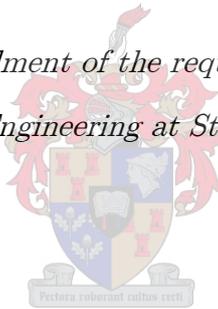


Simulating Domestic Hot Water Demand by means of a Stochastic End-Use Model

by

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Declaration

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Abstract

The heating of domestic hot water (DHW) requires a substantial component of the energy demand in the residential sector, yet limited DHW demand information is available. An improved understanding of DHW demand has benefits for management of both energy and water demand and can lead to significant water and energy savings. However, understanding DHW demand is reasonably intricate, involving a spectrum of users and end-uses with varying event volumes, flow rates, timings of use and temperatures. In order to understand DHW demand, information is required on an end-use and temporal basis.

Collecting data on DHW end-use consumption is expensive and involves complex field tests. A few previous studies were found that included comprehensive DHW consumption data, one of which was selected for use in this study. A stochastic model based on previous consumption data would be able to produce reliable DHW demand profiles.

A stochastic end-use model was constructed in this study to derive diurnal DHW demand profiles for single family residences on a temporal scale of one minute. The model was designed to simulate diurnal DHW demand from a database of total water demand, which was available from an earlier international study. The model was able to convert total water demand to DHW demand using volume balances and various factors that influence DHW demand. An existing database was used to populate the model with probability distributions describing end-use characteristics.

The model included five DHW end-uses in households. Each of the model iterations resulted in a diurnal demand profile with a hot water volume demand for each minute of the day. The profile is an aggregation of activated end-use events with stochastic frequencies, starting times and characteristics. The model applies a Monte Carlo method

to obtain average DHW demand profiles. Results are obtained after a finite number of iterations.

Typical results obtained from the model for various scenarios are presented in the study. The study found that, as the number of occupants increased the DHW demand increased. The per capita DHW demand decreased logarithmically. Comparison with previous studies indicated that the model yields accurate results for DHW demand values with sensible diurnal demand profiles. Cyclic end-uses such as the dishwasher and washing machine were relatively complex to model.

Furthermore, a sensitivity analysis revealed that the model result is most sensitive to the water heater temperature setting, with the cold water inlet temperature ranking second. Contrariwise, variables used to estimate heat loss from flow in pipes had an insignificant effect on total DHW demand.

Various key results were found using the end-use model created in this study. With the dishwasher and washing machine end-uses connected to the water heater, average diurnal DHW demands were found to range between 259 $\ell/h/d$ in summer to 313 $\ell/h/d$ in winter. On the other hand, when the dishwasher and washing machine were not connected from the water heater, the demands ranged between 171 $\ell/h/d$ in summer to 202 $\ell/h/d$ in winter. Similarly, per capita DHW demand, with the dishwasher and washing machine end-uses connected to the water heater, ranged between 106 $\ell/c/d$ in summer and 127 $\ell/c/d$ in winter. Without the dishwasher and washing machine connected the per capita values ranged from 69 $\ell/c/d$ in summer to 81 $\ell/c/d$ in winter. The model in this study could also identify DHW on a per-end use basis.

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Table of Contents

Declaration	i
Abstract	ii
Acknowledgements	iv
List of Figures	x
List of Tables	xii
Nomenclature	xiv
Symbols	xiv
Subscripts	xvi
Abbreviations and Acronyms	xvii
1 Introduction	1
1.1 Background	1
1.2 Terminology	2
1.1.1 Domestic Hot Water (DHW) Demand	2
1.1.2 Water Heater	2
1.1.3 End-use	2
1.1.4 Diurnal Demand Profile	3
1.1.5 Method (Java)	3
1.3 Problem Statement	3
1.4 Aim of the Study	4
1.5 Rationale	5
1.6 Delineation and Limitations	6
1.7 Brief Chapter Overviews	6

2	Literature Review	8
2.1	Domestic Hot Water Demand	8
2.1.1	Per Capita Diurnal Hot Water Demand	8
2.1.2	Number of Occupants - Effect on Hot Water Demand.....	11
2.1.3	Household Diurnal Hot Water Demand	13
2.1.4	Diurnal Demand Profiles	14
2.2	Domestic Hot Water End-Uses.....	19
2.3	Domestic Hot Water Systems.....	20
2.3.1	Water Heaters	20
2.3.2	Temperature Losses in Pipes	22
2.4	Desired Domestic Hot Water Use Temperature	25
2.5	Health and Safety Issues with DHW	26
2.6	Cold Water Supply Temperature	28
2.7	Domestic Hot Water Demand Modelling	34
2.7.1	Realistic Domestic Hot-Water Profiles in Different Time Scales.....	34
2.7.2	Tool for Generating Realistic Hot Water Event Schedules	34
2.7.3	EPRI Model	35
2.8	Previous Probabilistic End-Use Model.....	37
2.8.1	Model Structure.....	37
2.8.2	Data Input Source	39
2.8.3	Results and Conclusion.....	40
3	Data Used for Model.....	42
3.1	Data Selection.....	42
3.2	Study Sites.....	43

3.3	End-use Data Collection and Analysis.....	44
3.4	Climate Data	45
3.5	Cold Water Inlet Temperature.....	48
4	Stochastic End-use Model	52
4.1	Research Design	52
4.2	Software.....	53
4.2.1	End-Use Model Software choice	53
4.2.2	Other Software Used	54
4.3	General Model Design	55
4.3.1	Temporal Aspects and Climate.....	55
4.3.2	Limitations of the Model	57
4.3.3	End-uses Included in Model.....	57
4.4	Model Structure	58
4.4.1	Main Method and Overview	58
4.4.2	Main Method Inputs.....	60
4.4.3	Base DHW Demand Array	61
4.4.4	Household Size Calculation.....	62
4.4.5	Determining Average Diurnal Demand Profiles.....	63
4.4.6	Generate Diurnal Method	65
4.5	Event Modelling.....	67
4.5.1	Event Frequencies	67
4.5.2	Generating Discrete Event Frequencies in Java	68
4.5.3	Event Class Overview and Variables	70
4.5.4	Event Class Methods	71

4.5.5	Generate Event Method and Calculations.....	74
4.6	Converting total demand to DHW demand.....	78
4.6.1	Volume Balance and discussion	78
4.6.2	Desired User Temperature	80
4.6.3	Water Heater Temperature Setting.....	82
4.6.4	Heat Loss in Pipes.....	84
4.7	Individual Events.....	88
4.7.1	Shower Events.....	89
4.7.2	Bath Events	92
4.7.3	Tap Events.....	93
4.7.4	Dishwasher Events	95
4.7.5	Washing Machine Events	98
4.8	Model testing.....	101
4.9	User Interface.....	102
5	Results and Discussion.....	104
5.1	Number of Simulations.....	105
5.2	Diurnal DHW Demand by Month	106
5.3	Household Size Influence on Diurnal DHW Demand	109
5.4	Comparison of Results with those of Previous Studies.....	113
5.4.1	Total Average DHW Demand Comparison	113
5.4.2	Per Capita DHW Demand Comparison	114
5.4.3	Diurnal DHW Demand Profile Comparison	115
5.4.4	Per End-Use DHW Demand Comparison.....	117
6	Sensitivity Analysis.....	119

6.1	Water Heater Temperature Setting (T_{set})	119
6.2	Cold Water Inlet Temperature (T_c).....	122
6.3	Ambient Temperature (T_a)	124
6.4	Pipe Lengths	125
7	Conclusions and Recommendations	128
7.1	Summary of Findings	128
7.2	Conclusion	129
7.3	Suggestions for Further Research	131
	References	133
	Appendix A – Event Frequencies	140
	Appendix B – Starting Hour Frequencies	146
	Appendix C – Number of Cycles	148
	Appendix D – User Desired Temperature Database	150

List of Figures

Figure 2.1	Average per capita per day consumption in houses (Meyer, 2000).....	10
Figure 2.2	Average per capita per day consumption in apartments (Meyer, 2000) ...	10
Figure 2.3	Average per capita per day consumption in town houses (Meyer, 2000) ..	11
Figure 2.4	DHW electricity variation with number of occupants (Parker, 2003)	12
Figure 2.5	Residential water use variation with occupants (Evarts & Swan 2013) ...	13
Figure 2.6	Average hourly hot water consumptions in houses (Meyer, 2000).....	15
Figure 2.7	Average hourly hot water consumptions in apartments (Meyer, 2000)	16
Figure 2.8	Average hourly hot water consumptions in town houses (Meyer, 2000)...	16
Figure 2.9	Comparison of diurnal hot water use profiles (Fairey & Parker, 2004)	18
Figure 2.10	Modified diurnal hot water use profiles comparison with omissions (Fairey & Parker, 2004).....	19
Figure 2.11	Discomfort and thermal injury to skin (Lawrence & Bull, 1976)	27
Figure 2.12	Average monthly air and cold water temperatures comparison (adapted from Ladd & Harrison, 1985)	29
Figure 2.13	Diurnal variation in soil temperature in Santa Barbara, CA. (Durre <i>et al.</i> 2010; Menne <i>et al.</i> , 2012).....	32
Figure 2.14	Measured variation in mains water temperature (Parker, 2003)	33
Figure 2.15	Simplified schematic of end-use model by Scheepers (2012)	39
Figure 3.1	Study Sites used in REUWS (Scheepers, 2012)	43
Figure 3.2	Comparison of monthly climate of all study sites.....	47
Figure 3.3	Comparison of predicted T_c values to T_a values	51
Figure 4.1	Monthly average T_a comparison to daily temperatures.....	56
Figure 4.2	Monthly average T_c comparison to predicted values	56
Figure 4.3	Model main method structure flow chart.	59
Figure 4.4	Single household DHW demand profile	60
Figure 4.5	Cumulative probability distribution for household size	63
Figure 4.6	Overview of the diurnal profile generating method.....	66

Figure 4.7	Bath frequency discrete variable calculation in Java	69
Figure 4.8	Starting hour cumulative probabilities for shower events	73
Figure 4.9	Event variable value generating method flowchart	74
Figure 4.10	User desired temperature normal distribution and actual data.....	81
Figure 4.11	Water heater thermostat temperature setting ranges (adapted from Ladd & Harrison, 1985).....	83
Figure 4.12	Diurnal variation in ambient temperature	86
Figure 4.13	Stochastic hot water demand model user interface.....	103
Figure 5.1	Effect of number of simulations on diurnal results	105
Figure 5.2	Monthly total demand average results with and without DW and CW .	106
Figure 5.3	Critical month diurnal profile comparison with DW and WM.....	108
Figure 5.4	Critical month diurnal profile comparison without DW and WM.....	108
Figure 5.5	Total diurnal demand based on PPH with DW and WM.....	109
Figure 5.6	Diurnal demand profile comparison based on PPH, for winter with no DW and WM connected	110
Figure 5.7	Per capita DHW demand results based on PPH with logarithmic trend	112
Figure 5.8	Diurnal demand profile comparison with previous studies	116

List of Tables

Table 2.1	SANS (2012) per capita use values and storage volumes.....	9
Table 2.2	DHW use by water heater type (Thomas et al., 2011)	21
Table 2.3	Pipe flow temperature drop in pipes (Hiller, 2011)	25
Table 2.4	Derived event characteristics (Hendron & Burch, 2010)	35
Table 2.5	End-use share comparison (Scheepers, 2012)	41
Table 3.1	REUWS Data collection schedule (Mayer <i>et al.</i> , 1999)	45
Table 3.2	NCDC Stations used for climate data	46
Table 3.3	Climate data manipulation for the model in this study	49
Table 3.4	Predicted monthly cold water inlet temperatures for model	50
Table 4.1	Hot water end-uses from REUWS data.....	58
Table 4.2	Household size probabilities	62
Table 4.3	Bath event frequency for the 1 PPH category	67
Table 4.4	Event class list of variables.....	71
Table 4.5	Event class list of methods	72
Table 4.6	Example of a shower event added to a diurnal array	77
Table 4.7	Water heater temperature distribution used in model.....	84
Table 4.8	Hourly average ambient factors derived for the model	87
Table 4.9	Probability distribution parameter values for shower events (adapted from Scheepers, 2012)	91
Table 4.10	Probability distribution parameter values for bath events (adapted from Scheepers, 2012)	93
Table 4.11	Probability distribution parameter values for tap events (adapted from Scheepers, 2012)	94
Table 4.12	Probability distribution parameter values for dishwasher events (adapted from Scheepers, 2012).....	96
Table 4.13	Probability distribution parameter values for washing machine events (adapted from Scheepers, 2012)	101

Table 5.1	Summary of monthly average total and end-use demand results	107
Table 5.2	Per capita DHW demand results summary	111
Table 5.3	Total diurnal DHW demand comparison	113
Table 5.4	Per capita DHW demand comparison	114
Table 5.5	Per end-use DHW demand comparison.....	117
Table 6.1	Sensitivity analysis for water heater temperature setting	120
Table 6.2	Sensitivity analysis for cold water inlet temperature	123
Table 6.3	Typical pipe heat loss values from model output	124
Table 6.4	Sensitivity analysis for ambient temperature	126
Table 6.5	Sensitivity analysis for pipe lengths	127
Table A.1	Shower diurnal event frequency cumulative relative frequency	141
Table A.2	Bath diurnal event frequency cumulative relative frequency	141
Table A.3	Tap diurnal event frequency cumulative relative frequency.....	142
Table A.4	Dishwasher diurnal event frequency cumulative relative frequency	145
Table A.5	Washing Machine diurnal frequency cumulative relative frequency	145
Table B.1	Starting hour cumulative relative frequency.....	147
Table C.1	Number of cycles cumulative relative frequency.....	149
Table D.1	Modified user desired temperature database	151

Nomenclature

Symbols

$^{\circ}\text{C}$	Degrees Celsius
$^{\circ}\text{F}$	Degrees Fahrenheit
c	Capita
C_{pw}	Specific Heat of Water
d	Day
h	Household
i	Counter (Java)
ℓ	Litre
$\text{LMTD}_{\text{flowing}}$	Log mean temperature difference under flowing conditions
m	Metre
mm	Millimetre
q	Energy
Q	Heat loss rate
R	Ratio of amplitudes dependent on soil temperatures at different depths
SV	Seasonal Variables
t	Time

T_a	Ambient temperature
T_c	Cold water inlet temperature
T_h	Hot water temperature delivered to end-uses
$T_{\text{hot avg}}$	Log mean average pipe water temperature
$T_{\text{hot in}}$	Water temperature enter pipe
$T_{\text{hot out}}$	Water temperature leaving pipe
T_s	Soil temperature
T_{set}	Water heater thermostat temperature setting
T_{size}	Water heater tank size
UA_{flowing}	Pipe heat loss characteristic under flowing conditions
$UA_{\text{zero-flow}}$	Pipe heat loss characteristic with no flow
V_c	Cold water volume of an event
V_h	Hot water volume of an event
V_t	Total event volume (hot and cold water combined)
α	Shape parameter
α_1	Coefficients determined by Lutz <i>et al.</i> (1996)
α_2	Coefficients determined by Lutz <i>et al.</i> (1996)
β	Scale parameter

γ	Location parameter
δ	Offset factor
λ	Lag factor
ρ_w	Density of water
ϕ_a	Function of T_a (Burch & Christensen, 2007)
ϕ_c	Function of T_a (Burch & Christensen, 2007)
ω	Angular Frequency
x	Possible values of x

Subscripts

ann	Annual
avg	Average
dur	Diurnal
max	Maximum
min	Minimum
mon	Monthly

Abbreviations and Acronyms

ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
DHW	Domestic hot water
DW	Dishwasher
GOF	Goodness of Fit
IDE	Integrated Development Environment
PPH	People per household
REUWS	Residential end-uses of water study
SIMDEUM	Simulation of water demand, and end-use model
WM	Washing Machine

1 Introduction

1.1 Background

The heating of domestic hot water (DHW) is a significant component of the energy consumption in the residential sector; however, insufficient data is available on the ways in which hot water is used in households. In South Africa estimates vary, nonetheless figures as high as 40% to 50% of monthly electricity use have been quoted for water heating in average middle-to-upper class households (Meyer, 2000). Since 2000 the efficiency of water heating technology has increased. According to Booysen *et al.* (2013) water heaters consume as much as 30% of household electricity. In the United States of America, 24% of residential natural gas consumption is used for water heating (Schoenbauer *et al.*, 2012). In Canada, between 2000 and 2008, DHW demands accounted for 18% of all energy use in the housing sector (Behidj, 2011; Edwards *et al.*, 2015). The percentage of total energy use ought to be lower than the values for South Africa, since Canada uses a considerable amount of domestic energy for space heating. Similarly, in the USA space heating consumes the largest proportion of energy use, with water heating being the second largest (Meyer 2000).

South Africa relies on out-dated per capita demand values to estimate DHW in households. However, DHW demand is quite intricate, involving a spectrum of users and end-uses with varying volumes, flow rates, timings and temperatures from both the water heater and cold water inlet.

A major complication to collecting comprehensive data on DHW end-use consumption is the cost and complexity of the field tests (Lowenstein & Hiller, 2008). Improved data on DHW use can help manufacturers and energy programme designers to design better products, policies and programmes to reduce energy use, and water use as well as improve water heating performance and water savings.

1.2 Terminology

Studies use different terms to describe similar concepts. Certain terms are consistently used in this document and it is important that these terms are defined adequately.

1.1.1 Domestic Hot Water (DHW) Demand

Domestic hot water demand describes hot water required per time unit by domestic consumers within a household. Residential demand is another term used in literature, which has a meaning similar to domestic demand, referring to demand generated within a house. For the model in this study, DHW demand refers specifically to demand supplied by the water heater and does not include water heated by appliances or other means.

1.1.2 Water Heater

For this study the term water heater is defined as an entity that provides hot water to the DHW system at a specific temperature based on the water heater thermostat setting. Hot water cylinder and geyser are alternative terms used for the water heater.

1.1.3 End-use

An end-use of water is defined as a point where water is released from the pressurised water supply system to atmospheric pressure (Jacobs, 2004). End-uses generally include fixtures and appliances in the home, such as the toilet, bath, shower, washing machine, dishwasher and basin taps.

1.1.4 *Diurnal Demand Profile*

A demand profile with a period of 24 hours is termed a diurnal demand profile in this study. Draw profiles or patterns are other common terms used to describe demand profiles in other publications.

1.1.5 *Method (Java)*

A Java method is a collection of statements that are grouped together to perform an operation. A method can be analogous to a mathematical function ($G = f(x, y, z)$) that receives inputs (x, y, z) and produces an output (G) , but can also perform operations like manipulating variables without returning any values itself, or without receiving inputs. In Java, when a method is used or invoked, the phrase ‘call the method’ is commonly used. Method names, by convention, always start with a lowercase letter and does not include spaces, instead capital letters are used to start a new word within a method name, for example, ‘myMethod’. The naming convention is used so that classes and methods are not confused within programming code, since by convention, class names always start with a capital letter.

1.3 **Problem Statement**

Realistic DHW demand values are required to describe typical household demands comprehensively. Usually average diurnal demand expressed per household or per capita exposes limited information about DHW demand. Moreover, it is acknowledged that DHW demand is complex. User behaviour can vary significantly from day to day, even within a single household. Therefore it is necessary to gain a better understanding of factors that influence DHW demand, such as number of draws (events), draw length (event duration), volumes, flow rates and starting times of events. Additionally, seasonal

effects of DHW demand should also be investigated, as it is recognised that demand fluctuates annually.

Furthermore, information on an end-use basis is essential to better understanding of DHW demand. Research in this study determines which end-uses consume the most DHW within a household, which identifies targets for further investigation on possible savings.

DHW demand varies diurnally, which is studied further on a reasonably high temporal scale as part of this research. Accurate and dependable diurnal DHW demand draw profiles are essential to broadly describe hot water demand in households. Subsequently, these profiles can be used for various applications in further water or energy demand studies.

1.4 Aim of the Study

The fundamental aim of the study was to model DHW demand stochastically from a large water consumption database which was available from earlier research. In the absence of a recent and accurate hot water demand database, the study aims to extract hot water demand from normal all-inclusive domestic water consumption data. Consequently, hot water demand was calculated by the model from existing databases which did not discriminate between hot and cold water demand in the measurements. Therefore many factors that are required to populate the model were researched, including desired user temperatures, volume balances and cold water inlet and hot water supply temperatures.

One objective was to conduct a comprehensive literature review on previous work done on domestic hot water modelling and end-use modelling. The intention was to find values from previous studies that could be compared with values generated by the proposed stochastic model. A review of available water and hot water demand databases was also essential, in order to find a large database adequate to be used for modelling.

As part of this study, a computer based stochastic end-use model was developed that could simulate DHW demand on a diurnal basis for single-family households. The temporal scale of the model was selected to be one minute. Previous research (Becker & Stogsdill, 1990; Bouchelle *et al.*, 2000; Meyer 2000; Perlman & Mills, 1985) mainly used hourly temporal scales and this indicated that using a higher resolution time scale would be unnecessary. The model was intended to generate end-use events with probability-based characteristics like volume, duration, flow rate and starting time. Subsequently aggregation of all the generated end-use events within a simulated day provided a DHW demand profile for a single family household. Realistic average demand values and profiles were derived after sufficient iterations of the model

1.5 Rationale

By using the proposed model, hot water demand could be estimated on an end-use basis. The model could be used to evaluate possible hot water savings, which would subsequently lead to energy savings. Hot water saving is valuable from a financial and an environmental aspect, and holds more advantages than cold water savings. Furthermore, most hot water end-uses are linked directly to the wastewater system and form a large part of the grey-water stream. The isolation of hot water demand at end-use level allows for analysis of on-site wastewater reuse potential (Jacobs, 2004).

Becker & Stogsdill (1990) established that the consulting engineers, water heater manufactures and the utility industry were experiencing difficulties in developing new and more efficient equipment and systems. The difficulties were due to the shortage of reliable performance data on DHW demand and water heaters. An extensive DHW demand model would serve as a significant means to produce improved data.

Expanding the understanding of DHW draw profiles would support improved test procedures, sizing guidelines and system designs. Expanding DHW knowledge would be beneficial in support of energy policies and standards (Lutz & Melody, 2012). Diurnal

DHW demand profiles with better data could inform decisions in a number of areas, including standardised testing of water heaters, and solar water heaters for further potential energy savings.

1.6 Delineation and Limitations

The problem in the study is delineated by defining DHW demand to be the volume of hot water leaving the water heater to be consumed by domestic end-uses. The definition of DHW demand simplified the problem to a certain extent, since water heated by elements in appliances is not considered as DHW demand in this study. The limitations of the model itself are fully explained in section 4.3.2.

The model and the methods implemented to obtain and solve probability distributions are based on various statistical concepts. Explaining most statistical concepts used in this thesis was beyond the scope of this study. Therefore it is a prerequisite to have a general understanding of some statistical concepts, such as probability distributions, discrete and continuous variables.

The results produced are representative of typical North American houses from the study sites, as discussed in Chapter 3. The diurnal demand profiles may therefore not be representative of South African demands. However, the model forms a sound basis which can be used for further modelling of South African water and hot water demand, with correctly recorded local data.

1.7 Brief Chapter Overviews

This thesis document includes seven chapters, followed by three appendices. Chapter 2 is a literature review addressing DHW demand and factors influencing DHW demand. Chapter 3 provides a background to the residential end-uses of water study (REUWS)

database by Mayer *et al.* (1999), along with the climate data used to populate the stochastic DHW demand model in this study.

Chapter 4 describes the methodology followed to construct the computer based end-use model. The model structure, event modelling and individual end-use events are fully discussed. Chapter 5 presents results, including a comparison with results from previous studies reviewed in the literature. Chapter 6 contains a sensitivity analysis on selected model variables, accompanied by a discussion of each variable under analysis. Chapter 7 concludes the findings of the study and includes suggestions for further research on the topic.

2 Literature Review

The literature review aimed to provide an overview of DHW demand and the importance thereof. In order to achieve the goal of developing a stochastic hot water demand model, investigating previous studies on the topic was essential. For agreement and verification purposes, approximate figures of hot water demand were required for comparison with the results obtained using the model. Values were obtained in the literature for average daily use, both independent of household size, and on a per capita basis. Diurnal demand profiles were moreover, one of the key outputs for this study, therefore previous diurnal profiles describing DHW demand were reviewed.

Since the model developed in this study essentially converts total demand to hot water demand, investigating DHW systems and the factors that had an influence on the hot water demand in households was obligatory. The factors included the water heater, hot water temperatures, typical cold water inlet temperatures and losses in the DHW system. Additionally, the means by which certain end-uses generate hot water demand and the required user temperature for end-uses were reviewed.

Analysis of previous models that had been produced by other authors was important. A series of models is mentioned and examined to discover which of the models could influence the model developed in this study.

2.1 Domestic Hot Water Demand

2.1.1 Per Capita Diurnal Hot Water Demand

One way of expressing hot water demand is per capita demand per day. Typically, per capita demand is conveyed as the average volume of hot water that one person uses per day. Four sources of reference on DHW per capita demand are known in South

Africa. Basson (1983) quoted a value of 50 ℓ per capita per day. Meyer & Greyvenstein (1992) adapts the value for the seasonal changes with a cosine function. A suggestion is presented that the average hot water consumption per person varies between a minimum of 50 ℓ /c/d during summer and 75 ℓ /c/d during winter. A third source suggests that a figure of 35 ℓ /c/d for developing communities should be used (Beute, 1993). A South African end-use modelling study by Jacobs & Haarhoff (2004), predicted a DHW demand variation between 45 and 55 ℓ /c/d for summer and winter respectively. The most recent source in South Africa is the SANS 10252-1 code (SANS, 2012), which tabulates values for per capita use for different premises. Since this study focuses on domestic use, the relevant values from the SANS code are given in Table 2.1. The table also includes the required storage volume estimates per capita or per unit.

Table 2.1 SANS (2012) per capita use values and storage volumes.

Premises	Total hot water demand	Storage volume at 60°C
Dwelling houses:		
Low rental	(80 to 115) ℓ /c/d	(100 to 150) ℓ /unit
Medium to high rental	(115 to 140) ℓ /c/d	(40 to 50) ℓ /c
Flats (blocks):		
Low rental	(65 to 75) ℓ /c/d	(20 to 25) ℓ /c
Medium to high rental	(115 to 140) ℓ /c/d	(25 to 35) ℓ /c

Meyer (2000) conducted a review of DHW in South Africa based on measurements taken from 770 dwellings in Johannesburg, South Africa. The study included 200 shacks and 90 traditional homes, which were ignored for the purposes of this study, since low cost and traditional housing is beyond the scope of this study. The average hot water consumption for houses, apartments and townhouses in three density categories was measured (Meyer & Tshimankinda, 1997; Meyer & Tshimankinda 1998a; Meyer & Tshimankinda 1998b). The methodology included fitting water meters just upstream of the water heater. After installation the water heater thermostats were set to a temperature of 65°C, which is the factory setting on most water heaters (Meyer, 2000).

The annual hot water consumption for low-, medium- and high-density houses was 91.4, 59.3 and 25.4 $\ell/c/d$ respectively. For apartments, these figures were found to be similar, at 89.4, 56.0 and 21.6 $\ell/c/d$. Town houses had values of 88.6, 66.8 and 61.5 $\ell/c/d$ respectively (Meyer, 2000). Seasonal changes were also investigated and the results of the study for houses, apartments and townhouses are presented in Figure 2.1, Figure 2.2 and Figure 2.3. Results indicate that more hot water is used during the winter months.

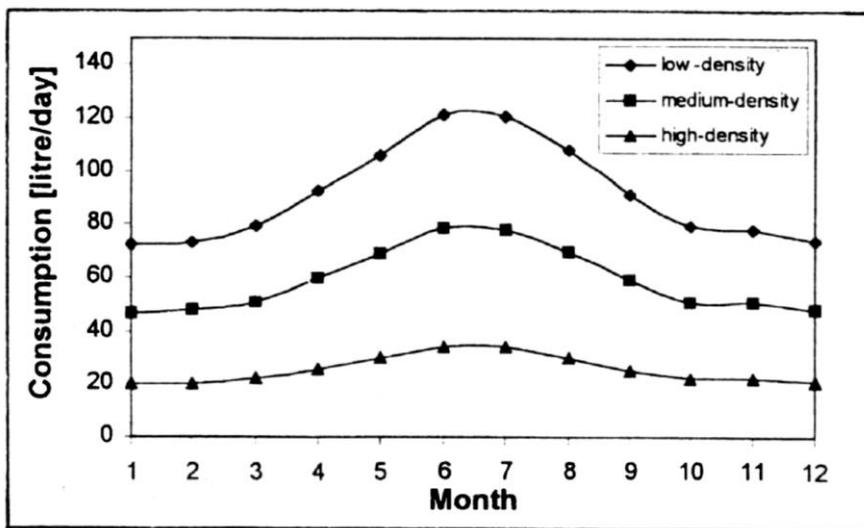


Figure 2.1 Average per capita per day consumption in houses (Meyer, 2000)

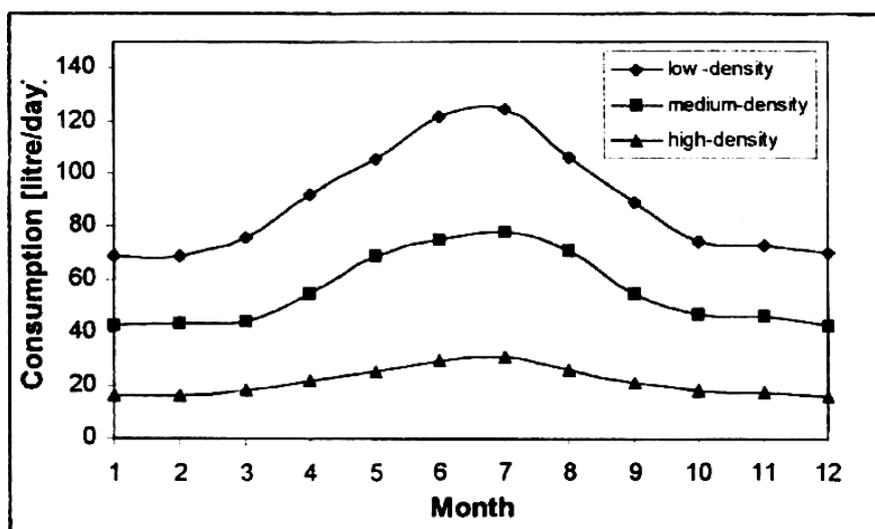


Figure 2.2 Average per capita per day consumption in apartments (Meyer, 2000)

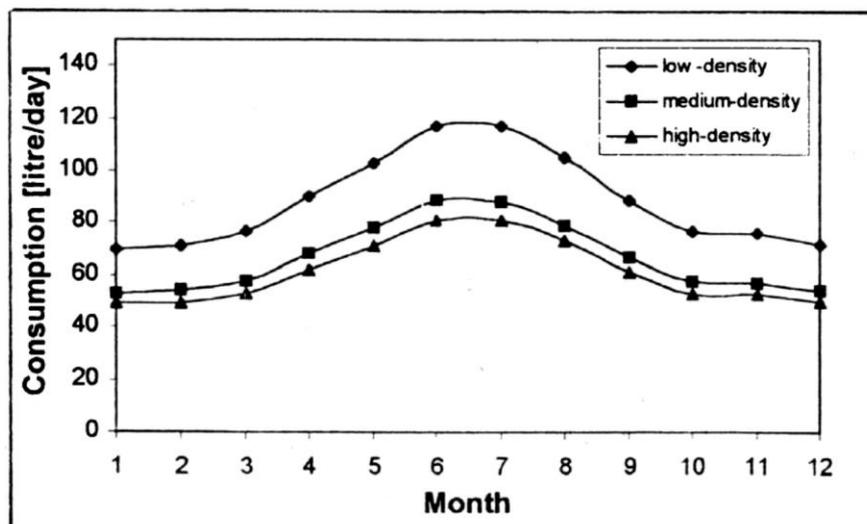


Figure 2.3 Average per capita per day consumption in town houses (Meyer, 2000)

International studies, similarly, give various values for per capita hot water use. A study completed in Greece on four apartment buildings from 1990 to 1991 concluded that the majority of families consume between 25 and 35 $\ell/c/d$ (Papkostas *et al.*, 1995). These demand values were relatively low volumes, compared with the other cited values. An older study on seven houses in the USA indicated values ranging from 44.5 up to 126.4 $\ell/c/d$ (Kempton, 1988).

2.1.2 Number of Occupants - Effect on Hot Water Demand

Hendron & Burch (2008) examined water heater energy use per occupant data from the USA Department of Energy and stated that it could be assumed that the number of occupants has a linear effect on total hot water use. The number of occupants primarily affected the event frequency, assuming that the behaviour of each occupant is similar. It can be argued that additional occupants after the first two are likely to be children; however, the examined data indicates that the relationship between the average number of occupants and average hot water use was fairly linear, independent of age.

The assumption of increasing demand with increasing number of occupants was confirmed in a large scale residential monitoring study of 204 residences in Florida, USA. (Parker, 2003). Figure 2.4 illustrates the daily DHW electricity use with an increasing number of occupants.

