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Re-engineering traditional urban water management practices with smart metering and informatics

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Abstract

Current practice for the design of an urban water system usually relies on various models that are often founded on a number of assumptions on how bulk water consumption is attributed to customer connections and outdated demand information that does not reflect present consumption trends; meaning infrastructure is often unnecessarily overdesigned. The recent advent of high resolution smart water meters and advanced data analytics allow for a new era of using the continuous 'big data' generated by these meter fleets to create an intelligent system for urban water management to overcome this problem. The aim of this research is to provide infrastructure planners with a detailed understanding of how granular data generated by an intelligent water management system (*Autoflow*©) can be utilised to obtain significant efficiencies throughout different stages of an urban water cycle, from supply, distribution, customer engagement, and even wastewater treatment.

Keywords: smart metering; pattern recognition; water demand management; artificial intelligence; network modelling.

Software/data availability

Section reference: Case Study 1
Name of software: Autoflow
Developer: Dr. Khoi Nguyen
Contact information: Dr. Khoi Nguyen, Research Fellow, Griffith School of Engineering
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Ph: +61 7 55527522
Email: k.nguyen@griffith.edu.au
First year available: 2015
Program language: MATLAB
Software availability: Restricted
Software size: 44 MB
Software requirements: MATLAB Compiler Runtime (MCR)
Hardware requirements: 2.4GHz processor and 2GB RAM
Data collection locations: Melbourne and Southeast Queensland - Australia
Size: 500 residential households
Duration: 2-week period in 2010, 2011 and 2014
Dataset Availability: Restricted
Reference articles DOI:
https://doi.org/10.1016/j.asoc.2015.03.007
https://doi.org/10.1016/j.jher.2013.02.004
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1. Introduction

Urban water management aims to provide a safe, reliable and sustainable water supply to consumers. Water Demand Management (WDM) usually attracts most attention from policy makers and infrastructure planners. WDM aims to develop and implement strategies to manage supply more efficiently, as well as enact water conservation measures and drought response plans when needed (Liu et al., 2016). The five categories of WDM include: (1) engineering, i.e. installing more efficient appliances; (2) economics, i.e. effective water tariffs; (3) enforcement, i.e. water restrictions; (4) encouragement, i.e. rebate schemes for water efficient appliances: (5) and education, i.e. promoting water saving practices such as shorter showers. However, successful and effective identification and implementation of suitable WDM strategies require reliable, preferably real-time information (Sahin *et al*. 2015).

There is an increasing repository of literature demonstrating the use of data collected from smart water meters to develop various water demand models to better understand factors contributing to peak demand (Willis *et al.* 2009b; Gurung *et al.* 2014a, 2016; Sahin *et al.* 2015, 2017; Beal *et al.* 2012, Savic *et al*. 2014), which will help avoid the need for costly water distribution network augmentations. However, currently there is limited research completed that comprehensively showcases how smart technologies, including smart meters and advanced informatics techniques, can be exploited to achieve operational efficiencies and water savings during the whole urban water life cycle process. This study introduces *Autoflow©*, an innovative water demand analysis software tool, which has been developed to deeply analyse high resolution residential water demand flow patterns from smart meters. Advanced metering systems coupled with *Autoflow©* software has the potential to provide near real-time end use data for both water authorities and consumers, that could significantly improve current decision making relating to a number of utility functions and significantly strengthen customer engagement practices. Specifically, this paper delivers on the following objectives:

1. To identify and discuss opportunities for applying smart metering systems and advanced data analytics tools to re-engineer some traditional urban water management processes within the urban water cycle.
2. To summarise the development of a novel software tool (*Autoflow©*) that autonomously disaggregates and synthesises high resolution water data received from customer smart meters into useful reports that can be used by utility operators and consumers for a range of urban water management purposes.

3. To demonstrate the various applications of *Autoflow*© for urban water management and customer engagement purposes.

2. Background

2.1. Current water management practices for the urban water cycle process

Cities in industrialised countries all include the key stages of a modern urban water cycle, such as, water source/storage, water treatment, water distribution system, urban water use, waste water collection, wastewater treatment and wastewater returning to environment. In most urban water providers servicing these cities, water suppliers and infrastructure planners are still relying on coarse or outdated information for most of their planning and development, which leads to inefficient management. Even more worrying is that satisfactory customer engagement is presently viewed as delivering a water bill with scarce consumption information every month or quarter.

Several studies have recently been completed that seek to better understand or improve each stage of the urban water cycle through the use of better water data. For example, during the water distribution stage, significant water and capital savings are achieved through early leak detection in the supply mains (Sønderlund *et al.* 2016; Savic *et al*. 2014), accurate determination of peak demand to optimise pumping schedules (Gurung *et al*. 2016b), or reductions in peak demand to avoid the need for costly pipe network augmentation (Gurung *et al.* 2014b; 2016a). However, greater levels of water efficiency can be realised through better understanding of customer demand and better engagement practices with high-consuming customers (Fielding *et al*. 2013). Recent studies indicated that significant water savings can be achieved when consumers are made aware of their consumption behaviours through detailed and targeted information dissemination (Stewart *et al.* 2011, Willis *et al.* 2011, Beal *et al.* 2012, Nguyen *et al.* 2013a, Liu *et al.* 2015, 2016; Britton *et al*. 2013). Detailed understanding of water demand (i.e. end use data) also provides wastewater system planners and operators with valuable information on the likely constituents of collected wastewater, which would assist them in moderating existing treatment plant capacity, planning of new treatment plants, and accurately estimating the amount of treatment chemical. The next section discusses how sensor networks and big data analytics will help transform certain segments of the urban water management process.

2.2. Sensors and big data analytics transforming the urban water management process

In recent decades, technological progress has led to advanced sensing tools being available for water utilities to remotely and independently control a number of critical parameters, both upstream and downstream of the water treatment stage, and in general for natural resources managers (Kennedy *et al*. 2009). For instance, most drinking water reservoirs have remote water quality sensor networks such as Vertical Profiling Systems (VPSs) that can be used for water column profiling capabilities; i.e. they can remotely monitor a range of parameters such as water temperature, pH, dissolved oxygen, turbidity, dissolved organic matter (DOM), cyanobacteria, etc. at different depths (Henderson *et al*. 2015; Bertone *et al.* 2015; 2016). From a water demand point of view, smart meters have been increasingly adopted around the world, and they represent a fundamental component for the development of smart cities (Lloret *et al.* 2016).

On the other hand, the relentless advancements in computing capabilities have led to an exponential growth of data-driven modelling applications for the water resources management and urban water fields (Bach *et al.* 2014; Maier and Dandy, 2000; Maier *et al.* 2014; Joorabchi *et al.* 2009, Kossieris *et al*. 2014, Creaco *et al.* 2016). The ability of advanced algorithms to intelligently and efficiently identify patterns in large datasets has led to a range of benefits for water utilities through cost reductions and better management of resources. In the context of this study, smart metering systems coupled with big data analytics have been explored to reveal opportunities for operational efficiencies and customer engagement for many aspects of the urban water management process as presented in the next section.

2.3. Smart metering technology for urban water management

Smart meters provide accurate water use information, such as high-resolution end-use or leakage data, which benefits water utilities and policy makers alike (Giurco *et al.* 2008b). A smart water meter configuration involves a high-resolution water meter linked to a data logger, which captures water use data that can be downloaded as an electronic signal and analysed using available technology (Britton *et al.* 2008; Stewart *et al.*, 2010, Beal *et al*. 2016). The electronic signals from smart meters can also be transferred to computers or central data hubs via data distribution technologies (Willis *et al.* 2013).

