably raise the stress on finite supplies of available
12 freshwater (McDonald et al., 2011a). Besides, climate and land use change will
13 further increase the number of people facing water shortage (McDonald et al.,
14 2011b). In such context, water supply expansion through the construction of
15 new infrastructures might be an option to escape water stress in some situa-
16 tions. Yet, geographical or financial limitations largely restrict such options
17 in most countries (McDonald et al., 2014). Here, acting on the water demand
18 management side through the promotion of cost-effective water-saving technolo-
19 gies, revised economic policies, appropriate national and local regulations, and
20 education represents an alternative strategy for securing reliable water supply
21 and reduce water utilities' costs (Gleick et al., 2003).

22 In recent years, a variety of water demand management strategies (WDMS)
23 has been applied (for a review, see Inman and Jeffrey, 2006, and references
24 therein). However, the effectiveness of these WDMS is often context-specific
25 and strongly depends on our understanding of the drivers inducing people to
26 consume or save water (Jorgensen et al., 2009). Models that quantitatively
27 describe how water demand is influenced and varies in relation to exogenous
28 uncontrolled drivers (e.g., seasonality, climatic conditions) and demand man-

29 agement actions (e.g., water restrictions, pricing schemes, education campaigns)
30 are essential to explore water users' response to alternative WDMS, ultimately
31 supporting strategic planning and policy design.

32 Traditionally, water demand models focus on different temporal and spatial
33 scales. At the lowest resolution, studies have been carried out, mostly in the
34 1990s, to model water demand at the urban or block group scale, using low
35 time resolution (i.e., above daily) consumption data retrieved through billing
36 databases or experimental measurement campaigns on a quarterly or monthly
37 basis. The main goal of these works is to inform regional water systems plan-
38 ning and management on the basis of estimated relationships between water
39 consumption patterns and socio-economic or climatic drivers (e.g., House-Peters
40 and Chang, 2011).

41 The advent of smart meters (Mayer and DeOreo, 1999) in the late 1990s
42 made available new water consumption data at very high spatial (household)
43 and temporal (from several minutes up to few seconds) resolution, enabling
44 the application of data analytics tools to develop accurate characterizations of
45 end-use water consumption profiles. Similarly to the recent developments in
46 integrated smart solutions (Hilty et al., 2014; Laniak et al., 2013), the use of
47 smart meters provides essential information to construct models of the individ-
48 ual consumers behaviors, which can be employed for designing and evaluating
49 consumer-tailored WDMS that can more effectively modify the users' attitude
50 favoring water saving behaviors. In particular, smart meters themselves consti-
51 tute technologies that promote behavioural changes and water saving attitudes
52 via tailored feedbacks (Fielding et al., 2013).

53 A general procedure to study residential water demand management rely-
54 ing on the high-resolution data nowadays available can be structured in the
55 following four phases (see Figure 1): *(i)* data gathering, *(ii)* water end-uses
56 characterization, *(iii)* user modeling, *(iv)* design and implementation of person-
57 alized WDMS. In the literature, a number of tools and techniques have been
58 proposed for each of these steps, with many works focused either on the data
59 gathering process (e.g., Cordell et al., 2003; Boyle et al., 2013) or on the anal-

60 ysis of WDMS (e.g., Inman and Jeffrey, 2006). Yet, to the authors' knowledge,
61 a systematic and comprehensive review of residential water demand modeling
62 and management is still missing. This review contributes the first effort of clas-
63 sification and critical analysis of 134 studies that in the last 25 years (Figure
64 2) contributed new methodologies and tools in one or more of the steps of the
65 above procedure (see Table 1).

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

70 **2. Data gathering**

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

76 *2.1. Low resolution data*

77 Periodically billed data are characterized by a low level of resolution and
78 recording frequency. Although water consumption is detected with the precision
79 of kilolitres, readings are generally recorded with the frequency of the quarter
80 of year at most (Britton et al., 2008). This low resolution restricts the use of
81 these data to regional planning, where statistical analysis estimating the amount
82 of domestic water consumption can be used to forecast the aggregated water
83 demand at the municipal or district level. In particular, such data have been
84 widely used to study the effect of economic variables and seasonality on the water
85 use at the regional scale since the seminal works by Howe and Linaweaver (1967);
86 Young (1973); Berk et al. (1980); Howe (1982); Maidment and Parzen (1984);
87 Thomas and Syme (1988) (for a review see House-Peters and Chang, 2011,

88 and references therein). Those approaches relied on simple econometric models
89 and time series models based on multivariate regression, and required limited
90 datasets and low computational resources. Their main drawback is related to
91 their limited capability of representing the spatial and temporal heterogeneity of
92 residential water demand, which can be understood and modelled using higher
93 resolution data. While data resolution depends on the installed meter, the
94 logging time can be shortened without installation of smart meters but simply
95 increasing the traditional reading frequency by the users. However, so far only
96 ad-hoc studies systematically collected and analyzed data at daily resolution
97 (e.g., Olmstead et al., 2007; Wong et al., 2010) and few water companies (e.g.,
98 Water Corporation in Western Australia and Thames Water in London) started
99 increasing their reading frequency by direct involvement of their customers,
100 who are invited to self-read their consumption and communicate it online to
101 the water company (e.g., Anda et al., 2013).

102 2.2. High resolution data

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

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

118 the household level into the different end-use categories (see Section 3).