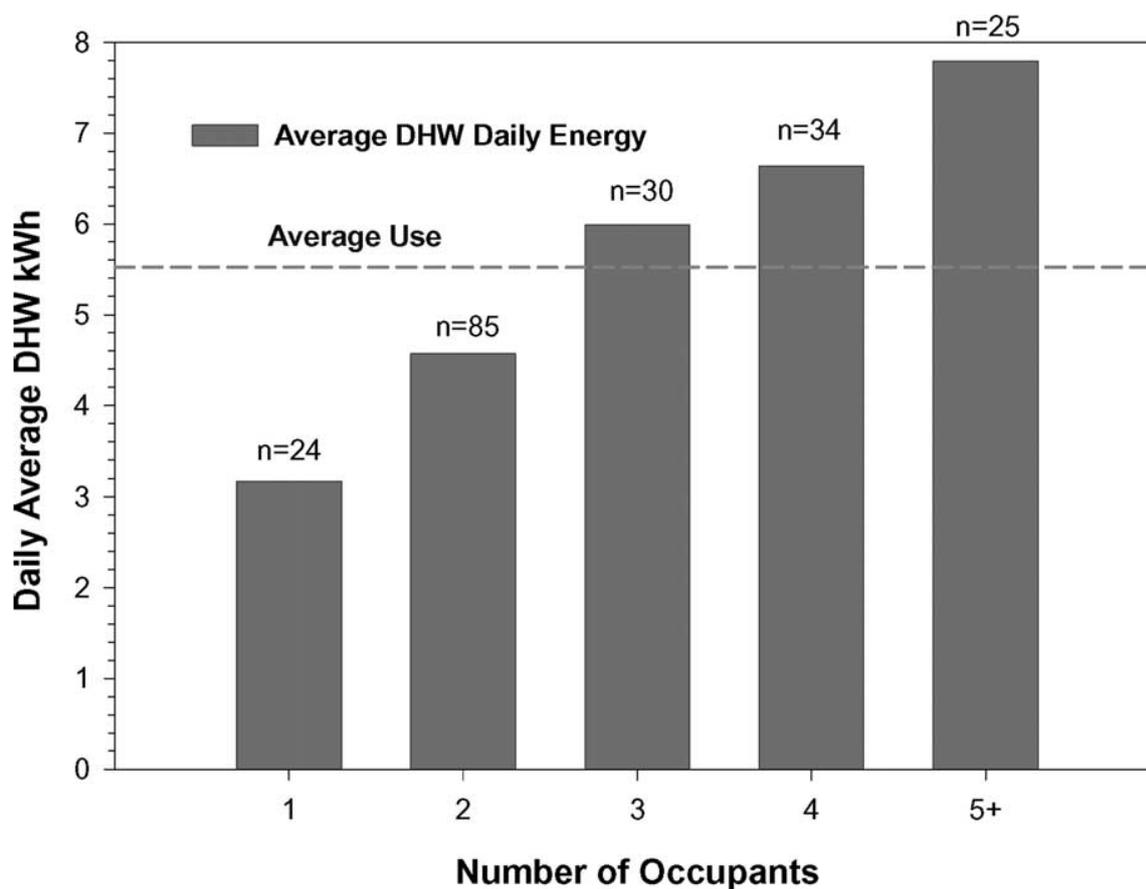


Figure 2.4 DHW electricity variation with number of occupants (Parker, 2003)

Another study, using billing data and occupant responses from 1594 residences, plotted the water consumption in $\ell/h/d$ with the increase in number of occupants as illustrated by Figure 2.5. The black bar represents the median, the boxes the middle quartiles and the circles the outliers (Evarts & Swan, 2013). The figure indicates total water use and not hot water use exclusively.

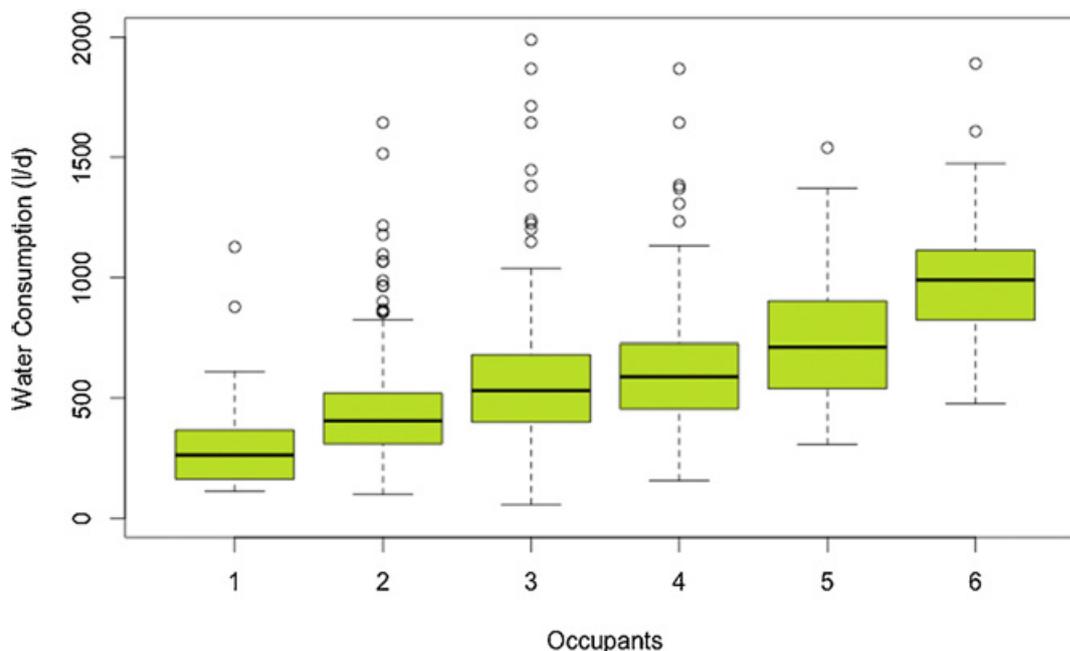


Figure 2.5 Residential water use variation with occupants (Evarts & Swan 2013)

On the other hand, Thomas *et al.* (2011) concluded from a study on 74 households in Canada, that family size did not have a significant effect on total household use. The study, however, used mostly household sizes including two to four adults in combination with one to three children.

2.1.3 Household Diurnal Hot Water Demand

Some studies present a diurnal average household hot water demand value, instead of per capita values. Thomas *et al.* (2011) gives values of 186.6 ℓ /d per household and compares the value to 243.4 ℓ /d per household that is used in Canadian and USA performance tests for water heaters. Thomas *et al.* (2011) concluded that over approximately 25 year prior to their study, total household average diurnal hot water volume had decreased, the average draw volume flow rates were lower and the average number of draws per day had increased.

Becker & Stogsdill (1990) conducted a review of earlier field studies on DHW consumption and created a database with measurements from five previous studies. The database by Becker & Stogsdill (1990) included measurements from 110 single-family residences from 11 utilities, reported by Ladd & Harrison (1985); 142 homes in Hood River Oregon area reported by Hirst *et al.* (1987); 24 homes in North Carolina and 74 homes in Florida reported by Merrigan (1988). Each of these data sets consisted of DHW demand data of one year or more, from which Becker and Stogsdill (1990) reported the average hourly demand.

Becker and Stogsdill (1990) established that averaged daily DHW consumption of the several hundreds of apartments and houses included in their study was 238 ℓ /d. The value is significantly higher than the 186.6 ℓ /d value found recently by Thomas *et al.* (2011). The large difference is due to the fact that the data from the Becker & Stogsdill (1990) review is three to four decades old and is believed to not represent more current demand patterns. Advancement in water heater technology plays a substantial role in reduced DHW use. Energy efficient clothes washers and dishwashers in the recent decade consume significantly less DHW (Bansal *et al.*, 2011).

A study by Schoenbauer *et al.* (2012) involved 10 houses in the USA with the number of occupants ranging from one to five. The study by Schoenbauer *et al.* (2012) reported an average diurnal household hot water use of 143 ℓ /d, with values ranging from 74 ℓ /d to 224 ℓ /d. Hendron & Burch (2008) states that the average daily DHW use can vary by an order of magnitude, from as little as 50 ℓ /h/d to as large as 500 ℓ /h/d, depending on habits and occupant density.

2.1.4 Diurnal Demand Profiles

Diurnal average demand volumes only gives limited information about hot water demand in households. DHW involves diverse user behaviours, habits and applications with

varying temperatures, flow rates, volumes, durations and timing of use. It is asserted that DHW demand patterns are idiosyncratic according to households (Hendron & Burch, 2008).

An alternative way to represent hot water demand is by means of a diurnal pattern or profile. Diurnal demand profiles is generally obtained by determining the volume of water used over a certain time-step for a 24-hour period. Typically, a resolution of volume demand per hour is used, but in some cases the temporal scale can be of higher resolution.

The study by Meyer (2000) based on measurements from 770 dwellings in Johannesburg, South Africa, additionally included hourly measurements from 120 dwellings, including 30 traditional homes which were ignored for this study. Consequently 30 houses, 30 town houses and 30 apartments (10 of each in each category of low-, medium- and high-density) were reviewed. These houses were fitted with digital flow meters to take measurements every hour. Average hourly hot water consumption patterns per person as found by Meyer (2000) for houses, apartments and town houses according to density, is shown in Figure 2.6, Figure 2.7 and Figure 2.8.

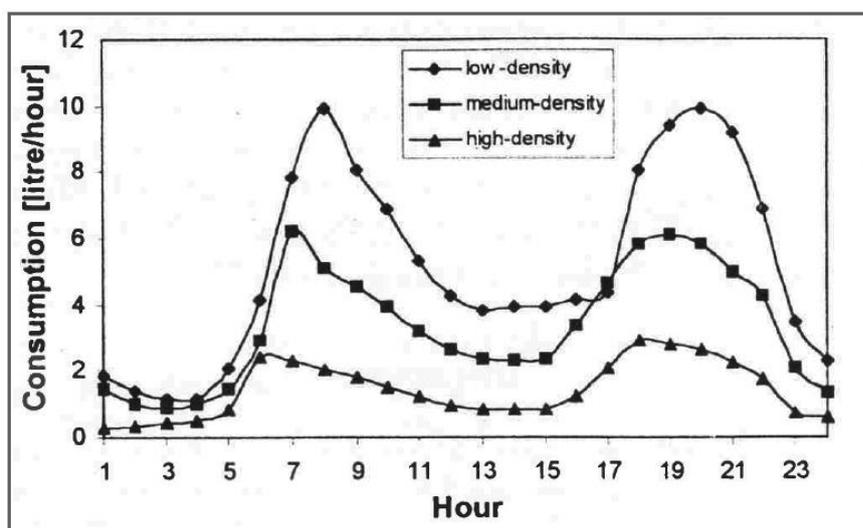


Figure 2.6 Average hourly hot water consumptions in houses (Meyer, 2000)

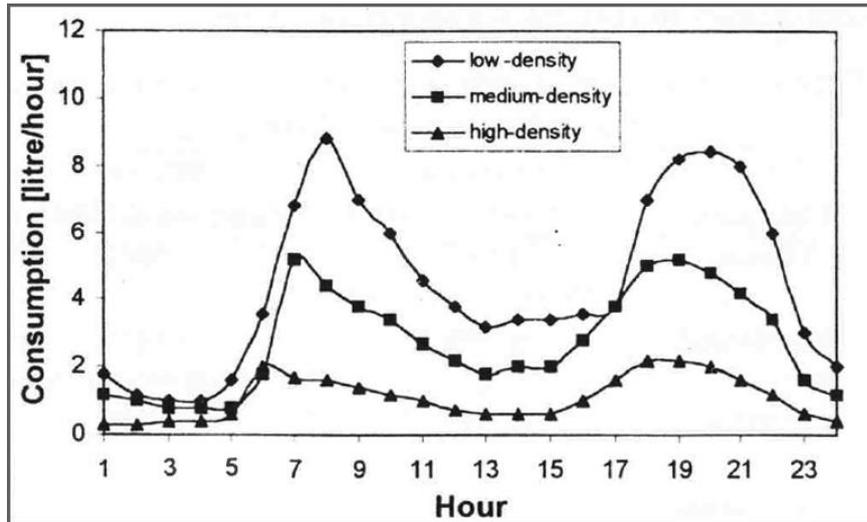


Figure 2.7 Average hourly hot water consumptions in apartments (Meyer, 2000)

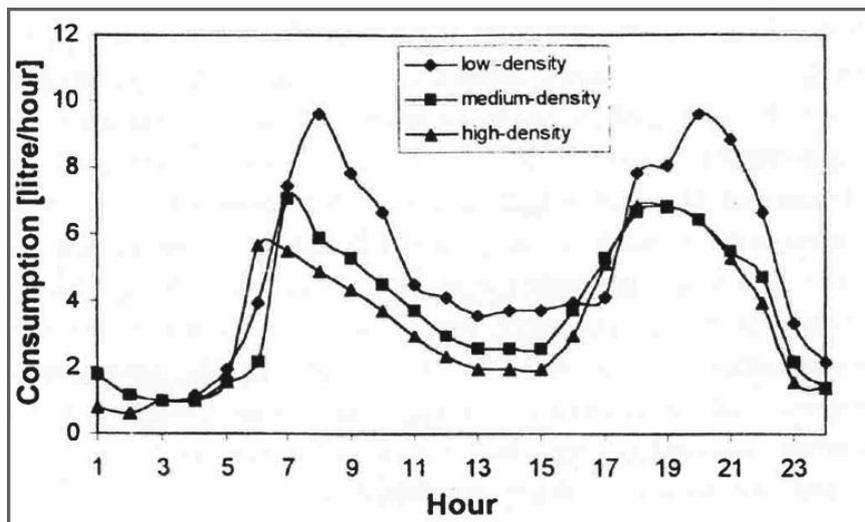


Figure 2.8 Average hourly hot water consumptions in town houses (Meyer, 2000)

Numerous DHW demand profiles exist internationally, mainly used for performance analysis of residential hot water systems. The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) daily draw profile is widely used. Two ASHRAE hot water demand profiles, one from the HVAC Applications Handbook (ASHRAE, 2007) and the second from the ANSI/ASHRAE Standard 90.2 (ASHRAE, 1993). The source of the profile in the ANSI/ASHRAE Standard is not provided. The HVAC Application handbook is based on the research conducted by Perlman & Mills (1985). Edwards *et al.* (2015) noted that the research by Perlman & Mills (1985) was

conducted three to four decades ago and might not be representative of current use. Another consideration is that one of the given DHW draw profiles is labelled as typical use, and the classification of a typical household does not agree with more recent demographics (Fairey & Parker, 2004). 'Typical' families included two adults and two children, in a household where a dishwasher and washing machine were present. Another profile, labelled 'all families', was also supplied by Perlman and Mills (1985). Bouchelle *et al.* (2000) reported on hot water demand profiles from a study on 204 homes in Florida. Similarly to the other studies Bouchelle's (2000) presented diurnal demand profiles on a temporal scale of one hour. The Solar Rating and Certification Corporation (SRCC, 2002) used tests that required an hourly hot water draw profile. The SRCC cites the hot water profile used as adapted from the 1995 ASHRAE Applications Handbook, as well as from the study by Becker & Stogsdill (1990).

Fairey & Parker (2004) conducted a review of DHW draw profiles used in performance analysis of DHW systems. Fairey & Parker (2004) also compared many of the above mentioned sources. Each of the profiles used may sum to a different total diurnal average hot water use volume. In order to make a direct comparison, each hourly volume was divided by total diurnal average hot water demand volume to normalise, which resulted in hourly DHW use profiles that give the fractional portion of the total diurnal use per hour. The comparison presented by Fairey & Parker (2004) is illustrated in Figure 2.9.

From investigation of the comparison shown in Figure 2.9, Fairey & Parker (2004) concluded that the SRCC (2002) and Perlman & Mills's (1985) 'typical' draw profiles stand out significantly from the other profiles. Fairey & Parker (2004) removed these profiles from the dataset to produce a modified comparison, illustrated in Figure 2.10. The new comparison showed significant similarities among the hot water draw profiles, when the Perlman & Mills (1985) and SRCC profiles were omitted. The Perlman & Mills 'all families' profile was also added to the comparison and found to be inconsistent (Fairey & Parker, 2004).

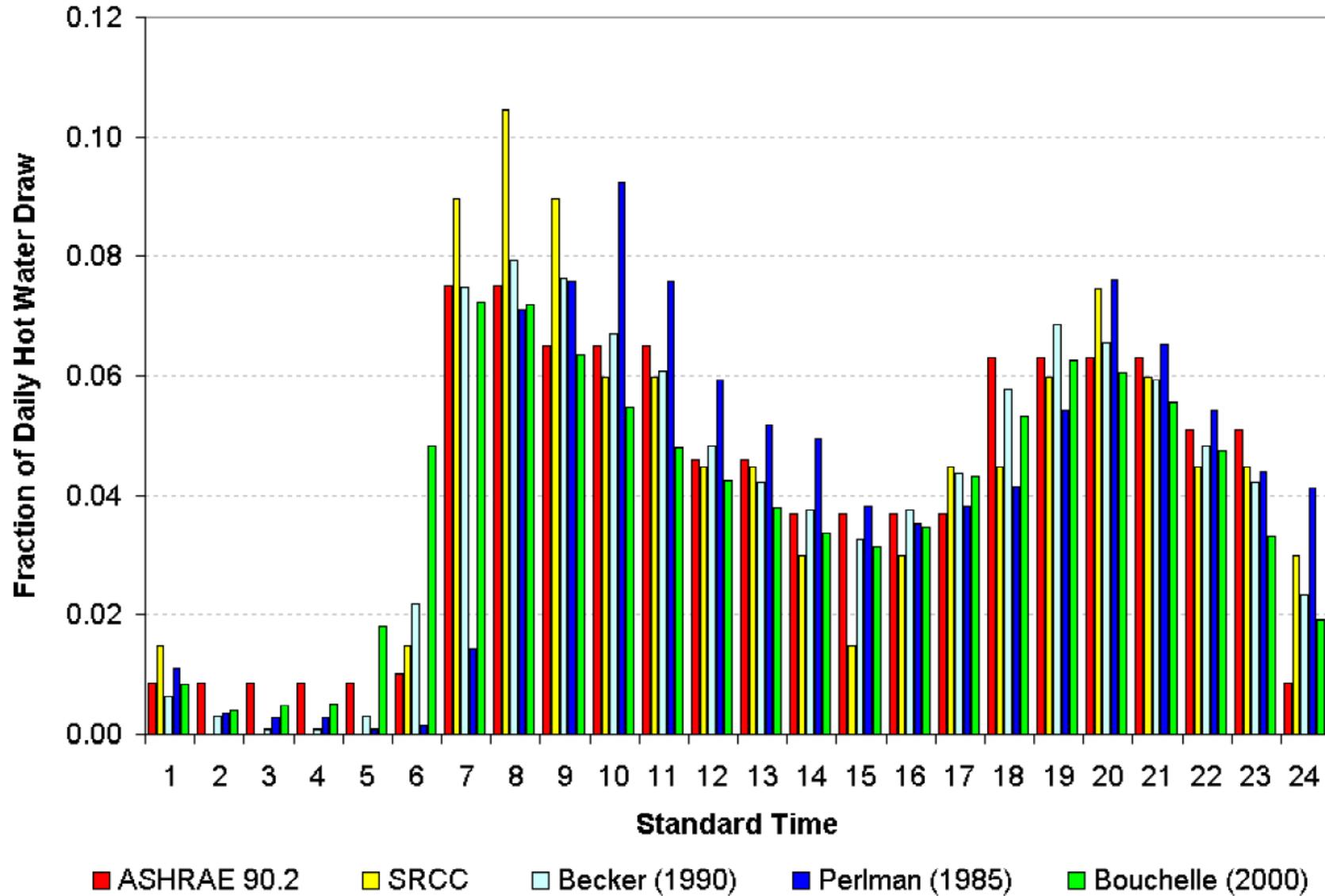


Figure 2.9 Comparison of diurnal hot water use profiles (Fairey & Parker, 2004)

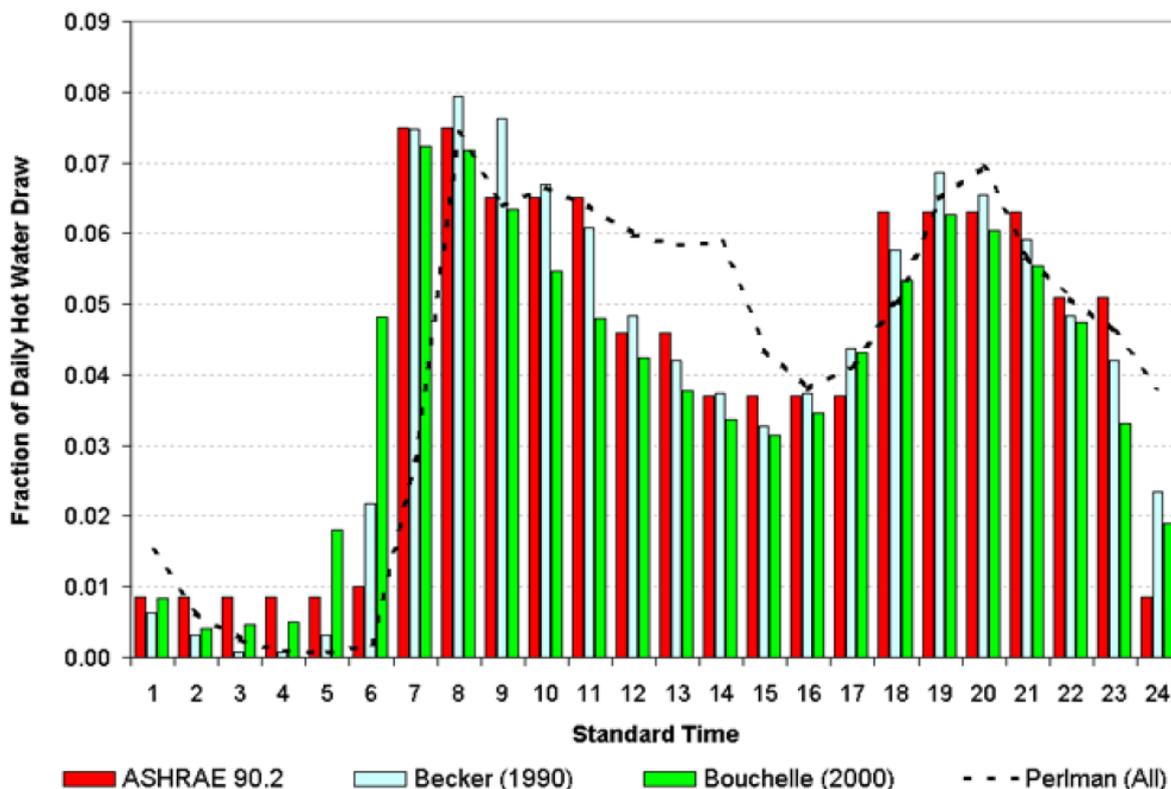


Figure 2.10 Modified diurnal hot water use profiles comparison with omissions (Fairey & Parker, 2004)

2.2 Domestic Hot Water End-Uses

A limited number of end-uses generate hot water demand in households. Typically the end-uses are showers, baths, taps and some appliances like dishwashers and washing machines. Limited studies have been conducted on the exact hot water demand at an end-use level and the studies available typically comprised small sample sizes.

Lowenstein & Hiller (1998) conducted a study to disaggregate residential hot water use at 17 study sites. A larger, more recent study by DeOreo & Mayer (2014) studied hot water demand in 100 homes using flow trace analysis. From these two studies some

values were obtained to observe the typical diurnal hot water demands of end-uses. The values were compared to model results and are presented later in section 5.4.4.

For designing the model proposed in this study, understanding how all hot water end-uses functioned was necessary, so that these end-uses could be modelled accurately. Showers, baths and taps are relatively easy to model, since these hot water events usually have a desired temperature which is achieved by the mixing of domestic hot and cold water supplies. Dishwashers and washing machines are harder to model due to different manufacturer specifications. Extra complexity is introduced when each appliance has a range of settings that can influence the number of cycles, cycle volumes and cycle temperatures. Additional complications with the dishwashers and washing machines are described and dealt with in section 4.7 where the modelling of these events is explained.

Jacobs (2004) investigated washing machines in South Africa and found that two types are commonly used: washing machines connected to both the hot and the cold water supply and those connected to the cold water supply only, thus heating water internally. Jacobs (2004) indicated that there was a strong contrast in user behaviour, as some users preferred hot water and others did a cold wash only. Further research indicated that each detergent had an optimum temperature range at which the detergent works most efficiently. Therefore many packets of information are required when modelling appliances.

2.3 Domestic Hot Water Systems

2.3.1 Water Heaters

The most common water heater fuel types are electricity, natural gas, solar energy and oil. Investigating whether different water heater types, or fuels, had a significant influence on the hot water demand was necessary. No reason to speculate that domestic hot water use would vary with different fuel types, and literature typically does not give

demand as a function of water heater fuel type. In a study by Thomas *et al.* (2011) the correlation between water heater type and hot water use was investigated. It was speculated that users with tankless water heaters (for example, gas water heaters) used more hot water than users with storage water heaters. This conjecture arose since tankless water heaters have an endless supply of hot water, whereas storage heaters are limited by their volume capacity. However, the study concluded that on a per person basis, there was a negligible difference in hot water use as a result of water heater type (Thomas *et al.*, 2011). The results found are presented in Table 2.2 and are also compared with Canadian Standards Association (CSA) test standards (Thomas *et al.*, 2011).

Table 2.2 DHW use by water heater type (Thomas *et al.*, 2011)

<u>Water Heater Type</u>	<u>Volume Demand (ℓ/c/d)</u>
Storage	66
Tankless	64
CSA test standard (Any type)	61

For this study a water heater is defined as the source of hot water to the domestic hot water system which provides hot water for end-uses. Most common water heaters have a specific temperature setting that can be changed by the user via a thermostat. Meyer (2000) used a thermostat setting of 65°C for all water heaters while conducting DHW demand measurements in dwellings in South Africa. The ASHRAE Guidelines (ASHRAE, 2000) suggests using temperatures above 60°C for service hot water. Similarly, Booysen *et al.* (2013) states that 60°C is a typical water heater thermostat setting in South Africa.

Although the water heater was simplified in this study, it was noted that water heaters has been identified as an area with potential for significant energy savings. Booysen *et*

al. (2013) proved that energy can be saved using time control units. Time control units switches the water heater on at planned times during the day, before DHW demand is expected. The proposed model in this study can be used to create typical event schedules which can assist water heater optimisation.

Nel *et al.* (2015) investigated water heater energy consumption using water heater outlet temperature. An algorithm was used to estimate total energy demand and the study concluded that the results had an error smaller than 10 percent for three out of four datasets considered. Future work on water heaters and improved algorithms are discussed in Nel *et al.* (2015).

2.3.2 Temperature Losses in Pipes

In any domestic household with hot water services, thermal losses occur in the water heater, as well as in the pipes that connect the heater to end-use fixtures in the household. The magnitude of these losses is dependent on the layout and location of the hot water distribution system, hot water draw frequencies, temperatures and various other factors. For this study, knowing the standby losses of the water heater is not essential. However, the temperature decrease of the water as it is distributed from the water heater to an end-use fixture was required for accurate modelling.

Mathematical models have been derived to calculate heat loss in pipes (Hiller, 2011). The models were based on laboratory tests on numerous DHW distribution systems. Various temperatures, flow rates, insulations and environments were used in the tests.

The pipe heat loss (UA) factors, were determined for zero-flow (cool-down) and flowing pipes. To determine UA_{flowing} , the steady-state temperature drop from the inlet to the outlet of the pipe was measured.

The flow rate and temperature drop were then used to calculate the UA_{flowing} from Equation 2.1.

$$\begin{aligned}
 Q &= (mC_p)_w(T_{\text{hot in}} - T_{\text{hot out}}) \\
 &= UA_{\text{flowing}}(T_{\text{hot avg}} - T_a) \\
 &= UA_{\text{flowing}}(\text{LMTD}_{\text{flowing}})
 \end{aligned}
 \tag{Equation 2.1}$$

Where:

Q	= heat loss rate
$(mC_p)_w$	= flow rate of water times specific heat of water
$T_{\text{hot in}}$	= water temperature entering pipe
$T_{\text{hot out}}$	= water temperature leaving pipe
$T_{\text{hot avg}}$	= log-mean average pipe water temperature
T_a	= surrounding ambient air temperature
UA_{flowing}	= pipe heat loss characteristic under flowing condition
$\text{LMTD}_{\text{flowing}}$	= log mean temperature difference under flowing conditions
$\text{LMTD}_{\text{flowing}}$	= $[(T_{\text{hot in}} - T_{\text{air}}) - (T_{\text{hot out}} - T_{\text{air}})] / \ln[(T_{\text{hot in}} - T_{\text{air}}) - (T_{\text{hot out}} - T_{\text{air}})]$.

The study also included tests to determine $UA_{\text{zero-flow}}$. The $UA_{\text{zero-flow}}$ values were determined by observing the temperature drop of the pipe over time, after flow in the pipe had stopped. The values of $UA_{\text{zero-flow}}$ were calculated at each minute during the cool-down process. The average $UA_{\text{zero-flow}}$ values were then computed. Best consistency for comparisons between various diameters and types of pipes was achieved by using $UA_{\text{zero-flow}}$ values calculated during the time the pipe was cooling down to the minimal usable temperature, defined as 40°C in the study (Hiller, 2011).

Hiller (2011), presented results of the cool-down duration of zero-flow pipes with water at an initial temperature of 57°C to 40°. Results yielded zero-flow pipe cooling down

times of 20 minutes for 13 mm diameter copper pipes with no insulation. With 19 mm thick foam insulation the temperature dropped to 40°C in 40 minutes. Full flowing copper pipes with a diameter of 19 mm yielded slower temperature loss rates, 23 and 64 minutes with and without insulation, respectively. Newer plastic piping, such as cross-linked polyethylene pipes (PEX), cools down around 100% faster than copper pipes (Hiller, 2011).

Pipe steady-state temperature drop is an important consideration. The UA factors that were determined in laboratory tests by Hiller (2011) can be used to determine temperature drop of water flowing in a pipe as a function of flow rate, pipe length and temperatures (incoming, outgoing and ambient). The expression used for determining steady-state temperature drop as water flows through a pipe was derived from Equation 2.1 by Hiller (2011) and is presented in Equation 2.2.

$$T_{\text{hot out}} = T_a + (T_{\text{hot in}})e^{[(UA)(L)/(mC_p)_w]} \quad \text{Equation 2.2}$$

Equation 2.2 includes the pipe length (L) and the expression $((UA)(L)/(mC_p)_w)$, which is dimensionless. If the pipe exit or end-use temperature is known, then the temperature drop through the pipe can be computed. Hiller (2011) used experimentally obtained UA values for different types of piping to obtain temperature drops for pipes at varying flow rates. Table 2.3 shows temperature drop values as presented by Hiller (2011) for various pipe materials, insulation thicknesses and other conditions. The results were tabulated for steady state flow in 30 m long pipes, with the incoming hot water at a temperature of 57°C and the ambient temperature chosen as 20°C.

Considering Table 2.3, a conclusion is made that temperature steady-state temperature drops can be significant and can influence DHW demand, especially at low flow rates. Therefore the temperature drop was considered to be important and was later added to the model developed as a part of this study.

Table 2.3 Pipe flow temperature drop in pipes (Hiller, 2011)

Nominal Pipe Size (mm)	Foam Insulation Thickness (mm)	Temperature drop (°C) in 30m pipes with flow rate of:						
		0.03 ℓ/s	0.06 ℓ/s	0.09 ℓ/s	0.13 ℓ/s	0.16 ℓ/s	0.25 ℓ/s	0.32 ℓ/s
13 rigid CU	0	4.7	2.5	1.7	1.3	0.9	0.7	0.5
13 rigid CU	19	2.0	1.1	0.8	0.6	0.4	0.4	0.3
19 rigid CU	0	5.8	3.2	2.2	1.6	1.1	0.8	0.7
19 rigid CU	19	2.5	1.4	1.1	0.9	0.6	0.5	0.4
13 PEX	0	6.1	3.2	2.1	1.6	1.1	0.8	0.7
13 PEX	19	1.9	0.9	0.7	0.5	0.3	0.2	0.2
19 PEX	0	5.0	2.7	1.8	1.4	-	-	-
19 PEX	19	1.8	0.9	0.6	0.5	-	-	-

2.4 Desired Domestic Hot Water Use Temperature

The desired user temperature in this section refers to the specific temperature that users require when using hot water for personal hygiene, using either a shower or a bath. The desired user temperature was crucial for the model in the study where hot water volume balances were used, since the desired temperature determines the volume of hot water required.

A study by Ohnaka *et al.* (1994) was conducted to investigate the preferred water temperatures of nine users. The participants measured the temperature of water from the shower head as soon as the desired water temperature was reached. The average preferred water temperature during showers was between 40.2°C and 43.8°C. Wong *et al.* (2010) had three participants shower for four weeks in a year, one week in each season. The study reported that the observed water temperature stayed relatively constant at 40.9°C, with a standard deviation of 1°C. Jacobs (2004) reported a suggested value of 40.2°C for desired user temperature of baths and showers. An older study by Lawrence & Bull (1976) found that the average bath water temperature was 40.5°C for a sample of 20 users.

Smith (2014) assessed household hot water temperatures for shower and bath events by measuring the desired user temperatures and ambient temperatures simultaneously for eight participants. The average desired water temperature for the study ranged between 41°C and 43°C, while the ambient temperature ranged from 13°C to 20°C. Smith (2014) concluded that the ambient temperature does not influence the user's desired temperature. The average desired temperature was reported as 41.8°C.

All reviewed sources provided similar values for desired user temperature and a constant value can be assumed for both the shower and bath end-uses. As a part of this thesis additional tests were conducted to confirm the desired user temperature. The additional tests and conclusions on desired user temperature are discussed later in section 4.6.2 of this thesis.

2.5 Health and Safety Issues with DHW

Human skin is susceptible to hot water burns (scalding) resulting from very hot water temperatures that could be found in domestic hot water systems. The correct safety precautions must always be taken and extremely hot water should be avoided where possible.

Lawrence & Bull (1976) reported that there are two important depths where skin burns can occur: partial thickness skin burns and burns where the entire depth of the skin is damaged. Partial skin burns are painful, but surviving epithelial skin tissue elements can heal partial thickness skin burns.

Full thickness are serious injuries and can only heal by ingrowth of new epithelium tissue from the edge of the wound. If the wound is larger than a few square centimetres then skin grafting is required to treat such burns. Lawrence & Bull (1976) indicated the time exposure required at specific temperatures in order to cause discomfort or skin burns, Figure 2.11.