With the advent of smart metering in recent years where water consumption data could be recorded at high resolution, several studies have been undertaken all over the world to unpack various benefits for both consumers and suppliers. Large scale smart water metering systems, having low resolution and only log at minute or hourly intervals, has been widely utilised for leak detection, peak demand identification and time-of-use tariffs (Stewart *et al.*, 2010, Loureiro *et al.* 2014a). Moreover, low and medium resolution data can be exploited to perform urban scale studies aimed at assessing the environmental impacts and costs of water-related energy (Loureiro *et al.* 2014b; Escriva-Bou *et al.* 2015), as well as exploring heterogeneous consumption patterns (Cardell-Oliver *et al.* 2016; Cominola *et al*. 2015; 2016). In contrast, detailed end-use water consumption data requires a smart metering system, with higher resolution water meters, as well as data loggers that record information in 5-10 second intervals (Giurco *et al.* 2008a; Fidar *et al.* 2010). Through combining various pattern recognition techniques, Nguyen *et at* (2011, 2013a, 2013b, 2014, 2015) has developed an intelligent water management system (*Autoflow©*), which can connect wirelessly to smart water meters to autonomously disaggregate water consumption data from high resolution smart meters into a repository of end-use demand data. Moreover, it provides a platform for customers to closely monitor water usage through logging into their user-defined online account where all detailed descriptions of daily, weekly and monthly consumption information for different end-use categories are provided. The next section will discuss some specific applications and benefits of using a high resolution smart metering system for a range of advanced urban water management functions.

3. Smart metering technology for advanced urban water management

3.1. Traditional water supply network planning and design procedure

Important parameters in the planning and design of the water supply network are the demand at the peak hour (PH) on the peak day (PD), which is the maximum day demand over a 12-month period, and the average day (AD) demand, which is the average water consumption over the same 12-month period. However, traditional methods of developing such profiles and peaking factors, necessary to carry out water distribution network modelling, are often founded on a number of assumptions on how top-down bulk water consumption is attributed to customer connections and outdated demand information that does not reflect present consumption trends; meaning infrastructure is often unnecessarily overdesigned (Gurung *et al.* 2014a).

3.2. Re-engineering the water supply planning & design procedure

Water demand varies through the day and is generally at its lowest from 12 to 4am and at its highest in the morning and evening; the higher of which is termed the daily peak hour demand. On the PD, this critical period is termed the PH, which is usually driven by seasonal influences (e.g. extended dry weather causes sharp spike in outdoor demand). Information on peak demand patterns is required for the design of water infrastructure such as pumps, pipes and storage reservoirs. Reductions in peak demand can mean that potential upgrades of water distribution infrastructure can be delayed or capital works funding reduced (Beal and Stewart, 2011; Cole and Stewart, 2013; Carragher *et al.,* 2012). Thus, as current demand-modelling techniques often rely on outdated demand data, unnecessary infrastructure augmentations of pipe networks that are not yet near capacity are not uncommon. Smart water meters enable much better understanding of current diurnal water demand patterns, thereby ensuring that only those necessary pipe network capital works are initiated.

Gurung *et al.* (2014a, 2014b, 2016a, 2016b) recently demonstrated the implications and benefits of using high resolution smart meters to categorise flow data into the various water end use categories across the daily diurnal demand pattern, and how this information can be used for better water infrastructure planning. In these studies, a water supply zone located in Southeast Queensland region was selected, which included 800 selected household, a reservoir, nine storage tanks, and reticulation (<200 mm) and trunk mains (≥200 mm) totalling 790 km in length. The studies utilised high resolution water consumption of single residential households [0.014 litres per pulse (L/pulse); 5 second intervals]. The data was collected fortnightly over seven periods between 2010 and 2012. Stock efficiency ratings of the various indoor household water appliances were also recorded to determine their potential water saving capabilities. The disaggregated end-use data from these studies provided evidenced-based research to demonstrate that: (1) water efficient appliances significantly reduce peak demand; (2) smart meter data can be utilised to improve water service delivery infrastructure planning and design; and (3) smart meters facilitate the introduction of novel water pricing approaches for reducing peak demand, such as a Time of Use Tariff (TOUT). The following section details these applications of smart meter data.

3.3. Smart meters enabling better management of peak demand

3.3.1. Utilisation of water efficient appliances

Gurung *et al.* (2014a) proposed a method of using up-to-date smart water meter data to define individual end-use's consumption patterns as a foundation for developing household water demand patterns. Gurung *et al.* (2014a) revealed that the peak demand of each end-use category was significantly affected by the efficiency rating of the associated appliance stock (e.g. toilet water efficiency rating). This finding is very important to water infrastructure network asset custodians that are required to maintain a specified level of service (i.e. flow and pressure) to customers during peak demand conditions. Hence, the utilisation of very efficient water devices in new high density developments within a water supply zone nearing capacity could potentially defer or reduce the requirement for system augmentation and the associated capital costs. Recurrent costs (e.g. maintenance and operation) could also be reduced through lower pressures in the pipelines meaning less pipe failures and extended asset life, while energy costs could be reduced from running smaller pumps and through treating and transferring lower volumes of water.

3.3.2. Smart meters end use data for enhanced water service infrastructure planning

Gurung *et al.* (2014b) provided empirical evidence to support the implementation of smart water meters for improving current water demand forecasting and network modelling practices. This study utilised a data-driven, bottom-up end use approach that derived a superior set of diurnal demand patterns and peaking factors that was then used for network modelling and subsequent planning and operational purposes.

The study determined that the modelled PD consumption developed using smart meter data was 12% lower than that used by the water utility, for the same area. This is in line with current consumption trends, whereby water demand generally has reduced over the years, with a reduction in peak demand also apparent from another study (Beal and Stewart, 2011).

3.3.3. Smart meters enabling demand-based pricing

Demand-based pricing is a useful strategy for influencing/changing customers' water use habits over the medium to long-term (Sahin *et al.,* 2017). Gurung *et al.* (2016a) suggested that with the presence of a smart water meter in each household, a TOUT could either be implemented to impose penalty charges for exceeding a consumption threshold over a specific period of the day (Cole and Stewart, 2013) or to provide monthly incentives for lowering peak hour consumption (House and House, 2012). The implementation of TOUT could be further supported with the development of a real-time web-portal visualisation tool, which would inform customers on exactly where their water is being consumed at what time (e.g. Stewart *et al*., 2010). Pricing, incentives and informative tools are all strategies that motivate consumers to reduce or shift their demand during peak periods (House and House, 2012; Beal *et al*. 2016, Harou *et al.* 2014, Rizzoli *et al*. 2014). In summary, various opportunities for water and capital savings could be realised when high resolution water consumption data is available for analysis. The next section introduces *Autoflow©*, a smart water management system that can autonomously disaggregate high-resolution consumption data into a repository of end-use consumption within each residential demand category. This software can be utilised to facilitate the water-saving initiatives presented in this section.

4. Development of *Autoflow©* water end use analysis software tool

With the availability of smart metering technology, high resolution data can be collected (i.e. 0.01 L every second). However, the challenge of usefully analysing this huge amount of data autonomously, remains. There are currently two approaches to the water end use classification problem: (1) simple decision tree methods based on three physical features of each event, namely volume, duration and flow-rate (e.g. *Trace Wizard* and *Identiflow*); and (2) sensor devices placed on individual water end use appliances supported by data mining techniques (e.g. *Hydro Sense).* However, these approaches have certain limitations (i.e. user intrusive or low accuracy) that prevent them from being widely implemented (Trace Wizard, 2003; Froehlich et al. 2009, 2011). Nguyen *et al*. (2015) recently introduced an advanced water end use disaggregation software called *Autoflow©* that overcomes these limitations through applying a hybrid combination of pattern recognition algorithms and data mining techniques to learn distinct flow signature patterns for each end use category. This software can actively monitor water consumption and provide real-time information about what, when, where and how water is consumed.