119

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

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

145 So far, only flow meters and pressure sensors have been employed in *smart*
146 *meters* applications because ultrasonic sensors are too costly and the use of

147 accelerometers requires an intrusive calibration phase with the placement of
148 multiple meters distributed on the pipe network for each single device of inter-
149 est (Kim et al., 2008). It is worth noting that the “smartness” of these sensors
150 is related both to their high sampling resolution and to their integration in
151 efficient systems combining data collection, transfer, storage, and analysis. Al-
152 though sensors can be equipped with data loggers requiring human intervention
153 to retrieve the data directly from the sensors (Mayer et al., 2004), bluetooth
154 and wireless connections have been recently exploited for improving data man-
155 agement. For example, Froehlich et al. (2009) installed a network of pressure
156 sensors communicating via bluetooth with a laptop deployed at each household,
157 which runs a custom data logger to receive, compress, and archive data. These
158 latter are then uploaded to a web server at 30-minute intervals.

159 *2.3. Research challenges and future directions*

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

- 163 1. The first open research question relates to the management of the me-
164 tered high resolution flow data. In particular, the development of robust,
165 automated processes to transfer the generated big data requires further
166 elaborations, both in terms of hardware and software performance due
167 to existing issues with respect to wireless network reliability, black spots,
168 power source and battery life (Stewart et al., 2010; Little and Flynn, 2012).
169 All these aspects appear key also because the possibility of integrating wa-
170 ter and energy meters and using the same data loggers and transmission
171 systems is expected to enhance the diffusion of high resolution water sen-
172 sors (Benzi et al., 2011; Froes Lima and Portillo Navas, 2012).
- 173 2. The second open challenge concerns the design of centralized or distributed
174 information systems to store the data collected by the smart meters (Ora-
175 cle, 2009). A centralized system would allow checking the accuracy of the
176 collected data, which can then be made easily available for data processing

177 and analysis. On the contrary, a distributed solution would reduce trans-
178 mission costs and facilitate providing immediate feedbacks to customers,
179 who can use this information to make decisions about their water use.

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

187 4. Finally, a challenge is posed by the actual deployment of large-scale high-
188 resolution metering network in the real world. While literature presents
189 a number of trials (e.g., Mayer et al. (2004); Heinrich (2007); Froehlich
190 et al. (2009)) that exploit smart sensors with extremely fine resolutions
191 (sub-minute), cost, privacy, and regulations may limit their scalability to
192 large-scale continuous operative smart meter installations. For example,
193 data protection and data security issues are being seriously considered by
194 the European Union, which is imposing some strict guidelines to utilities
195 willing to deploy smart meter solutions for their customers and many wa-
196 ter utilities collect data at lower resolution than the minute (e.g., Thames
197 Water in London reads data at 15-minute resolution, EMIVASA in Valen-
198 cia and SES in Switzerland at 1-hour resolution). This implies that the
199 theoretical capabilities of smart metering technologies may not be fully
200 exploited, potentially limiting the accuracy in characterizing the residen-
201 tial water consumption as studies relying on medium/low resolution data.
202 Large-scale smart-meters application would therefore benefit from a bet-
203 ter understanding of the consequences of different time resolutions on the
204 models accuracy and on the effectiveness of WDMS.

205 **3. Water end-uses characterization**

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

221 *3.1. Trace Wizard*

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

- 228 1. Conduct a detailed water device stock inventory audit for each household
229 to determine the efficiency rating of each household appliance/fixture;
- 230 2. Household occupants should complete a diary of water use events over a
231 one-week period to gain information on their water use habits;
- 232 3. Analysts use water audits, diaries, and sample flow trace data for each
233 household to create specific templates that serve to match water end-use
234 patterns depending on some basic flow boundary conditions.

235 4. Based on the developed templates, stock survey audit, diary information
236 and analysts' experience, the individual water end-uses are disaggregated.

237 It is worth noting that the human resource effort required by Trace Wizard
238 makes the overall process extremely time and resource intensive, with the quality
239 of the results that is strongly dependent on the experience of the analyst in
240 understanding flow signatures. It has been estimated that the classification of
241 two weeks of data approximatively requires two hours of works by the analyst
242 and attains an average classification accuracy of 70% (Nguyen et al., 2013a). In
243 addition, the prediction accuracy of Trace Wizard is significantly reduced when
244 more than two events occur concurrently (Mayer and DeOreo, 1999). However,
245 Trace Wizard still has an edge on disaggregation techniques and has been used
246 in several research works and projects (DeOreo and Mayer, 1994; Mayer and
247 DeOreo, 1995; DeOreo et al., 1996; Mayer and DeOreo, 1999; DeOreo and Mayer,
248 2000; Loh et al., 2003; Mayer et al., 2004; Roberts, 2005; Heinrich, 2007; Mead
249 and Aravinthan, 2009; Willis et al., 2009a,b; Aquacraft Inc., 2011; DeOreo et al.,
250 2011).

251 3.2. *Identiflow*

252 Similar to Trace Wizard, Identiflow (Kowalski and Marshallsay, 2003) re-
253 lies on a decision tree algorithm to perform a semi-automatic disaggregation
254 of the total water consumption at the household level. Identiflow uses fixed
255 physical features of various water-use devices (e.g., volume, flow rate, duration,
256 etc.) to classify the different end-use events. Although Identiflow has shown
257 better performance than Trace Wizard (i.e., 74.8% accuracy in terms of the
258 correctly classified volume over 3870 events (Nguyen et al., 2013a)), its classifi-
259 cation accuracy strongly depends on the physical features used to describe each
260 fixture/appliance. Two different water events are likely classified into the same
261 category if they exhibit similar physical characteristics. Moreover, it fails to
262 classify events when old devices are replaced by modern ones, since the physical
263 characteristics of these latter might be completely different compared to the old
264 ones.