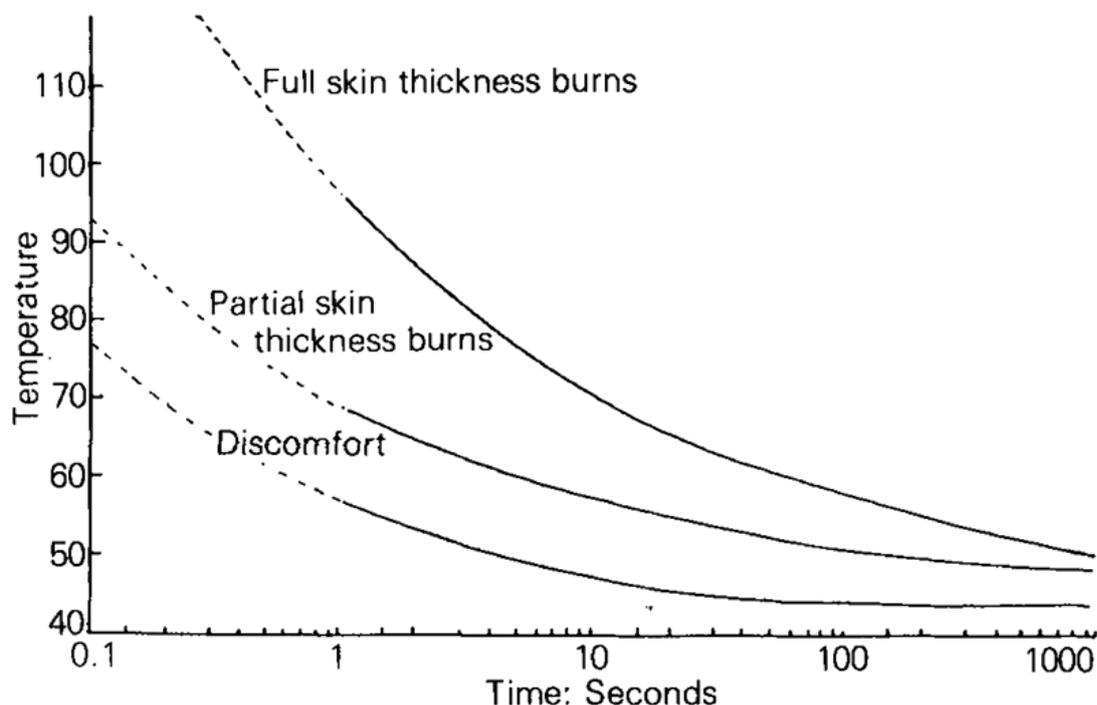


Figure 2.11 Discomfort and thermal injury to skin (Lawrence & Bull, 1976)

Typical water temperatures in domestic hot water system are in the range of 50°C to 70°C. At 70°C partial skin burns can occur at an exposure time of one second, while serious full thickness burns can occur when the exposure time is increased to ten seconds.

A solution to avoid scalding is to decrease the temperature setting on the water heater thermostat. However, the solution consequently increases the risk of harmful bacterial growth within the DHW system. *Legionella pneumophila* is the most common harmful bacteria that can be cultivated in DHW systems. Inhalation of the bacteria can cause Legionnaires' disease (a form of severe pneumonia). Ciesielki *et al.* (1984) determined that the bacteria can colonise hot water sustained at 46°C or lower. Stagnation points, such as water heaters, provide ideal breeding locations for the bacteria. Therefore a water temperature range of above 58°C is recommended to limit potential growth of *Legionella pneumophila* (Dennis *et al.*, 1984). In hospitals and health care facilities, periodic flushing with 77°C water is recommended. An increase in water temperature increases the death

rate of *Legionella pneumophila*, but a balance must be obtained so as to prevent temperatures that are too high and can cause scalding (ASHRAE, 2007).

2.6 Cold Water Supply Temperature

The temperature of the water supplied to a domestic household from the water distribution system and how this temperature can be determined was researched. The temperature in the water distribution system is assumed to be equal to the delivery temperature at end-uses for purposes of this study and is referred to as cold water supply temperature (T_c), but is also termed the mains water temperature (T_{mains}) in literature.

Cold water temperature has a significant effect in DHW demand because the cold water is mixed with hot water from the water heater to achieve a desired temperature (T_d) for a certain end-use. More hot water is required when the cold water supply temperature is low, conversely, less hot water is required to achieve T_d when T_c is high. The cold water temperature is governed by the average monthly ambient air temperatures and the depth at which pipes are buried. In the winter months the temperature is lower and in the summer months the ground temperature increases. But it has been found that a considerable lag is present before seasonal changes are reflected in the ground water temperature. Figure 2.12 graphically presents measured cold water supply and ambient temperatures by Ladd & Harrison (1985) in North America, it is evident that the amplitude of the cold water supply temperature is less pronounced than the ambient temperature.

Previous work on T_c has been limited and the algorithms used in modelling have not been well documented. Existing algorithms includes sinusoids to fit air temperature data and empirical fits, where T_c is expressed as a polynomial function of ambient temperature (T_a) on a monthly basis (Burch & Christensen, 2007).

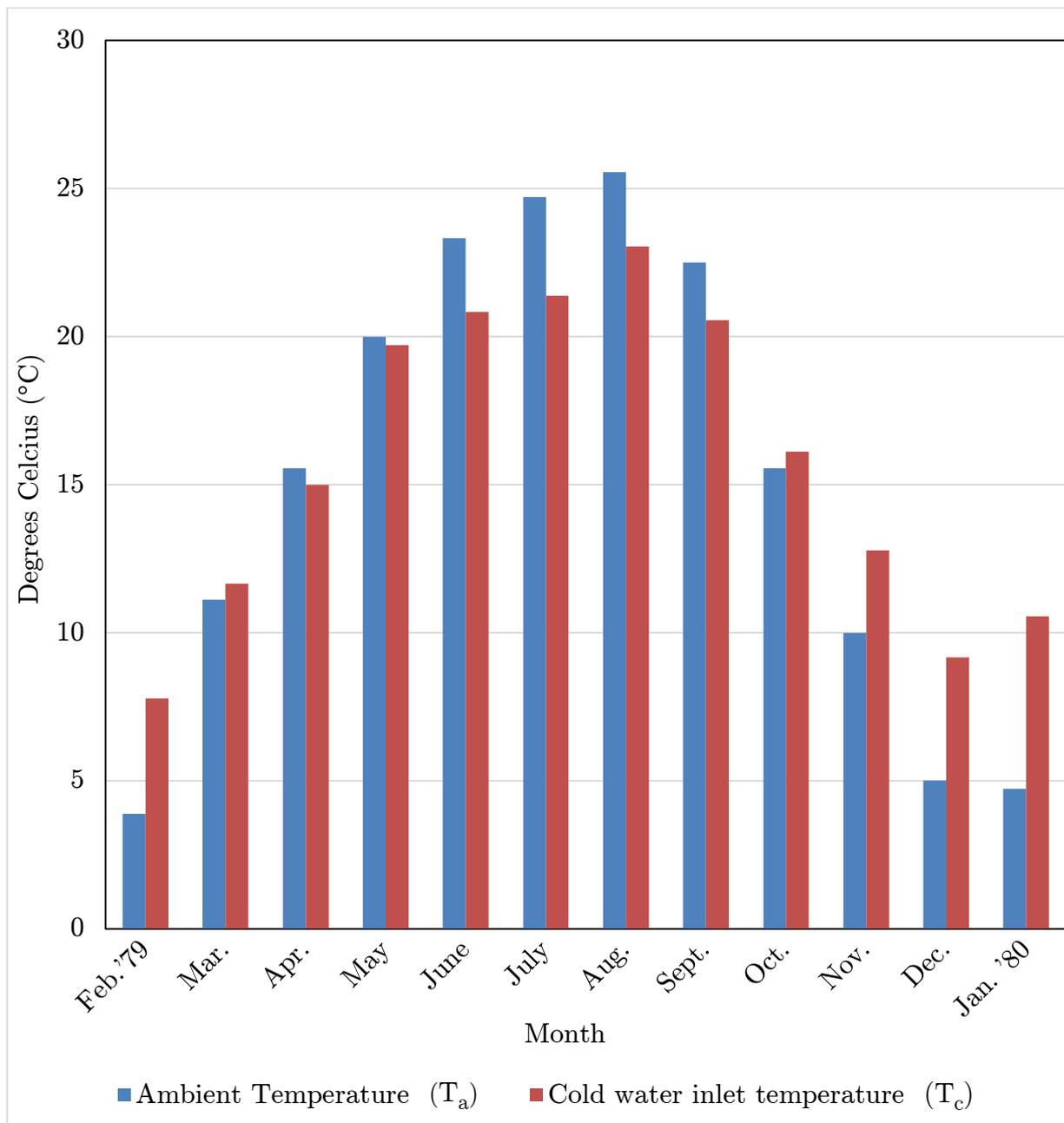


Figure 2.12 Average monthly air and cold water temperatures comparison (adapted from Ladd & Harrison, 1985)

Mains water temperature has a significant influence on the energy consumption of water heaters and is dominantly influenced by the surrounding ambient air temperature (T_a). The ambient temperature can be described by an annual sinusoid (Burch & Christensen, 2007), therefore T_c can be assumed to also be a sinusoid, where the mean value varies

directly proportionally to the annual average ambient temperature. T_c can be modelled as a sinusoid with parameters based on local weather, after recognizing that T_a is sinusoidal and T_c is a strong function of T_a . The sinusoidal model given by Burch & Christensen (2007) is given in Equation 2.3.

$$T_c = T_{a,ann} + R\Delta T_a \sin(\omega t - \phi_a - \phi_c) \quad \text{Equation 2.3}$$

Where:

R = ratio of amplitudes dependent on soil temperatures at different depths

$T_{a,ann}$ = average annual ambient temperature

ωt = angular frequency product with time

$\phi_{a,c}$ = functions of T_a

ΔT_a = maximum average monthly temperature difference.

Burch & Christensen (2007) modified Equation 2.3 by adding a constant observed offset from T_a and expressing the ratio R and the parameter ϕ_c as linear functions of T_a . The Building America Research Benchmark Definition (Hendron & Engebrecht, 2010) used this work to formulate an equation to calculate T_c . The factors for the equation were determined by fitting data from multiple locations (Hendron & Engebrecht, 2010). The equation also takes into account the seasonal lag, as found by Ladd & Harrison (1985), by incorporating a lag factor into the equation.

Wong *et al.* (2010) found a strong correlation between T_a and T_c while comparing locally measured data for a project in Hong Kong. The correlation coefficient was found to be 0.97. The method could be used as to determine cold water supply temperatures for a specific area, if enough measurements were taken.

Equation 2.4 was by Wong *et al.* (2010) with temperatures in units of degrees Celsius.

$$T_c = 10.4T_a^{0.29}; 13 \leq T_a \leq 28 \quad \text{Equation 2.4}$$

Another method to determine cold water supply temperature is with the use of soil temperature models, or data obtained by measuring soil temperature at certain depths. Meyer (2000) indicated that the cold water temperature could be assumed equal to ground temperatures at 300 mm, while Blokker & Pieterse-Quirijns (2013) stated that cold water temperature could be assumed to be equal to the soil temperature around the distribution mains at 1 m depth. The relevant depth depends on the depth of the distribution pipes.

Diurnal variation in supply water temperature is usually minimal. Few literature considers cold water supply temperature on a diurnal scale, but rather on a monthly basis, where a considerable difference in temperatures over the seasons is evident. Daylight radiation and diurnal air temperature variation usually has negligible effects on the soil temperatures at depths lower than 200 mm, and distribution pipes will rarely be found at such shallow depths.

The minimal diurnal variation was investigated by inspecting measured hourly soil temperature records from the National Oceanic and Atmospheric Administration records (Durre *et al.* 2010; Menne *et al.*, 2012). Figure 2.13 illustrates how the soil temperature stays relatively constant on a diurnal scale, in comparison with the minimum and maximum ambient temperatures. The data is obtained from one randomly selected day in a 2014 National Climatic Data Center's (NCDC) dataset, measured at a station in Santa Barbara, California (Durre *et al.* 2010; Menne *et al.*, 2012). Other days showed the same trend. Also, at a depth of one metre the soil temperature stays almost constant throughout the day, and at 200 mm the variation is not more than 1°C. Using the assumption from Blokker & Pieterse-Quirijns (2013) that the cold water temperature is

equal to the soil temperature at one metre, the assumption can be made that there is small variation in cold water supply temperature on a diurnal time scale. Thus monthly variation is a more sensible subject for further investigation.

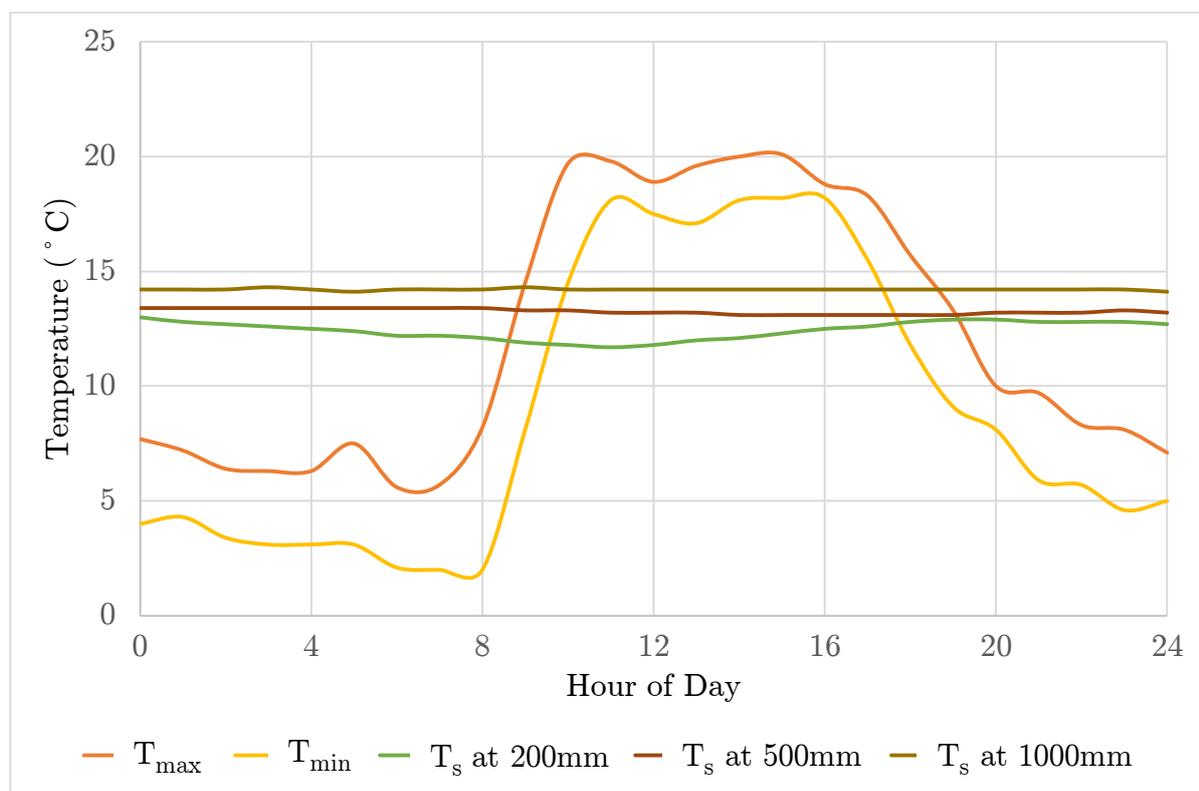


Figure 2.13 Diurnal variation in soil temperature in Santa Barbara, CA. (Durre *et al.* 2010; Menne *et al.*, 2012).

Blokker & Pieterse-Quirijns (2013) described a model for determining temperatures in the drinking water distribution with micrometeorology and concluded that soil temperatures at various depths could be predicted as a function of weather and environmental conditions. The model results were compared with measurements at specific locations in the water supply system. The predicted temperatures of the surrounding soil was clearly indicative of the water temperature. Consequently, the model could be used to predict water temperatures in the water distribution system,

since the residence time of the water in the system is over-sufficient for complete heat transfer between the soil and the drinking water (Blokker & Pieterse-Quirijns, 2013).

The most accurate way to determine the cold water supply temperature would be local measurements. However, it is not always possible to obtain local data when working with existing datasets that do not include these measurements.

An example of a project where local water mains temperatures were measured is documented in an article by Parker (2003). The electricity demand and use of end-uses in 204 residences were monitored in Florida, USA. Figure 2.14 exhibits the measured results of mains water temperatures in a year. Measuring data locally for a particular project can assist in obtaining more accurate results, if cold water inlet temperature is one of the variables required.

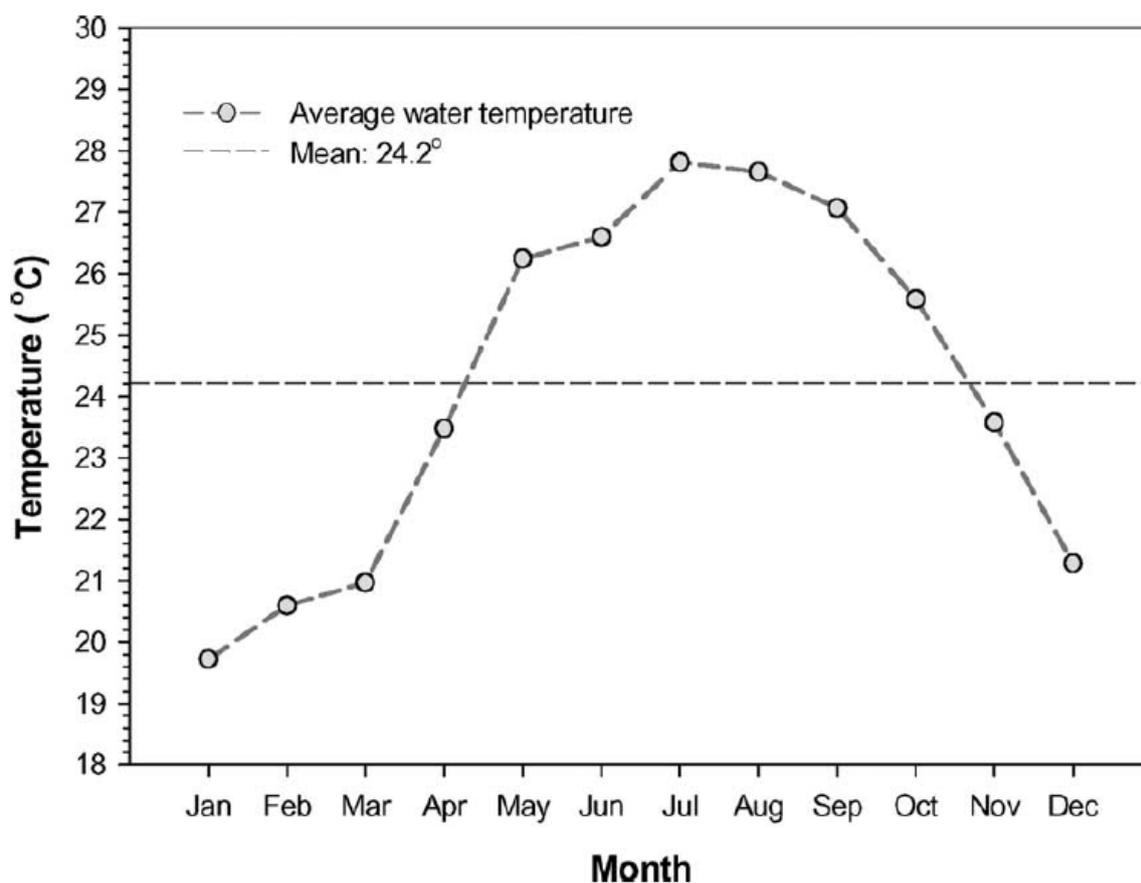


Figure 2.14 Measured variation in mains water temperature (Parker, 2003)

2.7 Domestic Hot Water Demand Modelling

2.7.1 *Realistic Domestic Hot-Water Profiles in Different Time Scales*

A software tool called DHWcalc, was developed by Jordan & Vajen (2001). DHWcalc generates random event schedules based on hourly profiles, average diurnal volumes, average event characteristics and other constraints that must be supplied by the user. Event volume and flow rate varies randomly around an average value based on the standard deviation entered by the user. Hourly probability distributions are entered by the user and the software modifies the distributions by accounting for seasonal change and weekday versus weekend variation. One minute, six minute and one hour time steps were available in the software. The model required educated inputs, and therefore the software was used by Hendron & Burch (2008) to develop standardised DHW event schedules. The fixed durations and simplifications used in the model instigated the authors to pursue alternatives for modelling DHW.

2.7.2 *Tool for Generating Realistic Hot Water Event Schedules*

Hendron & Burch (2010) developed a spreadsheet tool that generates random event profiles based on probability distributions for hot water event duration, flow rate, individual fixture use and duration between events. Their tool made use of two residential hot water studies conducted by Aquacraft (Mayer *et al.*, 1999; Aquacraft, 2008).

One of the features in the tool was clustering start times of events, as it was believed that hot water events tend to occur in clusters. Event characteristics were derived for five end-uses by use of simplified probability distributions for flow rate and duration. The distributions were derived from the DHW data obtained from the two studies (Mayer *et al.*, 1999; Aquacraft, 2008) and the values used in the tool are presented in Table 2.4.

Table 2.4 Derived event characteristics (Hendron & Burch, 2010)

Characteristics	Tap	Shower	Bath	WM	DW
Average duration (min)	0.6	7.8	5.7	3.1	1.5
Standard deviation for duration (min)	0.7	3.5	2.1	1.6	0.4
Probability distribution for duration	Exponential	Log-Normal	Normal	Discrete	Log-Normal
Average flow rate (ℓ/s)	0.072	0.142	0.278	0.139	0.088
Standard deviation for flow rate (ℓ/s)	0.038	0.043	0.074	0.039	0.013
Probability distribution for flow rate	Normal	Normal	Normal	Normal	Normal
Average event volume (ℓ)	2.9	63.3	88.8	26.3	8.1

The tool, however, did not disaggregate hot water use for the sink, shower, bath and dishwasher events; instead, volumes determined from flow rates and durations included a combination of hot and cold water. The model also assigned the demand to certain fixtures within a household, with the assumption that each house had two showers, two baths, four sinks and a dishwasher and washing machine. Another limitation of the model was that the model did not include demand based on the number of occupants in households.

2.7.3 EPRI Model

In 1985 the Electric Power Institute (EPRI) model was developed to estimate DHW demand on a specific temporal diurnal scale, using multiple regression analysis (Lutz *et al.*, 1996). The model included 16 equations that were used to calculate the amount of hot water consumed at eight separate time intervals during a day. The model classified occupants into three age groups and all households were assumed to have a dishwasher

and a washing machine. Additional variables included inlet water temperature, ambient air temperature, thermostat setting of the water heater, water heater tank size, and variables to reflect seasonal change.

Although the original EPRI model allowed for the estimation of DHW demand, its applicability is limited, due to the assumptions the model include, such as all the household demographics and end-uses being included, as well as the small sample size (110 households) on which the model was based. In order to obtain estimates for a comprehensive range of households, Lutz *et al.* (1996) expanded the model, including two new appliance variables and two new demographic variables. The demographic variables were expanded to include senior-only houses and houses that did not pay for water. The addition of 'no washing machine' and 'no dishwasher' variables was added to facilitate application of the model to households that did not have either both or only one of these appliances. The generic form of the modified model involves linear equations that have the following form:

$$\text{DHW Demand} = [f(\text{SV}, \text{PPH}, \text{age}_1, \text{age}_2, \text{age}_3, T_{\text{set}}, T_c, T_a, \text{athome}, T_{\text{size}}, g_1(\text{PPH}, \sqrt{\text{PPH}}) \cdot \text{nodw}, g_2(\text{PPH}, \sqrt{\text{PPH}}) \cdot \text{nocw}] (1 - \alpha_1 \cdot \text{senior})(1 + \alpha_2 \cdot \text{nopay})$$

Where:

SV	= seasonal variables
PPH	= total number of persons in household
age ₁	= number of preschool children, age 0-5 years
age ₂	= number of school age children, age 6-13 years
age ₃	= number of adults, age 14-64 years
T _{set}	= water heater thermostat setting, °F
T _c	= cold inlet water temperature, °F
T _a	= ambient air temperature, °F

T_{size}	= water heater nominal tank size, gallons
athome	= 1 if adults are at home during the day, = 0 otherwise
nodw	= 1 if no dishwasher, = 0 otherwise
nocw	= 1 if no clothes washer, = 0 otherwise
senior	= 1 if this is a seniors-only household, = 0 otherwise
nopay	= 1 if household does not pay for hot water, = 0 otherwise

α_1 and α_2 coefficients and the terms $g_1(\text{PPH}, \sqrt{\text{PPH}})$ and $g_2(\text{PPH}, \sqrt{\text{PPH}})$ are defined as determined by Lutz *et al.* (1996).

2.8 Previous Probabilistic End-Use Model

A probability based end-use model was constructed as part of a project at Stellenbosch University by Scheepers (2012). The model derived residential diurnal indoor water demand patterns on a high resolution temporal scale. The model specifically considered indoor water use without discriminating between hot water and cold water draws. The model included six indoor residential end-uses. The end-uses were described in terms of volume, duration and time of occurrence. The model was based on other previously successful models, such as SIMDEUM (Simulation of water demand, and end-use model) by Blokker *et al.* (2008).

The probability distributions that were used to define the end-use model parameters were derived from actual end-use measurements conducted in North America for the Residential end-uses of water study (REUWS) by Mayer *et al.* (1999). The original comprehensive database was purchased by Stellenbosch University for the project.

2.8.1 Model Structure

The model determined flow caused by water use events at a resolution of ten seconds. The model assumed that events had a constant flow rate for the entire duration of the

event. The end-use events could therefore be equated to rectangular pulses of flow rate and time. The same approach was followed in a study by Buchberger & Wu (1995), who showed that rectangular pulses can successfully describe indoor water demand. The model generated end-use event rectangular pulses, and added the generated pulses of individual end-uses together to obtain a total water demand profile for a single household.

The elements required in the model to generate the rectangular pulses were obtained from end-use specific probability functions for volume and flow rate. Probability distributions were also derived for starting hour for each end-use. A software package @Risk was used to manipulate data from the REUWS database in order to generate the required probability distributions.

Water demand was also found to be strongly related to the number of people per household (PPH). The frequencies of end-use events were therefore related to the number of people per household. The model included categories of one person per household to six PPH.

The first step in the model was to determine the household size. Once that has been established the number of events that occurred on the simulated day was determined for the selected household size. End-use-specific probability distributions were used to assign volume, flow rate and starting times to the events. The duration and ending times could then be calculated with the available information. Additional probability distributions were required for an end-use with cyclic water demand patterns, such as washing machines and dishwashers. The number of cycles and the duration between cycles were important for the model. All the probability distributions were derived from measured end-use water consumption collected in the REUWS database.

With all the model end-use event values available, the flow rates occurring in the day were aggregated. The diurnal pattern for one household was subsequently available. A Monte Carlo simulation method was applied in the model to produce numerous single

household water demand scenarios. A simple schematic representation of the model can be seen in Figure 2.15. The dashed lines show parameters that are applicable only to the washing machine and dishwasher.

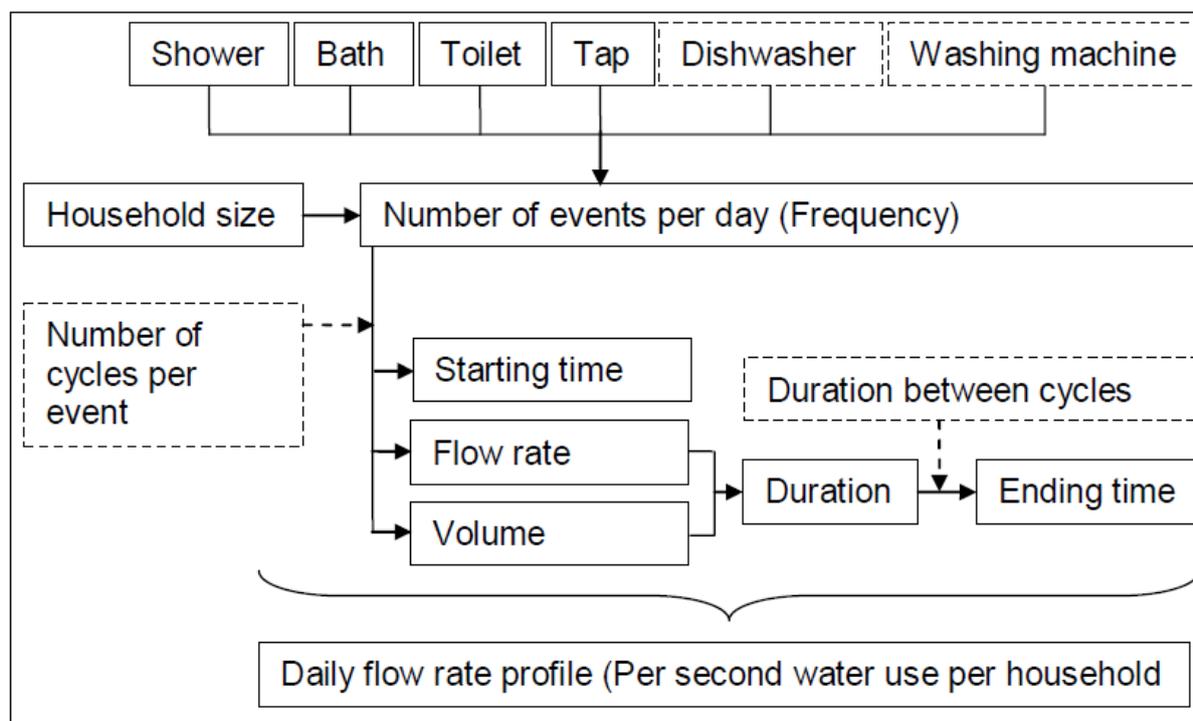


Figure 2.15 Simplified schematic of end-use model by Scheepers (2012)

2.8.2 Data Input Source

The parameters of the theoretical probability distribution functions in the end-use model were obtained from measured water consumption data. It was considered crucial that a large sample of households was included in the analysis to guarantee accurate data. The study made use of data collected in a previous project. The REUWS database was the largest known collection of measured end-use data that was available and was therefore selected as the main data source for the model.

The REUWS database comprised indoor and outdoor end-use data collected by Aqacraft, Inc. in Boulder, Colorado, USA. Twelve study sites were chosen, with

approximately 100 households within each study site. The study sites included fourteen cities in the United States and Canada. The water use data was collected by a portable data logger, attached to the water meter of each home in the study sample. The data logger captured the average volume through the meter every ten seconds. Data was collected at each home for two weeks in the winter and two weeks in the summer.

Trace flow analysis was used to disintegrate the measured flow data into end-use events. The process used a software package namely Trace Wizard. While the data was analysed and separate events were identified, the volume, duration, start time, end time, peak flow rate, mode flow rate and mode frequency were determined for each event. Trace Wizard was employed by applying user defined parameters for each household. The parameters contained ranges of possible values for flow rate, volume and duration, which were unique to a certain end-use. An analyst on the Trace Wizard team repeated the routine and fine-tuned the parameters to build an accurate parameter file that could correctly identify end-uses based on expert input (Mayer *et al.*, 1999).

2.8.3 Results and Conclusion

The model was executed for 99 500 iterations and the results were presented in the study. For each model iteration, the household size and the water demand from each of the modelled end-uses were recorded, and consequently the averages could be obtained.

The intention of the model was not to duplicate previously measured datasets, but some sort of agreement with existing data was expected. The share of the overall indoor demand was compared with other studies. The comparison is shown in Table 2.5, where 'This study' at the bottom of the table refers to the results obtained from the model by Scheepers (2012). The shares quoted from previous studies in Table 2.5 are presented as a fraction of the demand from the six relevant end-uses considered by Scheepers (2012). The values obtained were considered to compare reasonably well with results of other

studies on an end-use basis. Water demand profiles were also generated, and were deemed acceptable in terms of basic verification.

Table 2.5 End-use share comparison (Scheepers, 2012)

Reference	Study Area	End-use share (%)						
		Toilet	Shower	Washing Machine	Tap	Dish-washer	Bath	Total Indoor
(Edwards & Martin 1995)	UK, 100 homes	34.0	4.1	21.6	25.8	1.0	13.4	100.0
(DeOreo <i>et al.</i> 1996)	USA, 16 homes	29.3	19.5	28.2	16.7	3.4	2.9	100.0
(Mayer <i>et al.</i> 1999)	USA/Canada, 1,188 homes	31.9	19.9	25.7	18.7	1.8	2.0	100.0
(DeOreo <i>et al.</i> 2001) Pre-retrofit	USA, 37 homes	33.0	15.9	26.1	16.1	2.5	6.5	100.0
(DeOreo <i>et al.</i> 2001) Post-retrofit	USA, 37 homes	21.0	23.0	24.4	21.2	3.2	7.1	100.0
(Loh & Coghlan 2003)	Australia, 120 homes	22.0	34.1	26.8	17.1	–	–	100.0
Mayer <i>et al.</i> (2003) Pre-retrofit	USA, 33 homes	33.0	19.9	23.0	17.4	1.7	5.0	100.0
Mayer <i>et al.</i> (2003) Post-retrofit	USA, 33 homes	22.5	24.6	20.2	24.1	2.1	6.4	100.0
(Roberts 2005)	Australia, 100 homes	19.3	31.5	27.1	17.7	1.7	2.6	100.0
Heinrich 2007	New Zealand, 12 homes	19.5	39.4	23.7	13.6	1.3	2.5	100.0
(Willis <i>et al.</i> 2009)	Australia, 151 homes	15.4	36.4	22.0	19.8	1.6	4.7	100.0
This study		19.8	18.4	36.9	10.0	4.7	10.3	100.0

Scheepers (2012) noted that washing machine, dishwasher and bath end-use estimates were slightly over-estimated when compared with other studies and the REUWS per capita values. Scheepers (2012) concluded that the model could be improved; however, the model was a useful method for deriving domestic indoor water demand on a temporal scale of ten seconds. An end-use model of its sort had not previously been presented in South Africa. The end-use and total demand characteristics are not representative of water demand in South Africa, but the model provides an excellent basis for further research and development on the topic.

3 Data Used for Model

In order to determine DHW consumption in a stochastic routine, obtaining theoretical probability distributions for the parameters in the model was necessary. Various measured hot water use data was available but typically with small sample sizes. The aim of this study was to stochastically determine hot water use from probabilities obtained from a large sample size. Detailed larger scale end-use data projects can be time consuming and costly, especially when measuring hot water use. Therefore, for the purposes of this study it was decided to use a suitable database from a previous project.

3.1 Data Selection

Several hot water use databases are available. A database by Becker and Stogsdill (1990), as mentioned in section 2.1.1 of the literature, was a large, valued dataset. Findings in recent studies, however, indicated that the data was outdated and did not represent current use patterns (Edwards *et al.*, 2015). Therefore the model in this study used the largest known database of domestic water consumption to date, the REUWS by Mayer *et al.* (1999).

A more recent study named the REUWS2, was conducted by the same authors, and water consumption was measured between 2011 and 2013 (DeOreo & Mayer, 2014). The 2014 study used the same methodology and sample size as the original REUWS study, with only some changes in study sites. The REUWS2 database additionally included 110 homes that had water meters on the inflow pipes to the water heaters. During the logging period, data was obtained simultaneously from both the mains and hot water meters (DeOreo & Mayer, 2014). The comprehensive REUWS2 dataset, however, was not available for determining parameters for modelling in this study.