Developed using a database of nearly 200,000 samples collected from residential households located in cities in Australia, *Autoflow©* allows individual consumers to log into their user-defined water consumption web page to view their daily, weekly, and monthly consumption tables, as well as charts on their water demand across major end-use categories (e.g. leaks, clothes washer, shower, irrigation). This software also benefits water service providers by rapidly providing water end-use reports of any desired property or suburbs, thereby empowering them to: (i) develop more targeted conservation programs in water scarcity periods; (ii) improve water demand forecasting; and (iii) optimise pipe network modelling. The overall analysis process in *Autoflow©* can be separated into two distinct analysis stages: (1) Hidden Markov Model (HMM), Dynamic Time Warping (DTW) algorithm, Artificial Neural Network (ANN) and event probability techniques applied for autonomous water end use classification; and (2) Dynamic Harmonic Regression (DHR), Kalman Filter and Fixed Interval Smooth algorithm for short term water demand forecasting. Further, the system enables water utilities to intervene as soon as an exception alarm is raised for end-uses, such as major water leaks. The analytical report generated by the system helps water service providers to identify the water consumption patterns of different types of consumers. The following sections detail how the residential consumption dataset was collected, pattern recognition techniques were applied, and how the short-term demand forecasting technique was developed. This present paper is more focused on the development of the latter short-term demand forecasting technique.

4.1. Data collection for pattern recognition training and testing

To collect approximately 200,000 different consumption patterns as mentioned prior, smart water meter data utilised for the development of the model was sourced from 1000 residential households fitted with a smart meter and data logger, which were located in Melbourne and the urban south-east corner of the State of Queensland, Australia. Text files containing 0.014 L/pulse water consumption data for every five second logging interval for each sample household was collected. Three separate water end use analysis reads occurred during the study. The first read was conducted in winter 2010 from 14th to the 28th June. The second read was taken in the summer 2010-11 between 1st December 2010 and 21st February 2011. The final two-week period of analysis occurred in winter 2011, from the 1st to the 15th June. It was important to obtain a dataset for this study that included the entire spectrum of events across seasonal periods (i.e. irrigation). During this data collection process, household water appliance stock audits and self-reported water diaries were used to help determine household demographic characteristics, the water use stock present within the home, the efficiency of the water use stock, and the water use activities and behaviours of each household. At the time of the house visit to conduct the water audit, a water diary was left with the participant to fill out over a 14 day period. During the visit, the researchers talked through each question with the residents and walked around the home looking at, and recording, the water stock, and enquiring about the use of each device. The residents were asked to elaborate on any interesting comments or their thoughts on water use in their home, or in general. A range of information was recorded during the audit, including typical volume, typical flow rate, make, model and water rating of each appliance in the house. Additionally, residents were also asked to record all water consumption activities, including starting and ending time, and category of each consumption.

This process resulted in a database of water use fixtures, fittings and behaviours within the sample. The data were collected through the water audit was used to determine: the fixtures and fittings within the homes, the relative efficiency of fixtures, the perceived time of day and the duration of use, and the water usage patterns and behaviours unique to each household. The data enabled the creation of a repository of characteristic residential water end-use category templates for each home, which was subsequently used for machine learning processing described in the next section.

4.2. Machine learning techniques applied in Autoflow©

The core task in *Autoflow©* development was to explore smart algorithms that are able to categorise an unknown event pattern (Figure 1) collected from a customers' smart meter to its appropriate end use category. To achieve this goal, Hidden Markov Model (HMM), Artificial Neural Network (ANN) and Dynamic Time Warping (DTW) algorithms have been applied as explained below.

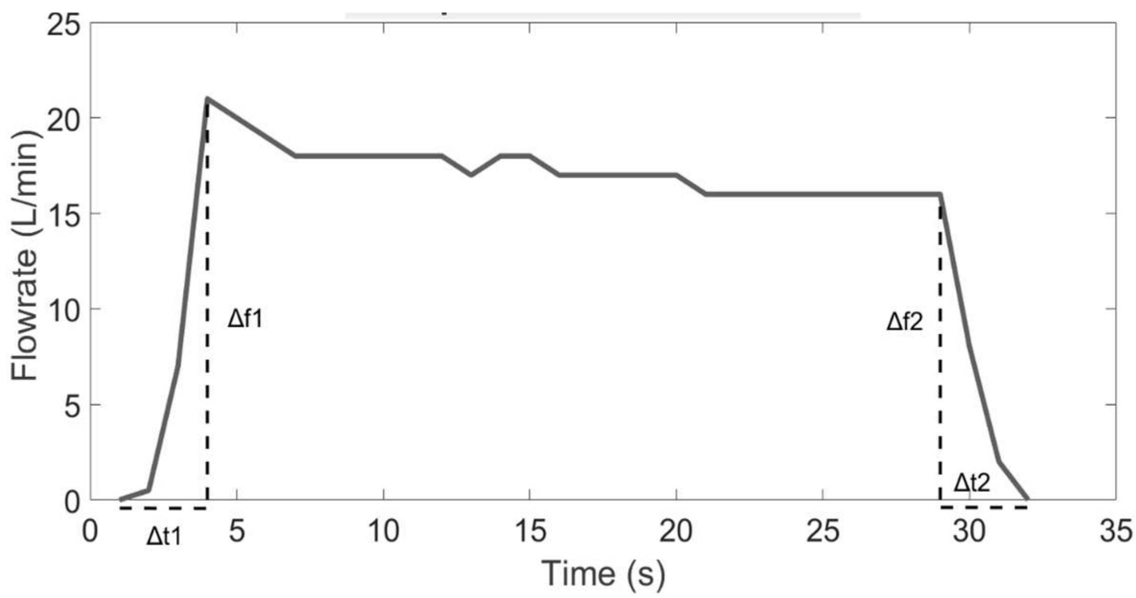

Figure 1. Example of an unknown event

4.2.1. *Hidden Markov Model*

HMM is a stochastic finite state automation defined by the parameter $\lambda = (\pi, a, b)$, where π is an initial state probability, a is state transition probability and b is an observation probability, defined by a finite multivariate Gaussian mixture. In this study, HMM was utilised as an initial classifier to provide classification likelihood for each unknown event based on its shape pattern. However, the weakness of this technique is that HMM does not adequately classify end use categories that are highly dependent on user behaviour such as showering; such end uses are highly variable meaning that they sometimes having features that closely resemble those in other categories. To illustrate this issue, Figure 2 shows that three different end use event categories (i.e. shower, bathtub and irrigation) can possess similar flowrate patterns (i.e. how the flow rate rises and drops). Although having significant difference in flowrate, duration and volume, the HMM classification process on these samples have resulted in very close likelihood values, which makes the classification process less accurate. As a result, an additional technique that can inspect the physical features of these events is required to help differentiate between them.

