This is a preprint version of the paper accepted for publication in the proceedings of the 2015 IEEE Symposium on Computational Intelligence Applications in Smart Grid (IEEE CIASG'15) - https://doi.org/10.1109/SSCI.2015.102

Electric water heater energy consumption determination using outlet temperature and volumetric estimation

P.J.C. Nel*, M.J. (Thinus) Booysen*, B. van der Merwe†
*Department of Electrical and Electronic Engineering, Stellenbosch University, Stellenbosch, South Africa.
†Department of Computer Science, Stellenbosch University, Stellenbosch, South Africa.
Email:{pjcnel, mjbooysen, abvdm}@sun.ac.za

***Abstract*—This paper presents the use of outlet temperature and water meter data as inputs to a physical model of a domestic electric water heater (EWH) for estimating the energy consumption for various control settings. Four sets of actual household data, consisting of at least 7 consecutive days each, is used to determine the accuracy of the energy consumption estimates in comparison to measured energy consumption. Both the outlet temperature and water meter data inputs used were able to estimate the total energy input with an error of less than 10 percent for 3 of the 4 datasets considered. Additionally, both methods are also implemented as a smartphone application that can be used to obtain input from users, as well as provide instantaneous feedback on the impact of control changes.**

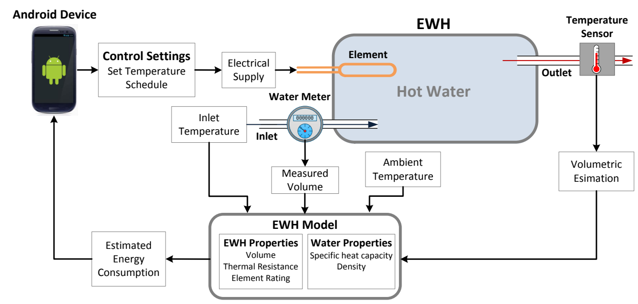

Fig. 1. Diagram of system inputs and feedback.

I. INTRODUCTION

South Africa is in the midst of an energy crisis, with the national electricity utility resorting to load shedding in order to cope with the lack of generation capacity. Additionally, major water shortages in certain parts of the country have lead to water rationing [1]. The heating of sanitary water, which consumes both energy and water, in South African commercial and residential buildings remains one of the largest contributors to the national electricity grid demand peaks [2]. These characteristics are not unique to South Africa, as warm water consumption is the second largest overall energy use activity in the residential sector in the USA (second to space heating) [2]. Also, residential usage of water constitutes two thirds of the total water consumption in Gold Coast, Australia [3].

Smart grid technologies, such as smart metering, have allowed for more intelligent control of household appliances that can reduce their overall energy consumption, as well as the cost of energy usage in certain instances (e.g. time of use tariffs) [4]. Appliances capable of storing energy, such as electric water heaters (EWHs), are ideal candidates for intelligent control as they provide the most flexibility in terms of their scheduling capabilities. The energy usage of EWHs can significantly be reduced with the use of a timer control unit and, if controlled correctly, these appliances are still able to provide warm water to meet household demand [5].

Smart metering technologies have also been leveraged to increase consumers' awareness of their energy and water usage through more timely and detailed feedback of consumption data. For example, Willis et al [3] installed alarming visual display devices in the showers of 44 households in Gold Coast, Australia. These devices are installed at the shower head and include a display that provides users with feedback on the flow rate, duration and temperature of their shower events. The device also produces a beep after 1 minute to indicate when a user should stop showering. The use of this device resulted in a mean reduction of 27% for shower water usage volumes for the households included in the study.

Due to their ubiquitous nature, mobile phones are increasingly being used in smart metering systems as a means of disseminating consumption information to users. PowerPedia, for example, is a community-based smartphone application that allows users to connect their smartphone directly to a smart electricity meter [6]. Users are then able to determine the electricity consumption for individual domestic appliances (e.g. energy efficient lightbulbs and low water-use dishwashers). This information can then be published on PowerPedia, as well as social networking platforms (Twitter and Facebook), where it can be compared to other similar devices that have been published by other users. The normative comparisons and ranking system provided by this application allows users to benchmark their consumption data for specific devices.

Smart metering and mobile devices can be leveraged in combination to provide users with immediate usage feedback and enhanced control functionality through a conveniently accessible application on a mobile device. Booysen et al [5] presents intelligent EWHs fitted with cellular modems and the use of an online interface to provide users with high resolution data (i.e. 1 minute sampling intervals) detailing the energy consumption of their EWHs. This functionality was extended in [7] to include warm water usage, time of day that the consumption occurred, and an Android smartphone application was implemented to allow users to monitor their usage and control the settings of their EWH from their mobile device. The mobile application was then utilised to analyse users' consumption patterns and provide recommended on and off times (i.e. schedules) for their EWHs based on their usage [8]. However, with this additional control functionality, users require a means of determining the impact on the EWHs energy consumption as a result of implementing schedules and other control decisions (e.g. set temperature).