3.2 Study Sites

The objective of the REUWS was to collect water consumption data from various locations in North America. Twelve study sites, covering fourteen cities within the US and Canada were selected as suitable for the project. The study sites could be divided into six distinct regions of North America (Mayer *et al.*, 1999):

- 1) West Coast – Walnut Valley Water District, San Diego, Las Virgenes MWD and Lompoc, California
- 2) Southwest – Phoenix, Scottsdale and Tempe, Arizona
- 3) Northwest – Seattle, Washington and Eugene, Oregon
- 4) Mountain – Boulder and Denver, Colorado
- 5) Midwest/Canada – Cambridge and Waterloo, Ontario
- 6) Southeast – Tampa, Florida.

The study sites were characteristic of their locations, but not essentially representative of all locations in North America. The study sites are geographically shown in Figure 3.1.



Figure 3.1 Study Sites used in REUWS (Scheepers, 2012)

3.3 End-use Data Collection and Analysis

The Mayer *et al.* (1999) study group selection was done by sending out surveys to 1 000 single family households within each of the twelve study sites. The survey target group was selected by subjecting the entire utility database to various quality assurance tests to determine whether the sample was statistically representative of the population. The survey included questions relating to water end-uses, appliances, habits, landscape features and some demographic information.

A sample of approximately 100 homes in each study site was selected by Mayer *et al.* (1999) in which to fit data-loggers. The households selected for consumption monitoring went through further quality assurance tests, to ensure that statistically representative houses were selected, before the sample was approved for logging. In all twelve study sites combined, 1 188 households were monitored with flow logging equipment for the study.

Portable data loggers were used by Mayer *et al.* (1999) to measure the flow at the water meter. The device logged that average volume of water flowing through the meter every ten seconds. The study sites rotated the loggers between them with the aim of recording during two winter weeks and two summer weeks for each site. The data was successfully collected during 1996 and 1997. A schedule of when the data was collected is presented in Table 3.1.

The recorded flow data was analysed using flow trace methods with Trace Wizard software, as mentioned in section 2.8.2 of this thesis. The software was used to disintegrate the flow data into end-use events. The data was stored in tables in a Microsoft Access document.

The logging data consisted of more than 1.9 million disaggregated end-use events from all the study sites over the logging period. Each event, with an event type, date of occurrence, start and end time, duration and volume is identified with flow trace analysis

software. The REUWS raw data set was obtained from the authors for further analysis as part of earlier work by Scheepers (2012) and work in this study.

Table 3.1 REUWS Data collection schedule (Mayer *et al.*, 1999)

Site	City	Data collection period	
		1	2
1	Boulder, Colorado	21 May-7 June, 1996	3 Sep-19 Sep, 1996
2	Denver, Colorado	5 June-21 June, 1996	27 May-13 June, 1997
3	Eugene, Oregon	24 June-11 July, 1996	1 Dec-20 Dec, 1996
4	Seattle, Washington	16 July-2 Aug, 1996	7 Jan-24 Jan, 1997
5	San Diego, California	6 Aug-26 Aug, 1996	3 Feb-21 Feb, 1997
6	Tampa, Florida	1 Oct-18 Oct, 1996	3 Mar-21 Mar, 1997
7	Phoenix, Arizona	6 May-23 May, 1997	4 Nov-21 Nov, 1997
8a,b	Scottsdale & Tempe, Arizona	29 Oct-15 Nov, 1997	2 Dec-19 Dec, 1997
9a,b	Waterloo & Cambridge, ON	24 June-11 July, 1997	7 Oct-24 Oct, 1997
10	Walnut Valley, California	22 July-8 Aug, 1997	6 Jan-23 Jan, 1998
11	Las Virgenes, California	12 Aug-29 Aug, 1997	27 Jan-13 Feb, 1998
12	Lompoc, California	9 Sep-26 Sep, 1997	24 Feb-13 Mar, 1998

3.4 Climate Data

Many variables that have an impact on hot water demand in households are affected by temperature. For the stochastic hot water demand model, it was important to have values for average ambient temperatures, as well as cold water inlet temperatures. No cold water inlet temperatures were specifically recorded during the REUWS study, but consulting the literature, the values could be estimated from ambient temperature values. Therefore, obtaining and preparing climate data for the model was necessary.

The REUWS Microsoft Access database file by Mayer *et al.* (1999) included tables named 'Daily Weather' and 'Weather stations'. The daily weather tables included daily minimum and maximum temperatures from 1993 to 1997 for most of the study sites, with most of the data coming of observations from the National Climatic Data Center's

(NCDC) Global Historical Climatology Network (GHCN) - Daily database (Durre *et al.*, 2010; Menne *et al.*, 2012).

For the stochastic hot water demand model developed as part of this research project, climate data parallel to the data logging years of 1996 and 1997 was used. For consistency and uniformity in the climate data, all the climate data was obtained from the nearest NCDC station to each of the study sites, instead of using the data given in the REUWS Microsoft Access file. The data given in the REUWS database was mostly identical, since the data was also obtained from NCDC stations mostly. However, the data for Waterloo and Cambridge in Ontario, Canada was from Environment Canada's database. Therefore, in this study, the climate data for Waterloo and Cambridge was taken from the closest NDCD station, namely, Hemlock, NY. The closest NDCD should be representative of the climate of the study site for the purposes of the study. A list of weather stations used for climate data in this study is presented in Table 3.2.

Table 3.2 NCDC Stations used for climate data

Site	City	NCDC Station used (Station number)
1	Boulder, Colorado	BOULDER, CO (050848)
2	Denver, Colorado	BOULDER, CO (050848)
3	Eugene, Oregon	NORTH BEND, OR (356073)
4	Seattle, Washington	CEDAR LAKE, WA (451233)
5	San Diego, California	CUYAMACA, CA (042239)
6	Tampa, Florida	TARPON SPGS, FL (088824)
7	Phoenix, Arizona	WICKENBURG, AZ (029287)
8a, 8b	Scottsdale and Tempe, Arizona	WICKENBURG, AZ (029287)
9a, 9b	Waterloo and Cambridge, Ontario	HEMLOCK, NY (303773)
10	Walnut Valley, California	PASADENA, CA (046719)
11	Las Virgenes, California	PASADENA, CA (046719)
12	Lompoc, California	PASO ROBLES, CA (046730)

For this research project, the climate data was manipulated in order to have values that could be used in the proposed end-use model. The average daily minimum and maximum temperatures for 1996 and 1997 were obtained from each of the weather stations. The

average of the two years was then taken, to obtain the minimum and maximum temperatures used in the final climate data set for the model. The average between the minimum and maximum values was also calculated, to obtain a daily average estimate. Consequently a climate dataset was created with minimum, maximum and average daily temperatures for each day of the year for each of the study sites. Monthly averages were also determined and compared, as illustrated in Figure 3.2. The average ambient temperatures used in the model had to be representative of all study sites. Therefore it was considered appropriate to use the average ambient temperatures from all study sites. Figure 3.2 clearly shows that the different study sites followed a similar seasonal pattern, with values generally offset from the mean in a normal manner, with the standard deviation being 5.5°C.

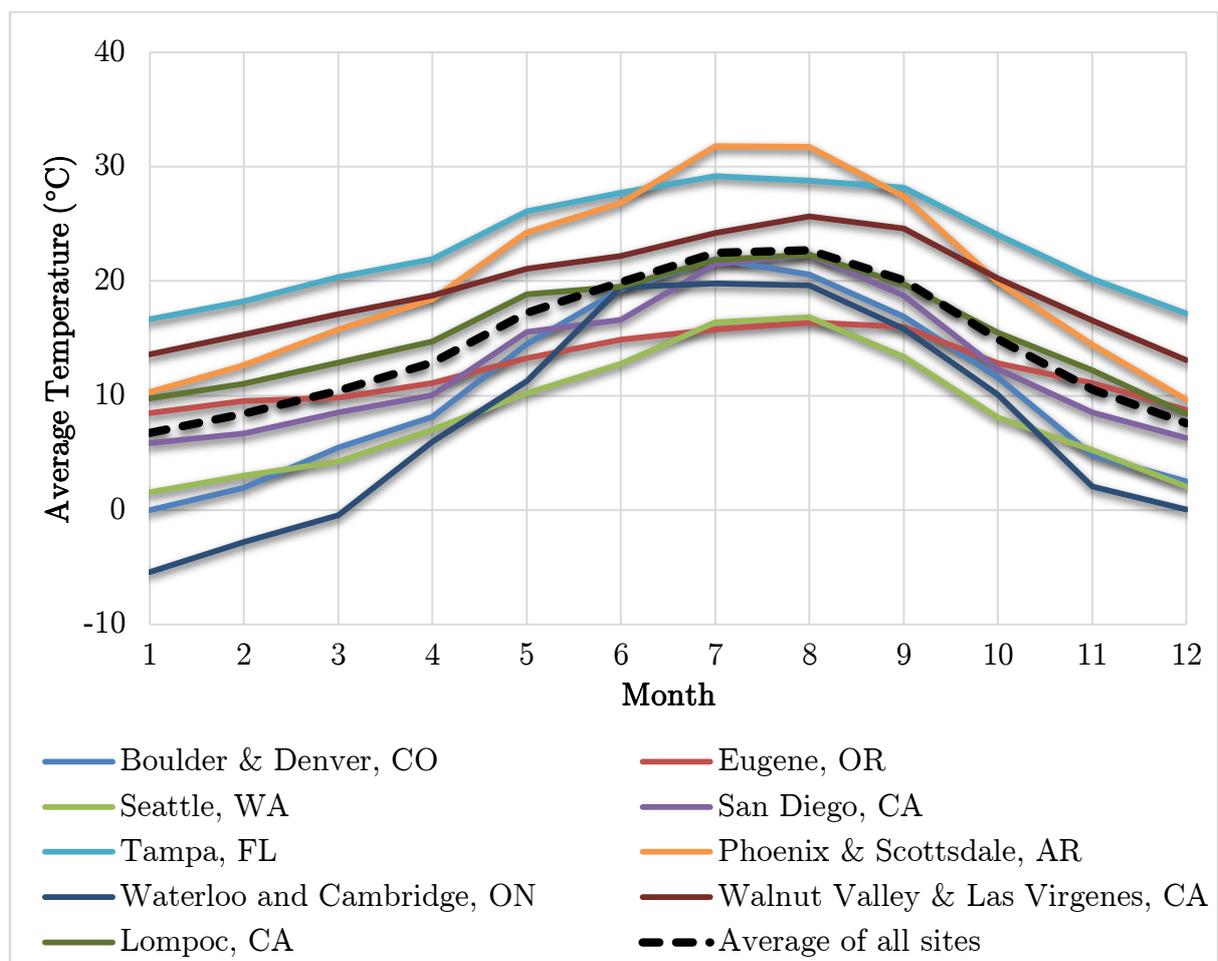


Figure 3.2 Comparison of monthly climate of all study sites

3.5 Cold Water Inlet Temperature

The approach to compute the cold water inlet temperatures (T_c) of households in the stochastic model was to estimate T_c from ambient temperatures. An existing algorithm that estimates T_c with a sinusoid fit as described in the literature (Burch & Christensen, 2007), was used in the model.

An equation based on the work by Burch & Christensen (2007) was published by (Hendron & Engebrecht, 2010). The equation was considered appropriate for the stochastic end-use model in this thesis, in the absence of better alternatives such as measured data at the study sites. The equation by Hendron & Engebrecht (2010) is presented as Equation 3.1. The offset (δ), ratio (R), and lag (λ) factors were determined by (Hendron & Engebrecht, 2010) through fitting available measured data.

$$T_c = (T_{a,avg} + \delta) + R\left(\frac{\Delta T_{a,max}}{2}\right)\sin(0.986(\text{day} - 15 - \lambda) - 90)$$

Equation 3.1

Where:

T_c	= cold inlet water temperature, °F
$T_{a,avg}$	= annual average ambient air temperature (°F)
$\Delta T_{a,max}$	= maximum difference between monthly average T_a (°F)
0.986	= degrees/day (360/365)
day	= Julian day if the year (1-365)
δ	= 6 (°F)
R	= $0.4 + 0.01(T_{a,avg} - 44)$
λ	= $35 - 1.0(T_{a,avg} - 44)$.

Equation 3.1 used units of Degrees Fahrenheit ($^{\circ}\text{F}$) and not the SI-unit degrees Celsius ($^{\circ}\text{C}$). However, the original climate data was correspondingly obtained in $^{\circ}\text{F}$, therefore all the calculations were done with $^{\circ}\text{F}$ and the values converted to $^{\circ}\text{C}$ afterwards.

The minimum, maximum and average temperature values for each day of the year were calculated, from historic data of 1996 and 1997, for each study site in this research project. For the model in the study, values that was representative of all study sites were determined by averaging the values of all nine study sites. Table 3.3 partially illustrates the climate data manipulation, where the temperatures for the first and last days of the year are shown for an example study site and the total combined averages. Consequently, the total combined averages consisted of average temperatures for each day, based on the data of two years, and is representative of all study sites. The temperatures from the total combined average column in Table 3.3 were accordingly used as ambient temperatures in the model in this study.

Table 3.3 Climate data manipulation for the model in this study

Day of the year	Walnut Valley, California			Repeat for all 9 weather stations			Total combined averages		
	Averages of 1996 and 1997			Averages of 1996 and 1997			Averages of 1996 and 1997		
	T_{\max}	T_{\min}	T_{avg}	T_{\max}	T_{\min}	T_{avg}	T_{\max}	T_{\min}	T_{avg}
1	69.5	48.0	58.8	-	-	-	59.6	39.9	49.8
2	69.0	50.0	59.5	-	-	-	59.1	42.2	50.6
364	72.0	52.0	62.0	-	-	-	60.0	37.7	48.8
365	70.5	49.5	60.0	-	-	-	59.9	38.8	49.3

The $\Delta T_{a,\max}$ value was calculated by taking the difference between the minimum and maximum monthly averages. Subsequently, $T_{a,\text{avg}}$ was calculated as the mean of all the daily average temperatures for all 365 days. The values for the offset (δ), ratio (R), and lag (λ) factors were used and calculated as in Hendron & Engebrecht (2010).

After executing Equation 3.1 for every day of the year a resulting column of cold water inlet temperatures (T_c) was obtained for each day of the year. These values had to be implemented in the model as a cold water inlet temperature variable. Investigating the T_c values, it was found that when the monthly averages were taken the average standard deviation of all months was only 0.64°C . Therefore it was deemed preferable to use monthly mean T_c values for the stochastic model envisioned in this study, since the day to day temperature differences would be small. Ultimately the model would be able to produce diurnal hot water demand patterns for any selected month. The process is further discussed in section 4.3.1.

The prepared T_c values for the model are given in Table 3.4. The predicted sinusoid comparison with the available ambient temperature values is illustrated in Figure 3.3. The temperature lag, as described stated by Ladd & Harrison (1985), is observed clearly and the predicted values appear similar to an example given by Hendron & Burch (2008). The predicted T_c values were deemed appropriate for the purposes of the model. The minimum, maximum and average daily temperatures occasionally fluctuate significantly from day to day, since the values were obtained using temperature data from two years.

Table 3.4 Predicted monthly cold water inlet temperatures for model

Month	Predicted T_c ($^\circ\text{C}$)	Monthly Standard Deviation ($^\circ\text{C}$)
January	11.29	0.34
February	11.00	0.16
March	12.32	0.63
April	14.98	0.93
May	18.28	0.99
June	21.31	0.76
July	23.26	0.37
August	23.60	0.18
September	22.23	0.62
October	19.53	0.94
November	16.23	0.96
December	13.23	0.77
Average	17.27	0.64

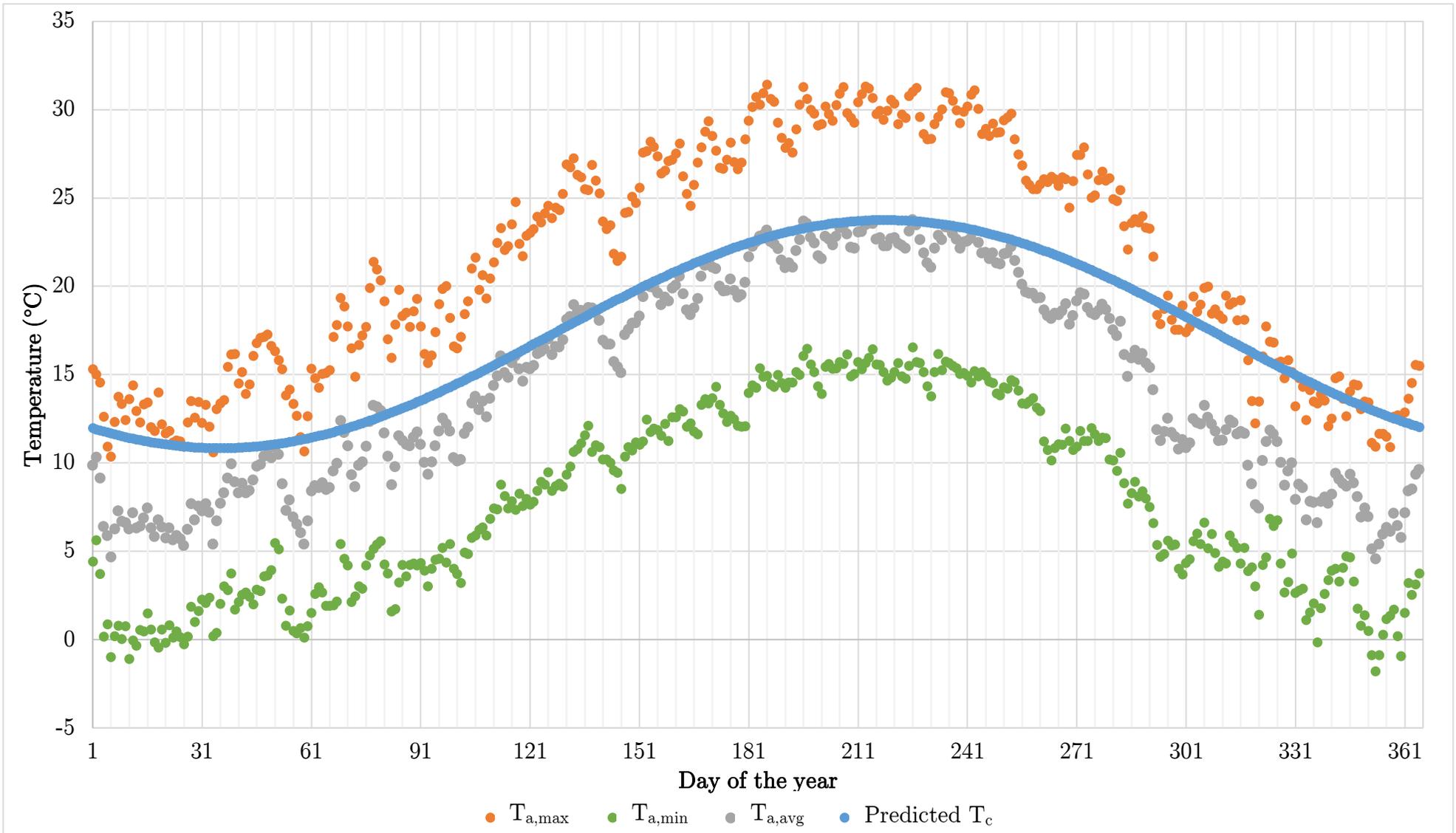


Figure 3.3 Comparison of predicted T_c values to T_a values

4 Stochastic End-use Model

The main deliverable of the study was to develop a computer based stochastic end-use model to generate diurnal domestic hot water demand patterns. The approach was to generate a finite number of single household profiles, based on data recorded in earlier studies, and aggregate the profiles to determine mean hot water demand on a temporal scale of one minute.

The model is discussed fully in this chapter and explanations are provided for the parameters that were included in the model structure. The methodology of the model's creation and population is completely described, including the procedure of compilation of diurnal patterns by the model. Thereafter a definition of each end-use, and its characteristics, are discussed.

4.1 Research Design

A model was required to simulate domestic hot water demand in the form of diurnal demand patterns. Ideally this would entail a repetitive mathematical model. One of the fastest growing norms in engineering modelling is the introduction of informatics to aid modelling. Using computer programming to develop or assist in models can be advantageous. Therefore it was decided to use a programming language in creating the desired model.

A number of previous demand estimation models were reviewed in sections 2.7 and 2.8. The probabilistic end-use model developed by Scheepers (2012) was used successfully in earlier studies (Scheepers & Jacobs, 2014) to construct diurnal demand patterns for indoor water demand with probability distributions for each end-use. The model presented by Scheepers (2012) was based on other established models, such as

SIMDEUM by Blokker *et al.* (2009). A similar stochastic simulation model was therefore selected as the one to be developed in this study.

The model by Scheepers (2012), however, included all residential indoor water demand, whereas this study was limited to hot water demand. The concept was to develop a similar model to that of Scheepers (2012), but to convert total water demand to hot water demand. The model first required considering only end-uses that are known to use hot water, which led to the omission of some events, like toilet flushing. Secondly, the hot water used, as a fraction of the total water demand, was modelled for each end-use. Therefore influences such as thermodynamics, human behaviour, seasonal climate changes and historical demand data were integrated into the demand conversion calculations where necessary.

Consider, for instance, a shower event of 80 ℓ with a known flow rate and duration. The fraction of hot water can be calculated by doing a volume balance, if the hot water and user desired temperatures are known. After calculation results could be found, for example, that 50 ℓ of the 80 ℓ used by the shower event was hot water. Aggregating all the total hot water volumes of all events for a day would result in the total diurnal hot water demand.

Several fragments of the model discussed in this chapter were based on the work done by Scheepers (2012), since the same data set was used. This was done to avoid unnecessary duplication of work. Most of the probability distributions used in the model were predetermined from the REUWS database.

4.2 Software

4.2.1 *End-Use Model Software choice*

A number of software options were available to develop the stochastic end-use model. The model by Scheepers (2012) was developed mainly in Microsoft Excel, due to the fact

that Excel has an easily understandable structure. Using excel led to large workbooks with masses of data. The recommendations by Scheepers (2012) indicates that software programming might have been a superior option for modelling. Therefore an object orientated programming language, Java, was used for modelling as part of this research.

Java is a class based, concurrent, general-purpose, object-oriented language. Java is intended to be simple enough that many programmers can become accomplished and fluent in the programming language (Gosling *et al.*, 2015). Object-oriented programming is widely used in engineering practices for modelling real world entities in a programming environment.

Other programming language options were available such as C++, Python, Fortran and Visual Basic. Java was selected as the main development language for the stochastic end-use model for the reason that Java is a suitable and prevalent programming language for engineering practices. The program was developed in a freeware Java Integrated Development Environment (IDE) software package namely Eclipse.

4.2.2 Other Software Used

Microsoft Access is a Microsoft Office application used for creating and managing large databases. Microsoft Access was used to extract and utilise data from the REUWS database used in this study.

Microsoft Excel and the @Risk analysis and simulation add-in were also crucial in obtaining the data used for the stochastic end-use model in this study. The @Risk software comprises several functions which allow diverse distribution types to be specified for cell values. The software can also perform goodness of fit tests on samples. The Kolmogorov-Smirnov, Anderson-Darling and Chi-Squared tests are used to compare theoretical probability distributions to the given data and to rank each distribution. The available distributions, as well as the goodness of fit tests, were discussed in Scheepers (2012).

4.3 General Model Design

4.3.1 *Temporal Aspects and Climate*

The data used to determine the parameters of the theoretical probability distribution functions in the end-use model was recorded at an interval of ten seconds, which indicates the minimum temporal scale. The model was selected to have a temporal scale of one minute, for two main reasons. It was common in the cited literature in section 2.1 of this thesis that most previous works had determined DHW use on a temporal scale of one hour, therefore a high resolution scale might be unnecessary. The second reason was faster computational speeds in the model routine execution. Using a one minute temporal scale resulted in generating diurnal hot water demand patterns with a volume of hot water used for every minute of the day. Subsequently an array of 1 440 elements is created, each containing the volume of DHW demand for a specific minute of the day.

A decision that had to be made was whether the model would calculate a demand profile of a certain day, or a monthly or annual average demand profile. The acquired climate data and the calculated cold water supply temperature were available for every Julian day of the year. Consequently the model could, for example, run 1000 simulations of 1 January with the given climate data for that day and produce the average demand pattern. The process could be repeated for all days or for critical days, however such fine calculation would be unnecessary. For that reason the average monthly temperatures were used, along with the average monthly cold water inlet temperatures. The model therefore allows the user to select a month of the year to be simulated.

Figure 4.1 illustrates that the average monthly ambient temperatures yield a value that represents the average daily values adequately. Contrariwise, the daily values are too inconsistent and variable from day to day, therefore using daily was considered illogical values. The monthly average cold water supply temperature is compared to the predicted T_c values in Figure 4.2. The average monthly values are a good representation of the

cold water temperatures during the month. The difference in cold water supply temperature values from day to day is diminutive. Therefore, monthly average values will provide a suitable range of cold water supply temperature values to determine the extent of seasonal change in the model.

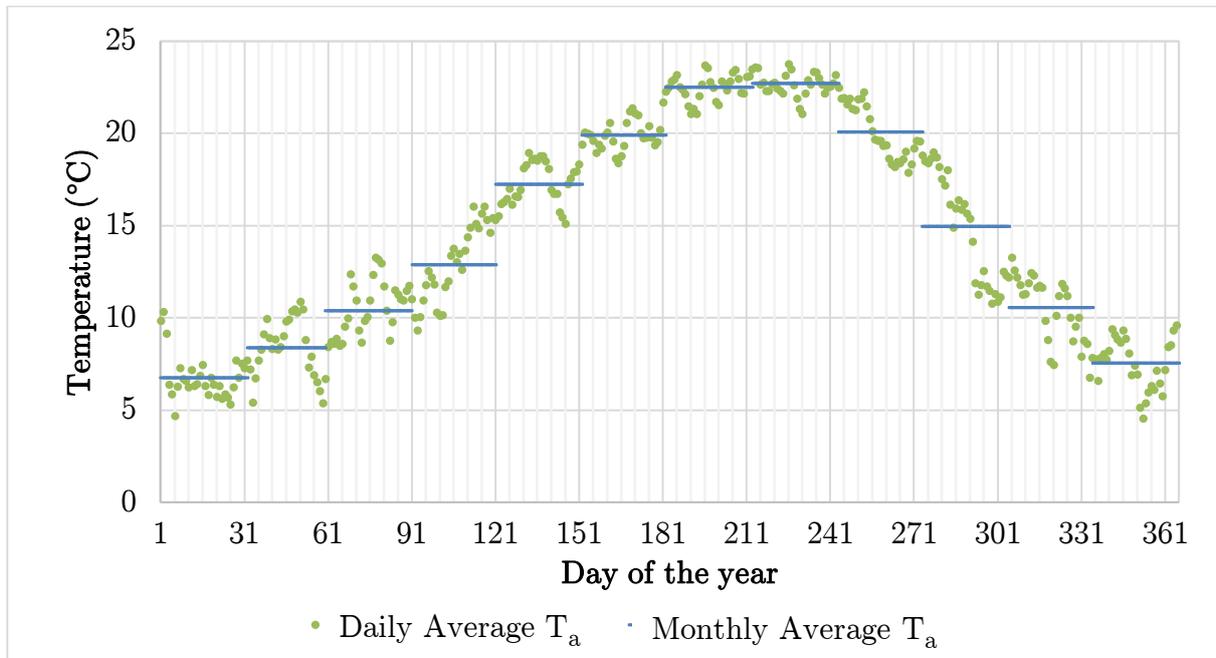


Figure 4.1 Monthly average T_a comparison to daily temperatures

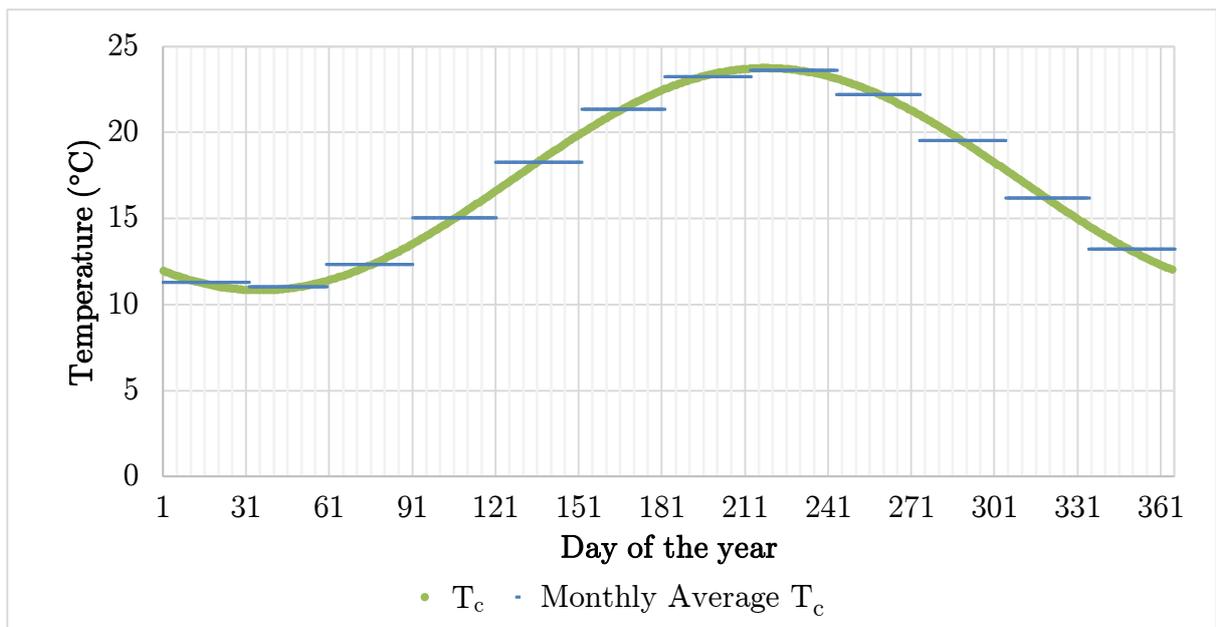


Figure 4.2 Monthly average T_c comparison to predicted values

4.3.2 *Limitations of the Model*

The model does not discriminate between diurnal hot water demand patterns for weekdays and for weekends. Although some studies (Papkostas *et al.*, 1995) show that there are variations in weekday and weekend hot water use, most studies do not take the variation into account when producing hot water demand profiles. All the standard known hot water draw profiles as in Figure 2.10 in Chapter 2 are based on an overall demand, without considering weekend variation separately.

No physical characteristics are given to the water heater in the modelling process. The water heater is seen as an entity that produces hot water of a certain temperature according to the thermostat setting. The water heater also does not have a volume, which meant that when events in the model are generated there will always be hot water available and the events will be added to the demand profile. In a real situation there might not be hot water available because the water heater has not had sufficient time to heat water again after the water heater had delivered a large volume for recent events.

The model omits any hot water leakages that may occur from the water heater or within the household plumbing, although DeOreo & Mayer (2014) had found approximately 8 ℓ per day of hot water leaks in households on average. Furthermore there could also be miscellaneous end-uses connected to the water heater that generate hot water demand, but only the most common end-uses are considered in the model.

4.3.3 *End-uses Included in Model*

The REUWS database identified 14 end-uses, six of which use hot water or a combination of hot water and cold water. The six hot water end-uses are shown in Table 4.1. The hot tub end-use had a considerably lower frequency of occurrence and not numerous recorded events. Consequently, the hot tub event was not considered for the end-use model in this study since hot tub events occurred in only 3.2% of households.

Thus the model included five events namely tap, shower, bath, dishwasher and washing machine.

Table 4.1 Hot water end-uses from REUWS data

End-use name	Number of households	Number of records	% of households
Tap	1 187	1 150 872	99.9
Washing Machine	1 160	120 756	97.6
Dishwasher	906	33 832	76.3
Shower	1 172	50 286	98.7
Bath	556	4 105	46.8
Hot tub	38	896	3.2

The model was designed in such a way that DHW demand is estimated by determining the volume of hot water that flows from the water heater to the end-uses. Therefore, events such as heating water in a kettle or other appliances with internal heating elements, were not added to the hot water demand determined by the model. In South Africa, dishwashers are typically connected to the cold water supply and heat water internally. However in the USA, the REUWS2 study by DeOreo & Mayer (2014) indicated that all recorded dishwasher events used water from the water heater. Washing machines may be connected to the cold water supply only, or connected to both the hot and cold water supplies. Determining hot water demand of dishwashers and washing machines is discussed further in the individual events sections later in this chapter.

4.4 Model Structure

4.4.1 Main Method and Overview

In Java programming a method is usually a function that has a specific goal and can return variables or display information. The main method is where the program starts executing the code, once the program has been asked to execute. For the stochastic end-use model the goal of the program was to produce and display a matrix of volumes for

each minute of the day, which should represent a typical DHW demand profile. Therefore the main method was logically used to reach the final goal of the program. The main method also uses a series of other methods to achieve the goal. In this section and the following sections the aim was to describe the model logically, step by step, as the model code is executed. The steps should give an understanding of exactly how the diurnal hot water use patterns are generated and what parameters have an influence on the results.

The main method should give an overview of the model structure. Some functions and inputs will not be described immediately in the overview, but its entirety is described later in the chapter. Figure 4.3 illustrates how the main method is logically executed to reach the final objective.