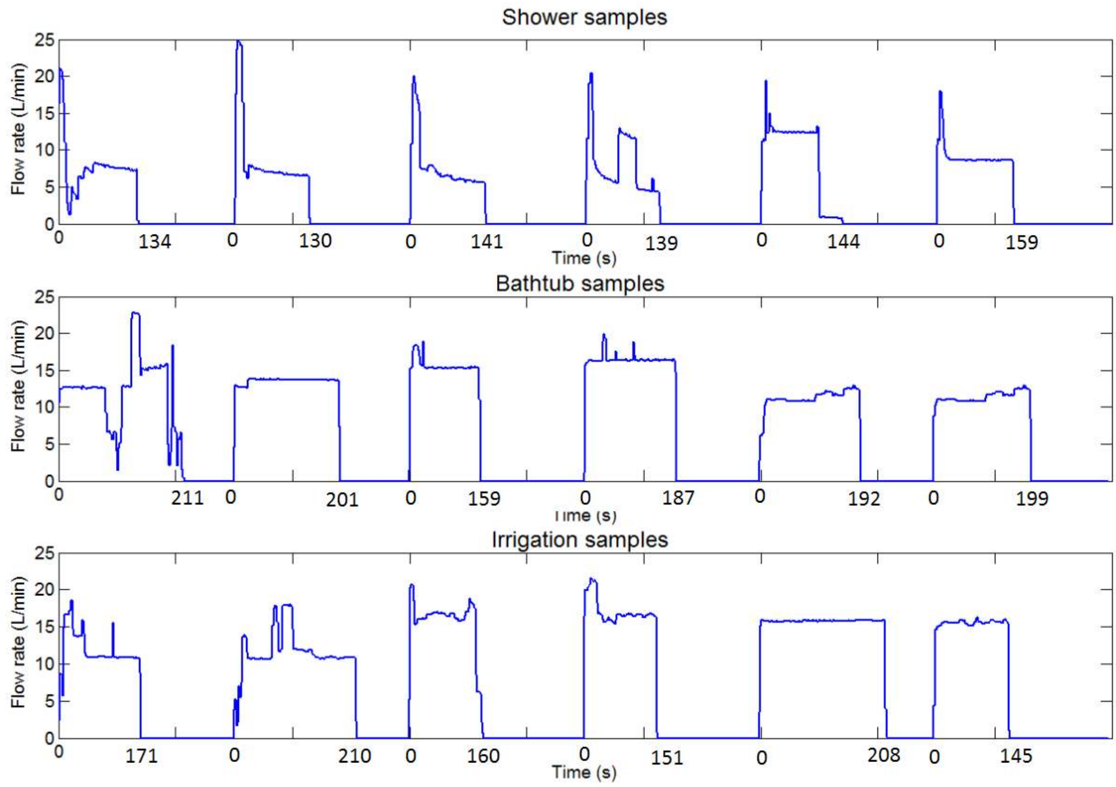

Figure 2. Similar samples extracted from three different end-use categories

4.2.2. Artificial Neural Network

To overcome the above mentioned issue, ANN was employed. A feed-forward network with back-propagation training algorithm was selected as the main tool to learn a typical pattern of each category in terms of physical characteristics, including (i) volume; (ii) duration; (iii) maximum flow-rate; (iv) most frequent flow-rate; (v) frequency of most frequent flow-rate; (vi) magnitude of initial flow-rate rise; (vii) magnitude of flow-rate drop at the end of event; (viii) gradient of initial flow-rate rise; and (ix) gradient of flow-rate drop at the end of event. Features (vi) to (ix) are defined below and are also illustrated in Figure 1:

(vi) *Magnitude of initial flow-rate rise (Δf_1)* is defined as the flow-rate rise at the initial phase of the event when the consumer starts using water.

(vii) *Magnitude of flow-rate drop at the end of event (Δf_2)* is the flow-rate drop at the end phase of the event when the valve is shut.

(viii) *Gradient of initial flow-rate rise (g_1)* is determined by dividing Δf_1 by the time it takes to reach this flow-rate (Δt_1).

$$g1 = \Delta f_1 / \Delta t_1 \qquad (1)$$

(ix) *Gradient of flow-rate drop at the end of event ($g2$)* is determined by dividing Δf_2 by the time it takes for the flow to revert to zero *(Δt_2)*.

$$g2 = \Delta f_2 / \Delta t_2 \qquad (2)$$

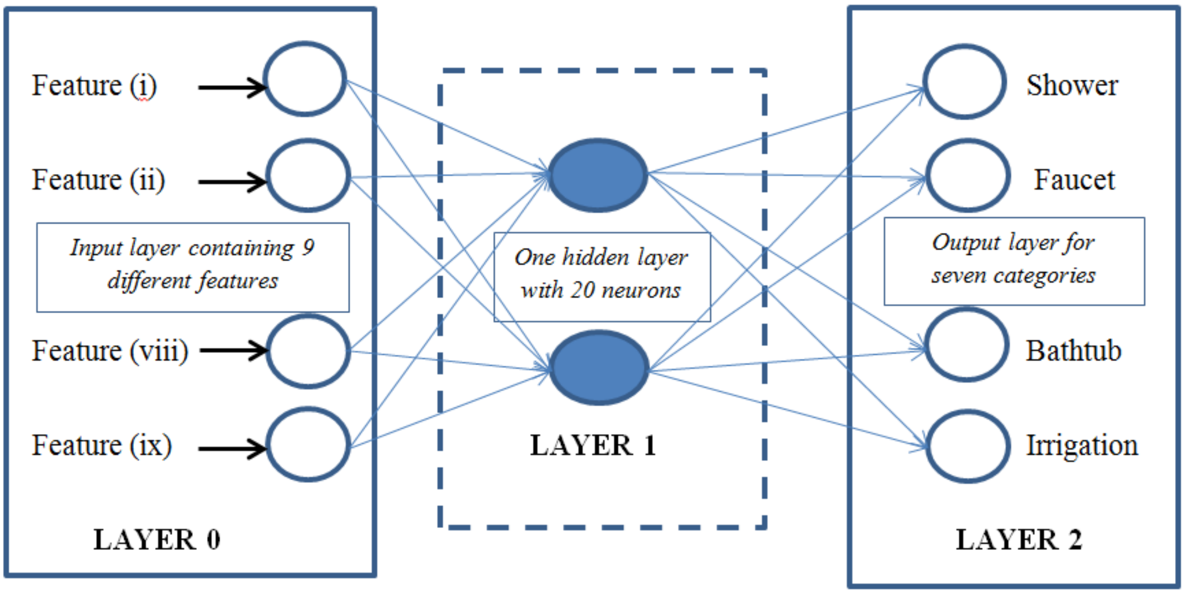

Figure 3. ANN model for water end use classification

Once the required features of all events have been obtained, the ANN training process using the back-propagation algorithm can be started following the network presented in Figure 3. The output of this process is an ANN model that is able to turn any unclassified event into one of the seven end-use categories, namely shower, faucet, clothes washer, dishwasher, toilet, bathtub, and irrigation. Classification likelihood obtained from this process for each event was then combined with that from HMM model to provide the final likelihood for decision making.

4.2.3. Dynamic Time Warping algorithm

The last applied mathematical tool was the DTW algorithm, which is a popular method for measuring the similarity between two time series of different lengths. The sequences are extended or shortened in the time dimension to determine a measure of their similarity independent of certain non-linear variations in the time dimension (Myers and Rabiner, 1981). DTW played an important role in the water end use pattern recognition process since it was utilised for the task of searching for linked cycles of water use related to one particular end-use event for mechanised end-use events (e.g. clothes washer and dishwasher) that were misclassified by HMM and ANN. In essence, clothes washers and dishwashers have patterns of cycles of water use associated with a particular customer 'wash' selection, which can be recognised using DTW.