A. *Contribution*

This paper presents two methods for estimating the energy consumption of a domestic EWH for various control settings with the use of a physical model, as shown in Figure 1. The first method consists of a water meter that measures the total volume of warm water consumed by a household. The second method uses a single outlet temperature sensor to determine when usage events occur using the algorithm and system presented in [8] and then estimates the volume of warm water consumed by using typical flow rates of end uses of warm water. The data generated by these methods is used to create a usage profile for a household that is subsequently utilised as an input to a physical model of an EWH to estimate energy consumption. These methods are evaluated using actual household data to determine the accuracy of their estimates in comparison to measured energy consumption. Both methods are also implemented as a smartphone application that can be used to obtain input from users, as well as provide instantaneous feedback on the impact of control changes.

The rest of this paper is organised as follows: section II describes related work in detecting usage events and estimating EWH energy consumption; section III presents a model of the EWH outlet pipe used in the event detection algorithm; section IV describes the classification of domestic warm water usage events used in estimating typical usage event volumes and flow rates; section V details the results and accuracy of the EWH energy estimation using outlet temperature data and water meter data; section VI outlines future work to be done; and section VII concludes the paper.

II. Related Work

Paull et al [9] extracted electric water heater load from household load data recorded by smart meters with a 15 minute sampling interval. EWH have a large energy rating (typically 2 kW or higher) and therefore generate a rapid increase in the household load. These rapid increases and subsequent decreases were extracted from household data and used to estimate the warm water usage. These results were then used to develop a water usage profile which was, in turn, used in conjunction with a physical EWH model to estimate the temperature of the water in the EWH tank. Although this method is able to determine the household water usage profile for an EWH under normal thermostat control, it is not applicable if an EWH is controlled using a schedule as energy input may not coincide with usage events. Additionally, the method may be prone to errors when multiple high-power devices (e.g. kettle, stove) are operating simultaneously, which is likely to occur in a 15 minute interval, and create a similar load curve to the EWH.

Beal et al [10] used high resolution water meters (0.014 litres/pulse logged in five second intervals) for 252 residences in South-east Queensland, Australia over a two week continuous period. This data was then analysed using flow trace analysis software capable of disaggregating the data into end usage events, even when events occur simultaneously. This paper highlights the importance of feedback to users as actual and perceived consumption for these households were not well matched. Additionally, this misperception held across gender, education and socio-demographic groups. This method of determining end uses is very effective but requires the use of sophisticated software and high resolution hardware that is expensive and generates a significant volume of data that needs to be stored and analysed. Such high resolution data is not necessary for making useful estimates of EWH energy and water consumption.

Weihl and Kempton [11] describe the development of an instrumentation system based on a single flow meter at the EWH inlet and temperature probes on the EWH outlet pipe and at each end point (i.e. outlet) in the domestic warm water distribution system. The proposed system is used to disaggregate measured warm water usage into end uses. The temperature at each outlet is recorded in one minute intervals when the warm water flow reaches at least 0.1 litres per minute and continues for an additional five minutes after flow drops below this minimum threshold. A five-step algorithm is then used to infer which tap used the water for a specific usage event by determining the outlet with the highest rise in absolute temperature. This method requires at least one minute of zero flow to distinguish between subsequent water events, and multiple events occurring simultaneously will be treated as a single event (although an attempt is made at attributing a secondary usage event if two events occur together, but the success of this is limited). If the system is unable to determine which tap consumed the water, then the event is considered as undetermined but is still included in the total volumetric usage of the EWH. A sample of 5 houses in central Michigan (USA) with a total of 231 days of measurement data including 7075 total usage events were used to evaluate the efficiency of the system. The end usage point of 96% of all events was inferred, with most of the undetermined events being smaller usage events (typically less than 1 litre). These results are similar to the system used in [8] to detect events using thermal transients at the outlet.

Fogarty et al [12] presents a low-cost microphone-based sensor system for elder activity sensing. Battery powered sensors are attached to pipes at critical locations in the household's water distribution system. These sensors collect audio samples every 2 seconds which can be used to identify end use activities. Although water pipes are good conductors of sound, this also implies that they will conduct the ambient noise well (e.g. sound of central air conditioning) which can lead to erroneous detection of events. Since the sensors are mounted to pipes, a plumber is not needed for installation. However, the suitable placement of the sensors is essential for the system to function correctly and professional installation of the system will be required. However, proper placement of the sensors leads to accurate detection of events including: 94% of shower usage; 95% of dishwasher usage; as well as 73 and 81% of bathroom and kitchen sink activity, respectively, lasting 10 seconds or longer.

Larson et al [13] uses a centralised low-cost pressure-based sensor for automatic disaggregation of water usage events in ten households. The opening and closing of water fixtures causes a pressure wave (i.e. surge/water hammer) which propagates through the water distribution system which

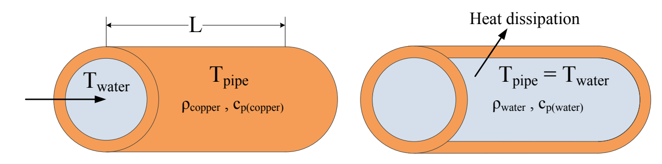

Fig. 2. Temperature distribution for heating (left) and cooling (right) states.

is observed by the sensor. This pressure wave signature differs depending on the valve type, location and the way in which the valve is opened or closed. These pressure transients are then classified into specific end uses as well as individual fixtures. For example, if two identical toilets are located in two separate bathrooms of a single household, each pressure wave traverses a different path to the sensor, creating unique signatures which can be used to differentiate between the two fixtures. The system is able to classify the end uses of water, the specific valve used during usage events and classify events as hot or cold water events with accuracies greater than 90%. Additionally, the flow rates of individual fixtures were estimated in four households and with three of the four had error rates less than 8%. The fourth household had an error rate of 22%which is believed to be as a result of incorrect placement of the sensor.

