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ANN-based residential water end-use demand forecasting model

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ABSTRACT

Bottom-up urban water demand forecasting based on empirical data for individual water end uses or micro-components (e.g., toilet, shower, etc.) for different households of varying characteristics is undoubtedly superior to top-down estimates originating from bulk water metres that are currently performed. Residential water end-use studies partially enabled by modern smart metering technologies such as those used in the South East Queensland Residential End Use Study (SEQREUS) provide the opportunity to align disaggregated water end-use demand for households with an extensive database covering household demographic, socio-economic and water appliance stock efficiency information. Artificial neural networks (ANNs) provide the ideal technique for aligning these databases to extract the key determinants for each water end-use category, with the view to building a residential water end-use demand forecasting model. Three conventional ANNs were used: two feed-forward back propagation networks and one radial basis function network. A sigmoid activation hidden layer and linear activation output layer produced the most accurate forecasting models. The end-use forecasting models had R^2 values of 0.33, 0.37, 0.60, 0.57, 0.57, 0.21 and 0.41 for toilet, tap, shower, clothes washer, dishwasher, bath and total internal demand, respectively. All of the forecasting models except the bath demand were able to reproduce the means and medians of the frequency distributions of the training and validation sets. This study concludes with an application of the developed forecasting model for predicting the water savings derived from a citywide implementation of a residential water appliance retrofit program (i.e., retrofitting with efficient toilets, clothes washers and shower heads).

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1. Introduction

The urbanised South East Queensland (SEQ) region in Australia, like many other inhabited regions, faces a series of complex problems involving the supply and demand management of water resources. From 2005 to 2008, SEQ endured a severe drought in conjunction with high population growth (Queensland Water Commission, 2009). In response, water demand management programs and policies were instituted to reduce demand and prolong the duration of an adequate supply of water. However, given that there was inadequate understanding of the relationship between end-use water demand (e.g., for showers) and household characteristics, the effectiveness of the water demand management schemes (e.g., a shower head replacement program) was difficult to determine with any degree of precision (Queensland Water Commission, 2009). In response to this limited understanding of residential water end-use demand, the South East Queensland Residential End Use Study (SEQREUS) was funded by the Queensland State Government (see Beal & Stewart, 2011c). The SEQREUS resulted in a large database containing aligned water end-use data for over 250 households, water appliance stock efficiency data, demographic data and socio-economic data. Artificial neural networks (ANNs) was deemed the most suitable technique to exploit this database to develop a residential water end-use demand forecasting model for the primary purpose of determining the effectiveness of a range of water demand management programs (e.g., household appliance stock retrofit programs).

2. Background

2.1. Residential water end-use studies

Residential water end-use studies utilise high-resolution smart water metering, data logging, flow trace analysis and surveys to determine the volume and features of each water end use, such as tap water use, clothes washer, dishwasher, shower, toilet, bath, irrigation and miscellaneous. These studies result in a comprehensive registry of disaggregated water consumption end uses (Beal & Stewart, 2011c; Beal, Stewart, & Huang, 2010; Gato, Jayasuriya, & Roberts, 2011; Loh & Coghlan, 2003; Willis, Stewart, Panuwatwanich, Capati, & Giurco, 2009; Willis, Stewart,

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Panuwatwanich, Williams, & Hollingsworth, 2011). Information gathered from end-use studies and associated stock efficiency, socio-demographic and intervention studies allows greater understanding of the predictors of end-use water demand (Beal, Stewart, & Fielding, 2011b; Gato et al., 2011; Heinrich, 2009; Loh & Coghlan, 2003; Makki, Stewart, Panuwatwanich, & Beal, 2011; Mayer, De Oreo, Optiz, Kiefer, Davis, 1999; Willis, Stewart, Panuwatwanich, Jones, & Kyriakides, 2010; Willis et al., 2011). Such detailed stochastic information can inform enhanced urban water demand practices and policy. The end-use study dataset underpinning this empirical modelling study is described briefly in the next section.

2.2. SEQREUS

The SEQREUS was a $1 M research project funded by the Urban Water Research Security Alliance (UWRSA) from 2009 to 2011 and completed by the Smart Water Research Centre (SWRC) located at Griffith University. The objectives of the greater SEQREUS were to calculate household and per capita disaggregated consumption, reveal key determinants of water end-use demand, study diurnal demand patterns at an end-use level and assess the influence of water-efficient appliances (Beal & Stewart, 2011c). This particular sub-study utilises an end-use dataset collected in June 2010 covering 252 detached households in four interconnected cities (i.e., Brisbane, Gold Coast, Ipswich and Sunshine Coast) located in the greater SEQ region. Moreover, this sub-study employs a comprehensive aligned dataset consisting of appliance stock efficiency, demographic and socio-economic variables for each of these households. These aligned datasets provided the foundations of the ANN-based residential water end-use demand forecasting model discussed here and associated water efficiency retrofit program simulation. The model focused on the internal demand end uses, which were consistent over the study period. The irrigation or outdoor end-use category was not included in this forecasting model because this end-use category is highly variable from day to day and requires end-use data over numerous seasonal periods over many years to provide a satisfactory dataset. However, the omission of the outdoor end-use category is not considered a limitation of this present study, as the key goal was to model scenarios of water stock efficiency and demographic parameters for different households, thereby informing best-practice water efficiency programs.

2.3. Reported predictors of water end-use demand

The predominant variables influencing total and disaggregated water demand include socio-economic and demographic variables, regional and climatic variables and appliance stock efficiency (Beal et al., 2010; Beal et al., 2011b). This purpose of this section is to outline the reported variables affecting total and disaggregated water demand.