265 3.3. *HydroSense*

266 HydroSense (Froehlich et al., 2011) is a probabilistic-based classification ap-
267 proach which relies on data collected through pressure sensors. Water end-use
268 events are classified with respect to the unique pressure waves that propagate
269 to the sensors when valves are opened or closed. Specifically, when a valve is
270 opened or closed, a pressure change occurs and a pressure wave is generated in
271 the plumbing system. Based on the pressure wave (which depends on the valve
272 type and its location), water end-use events are classified by using advanced pat-
273 tern matching algorithms and Bayesian probabilistic models. HydroSense has
274 been demonstrated to attain very high levels of classification accuracy, namely
275 90% and 94% with one or two pressure sensors, respectively (Froehlich et al.,
276 2011). However, the calibration of the algorithm requires an intrusive moni-
277 toring period with the installation of a much larger number of pressure sensors
278 connected to each water device (i.e., Froehlich et al. (2011) used 33 sensors in
279 a single household). This requirement significantly constrains the portability of
280 this approach to a wide urban context as it would entail large costs and privacy
281 issues.

282 3.4. *SEQREUS*

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

- 290 1. The disaggregated data are used for training multiple HMMs, one for each
291 end-use category (excluding the inconclusive event);
- 292 2. The physical characteristics of each end-use category are used to refine
293 the estimate given by the HMMs (e.g., any shower event with a volume

- 294 less than 7 liters or any bathtub event with duration less than 4 minutes
295 is placed in the inconclusive event for future analysis);
- 296 3. A DTW algorithm determines if any event in the inconclusive dataset
297 is similar to an event in categories having clearly defined consumption
298 patterns, namely the washing machine and dishwasher cycles;
 - 299 4. Time of day probability is used to assign inconclusive events to an end-use
300 category.

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

307 *3.5. Research challenges and future directions*

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

- 311 1. First, most of the approaches used in the water sector requires time con-
312 suming expert manual processing and intensive human interactions via
313 surveys, audits and water event diaries, while the development of auto-
314 matic procedures is fundamental to further extend the application of these
315 methods beyond experimental trials and research projects (Stewart et al.,
316 2010). Moreover, the existing methods have limited accuracy in identify-
317 ing overlapping events.

318 The disaggregation problem has been addressed in other research fields as
319 a general problem of *blind identification*, or output-only system identifi-
320 cation (Reynders, 2012). The real state of the system (i.e., the set of the
321 working states and water consumption of each single fixture in the house-
322 hold) is unknown and only observations of the system output (i.e., the

323 total water consumption) are available. Starting from the 1990s, several
324 techniques have been proposed to address blind identification problems
325 in different research field, such as signal processing, data communication,
326 speech recognition, image restoration, seismic signal processing (see Abed-
327 Meraim et al., 1997, and references therein).

328 With the development of smart electricity grids (Kramers et al., 2014;
329 Niesse et al., 2014), this problem has been largely studied in the energy
330 sector to develop automatic disaggregation methods, also known as Non
331 Intrusive Load Monitoring (NILM) algorithms, which aim at decomposing
332 the aggregate household energy consumption data collected from a single
333 measurement point into device-level consumption data (for a review, see
334 Zeifman and Roth, 2011; Zoha et al., 2012; Carrie Armel et al., 2013,
335 and references therein). These methods show promising results and seem
336 effective also up to 6-10 appliances (Figueiredo et al., 2014; Makonin et al.,
337 2013). Yet, the portability of such techniques in the water field has not
338 been assessed. Some additional challenges in characterizing water end-
339 use events might be introduced by the larger human dependency than
340 the one of electric appliances, which are more automatic. These concerns
341 primarily involve manually controlled fixtures (e.g., bathtubs, showers,
342 faucets), which might be used not at the maximum capacity (Froehlich
343 et al., 2009).

344 2. The second main open question relates to the acquisition of the ground
345 truth for initial calibration. All the algorithms used for disaggregating
346 water data, but also the majority of the ones used for energy data, need an
347 intrusive period to collect a dataset of disaggregated end-use events, which
348 incurs extra cost and human effort, ultimately challenging their large-
349 scale application. Researchers are actively looking to devise completely
350 unsupervised or semi-supervised methods that avoid the effort of acquiring
351 the calibration ground truth data (e.g., Gonçalves et al., 2011; Parson
352 et al., 2014).

353 3. Finally, most of the approaches developed in the energy sector are cur-

354 rently focused on correctly characterizing the on/off status of the devices
355 and, possibly, the fraction of total energy assigned correctly, while their
356 performance in reproducing the timings and frequencies of each device
357 are lower (Batra et al., 2014). Yet, timings and frequencies represent key
358 information to understand consumers behaviors and design personalized
359 demand management strategies (e.g., deferring the use of some appliances
360 to peak-off hours). Accordingly, knowledge about use frequencies, timing
361 and peak-hours in the water sector would constitute crucial information for
362 identifying both typical consumption behaviours and patterns, as well as
363 consumption anomalies (e.g., leakages (Loureiro et al., 2014; Ponce et al.,
364 2014; Pérez et al., 2014; Perez et al., 2014)). This knowledge would aid
365 the activities of water utilities at different levels: demand management,
366 network maintenance, and strategic planning.

367 **4. User modeling**

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

377 *4.1. Descriptive models*

378 The first class of models, namely descriptive models, aims at analyzing the
379 observed water consumption behaviors of water users. Depending on the res-
380 olution of the data available, the analysis can focus on identifying aggregated
381 consumption patterns or on defining users' profiles on the basis of the disaggre-
382 gated end-uses (e.g., Loh et al., 2003; SDU, 2011; SJESD, 2011; Gato-Trinidad

383 et al., 2011; Willis et al., 2011; Beal et al., 2011b, 2013; Cardell-Oliver and
384 Peach, 2013; Cole and Stewart, 2013; Beal and Stewart, 2014; Beal et al., 2014;
385 Gurung et al., 2014, 2015).