III. EWH Outlet Pipe Model

In order to detect water usage events, the outlet temperature is monitored with the use of a temperature sensor mounted on the pipes surface. A usage event is defined by a sudden increases in outlet temperature as warm water flows through the pipe, followed by a gradual decrease in this temperature as the pipe cools. The optimal values for these start and stop conditions can be determined using a combined analytical and empirical approach.

A lumped-heat-capacity analysis is used to model the temperature of the cross-section of a copper outlet pipe and the water inside it. This implies that the water and the pipe can be considered to have a uniform temperature which only varies with time. During the heating state, the warm water and pipe temperatures are not identical and only the pipe is being heated. In the cooling state, the pipe and the water are at the same temperature and are therefore cooling together. These two states are shown in Figure 2. For this analysis, we assume a starting condition in which the pipe has been exposed to some ambient temperature for a prolonged period of time and that the water in the EWH tank is warm. A standard 22 mm residential copper piping 100 mm in length (L), with an outer diameter (d_o) of 22.22 mm and an inner diameter (d_i) of 18.92 mm [14], is considered during the analysis. Additionally, only heat transferred in the radial direction is considered. Although this analysis is performed on a copper tube of a specific size, the parameter values may be adjusted for pipes of other materials and dimensions, as long as the Biot number of the system remains at a suitable level to justify the use of a lumped analysis [15]. Weihl and Kempton [11] compared the response of copper and steel pipes and determined that, although steel has a more sluggish response, it still exhibited a clear rise in temperature.

During the heating state warm water flows through the outlet pipe as a result of being drawn from the EWH for a usage

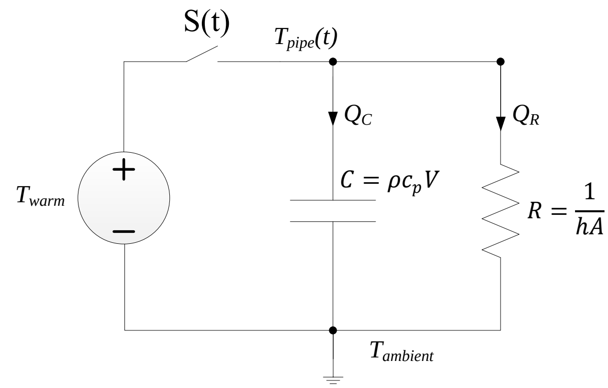

Fig. 3. Thermal equivalent circuit for outlet pipe.

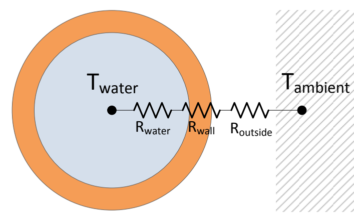

Fig. 4. Total thermal resistance of system.

event. The temperature of the water is higher than that of the pipe, which causes heat transfer from the water to the pipe. This results in an increase in the temperature of the pipe to a maximum value of the temperature of the water. When the temperature of the pipe reaches this maximum value, it will be maintained at this value until the end of the usage event. During this state, we consider the temperature increase of the pipe in isolation and therefore make use of the specific heat capacity ($c_{p(Cu)}$) and density (ρ_{Cu}) of copper when calculating the temperature of the pipe.

In the cooling state no water is being drawn from the EWH and the water inside the pipe is stagnant. The temperature of the outlet pipe and the water are equivalent and can be assumed to remain in good agreement throughout the duration of this state as the thermal conductivity of copper is high and the pipe wall is thin, therefore the temperature drop across the pipe wall is negligible [15]. Since the temperature of the system is higher than the ambient temperature of its surroundings, heat is dissipated to the environment through the pipe surface during this state as a result of the temperature difference. The temperature of the system will continue to decrease until it reaches the ambient temperature of the air surrounding the pipe, or another usage event occurs.

Figure 3 shows the thermal equivalent circuit for the outlet pipe system as sensed by the temperature sensor. R and C are the total thermal resistance and capacitance, respectively, for the outlet pipe system during a specific state. The temperature of the pipe at a given time (t) can therefore be modelled using an RC transient circuit analysis and is determined using the following equation:

$$T_{pipe}(t) = T_\infty - \left[T_\infty - T_{pipe}(0)\right] e^{\frac{-t}{RC}} \tag{1}$$

Where: $T_{pipe}(t)$ is the temperature of the outlet pipe system at time t; T_∞ is the temperature that the system is being exposed

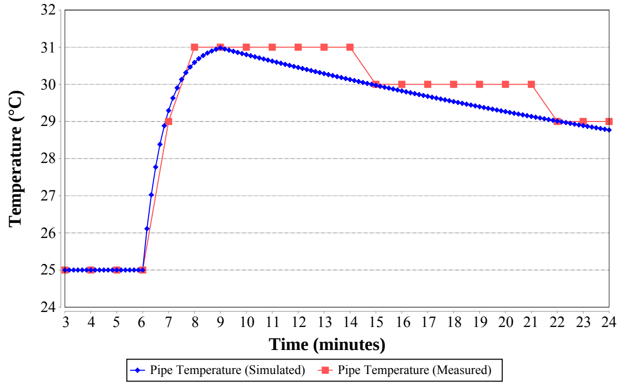

Fig. 5. Measured and simulated outlet pipe temperatures for small, low temperature usage event - the resolution of the sensor is 1 °C.