Socio-economic and demographic variables include household size, number of adults, number of children, number of teenagers, gender, age, income and education. Socio-economic and demographic variables are not generally independent and can thus be correlated with one another (Neter, Wasserman, & Kutner, 1983). Highly correlated socio-economic and demographic variables can therefore be used as proxy variables (Arbues, Garcia-Valinas, & Martinez-Espineira, 2003). The typical practice when developing linear regression models is to include interaction terms between interrelated variables to reduce over-explanation of the system and error terms (Neter et al., 1983).

Household size or occupancy has a highly significant causal relationship to both per household demand and per capita demand. As expected, as occupancy of a household increases, so does its demand for water. However, an increase in water demand with an increasing number of household occupants is by no means a linear relationship (Beal, Stewart, Huang, & Rey, 2011a; Gato et al., 2011; Heinrich, 2009; Lee, Park, & Jeong, 2012). Conversely, when analysing per capita demand against household occupancy, household per capita consumption decreases as household size increases (Beal et al., 2010; Gato et al., 2011). The decrease in per capita consumption with increasing consumption relates to an 'economy-of-scale' effect within the household (Beal et al., 2011a). Additionally, reduced per capita consumption could be related to greater competition for water using devices in peak periods, thereby reducing each occupant's usage (i.e., reduced time in the shower during the morning rush).

Considering the age characteristics of household occupants provides a better estimate of end use consumption (Makki et al., 2011). On average, households with younger children are lower water consumers than households containing predominantly teenagers, especially for shower use. Arbues et al. (2003) describes an optimum household size as well as the point where the economies of scale vanish, based on a correlation between the age gap between offspring and, hence, a greater possibility of more teenagers occurring in a larger household.

Beal et al. (2011a) observed that older households, based on average occupant age, used more water per capita than younger households. Willis et al. (2009) hypothesised that retired individuals spend a relatively greater proportion of their time at home and thus have a greater opportunity to use water-dependent appliances. Similarly, Kenney, Goemans, Klein, Lowrey, and Reidy (2008) observed that as the mean age of a household increases, so does household water consumption. Kenney et al. (2008) also outlined the correlation between age, household income and wealth, noting that the increase of water consumption per household is a result of the combination of these variables.

Household income has been reported to have a variety of relationships with water consumption. Loh and Coghlan (2003) found that households with greater incomes have greater per capita and household water consumption than households with lower incomes, due mainly to much higher discretionary irrigation end-use demand. Beal et al. (2011a) outlined a trend of larger, high-income households using less water per capita than smaller, low-income households. Kenney et al. (2008) also observed that higher income households consume more water on a household basis than lower income households. The conflicting results highlight the importance of reporting water demand in water end-use categories (e.g., shower use) and on a per capita basis. Such reporting provides a levelised comparison.

Water-use stock and appliance efficiency, commonly measured by water efficiency labelling schemes (e.g., *WELS* in Australia and *WaterSense* in the United States), is the unit amount of water used or consumed per unit of time (e.g., min) for a particular water end use device. Higher efficiency ratings (e.g., 5 stars) have lower water consumption (i.e., 6 L/min). Beal et al. (2011a) analysed the efficiency of clothes washers and shower heads against daily per capita water consumption. Clothes washers rated 3 stars or less had an average of 35.1 L/p/d consumption, whereas clothes washers having 4 stars or less had an average consumption of 28.3 L/p/d. This difference equates to a saving of 6.6 L/p/d (Beal et al., 2011a). Similar stock efficiency comparisons for shower heads showed a significant 13.9 L/p/d saving (Beal et al., 2011a). Other studies have reinforced this finding, showing that water efficient appliances result in decreased water demand (Gato, 2006; Heinrich, 2009; Kenney et al., 2008).

2.4. Residential water end use demand modelling

The modelling of residential water end-use demand requires the application of analytical techniques (e.g., Bayesian networks, multi-variable regression and stochastic modelling) and an extensive database of predictor variables. While a number of studies have presented models that are capable of predicting total residential demand (Froukh, 2001; Jorgensen, Graymore, & O'Toole, 2009; Polebitski & Palmer, 2010), far fewer studies have attempted to predict water end-use demand. The advent of high-resolution smart metering and water end-use disaggregation software tools have allowed end-use modelling to be performed with a reasonable degree of accuracy.

Gato (2006) employed a multi-variable regression approach, applying empirical information collected from the Melbourne Residential End Use Study. Various tailored demographic variables were used to predict the demand of particular water end uses. Predictor variables identified from regression modelling included the number of adults, the number of children less than 12 years of age, the number of children 12 and older, and appliance information, such as ownership of a dishwasher, the type of clothes washer and the fraction of dual flush toilets in the household. Significant prediction models were produced for the following water end uses: total internal demand; toilet demand; shower demand; clothes washer demand; dishwasher demand; and tap demand.

Blokker, Vreeburg, and Dijk (2010) developed a stochastic end-use model based on demographics, end-use category frequency of use, flow duration and event occurrence likelihood to simulate water demand patterns. To develop this stochastic end-use model, a Poisson rectangular pulse model was derived from smart water metering studies and surveys (Blokker et al., 2010). The final stochastic end-use model approach developed by Blokker et al. (2010) accounted for 0.93 of the observed variance for the diurnal pattern of water demand.

Hsiao, Mountain, and Illman (1995) adapted a Bayesian conditional demand framework to develop a forecasting model to predict electric water heating associated with residential water demand end uses. The construction of the Bayesian models involved the formation of appliance dummy variables and transforming the variables into fractions of demographics and weather variables (Hsiao et al., 1995). The variables were then combined with aggregated loads, appliance ownership and demographic information. The method was applied to two data sets containing 49 and 347 homes, respectively, and produced models with acceptable relative errors ranging from 0.081 to 0.298.