4.3. Water end-use disaggregation model development

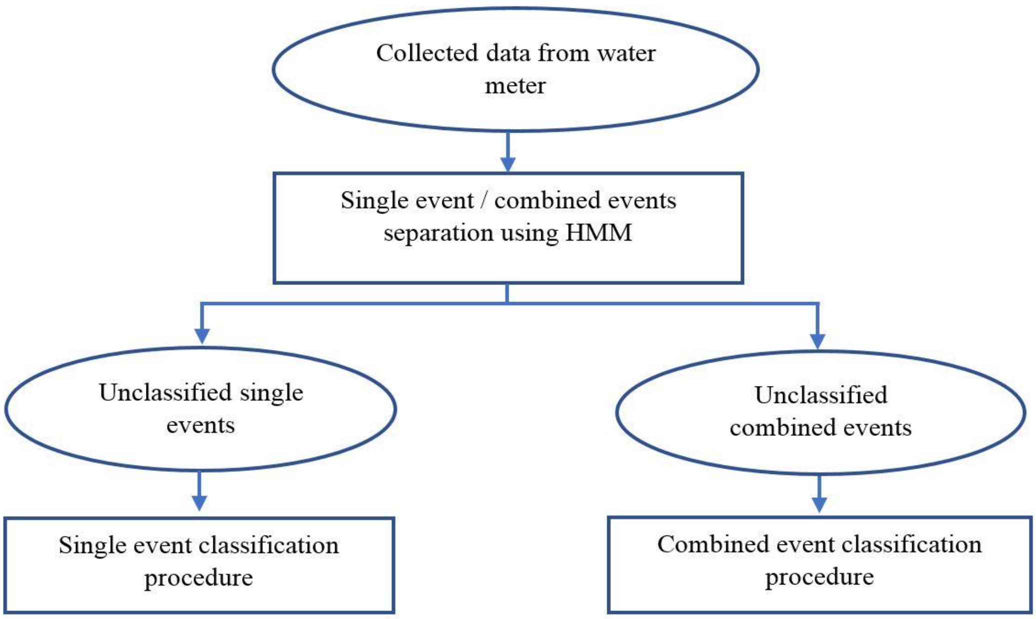

Figure 4. Water end-use disaggregation process

With the available database, the disaggregation process of water end use events from the raw data was developed. As mentioned previously, single events are defined as those which occur in isolation (e.g. toilet flushing only), while combined events have simultaneous occurrences of water usage (e.g. a shower occurring while someone else is using a tap). Combined events are more challenging to disaggregate into discrete single events. As the very first step of the classification process (Figure 4), the HMM algorithm is used to recognise if an event can be clearly allocated to a particular single event category or is most likely a combined event. Remaining events from this process are placed into two groups, namely, unclassified single events and combined events. In the case of unclassified single events, a combination of HMM, ANN and DTW was then employed to assign them to appropriate end use categories. The next important task involves the combined event classification, which is one of the most complicated problems in the field of pattern matching. To address this question, a combination of DTW, HMM, ANN, Data filtering and Time-of-day probability techniques has been employed. Presented in the next sections is a summary of single and combined event analysis models.

4.3.1. Single event analysis

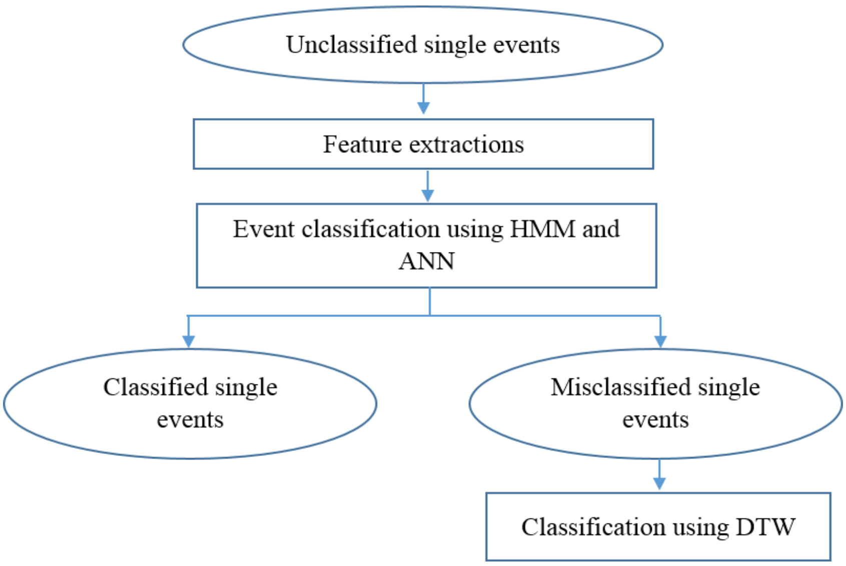

Figure 5. Single event classification procedures

As shown in Figure 5, to enable a classification process using ANN, distinct physical features, explained in Section 4.2.2, from each event have to be initially extracted and used as the main input for the classification process. The likelihood estimation of each event using HMM and ANN is then conducted, which allows the final decision to be made. At the end of this step, most unclassified single events will be assigned to appropriate categories. However, even after these procedures are completed, there are often a small number of misclassified events due to their complicated patterns or highly similar patterns to other end use categories making it difficult to assign them. To capture the majority of these unclassified events a further analysis procedure was developed, which essentially searched for wash-cycle patterns evident in the mechanised end use categories (e.g. clothes washer). The searching process starts with selecting clothes washer and dishwasher prototypes from the already classified events of these two categories. With the availability of the representative clothes washer and dishwasher samples, the searching can be performed by looking for any event that has similar shape to these prototypes using DTW.

4.3.2. Combined event analysis

The overall procedure for combined event disaggregation is detailed in Nguyen et al. (2013b). Therefore, only a brief summary of the techniques applied for this module is presented herein (Figure 6).

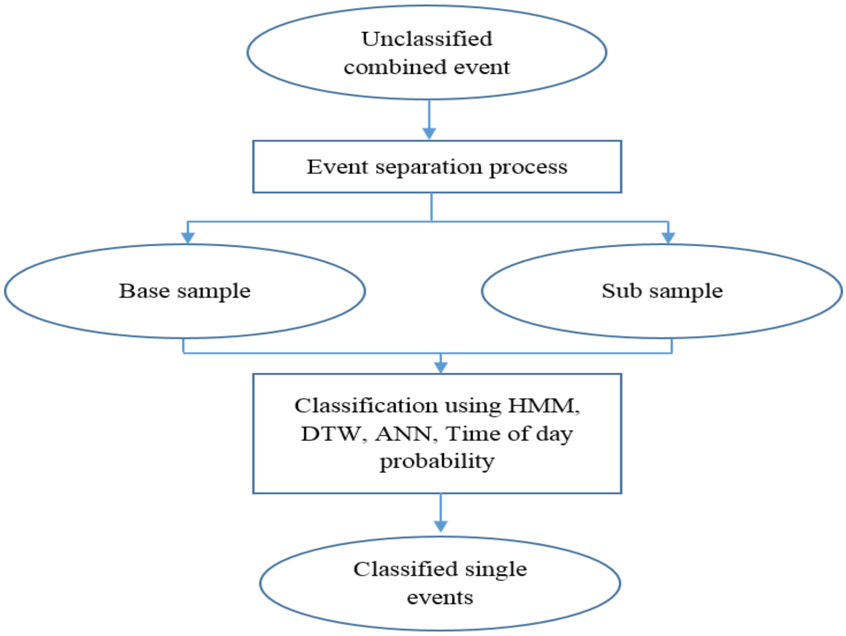

Figure 6. Combined event classification procedures

The established HMM-ANN-DTW hybrid model for single event recognition also plays a major role for combined event disaggregation along with other pre-determined criteria. The whole combined event analysis process is separated into two main stages: (1) Sub-event analysis; and (2) Base-event analysis. In the first stage of analysis, a separation process employing the modified gradient vector filtering method is applied to disaggregate the uncategorised combined event into one base sample and several sub samples, where the term "sample" is used to refer to the products obtained from the separation process before the classification. Once these samples are assigned to their proper categories, they are called "events". The HMM, DTW and ANN method are applied to the sub samples to determine whether they are actual complete single events or just parts of other events within the combined event.