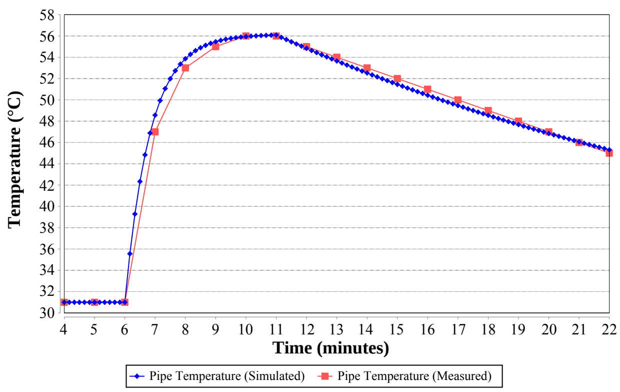

Fig. 6. Measured and simulated outlet pipe temperatures for large, high temperature usage event.

to (T_{warm} for heating and $T_{ambient}$ for cooling); and $T(0)$ is the initial/starting temperature of the system. The value of the time constant can be determined using:

$$R = \frac{1}{hA} \quad ; \quad C = \rho c_p V \tag{2}$$

Where C is given by the product of the density (ρ), specific heat capacity (c_p) and volume (V) of the material under consideration. The value of R is determined from the inverse of the product of the surface area for convection (A) and the overall heat transfer coefficient (h) of the system. The overall heat transfer coefficient can be broken down into three components [16]: convective heat transfer between the water inside the pipe and the inner pipe wall; conductive heat transfer from the inner and outer surfaces of the pipe; and convective heat transfer from the outer pipe wall to the surrounding environment. Figure 4 shows the total thermal resistance network for the outlet pipe system. The value of h is dependent on the flow rate of the water in the pipe but, if the algorithm is designed to capture the minimum increase in temperature as a result of smaller usage events with lower flow rates, then the larger events with higher flow rates will also be detected.

The overall heat transfer coefficient for each state was determined empirically using measurement data and by rearranging Equation 2 to obtain:

$$h = \frac{\rho c_p V}{A \cdot t} \; ln\left[\frac{T(t) - T_\infty}{T(0) - T_\infty}\right] \tag{3}$$

Table I shows the parameter values used for Equation 3 to determine the overall heat transfer coefficient for the heating and cooling states. The value of A for the heating state is given by the inner surface area of the pipe which is exposed to the warm water and for the cooling state it is given as the outer surface area of the pipe, which is exposed to the environment. The value of V for the heating state is given by the volume of the copper tube that makes up the outlet pipe and for the cooling state it is given by the volume of the water inside the pipe as all the thermal energy of the system is stored in the water as copper has a much lower heat capacity than water. The simulated and measured pipe temperatures are shown in Figure 5 for a small usage event (7 litres) for an EWH with a set temperature of 65 °C. The EWH implemented schedule control and was only allowed to turn the element on from 04:15 to 06:00. The event shown occurred mid morning after two significant usage events (25 and 95 litres), resulting in a lower tank temperature. Additionally, it was a warm day with a maximum temperature of 28 °C which lead to an increased pipe temperature. Figure 6 shows the measured and simulated outlet pipe temperatures for a large usage event (74.5 litres) for an EWH with a set temperature of 65 °C. The EWH implemented regular thermostat control (i.e. on all day) and the event shown occurred 8 hours after the previous event.

The simulated temperature of the pipe was calculated in 10 second intervals to clearly illustrate the overall shape of the temperature curve. It should be noted that the initial start of the temperature may lag or lead the measured data as it is not possible to determine when exactly during the one minute sampling interval the usage event started. Additionally, since the temperature at the surface of the pipe was measured, the temperature sensor reading reaches a maximum value that is lower than the set temperature of the water in the tank. The exposed temperature value for the heating state in Equation 3 was adjusted accordingly in order to obtain more accurate simulation results. The simulation results have a similar shape to the EWH outlet temperatures measured in 10 second intervals by Weihl and Kempton [11] and are in good agreement with the measured outlet temperature values. From Figure 5, it can be seen that the minimum rise in temperature that needs to be detected for a small usage event is 6 degrees over 2 samples and that the pipe takes approximately 13 samples to fall by 2 °C. However, in order to obtain accurate duration estimates of the events, the decay must be adjusted for events that cause the outlet temperature to rise by a more significant amount (i.e. closer to the set temperature), as shown in Figure 6. Therefore an increase of 4 °C over 2 samples was chosen as the characteristics of a start event. For a stop event, a decrease in 2 °C was chosen and the number of samples was varied depending on the maximum outlet temperature reached after a start event. A value of seven samples was chosen for events that increase the outlet temperature above 35 °C and a value of 14 samples for an outlet temperature below 35 °C.