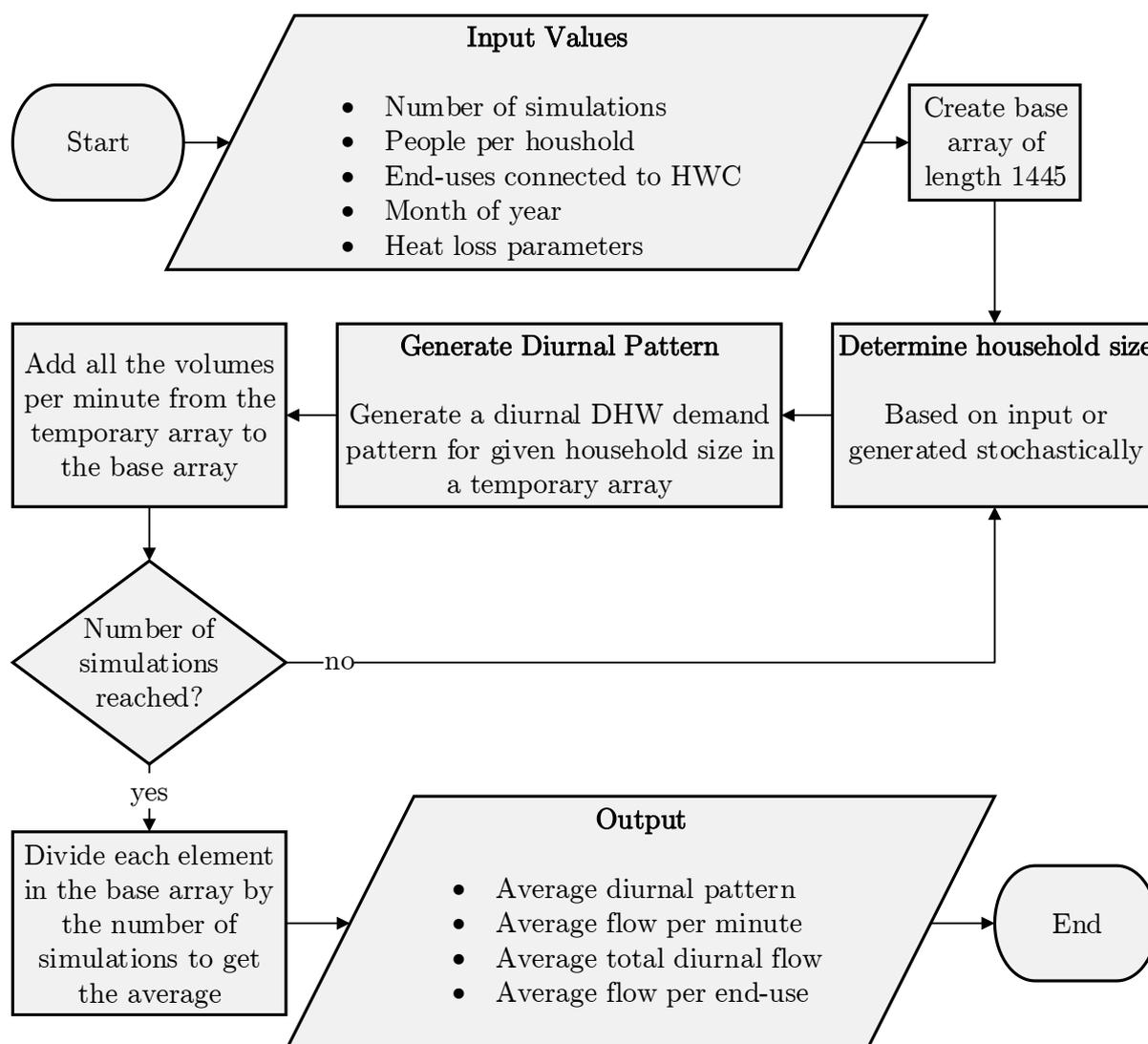


Figure 4.3 Model main method structure flow chart.

4.4.2 Main Method Inputs

Initially the end-use model obtains the necessary input parameters, from either probability distributions or user input. The number of simulations can be selected, which will determine how many single household profiles will be created. One simulation will provide an average diurnal demand profile of an average single household as shown in Figure 4.4. Each bar in the figure represents a per minute DHW demand. It is evident from the figure that end-uses create a rectangular demand pulse when activated. If the number of simulations is set to 1 000, a thousand single household profiles will be created, aggregated and normalized to form an average demand profile.

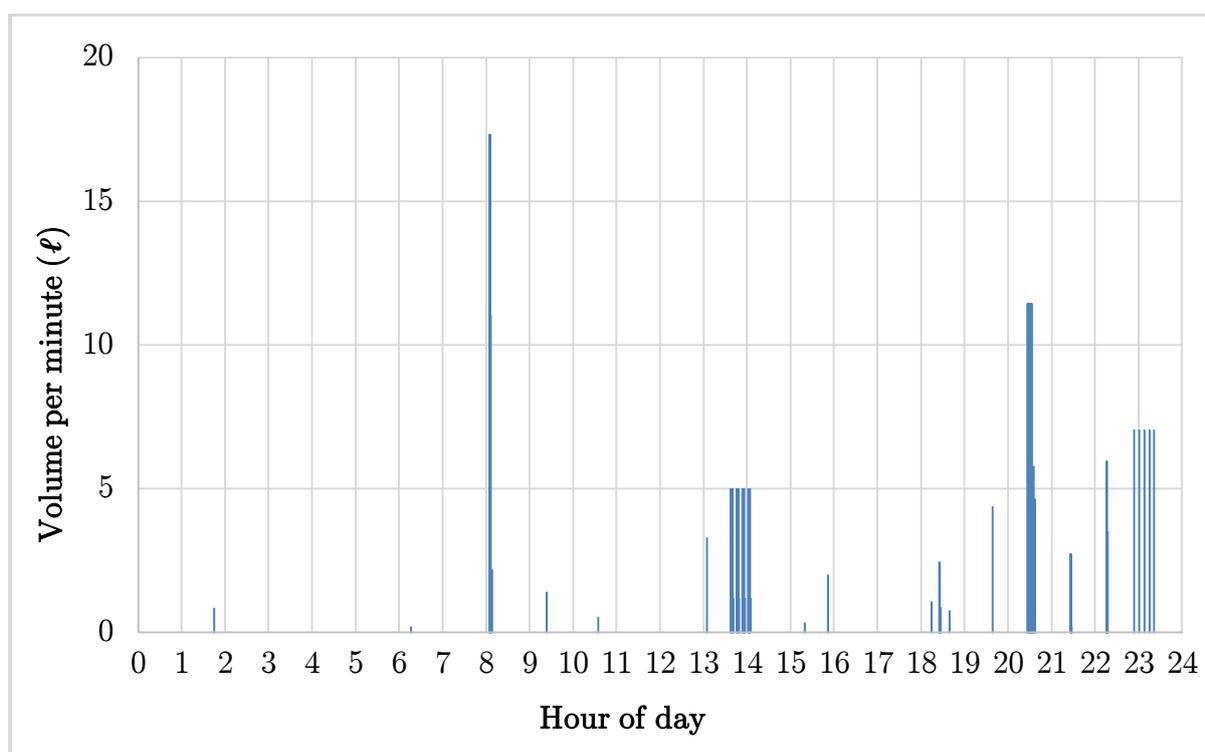


Figure 4.4 Single household DHW demand profile

A user defined household size can be entered manually as an input, otherwise one will be automatically computed by the model, based on probability. Other user defined inputs can be to exclude the dishwasher and/or the washing machine from the model, by

selecting to indicate that these end-uses are not connected to the water heater but heat water internally instead or do not use hot water at all. The month to be simulated can be selected, which will influence which of the 12 average monthly T_a and T_c climate data values will be used. The T_a and T_c values are stored in matrices in the model, and the selected month number serves as an index to select the correct corresponding temperature values to be used in the model execution. The final input is the heat loss parameters, which are fully discussed later in this chapter.

4.4.3 Base DHW Demand Array

Once the inputs have been selected and processed the model generates an empty base array with 1 445 elements. Which is similar to a 1 445 by 1 matrix filled with zeros. In the Java model the array is called totalDiurnal. The first 1 440 elements represent each minute of the day. After the array has been populated, the value stored in each element will represent the volume of hot water demand for the corresponding minute of the day. The last five elements stores the total volume used by each of the five end-uses on a diurnal basis. The total diurnal demand can be calculated by summing either these five elements or the first 1 440 elements. The indexes of the array are defined as follows:

- 1-1440) Per minute hot water volume demand
- 1441) Total daily average shower demand
- 1442) Total daily average bath demand
- 1443) Total daily average tap demand
- 1444) Total daily average dishwasher demand
- 1445) Total daily average washing machine demand.

4.4.4 Household Size Calculation

Hot water demand is strongly related to the number of occupants in a household. Household size governs how many times end-uses were activated (the frequency) during a single diurnal simulation. The REUWS database included household sizing obtained from the surveys of each household. The values ranged from one to nine people per household (PPH). Households from six to nine PPH were responsible for less than 5% of the recorded total number of events. Therefore, for the model, the 6 PPH, 7 PPH, 8 PPH and 9 PPH categories were grouped into a single category named 6 PPH, which in turn represents households of six or more occupants. The household size categories were used in a similar way as in Scheepers (2012).

The household size or PPH was defined as a discrete variable in the model and was determined in the main method with a sub method named `genHouseholdSize`. The method receives no inputs and returns an integer value from one to six based on probability. If the user has defined a household size manually, that household size is used for all the simulations in the model instead of using the `genHouseholdSize` method. The modified household size data from the RUEWS database is shown in Table 4.2 and the frequency of occurrence indicates the total number of events occurring in each household size category.

Table 4.2 Household size probabilities

Household Size (PPH)	Frequency of occurrence	Relative frequency (Probability)	Cumulative relative frequency distribution
1	214 932	0.129	0.129
2	586 075	0.352	0.482
3	323 637	0.195	0.676
4	305 498	0.184	0.860
5	153 744	0.092	0.952
6	79 392	0.048	1.000
Sum	1 663 278	1.000	

The cumulative relative frequency distribution was applied in the model function when generating a household size. Whenever the `genHouseholdSize` method was called, a random number with a uniform probability distribution between zero and one was generated by a built-in Java function. The random number was then kept constant and compared to the cumulative relative frequency distribution to determine the corresponding household size. The selected household size was then returned by the method to be used for the next model simulation. Figure 4.5 illustrates how a household size is selected; for example, if the random number generated was 0.5, the method would return a household size of three, as indicated by the dotted line. This discrete variable solving technique was used in various parts of the model to determine discrete parameters from cumulative probability distributions.

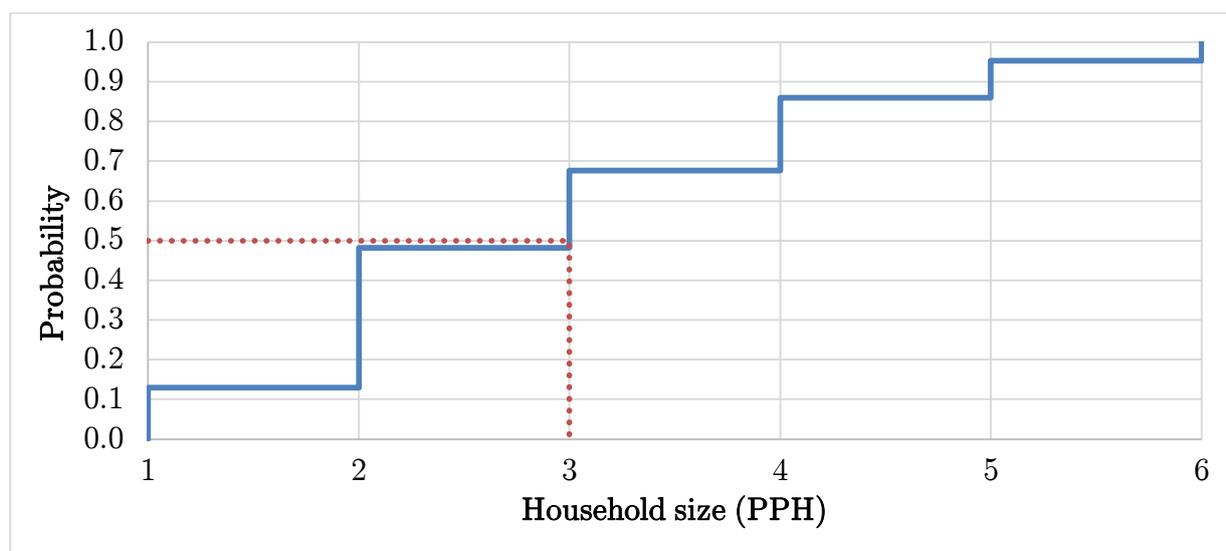


Figure 4.5 Cumulative probability distribution for household size

4.4.5 Determining Average Diurnal Demand Profiles

Once the household size had been determined, a diurnal DHW demand pattern was generated for the specified household size using a new method named `genDiurnal`. Generating diurnal demand profiles is an extensive process and is therefore discussed independently in the next section. Nevertheless, it can be assumed that the `genDiurnal`

method creates and returns a temporary array of 1 445 elements populated with values. Consequently, diurnal per minute demands are stored in the first 1 440 elements and total end-use demands in the last five elements. When the genDiurnal method is called, the method receives a household size as an input and returns a populated diurnal DHW demand array for the specified household size. Event frequencies are determined in the method and are based on the given household size. The volumes and flow rates are determined for each end-use event. Per minute flow rates of activated events are placed into the array at stochastically determined starting times. The specifics of the technique in which all the steps are executed in the model is described fully later in this chapter.

Referring back to Figure 4.3, it can be comprehended that the step after generating a single diurnal demand profile is to add the profile to the base array. The array of values received from the genDiurnal method are added to the base array. At this point the model refers to the number of simulations that have to be done. If the model has not reached the required number of simulations, the model loops back to the step where a new household size is generated. The new household size is then used in another execution of the genDiurnal method. Subsequently the loop process is repeated, until the correct finite number of simulations has been reached, aggregating single household demand profiles into the base array for every simulation.

Once the specified number of simulations have been completed by the model, a base array consisting of the sum of multiple single household DHW demand profiles, is available. Each element in the base array is then normalized by dividing by the total number of simulations, subsequently determining the averages of all simulations. In other words, a Monte Carlo simulation is done by the model to create many unique hot water demand scenarios. A Monte Carlo method involves repetitive calculation of the model, each time using randomly generated numbers to select inputs from probability distributions. The final output of the model is the average DHW volume demand, in increments of one minute, as well as the total average diurnal per-end-use hot water volume demand.

4.4.6 *Generate Diurnal Method*

As mentioned, the process of creating a stochastic diurnal demand profile is intricate. The developed Java method that generates these profiles, namely `genDiurnal`, is explained in this section. The sub techniques in which event frequencies and event parameters are generated are not discussed in this section, but pro tempore it can be assumed that events are created correctly, with probability based parameters.

An overview of the method is illustrated in the flow diagram in Figure 4.6. Initially, the method receives a household size, when the method is called in the main method. The number of events that occur on the simulated day is correspondingly determined, based on the PPH value. Once all the event frequencies have been determined, the model can start generating the events with random parameters and add the events to the temporary array. The order in which events are added is mutually exclusive, although performed in a certain order when the program is run.

The way in which events are added to the temporary array is similar, therefore a sub method named `addEvent` was created to assist with the repetitive process. Continuous events are added into the array easily, at a generated starting time and duration. Cyclic events, such as the dishwasher and washing machine events, have their cycles added separately by repeating the `addEvent` method for the number of cycles. The duration between cycles is determined from a probability function and the cycles are placed into the array with an offset from the starting time. These cyclic events are discussed later in this chapter, in the individual event sections.

If, for example, a day was simulated and the event frequencies were selected as follows: two showers, one bath and five tap events, the `genDiurnal` method will generate a unique shower event, add the event to the temporary array, then generate another unique shower event with different parameters and similarly add it to the array. Similarly, the process is repeated for all the other events. Events in the model are allowed to overlap, the overlapping volumes are simply summed in the temporary array as the events are

added. The aggregation of these events creates the unique demand scenario that is returned once the method ends. The temporary array that is returned to the main method can now be added to the base array. The process is repeated for the number of simulations required to create average hot water demand profiles.

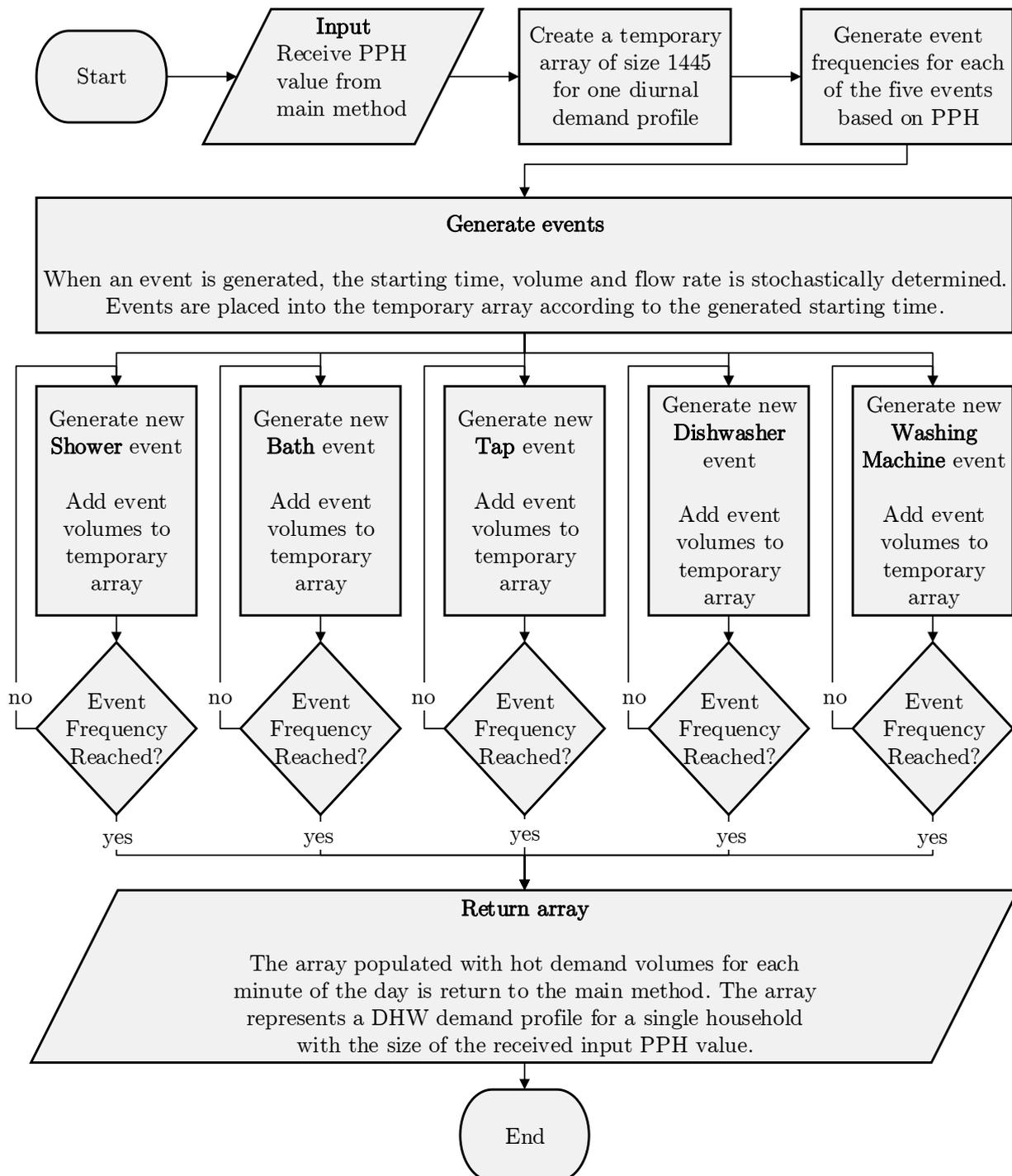


Figure 4.6 Overview of the diurnal profile generating method

4.5 Event Modelling

4.5.1 Event Frequencies

Before the events themselves were generated, the daily frequency occurrence of each of the events was determined. Event frequencies, similar to the household size, were discrete variables, since the frequencies indicated the precise number of events for a simulated household in a day. The daily event frequencies were strongly related to household size.

From the REUWS database it was determined how many events occurred on one day, for each household size category. For instance all the households with 1 PPH were considered, then the number of bath events that occurred on each day was counted. Next, the number of days that had one bath event were counted, similarly for two bath events etc. This process provided a frequency distribution that was converted to a probability of occurrence distribution, which indicated the probability of only one bath event occurring on one day, or the probability of two bath events occurring on one day etc. Consequently a cumulative relative frequency distribution could be constructed as illustrated in Table 4.3. This procedure was repeated for all household size categories, from 1 PPH to 6 PPH. The entire process was also done for all the end-uses included in the model. Scheepers (2012) completed the data manipulation process and all the cumulative relative frequency distributions for all household size categories and events are available in Appendix A.

Table 4.3 Bath event frequency for the 1 PPH category

Number of baths per day	Frequency of occurrence	Probability of occurrence	Cumulative relative frequency
0	284	0.612	0.612
1	123	0.265	0.877
2	39	0.084	0.961
3	14	0.030	0.991
4	4	0.009	1.000
Sum	464	1.000	

Similarly to how the household size was calculated, a random number was generated within Java and a corresponding event frequency was obtained from the cumulative relative frequency distribution. In the model the cumulative frequency distributions were stored in a two dimensional array, similar to a two dimensional matrix, where each row stored values for a certain household size category from 1 to 6.

A separate Java class was created where all these event frequency arrays were stored. Each event had its own method to generate a frequency, for instance the method `genNumBaths` would return the number of bath events that would occur on the simulated day. Each of these methods had one argument as the input, the household size. Consequently, when an event frequency for the simulated day was required, the `genDiurnal` method passed the generated PPH value to the event frequency method. The frequency method then used the PPH value to select which row of probabilities in the array was considered to determine the event frequency for the simulated day. The higher the PPH values, the more likely it was for a higher daily event frequency. Once a discrete number of events was selected the number was returned to the `genDiurnal` method. When a single household simulation had been completed, the event frequencies of all five the end-uses were mutually exclusively generated.

4.5.2 Generating Discrete Event Frequencies in Java

Figure 4.7 presents sample Java code developed to generate the bath event frequency for a given PPH. This section can be related to section 4.4.4 for full comprehension of the method for determining discrete variables in the model.

In Figure 4.7, the first line states that an integer value should be returned by the method, and the text in the brackets indicates that the method must receive an integer (the PPH) when the method is called. Initially, the array that stores the cumulative relative probabilities is created. The `numBaths` integer that will be returned by the method is created and given a value of -1. The negative value gives an indication that the event

frequency has not yet been assigned to the variable. Next, a random number between zero and one is generated by the `Math.random()` method in Java. Afterwards a loop process is started, which continues while the `numBaths` variable is equal to -1 and ends once the variable is assigned a frequency value for the given PPH. The integer variable `i` represents a counter, and counts how many times the loop has reoccurred.

```
public static int genNumBaths(int pphi){
    double[][] BathFreq = {
/*1 PPH */ {0.6121, 0.8772, 0.9612, 0.9914, 1},
/*2 PPH */ {0.1282, 0.7654, 0.9297, 0.9829, 0.9924, 1},
/*3 PPH */ {0.2192, 0.7861, 0.9580, 0.9895, 0.9974, 0.9987, 1},
/*4 PPH */ {0.1995, 0.7898, 0.9558, 0.9893, 0.9933, 0.9973, 0.9987, 1},
/*5 PPH */ {0.3301, 0.8010, 0.9450, 0.9871, 0.9903, 0.9951, 0.9984, 1},
/*6 PPH */ {0.5304, 0.8198, 0.9393, 0.9757, 0.9899, 0.9939, 1}
    };

    int numBaths = -1;

    int i = 0;

    double rand = Math.random();

    while(numBaths == -1){
        if(rand <= BathFreq[pphi-1][i]){
            numBaths = i;
        }
        else{
            i++;
        }
    }
    return numBaths;
}
```

Figure 4.7 Bath frequency discrete variable calculation in Java

If the random number generated was 0.5 and a household of 2 PPH was simulated, for the first iteration of the loop the value of `i` is zero. Within the first loop the random number is compared to the first element in the second row of the array. A logical IF statement then determines whether 0.5 is smaller than the value in that element of the

array. For 0.5 the IF statement was false (0.5 is greater than 0.1282), and the loop executed a second time, with *i* having increased from zero to one. In the second loop the value in the element, 0.7654, was greater than 0.5, thus the logical statement was true. Upon inspection it can be understood that the value of *i* also represents the number of events. Subsequently the *numBaths* variable was assigned the value of *i*, which was one in this case. The method accordingly returned the value of one as the number of bath events to occur on the simulated day. The first element in a Java array has an index of zero and the second element an index of one, and so on.

4.5.3 Event Class Overview and Variables

Java is a class based, object-oriented programming language. In domestic hot water use there may be a hundred events occurring each day. Each event uses hot water and has a certain volume and duration, and therefore all events can all be created from the same blueprint. In object-oriented terms, a single event (like a shower with a volume and a flow rate) is an instance of the class of objects known as events. A class is the blueprint from which individual objects are created.

In the model the class *Event* was created, which was used to model all 5 of the end-uses. The class contained a list of the variables that a typical hot water end-use event has. All the variables of the class are listed in Table 4.4 with a short description of each. Every event started at a certain minute of the day, which was stochastically calculated. Likewise each event had a duration, flow rate and hot water demand volume. Some variables are measured in seconds, according to their definition in the REUWS database, and then converted to minutes for the purposes of the model. The use of all the variables is clarified in the following section.

Table 4.4 Event class list of variables

Variable Name	Variable Type	Units	Description
startMin	integer	minute	The minute of the day that the event starts
durMin	integer	minutes	The duration of the event in minutes
durSec	integer	seconds	The duration of the event in seconds
volMin	double	ℓ /minute	The volume of hot water demand of the event per minute
volExtra	double	ℓ	The volume of hot water demand in the last minute of the event
flowrate	double	ℓ /second	The flow rate of the event
volTot	double	ℓ	The total volume of hot water demand for the event
Tset	double	$^{\circ}\text{C}$	The water heater thermostat setting value

The Event class is an abstract class, which means that an instance of the event class itself could not be created. The idea is analogous to how a triangle is a shape, but a shape itself is an abstract concept. Similarly, a shower is an event, but an event itself is abstract. A new class extending the Event class can be created; for example, a class named Shower. The Shower class inherits all the variables and methods or functions from the Event class. Classes extending the Event class were created for all five end-uses and were named Shower, Bath, Tap, Dishwasher and WashingMachine. The abstract Event class aided the homogeneity and ease with which the event modelling process could proceed.

4.5.4 Event Class Methods

A number of methods were available in the Event class to calculate all the event variables and ultimately to populate a created instance of an event with values such as durations and demand volumes. A list of the methods in the Event class is presented in Table 4.5.

Table 4.5 Event class list of methods

Method Name	Abstract Method	Return	Description
genStartMin()	yes	integer	Determines the starting minute of the event based on starting time probabilities
genFlowrate()	yes	double	Determines the flow rate of the event based on derived flow rate probability distributions
genVolTot()	yes	double	Determines the total hot water demand of the end-use event based on probability.
CalcDurSec()	no	void	Sets the value of the durSec variable to a value calculated.
CalcDurMin()	no	void	Sets the value of the durMin variable to a value calculated.
CalcVolExtra()	no	void	Sets the value of the volExtra variable to a value calculated.
CalcVolMin()	no	void	Sets the value of the volMin variable to a value calculated.
genEvent()	no	void	Uses all the methods in the Event class to generate values for the Event class variables

Three of the methods are abstract methods, meaning the body for the method must be supplied in a class that extends the Event class, for instance the Shower class. For example, genStartMin is an abstract method, as each end-use will determine the starting minute based on a probability distribution specifically for that end-use. Similarly, the flow rate and total hot water demand are determined differently for each end-use. Classes like the Shower class that extends the Event class are obligated to implement abstract methods. Therefore the methods in the abstract Event class can use the values generated by the abstract methods. The unique methods that generate a flow rate and volume for each activated end-use event is discussed in the individual events section later in this chapter. Classes that extend the Event class could also contain new unique methods that have not been defined in the Event class. For example the Dishwasher and WashingMachine included a method to generate a duration between the cycles of the event.

The genStartMin method returns an integer value that represents the minute of the day at which a certain event will occur. The event starting times are determined by selecting an hour of the day from a probability distribution based on the REUWS database and then adding random minutes within that hour. The hour selected from the probability distribution is converted to minutes and then a random number of minutes between zero and 59 is added. The starting hour is also a discrete variable and is calculated in a similar technique to that used for determining the household size and event frequencies.

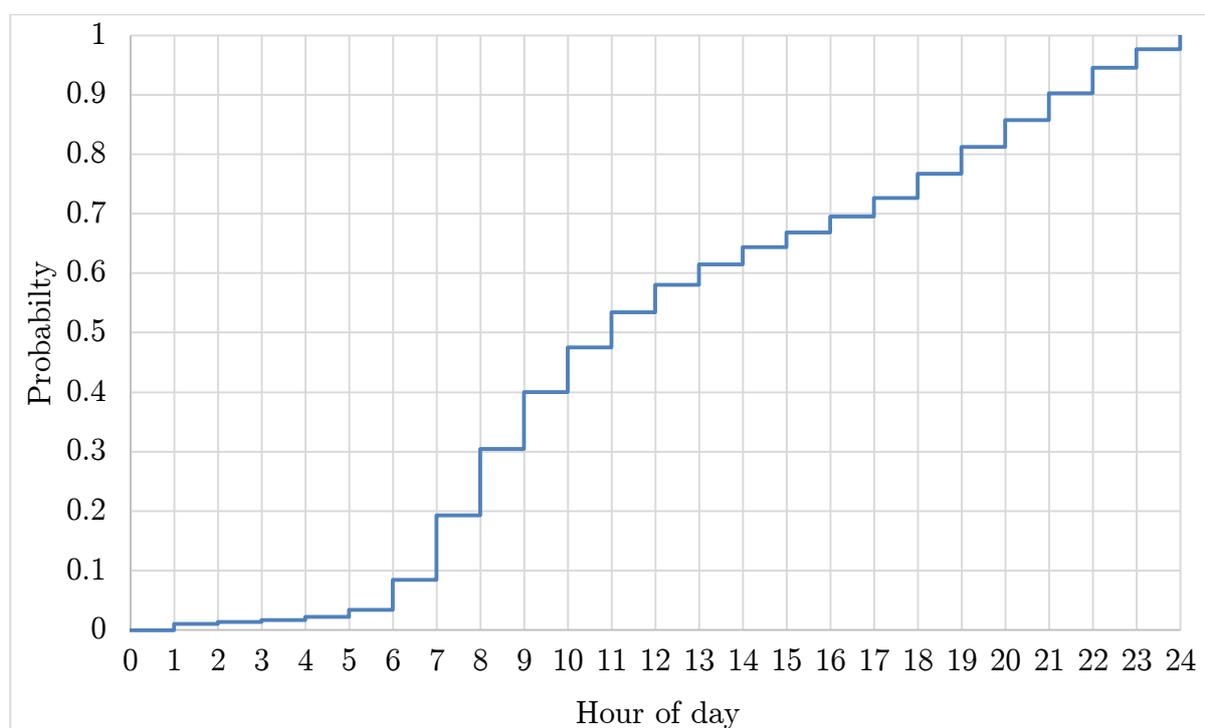


Figure 4.8 Starting hour cumulative probabilities for shower events

The cumulative probability distribution for the starting hour of shower events is illustrated in Figure 4.8. By inspection of Figure 4.8, it is evident that the probability of a shower occurring in the first five hours of the day is small; contrariwise, shower events have a high probability of being activated between 6h00 to 10h00. Similarly, all events had probability distributions which indicated the likelihood of events occurring at certain hours of the day.

A cumulative relative frequency distribution independent of the PPH were derived for each end-use. These distributions could be derived from the REUWS database, since all recorded events in the database included the time of occurrence. All the starting hour cumulative relative probabilities representing the starting hours for all events is provided in Appendix B as derived by Scheepers (2012).

4.5.5 Generate Event Method and Calculations

The genEvent method is used to populate the variables within an instance of an event with values determined from probability distributions and calculations. A flowchart representation of the genEvent method is illustrated in Figure 4.9.

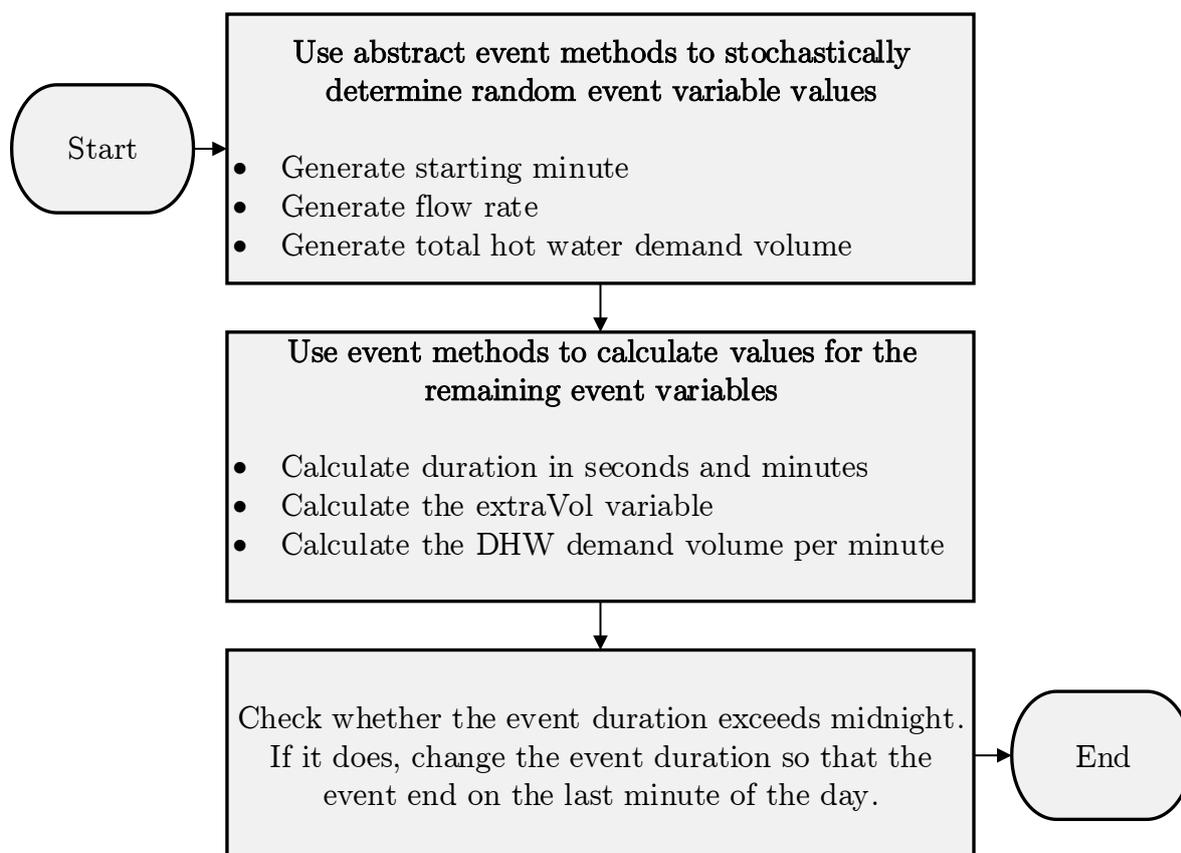


Figure 4.9 Event variable value generating method flowchart

If a new shower event had to be generated, the genDiurnal method created a new instance of a shower object and then requested the shower object to execute the genEvent method. The method is best demonstrated by showing the calculation process with an example. Thus consider a household simulated by event frequencies and a PHH, determined as previously described. Now a single shower event had to be generated, therefore an instance of the Shower object was created and the genEvent method is called.