A base event, as previously defined, is the longest single event within the combined event. However, in the second stage of the analysis, the classification of the base sample, achieved after the initial separation process, often remains problematic; that is, the decision needs to be made whether this event is now a single event or another combined event. This uncertainty arises because it is just the remaining product after small or spiky sections are taken away from the original combined event. To tackle this issue, the subjected base sample is dissected into many smaller parts, using the same gradient vector filtering technique, for further analysis. The outcome of the second stage analysis, following the HMM and ANN classification process, is a classified a single base event, with the potential for other classified sub events, where they exist.

4.3.3. Model verification

Table 1. Model verification

Category	No. of samples for training	No. of samples for testing	Achieved accuracy (%)
Shower	14,903	3,000	93.8
Faucet	21,985	3,000	90.8
Clothes washer	15,211	3,000	91.7
Dishwasher	13,342	3,000	96.0
Toilet	15,222	3,000	94.4
Bathtub	1,080	500	88.1
Irrigation	1,020	500	85.9
All categories	82,763	16,000	92.9

The overall verification process is presented below where 16,000 samples (20% reserved data) were used to illustrate the accuracy achieved. End use event classification accuracy was calculated by dividing the number of correctly classified events for each end use category by the total number of events within the testing sample for each end use category (Table 1). For example, for the classification of shower events, the number of testing samples was 3,000 and the number of events correctly identified was 2843, which resulted in an accuracy of 93.8 %.

4.4. *Autoflow*© populated water demand forecasting model development

The next important task was to develop water demand forecasting functionality for *Autoflow*©. Given that the collected hourly water consumption data from a sample of 100 homes in a surveyed suburb displays a periodic pattern (Figure 7), a state-space model was required that combines both stochastic and regression models. Seasonality, temperature effect and residual were modelled as stochastic processes.

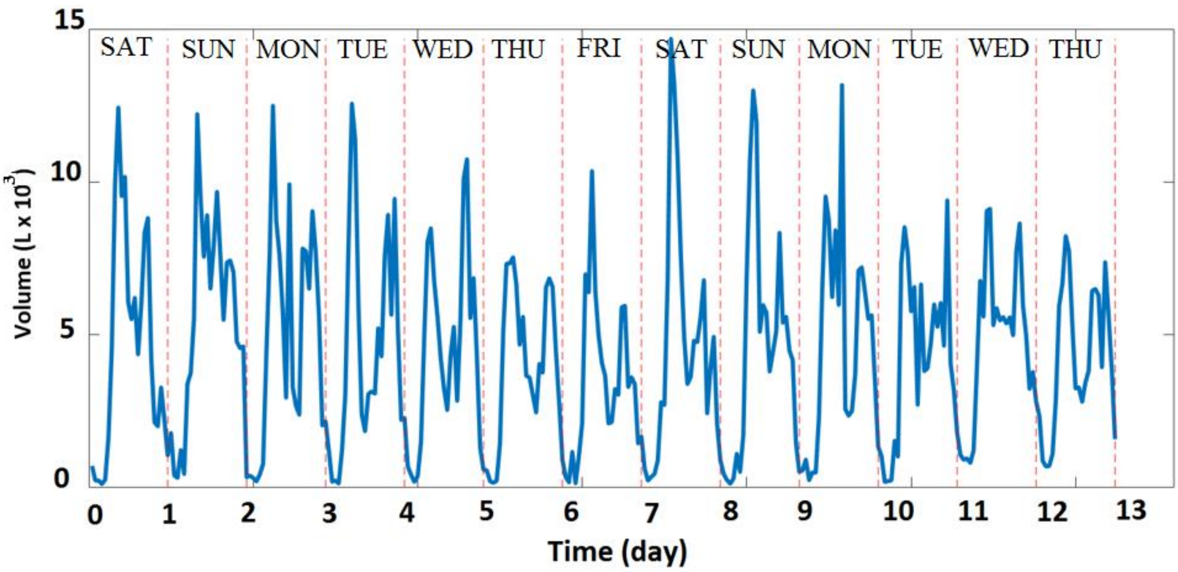

Figure 7. Collected hourly water consumption data for suburban area (*N*=100 homes)

The model is considered as an observation equation of a discrete time. Stochastic state models and the associated state equations were used to model each of the components in Gauss-Markov (GM) terms. The forecasting model in *Autoflow*© has the form of:

$$y(t)=S(t)+F(t)+e(t) \quad \text{where} \quad e(t)\sim N\{0, \sigma2\} \tag{3}$$

where y(t) is the forecasted hourly water consumption data (L/hr) at time t; $S(t)$ is a seasonal component that directly reflects the periodic pattern of the data; $F(t)$ is the function that describes the influence of daily temperature (℃) on periodic pattern of the data; and $e(t)$ is the noise component used to model the random changes in water consumption due to water consumption behaviours.

To account for the nonstationary characteristics of this time series data, all components in Eq. (3) were characterised by stochastic, time dependant parameters (Young, 1998; Young and Pedregal 1999a). In this model, the most important component is the seasonal term *S(t)* that determines the periodic pattern of the water consumption data signal, and is defined as:

$$S(t) = \sum_{i=1}^{R} \{a_{i,t} \cos(\omega_i t) + b_{i,t} \sin(\omega_i t)\} \tag{4}$$

where $a_{i,t}$ and $b_{i,t}$ are stochastic parameters and w_i, (i=1,2,…R) are the fundamental and harmonic frequencies associated with the seasonality in the series.

$F(t)$ is characterised by the following deterministic transfer function:

$$F(t) = \frac{B(z^{-1})}{A(z^{-1})} u(t - \delta) \tag{5}$$

Where u is the input temperature and δ is the time lag, $A(z^{-1})$ and $B(z^{-1})$ are the polynomials in the backward shift operator (z^{-1}) that define the transfer characteristics between the temperature and the water consumption, and have the following form of:

$$A(z^{-1}) = 1 + a_1(z^{-1}) + a_2(z^{-2}) \ldots + a_n(z^{-n}) \tag{6a}$$

$$B(z^{-1}) = 1 + b_1(z^{-1}) + b_2(z^{-2}) \ldots + b_n(z^{-n}) \tag{6b}$$

Given that the relationship between weather conditions and residential water consumption is determinable, the first order of the transfer function was recommended. In terms of state-space form, (t) can be presented as:

$$x_f(t) = F_f x_f(t-1) + F_f \varphi_f(t-1) \tag{7a}$$

$$F(t) = H_f x_f(t) \tag{7b}$$

where $F_f = 1$, $G_f = 1$ and $H_f = 1$ when the first order transfer function was adopted (Harvey 1989).

With the availability of observation and state-space equations of all components, the aggregation of all subsystem matrices into a standard state space format can be undertaken as presented in Eq. (8).

State-space equation:

$$X(t) = Fx(t-1) + G\varphi(t-1) \tag{8a}$$

Observation equation:

$$y_t = HX(t) + G\varphi(t-1) \tag{8b}$$

Where, the state vector $\boldsymbol{X}$ (t) is composed of all state variables from the seasonal and external temperature input model. The white noise vector $\varphi(t)$ is defined by the white noise disturbance input of the constituent model. In order to have a good approximation of the collected water consumption data $y(t)$ from the state-space model, the key task is lying at an accurate estimation of the time variable parameters $X(t)$ which can be done using Kalman Filtering accompanied by the optimal smoothing procedures as described in (Kalman, 1960 and Young & Ng, 1989).