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

394 4.2. Predictive models

395 The second class of models, namely predictive models, aims at estimating
396 the water demand at the individual (household) level. Some works developed
397 predictive models that mostly provide short-term forecast of the water demand
398 on the basis of time series analyses (e.g., Homwongs et al., 1994; Molino et al.,
399 1996; Altunkaynak et al., 2005; Alvisi et al., 2007; Nasserri et al., 2011). Yet,
400 these approaches are ineffective in supporting the design and implementation
401 of WDMS as the predicted water consumption of a user is not related to his
402 socio-psychographic factors or his response to different WDMS. An alternative
403 approach can be structured in the following two sub-steps: (i) *multivariate*
404 *analysis*, which consists in the identification and selection of the most relevant
405 inputs to explain the preselected output, and (ii) *behavioral modeling*, which
406 means model structure identification, parameter calibration and validation.

407 The multivariate analysis phase (i.e., variable selection as called in data-
408 driven modeling (George, 2000)) is a fundamental step to build predictive mod-
409 els of urban water demand variability in space and time. In most of the works,
410 the identification of the most relevant drivers relies on the results of data min-
411 ing techniques (e.g., correlation analysis) between a pre-defined set of variables
412 (candidate drivers) and the water consumption data. This approach is also re-

413 ferred to as *inductive* modelling (Cahill et al., 2013). An alternative to this
414 data-driven approach is the *deductive* construction of models according to em-
415 pirical or theoretical causality (Cahill et al., 2013). Depending on the specific
416 domains from which the candidate drivers are extracted, which is often delimit-
417 ed by data availability (Arbués et al., 2003), we can distinguish the following
418 three main approaches:

- 419 • *economic-driven studies*, which focus on studying the correlation between
420 water consumption and purely economic drivers, such as water tariff struc-
421 tures or water price elasticity (e.g., Schneider and Whitlatch, 1991; Espey
422 et al., 1997; Brookshire et al., 2002; Dalhuisen et al., 2003; Olmstead et al.,
423 2007; Olmstead and Stavins, 2009; Rosenberg, 2010; Qi and Chang, 2011);
- 424 • *geo-spatial studies*, which assess the correlation between hydro-climatic
425 variables and seasonality with water consumption (e.g., Miaou, 1990; Grif-
426 fin and Chang, 1991; Zhou et al., 2000, 2002; Fullerton and Elias, 2004; Aly
427 and Wanakule, 2004; Gato et al., 2007; Balling and Gober, 2007; Balling
428 et al., 2008; Lee and Wentz, 2008; Praskievicz and Chang, 2009; Corbella
429 and Pujol, 2009; Chang et al., 2010; Polebitski and Palmer, 2010; Lee and
430 Wentz, 2010; Lee et al., 2011);
- 431 • *psycographic-driven studies*, which infer the influence of users’ personal
432 attributes on their water consumption, including income, family compo-
433 sition, lifestyle, and households physical characteristics (e.g., number of
434 rooms, type, presence of garden) (e.g., Syme et al., 2004; Wentz and Gober,
435 2007; Fox et al., 2009; Jorgensen et al., 2009; Russell and Fielding, 2010;
436 Grafton et al., 2011; Willis et al., 2013; Suero et al., 2012; Matos et al.,
437 2014; Talebpour et al., 2014; Romano et al., 2014).

438 Note that this classification is not stringent, in the sense that hybrid ap-
439 proaches dealing with more than one of the mentioned domains have already
440 been developed (e.g., Makki et al., 2015). Similarly to the descriptive models
441 discussed in the previous section, the development of predictive models could

442 significantly benefit from smart metering technologies and high-resolution wa-
443 ter consumption data. Indeed, the availability of high-resolution and end-use
444 characterization of the water consumption allows predicting the effects of cus-
445 tomized WDMS focused on specific end-uses (e.g., Makki et al. (2013)). In
446 most of the literature, the user modeling is limited to the multivariate analysis,
447 which however provides only qualitative information to water managers, water
448 utilities, and decision makers. Only few works completed the second phase (i.e.,
449 behavioral modeling) and provide a quantitative prediction of the water demand
450 at the household level, thus representing better decision-aiding tools as they can
451 use these models to develop what-if analysis as well as scenario simulation and
452 analysis.

453 The construction of behavioral models aims at the identification, calibra-
454 tion, and validation of mathematical models, which describe the water demand
455 (i.e., output variable) as a function of the drivers identified in the multivariate
456 analysis. In the behavioral modeling literature, we can identify a first class of
457 models, named *single-user models*, which describe the consumption behavior
458 of individual users considered as isolated entities. These works (e.g., Lyman,
459 1992; Gato, 2006; Kenney et al., 2008; Maggioni, 2015) generally rely on dy-
460 namic models based on sampling of statistical distributions describing average
461 users and end-uses (e.g., number of people per household and their ages, the
462 frequency of use, flow duration and event occurrence likelihood). Water demand
463 patterns can be then estimated via model simulation and comparison of the re-
464 sults with the observed data. Yet, this approach often reduces the heterogeneity
465 of the water users, which can be preserved by running Monte Carlo simulations
466 that sample also the extreme values of the associated statistical distributions
467 (Rosenberg et al., 2007; Blokker et al., 2010; Cahill et al., 2013). Recently,
468 different approaches (Bennett et al., 2013; Makki et al., 2013, 2015) combining
469 non-parametric statistical tests and advanced regression models to identify key
470 water consumption drivers and forecast urban water consumption have been
471 demonstrated to successfully identify the main drivers of water consumption
472 and to attain good forecast accuracy levels.