From these results, it can be seen that the minimum rise in temperature that needs to be detected for a small usage event is 6 degrees over 2 samples and that the pipe takes approximately 13 samples to fall by 2 °C. However, in order to obtain accurate duration estimates of the events, the decay

TABLE I. THERMAL CIRCUIT PARAMETER VALUES FOR HEATING AND COOLING STATES [15], [17].

	$\rho(\frac{kg}{m^3})$	$c_p(\frac{J}{kg\cdot K})$	$A(m^2)$	$V(m^3)$
Heating	ρ_{Cu}= 8740	$c_{p(Cu)}$= 385	$\pi d_i \times L$	$\frac{\pi}{4}(d_o^2 - d_i^2) \times L$
Cooling	ρ_{H_2O}= 1000	$c_{p(H_2O)}$= 4180	$\pi d_o \times L$	$\frac{\pi}{4} d_i^2 \times L$

TABLE II. TOTAL VOLUME OF WATER USED PER EVENT FOR SPECIFIC END USES [18], [19].

End Use	**Low**	**Typical**	**High**	$\dot{V}_{typical}(\frac{litres}{min})$
Bath	39.0	80.0	189.0	9.0
Shower	7.6	59.1	303.0	30.0
Bathroom basin	0.3	3.8	60.0	4.8
Kitchen sink	0.6	6.7	73.0	9.0
Washing machine	60.0	113.6	200.0	8.5
Dishwasher	15.1	25.0	43.0	3.8

must be adjusted for events that cause the outlet temperature to rise by a more significant amount (i.e. closer to the set temperature). Therefore an increase of 4 °C over 2 samples was chosen as the characteristics of a start event. For a stop event, a decrease in 2 °C was chosen and the number of samples was varied depending on the maximum outlet temperature reached after a start event. A value of seven samples was chosen for events that increase the outlet temperature above 35 °C and a value of 14 samples for an outlet temperature below 35 °C.

IV. EVENT CLASSIFICATION

Warm water in residential buildings is used for indoor-type events and can be broken down into 6 end uses [18]: bath; shower; bathroom basin; kitchen sink; washing machine; and miscellaneous indoor usage. Table II shows the typical volumetric usage amounts for specific indoor end uses (combined hot and cold water consumption) in South African suburbs [18]. Warm and cold water are mixed to create a blended (i.e. desired) water temperature for usage events at an end point. The desired temperature is typically 40.2 °C and can be assumed to remain constant over different seasons for specific individuals [18]. From Table II, the volume of water used for events can differ significantly depending on the duration of the event and the type of fixture at the tap (e.g. low-flow shower heads). For example, the total volume of water consumed by a shower event can be as low as 7.6 litres and as high as 303 litres. The algorithm used in this paper to detect events at the outlet is able to determine the duration of events with reasonable accuracy [8] and, therefore, only approximate warm water flow rates for specific end uses are required in order to estimate the energy consumption of the EWH.

Usage events can be classified as being either fixed energy or fixed volume [20]. A shower or bath, for example, can be considered as fixed energy events as the hot and cold water are mixed to create a certain blended (i.e. desired) temperature at an outlet tap. If the temperature of the warm water is lower, a higher ratio of warm water will be required to deliver the same desired temperature (i.e. thermal energy) at the tap. Washing machine and dishwasher events, however, can be considered fixed volume events as they draw a specific volume of warm water regardless of the set temperature [20]. Fixed energy events need to have their flow rate scaled according to the set temperature of the EWH. The nominal warm water temperature setting for EWHs in South Africa is 65°C and is used to determine the flow rates of events [21]. Typical

TABLE III. CLASSIFICATIONS OF WARM WATER END USES.

End Use	**Small**	**Medium**	**Large**
Bath			×
Shower		×	
Bathroom basin	×		
Kitchen sink	×		
Washing machine			×
Dishwasher	×		

flow rates for water at 65°C can be used and scaled according to the set temperature of the EWH using the first law of thermodynamics [21], based on the assumption that the amount of energy used by each event will remain constant and that water at the inlet temperature is at baseline energy [5]:

$$E_{adjusted} = E_{typical} \tag{4}$$

$$\rho c_p \dot{V}_{adjusted}(T_{adjusted} - T_{inlet}) = \rho c_p \dot{V}_{typical}(T_{typical} - T_{inlet}) \tag{5}$$

$$\dot{V}_{adusted} = \dot{V}_{typical} \cdot \frac{(T_{typical} - T_{inlet})}{(T_{adjusted} - T_{inlet})} \tag{6}$$

Warm water events can be classified into three separate categories: small, which consists of warm water usage events that consume 15 litres or less; medium, where more than 15 but less than or equal to 30 litres are used; and large, which are events for which more than 30 litres of warm water are consumed. The amount of water used by typical end use events (m_{warm} can be calculated using the typical combined usage (m_{total}) shown in Table II in combination with the energy balance equation as follows:

$$E_{warm} = E_{total} \tag{7}$$

$$m_{warm} c_p (T_{warm} - T_{inlet}) = m_{total} c_p (T_{water} - T_{inlet}) \tag{8}$$

$$m_{warm} = m_{total} \frac{(T_{water} - T_{inlet})}{(T_{warm} - T_{inlet})} \tag{9}$$

