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AUTOFLOW© - A novel application for Water Resource Management and Climate Change Response using smart technology

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Abstract: Urban areas are increasingly at risk from climate change, with negative impacts predicted for human health, the economy and ecosystems. These risks require responses from cities to improve their resilience. Several analysis platforms have been developed worldwide to help effectively control and response to these impacts from different angles, including water resources management, energy production and consumption management, air pollution control, or other natural resources management. To contribute to this goal, Griffith University in Australia has developed *Autoflow©*, a smart application for water demand analysis and carbon emission monitoring and prediction. Various advanced mathematical models have been embedded into this system, from machine learning and pattern recognition techniques for water end use analysis, to Dynamic Harmonic Regression, Kalman Filter and Fixed interval smooth algorithms for water demand forecasting. Once being deployed, *Autoflow©* will be an effective environmental management tool that can: (i) provide water utilities and water consumers with detailed real-time information on how, when, where water has been consumed (e.g. shower event at 11:23:35 AM or clothes washer at 4:00:15 PM on Monday 11/12/2014),(ii) perform water demand forecasting at end-use level (e.g. expected 1.5 mega litres of shower consumption from 6pm – 7m in suburb A tomorrow), (iii) real-time monitor and predict carbon emission level from water consumption (e.g. Property A: Carbon emission from 6am-6pm tomorrow is 12.4kg), and (iv) suggest options for reducing water consumption and carbon emission.

Keywords: water end-use, water demand forecasting, carbon emission, climate change, water resource

1. Introduction

Urban water supplies need to be ingeniously managed to navigate rising demand from growing cities and less reliable supplies from dams. The advanced management of urban water consumption is essential to maintain a sustainable water future. This requires collecting and interpreting data on how, when and why water is used to underpin forecasting, equitable management and water planning (Stewart et al. 2010). Current intelligent water metering systems allow for the high-resolution time-series reading of water consumption in households (Beal et al. 2011). Such high-resolution data is necessary to classify the flow patterns of every water end-use event (i.e. tap use, clothes washer use, shower use, etc.) in any household at any recording period. However, the current water end-use classification techniques require extensive use of human resource to collect a combination of water use behaviours and appliance/fixture stock inventory data through a household audit followed by 2-3 hours of analyst time for each home (Stewart et al., 2010). It is not economically viable for the citywide provision of this level of data due to these deficiencies in the currently available tools and techniques. Industry demands cutting-edge science to deliver autonomous, accurate and cost-effective information processing. To automate this process and thus enhance current practices in the urban water industry, *Autoflow©*, an integrated environment and water resources management system has been developed that employed a robust hybrid combination of Hidden Markov model, Dynamic Time Warping Algorithm, Artificial Neural Network and event probability techniques for autonomous water end classification, and Dynamic Harmonic Regression, Kalman Filter and Fixed Interval Smooth algorithm for short term water demand forecasting (Figure 1).

Once being deployed, the proposed system will allow 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). It can also rapidly alert customers of leak events so that they can immediately be addressed rather than waiting for the present slow feedback process from the traditional metering technology (e.g. quarterly bill). This system will also benefit water businesses 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. In terms of environmental management, the system will provide almost real time information with regard to the amount of carbon emission from consumed water as well as detailed prediction of carbon emission based on water consumption habits.

Figure 1 *Autoflow*© system's functions

2. Data collection

Data collection process was separated into four different tasks, which aimed: to determine the required data and technology employed for the study, to determine the sample size and research region, to conduct a stock survey and household audit for each household, and to perform analysis of collected end-use data based on the assistance of the obtained water audit and stock survey.

2.1 Data requirement and technology

The research objectives of this study stipulated the need for high resolution water end use consumption data to assist in determining all individual events within homes, such as showering, irrigation or leakage, etc. An investigation into water metering and data logger technology was carried out, considering this study, as well as other domestic end use studies completed throughout the world (DeOreo and Mayer, 1996; DeOreo *et al.*, 2004; Heinrich, 2007).

2.2 Determination of sample size and research region

For the end use sampling in this study, a total of nine (9) end use categories were determined (clothes washer, shower, tap, toilet, dishwasher, bathtub, irrigation, evaporative air cooler and leak). In terms of the research region, the study was conducted with the collected data from five major cities in Australia, including Melbourne, Brisbane, Gold Coast, Sunshine Coast and Ipswich. The socio-economic status was a primary consideration for these areas to ensure that the sample included a range of household incomes. A total of 1000 homes, from the above mentioned regions, were investigated to obtain water consumption data to facilitate the study.