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

492 *4.3. Research challenges and future directions*

493 Given the current status of user modeling studies and the room for improve-
494 ment given by the use of high resolution, smart metered data, several research
495 challenges and future directions emerge:

- 496 1. The first open question in terms of descriptive models concerns matching
497 the analysis of the water consumption patterns with the potential drivers
498 generating the observed users' behaviors. This would allow validating the
499 results of the classification of the users on the basis of their consumption
500 and understanding if this latter is a good proxy representing different
501 characteristics of the users.

- 502 2. The use of spatially explicit models to take advantage of the high tem-
503 poral and spatial resolution of smart metered data is often hindered by
504 the aggregation of individual household data to a larger spatial scale to
505 protect customers' privacy as well as by the difficulties in collecting and
506 sharing data coming across multiple water authorities and administrative
507 institutions (House-Peters and Chang, 2011).
- 508 3. The third major challenge relates to the validation of the agent-based be-
509 havioral models. As in the construction of complex process-based models,
510 accurately describing the single user (agent) behavior and connecting mul-
511 tiple users within an agent-based model does not ensure the validity of the
512 results, although these latter are contrasted with observed data. In addi-
513 tion, given the large number of assumption and parameters, the problem
514 of equifinality (i.e., the potential existence of multiple, alternative pa-
515 rameterization leading to same simulation outcomes) has to be addressed
516 (Ligtenberg et al., 2010).
- 517 4. It is worth noting that the type of candidate drivers considered in the
518 user modeling phase impacts the statistical representativeness of the re-
519 sults. The construction of sufficiently large datasets to estimate the re-
520 lationships between water consumption data and the uncontrolled drivers
521 (i.e., hydro-climatic and psychographic variables) is generally easy, pro-
522 vided that the time period is long enough and the number of involved
523 users is sufficiently high. On the contrary, in most of the cases there is
524 a single historical realization of the controllable drivers, namely the ones
525 subject to human decisions (e.g., the existing pricing scheme). In such
526 cases, the response of the users to different options is generally estimated
527 via economics principles or surveys. Yet, economic principles introduce a
528 priori general rules that might be inaccurate in characterizing the specific
529 users under study, and the surveys provide only a static snapshot of the
530 system conditions. The potential for using experimental trials (e.g., Gilg
531 and Barr, 2006; Borisova and Useche, 2013; Fielding et al., 2013) and gam-
532 ification platforms (e.g., Mühlhäuser et al., 2008) to validate behavioral

533 models results by retrieving information to the real users in large-scale
534 applications has not been tested yet.

535 5. Finally, a major opportunity is represented by the development of in-
536 tegrated models that cross-analyze water and water-related energy con-
537 sumption data to improve residential water demand models (Abdallah and
538 Rosenberg, 2014; Escriva-Bou et al., 2015b,a).

539 **5. Personalized water demand management strategies**

540 Literature reports of a variety of management policies acting on the demand
541 side of residential water consumption, designed with the purpose of improving
542 water conservation and safeguarding water security in urban contexts. Accord-
543 ing to Inman and Jeffrey (2006), they can be classified in the following five
544 categories (Table 5): *technological*, *financial*, *legislative*, *maintenance*, and *edu-*
545 *cational*. These strategies differ in the time scales they act on: price and pre-
546 scriptive (i.e., command-and-control) approaches have been shown to achieve
547 significant reductions of water demand in the short-period, but also have some
548 drawbacks (such as equity issues and limits in consumers' price elasticity) that
549 may limit the effectiveness of such strategies in the long term, if not integrated
550 with other water conservation interventions (Fielding et al., 2013; Renwick and
551 Green, 2000). In contrast, users' awareness and educational approaches allow
552 for smaller reductions in the short period, but appear to be crucial to pursue
553 reductions on the long run, as they require a change in users' behaviors (Geller,
554 2002).

555 Technological strategies involve the installation of water efficient household
556 appliances (e.g., Mead and Aravinthan, 2009; Suero et al., 2012; Carragher et al.,
557 2012; Froes Lima and Portillo Navas, 2012; Gurung et al., 2015). This option of-
558 fers great potential for reducing indoor and outdoor water consumption (Mayer
559 et al., 2000, 2003, 2004; DeOreo, 2011). Yet, the benefits associated to these
560 advanced systems are inconstant (Maggioni, 2015). For example, an incorrect
561 use of automatic sprinkler may consume more water than manually operated

562 irrigation systems (Syme et al., 2004), thus requiring educational programs to
563 ensure an appropriate use.

564 Financial strategies, (also called market-based or price approaches (Olm-
565 stead and Stavins, 2009)), consist in water tariffs control associated to analysis
566 of water demand elasticity (e.g., Dandy et al., 1997; Dalhuisen et al., 2003;
567 Arbués et al., 2003; Kenney et al., 2008; Cole et al., 2012; Molinos-Senante,
568 2014; Maggioni, 2015). Even though some authors claim that price-based strate-
569 gies are more cost effective than other conservation programs (Olmstead and
570 Stavins, 2009), the effectiveness of this strategies seems uncertain as water de-
571 mand has been shown to be relatively price inelastic (Worthington and Hoff-
572 man, 2008) and to rebound to the same or even higher levels after an initial
573 decrease (Kanakoudis, 2002). Yet, a careful assessment of the effectiveness of
574 these strategies would benefit from longer dataset gathered in multiple jurisdic-
575 tions and contexts (Worthington and Hoffman, 2008). In addition, the are also
576 concerns about the equity of raising prices (Duke et al., 2002).