There have been some recent attempts to predict residential water end-use demand. While these techniques appeared satisfactory by meeting certain statistical significance or reliability thresholds, each technique had particular advantages and weaknesses. The multi-variable regression modelling approach applied by Gato (2006) benefits from being less complex than the other methods but is susceptible to over-predicting the system due to multicollinearity of independent variables (Hsiao et al. 1995). The stochastic modelling approach benefits by its universal applicability because it is not reliant on direct measurements (Blokker et al., 2010). The Bayesian conditional demand framework using a small sample of metered houses and aggregated load information can produce accurate models (Hsiao et al., 1995).

Modelling residential water end-use demand invariably is a process mired in the highly variable preferences of consumers and intercorrelated nonlinear demographic information. High-income category households, as compared to other income categories, are observed to have a higher frequency of children in the household. The reasoning behind this observation is that, as people age, they move into higher income brackets corresponding to their experience in the work force, and with age they are more likely to get married and have children. ANN modelling techniques have an ability to adapt, learn and generalise relationships occurring within input information (Karayiannis & Venetsanopoulos, 1993). To improve on the modelling of residential water demand end uses, due to the properties of the ability to adapt, learn and generalise, ANN modelling techniques are predicted to be better suited to dealing with highly variable data sets and intercorrelated nonlinear inputs.

3. Artificial neural networks

3.1. Overview

ANNs are comprised of one or more processing units called 'artificial neurons' or 'perceptrons' (Karayiannis & 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.

3.2. Perceptron

The perceptron is comprised of several components including the weights of the inputs, the summation function, the activation function and the output (Karayiannis & Venetsanopoulos, 1993). The weights of the inputs act as a linear multiplier to change the magnitude of the input value. There is an input weight connected to the neuron for each input variable. The summation function acts to sum all weighted input signals. The summation term is then inputted into the activation function to produce an output. The activation function of the perceptron is dependent on the type of ANN and the desired application.

3.3. ANN structure

The structure of an ANN falls into one of two main categories: single-layer networks and multiple-layer networks. Single-layer networks comprise an input layer of values and an output layer of perceptrons. Multi-layered networks consist of an input layer of values, one or more hidden layers of perceptrons and an output layer of perceptrons. The number of perceptrons in each layer is dependent on the nature of the model being predicted.

3.3.1. Linear Activation Perceptron

Eqs. (1)–(3), below, display the function of the linear activation perceptron.

$$v_j = \sum_{h=1}^{m} w_{jh} x_h \tag{1}$$

$$\sigma(v_j) = v_j \tag{2}$$

$$Y_j = \sigma(v_j) \tag{3}$$

where x is the input vector of input variables, x_h is the input variable h of the input vector, m is the number of input variables, w_{jh} is the weighted connection from input variable h to perceptron j, vj is the summation term of perceptron j, σ is the perceptron activation function, and Y_j *is the* output from perceptron j.

3.3.2. Sigmoid activation perceptron

Eqs. (4)–(6), below, display the function of the sigmoid activation perceptron,

$$v_j = \sum_{h=1}^{m} w_{jh} x_h \tag{4}$$

$$\sigma(v_j) = \frac{6}{1 + e^{-\alpha v_j}} - 3 \tag{5}$$

$$Y_j = \sigma(v_j) \tag{6}$$

where the variables are defined as above.

3.3.3. Radial basis function perceptron

Eq. (7), below, displays the function of the radial basis function perceptron.

$$Y_j(x) = \sqrt{1 + \frac{h}{d^2} ||x - c_j||} \tag{7}$$

where x is the input vector of input variables, c_j is the radial basis centre of perceptron j, h is the number of hidden perceptrons, d is the greatest Euclidean distance between radial basis centres, and Y_j *is the* output from perceptron j.

3.3.4. Error back propagation

The weights connecting the hidden layer to the output layer are updated according to error back propagation by Eq. (8) below.

$$w_{ki}(t+1) = w_{ki}(t) + \alpha(Y_{jk} - Y_k)\sigma'(v_k)Y_i \tag{8}$$

where Y_i is the output from perceptron i of the hidden layer, Y_{jk} is the output from perceptron k of the output layer, Y_k is the observed value of perceptron k, v_k is the summation term of perceptron k, α is the training rate, w_{ki} is the weighted connection from the output of the hidden perceptron i to perceptron k, $w_{ki}(t)$ is the weight of the current epoch, and $w_{ki}(t+1)$ is the weight of the next epoch.

The weights connecting hidden layers are updated according to error back propagation by Eq. (9), below.

$$w_{ih}(t+1) = w_{ih}(t) + \alpha\left(\sum_{k=1}^{m}(Y_{jk} - Y_k)\sigma'(v_k)w_{ki}\right)\sigma'(v_i)x_h \tag{9}$$

where Y_i is the output from perceptron i of the hidden layer, Y_{jk} is the output from perceptron k of the output layer, Y_k is the observed value of perceptron k, v_k is the summation term of perceptron k, α is the training rate, w_{ki} is the weighted connection from the output of the hidden perceptron i to perceptron k, x is the input vector of variables, x_h is the input variable h, m is the number of output perceptrons, v_i is the summation term of perceptron i, w_{ih} is the weighted connection from the input variable x_h to perceptron i, $w_{ih}(t)$ is the weighted connection of current epoch, and $w_{ih}(t+1)$ is the weighted connection of the next epoch.

3.3.5. Hybrid training method

The radial basis centre is selected according to the minimum Euclidean distance between the input vector and the radial basis centres.

$$c_{\min} = \min(||x - c_i||_{i=1}^{n}) \tag{10}$$

where x is the input vector, c_i is the radial basis centre of perceptron i, n is the number of radial basis perceptrons, and $c_{\min}$ is the radial basis centre pertaining to the minimum Euclidean distance.

