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# Smart meters for enhanced water supply network modelling and infrastructure planning

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ABSTRACT

To design water distribution network infrastructure, water utilities formulate daily demand profiles and peaking factors. 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founded on a number of assumptions on how top-down bulk water consumption is attributed to customer connections and outdated demand information that does not reflect present consumption trends; meaning infrastructure is often unnecessarily overdesigned. The recent advent of high resolution smart water meters allows for a new novel methodology for using the continuous 'big data' generated by these meter fleets to create evidence-based water demand curves suitable for use in network models. To demonstrate the application of the developed method, high resolution water consumption data from households fitted with smart water meters were collected from the South East Queensland and Hervey Bay regions in Australia. Average day (AD), peak day (PD) and mean day maximum month (MDMM) demand curves, often used in water supply network modelling, were developed from the herein created methodology using both individual end-use level and hourly demand patterns from the smart meters. The resulting modelled water demand patterns for AD, PD and MDMM had morning and evening peaks occurring earlier and lower main peaks (AD: 12%; PD: 20%; MDMM: 33%) than the currently used demand profiles of the regions' water utility. The paper concludes with a discussion on the implications of widespread smart water metering systems for enhanced water distribution infrastructure planning and management as well as the benefits to customers.



## 1. Introduction

### 1.1. Water distribution network modelling and infrastructure planning

Water distribution network modelling is an essential component of water supply planning, as it allows water engineers and planners to understand how the water supply system operates, enabling them to make informed decisions regarding operation and planning to achieve the required standards of service. Water supply network design usually incorporates parameters such as water consumption values and flow rate, design peak factors, pressure requirements and physical pipe properties (e.g. material and size). While information on pressure requirements is readily available from local guidelines (e.g. DERM, 2010; SEQ Code, 2013) and pipe properties can be ascertained from the relevant hydraulic literature and local guidelines, estimating water demands accurately is more difficult due to highly variable influencing factors such as demographics and land use, climate, economic and social factors, technology, government intervention, and pricing (Beal and Stewart, 2013; Browne et al., 2013; Lee et al., 2011; Parker and Wilby, 2013).

Water demand varies during the day, with demand generally lowest during the night and highest in the morning and early evening hours, resulting in double peaks concentrated over these two periods; the higher of which is termed a daily peak demand. This variation in daily water demand is also referred to as a diurnal demand curve. Over an annual analysis period, water utilities define certain peak demands to assist in infrastructure design. Peak hour (PH) demand exists in a peak day (PD), which is the maximum day demand over a 12-month period, and is utilised mainly in the design of pipe infrastructure. Additionally, in Queensland,

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**Table 1**
Range of peaking factors from various sources.

| Source | Location | Population/res. density | PD:AD | PH:AD | MDMM:AD |
|---|---|---|---|---|---|
| WSAA (2004) | Australia | >10,000 | 1.5 | 2.0 | N/A |
| | | <2000 | 2.0 | 5.0 | |
| DERM (2010) | Queensland, Australia | >5000 | 1.5–2.7 | 3.6–4.0 | 1.4–1.5 |
| | | <5000 | 1.9–2.3 | 3.6–4.5 | 1.5–1.7 |
| SEQ Code (2013) | Gold Coast, Australia | Residential single (detach) | 2.12 | 6.03 | 1.75 |
| | Brisbane, Redland, Ipswich, Logan, Moreton Bay, Australia | Low–high density | 2.0 | 3.5–4.0 | 1.5 |
| CSIR (2003) | South Africa | Low–high density | 1.5 | 3.6–4.0 | N/A |
| Ysusi (2000) | United States | Undefined | 1.8–2.8 | 2.5–4.0 | N/A |
| MOE (2008) | Canada | >10,000 | 1.5–1.9 | 2.25–2.85 | N/A |
| | | <10,000 | 2.0–2.75 | 3.0–4.13 | |
| Twort et al. (2000) | UK | Undefined | 1.22–1.7 | 1.9–3.0 | N/A |

Australia, the average of the highest moving average 30-day water demand, the mean day at maximum month (MDMM), is utilised to reflect demand persistence in response to climatic condition (DERM, 2010). This average is used mainly in the sizing of pumps and reservoirs. Peaking factors are thus derived relative to average day (AD) demand; that is, average consumption over a 12-month period, to assist water utilities in designing water infrastructure. A review of peaking factors is presented in Table 1.