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

585 Maintenance strategies consist in operations aiming at reducing or eliminat-
586 ing leakages in the water supply networks (e.g., Britton et al., 2008, 2013), which
587 generally account for a significant fraction of the water consumption (e.g., EEA
588 (2001) estimated losses due to leakage equal to 30% in Italy and 50% in Bul-
589 garia). The identification and repair of leakages, which are often associated to
590 a small number of households (Roberts, 2005; Mayer and DeOreo, 1999; Mayer
591 et al., 2004), allows substantial increase in the efficiency of the water supply
592 systems at lower costs with respect to augmenting the water supplied without

593 repairing the network (Garcia and Thomas, 2001; Brooks, 2006).

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

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

623 *5.1. Research challenges and future directions*

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

- 627 1. The first challenge is the identification of more effective strategies for in-
628 fluencing the users behaviors. Technological strategies mostly impact on
629 a limited number of end-uses (e.g., clothes or dish washers), whereas are
630 less effective in inducing water savings in more human-controlled end-uses,
631 such as showering or tap water. Moreover, investment inefficiencies can
632 limit the effectiveness of these strategies causing the *Efficiency Gap* that
633 is well-known in the energy field (Allcott and Greenstone, 2012). Educa-
634 tional intervention and programs can be more effective in controlling these
635 latter, for example by providing feedbacks to the users as already applied
636 in the energy sector (e.g., Abrahamse et al., 2007; Costanza et al., 2012).
637 Yet, there are still open questions on the use of feedbacks to reduce water
638 (or energy) consumption, particularly with respect to the most effective
639 feedback format, whether the effect persists over time, as well as assess-
640 ments of costs and benefits of feedback (Strengers, 2011; Desley et al.,
641 2013).
- 642 2. The second main open question relates to the long-term effect of WDMS,
643 especially for educational programs and awareness campaigns (e.g., Peschiera
644 et al., 2010; Pereira et al., 2013). Although they showed promising results
645 during the program and some months afterwards, their effect eventually
646 dissipated and water consumption returned to pre-intervention levels after
647 approximately 12 months (Fielding et al., 2013).
- 648 3. Finally, further effort should be devoted to examine the role of social
649 norms and social influence in promoting water conservation (Rixon et al.,
650 2007; Van Der Linden, 2013; Schultz et al., 2014). In particular, the po-
651 tential for using gamification platforms and social applications to allow
652 users monitoring their consumption coupled with normative information

653 about similar households in their neighborhood should be assessed (Bo-
654 gost, 2007; Rizzoli et al., 2014; Harou et al., 2014; Clifford et al., 2014;
655 Curry et al., 2014; Savić et al., 2014; Vieira et al., 2014; Kossieris et al.,
656 2014; Magiera and Froelich, 2014; Laspidou, 2014). Water utilities can
657 indeed take advantage of people’s tendency to mimic the behavior of their
658 neighbors in order to target their efforts to “early adopters” and encourage
659 technology diffusion (Janmaat, 2013).

660 **6. Discussion and conclusions**

661 Designing and implementing effective water demand management strategies
662 is becoming more and more important to secure reliable water supply and re-
663 duce water utilities’ costs over the next years. The advent of smart meters made
664 available new water consumption data at very high spatial and temporal res-
665 olution, enabling a more detailed description of the drivers inducing people to
666 consume or save water. A better understanding of water users’ behaviors is in-
667 deed fundamental to promote water savings actions as it allows (*i*) selecting the
668 specific behaviors to be changed, (*ii*) examining the factors causing those behav-
669 iors, (*iii*) applying well-tuned interventions, and (*iv*) systematically evaluating
670 the effects of these interventions on the resulting behaviors (Geller, 2002).

671 In this paper, we reviewed 134 papers (Table 1) that contributed new method-
672 ologies and tools in one or more of the blocks underlying the general 4-step pro-
673 cedure represented in Figure 1. A “roadmap” of the main research challenges
674 that need to be addressed in order to move the application of smart meters
675 forward over the next decade is shown in Table 6 and summarized below:

- 676 1. Data gathering: (*i*) how to efficiently and reliably manage the big data
677 generated by the acquisition of high resolution smart metered flow data;
678 (*ii*) understanding the best information system architecture (i.e., central-
679 ized or distributed) to store the data collected by the smart meters; (*iii*)
680 how householder privacy is impacted by collection and communication of
681 detailed water-use information;

- 682 2. Water End-uses characterization: *(i)* development of automatic proce-
683 dures for disaggregating water consumption data at the household level to
684 reduce the manual processing and intensive human interactions required
685 by current methods; *(ii)* development of unsupervised methods that avoid
686 the effort of acquiring the ground truth for training the algorithms; *(iii)*
687 enhancing the accuracy of the methods in reproducing the timings and
688 frequencies of each device usage.
- 689 3. User modeling: *(i)* matching the analysis of the observed water consump-
690 tion profiles identified in the descriptive models with the potential drivers
691 generating the observed users' behaviors; *(ii)* better exploit the high spa-
692 tial resolution of smart metered data to identify water use patterns across
693 geographic areas; *(iii)* validation of the agent-based behavioral models'
694 simulation against observed data; *(iv)* testing of experimental trials and
695 gamification platforms to support the validation of the behavioral models
696 as well as to retrieve information from the water users; *(v)* developing
697 integrated models for water and water-related energy.
- 698 4. Personalized water demand management strategies: *(i)* identification of
699 more effective strategies for influencing the users behaviors, particularly
700 by means of customized feedbacks to the water users providing information
701 about their water consumption or suggestions on water savings practices;
702 *(ii)* how to ensure a long-term effect of the implemented water demand
703 management strategies, especially for educational programs and awareness
704 campaigns; *(iii)* a better understanding of the role of social norms and
705 social influence in promoting water conservation;