The accuracy of the RBFN is calculated using the RMSE function. If the minimum Euclidean distance between the input vector and the radial basis centres is above a specified threshold v and the RBFN accuracy *acc* is less than the desired level, the associated radial basis centre is shifted towards the input vector:

$$c_{\min}(t+1) = \begin{Bmatrix} c_{\min}(t) + \alpha[x - c_{\min}], & \mathit{if}(||x - c_{\min}|| \geqslant v \wedge \mathrm{RMSE} \geqslant acc \\ c_{\min}(t), & \mathit{otherwise} \end{Bmatrix} \tag{11}$$

where x is the input vector, c_i is the radial basis centre of perceptron i, n is the number of radial basis perceptrons, and $c_{\min}$ is the radial basis centre pertaining to the minimum Euclidean distance, v is the threshold, *acc* is the level of accuracy in terms of RMSE, α is the training rate, $c_{\min}(t)$ is the radial basis centre of the current epoch, and $c_{\min}(t+1)$ is the radial basis centre of the next epoch.

The weights connecting the radial basis function perceptrons to the output layer are calculated by error back propagation.

3.4. Hidden layer sigmoid activation

The Hidden Layer Sigmoid Activation (HLSA) Network consists of one input layer, a hidden layer of sigmoid activation perceptrons and an output layer of sigmoid activation perceptrons. The sigmoid activation function of the HLSA has been modified so that the output of the function can incorporate normalised values from −3 to +3 to allow the network to process transformed data. The HLSA is trained according to Error Back Propagation.

3.5. Hidden layer sigmoid activation linearly activated output

The Hidden Layer Sigmoid Activation Linearly Activation Output (HLSALAO) network is a hybrid network consisting of an input layer, a hidden layer of sigmoid activation perceptrons and an output layer of linearly activation perceptrons. The sigmoid activation function of the HLSALAO has been modified so that the output of the function can incorporate normalised values from −3 to +3 to allow the network to process transformed data. The HLSALAO is trained according to Error Back Propagation.

3.6. Radial basis function network

The Radial Basis Function Network (RBFN) is structured according to an input layer, a hidden layer comprised of radial basis function perceptrons and an output layer consisting of linearly activated neurons. The radial basis centres of the radial basis function perceptrons are selected from the sample training set at random. The RBFN is trained according to the hybrid training method.

4. Research objectives

The objectives of this research investigation were the following:

1. Explore the feasibility of applying ANNs to the problem of residential water end use demand forecasting;
2. Develop an ANN-based residential water end use demand forecasting model; and
3. Apply the developed ANN-based model to simulate the potential savings derived from a water demand reduction retrofit program (e.g., retrofitting low efficiency shower heads and clothes washers with others of higher efficiency).

5. Method

5.1. Overview

To achieve the stated research objectives, the following key research stages were followed:

1. Identification of key determinants influencing residential end use demand.
2. Normalisation of the training and validation dataset provided.

3. Training of ANNs to produce disaggregated residential water demand end use models.
4. Statistical analysis of ANN-produced results related to both the training and validation sets to ensure that they meet accuracy statistical significance criteria.
5. Development of an interactive water end use demand forecasting tool that can be used for a number of purposes, including examining the potential savings achievable from water appliance/fixture retrofit programs.

5.2. Information and ANN input

The SEQREUS provided a usable sample of 205 households that contained the entire dataset (i.e., water end-use data, water stock efficiency data, and demographic data for each household). For the analysis, a training set containing 175 samples was randomly selected, with the remaining 30 samples used for model validation

The numerous socio-economic, demographic and appliance efficiency variables within the dataset were selected as independent variables. These variables were the following: region; income; education level; occupancy; number of adults; number of children; number of teenagers; star rating of fixtures/appliances (i.e., tap, shower, clothes washer); and the installation of a dishwasher. The end use (e.g., shower) mean daily per household water consumption (i.e., L/hh/d) determined from the end use analysis process was set as the dependent variable.

For the purpose of identifying the significant determinants and subsequent inputs into the ANN models, the participant data collected by the SEQREUS was organised in ordinal categories. Table 1 details the established ordinal categories for the independent variables (i.e., socio-economic and demographic information).

The efficiency of the water stock fixtures and appliances has been recorded and categorised in an ordinal manner according to the Water Efficiency Labelling Scheme (WELS) (AS/NZS 6400:2005). Table 2 displays the WELS categories for the various water use appliances such as taps, showers, clothes washers, dishwashers and toilets.

5.3. Models

Model development was limited to predicting the homogeneous internal demand component of total residential demand. Outdoor irrigation demand was not included in the forecasting model. While these end-use data (i.e., irrigation end-use consumption) was available for three seasonal periods, this amount of data was not considered sufficient for a predictive model due to the highly variable nature of this end use (i.e., irrigation volumes change from day to day depending largely on environmental conditions such as temperature, humidity and rainfall). Additionally, household leakage was not considered in this internal demand model as this end use is also highly inconsistent, and its prediction is related to a range of other predictor variables not collected in this particular study (i.e., age of home, pipe material, toilet type, etc.).

In summary, the ANN methodology and the refined dataset of independent variables were used to develop a forecasting model to predict the consumption values of each of the following dependent variables (i.e., end-use categories and total indoor) on a litre per household per day (L/hh/d) basis: toilet demand; clothes washer demand; shower demand; dishwasher demand; tap demand; and total internal demand.

Table 1
Evaluated predictor variable descriptions.