Initially the genEvent method uses the three abstract event methods to determine the values of the three variables that are unique to each end-use. If the first abstract method, genStartMin, determined that the shower event started at 8h00 then the method will return a value of 480 (8 times 60 minutes). The next method used is genFlowrate, which generates a continuous random variable that represent the flow rate of the shower event, for example 1.667 ℓ per second. The final abstract method, genVolTot, is then used to determine the total hot water demand for the shower, for example 75 ℓ. The distributions used to determine the flow rate and event total volumes are displayed in the individual event sections in this chapter, because these distributions are different for each end-use.

With the three abstract methods completed, the rest of the event variables can be obtained by simple calculations in sequence. First the calcDurSec method divides the generated total DHW demand volume (volTot) of the shower by the generated flow rate:

$$\begin{aligned} \text{durSec} &= \text{volTot}/\text{flowrate} \\ &= 75/1.667 \\ &= 450 \text{ seconds.} \end{aligned}$$

Sequentially, the calcDurMin method is used to convert the value of the duration in seconds to a duration in minutes for the purposes of the model. A logical check is done to check whether the event is shorter than 60 seconds; if true, the event durMin variable is set to zero. If false, the durMin is calculated by dividing the durSec value by 60. The

duration in minutes variable is an integer, meaning that when the division calculation takes place the value is always rounded down. So if the shower event of 450 seconds is divided by 60 the real answer 7.5 minutes, but the durMin variable will be set to the rounded down number of 7 minutes. To compensate for the 0.5 minutes or 30 seconds which is not taken into the durMin variable, the genEvent method sequentially uses the calcVolExtra method. The calcVolExtra method calculates the volume of hot water demand in the seconds lost by the rounding in the genDurMin method. For the shower event considered, the calcVolExtra populates the volExtra variable using the modulus or remainder operator (%) in Java as follows:

$$\begin{aligned}
 \text{volExtra} &= (\text{durSec} \% 60) \cdot \text{flowrate} \\
 &= 450 \% 60 \cdot 1.667 \\
 &= (30) \cdot 1.667 \\
 &= 5 \ell.
 \end{aligned}$$

The last variable that is calculated is the volume per minute (volMin), which is obtained by using the calcVolMin method. Firstly the method checks whether the durMin is zero; if true, then the volMin is set to zero as well. The volMin is zero for events with a duration of less than one minute, and the entire volume of the event is stored in the volExtra variable. The calcVolMin method computes the volume per minute demand for the first seven minutes of the shower event. The volExtra variable is required for the calcVolMin method and that is why the calculation is done last in the genEvent method. The volume per minute for the shower event is calculated as follows:

$$\begin{aligned}
 \text{volMin} &= (\text{volTot} - \text{volExtra}) / \text{durMin} \\
 &= (75 - 5) / 7 \\
 &= 10 \ell \text{ per minute.}
 \end{aligned}$$

Now all the shower event variables are populated with stochastically generated values and the event is ready to be added to a diurnal demand pattern. Table 4.6 illustrates how the example shower event was added to a part of a diurnal demand array. The total volume of the event is 75 ℓ. The event volumes are uniformly distributed over the duration, except for the last minute, where the remaining volume is added using the volExtra variable. This approach changes the flow rate of the last minute of the event, but the generated event volume is conserved. The approach was considered to be more accurate than alternatives like rounding the event duration to the nearest minute and spreading the volume evenly over the new duration.

Table 4.6 Example of a shower event added to a diurnal array

Diurnal Array Index	DHW Demand (ℓ/min)
479	0
480	10
481	10
482	10
483	10
484	10
485	10
486	10
487	5
488	0
489	0
490	0
Total	75

In order to get the event demand volumes into the array the model uses the addEvent method in the genDiurnal method, as mentioned previously. The addEvent method requires five arguments when used: the duration in minutes, the starting minute, the volume per minute, the volExtra variable and the temporary array to which the event has to be added. If the duration in minutes is zero then the method simply assigns the volExtra value to the starting minute index in the array. Otherwise, the method adds

the volume per minute to every index from the starting minute for the duration in minutes, and then the `volExtra` value to the next minute. The `addEvent` method uses the same temporary array every time an event is added when simulating a single household diurnal profile. When another iteration of the model is done for a new household diurnal profile, a new temporary array is created after the previous one has been added to the total diurnal base array.

4.6 Converting total demand to DHW demand

4.6.1 Volume Balance and discussion

The REUWS database recorded total water use volumes and did not distinguish between hot water and cold water use by events. An alternative option existed, to use recorded hot water data, but the available hot water datasets were either outdated or of small sample size. The REUWS database was remarkably extensive and considered as the best alternative. Measuring hot water use is also expensive, when compared to measuring end-use events with existing non-intrusive technologies such as flow trace. Therefore this study is an investigation into how to convert total end-use water demand into total hot water demand. Consequently, it was determined which parameters had a significant influence on the conversion process and which end-uses required conversion.

One way to determine hot water demand from a total volume demand is a volume balance. The volume balance was suitable for events that used a combination of hot water and cold water - for instance, shower and bath events and, in some cases, washing machines. Tap events and dishwasher events are discussed in the individual event sections later in this chapter. Starting from the conservation of energy equation, a formula can be derived to determine the volume of hot water used. The amount of energy (q) leaving the hot water must be equal to the amount of energy entering the cold water.

$$q_{\text{lost}} = q_{\text{gained}}$$

For water the energy change can be written in terms of mass and temperatures by including the specific heat of water (C_{pw}) and then, knowing that the mass is equal to the product of the volume and density, a new expression for q can be obtained.

$$q = m\Delta tC_p$$

$$q = \rho_w V\Delta tC_{pw}$$

Going back to the energy balance and substituting the expression for q , it can be seen that both sides of the equation can be divided by the density and specific heat of water. The total volume (V_t) is the sum of V_h and V_c . Thus as an expression for the volume of hot water is required, V_c can be written in terms of V_h and V_t .

$$\rho_w V_h \Delta t C_{pw} = \rho_w V_c \Delta t C_{pw}$$

$$V_h(T_h - T_d) = (V_t - V_h)(T_d - T_c)$$

From further manipulation of the balance an expression can be obtained isolating the volume of hot water required. The expression found is shown in Equation 4.1. With the hot water, cold and desired water temperatures known, along with the total volume of water, the volume of hot water required can be calculated.

$$V_h = V_t \frac{(T_d - T_c)}{(T_h - T_c)} \quad \text{Equation 4.1}$$

Equation 4.1 was used throughout the model where an end-use event used a mixture of hot and cold water. The shower and bath events had desired user temperatures, where the washing machine could have a desired cycle temperature. For an event the total volume was determined from a probability distribution based on the REUWS data. The cold water inlet temperature was selected based on the chosen month of the simulation. In the following section the method for determining the values for the desired temperature and hot water temperature delivered at the end-use is explained.

4.6.2 *Desired User Temperature*

Previous studies (Smith, 2014) have shown that for showers and baths the desired end-use temperature T_d is relatively constant. Water colder than a certain temperature is unpleasant for the user and very hot water can cause discomfort and scalding. Using previously measured data by Smith (2014) and additional data measured for this study, conclusions were drawn about desired user temperature. Smith (2014) found that all users prefer a temperature a few degrees Celsius above body temperature (37°C).

The database by Smith (2014) was investigated and extended by conducting additional measurements. The modified dataset (available in Appendix D) consisted of temperature measurements for 152 shower events and 30 bath events. The data was recorded by ten participants and included ambient temperatures ranging from 13 to 30°C . Recording locations were primarily in the Western Cape Province, South Africa and some in Namibia. Similarly as had been found by Smith (2014), there was still no correlation between ambient temperatures and desired temperatures with the modified database.

For the purposes of the end-use model, it was necessary to know the temperature at the shower head, since this temperature represented the desired temperature after hot and cold water had fully mixed within the domestic water distribution system. Thus only the temperature measured closest to the shower head was used. The average temperature for all shower and bath events was 40.8°C and 41.5°C respectively. These results agree with earlier work (Ohnaka *et al.*, 1994; Jacobs, 2004; Wong *et al.*, 2010) that the desired water temperature in showers and baths remains relatively constant, at approximately 41°C , and is independent of the ambient temperature and user. Since the sample of bath events was small, the data was not suitable for theoretical probability distribution fitting. Consequently, considering the difference between the means of the bath and the shower data, the assumption was made that shower and bath events had the same range of user desired temperatures for the purposes of the model in this study.

The modified dataset was used to fit a theoretical probability distribution. After inspection it was found that the data was normally distributed with a sample size of 165 entries. More data points could help improve the distribution, but was unnecessary since the value has such a small range and agrees with previous work. A normal distribution was fitted to the data and the standard normal distribution parameters were identified. The mean was found to be 40.81°C and the standard deviation 1.59°C . Figure 4.10 shows the constructed cumulative probability normal distribution and the comparison to the actual data. A noteworthy comparison was observed between the actual data and the normal distribution, therefore the normal distribution was used in the model to calculate desired temperatures for shower and bath events.

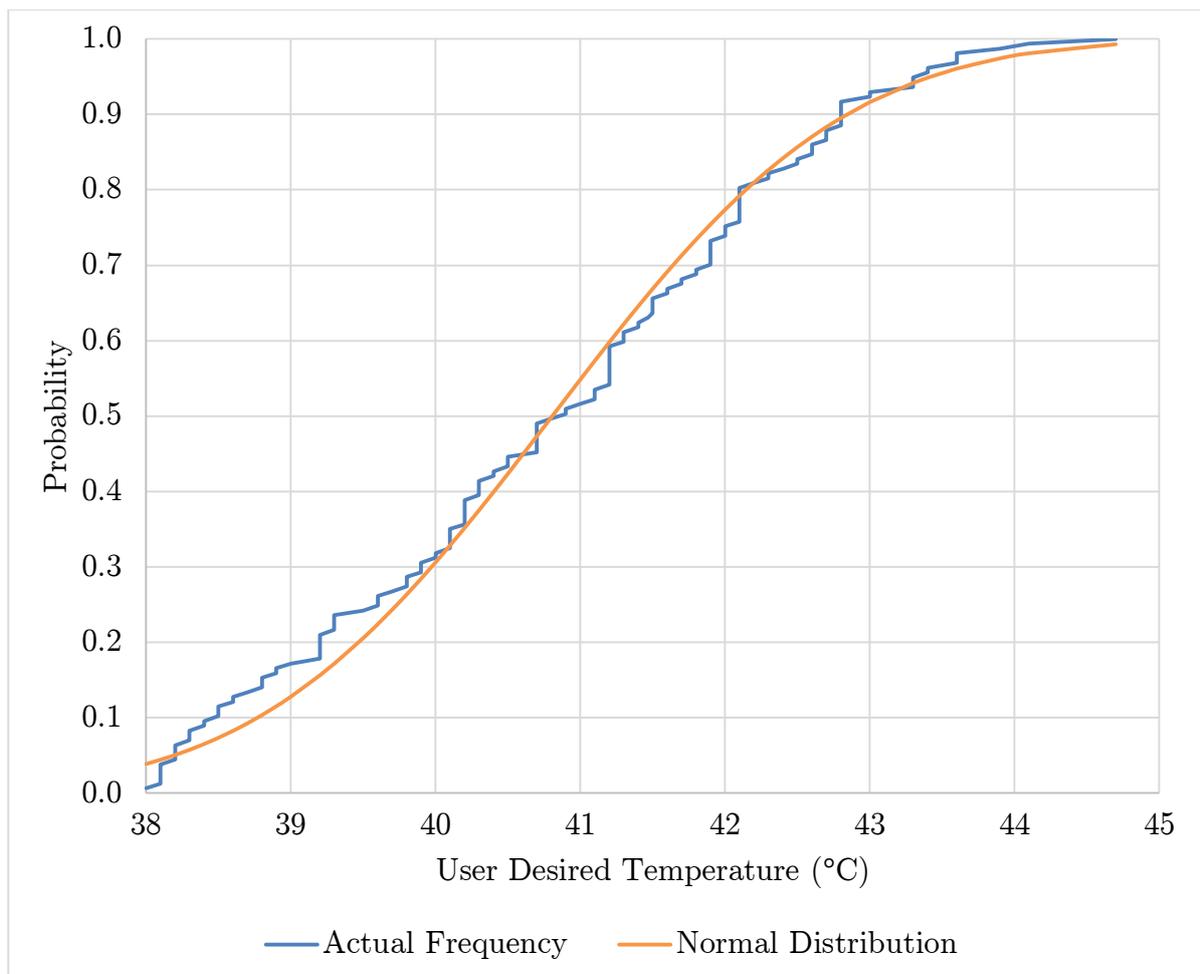


Figure 4.10 User desired temperature normal distribution and actual data

In the model the derived normal distribution parameters were used to create a new normal distribution within the model. An imported math distribution package, Apache Math Commons, was used for the modelling of theoretical probability distributions. Every time a shower or bath event was generated, the desired user temperature (T_d) for the event was generated. The normal distribution that was created had a built-in method named `inverseCumulativeProbability` which was used to solve for a T_d value. The cumulative normal distribution function was solved inversely with a randomly generated value between zero and one and a corresponding T_d value was produced.

4.6.3 Water Heater Temperature Setting

In order to complete the volume balance a value for the temperature of the hot water coming from the water heater supplying to the end-uses was required. Typical electric water heaters are known to have a thermostat that can be set to a certain temperature. The assumption was made in this study that all the households used an electric water heater with an adjustable thermostat. The assumption was considered fair, since the water heater type generally does not influence DHW demand greatly. Whether the water heater is tankless or has a storage tank was found to be irrelevant for the model, since Thomas *et al.* (2011) found that the demand generated by these two types is similar.

As found in the literature, the most common value is to have the thermostat set to around 60°C. In a study where 115 homes were investigated, a frequency distribution of water heater thermostat temperature setting ranges was obtained (Ladd & Harrison, 1985). The study was conducted in North America and was therefore considered appropriate for the model. The results found are displayed in Celsius in Figure 4.11.

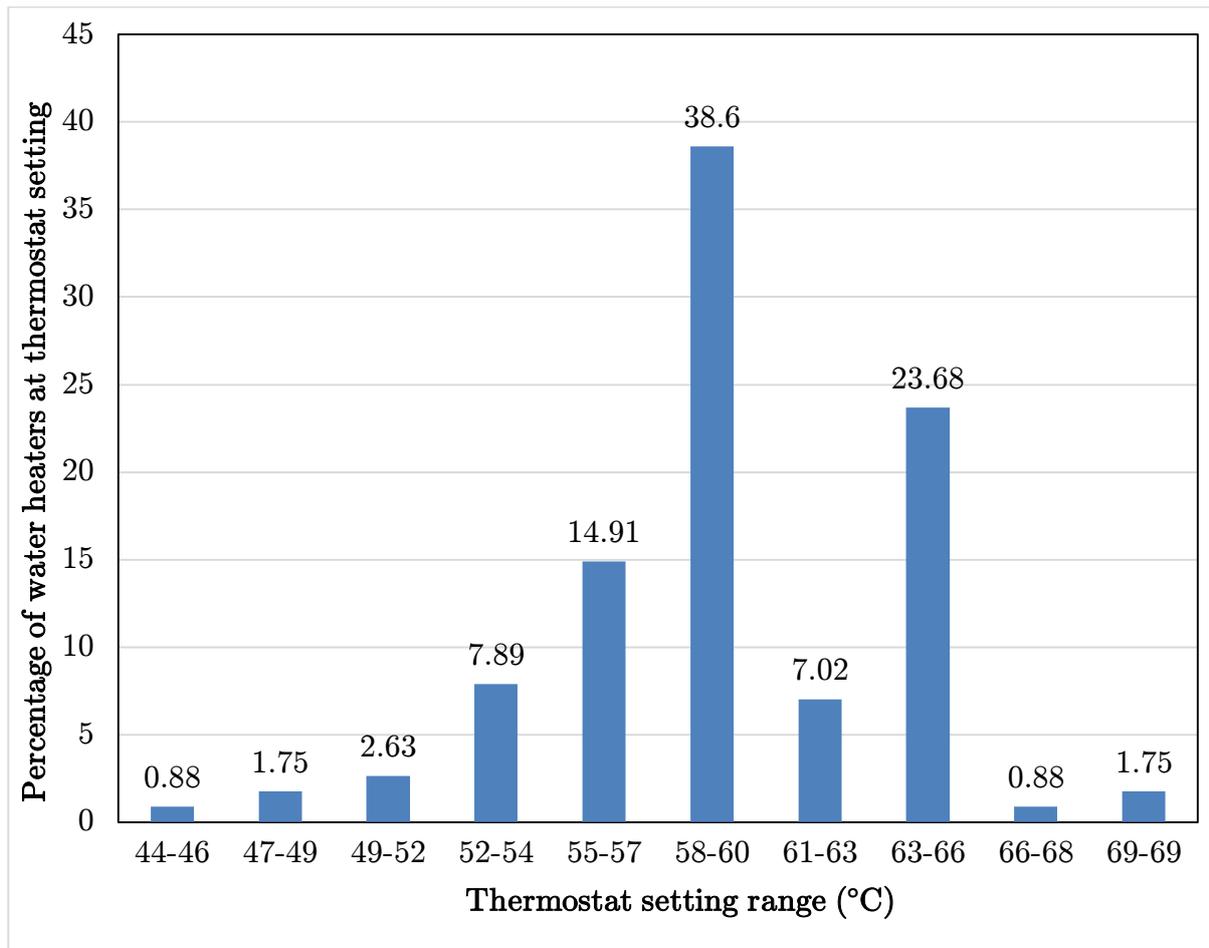


Figure 4.11 Water heater thermostat temperature setting ranges (adapted from Ladd & Harrison, 1985)

All the intervals were averaged to create discrete variables, each with a certain probability. A cumulative probability distribution was created for the thermostat setting and was used in a new method, named `getTset`, which returned the water heater temperature setting (T_{set}) when requested by the model. The value for T_{set} was calculated only once every time a new iteration of the model was done, so that logically every simulated household had only one water heater thermostat setting. Table 4.7 presents the values used in the model to determine T_{set} . The Java method was similar to the methods that calculated other discrete variables like household size and event frequencies, as earlier described. Using the distribution was a superior approach than using a constant T_{set} value for all households.

Table 4.7 Water heater temperature distribution used in model

Water Heater Temperature Setting (T_{set})	Cumulative Probability
45.0	0.009
47.8	0.026
50.6	0.053
53.3	0.132
56.1	0.281
58.9	0.667
61.7	0.737
64.4	0.974
67.2	0.982
70.0	1.000

4.6.4 Heat Loss in Pipes

Water flowing from the water heater towards the end-uses is subject to temperature loss as the water is delivered through the hot water distribution system. Section 2.3.2 of the literature review investigated how the temperature loss develops and what parameters have an influence. For the model Equation 2.2 was used, using the water heater set temperature as the temperature at which hot water enters a pipe leading to an end-use. The modified equation with the variables as used in this research, is presented in Equation 4.2.

$$T_h = T_a + (T_{\text{set}})e^{[(UA)(L)/(mCp)]} \quad \text{Equation 4.2}$$

The equation is to used calculate the temperature at which hot water is delivered at an end-use (T_h). At the point where T_h was calculated in the model, a value for T_a would be available, and varied depending on the month that was being simulated. The T_{set} value is also known and is generated as described in the previous section. The value of

the mC_p term was calculated by multiplying the generated event flow rate by the specific heat of water, which was assumed to be a constant $4185.5 \text{ (W}\cdot\text{s)/(kg}\cdot\text{K)}$. The value for UA in the equation had to be chosen by selecting a type of pipe and a diameter. All pipes in the model were assumed to be nominal 19 mm copper pipes. Although a distribution system is allowed by code (SANS, 2012) to use nominal 13 mm piping, 19 mm is used in most homes (Wiehagen & Sikora, 2002). Therefore the UA constant value derived by Hiller (2011) was used in the model. The UA value for 19 mm copper piping with no insulation was $0.763 \text{ (W)/(m}\cdot\text{K)}$.

The only uncertain input value in Equation 4.2 is the length of the pipe (L), from the water heater to the end-use. A length of pipe from the water heater to the end-use was required in metres to complete the variables in the equation to solve for T_h . The REUWS database did not include any detail about pipe lengths in households. Wiehagen & Sikora (2002) modelled domestic hot water systems in a previous study. The water distribution system modelled was based on ICC (2000). A tree piping system and a parallel piping system were considered in the study by Wiehagen & Sikora (2002). The layout with the pipes lengths were available for two systems, each with seven end-uses connected to the water heater. The pipe lengths ranged from 2.7 metres to 18.4 metres.

For the stochastic end-use model in this study the pipe lengths were chosen to have an upper and a lower boundary based on the systems modelled by Wiehagen & Sikora (2002), in the absence of a better alternative. The lower bound and upper bound was chosen to be 3 and 19 metres respectively. Whenever Equation 4.2 was used in the model, a random number with a uniform probability distribution between 3 and 19 was generated and used as the pipe length from the water heater to the end-use.

The T_a value used in Equation 4.2 can be assumed to be equal to the monthly T_a value. However, because the time of the event is generated by the model, the ambient temperature value (T_a) can be calculated, based on the hour of the day that the event is activated. Ambient temperature varies on a diurnal basis as the sun rises and sets. A

practical assumption would be to assume that the daily ambient temperature is lowest at midnight and highest at midday. A sinusoid was created to model the diurnal temperature variation and is shown in Figure 4.12. The sinusoid was created using the average T_{\max} and T_{\min} values of all months, from the climate data.

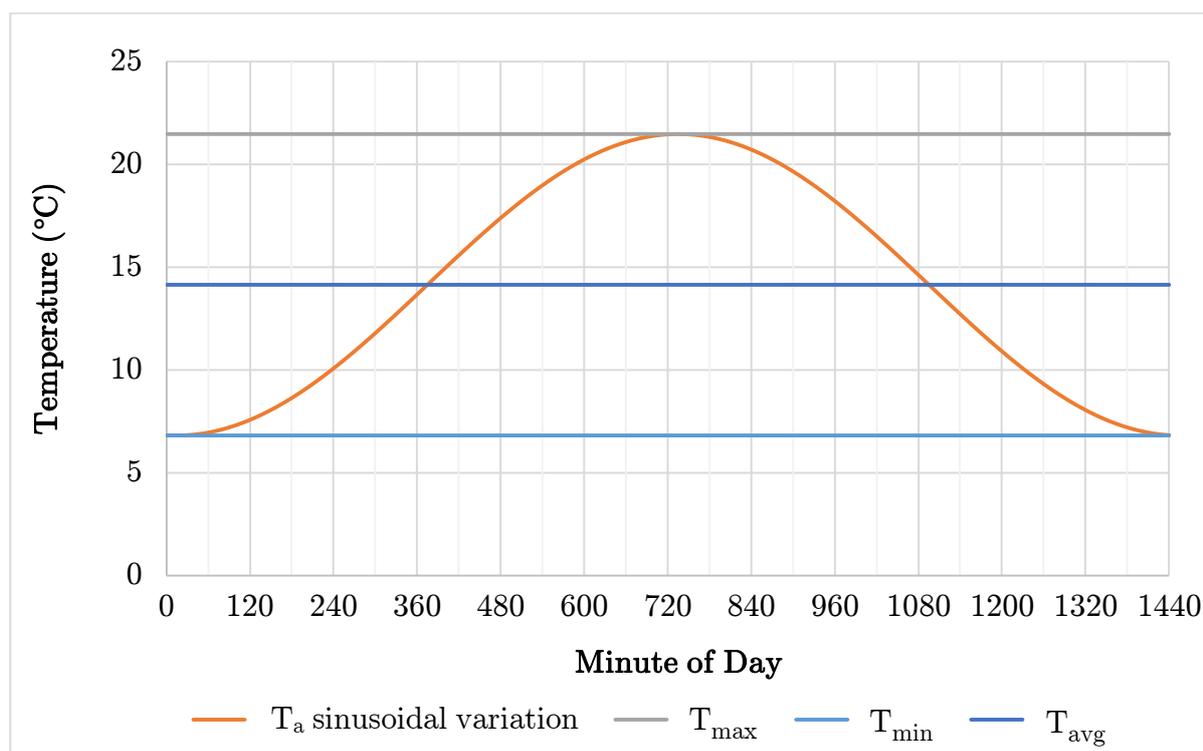


Figure 4.12 Diurnal variation in ambient temperature

The sinusoid was then used to derive factors that could be applied to any average daily temperature to convert the daily temperature to hourly temperatures. A method named `getTa` was created that returns the hourly average ambient temperature based on the starting hour of the event. The method was used every time the pipe heat loss equation was used to determine the hot water temperature, arriving at a specific end-use that was generated. The starting minute of the event was passed to the `getTa` method and it was calculated at what hour the event had started. The method then used the average temperature of the month being simulated and applied an hourly factor to the average

monthly temperature corresponding to the hour in which the event took place. The hourly factors that were derived from the daily T_a sinusoid are presented in Table 4.8.

Table 4.8 Hourly average ambient factors derived for the model

Hour of Day	Hourly Temperature factor
1	0.484
2	0.511
3	0.571
4	0.660
5	0.772
6	0.900
7	1.035
8	1.167
9	1.288
10	1.390
11	1.465
12	1.508
13	1.516
14	1.490
15	1.430
16	1.340
17	1.228
18	1.100
19	0.965
20	0.833
21	0.712
22	0.610
23	0.536
24	0.492

Given the information presented in section 4.6, the pipe heat loss equation can be solved. Consequently T_h , in conjunction with T_c and T_d , can be used for the volume balance to determine end-use hot water demand from total water demand.

4.7 Individual Events

In the stochastic end-use model developed in this study, the volume, flow rate and starting times were different for each of the five end-use events modelled. The starting times were modelled as discrete variables, as previously described in this chapter. Conversely, the volume and flow rate were modelled as continuous variables. The REUWS database contained thousands of measured values for volumes and flow rates that were used for the model. For the purposes of the study, the REUWS sample data was fitted to theoretical probability distributions. Scheepers (2012) fitted theoretical distributions to flow rate and total volume data for all five the end-uses used in this study. Therefore the distributions derived by Scheepers (2012) was used directly in this study. The validity of the distributions is discussed in Scheepers (2012).

Goodness of fit (GOF) tests were used to determine which distributions provided the best fit to the actual data. The @Risk software was used to apply three different goodness of fit tests to the 17 different theoretical distributions that were available in the software. Scheepers (2012) conducted the distribution fitting research and ranked the best fit distributions based on a combination of the three GOF tests. Consequently, for each end-use, a flow rate and total volume distribution could be selected, based on the best fit rank according to the GOF tests.

The flow rate distributions derived by Scheepers (2012) were used directly in the model to generate event flow rates. Conversely, the total volume distributions could not be used directly, instead the distributions were used to obtain a total mixed (hot and cold) volume that was converted to a total hot water demand where necessary.

The duration between cycles in washing machines and dishwashers were also required for the model to have an offset time between cycles, as these events were added into the diurnal demand profile. The durations between cycles were modelled as continuous variables, since Scheepers (2012) had derived best fit theoretical probability distributions which were readily available.

The following sections describe each of the end-uses individually, including the Java class created to simulate each event. In each section the methods that calculate hot water volume and flow rate are described. The probability distributions that were used for each end-use are presented, along with other information relevant to the specific end-use.

4.7.1 Shower Events

As previously discussed, each end-use was modelled by creating a new class that extends the abstract Event class, with all the variables and methods as explained in sections 4.5.3 and 4.5.4. When the Shower class was created the new class inherited all the variables and methods from the Event class. Only the abstract method bodies had to be completed in the Shower class.

The first abstract method was the genStartMin method, which had to return a probable starting minute when a shower event is most likely to occur. The appropriate starting minute relative frequency distribution was stored in an array within the method. Code similar to the genHouseholdSize method was used, to ensure that the method returned a starting minute based on probability when called.

The shower flow rate was the next variable that had to be generated in the Shower class, by completing the body for the genFlowrate abstract method. For the continuous flow rate variable a suitable theoretical probability distribution was required. GOF tests by Scheepers (2012) determined that a log logistic was the best fit distribution for shower flow rate. Similarly a probability distribution was required for the total shower volume. A Log-Logistic distribution was found to fit the shower total volume data the best.

It is a coincidence that both the shower flow rate and total volume data were best fit by a Log-Logistic distribution. The Log-Logistic distribution was subsequently used to demonstrate how the model solved for the distributions with randomly generated numbers during the Monte Carlo Simulation. The cumulative distribution function for

the Log-Logistic is given in Equation 4.3. The value of $F(x)$ is between zero and one, and x represents the corresponding total volume, or flow rate, depending on the parameters used for α , β and γ .

$$F(x) = \frac{1}{1 + \left(\frac{\beta}{x-\gamma}\right)^\alpha} \quad \text{Equation 4.3}$$

The objective was to solve the equation for x to obtain either a volume or a flow rate in this case. The $F(x)$ was replaced by a randomly generated number between zero and one and the parameters α , β and γ had unique known values for each end-use, as determined by best fit distribution in the @Risk software. Changing the subject of Equation 4.3 to solve for x resulted in Equation 4.4.

$$x = \frac{\beta}{\left(\frac{1}{F(x)} - 1\right)^{\frac{1}{\alpha}}} + \gamma \quad \text{Equation 4.4}$$

Equation 4.4 is known as an inverse cumulative probability equation. These type of equations was solved every time a flow rate or total volume was required for an end-use. The imported math distribution package, Apache Math Commons, included objects for all the distributions used in the model. Every time a distribution was required, a new object of that distribution type was created in the volume or flow rate method. The distribution was given the required parameters for α , β and γ where necessary and the `inverseCumulativeProbability` method was used to solve for the required value. The `inverseCumulativeProbability` method required a value between zero and one when used, therefore a random variable was generated and passed to the method. A summary of the parameters used in the Shower event class is presented in Table 4.9.

Table 4.9 Probability distribution parameter values for shower events (adapted from Scheepers, 2012)

Variable	Distribution	Parameter	Parameter value
Flow rate	Log-Logistic	γ	0.000
		β	55.197
		α	2.828
Total volume	Log-Logistic	γ	0.000
		β	0.127
		α	4.158

The `genFlowrate` abstract method body was completed by creating a Log-Logistic distribution with the appropriate parameter values, then solving the inverse cumulative probability equation for the distribution with a randomly generated value between zero and one. Consequently, a flow rate value is obtained for the shower event whenever the method is used.

The `genVolTot` abstract method body was completed differently. The objective of the method was to return the total volume of hot water demand for a shower event. First a Log-Logistic probability distribution was created with the parameters as determined in @Risk by Scheepers (2012). Then the inverse cumulative probability equation was solved to obtain a total event volume value. The value solved from the probability distribution represented the mixed total volume of the hot and cold water and had to be converted to a hot water only volume. Therefore, code was created for the conversion process to extract only the hot water demand from the obtained value using a volume balance. Consequently, cold water inlet and desired user temperatures were required, as well as the temperature of the hot water delivered to the end-use. The cold water temperature was obtained from the values in Table 3.4 based on the simulated month. The user desired temperature for the shower was obtained with a normal distribution, as described in section 4.6.2. The heat loss in pipes equation (Equation 4.2) was applied to the water heater set temperature to obtain the temperature of the hot water delivered to the end-use. In other words, the water heater temperature setting was used as the starting

temperature of the hot water at the water heater and the pipe flow heat loss equation determined what the temperature of the water was when delivered at the end-use.

With all the required values known, the volume balance equation (Equation 4.1) was solved within the method and the total hot water demand for the shower event was returned by the method. Consequently, the shower event object could then use the `genEvent` method to populate all variables in the object, enabling the event to be added to the diurnal demand profile.

4.7.2 Bath Events

Bath events were similar to shower events in the way flow rates and total hot water volumes were calculated. The only difference was that the probability distributions used were understandably different, since these distributions were derived from bath event data from REUWS.

Firstly the `genStartMin` method for the bath event was populated with the appropriate distribution describing probable bath event starting times. Afterwards distributions to describe the bath flow rate and bath total volumes were required. Again the best fit distributions, as determined by Scheepers (2012), were used. A Weibull distribution was found to be the best fit for bath flow rate and Raleigh distribution best fit the REUWS data for bath total volume.

The bath flow rate abstract method was completed in the same manner that the shower `genFlowrate` method was completed to return a probability based flow rate for the event. Similarly the `genVolTot` event was also completed exactly as in the shower event, only the distribution describing the probable total event volume differed. The other variables for the volume balance equation were determined as for shower events, and consequently a hot water demand could be calculated for the bath event when the method was used. A summary of the parameters used in probability distributions in the Bath event class is presented in Table 4.10.

Table 4.10 Probability distribution parameter values for bath events (adapted from Scheepers, 2012)

Variable	Distribution	Parameter	Parameter value
Flow rate	Weibull	β	2.578
		α	0.340
Total volume	Raleigh	β	65.985

4.7.3 Tap Events

Tap events were modelled differently from both bath and shower events, which had desired user temperatures. It is common for tap events in households to use either hot or cold water exclusively, or a mixture of the two. Not all tap events require a specific small range of user desired temperatures, as bath or shower events do. Therefore the events were not modelled to have a fixed temperature. A study on ten homes in Minnesota, USA, found that for 91% of hot water draws, no hot water reached the end-use. These draws accounted for 11% of the total volume and were mainly because of short draws by kitchen and bathroom sinks (Schoenbauer *et al.*, 2012). Although the sample size was small, it meant that the temperature of the water coming from tap end-uses was sometimes insignificant. Other events, such as filling a kitchen sink for dishwashing, might use mainly hot water; contrariwise, filling a bucket at a tap could use only cold water. Many households use mixer tap fixtures which include using a mixture of hot water and cold water by default every time a tap is used. Therefore modelling tap event hot water use is difficult, and human behaviour has a significant influence.