2.3 Stock survey and water audit

The stock survey and water use behaviour audit was undertaken with almost every household to determine the basic demographic information, the water use stock present within the home, the efficiency of the water use stock, and the water use activities and behaviours of the residents. This task was relevant to assisting in the analysis and verification of end use water consumption within each household. The water audit consisted of determining some basic demographic information for the household, determining the water use fixtures and fittings within the household, and asking residents to explain how, and the duration of water fixture use and associated behaviours. This process enabled the establishment of the current water usage stock within the community and allowed for an understanding of how and when the residents consumed water within the home. The data was essential in the determination of fixtures and fittings within homes, the relative efficiency of fixtures, the perceived time of day and duration of use, and the water usage patterns and behaviours unique to each household. Additionally, this data enabled the development of Trace Wizard© templates for each home; they were used to determine the efficiency of the fixtures and to carry out the end use water consumption data analysis.

2.4 Trace Wizard analysis of end-use data

The data analysis, using the Trace Wizard©, included a visual inspection of the data, the checking of the consumption trends, and the representation of the results in tables and figures. Once the data set was established for each home, a validation process occurred through the revisiting of the water audit information and a cross-check with the bulk meter water consumption data from the conventional government billing system. This information assisted in ensuring that the daily and weekly end use water consumption data, and was on par with the households' bulk metered water consumption data. The water end use event obtained at the end of this analysis was the main resources for the overall model development

3 *Autoflow*© – A smart tool for water end use analysis

3.1 Overview of applied techniques

3.1.1 Hidden Markov Model (HMM)

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 observation probability, defined by a finite multivariate Gaussian mixture. Given an observed sequence $\mathbf{O} = (o_1,\ o_2, \dots o_t, \dots, o_T)$, a HMM model can be used to compute the probability of $\mathbf{O}$, denoted as $P(\mathbf{O}|\lambda)$ and to find the corresponding state sequence (Q) that maximises the probability of $\mathbf{O}$, denoted as $P(Q|\mathbf{O}, \lambda)$. In this study, HMM was utilised as one of the classifiers for water end use classification decision making based on the event shape pattern. However, the weakness of this technique is that HMM does not adequately classify end use categories that are highly dependent on user behavious. As a result, an additional technique that can inspect the physical features of these events was required to help differentiate between them.

3.1.2 Artificial Neural Network

To overcome the above mentioned issue, a technique called Artificial Neural Network (ANN) was employed. ANNs are comprised of one or more processing units called 'artificial neurons' or 'perceptrons' (Karayiannis and Venetsanopoulos, 1993). Perceptrons of an ANN are interconnected with one another by a series of weighted connections. The perceptrons of an ANN, depending on the system being replicated, are arranged in layers, with each perceptron of the preceding layer having a weighted connection with each neuron of the proceeding layer. In the process of ANN training to replicate a system, a training data set is fed through the network. Each perceptron processes the input data or input signal from either the input layer or the preceding perceptrons. The final layer of the ANN produces an output signal. The weights and structure of the network are altered in a manner depending on the specific training algorithm. In this study, a feed-forward network with back-propagation training algorithm is selected as the main tool to learn the typical pattern of each category in terms of physical characteristics (e.g. volume, duration, maximum flow rate, etc.).

3.1.3 Dynamic Time Warping algorithm

The last applied mathematical tool was Dynamic time warping (DTW) algorithm, which is a popular method for measuring the similarity between two time series of different lengths. In general, this task is performed by finding an optimal alignment between two series with certain restrictions. 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). The goal of DTW is to find a mapping path which has the minimal mapping distance. DTW played an important role in this study as 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.