Diurnal consumption patterns and their peak demands and periods provide useful information on system flow rates, enabling the configuration and calibration of network distribution models and for integrated urban water planning (Cole and Stewart, 2012). The ability to estimate and predict present and future consumption demand is a key component in a water supply system to ensure levels of service standards are not compromised. Short-term forecasts are most useful in the daily management and operation of a network, while long-term forecasts are more suited for future planning and design, as projected population growth typically results in an increased demand (Carragher et al., 2012; Parker and Wilby, 2013). In current industry practice, two approaches are used in developing these forecasts, namely, top-down modelling and bottom-up modelling. A brief description of the two modelling techniques is presented below, however, in brief, top-down modelling is often plagued with a number of assumptions on how demand is proportioned to different categories, with the latter approach often completed with poor resolution data coupled with statistical models. The herein formulated method overcomes these problems by utilising up-to-date high resolution smart meter datasets in order to disaggregate consumption into end use or micro-component categories for bottom-up diurnal demand patterns of indoor consumption, and hourly demand disaggregation to identify outdoor proportions of consumption over a range of seasons. This approach provides an evidence-based bottom-up model of daily diurnal demand, which differentiates itself from the current approach that is highly dependent on outdated secondary data to create end use demand estimates.

#### 1.1.1. Top-down modelling

A top-down approach to water demand modelling allocates a demand multiplier pattern to demand nodes across a broad spatial scale, and assigns correction factors to account for total water demand for each of the nodes (Blokker et al., 2010a; Carragher et al., 2012). Traditional network modelling essentially requires the gathering of information, such as bulk meter data, water production, demand patterns from pumping stations and customer billing data, and a series of assumptions made to separate the information into the relevant demand components. Historically determined water demand patterns are also utilised and adjusted accordingly to reflect the change to recent consumption values and peak factors, with the assumption that base consumer usage patterns remain the same (GCW, 2009).

The standard demand patterns are not able to represent water demands' stochastic nature (Todorovic et al., 2011) or the inverse relationship of peaking factors to connections/population size – peaking factors reduce with increasing connected households (Todorovic et al., 2011). Furthermore, water demand profiles are usually gathered after long intervals, such as every three to five years, and may be outdated and not relevant to current periods. Hence, such patterns are of little use in modelling small or detailed network models or for predicting future water demands (Todorovic et al., 2011).

#### 1.1.2. Bottom-up modelling

A bottom-up demand modelling approach combines water demand patterns modelled for each household within a supply zone, and allocates individual demand patterns to each connection within the network to more accurately determine demand on a small spatial scale (Blokker et al., 2010a; Carragher et al., 2012). This essentially requires the collection of information on a smaller scale, normally at an individual household level, providing a finer level of detail of the gathered water consumption data. Furthermore, as the data is empirically gathered for each household, this eliminates the need to make assumptions required in the top-down approach.

Recent studies have featured the development of diurnal water consumption patterns that do not use direct-demand measurements. This includes stochastic and probabilistic methods of demand modelling using statistical information of water appliances and residential users at varying levels of temporal and spatial variability (e.g. Blokker et al., 2010b; Duncan and Mitchell, 2008; Thyer et al., 2009). While these models present a good fit of simulated patterns to observed data, they are not supported fully by empirically gathered mode of demand generation, and require calibration and validation to predict future and instantaneous diurnal demand patterns. However, the absence of leakage estimation in such models, which can account for around 2–6% (Athuraliya et al., 2012; Beal and Stewart, 2011) of overall household consumption, makes calibration more difficult (Rathnayaka et al., 2011). Furthermore, the difficulty in managing the complex correlations between the various parameters, and the lack of data representing the relationships between individual end uses and the factors influencing their water consumption, limits the ability of these models to simulate end-use patterns at development, city and regional scales (Rathnayaka et al., 2011).

### 1.2. Advent of smart water metering

Advancements in metering and data communications technology have made it possible to record household water usage data through smart water meters. They can automatically and electronically capture, collect and communicate water usage readings in real time or close to real time (Boyle et al., 2013; Cole and Stewart,