In the model in this study, the tap modelling problem was solved by assuming a certain percentage of the total water demand was hot water demand, based on values obtained from DeOreo & Mayer (2014). The REUWS database used did not discriminate between hot water and cold water used at tap events. Thus all the measured tap events

represented typical flow rates and volumes of tap events that could have been hot water, cold water or a combination. However, the newer REUWS2 study had results available on hot water use. By measuring water use with flow trace at the cold water inlet and water heater inlet simultaneously, a better understanding of hot water demand by taps was obtained. Out of approximately 496 000 measured tap events in the REUWS2 hot water records, it was found that 57% of the total water used by taps was hot water (DeOreo & Mayer, 2014). Therefore, for the model in this study, the original REUWS data was used to obtain a total volume for an activated tap event, and then it was assumed that 57% of the total demand volume was hot water demand.

The distributions for the tap flow rate and total volume were required. The best fit distribution for the flow rate was a Gamma distribution and a Log Normal distribution was used in the model to describe the tap event total volume (Scheepers, 2012). A summary of the parameters used in probability distributions the Tap event class is presented in Table 4.11.

Table 4.11 Probability distribution parameter values for tap events (adapted from Scheepers, 2012)

Variable	Distribution	Parameter	Parameter value
Flow rate	Gamma	β	0.023
		α	3.262
Total volume	Log Normal	β	0.276
		α	1.064

In the genVolTot method of the Tap event class, the Log Normal distribution was used to calculate the total mixed volume demand of an activated tap event. Then the value was multiplied by 0.57 to apply the assumption that 57% of the total tap event volume is hot water. The method returned the modified value as the final total hot water volume for the event.

4.7.4 Dishwasher Events

A typical household dishwasher can be connected to either the cold water supply or to the water heater. In the case where the dishwasher is connected to the cold water inlet, the dishwasher heats water internally with an element and therefore the hot water demand from the water heater for the end-use will be zero. However, if the dishwasher is connected to the hot water supply the end-use will use hot water. DeOreo & Mayer (2014) studied 100 homes in North America and found that all the dishwasher events in the study used hot water exclusively. Because there are so many different manufacturers of dishwashers it is complex to model the dishwasher end-use. In the model in this study it can be indicated whether the dishwasher is connected to the water heater or not. The selected option will then be used for all iterations of the model.

Dishwasher events usually have a number of cycles when used. Therefore in the created Dishwasher event class new methods were added (additional to the mandatory abstract methods) to stochastically generate the number of cycles, as well as the duration between cycles. From the REUWS data it could be determined how many cycles an event had. The number of cycles was a discrete variable and was modelled within the Dishwasher event class with a new method named `genNumCycles`. Similarly to other methods that calculate discrete variables in the model, the number of cycles was determined from a cumulative probability distribution derived from the REUWS database by Scheepers (2012). The values for the 'number of cycles' distribution is available in Appendix C.

The duration between cycles, conversely, was modelled as a continuous variable, since a probability distribution derived by Scheepers (2012) was available that described the duration between dishwasher cycles in seconds. The value obtained for the duration between cycles was rounded to minutes to fit the temporal scale of the model. A Log-Logistic distribution was used in the model.

The second new method added to the Dishwasher event class was `genDurBC`, which generated the duration between cycles by solving the derived Log-Logistic distribution

inversely. The obtained value was converted to minutes, rounded and then returned by the method. Similar to previous events, probability distributions for the flow rate and total volume for dishwasher events were available. The distributions described a single cycle of a dishwasher event. For the purposes of the model, an assumption was made that when a dishwasher event was activated, a cycle volume and flow rate was generated and kept constant for each of the cycles of the event. A similar approach was followed by Blokker *et al.* (2009), where a constant predetermined cycle volume was used and repeated for all cycles. Conversely, in the model in this study, the cycle volume is stochastically generated from the REUWS data.

An Erlang distribution was found to be the best fit to dishwasher cycles flow rates (Scheepers, 2012) and was used in the Dishwasher class `genFlowrate` method. The dishwasher event total cycle volume was described by a Log-Logistic distribution (Scheepers, 2012). In the case of the dishwasher, the total cycle volume was used as determined from the distribution, because if the dishwasher is connected to the hot water supply, the demand generated will be exclusively hot water demand. Therefore the `genVolTot` method in the Dishwasher event class inversely solved the Log-Logistic distribution with a random number and returned the value without any conversion calculations as were necessary in other end-uses. A summary of the parameters used in probability distributions the Dishwasher event class is presented in Table 4.12.

Table 4.12 Probability distribution parameter values for dishwasher events (adapted from Scheepers, 2012)

Variable	Distribution	Parameter	Parameter value
Flow rate	Log-Logistic	γ	0.000
		β	7.101
		α	4.319
Total volume	Erlang	β	11.000
		α	0.009
Duration between cycles	Log-Logistic	γ	0.000
		β	314.920
		α	1.731

The method in which dishwasher events were added to the diurnal profile array in the genDiurnal method varied from that of the other events, because the dishwasher was a cyclic event. When a dishwasher event was added, a new instance of a Dishwasher class object was created and the genEvent method was called to populate the event with values. The number of cycles and the duration between cycles were sequentially determined.

The duration between cycles was defined as the duration between the start of one cycle and the beginning of another cycle. Therefore, if the duration between cycles was smaller than the dishwasher's generated duration in minutes, the cycles would overlap. Consequently an IF statement was added to check for this occurrence. If the duration between cycles was smaller than the cycle duration in minutes, then the duration between cycles was changed to be equal to the cycle duration in minutes plus an additional minute to ensure that there was at least one minute minimum between cycles.

A loop process reoccurred for the generated number of cycles to add each cycle's volume per minute to the diurnal demand array. For every iteration of the loop, the cycle starting minute was calculated by Equation 4.5.

$$\text{Cycle start minute} = \text{startMin} + i \cdot \text{durBC} + i \cdot \text{extraMin}$$

Equation 4.5

Where startMin is the generated starting minute for the dishwasher event, durBC is the duration between cycles and i indicates the iteration number of the loop starting with i equal to zero. The extraMin value was equal to zero when the generated dishwasher event's volExtra variable was zero, which did not occur often but, when doing numerous simulations, was possible. Otherwise the value of extraMin was equal to one. The extraMin variable was added to compensate for the fact that the duration in minutes of the event did not include the last minute, where the volExtra value was added. For the

first iteration i will be zero, thus the first cycle is added at the generated event starting minute. For the second iteration the cycles starting minute is offset by one times the duration between cycles, and then two times the duration between cycles for the third iteration and so forth, until the number of cycles is reached. The previously described `addEvent` method was used to add the cycles to the diurnal demand array with the calculated cycle starting minutes.

4.7.5 *Washing Machine Events*

Equivalent to the dishwasher events, washing machine events are also cyclic events. However modelling hot water demand in washing machines from the REUWS total event volumes and flow rates was more complex. The complication arose because there are many manufacturers and various types of washing machines which could be connected to both the hot and cold water supplies as reviewed in the literature. On the contrary, some washing machines are connected only to the cold water supply and will not generate hot water demand.

The cycles of washing machines can also be intricate. Some cycles use only cold water, some cycles only hot water and other cycles a combination of the two to reach a desired cycle temperature. Hot water demand can also depend on the settings or washing mode that is selected by the user. Omitting washing machine events from the model was considered, because of the complexity thereof, nevertheless a simplified approach was used to model to end-use, rather than complete omission. Similar to the dishwasher, in the model an option was available to select that the washing machine was not connected to the water heater and did not contribute to hot water demand.

The previously successful water demand model SIMDEUM used a simplified approach to modelling washing machine events by assigning a constant number of cycles, duration and volume to the event (Blokker *et al.*, 2009). Although SIMDEUM was for total water demand and not hot water demand, the simplification idea is similar. Constant cycle

volumes were not used in the model in this study. Instead the cycle volumes and flow rates were determined from available probability distributions derived by Scheepers (2012) from the REUWS data. The rest of the simplification depended on a number of reasoned assumptions mentioned in this section.

An extensive telephone survey by Procter & Gamble on clothes washing habits of 1522 households was investigated and some information about hot water cycles was obtained (Lutz *et al.*, 1996). Lutz *et al.* (1996) found that washing machines typically have three cycles that could use hot water, namely hot wash, warm wash and warm rinse. In the model in this study, the washing machine was selected to have two cycles that generated hot water demand, either hot wash or warm wash, and always a warm rinse cycle. The reason for only choosing two cycles was to not overestimate hot water demand by the simplification, since Scheepers (2012) had stated that washing machine events were overestimated as a result of the derived probability distributions that are used in the model. The approach of using a constant two cycles attempted to not overestimate demand, as the large number of cycles in the model by Scheepers (2012) was a probable cause for the over estimation. The cycle volumes and flow rates used in the model in this study were realistic, as derived from actual washing machine cycles from the REUWS data.

When a washing machine event was activated the first cycle was selected to be either hot wash or warm wash. The difference was that warm wash cycles had a desired temperature (T_d) of 34°C (Lutz *et al.*, 1996) and hot wash cycles used the hot water at the delivery temperature from the water heater. Lutz *et al.* (1996) presented a table with average cycle frequencies for each of the cycles and from the table it was determined that on average, the probabilities of hot and warm wash cycles were 25% and 75% respectively. A new integer variable was introduced in the WashingMachine event class named cycleNum, which indicated whether the cycle used hot water (cycleNum = 1) from the water heater or warm water (cycleNum = 2) at a desired temperature of 34°C. The cycleNum variable started equal to 1 when the first cycle was added, which indicated

that the first cycle was a hot wash cycle. Then an IF statement had a 75% probability of changing the cycleNum to 2 before the first cycle's hot water demand was calculated. Consequently, the first cycle could be calculated as hot wash or warm wash. The warm wash used a volume balance and the heat pipe loss equation to determine the hot water demand for the desired warm temperature.

The second cycle was calculated independently and the cycleNum was manually set to 2, specifying that the second cycle was always a warm rinse cycle (calculated in the same way as a warm wash cycle). Because the two cycles were determined separately, each cycle had a unique volume and flow rate determined from derived probability distributions. The cycles were added into the diurnal demand profile offset from one another in the same way as dishwasher cycles, by using a duration between cycles probability distribution derived for washing machine cycles.

In the WashingMachine event class the genFlowrate, genVolTot and genDurBC methods required probability distributions describing possible values for the washing machine characteristics. A Weibull distribution, as derived by Scheepers (2012), was used to describe the washing machine cycle flow rate. The washing machine cycle total volume was also modelled using a Weibull distribution, which was established to be the best fit to the actual data (Scheepers, 2012).

The final probability distribution that was required was to describe the duration between the two modelled washing machine cycles in the model. Using the three goodness of fit tests previously described, Scheepers (2012) determined that a Beta General distribution was the best fit distribution for the duration between the washing machine cycles.

In view of all the assumptions, the method in which the washing machine end-use was modelled in this study was considered sensible, and superior to a complete omission of the end-use. A summary of the parameters used in probability distributions the WashingMachine event class is presented in Table 4.13.

Table 4.13 Probability distribution parameter values for washing machine events (adapted from Scheepers, 2012)

Variable	Distribution	Parameter	Parameter value
Flow rate	Weibull	β	2.344
		α	0.288
Total Volume	Weibull	β	0.823
		α	32.226
Duration between cycles	Beta General	β	0.540
		α	7.762
		min	0.000
		max	5630.200

4.8 Model testing

The primary method in which the model was tested during the programming process was with sample outputs and analysis thereof. Whenever a value was required in the model and some method had to generate that value, an extra line of programming code was added at the end of the method to display the value that was generated by the method. After the method had been examined and verified, the line of code was removed. Accordingly, this testing procedure was done for all variables, for example, the household size, cold water supply, ambient and water heater set temperatures, as well as pipe flow heat loss, pipe lengths and all end-use characteristic values.

Every time a method was tested, the number of simulations was set to a value of 100 and the model was executed. Consequently, numerous generated values for the method were displayed and the validity was verified by means of systematic inspection. A large number of verification tests were performed this way, at least 100 simulations for each Java method in the model. For example, shower events was tested by altering the model to display the total mixed volume generated, the water heater temperature setting, the temperature of the water delivered to the end-use after losses and the final hot water demand of the event. Displaying all these variables allowed for inspection and verification

of all aspects of the model program. Subsequently, this method of analysis helped in fixing all problems in the model programming process.

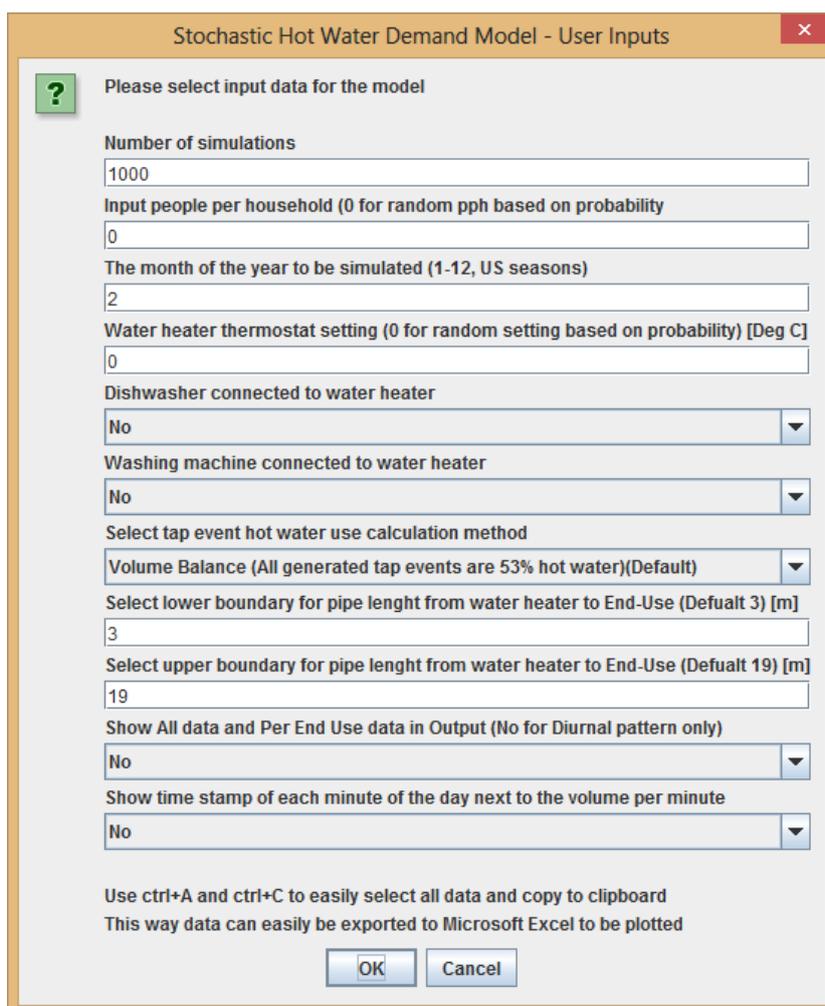
The inverse solving process of the cumulative probability distributions was also extensively tested. The randomly generated number was, for example, replaced with 0.5 manually and then the result of the Java method was compared to results obtained in Microsoft Excel, as calculated by Scheepers (2012), to verify all the end-use methods.

Another method used to test some aspects of the model was used with tap events. In the model, the assumption that the hot water demand of a tap end-use was 57% of the total use. Another approach was to assume 57% of tap events were exclusively hot water and the rest were exclusively cold water. The approach included multiplying the generated daily tap event frequency by 0.57, essentially to lower the number of events, and then using the total volume as the hot water volume. For a large number of simulations, statistically the Monte Carlo method should give the same average value for each of the methods. The only difference is that the method of lowering events would have fewer tap events in the diurnal profiles generated, compared to the other method that would have more events but with lower volumes per event. After executing the model once for each method, the two average diurnal tap hot water demands were found to be 48.76 ℓ and 48.81 ℓ respectively, indicating that the model was working properly.

4.9 User Interface

A graphical user interface was created in Java to assist a user in selecting a scenario to be modelled. The window that is displayed whenever the program is executed is shown in Figure 4.13. Most of the fields are populated with default values, or provide the user with a drop down menu from which to select possibilities. The default setting for number of simulation is 1 000 and should take less than five seconds to obtain results (ten thousand simulations would take about 30 seconds depending, on the computer's processor speed).

The interface also allows the user to select whether the dishwasher and washing machine events should be included in the simulations, by selecting whether these end-uses are connected to the water heater. The tap event calculation method permits the user to select which of the two methods described in section 4.8 will be used. The upper and lower bounds for the pipe lengths are defaulted at 3 metres and 19 metres respectively, as discussed in section 4.6.4 but can be changed by the user if required. The last two drop down boxes allow the user to select what should be displayed in the model output window. All data can be displayed, or only the list of 1 440 values describing average diurnal per minute use with or without minute of day timestamps. The executable Java model is available on the CD in the back cover of this thesis (note that certain Java runtime environment is needed on the computer in order to execute the file).



The screenshot shows a dialog box titled "Stochastic Hot Water Demand Model - User Inputs". It contains the following fields and options:

- Number of simulations:** Text input field with value "1000".
- Input people per household (0 for random pph based on probability):** Text input field with value "0".
- The month of the year to be simulated (1-12, US seasons):** Text input field with value "2".
- Water heater thermostat setting (0 for random setting based on probability) [Deg C]:** Text input field with value "0".
- Dishwasher connected to water heater:** Dropdown menu with "No" selected.
- Washing machine connected to water heater:** Dropdown menu with "No" selected.
- Select tap event hot water use calculation method:** Dropdown menu with "Volume Balance (All generated tap events are 53% hot water)(Default)" selected.
- Select lower boundary for pipe length from water heater to End-Use (Default 3) [m]:** Text input field with value "3".
- Select upper boundary for pipe length from water heater to End-Use (Default 19) [m]:** Text input field with value "19".
- Show All data and Per End Use data in Output (No for Diurnal pattern only):** Dropdown menu with "No" selected.
- Show time stamp of each minute of the day next to the volume per minute:** Dropdown menu with "No" selected.

At the bottom, there are "OK" and "Cancel" buttons. A note at the bottom states: "Use ctrl+A and ctrl+C to easily select all data and copy to clipboard. This way data can easily be exported to Microsoft Excel to be plotted."

Figure 4.13 Stochastic hot water demand model user interface

5 Results and Discussion

The results obtained with the stochastic end-use model are reviewed in this chapter. Results for different months and household sizes are exhibited and discussed. Additionally, the influence of having the dishwasher and washing machine end-uses connected to the water heater was investigated.

The results are typically representative of North American households, but the purpose was not to simulate North American DHW demand. Instead, the intention was to exhibit that the presented stochastic end-use model can produce realistic DHW demand results from total domestic water consumption data. The study was intended to corroborate that the stochastic end-use modelling technique is viable and that the model can be used with recorded data from any geographical location to estimate local demands if required. The results obtained with the model are compared with results of previous studies, to provide some validity to the results obtained with the stochastic model in this study.

Two primary types of result were extracted from the model, total average demand volumes and diurnal demand profiles. Total average demand values were typically represented as the average total litres of DHW demand per day for all simulations. Furthermore, the total average litres per day demand of each end-use could also be obtained for all simulations.

Graphical representations of diurnal DHW demand profiles are typically shown with an X-axis indicating the hour of the day. This modification made comprehension of the results more intuitive, compared to what the results would be with an axis indicating minute of the day. Nevertheless, there were still 60 data points in each hour, one for each minute.

5.1 Number of Simulations

The number of simulations or iterations per execution of the model, with the objective of obtaining results, was usually set to 10 000, especially where total demand volumes were required. For instance, if results were obtained for a pre-set household size of two occupants in the second month of the year, consequently 10 000 unique diurnal profiles of the household type were generated and averaged. For cases where diurnal profiles were important, 50 000 iterations were used to smooth the results.

Figure 5.1 illustrates how the number of simulations affects the smoothness of the diurnal demand profile. The difference between 10 000 simulations, indicated in red, and 100 000 simulations, indicated in light blue, is small when compared to the graph roughness of using only 100 simulations.

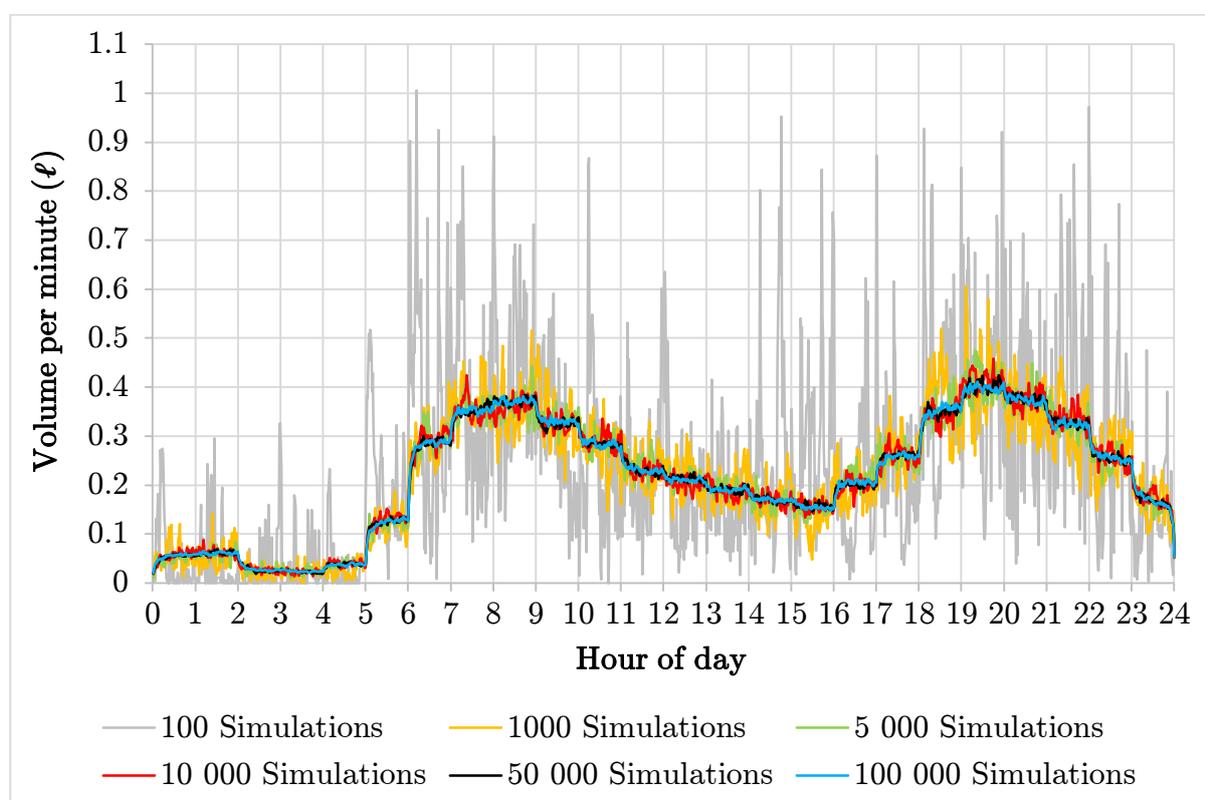


Figure 5.1 Effect of number of simulations on diurnal results

5.2 Diurnal DHW Demand by Month

The model allowed the user to select a month to be simulated, which affected the climate values used in the execution of the model. A value of 1 to 12 indicated the selected month, based on North American seasons. Thus the months around month 1 typically represent winter, and the months around month 6 indicate the summer months.

A total of 10 000 model iterations were used to simulate each month of the year for the case with the dishwasher and washing machine connected to the water heater (With DW and WM) and without (Without DW and WM). Thus a total of 24 000 simulations was used to obtain the total average demands of each month for both cases, and the results are compared in Figure 5.2. The results were obtained by using a stochastically generated household size for each simulation, therefore results can be seen as an average for all household sizes.

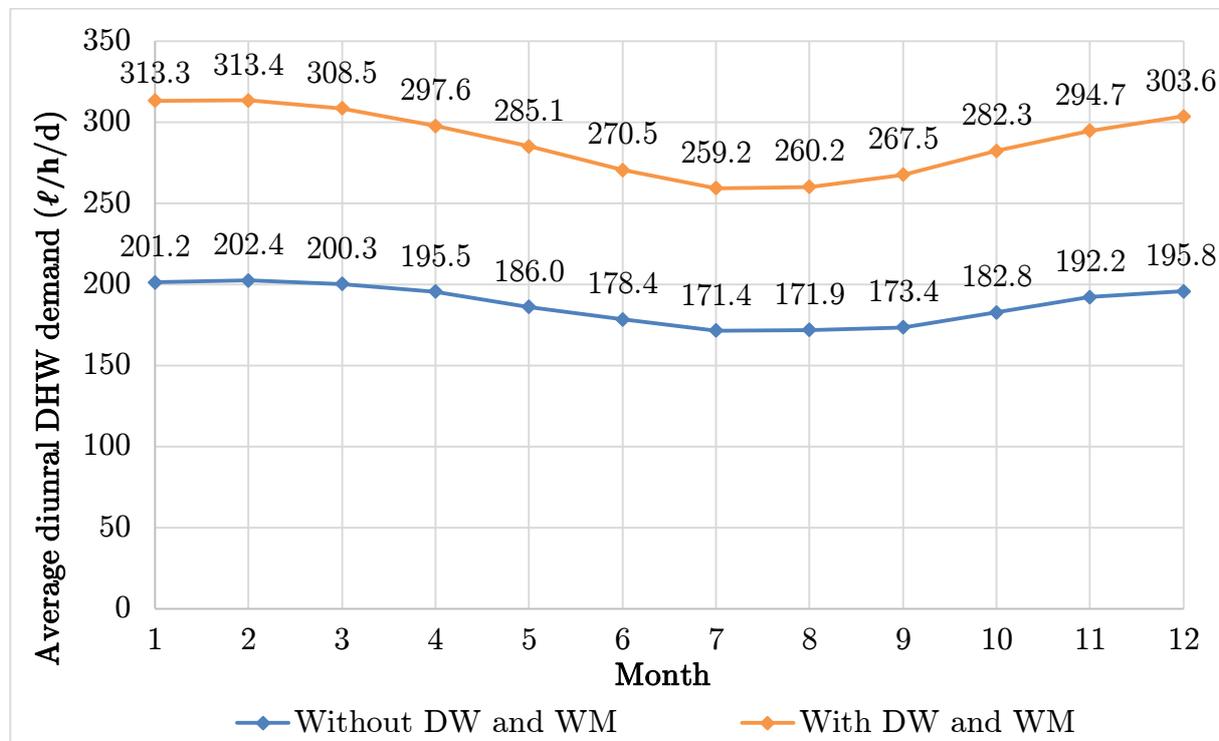


Figure 5.2 Monthly total demand average results with and without DW and WM

From Figure 5.2, it is evident that the highest demand occurs in the second month of the year, and the lowest demand in the seventh month. The demand variation is due to the difference in the cold water supply temperatures for these months. For further results in this study, month 2 (February) and month 7 (July) were used as the critical winter and summer months respectively (North American seasons). Calculating results for all twelve months is unnecessary, as the two critical months will indicate sufficient information about DHW demand.

A summary of all the total average daily demand values obtained is presented in Table 5.1. The table includes total average demand values on an end-use basis, as well as a total diurnal demand value for each month of the year.

Table 5.1 Summary of monthly average total and end-use demand results

Month	With DW and WM						Without DW and WM			
	Shower (ℓ/d)	Bath (ℓ/d)	Tap (ℓ/d)	DW (ℓ/d)	WM (ℓ/d)	Total (ℓ/d)	Shower (ℓ/d)	Bath (ℓ/d)	Tap (ℓ/d)	Total (ℓ/d)
1	99.5	53.5	48.6	31.2	80.3	313.3	99.7	52.5	48.7	201.2
2	98.6	53.5	49.5	31.2	80.5	313.4	99.5	53.2	49.1	202.4
3	97.9	52.1	48.5	30.7	79.2	308.5	98.8	52.5	48.7	200.3
4	93.9	50.2	49.0	30.5	78.6	297.6	94.6	51.2	49.3	195.5
5	88.8	47.6	49.0	30.7	68.9	285.1	89.2	47.8	48.8	186.0
6	83.9	44.4	49.4	30.6	62.1	270.5	84.2	45.7	48.4	178.4
7	79.8	42.9	48.4	30.7	57.3	259.2	79.7	43.0	48.4	171.4
8	79.5	43.2	48.9	30.8	57.6	260.2	79.5	43.1	48.9	171.9
9	83.8	43.9	48.9	30.8	60.1	267.5	81.1	43.6	48.3	173.4
10	89.5	47.5	48.5	30.1	66.6	282.3	87.4	46.2	48.9	182.8
11	92.7	49.6	48.8	31.0	72.3	294.7	93.4	49.8	48.7	192.2
12	94.2	52.2	48.6	30.5	78.4	303.6	95.4	51.0	49.1	195.8
Avg.	90.2	48.4	48.8	30.7	70.2	288.0	90.2	48.3	48.8	187.6

The results obtained from the model also included the per minute volume demand for each of the 12 months with and without the dishwasher and washing machine. Plotting all the profiles would be meaningless. Therefore only the critical winter and summer months were compared for the cases with and without the dishwasher and washing

machine, respectively. The comparison of the results for two cases is illustrated in Figure 5.3 and Figure 5.4. From the figures it can be seen that sensible realistic diurnal profiles were obtained for the critical summer and winter months.

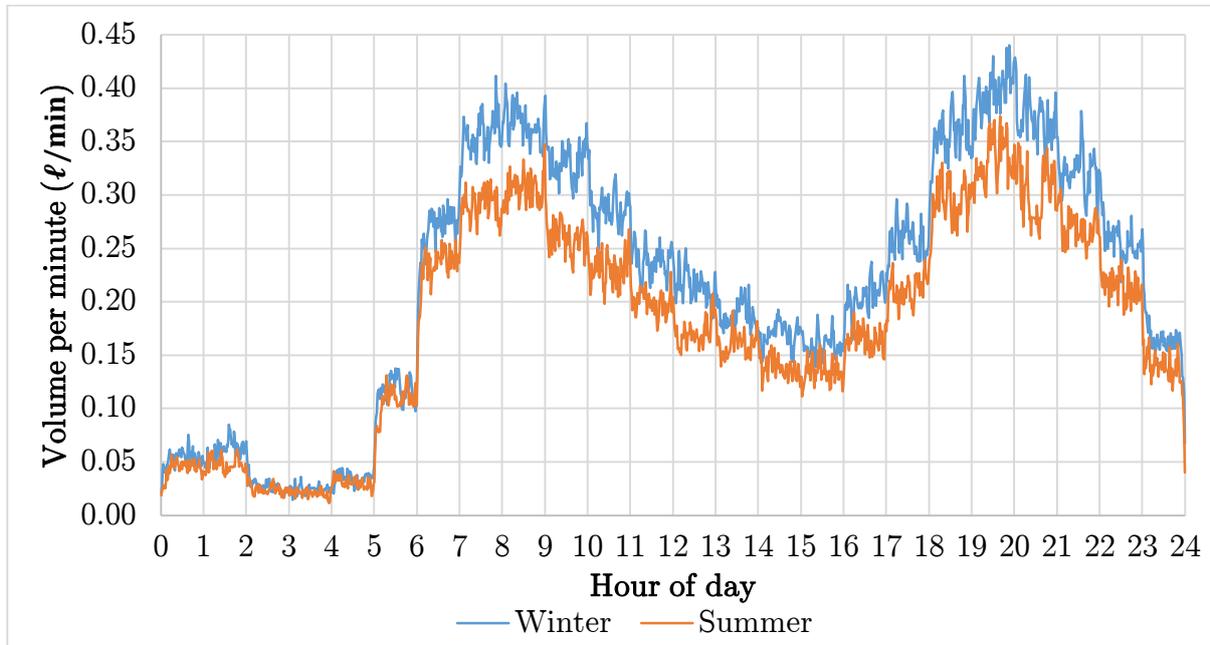


Figure 5.3 Critical month diurnal profile comparison with DW and WM

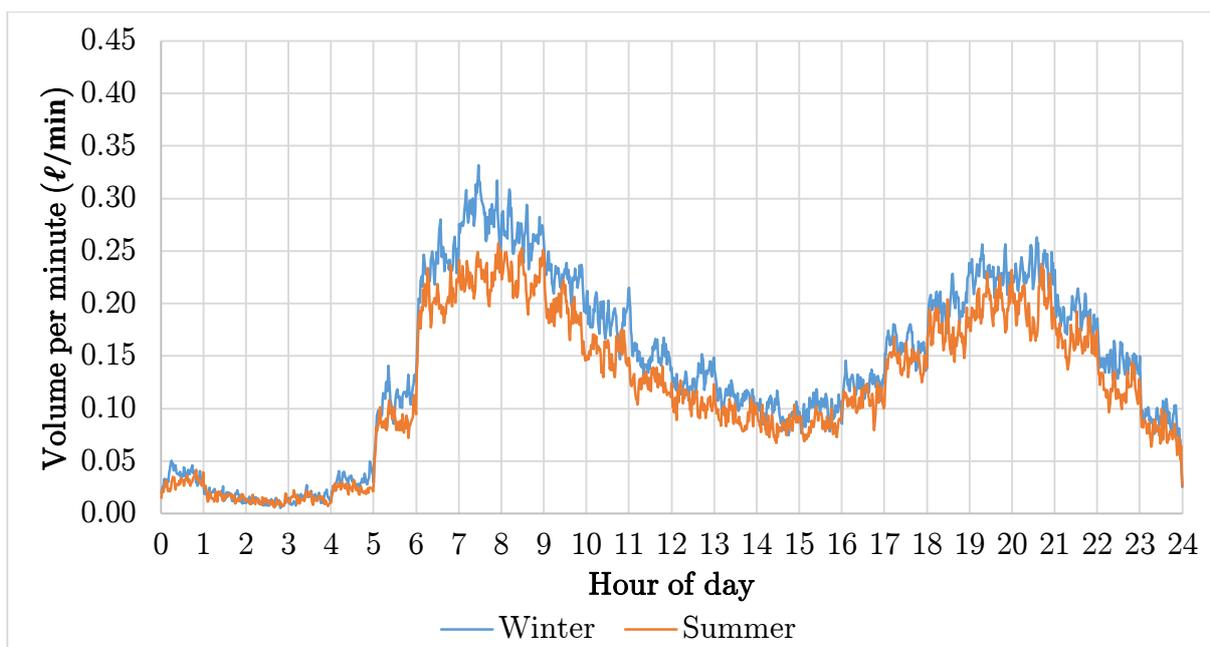


Figure 5.4 Critical month diurnal profile comparison without DW and WM

5.3 Household Size Influence on Diurnal DHW Demand

As found in the literature, household size has a significant influence on DHW demand. Previous results presented in this chapter used a stochastic household size value, whereas in this section the household size was adjusted manually to show the influence thereof in the model. Manual household sizes allowed for per capita use values to be determined, which were helpful for comparison with values found in previous studies.