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

712 Moreover, we can observe that the case study locations are not homoge-
713 neously distributed: 79% of the papers reviewed are applied in the United States
714 (36%) or Australia (43%), while the remaining studies were developed in Eu-
715 rope (13%) or Asia (6%) and a single application found in South America and
716 no one in Africa. However, we expect that the challenges posed by climate
717 change impacts, growing population demands, and constrained sources of wa-
718 ter supply will call for the application of integrated residential water demand
719 modeling and management in several countries across the world. Finally, we
720 foresee that the investments for smart technologies in fields other than urban
721 water management (e.g., Fernandez et al., 2014; Niese et al., 2014; Kramers
722 et al., 2014; Rezgui et al., 2014; Zarli et al., 2014) will create opportunities for
723 collaborations and common actions among different spheres. Residential wa-
724 ter demand modelling and management can benefit from these collaborations
725 because smart technologies and networks have already been deployed in other
726 fields, like domestic energy, thus representing a benchmark for learning and in-
727 tegration. Moreover, the existing nexus between energy and water is expected
728 to foster synergies and cross-influences for addressing future demands (WWAP,
729 2014; Escriva-Bou et al., 2015b). Integrated, interdisciplinary science will thus
730 support policy makers and planners addressing the major sustainability chal-
731 lenges placed by modern urban contexts and their evolution towards smart cities
732 (Hilty et al., 2006; Laniak et al., 2013; Letcher et al., 2013).

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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 Zeland	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	

Table 1: (Continued) Details of the papers reviewed.

Reference	Location	Data gathering	Water end-uses	User modeling	Personalized WDMS
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	
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)	USA				x
Renwick and Archibald (1998)	USA				x
Dandy et al. (1997)	Australia				x
Gurung et al. (2015)	Australia			x	x
Gurung et al. (2014)	Australia			x	
Suero et al. (2012)	USA			x	x

Table 1: (Continued) Details of the papers reviewed.

Reference	Location	Data gathering	Water end-uses	User modeling	Personalized WDMS
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

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)	USA	high	flow meter	0.014-0.029
Evans 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)	N/A	high	pressure	0.0600
Froehlich et al. (2011)	N/A	high	pressure	0.0600
Kowalski and Marshallsay (2005)	UK	high	flow meter	0.014-0.029
Heinrich (2007)	New Zeland	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

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 Zeland	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)	USA	Trace Wizard	16
Mayer and DeOreo (1995)	USA	Trace Wizard	16
DeOreo and 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	11000
Cardell-Oliver (2013b)	Australia	Water Use Signature Patterns	187

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

Reference	Location	Modeling approach	Multivariate analysis	Behavioural model	Spatial scale
Loh et al. (2003)	Australia	descriptive	-	-	household
Gato-Trinidad et al. (2011)	Australia	descriptive	-	-	household
SDU (2011)	USA	descriptive	-	-	household
SJESD (2011)	USA	descriptive	-	-	household
Cardell-Oliver and Peach (2013)	Australia	descriptive	-	-	household
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)	Australia	descriptive	-	-	household
Willis 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 (2011)	N/A	predictive	E+GS+P	single+multi	N/A
Schneider and Whitlatch (1991)	USA	predictive	E	-	district
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)	USA	predictive	AR	-	urban
Molino et al. (1996)	Italy	predictive	AR	-	urban
Altunkaynak et al. (2005)	Turkey	predictive	AR	-	urban
Alvisi et al. (2007)	Italy	predictive	AR	-	household
Nasseri et al. (2011)	Iran	predictive	AR	-	urban
Brookshire et al. (2002)	N/A	predictive	E	-	N/A
Olmstead and Stavins (2009)	N/A	predictive	E	-	N/A
Rosenberg (2010)	Jordan	predictive	E	-	household
Qi and Chang (2011)	USA	predictive	E	-	urban
Griffin and Chang (1991)	USA	predictive	GS	-	district
Zhou et al. (2000)	Australia	predictive	GS	-	urban
Zhou et al. (2002)	Australia	predictive	GS	-	district
Fullerton and Elias (2004)	USA	predictive	GS	-	urban
Aly and Wanakule (2004)	USA	predictive	GS	-	urban
Gato et al. (2007)	Australia	predictive	GS	-	urban
Balling and Gober (2007)	USA	predictive	GS	-	urban
Balling et al. (2008)	USA	predictive	GS	-	census tracts
Lee and Wentz (2008)	USA	predictive	GS	-	census tracts
Praskievicz and Chang (2009)	Korea	predictive	GS	-	urban
Corbella and Pujol (2009)	N/A	predictive	GS	-	N/A
Chang et al. (2010)	USA	predictive	GS	-	household
Lee and Wentz (2010)	USA	predictive	GS	-	urban
Syme et al. (2004)	Australia	predictive	P	-	household
Wentz and Gober (2007)	USA	predictive	P	-	household
Fox et al. (2009)	UK	predictive	P	-	household
Russell and Fielding (2010)	N/A	predictive	P	-	N/A
Grafton et al. (2011)	10 OECD countries	predictive	P	-	household
Suero et al. (2012)	USA	predictive	P	-	household
Matos et al. (2014)	Portugal	predictive	P	-	household
Talebpour et al. (2014)	Australia	predictive	P	-	household
Romano et al. (2014)	Italy	predictive	P	-	water utility
Gato (2006)	Australia	predictive	GS	single	urban

Table 4: (Continued) Studies contributing in the user modeling step.