Category	Income category ($)	Education category	Age category	Region	Occupancy
1	<30,000	Primary school	15–24	Gold coast	1
2	30,000–59,999	High school	25–54	Brisbane	2
3	60,000–89,999	Trade/TAFE/Tertiary	55–64	Ipswich	3
4	90,000–119,999	Undergraduate	>64	Sunshine coast	4
5	>120,000	Postgraduate	–	–	5
6	–	–	–	–	6

Table 2
WELS summary.

Star rating	Tap (L/min)	Shower (L/min)	Clothes washer	Dishwasher	Toilet (L/flush)	
					Half	Full
0	>16	>16	Star rating of clothes washer is calculated according to the outline in section 2.3.5 of the AS/NZS 6400:2005.	Star rating of dishwasher is calculated according to the outline in section 2.3.5 of the AS/NZS 6400:2005.	–	–
1	12–16	12–16			<4.5	<9.5
2	9–12	9–12			<4.5	<9.5
3	7.5–9	7.5–9			<3.5	<6.5
4	6–7.5	6–7.5			<3.2	<4.7
5	4.5–6	4.5–6			–	<4.7
6	<4.5	–			–	<4.7

6. Identifying key determinants

The demographic and stock efficiency variables did not fulfil the requirements of normality of distribution and homogeneity of variances. Therefore, to identify key determinants that can be attributed to the effects of residential end uses, non-parametric tests such as the Kruskal-Wallis (KW) test and the *Mann–Whitney* Wilcoxon (MW) rank sum test were used to determine difference in distributions. A confidence interval of 90% was used to determine statistical significance. Linear regression analysis was applied to observe the statistical power of continuous variables to predict and account for the variance of residential water demand end uses. Table 3 below displays the independent variables, the mean values of the variables organised into ordinal categories, the statistical tests performed, the associated chi-square p-values and the linear regression analysis.

The predominant key determinants affecting residential water demand end uses include household income, occupancy, the occurrence of children and the occurrence of teenagers. According to the WELS system, appliance stock efficiency was statistically significant only pertaining to toilet demand. Shower stock efficiency was found to be statistically significant when re-clustering star ratings into below two and above and equal to two. The identification of key determinants has revealed that each independent variable has at least one relationship of statistical significance with residential water demand end uses. Table 4 displays the input variables used to develop the disaggregated residential water demand end use models.

7. Results and discussion

7.1. Examined ANN algorithms

Table 5 displays the absolute relative error (ARE), average absolute error (AAE), root mean squared error (RMSE), Mann–Whitney

Table 3
Identification of significant determinants.

Independent variable	Ordinal category distribution mean (L/hh/d)						ANOVA			Regression	
	0	1	2	3	4	5	Test	df	p-value	Gradient	R^2
Total internal demand											
Region		352.26	338.19	286.22	333.86		KW	3	0.50		
Income		247.21	330.05	375.50	443.78	343.69	KW	4	0.00		
Education		344.75	303.95	330.09	338.92	373.00	KW	4	0.28		
No. of adults		241.74	342.45	406.23	493.13		KW	3	0.00	68.87	0.10
No. of children		421.72	390.35	478.73			KW	2	0.43	61.21	0.07
No. of children*	303.23	421.59					MW	–	0.00		
No. of teenagers		454.1	543.9				MW	–	0.24	150.57	0.18
No. of teenagers*	306.73	506.74					MW	–	0.00		
Toilet demand											
Region		47.54	50.54	50.09	59.77		KW	3	0.03		
Income		49.72	53.99	51.21	64.36	55.75	KW	4	0.14		
Education			47.65	52.73	44.36	55.71	KW	3	0.59		
No. of adults		0.00	0.00	0.00	0.00		KW	4	0.00	11.51	0.10
No. of children		45.96	56.8	66.04			KW	2	0.652	4.23	0.01
No. of children*	52.66	55.43					MW	–	0.38		
No. of teenagers		59.06	59.06				MW	–	0.203	22.41	0.05
No. of teenagers*	51.57	65.51					MW	–	0.04		
Star rating	69.02	55.25	47.69	39.87			KW	5	0.01	−9.39	0.11
Tap demand											
Region		87.86	54.17	55.08	49.85		KW	3	0.00		
Income		50.91	60.32	56.15	73.85	57.12	KW	4	0.14		
Education			57.93	55.47	59.33	61.84	KW	3	0.59		
No. of adults		39.38	65.05	71.22	104.24		KW	3	0.00	13.00	0.07
No. of children		60.76	56.87	60.76			KW	2	0.652	4.23	0.01
No. of children*	59.7	65.15					MW	–	0.22		
No. of teenagers		87.24	54.86				MW	–	0.203	38.96	0.17
No. of teenagers*	59.7	65.15					MW	–	0.03		
Star rating	57.41	79.01	25.91	27.18	25.43	21.86	KW	4	0.34	−0.17	0.00
Shower demand											
Region		93.50	94.80	103.90	106.20		KW	3	0.93		
Income		62.54	97.50	122.98	118.10	116.27	KW	4	0.00		
Education			88.24	91.51	95.57	90.28	KW	3	0.65		
No. of adults		73.21	104.15	129.11	126.43		KW	3	0.00	16.20	0.03
No. of children		99.42	123.2	179.4			KW	2	0.01	22.01	0.04
No. of teenagers		147.9	166.1				MW	–	0.06	53.32	0.11
Star rating	140.16	111.12	86.59	89.94	104.04	115.66	KW	–	0.59	−5.90	0.02
Star rating*		124.92	86.21				MW	–	0.04		
Dishwasher demand											
Region		5.24	6.18	4.55	5.31		KW	3	0.79		
Income		3.69	4.74	7.58	8.61	6.71	KW	4	0.03		
Education		2.30	5.51	4.41	7.03	8.25	KW	3	0.04		
No. of adults		9.25	9.59	12.66	16.90		KW	3	0.40	2.06	0.04
No. of children		7.62	9.31	9.80			KW	2	0.66	2.65	0.07
No. of children*	4.49	8.89					MW	–	0.00		
No. of teenagers		5.63	6.33				MW	–	0.81	1.29	0.01
No. of teenagers*	5.78	6.69					MW	–	0.09		
Has dishwasher	0.00	9.23					MW	–	0.00		
Clothes washer demand											
Region		63.23	89.65	57.96	60.81		KW	3	0.01		
Income		40.84	66.64	97.64	102.73	70.50	KW	4	0.00		
Education		62.86	64.98	74.06	83.84	68.61	KW	3	0.26		
No. of adults		46.42	80.12	84.20	120.70		KW	3	0.00	14.14	0.04
No. of children		104.68	97.47	109.60			KW	2	0.92	23.86	0.10
No. of children*	61.31	105.9					MW	–	0.00		
No. of teenagers		87.88	112.69				MW	–	0.98	22.38	0.08
No. of teenagers*	67.52	104.33					MW	–	0.01		
Loading (front/top)		50.74	79.21				MW	–	0.00		
Rating		118.14	81.18	84.36	64.37		KW	2	0.11		
Bath demand											
Region		7.76	5.75	0.23	3.84		KW	3	0.02		
Income		2.43	2.91	6.15	9.27	7.44	KW	4	0.04		
Education			2.20	5.51	7.67	4.55	KW	3	0.03		
No. of adults		5.20	27.61	31.82	7.20		KW	3	0.09	0.90	0.00
No. of children		9.38	6.54	3.61			KW	2	0.603	4.21	0.06
No. of Children*	2.78	10.86					MW	–	0.00		
No. of teenagers		4.41	7.77				MW	–	0.963	0.48	0.00
No. of teenagers*	4.66	5.38					MW	–	0.97		