3.2 System development

The first aim of this project was to develop a system for autonomous and intelligent residential water end-use classification, customer feedback and enhanced urban water management, which could interface with customers and water business managers via a web-portal to computer or mobile phone application. Figure 2 summarised three key tasks to achieve the proposed aims of the project and their implications on current urban water management practices:

- *Stage 1a*: Develope an intelligent model that autonomously disaggregates collected water flow trace signatures collected from the intelligent water meters into a categorised registry of water end-use events.
- *Stage 1b*: Equip the model with self-learning capabilities that enableed it to interpret untrained water end-use signature traces and apply the model in new regions in Australia and overseas. In the smart meter prototype stage of the project development, all analysis routines in Stages 1a and 1b were designed as firmware for smart meter on-board processing as well as software for cloud-based processing where required.
- *Stage 2*: Develope a commercial prototype smart meter that incorporates the Stage 1 developed intelligent and user-friendly water end-use pattern recognition system (e.g. cloud-based web and smartphone application) for both water consumers and water businesses

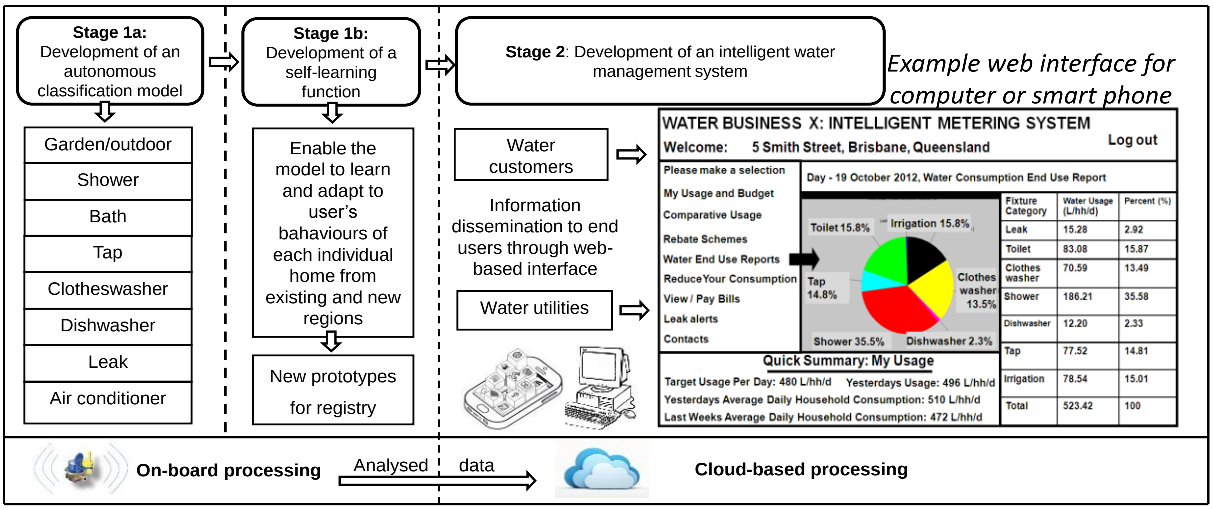

Figure 2 Autoflow© system development

3.3 System functionality

The system is currently being developed with two separate packages for water consumers (Figure 3.2a) and water utilities (Figure 3.2b). Once in place, it will allow the customer to track almost real-time water consumption on how and when water was consumed on their smartphone or web portal application. The "Set Target" function allows customer to set their targeted water consumption for the next 3-month period, and SMS notification will be sent to customer when the consumption reaches any predefined threshold. Additionally, the "Comparative Usage" function will help customer to locate their water consumption level among other properties within the street or suburb, thus providing them more awareness and guidance on how to reduce the consumption.

With the package for water utility, model functions are being developed on a macro-level that allow various analyses to be undertaken. Some of the key modules can be described as follows:

(i) Overall End Use Analysis module to perform water end-use analysis for a large population
(ii) Demand forecasting module to forecast water demand on the next day based on consumption data of the last two weeks.
(iii) Customer demand feedback analysis module to conduct survey on customer satisfaction about the system as well as analyse the benefits obtained when implementing this system.
(iv) Diurnal pattern/Peak demand analysis module to analyse how the water was consumed in a 24-hour basis so that appropriate planning can be undertaken.