With the availability of *(t)* obtained from the previous step, forecasting of future water consumption can be performed straightforwardly by the applying the state-space filtering/smoothing algorithm. The f-step-ahead forecasts of the aggregate state vector *(t)* in Eq. (8) are obtained at any point in the time series by using Eq. (9a):

$$\hat{X}(t+f|t) = F^f\hat{X}(t) \tag{9a}$$

Where (f) denotes the forecasting period. The associated forecast of (t) is provided by Eq. (9b):

$$\hat{y}(t+f|t) = H\hat{X}(t+f|t) \tag{9b}$$

The water demand forecast model of hourly demand can be coupled with *Autoflow*© analytical procedures in order to disaggregate this hourly demand into water end use components, as described in the below steps:

(i) Perform an automated water end-use analysis using *Autoflow*© for the previous two weeks of smart meter data, in order to create the hourly end use breakdown of residential water consumption for each day of the week.

(ii) With the disaggregated volume of all events obtained from step (i), determine the volume distribution for each category through Eq. (10), which is a (m by 24) matrix

P, where m is the number of end-use component and $volume_{i,j}$ is the total volume of category i collected at time j of the day.

$$P_{i,j} = \frac{volume_{i,j}}{\sum_{i=1}^{m} volume_j} \qquad i = 1, 2, \ldots, \text{ and } j = 1, 2, \ldots, 24 \qquad (10)$$

(iii) Allocate this volume distribution on the predicted 24-hour demand ahead. Eq. (10) can be interpreted as: if $i = 1$ corresponds to shower category, $P_{1,1}$ will represent the percentage of shower volume in comparison with the total volume collected, for instance, at 1 am during the last two weeks. For example, if $P_{1,1} = 15\%$, and the predicted water consumption at 1 am of the next day is 100 litres, then the predicted shower at 1 am is 15 litres. By doing this, predicted volumes of all categories can be determined as presented in Figure 8. Readers should note that Figure 8 displays the next day disaggregated demand prediction for a sample of 100 homes fitted with smart water meter.

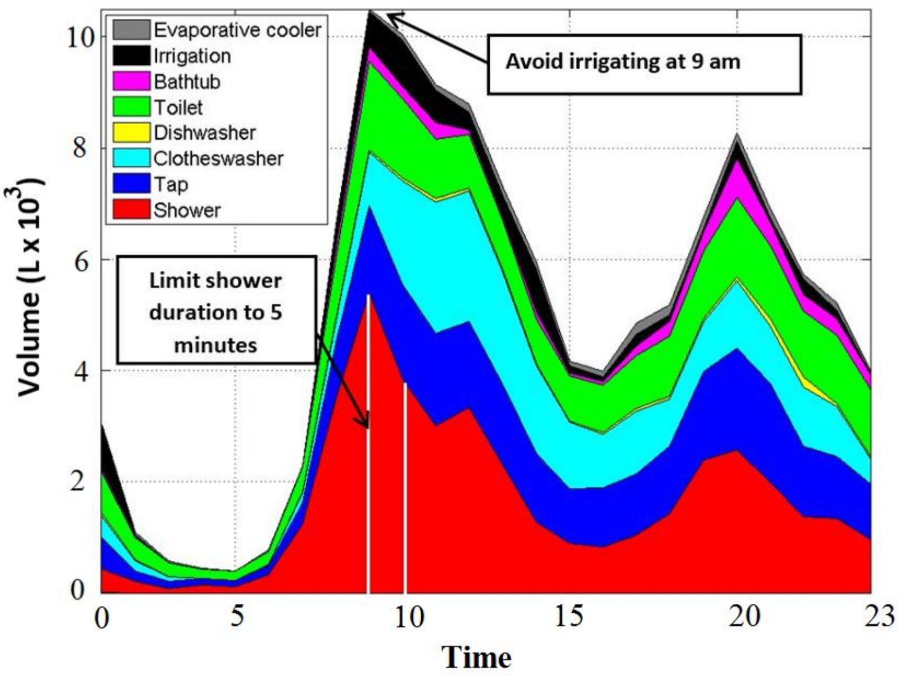

Figure 8. Disaggregation of forecasted total water consumption for 100 homes

5. Applications of *Autoflow*©

5.1. Water service provider urban water management and Customer engagement

Developed using a combination of several complex pattern recognition and demand forecasting techniques, *Autoflow©* facilitates water demand disaggregation into end use categories, short-term water demand forecasting at an end-use level, and water end use appliance stock efficiency identification for individual or clusters of smart metered household. The following sections detail the benefits of these applications for water service providers.

5.1.1. Water end-use disaggregation function

The primary function of the *Autoflow©* software is to autonomously disaggregate high resolution data collected from smart waters into a repository of end-use categories. In addition to the benefits of having water end-use data as described in Section 3, a water service provider can utilise *Autoflow©* for real time monitoring of water consumption in a particular service area, or detecting leakage in the water supply network by comparing consumed water for a particular supply zone with the total supplied water for that zone.

5.1.2. Water demand forecasting process

Based on the analysis of high-resolution data collected from the previous two week period, *Autoflow©* is able to perform a short-term end use demand forecast for the next day. This information will assist water supply infrastructure engineers and demand management planners in their roles. Specifically, *Autoflow©* greatly enhances the ability of water service providers to plan for future peak demand events and to put in place strategies to proactively management them. Such targeted information coupled with incentives (i.e. discounts, rewards, etc.) for reducing peak demand, has the potential to defer infrastructure upgrade augmentations (e.g. Gurung *et a*l. 2014a), reduce pumping requirements and associated electricity costs (Dejan, 2011), reduce pipe bursts and network leakage (Girard and Stewart, 2007), and extend the pipe network asset life cycle.

5.2.Customer engagement

Autoflow© provides water service providers with an opportunity to closely engage with their customers. Once the system is in place customers will gain significant benefits, including: (1) smart application to view real-time water consumption as well as other statistical reports, including comparisons with other households with similar demographic patterns, detailed end use disaggregation, or recommendations to help reduce consumption; (3) be immediately alerted when water demand is uncharacteristic (e.g. water leak in home); (4) be informed about the current efficiency status of water appliances and devices; (5) trade unused resource for profits (Figure 9).