Reference	Location	Modeling approach	Multivariate analysis	Behavioural model	Spatial scale
Rosenberg et al. (2007)	Jordan	predictive	GS+P	single	household
Blokker et al. (2010)	Nederland	predictive	P	single	household
Cahill et al. (2013)	USA	predictive	P	single	household
Bennett et al. (2013)	Australia	predictive	GS+E+P	single	household
Rixon et al. (2007)	Australia	predictive	E+P	multi	household
Galán et al. (2009)	Spain	predictive	P	multi	household
Chu et al. (2009)	China	predictive	E+P	multi	household
Kanta and Zechman (2014)	N/A	predictive	GS+P	multi	household
Jorgensen et al. (2009)	N/A	predictive	P	-	household
Kenney et al. (2008)	USA	predictive	E+GS+P	single	household
Makki et al. (2013)	Australia	predictive	E+P	single	household
Giacomoni and Berglund (2015)	USA	predictive	GS	multi	urban
Escriva-Bou et al. (2015a)	USA	predictive	P	single	household
?	USA	predictive	P	single	household

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)	USA	E	
Howarth 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	

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	

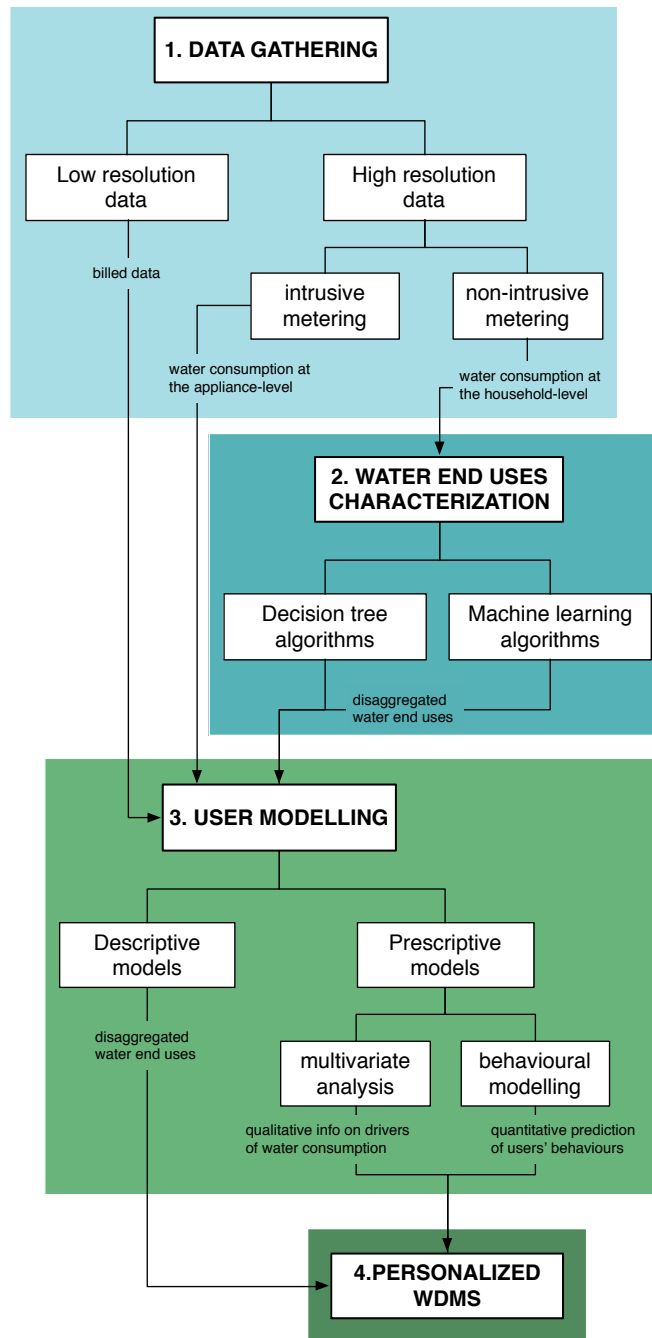


Figure 1: Flowchart of the general procedure for studying residential water demand management.

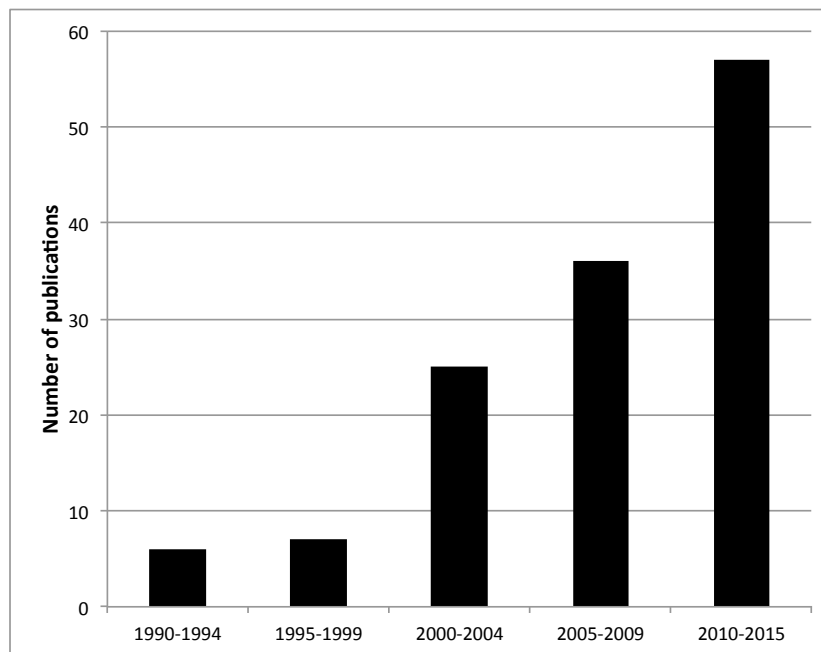


Figure 2: Five-years count of the 134 publications reviewed in this study.