* Represents a re-clustering of demographic or appliance variables to identify relationships between the variable the respected water demand end use to identify key determinants.

Table 4
Residential water demand end use forecasting model input variables.

Total internal demand	Toilet	Tap	Shower	Clothes washer	Dishwasher	Bath
Income	Income	Income	Income	Income	Income	Income
No. of adults	No. of adults	No. of adults	No. of adults	No. of adults	No. of adults	Education
No. of children	No. of children	No. of children	No. of children	No. of children	No. of children	No. of children
No. of teenagers	No. of teenagers	No. of teenagers	No. of teenagers	No. of teenagers	No. of teenagers	
Toilet star rating	Toilet star rating		Shower star rating 1	Clothes washer loading	Dishwasher installed	
Shower star rating 1			Shower star rating $\geqslant 2$	Clothes washer star rating		
Shower star rating $\geqslant 2$						
Clothes washer loading						
Clothes washer star rating						

Wilcoxon (MW) *P-value* and coefficient of determination (R^2) for each residential water end use demand forecasting model produced corresponding to the applied ANN algorithms. The ANN algorithms resulted in a number of residential water end use demand forecasting models with varying degrees of accuracy. The HLSALOA model had the highest R^2 and the least error. This model will be discussed further below.

7.2. HLSALOA residential water demand end use forecasting models

7.2.1. Analysis of error and variance

Table 6 displays the different residential water end-use demand values, ARE, AAE, RMSE, RMSE as % of mean and R^2 for the training set applied to the HLSALOA. The forecasting models produced by the HLSALOA varied in their ability to accurately predict demand. The forecasting model which had the least relative error was toilet demand and total internal demand, while dishwasher and bath demand forecasting models had the greatest error.

The forecasting models relating to toilet, tap, shower, clothes washer, dishwasher and total internal demand are statistically reliable because the RMSE is less than the observed means. Conversely, the bath demand forecasting model is not considered reliable because the RMSE value is greater than the observed mean. The R^2 values for the end use demand forecasting models ranged from 0.21 for bath demand to 0.6 for shower demand. Given that most end use demand models explained 50% or greater of the observed variance, the demand forecasting models are deemed moderately reliable.

Table 7 below displays the statistical analysis results when applying the validation data set to the forecasting models produced by the HLSALOA. Findings presented similar error levels to those of the training set. For the validation data set assessment, toilet, tap, shower, dishwasher and total internal demand forecasting models had prediction errors less than the observed means, indicating that they are reliable for predicting end-use demand levels in a household.

The ability of the developed tap, toilet, shower and dishwasher demand forecasting models to explain variability of the validation set was actually better than for the training set. The increased accuracy was likely a product of the random sampling to compile the set. The validation set has demand values closer to the predicted values of the models and or the expected values of the training set. With similarity to the training set, the clothes washer, bath and total internal demand forecasting models accounted for a level of variance similar to the training set. Prediction accuracy remaining robust for the validation testing analysis stage provides confidence that the input variables used to construct the forecasting models are reliable.

7.2.2. Analysis of prediction accuracy

The purpose of the following analysis is to determine whether the forecasting models can reproduce the residential water demand end use frequency distributions. If the forecasting models can reproduce the means and the medians of the distributions, the forecasting models are applicable on a macro or region-wide level. In turn, the forecasting models can be used for purposes such as simulating appliance retrofit programs.

Table 5
Applied artificial neural networks.