The amount of warm water used by each typical end use was calculated using Equation 9 with: a set temperature of 65 °C (T_{warm}); a blended temperature of 40.2 °C (T_{water}); and a inlet temperature (T_{inlet}) of 20 °C . This usage amount was then used to classify each event into one of the three categories mentioned above and the results summarised in Table III. Bathroom basins, kitchen sinks and dishwashers are categorised as small events as their usage volumes are typically quite low. The flow rate for small usage events was therefore chosen as 3 litres per minute to allow all of these events to be captured by this category. Showers are the only event categorised as a medium event size. A typical shower is 3 to 4 minutes in duration and typically consumes 26 litres of warm water. A flow rate of 6 litres per minute was designated to medium events in order to capture both of these typical events. Since both washing machines and baths are considered large events, the flow rate for a large event was chosen as 9 litres per minute. The flow rates used are for typical events in South Africa but can be modified further for: different regions (e.g. USA); additional end uses (e.g. washing of face or hands); sub-categorisation of end uses (e.g. large or small shower); or even specific types of fixtures (e.g. low-flow shower head).

Figure 7 shows screenshots of the mobile application that users can utilise to determine the energy usage of their EWHs. The left screenshot shows the use of outlet tempreature data for

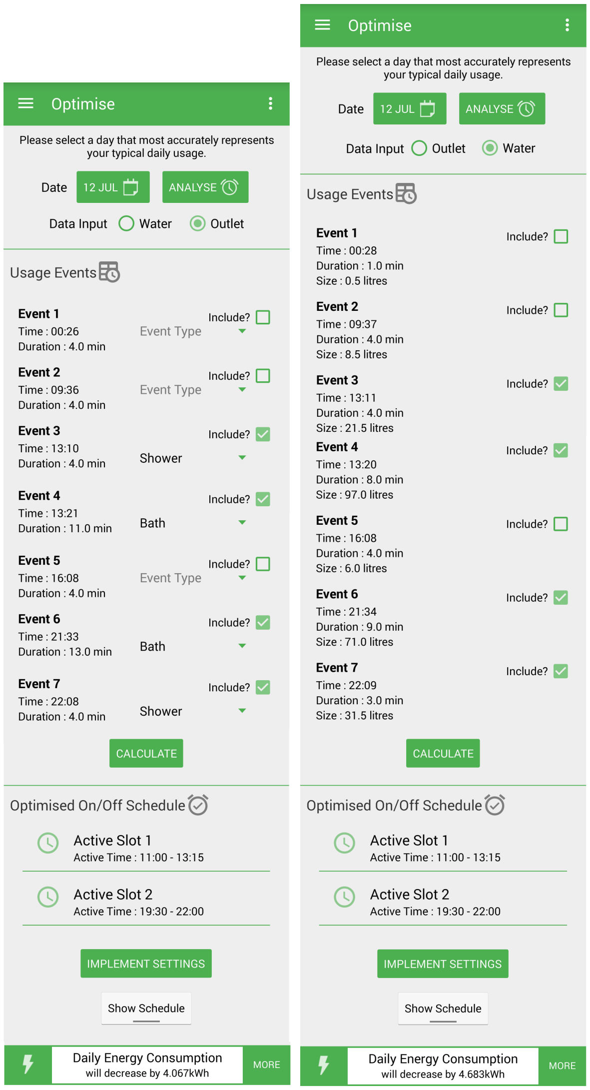

Fig. 7. Screenshot of mobile application using outlet temperature (left) and water meter (right) data.

event detection and the user input required for manual event classification. The right screenshot shows the same day's data using water meter data for event detection (no classification required).

V. Results

A water meter was installed on the water inlet pipe of the EWH, as shown in Figure 8, to determine the actual volume of warm water consumed by usage events to test the thermal approach. The water meter outputs a pulse for every 0.5 litres of water used, but requires a flow of more than 2 litres per minute. The total number of pulses generated in a sampling interval (typically a minute) is reported to an online server. The mobile application can typically be used to obtain input from users in order to classify events. However, in the absence of user input, the events were classified using water meter data.

Each detected event was classified as small, medium or large according to the amount of water recorded by the water meter. Once classified, the relevant flow rate was assigned to each usage event over the duration detected by the outlet temperature algorithm. In some instances, events with very low usage amounts (i.e. less than 0.5 litres) or flow rates (i.e. less than 2 litres per minute) are detected using the outlet temperature but are not registered by the water meter. These events consume little warm water and are therefore classified as small events.

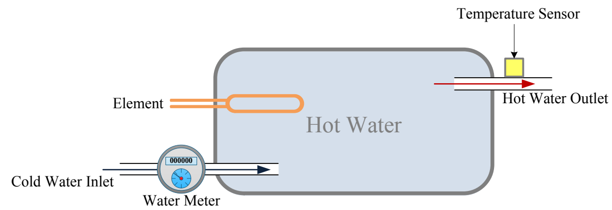

Fig. 8. Hardware configuration of EWH system used during testing.

TABLE IV. Description of datasets.