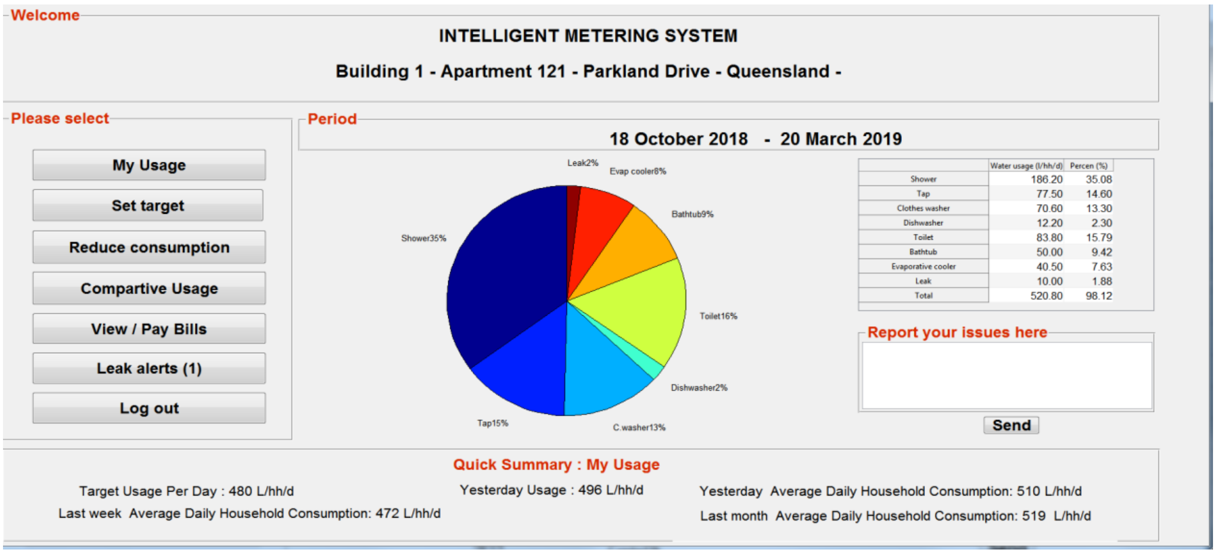

Figure 3a *Autoflow©* package for water consumer

Figure 3b *Autoflow©* package for water utility

4 *Autoflow©* – A smart tool for water demand forecasting

The urban water demand forecasting task usually involves a range of variables measured at different periodicities, therefore, the question regarding which method to be employed for urban water demand forecasting cannot be adequately answered without specifying the forecast variable, its periodicity (i.e. daily, weekly, or monthly), and the horizon (i.e short term, medium term or long term forecast). A study conducted by Donkor et al., 2014 has shown the priorities of water utilities (in decreasing order) as forecasting demand for peak day; daily total system demand; monthly total system demand; annual per capita demand; annual demand by customer class; and revenue , each of which required different input variable to perform the task. This study focuses on modelling the top two priorities, *daily peak demand* and *daily total system demand*, by using the collected hourly water consumption data and average environment temperature in the previous 2-week period to predict the next day consumption.

4.1 Applied model for water demand forecasting

There are several models that have been used for water demand forecasting, including Univariate Time Series, ANN, Stochastic Process, Composite Model, Regression Model, Scenario based and Decision Support System. ANN and Composite models are powerful in dealing with complex data profile; however, they are only useful when long historic data is available for the training process. In a situation of limited data availability as is the case in this study (i.e. two week period), these models are not able to capture the overall data structure, and as a result, can lead to significant forecast error, especially when a multiple-steps-ahead forecast is required. Univariate Time series analysis is suitable only to a dataset that has repeated pattern and it does not allow the incorporation of effects from other independent variables. The stochastic process model and regression models are the two techniques that are able to handle problems with limited historic data for model development and also allow the incorporation of external input to help improve the overall forecast as in this study. Given the collected hourly water consumption having a periodic pattern as presented in Figure 4, a state-space model which is a combination of these two methods was obtained where its component including seasonality, temperature effect and residual were modelled as stochastic process.

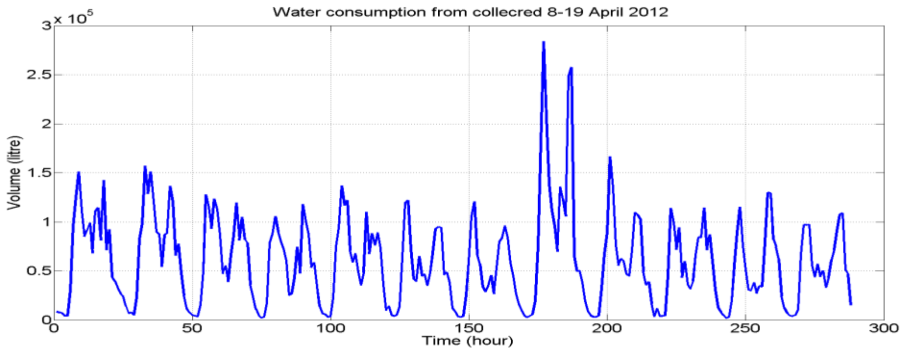

Figure 4 Collected water consumption at hourly interval

The model is considered as the observation equation of a discrete time, stochastic state model and the associated state equations were used to model each of the components in Gauss- Markov (GM) terms. The forecasting model in this study has the form of:

$$y(t) = S(t) + F(t) + e(t) \qquad e_t \sim N\{0, \sigma^2\} \qquad (1)$$

where $y(t)$ is the forecasted hourly water consumption data (litre/hour) 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 the external factor on the water consumption, which is the daily temperature in this case; and $e(t)$ is the noise component used to model the random changes of water consumption due different user behaviour. In order to allow for the nonstationary in the time series, all components in Eq. (1) can be characterised by stochastic, time variable parameters (Young, 1998, 1999). In this model, the most important component is the seasonal term $S(t)$ that determines the periodic pattern of the consumption data signal. Through the application of Kalman Filter to estimate each component of Eq. (1), the forecasted water consumption can be obtained.

4.2 Forecasting water demand of each end use category

The establishment of the forecast model developed in previous section allows future water demand to be predicted at an hourly basis. With the assistance of *Autoflow©*©, this predicted demand can be further disaggregated into an end-use level using the following steps:

(i) Perform an end-use analysis using the previous two-week data, whose pattern would reflect the current consumption trend of the predicted day

(ii) With the disaggregated volume of all events obtained from step (i), determine the volume distribution for each category through Eq. (2), 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.

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

(iii) Apply this volume distribution on the predicted 24-hour demand ahead. Eq. (2) can be interpreted as: if $i = 1$ corresponds to shower category, $P_{1,7}$ will represent the percentage of shower volume in comparison with the total volume collected at 7 am during the last two weeks. For example, if $P_{1,7}$ = 25%, and the predicted water consumption at 7am of the next day is 1000 litres, then the predicted shower at 7 am is 250 litres. By doing this, predicted volumes of all categories can be determined (Figure 5).

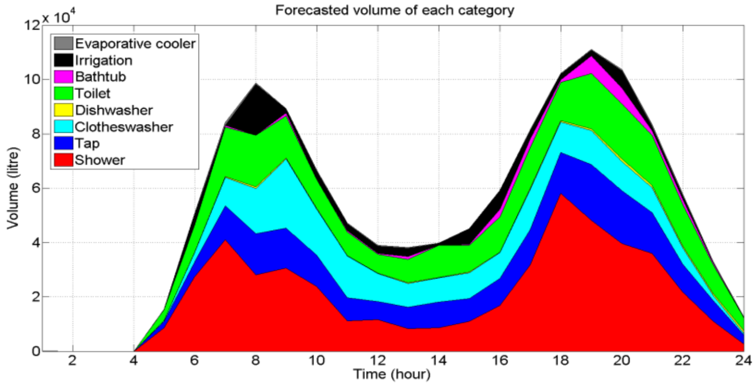

Figure 5 Forecasted volume of each end use category

5 *Autoflow©* – A smart tool for monitoring and predicting carbon emission

Table 1 Estimated carbon footprint of each category (National Greenhouse Account Factors, 2014)

Water end-use	Hot water (%)	Carbon emission for supply (gCO_2/litre)	Carbon emission for heating (gCO_2/litre)	Carbon emission for treatment (gCO_2/litre)	Total carbon emission (gCO_2/litre)
Bath	78.2	0.59	42	1.25	43.84
Clothes washer	27.8	0.59	15	1.25	16.84
Dishwasher	100	0.59	53	1.25	54.84
Tap	72.7	0.59	38	1.25	39.84
Leak	26.8	0.59	14	1.25	15.84
Shower	73.1	0.59	39	1.25	40.84
Toilet	0	0.59	0	1.25	1.84
Irrigation	0	0.59	0	1.25	1.84