ANN applied	End use	ARE	AAE (L/hh/d)	RMSE (L/hh/d)	MW *p*-value	R^2
HLSA	Toilet	0.35	14.89	17.03	0.32	0.33
	Tap	0.62	20.36	26.25	0.10	0.28
	Shower	0.83	35.64	49.92	0.27	0.51
	Clothes washer	–	24.19	31.77	0.17	0.5
	Dishwasher	–	2.95	4.48	0.59	0.56
	Bath	–	5.87	11.52	0.00	0.25
	Total internal	0.34	79.59	102.36	0.29	0.28
HLSALOA	Toilet	0.36	14.19	18.03	0.24	0.33
	Tap	0.52	18.53	24.47	0.3	0.37
	Shower	0.81	32.44	45.25	0.17	0.6
	Clothes washer	–	25.81	32.86	0.17	0.57
	Dishwasher	–	2.91	4.43	0.48	0.57
	Bath	–	6.03	11.80	0.00	0.21
	Total internal	0.30	69.48	87.77	0.47	0.47
RBFN	Toilet	0.34	13.73	17.70	0.34	0.36
	Tap	0.63	20.30	26.21	0.20	0.28
	Shower	0.90	38.56	54.60	0.13	0.42
	Clothes washer	–	27.53	36.54	0.08	0.47
	Dishwasher	–	3.31	5.04	0.17	0.45
	Bath	–	5.96	11.81	0.00	0.21
	Total internal	0.31	70.37	91.32	0.38	0.43

Table 6
Training set analysis statistics.

End use	Mean of observed	ARE	AAE (L/hh/d)	RMSE (L/hh/d)	RMSE % of mean	R^2
Toilet	49.69	0.36	14.19	18.03	36	0.33
Tap	56.64	0.52	18.53	24.47	43	0.37
Shower	92.24	0.81	32.44	45.25	49	0.6
Clothes washer	66.53	–	25.81	32.86	49	0.57
Dishwasher	5.40	–	2.91	4.43	82	0.57
Bath	3.96	–	6.03	11.80	297	0.21
Total internal	284.89	0.30	69.48	87.77	30	0.47

Table 7
Validation set analysis statistics.

End use	Mean of observed	ARE	AAE (L/hh/d)	RMSE (L/hh/d)	RMSE % of mean	R^2
Toilet	51.26	0.37	13.82	18.57	36	0.51
Tap	55.13	0.36	13.96	18.83	34	0.69
Shower	91.97	0.82	24.36	31.17	33	0.75
Clothes Washer	65.96	0.35	19.61	26.26	29	0.56
Dishwasher	4.46	–	2.08	3.21	71	0.66
Bath	2.84	–	4.93	8.85	311	0.23
Total Internal	282.98	0.31	62.34	80.01	28	0.47

Fig. 1 displays the mean of the observed and predicted standard mean and the t-test p-value for the training set and validation set of each end use forecast model produced by the HLSALOA. The t-test derived p-values range from 0.85 for dishwasher demand to 0.96 for total internal demand for the training set. The t-test derived p-values range from 0.74 for dishwasher demand to 0.97 for toilet demand for the validation set. In all cases, the residential water demand end-use models produced distributions according to the training and validation sets that did not deviate from the observed water demand distributions to a statistically significant level, providing evidence that the models produced can accurately forecast the distributions of residential end-use demands for a set of households.

A similar analysis was performed for the analysis of the replication medians for the training and validation sets under the Mann–Whitney Wilcoxon rank sum test. Apart from bath residential water demand end use, predicted demand distributions reproduced the medians of the observed demand distributions without deviating to a statistically significant level. In conjunction with the analysis of means, this correspondence of predicted values to observed values provides further evidence that the forecasting models, with bath demand as the exception, can accurately forecast the distributions of residential end-use demands for a set of households.

8. Model application: appliance retrofit program simulation

The most valuable application of the residential water end-use demand forecasting models developed in this study is for the estimation of water savings attributed to a range of water appliance retrofit programs (e.g., retrofitting toilets from low to high efficiency). Toilet demand, shower demand and clothes washer demand retrofit programs have been selected to exemplify the application of the residential water end use demand forecasting models. To aid in the retrofit program simulations, an interactive residential water end use demand forecasting tool was developed populated by the forecasting models. The 205 household samples from the SEQREUS were used for the appliance retrofit program simulations discussed below.

8.1. Retrofit programs and results

Table 8 displays the distribution of the sample based on their clustered star ratings and the associated demand values for the toilet, shower and clothes washer end use categories. Also, the overall average mean household demand for these end use categories is provided. Three retrofit programs were simulated using the developed ANN-based water end use demand forecasting model, namely:

- Toilet retrofit program simulating the installation of 3 star-rated toilets in residential premises that have toilet star ratings of <2;
- Shower head retrofit program simulating a retrofit of shower-heads of <2 star rating shower head with those having ⩾2 star rating; and
- Clothes washer retrofit program simulating the installation of 4 star front loading clothes washers to replace those having <4 star rating and not being front loading.

The program is assumed to have a 100% penetration rate. Table 9 details the baseline mean household demand for each of the retrofitted end use appliances, the projected post-retrofit water demand pertaining to each end use, and the mean household savings. The toilet retrofit program had the highest mean daily household saving of 20.54 L/hh/d (i.e. 7.55 kL/hh/y). Conversely,