Dataset	# Days	Control Mode	Season	Inlet Temperature (°C)
1	9	Schedule	Summer	22
2	10	Schedule	Autumn	19
3	7	Thermostat	Summer	20
4	10	Thermostat	Winter	17

After the event classification process, a one node model was used to simulate an EWH with a set temperature of 65 °C for 4 datasets with varying schedule settings spanning several seasons, as shown in Table IV. Additionally, Table V shows a summary of the number of each type of usage events included in the datasets, as well as the total volume of warm water measured by the water meter (V_{total} $Measured$) and the estimated amount of warm water consumed using the outlet data (V_{total} $Estimated$). Finally, Table VI contains the results of the simulations for each dataset using the water meter and the outlet temperature data.

The overall estimated energy input of the EWH (E_{input}) was in good agreement with the measured values for both the water meter and outlet temperature data. The calculated energy input error was less than 10% for the first 3 datasets, with dataset 4 yielding inaccurate results. As expected, the water meter data yielded more accurate results for the energy estimation than the outlet temperature data for all the datasets. However, the volumetric estimation of the outlet temperature data was able to estimate the volume of water consumed within 10 percent accuracy for the first 3 datasets.

Dataset 4 includes several extremely large usage events that warrant further consideration. Six of the 18 large events in dataset 4 consumed more than 95 litres of water each. This results in a significant error in the estimation of the EWHs energy usage when using both the water meter and outlet temperature data. This is because the one node model is not able to accurately model such large events as it does not account for the stratification that occurs within the tank when large amounts of water are withdrawn [22]. Additionally, the duration estimates from the outlet temperature for such large events are inaccurate. This is because the events consume enough warm water to empty the EWH tank and reduce the water temperature flowing through the outlet pipe to the inlet temperature. This causes a sudden drop in the outlet pipe temperature which, in turn, leads the event detection

TABLE V. SUMMARY OF USAGE EVENTS FOR DATASETS.

Dataset	# Small Events	# Medium Events	# Large Events	Total Events	Total Volume Measured [litres]	Total Volume Estimated [litres]	Error [%]
1	14	12	7	33	650	687	5.69
2	9	9	7	25	706	648	8.21
3	2	5	4	11	343	315	8.16
4	13	1	18	32	1489	576	61.3
Total	**38**	**27**	**36**	**101**	**3188**	**2226**	30.18

TABLE VI. ENERGY ESTIMATES USING WATER METER AND OUTLET TEMPERATURE DATA.

		Water Meter		Outlet Temperature	
Dataset	Energy Input (Measured) [kWh]	Energy Input (Calculated) [kWh]	Error [%]	Energy Input (Calculated) [kWh]	Error [%]
1	38.90	38.81	0.25	38.50	1.05
2	41.86	42.23	0.88	41.25	1.46
3	34.73	32.16	7.41	31.55	9.17
4	115.20	92.89	19.37	61.21	46.9

algorithm to significantly underestimate the duration of these events and therefore the amount of water consumed. It may therefore be necessary to further classify larger end uses, such as showers and baths, as the volume of water consumed by these events can vary drastically, which concurs with the findings in Table II.

VI. FUTURE WORK

Future work will include further research into accurate flow rates for various fixtures and end uses as well as the differences in these flow rates across seasons. Water meter data will be used in conjunction with water diaries kept by users in order to classify events more accurately in terms of their end uses and obtain more accurate estimates of usage volumes for events. Additionally, the system presently uses a flat rate cost structure and can be extended to include a dynamic price schedule in order to more accurately estimate the cost of specific events, especially for DSM programs where time of use tariffs are in effect. This data could then be used to provide the user with the cost of specific events and the potential financial and energy savings as a result of deferral of the event to a cheaper tariff time or curtailment (e.g. results of reducing shower time by one minute). The EWH was set at 65 °C for all the datasets analysed. Investigation into the change in energy and warm water consumption of an EWH for various set temperatures will be performed.

VII. CONCLUSION

This paper presents the use of outlet temperature and water meter data as inputs to a physical model of a domestic EWH for estimating the energy consumption for various control settings. Both the outlet temperature and water meter data inputs used were able to estimate the total energy input with an error of less than 10 percent for 3 of the 4 datasets considered. The limitations of the volumetric estimation as well as the one node EWH model when estimating energy usage for high volume usage events as a result in differences of user behaviour (e.g. shower/bath duration) are illustrated.

ACKNOWLEDGMENT

The authors would like to acknowledge: Trinity Telecoms for their technical support and guidance, and providing access to the SMART M2M-enabling system; and MTN for their continued support and funding through the MTN Mobile Intelligence Lab.

REFERENCES

[1] G. Stolley. (2015, June) Water rationing kicks off in some KZN municipalities. [Online]. Available: http://www.news24.com/SouthAfrica/News/Water-rationing-kicks-off-in-some-KZN-municipalities-20150621

[2] R. Rankin and P. G. Rousseau, "Sanitary hot water consumption patterns in commercial and industrial sectors in South Africa: Impact on heating system design," *Energy Conversion and Management*, vol. 47, no. 6, pp. 687–701, 2006, DOI: 10.1016/j.enconman.2005.06.002.

[3] R. M. Willis, R. A. Stewart, K. Panuwatwanich, S. Jones, and A. Kyriakides, "Alarming visual display monitors affecting shower end use water and energy conservation in Australian residential households," *Resources, Conservation and Recycling*, vol. 54, no. 12, pp. 1117–1127, 2010, DOI: 10.1016/j.resconrec.2010.03.004.