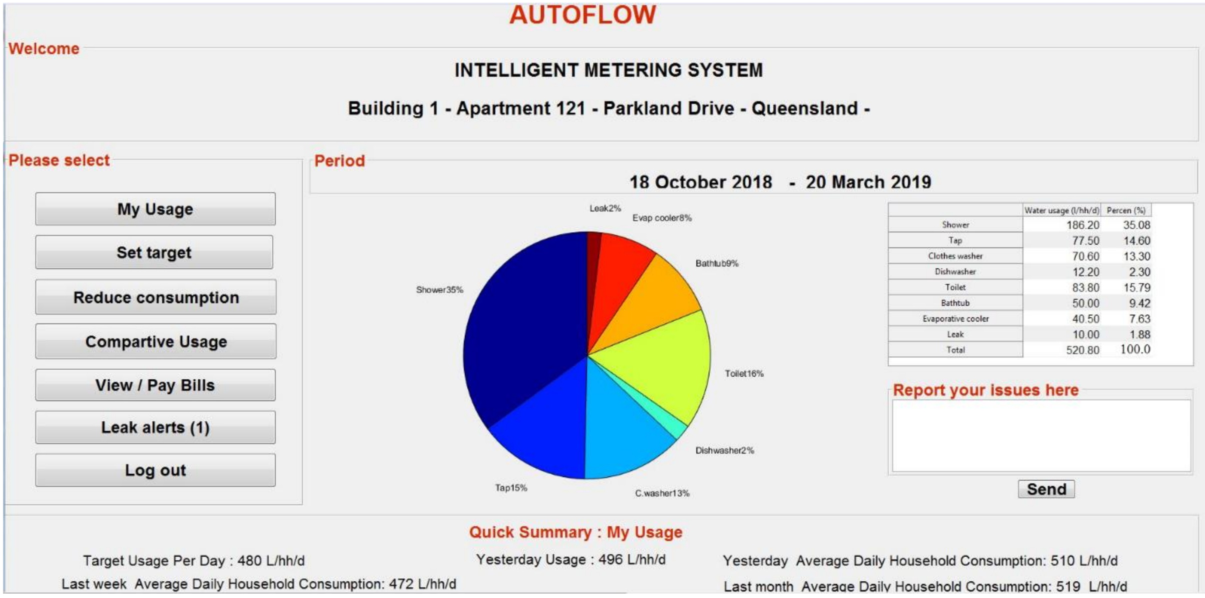

Figure 9. *Autoflow©* - Customer version user interface

5.3. Wastewater treatment process

5.3.1. Wastewater treatment plant planners and operators

Understanding how water was used by customers is vital for planning and managing wastewater treatment processes. *Autoflow©* provides detailed understanding of the current and forecasted end use demand of residential customers (e.g. shower, tap, clothes washer) at different times of the day. Knowing the extent of outdoor consumption used mainly for irrigation purposes is helpful for understanding the amount of wastewater entering the sewerage system from each household. Detailed information of wastewater released from an area will provide infrastructure planner with strong evidence during the design and planning of new adjacent development zones. The planner would have a more accurate estimate of the actual capacity of the current sewerage system, from which a decision on having a system upgrade or using the existing sewerage pipe network could be made. Finally, understanding the volume of water and typical chemical constituents of each end use category (e.g. clothes washing wastewater properties) at particular times of the day can be used for more proactive wastewater treatment plant operations management.

5.3.2. Equitable wastewater billing

Most cities charge residential customers with a simple fixed wastewater charge or a simplistic volumetric wastewater charge based on their water consumption. *Autoflow*© provides end use data for each household, which allows water service providers to consider more sophisticated wastewater tariffs that better reflect the true cost of treating a particular households' wastewater. Such cost-reflective tariffs could be based on the volume of water entering the sewerage system (i.e. exclude irrigation end use) and the characteristics of wastewater from each household. The characteristics of an individual households' wastewater could be estimated using the water end use data obtained from *Autoflow*© and the typical chemical constituents of those end use categories (e.g. wastewater from dishwasher requires more treatment than bath wastewater).

6. Conclusion

While the rate of diffusion has been slower than initial expectations, it is inevitable that water utilities will embrace digital technologies to more efficiently and effectively manage their assets, while significantly enhancing their level of engagement with customers. This study has explained how these goals could be achieved through describing the applications of collecting high resolution end use data from smart metering technologies coupled with the herein described *Autoflow*© software for most stages of the urban water management process. Such a system once in place will result in significant benefits for utilities and customers. From the utility perspective, water and capital cost savings can be extracted from better leak detection, network infrastructure upgrade deferral as a result of reduced peak demand, optimised pumping schedules, and improved wastewater operations management. In terms of the customer, continuously updated and highly detailed water end use data provided through web and phone applications would significantly enhance their awareness of consumption trends, providing them with the impetus to manage their demand

The prototype *Autoflow*© software architecture and applications have been outlined in this paper. Current work is being undertaken to embed *Autoflow*© into smart water meter so that all analyses can be performed on board to save to energy used to transmit high resolution data into web server for analysis. Self-learning algorithm is also being developed to allow each meter with embedded *Autoflow*© to learn and adapt to each customer water consumption habit, which will help significantly the overall software performance.

7. Future work

Within a decade, technology has rapidly become more sophisticated, from needing separate hardware and software to collect, store, transfer and analyse a gigabyte of data, to now having one piece of technology that combines hardware, software and firmware to provide near-real time, tailored reports to utilities and customers as explained in the previous section. Initial success in water end-use disaggregation has allowed the research team to make another step to explore a completely new area, the potential for a digital multi-utility service provider. The overall concept here is that a multi-utility service provider will be able to concurrently collect a customers' medium-high resolution water, electricity and gas demand data and provide user-friendly platforms to feed this information back to customers and supply/distribution utility organisations. The primary benefit to a multi-utility digital retailer is access to intelligently processed and synthesised customer 'big data'. From such data, digital multi-utilities can for example create innovative tariff structures, manage peak demand, unpack the water-energy nexus, and derive innovative tailored resource conservation products and rebates. The scale of customers served, multi-utility services offered, and data-driven value-adding to the entire utility generation/supply/distribution grid system, means that the utility can optimise the management of the system being used, potentially providing extensive financial capital and operational benefits, and the customers can benefit from significantly lower overall utility bills.

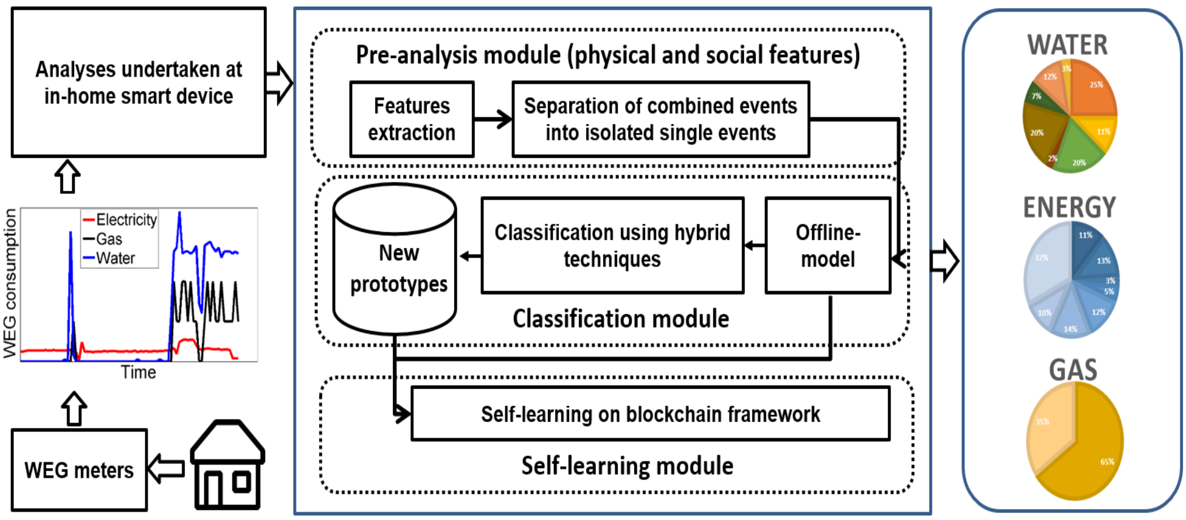

Figure 10. Proposed Water-Energy-Gas analysis model

To establish such a system, the core and most challenging part is to develop the classification model to analyse the concurrently collected water-energy-gas consumption data from smart meters. The architecture and methodology for autonomously categorising this complicated data have been conceptualised by the researchers (Figure 10), and future work seeks to develop mathematical platform for each analysis module in this system. Once the overall system has been completed, a resource trading platform will be developed that allows customer to prepay for their future water, energy or gas consumption, and trade (i.e. buy/sell) any unused resource with other customers in the network. Such system will significantly enhance Water-Energy-Gas consumption saving as customers are now aware that the more resource saved, the more they have for trading to earn profits.

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