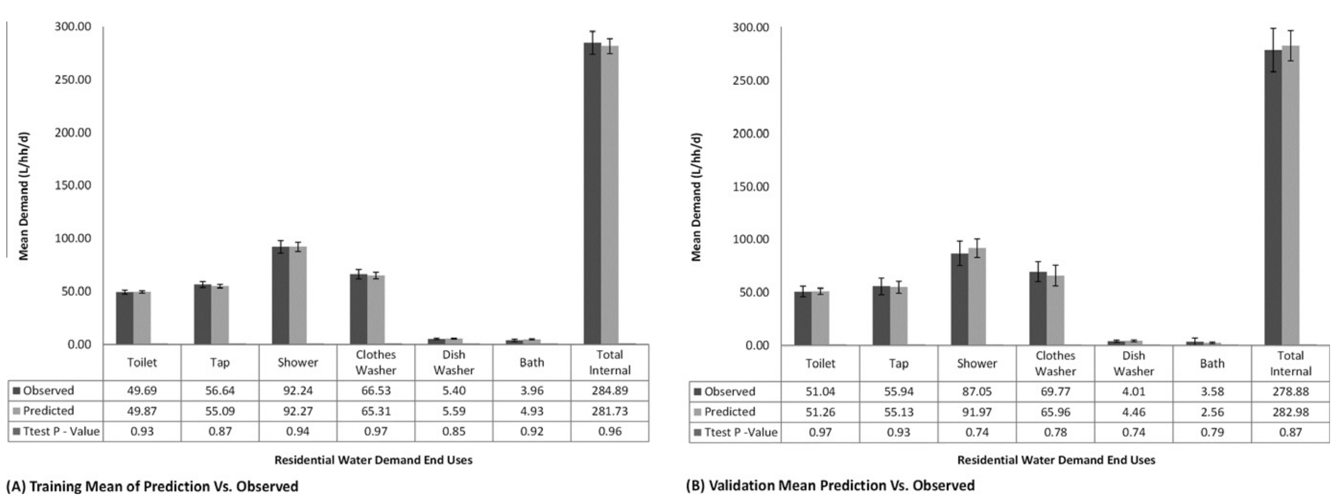

Fig. 1. Analysis of training and validation predicted demand distributions vs. observed demand distributions.

Table 8
Retrofit program water end uses demand distribution.

Category	WELS star rating					
Toilet end use	0	1	2	3	4	Overall
Number of samples	52	68	56	29		205
Percent of sample set (%)	25.37	33.17	27.32	14.15		100.00
Mean household demand (L/hh/d)	88.84	60.29	45.17	38.96		60.39
Shower	<2[a]		⩾2[a]			Overall
Number of samples	40		165			205
Percentage of sample set (%)	19.55		80.45			100.00
Mean household demand (L/hh/d)	104.25		86.61			90.05
Clothes washer	0	1	2	3	4	Overall
Number of samples	20	5	19	58	103	205
Percentage of sample set (%)	9.76	2.44	9.27	28.29	50.24	100.00
Mean household demand (L/hh/d)	58.51	108.02	77.36	69.82	52.71	61.76

[a] Demand difference in shower head efficiencies was found to be statistically significant when clustered in ratings <2 and ⩾2.

Table 9
ANN model predicted savings from retrofit programs.

Retrofit program	Baseline demand (L/hh/d)	Post-retrofit demand (L/hh/d)	Mean saving predicted	
			(L/hh/d)	(kL/hh/y)
Toilet	60.39	39.85	20.54	7.50
Shower	90.05	85.51	4.54	1.66
Clothes washer	61.76	48.20	13.56	4.95

the shower retrofit program had the lowest mean daily household saving of 4.54 L/hh/d (1.66 kL/hh/y). A respectable 13.56 L/hh/d (4.95 kL/hh/y) saving was predicted for retrofitting clothes washers. Showering is a behaviourally influenced water use activity while toilets and clothes washers are mechanised appliances. Potentially, the lower shower end use saving may be due to households having efficient shower heads compensating lower flow rates by longer showers.

8.2. Model implications for citywide water appliance retrofit program estimation

The toilet, shower and clothes washer residential water demand end-use forecasting models have demonstrated their intended usefulness at predicting the expected change in demand for various water use appliance retrofit programs. Combining the most effective programs from the toilet, shower and clothes washer program categories, a predicted 14.14 kL/hh/y or a 12.7% mean reduction in household demand is expected to be achieved. The Gold Coast City Council (GCCC) region in Queensland, Australia where this study was conducted has 206,000 households (GCCC, 2011). If the combination of the most effective programs were instituted over the GCCC municipality and assuming that 50% of households partake, the expected reduction in demand would be 1.45 GL/year, which equates to 582 Olympic sized swimming pools.

9. Conclusion

The identification of key determinants of residential end use water demand showed that household income, number of adults, number of children, number of teenagers, and appliance stock efficiency regarding toilet, shower and clothes washer end uses were the predominant determinants. The identification of key determinant results mirrored previous studies such as Kenney et al. (2008), Heinrich (2009), Beal et al. (2010), Beal et al. (2011a), Beal et al. (2011b), Gato et al. (2011) and Makki et al. (2011).

The results of applied ANN algorithms demonstrated that the HLSALOA produced the highest level of accuracy. The HLSALOA produced residential end use demand forecasting models with R^2 ranging from 0.21 for the bath demand forecasting model to 0.60 for the shower demand forecasting model. The clothes washer demand, dishwasher demand and total internal demand account for nearly half or more of the observed variance. The root mean standard errors (RMSEs) of the models were less than half in all cases apart from dishwasher and bath demand forecasting models. The models applied to the validation set produced similar results. The HLSALOA was able to predict the means and medians of the observed demand frequency distributions except in the case of the bath demand forecasting models.

The study demonstrated that applying ANN-based modelling methodology is a feasible means of producing residential water demand end use forecasting models. The most accurate ANN algorithm employed produced models that have a moderate forecast accuracy applying to all end uses with the exception of bath demand. The applicability of the produced residential water demand end-use forecasting models was displayed by their ability to reproduce the demand frequency distributions of the training and validation sets with bath demand being the exception. In turn, the residential water demand end uses forecasting models could be used to simulate water demand reduction retrofit programs. Improvements can be made on this study by testing more complex ANN algorithms, identifying determinants of greater applicability and using empirical data with less noise to construct the models.

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