[4] M. A. A. Pedrasa, T. D. Spooner, and I. F. MacGill, "Coordinated Scheduling of Residential Distributed Energy Resources to Optimize Smart Home Energy Services," *IEEE Transactions on Smart Grid*, vol. 1, no. 2, pp. 134–143, 2010, DOI: 10.1109/TSG.2010.2053053.

[5] M. J. Booysen, J. A. A. Engelbrecht, and A. Molinaro, "Proof of concept: Large-scale monitor and control of household water heating in near real-time," in *Proc. of International Conference on Applied Energy (ICAE)*. Pretoria, South Africa, July 2013, URL: http://hdl.handle.net/10019.1/95703.

[6] M. Weiss, T. Staake, F. Mattern, and E. Fleisch, "PowerPedia: changing energy usage with the help of a community-based smartphone application," *Personal and Ubiquitous Computing*, vol. 16, no. 6, pp. 655–664, 2012, DOI : 10.1007/s00779-011-0432-y.

[7] P. J. C. Nel, M. J. Booysen, and B. van der Merwe, "ICT-enabled solutions for smart management of water supply in Africa," in *Proc. of First International Conference on the Use of Mobile Information and Communication Technology in Africa (UMICTA 2014)*. Stellenbosch University, December 2014, URL: http://hdl.handle.net/10019.1/95703.

[8] P. J. C. Nel, M. J. Booysen, and B. van der Merwe, "Using thermal transients at the outlet of electrical water heaters to recognise consumption patterns for heating schedule optimisation," in *Proc. of 7th IFIP Conference on New Technologies, Mobility and Security*. Paris, France, In press July 2015.

[9] L. Paull and H. L. ad Liuchen Chang, "A novel domestic electric water heater model for a multi-objective demand side management program," *Electric Power Systems Research*, vol. 80, no. 12, pp. 1446–1451, 2010, DOI: 10.1016/j.epsr.2010.06.013.

[10] C. D. Beal, R. A. Stewart, and K. Fielding, "A novel mixed method smart metering approach to reconciling differences between

perceived and actual residential end use water consumption," *Journal of Cleaner Production*, vol. 60, pp. 116–128, 2013, DOI: 10.1016/j.jclepro.2011.09.007.

[11] J. S. Weihl and W. Kempton, "Residential hot water energy analysis: Instruments and algorithms," *Energy and Buildings*, vol. 8, no. 3, pp. 197–204, 1985, DOI: 10.1016/0378-7788(85)90004-0.

[12] J. Fogarty, C. Au, and S. E. Hudson, "Sensing from the Basement: A Feasibility Study of Unobtrusive and Low-Cost Home Activity Recognition," in *Proc. of 19th Annual ACM Symposium on User Interface Software and Technology*. Montreux, Switzerland, October 2006, pp. 91–100, DOI: 10.1145/1166253.1166269.

[13] E. Larson, J. Froehlich, T. Campbell, C. Haggerty, L. Atlas, J. Fogarty, and S. N. Patel, "Disaggregated water sensing from a single, pressure-based sensor: An extended analysis of HydroSense using staged experiments," *Pervasive and Mobile Computing*, vol. 8, no. 1, pp. 82–102, 2012, DOI: 10.1016/j.pmcj.2010.08.008.

[14] EngineeringToolbox. (N.d.) Copper Water and Gas Tube according ASTM B 88 – imperial units. [Online]. Available: http://www.engineeringtoolbox.com/astm-copper-tubes-d_779.html

[15] J. P. Holman, "Steady-State Conduction – One Dimension," in *Heat Transfer*, 10th ed. McGraw-Hill, 2009, pp. 27–76.

[16] E. J. Mirjam-Blokker and E. J. Pieterse-Quirijns, "Modeling temperature in the drinking water distribution system," *Journal – American Water Works Association*, vol. 105, no. 1, pp. E18–E28, 2013, DOI: 10.5942/jawwa.2013.105.00118.

[17] EngineeringToolbox. (N.d.) Specific Heat of some common Substances. [Online]. Available: http://www.engineeringtoolbox.com/specific-heat-capacity-d_391.html

[18] H. E. Jacobs and J. Haarhoff, "Structure and data requirements of an end-use model for residential water demand and return flow," *Water SA*, vol. 30, no. 3, pp. 293–304, 2004, DOI: 10.4314/wsa.v30i3.5077 .

[19] EngineeringToolbox. (N.d.) Hot Water Flow Rates to Fixtures. [Online]. Available: http://www.engineeringtoolbox.com/fittings-hot-water-flow-rate-d_90.html

[20] E. Hirst and R. A. Hoskins, "Residential Water Heaters: Energy and Cost Analysis ," *Energy and Buildings*, vol. 105, no. 1, pp. 393–400, 1978, DOI: 10.5942/jawwa.2013.105.00118.

[21] J. P. Meyer, "A review of domestic hot water consumption in South Africa," *Research & Development Journal of the South African Institution of Mechanical Engineering*, vol. 16, no. 3, pp. 55–61, 2000.

[22] Z. Xu, R. Diao, S. Lu, J. Lian, and Y. Zhang, "Modeling of Electric Water Heaters for Demand Response: A Baseline PDE Model," *IEEE Transactions on Smart Grid*, vol. 5, no. 5, pp. 2203–2210, 2014, DOI: 10.1109/TSG.2014.2317149.