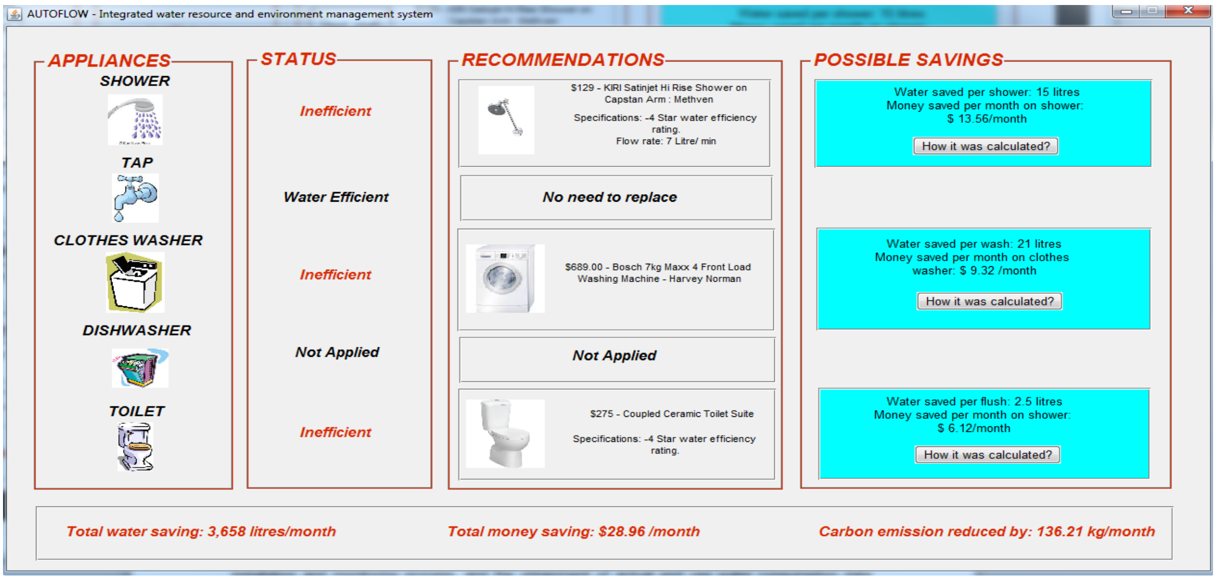

Figure 6 Suggestion for water saving

Carbon dioxide is a major contributor to climate change, and the need to offset or reduce carbon production has risen high in national and international political agendas. An effective water demand management strategy would result in lower energy use, which allows offsetting future energy pressures and reducing carbon emissions. Operating based on intelligent machine learning algorithms, once in-place, *Autoflow©* will allow this goal to be achieved from various angles:

- From customer side, reduction in carbon emission can be achieved in two ways: (i) An alert message will be automatically sent to customer when there is a leak present in their property, and (ii) A detailed notification about customer's water efficiency status for each water fixture is provided in association with suggestions for replacement (Figure 6). These two functionalities will enable customer to proactively address their water usages issues, thus allow water consumption as well as carbon emission to be cut off immediately. Table 1 summarised the estimated carbon footprint for one litre of water consumption for each residential end use category. From this, the total amount of carbon emission can be calculated and predicted based on the consumed and predicted water demand.

- From water utility side, the demand forecasting module will allow water utilities to better forecast and manage their water supply, as well as optimise their pipe network operation. Carbon emission can also be cut off through the reduction in power consumption to produce and treat excessive water. A two-way customer-water utility communication channel provided by *Autoflow*© will allow innovative management, incentive or rebate schemes initiated by the utility to be conveyed to customer instantly. The quick implementation of these strategies, rather than the currently slow process, will help save a significant amount of water, and hence lead the large reduction in carbon emission.

6 Conclusion

The establishment of an integrated water and environment management system, which employs smart water metering technology, is becoming increasingly feasible due to the work of the research team. The present study has proposed a novel approach for building such a complex system, which incorporated a wide range of machine learning, pattern recognition, predictive analysis, statistical and data analysis techniques. Still being in development phase after some initial successful trials conducted across Australia, it is expected that this research once completed will contribute to the development of new urban water and environment management systems that can deliver smart information to both customers and water businesses. This information will significantly enhance the awareness that customers have with their conventional water consumption habits, and contribute to the operational efficiency (and sustainability) of water businesses. The system will also have significant contribution to overall environment protection theme through providing water business with an effective tool to better forecast water demand, evaluate appliance rebate programs (e.g. showerhead replacements) and better model and manage hydraulic networks, thus allow the reduction of the carbon amount released to the atmosphere.

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