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journal homepage: www.elsevier.com/locate/eswa



ANN-based residential water end-use demand forecasting model

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ARTICLE INFO

Keywords: Artificial neural network Residential water demand forecasting Water end use Water micro-component Water demand management

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 SEOREUS 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,

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