The model was used to simulate 12 different scenarios, one for each of the six possible PPH values, for both winter (month 2) and summer (month 7). The number of iterations was selected to be 50 000 for each of the 12 scenarios, since the number of iterations smoothed out the diurnal profiles for better comparison with one another. These 12 scenarios all included the dishwasher and washing machine end-uses connected to water heater.

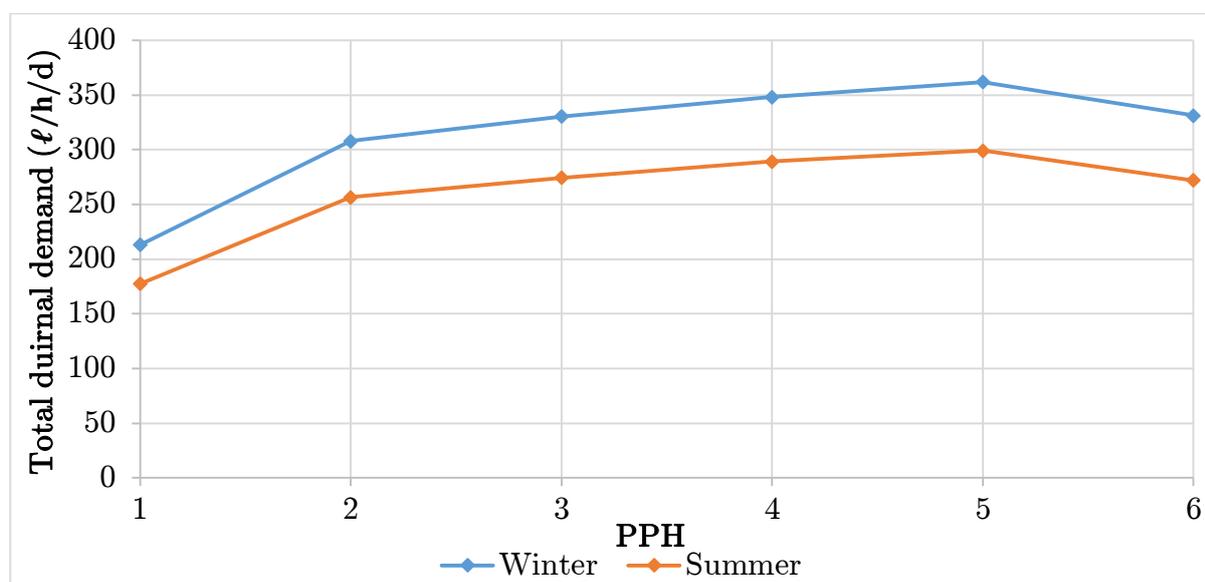


Figure 5.5 Total diurnal demand based on PPH with DW and WM

Initially the total average diurnal demands for each of the 12 scenarios are compared as illustrated in Figure 5.5. From Figure 5.5 it is evident that the total demand increases fairly linearly as the PPH increases, with a larger increase in demand from 1 PPH to 2 PPH. An unexpected drop in average demand appeared when the PPH was set to 6.

The demand decrease could be attributed to the fact the sample size of such households was small in the dataset. Thus the small sample of 6 PPH households in the original data set may have included people who were below average hot water users. Another reason could be that the demographic data was obtained from surveys, and the participants might have not given the actual number of occupants who resided at the house during the recording period.

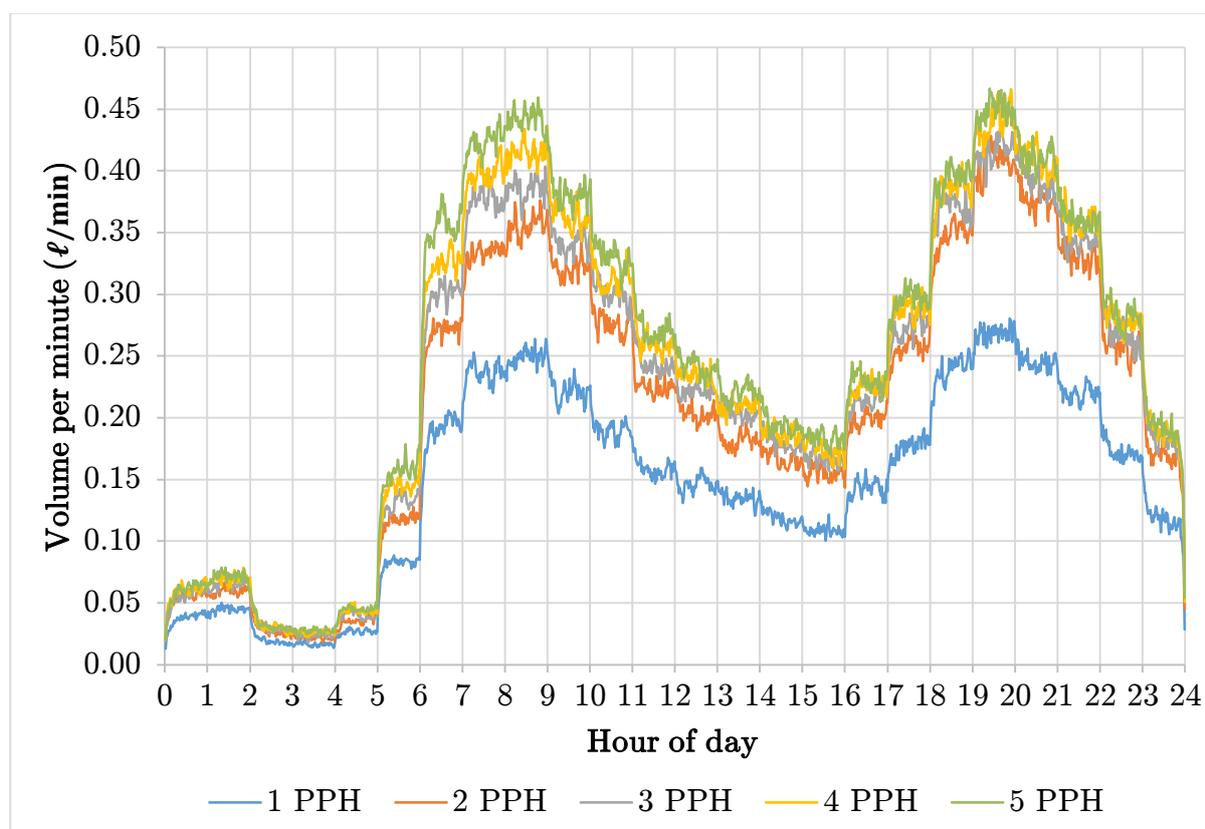


Figure 5.6 Diurnal demand profile comparison based on PPH, for winter with no DW and WM connected

Figure 5.6 illustrates the diurnal demand profiles for winter as the PPH increases. The 6 PPH results have been omitted, since these results were found not to be sensible. The results for the diurnal profiles of DHW demand in summer are similar to the results displayed in Figure 5.6, except for a slight expected decrease in demand in all profiles because of the higher ambient temperatures.

The per capita values were calculated from the results by dividing the total average diurnal demand by the PPH. For comprehensiveness, the 12 scenarios with different PPH values for summer and winter were also computed for the case without the dishwasher and washing machine connected to the water heater. Each of these scenarios was also simulated with 50 000 iterations to obtain results.

By combination of the results obtained with and without the dishwasher and washing machine end-uses, a summary of the calculated per capita DHW demand values is presented in Table 5.2.

Table 5.2 Per capita DHW demand results summary

PPH	Per capita demand with DW and WM ($\ell/c/d$)		Per capita demand without DW and WM ($\ell/c/d$)	
	Winter	Summer	Winter	Summer
1	213.1	177.6	132.7	114.4
2	154.0	128.3	98.8	83.9
3	110.1	91.4	70.8	59.6
4	87.0	72.3	57.0	48.2
5	72.4	59.9	47.9	40.5
Average	127.3	105.9	81.4	69.3

Since the results for the 6 PPH category were found to be not entirely sensible, the 6 PPH category results were once again omitted in the calculation of the per capita demand values. From the values obtained it can be perceived that the per capita demand values decrease as the household size increases. Thus, from the results established by the model, it appeared that constant per capita values are not practical. Rather, the trends indicate that a base hot water demand is present in all households and then additional occupants add demand in a logarithmically decreasing manner as occupants increase. The comparison of per capita DHW demand and PPH is illustrated in Figure 5.7 with logarithmic trend lines indicated on the graph.

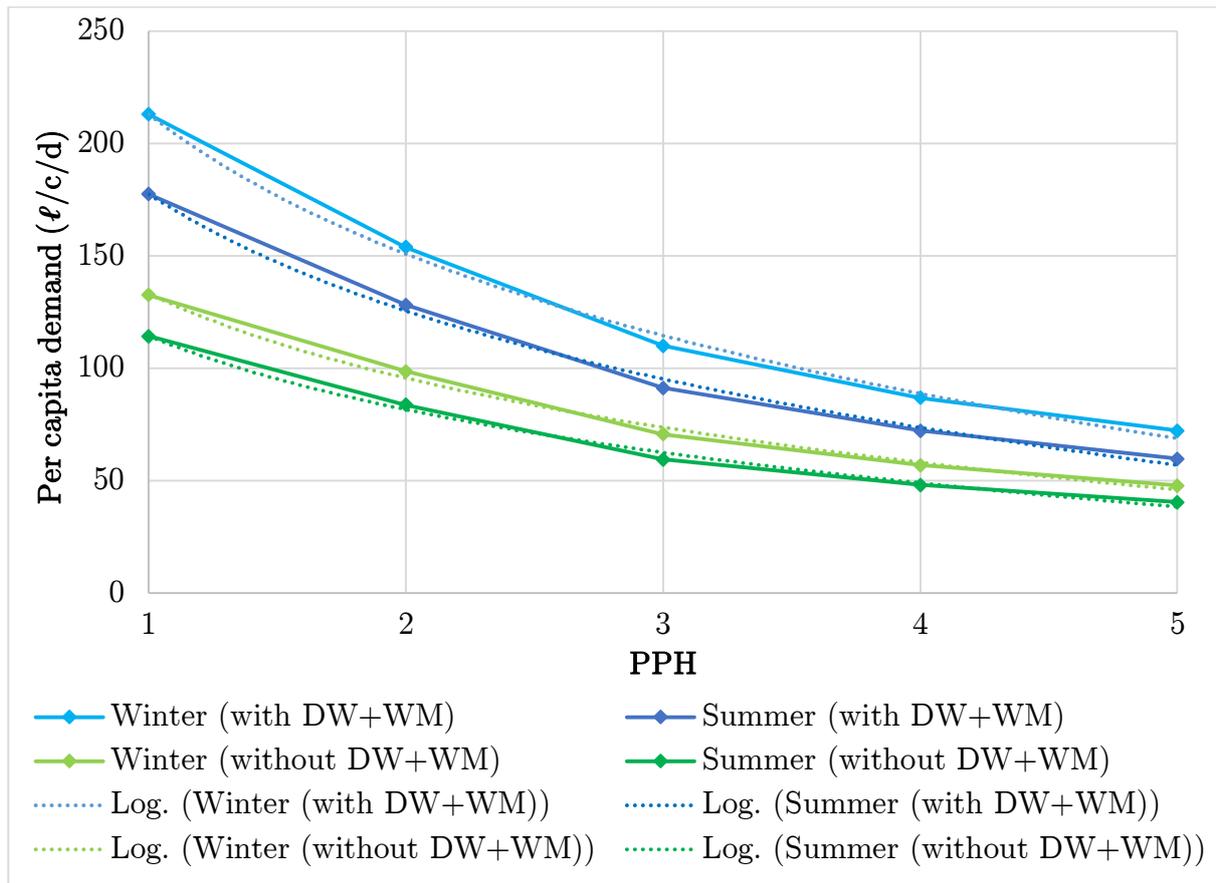


Figure 5.7 Per capita DHW demand results based on PPH with logarithmic trend

Considering the results found, it was realised that a logarithmic equation best describes per capita hot water demand. Although the values obtained in this study would not necessarily represent all geographical areas, it was found that by using results obtained from the model, logarithmic equations describing per capita DHW demand can be derived. For example, per capita hot water demand in winter, for a household where the dishwasher and washing machine are not connected to the water heater, can be described by the derived equation presented in Equation 5.1.

$$\text{Per capita demand} = -54.18 \cdot \ln(\text{PPH}) + 133.3 \text{ (}\ell/\text{c/d)} \quad \text{Equation 5.1}$$

5.4 Comparison of Results with those of Previous Studies

The intention of the model was not to duplicate existing datasets. However, some sort of agreement would be expected when comparing the results obtained from the model with other formerly publicised results and available data. Therefore all the relevant values for DHW demand found in the literature review were summarized and prepared for comparison with the results of this study.

5.4.1 Total Average DHW Demand Comparison

Considering total average demand for all households, a list of values from previous studies was compiled and compared with values found by the stochastic model in this study. A range of values from this study was used for comparison, with the minimum and maximum values being the summer and winter DHW demands, respectively. The total average diurnal demand comparison is presented in Table 5.3.

Table 5.3 Total diurnal DHW demand comparison

Reference	Note	Total Demand (ℓ/h/d)
Thomas <i>et al.</i> (2011)	-	187
CSA (2004)	Canadian testing standard	243
Becker & Stogsdill (1990)	-	238
Schoenbauer <i>et al.</i> (2012)	Study of 10 houses	74 - 224
Hendron & Burch (2008)	-	50 - 500
This study	without DW and WM	171 - 202
This study	with DW and WM	259 - 313

The total demands obtained from the model were in agreement with results from previous studies. In general, the results where the dishwasher and washing machine were included produced larger total diurnal demands. The high demands can be seen in the comparison (with DW and WM) where the maximum value was higher than most

previous results. However, the values obtained were considered to be realistic, over-estimation was not too drastic. In the comparison it appears that results would agree with most other sources if values between the cases with and without the dishwasher and washing machine were used. This meant that there needed to be some probability distribution determining whether each household in a simulation had the dishwasher and/or washing machine connected to the water heater. Unfortunately, for this study, no such data was available, nor did the REUWS data include such information.

5.4.2 Per Capita DHW Demand Comparison

Per capita demand was common in the cited literature, therefore the per capita demand values derived in this study were used for comparison. It was found in this study that a constant per capita use is not always a good indication of hot water demand. However, the average per capita demands found in this study were used for comparative purposes. Again a range of values was used, indicating the variation in demand accord to seasonal change. The comparison to relevant values from the literature review is presented comprehensively in Table 5.4.

Table 5.4 Per capita DHW demand comparison

Reference	Note	Per Capita Demand (ℓ/c/d)
Basson (1983)	-	50
Meyer & Greyvenstein (1992)	-	50 - 75
SANS 10252-1 (2012)	Medium to high rental houses and flats	115 - 140
Meyer (2000)	Low density houses	91
Meyer (2000)	Medium density houses	59
Thomas <i>et al.</i> (2011)	Houses with storage water heaters	66
Kempton (1988)	Small sample size (7 homes)	45 – 126
This study	without DW and WM	69 - 81
This study	with DW and WM	106 - 127

The per capita value ranges derived from the model in this study had good agreement with values from previous studies. The range of values found for per capita demand without the dishwasher and washing machine was similar to most results from previous studies. Although the values with the dishwasher and washing machine end-uses included appeared to be excessively high, these values compared well to the values given in SANS 10252-1 (2012).

5.4.3 Diurnal DHW Demand Profile Comparison

The total average diurnal volume demands and per capita demands have been found to be fairly accurate when compared to previous values. These values were determined by summing the per minute volume demands from the derived diurnal DHW demand profiles from the model. Validation on the manner in which the demand volumes were distributed over the day was required.

In the literature Fairey & Parker (2004) conducted a review of available DHW demand profiles. A series of profiles was selected that was considered to be the most accurate and current. These profiles were modified to indicate the fraction of total diurnal demand used in each hour. Therefore, only the distribution of the values over the day is indicated and the result does not indicate total demand volumes, as the values are normalised.

All the profiles reviewed indicated diurnal DHW demand on a temporal scale of one hour. Therefore the results obtained from the model in this study had to aggregate the minute demand to obtain demand volumes for each hour of the day. There were a few scenarios that could be selected to derive results for comparison with previous studies. Seasonal change would not influence the diurnal demand distribution much, since the starting hours did not depend on the simulated month, therefore an average month (month 5) was used. An additional 50 000 iterations were conducted for each of the cases with and without the dishwasher and washing machine. The comparison with the diurnal profiles from previous studies is illustrated in Figure 5.8.

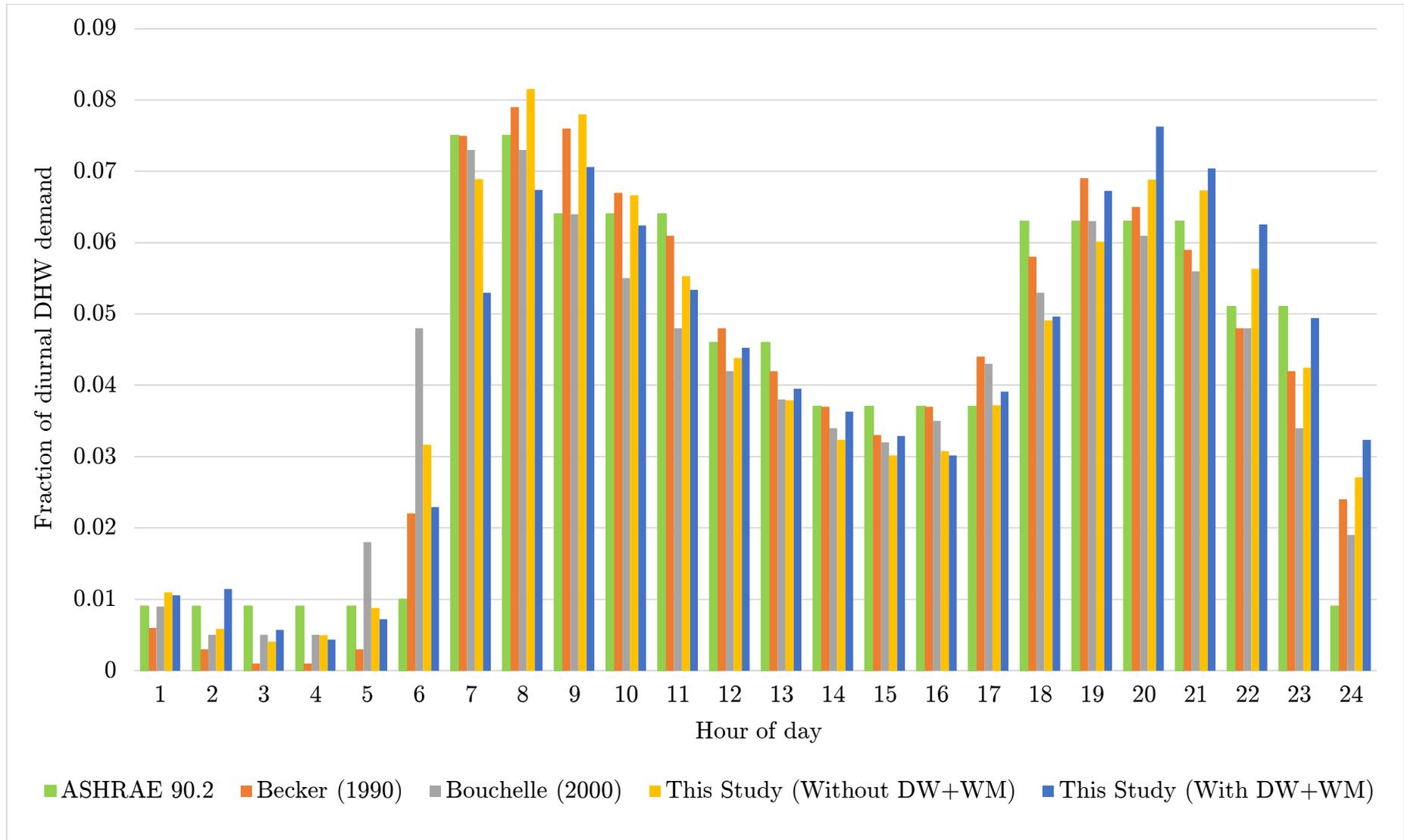


Figure 5.8 Diurnal demand profile comparison with previous studies

The diurnal demand distribution found using the model in this study compared well with previous studies, especially the case where the dishwasher and washing machine were not connected to the water heater. The case without the dishwasher and washing machine connected to the water heater is also considered more typical in South Africa, with the exception of many top loading washing machine models that connect to the DHW supply.

It is evident that the fraction of DHW demand shifts more to the second half of the day when the dishwasher and washing machine end-uses are included. The shift happens because these end-uses have a high probability of being activated in the afternoon and in the evening, based on the input data used. Nevertheless, even with the high fractions of demand towards the last hours of the day, the profile where the dishwasher and washing machine were included still provided a reasonable comparison to previous studies.

5.4.4 Per End-Use DHW Demand Comparison

Limited data was available for hot water demand on an end-use basis. Most studies on this topic had small sample sizes and were excluded from this comparison. Nonetheless, some previous studies were used to compare total average diurnal end-use volumes, including the REUWS2 project results by DeOreo & Mayer (2014). The comparison of values derived from the model in this study with previous studies is presented in Table 5.5.

Table 5.5 Per end-use DHW demand comparison

Reference	Note	Shower (ℓ/d)	Bath (ℓ/d)	Tap (ℓ/d)	DW (ℓ/d)	WM (ℓ/d)
DeOreo & Mayer (2014)	100 study sites	67.4	9.8	58.3	8.3	16.7
Lowenstein & Hiller (1998)	17 study sites	93.1	17.8	60.5	24.2	28.4
This study	-	90.2	48.4	48.8	30.7	70.2

The values used for this study in the comparison were obtained from calculating the average total per-end-use demand of all months from Table 5.1. In line with the results for indoor water demand produced by Scheepers (2012), some of the end-uses appeared to be over-estimated, specifically the bath, dishwasher and washing machine events. Even with the different approach of using only two hot water cycles for the washing machine, the results are still high compared to those in other studies.

The assumption that all dishwashers and washing machines were connected to the water heater leads to the relatively high values, since these end-uses do not use hot water from the water heater in all homes. All results for total, per capita and diurnal demand that were compared with previous studies were found to have reasonable to good agreement. The comparison results gave an indication that the demand values and profiles determined by the model could be considered accurate and realistic.

6 Sensitivity Analysis

A sensitivity analysis was conducted on some of the variables in the model where possible. The sensitivity analysis gave an indication of how the uncertainty in the output of the mathematical model could be apportioned to different sources of uncertainty in the inputs. Some input variables like PPH, simulation month and number of simulations, have been reviewed in the results chapter. The inputs of the derived probability distributions could not be changed, since the distributions were based on recorded data.

Four variables were identified that were then used in the sensitivity analysis of the stochastic end-use model in this study. The variables were the water heater setting, the cold water inlet and ambient temperatures, as well as the assumed pipe lengths within the simulated households.

The process of recalculating results under alternative assumptions was used to determine the impact of the variable under analysis. For the model in this study every variable was evaluated by investigating the change in four results. The results used were the total average diurnal DHW demand volume, with and without the dishwasher and washing machine connected, for winter and summer respectively. Each of the results was obtained by performing 10 000 model iterations. Percentage increase and decrease were used on base values for each of the variables analysed. The percentage increase or decrease in the value of the variable was then compared to the average DHW demand percentage of change to indicate the sensitivity of the model to the variable under analysis.

6.1 Water Heater Temperature Setting (T_{set})

A similar worksheet was created and used for all the variables in the sensitivity analysis. The first variable analysed was the water heater temperature setting, and the worksheet with the comprehensive sensitivity results is presented in Table 6.1.

Table 6.1 Sensitivity analysis for water heater temperature setting

Variable under sensitivity analysis: T_{set} (°C)		Demand without DW and WM				Demand with DW and WM				Average Total Diurnal Demand (ℓ/h/d)	Average Demand change (%)
Variable Value (°C)	Variable adjustment (%)	Winter		Summer		Winter		Summer			
		Total Demand (ℓ/h/d)	Demand change (%)	Total Demand (ℓ/h/d)	Demand change (%)	Total Demand (ℓ/h/d)	Demand change (%)	Total Demand (ℓ/h/d)	Demand change (%)		
78.0	30.0%	160.1	-19.7%	130.4	-22.3%	252.4	-18.7%	204.4	-19.6%	186.8	-19.8%
72.0	20.0%	169.7	-14.9%	139.4	-16.9%	268.7	-13.4%	216.9	-14.7%	198.7	-14.7%
66.0	10.0%	181.8	-8.8%	152.4	-9.2%	283.9	-8.5%	231.9	-8.8%	212.5	-8.8%
60.0	base	199.4	0.0%	167.8	0.0%	310.4	0.0%	254.2	0.0%	232.9	0.0%
54.0	-10.0%	221.1	10.9%	190.8	13.7%	334.4	7.7%	284.2	11.8%	257.6	10.6%
48.0	-20.0%	248.2	24.5%	219.9	31.1%	372.8	20.1%	329.3	29.5%	292.6	25.6%
42.0	-30.0%	283.2	42.0%	276.6	64.8%	431.1	38.9%	402.7	58.4%	348.4	49.6%

Note: Colour scale indicates the lowest (green) to highest (red) demand values and percentage change.

Initially, the base value of the water heater setting variable was selected as 60°C. The base value was increased and decreased in percentage increments of ten, and all the demands were calculated and converted to a percentage change in each case.

Increasing the temperature of the water that is delivered to the DHW system by 30% would result in an average demand decrease of 19.8%. A 10% increase in water heater temperature setting from 60°C to 66°C would decrease the DHW demand by 8.8%. Careful consideration should be taken when selecting the water heater thermostat setting, since a higher water heater setting could result in higher energy costs, along with a greater risk of scalding.

Conversely, decreasing the water heater setting temperature could cause an increase in DHW demand, since more hot water is required in the volume balance to obtain the desired user temperatures. Lower water heater setting might be preferred because of lower energy cost, but the model indicates that a 10% decrease in thermostat setting would result in a 10.6% hot water demand increase on average. These advantages and disadvantages should be taken into consideration, along with health and safety issues like legionella growth at lower water heater settings.

Decreasing the water heater temperature by 30% gives a variable value of 42°C which, in turn, could cause the desired temperature to be greater than the water heater can supply in the model. This anomaly causes significant increases in demand, since the volume balance equation gives required hot water volumes larger than the total volume derived from the probability distributions. Therefore the 30% decrease results were assumed trivial. Additionally, setting the water heater to such low temperatures is not recommended for health reasons, such as growth of *Legionella pneumophila* bacteria (Dennis *et al.*, 1984).

6.2 Cold Water Inlet Temperature (T_c)

The sensitivity of the model to change in the cold water inlet temperature was also analysed with the same method and worksheet as the water heater setting, although it might not be sensible to compare summer and winter results, since the cold water inlet temperature is linked directly to seasonal change. Nevertheless, all the simulations were conducted for extensiveness.

It should also be noted that even with 10 000 model iterations to obtain each result, every 10 000 iterations yielded a slightly different result for the same inputs. Thus it is statistically possible for some values to be outliers, and the percentage change in demand could vary, but was considered realistic.

For the base value of T_c the average of all the monthly values was used. Again, increasing and decreasing the base value indicated the model's sensitivity and the results of the worksheet are presented in Table 6.2. Increasing and decreasing T_c by 30% resulted in a fairly linear demand increase and decrease between 5% and 8%, as indicated in the table.

An additional increase and decrease of 70% was tested to investigate what effect these extreme changes would have on the model. A low temperatures of 5.2°C only increases the demand by 12.4% on average, whereas a very high temperature of 29.4°C decreases the demand considerably more significantly, by 23.3%. Nevertheless, Blokker & Pieterse-Quirijns (2013) state that temperatures above 25°C should be avoided in a water distribution network. Similarly, low temperatures close to the freezing point of water are also avoided in water distribution networks, to avoid freezing the mains.

Table 6.2 Sensitivity analysis for cold water inlet temperature

Variable under sensitivity analysis: T_c (°C)		Demand without DW and WM				Demand with DW and WM				Average Total Diurnal Demand (ℓ/h/d)	Average Demand change (%)
Variable Value (°C)	Variable adjustment (%)	Winter		Summer		Winter		Summer			
		Total Demand (ℓ/h/d)	Demand change (%)	Total Demand (ℓ/h/d)	Demand change (%)	Total Demand (ℓ/h/d)	Demand change (%)	Total Demand (ℓ/h/d)	Demand change (%)		
22.5	30.0%	174.5	-8.0%	176.5	-6.1%	268.9	-8.4%	264.1	-8.5%	221.0	-7.9%
20.7	20.0%	181.3	-4.4%	178.1	-5.3%	280.3	-4.5%	270.2	-6.3%	227.5	-5.2%
19.0	10.0%	186.3	-1.7%	181.4	-3.5%	284.0	-3.3%	278.8	-3.4%	232.6	-3.0%
17.3	base	189.6	0.0%	187.9	0.0%	293.7	0.0%	288.5	0.0%	239.9	0.0%
15.5	-10.0%	192.5	1.5%	193.9	3.2%	299.7	2.1%	296.6	2.8%	245.7	2.4%
13.8	-20.0%	197.0	3.9%	196.7	4.7%	301.4	2.6%	304.4	5.5%	249.9	4.2%
12.1	-30.0%	201.3	6.2%	199.7	6.2%	309.9	5.5%	313.1	8.5%	256.0	6.7%
29.4	70.0%	149.3	-21.2%	147.1	-21.7%	221.4	-24.6%	218.3	-24.3%	184.0	-23.3%
5.2	-70.0%	209.1	10.3%	210.4	11.9%	330.4	12.5%	328.4	13.8%	269.6	12.4%

Note: Colour scale indicates the lowest (green) to highest (red) demand values and percentage change.

6.3 Ambient Temperature (T_a)

The ambient temperature (T_a) was another variable that was used in the sensitivity analysis. Similarly to the T_c , T_a is also strongly related to summer and winter. Nonetheless, all results were calculated again, for extensiveness.

In the model T_a was only used in the pipe heat loss equation to describe the temperature around the pipe when hot water was flowing through the pipe. Typical output results for heat loss values were obtained from the model by extracting values from the pipe heat loss calculation method. Some example outputs are displayed in Table 6.3 along with the averages obtained from 300 samples.

Table 6.3 Typical pipe heat loss values from model output

Example	Water heater set temperature (T_{set}) (°C)	Temperature of hot water delivered to end-use (T_h) (°C)	Temperature loss (°C)
1	58.9	58.4	0.46
2	64.4	63.8	0.62
3	61.7	59.1	2.54
4	58.9	57.3	1.63
5	56.1	54.5	1.60
6	58.9	56.3	2.55
7	58.9	58.6	0.25
8	58.9	58.1	0.82
9	64.4	62.1	2.35
10	64.4	63.5	0.96
Average (Sample size 300)	59.1	57.9	1.14

It is evident that heat loss is relatively small in general, ranging from approximately 0.5°C to 2.5°C. Therefore it was expected that T_a would have a negligible influence on demand as calculated in the model, if T_a only influenced the heat loss calculation.

This postulation is confirmed by the sensitivity analysis results presented in Table 6.4. Even for relatively large adjustments of 150% from the base value, the demand changes remained minor.

6.4 Pipe Lengths

Similarly to the ambient temperatures, the pipe length used in the model only affected the pipe heat loss equation. To test the sensitivity of the pipe length variable, the lower and upper length approach was changed to having just a single pipe length. By analysing the results of model sensitivity to the pipe length as presented in Table 6.5, insignificant impact on DHW demand was found. An approximate demand increase and decrease of 1.5% was observed with a 30% adjustment of the pipe length. An extreme increase in pipe length of 200% resulted in a demand increase of 6.7%. However, 57 metre pipes are rare in domestic households.

The sensitivity analysis on the pipe length verified that the assumptions concerning pipe length in the model were acceptable, since the influence of the variable is slight. Consequently, reasonably approximate assumptions are sufficient for the purposes of the model in this study.

Based on the sensitivity analysis, the conclusion was made that the water heater temperature setting and cold water inlet temperature had the most significant influence on DHW demand in a household. The model was most sensitive to the water heater thermostat setting, and many factors could influence the optimal water heater thermostat setting. The impact of changes in ambient temperature and length of the pipes within the DHW system is negligible when calculating demand.

Table 6.4 Sensitivity analysis for ambient temperature

Variable under sensitivity analysis: T_a (°C)		Demand without DW and WM				Demand with DW and WM				Average Total Diurnal Demand (ℓ/h/d)	Average Demand change (%)
Variable Value (°C)	Variable adjustment (%)	Winter		Summer		Winter		Summer			
		Total Demand (ℓ/h/d)	Demand change (%)	Total Demand (ℓ/h/d)	Demand change (%)	Total Demand (ℓ/h/d)	Demand change (%)	Total Demand (ℓ/h/d)	Demand change (%)		
18.8	30.0%	201.4	-0.2%	171.9	-0.4%	311.4	-0.5%	262.4	0.9%	236.8	-0.1%
17.4	20.0%	201.0	-0.4%	171.8	-0.5%	312.7	-0.1%	261.7	0.6%	236.8	-0.1%
15.9	10.0%	200.3	-0.7%	171.9	-0.4%	314.9	0.6%	261.1	0.3%	237.1	0.1%
14.5	base	201.8	0.0%	172.7	0.0%	313.0	0.0%	260.2	0.0%	236.9	0.0%
13.0	-10.0%	202.3	0.2%	174.0	0.8%	310.6	-0.8%	260.7	0.2%	236.9	0.0%
11.6	-20.0%	203.7	0.9%	171.8	-0.5%	311.5	-0.5%	260.5	0.1%	236.9	0.0%
10.1	-30.0%	202.7	0.4%	172.5	-0.1%	314.7	0.5%	260.0	-0.1%	237.5	0.2%
36.2	150.0%	200.6	-0.6%	170.9	-1.0%	310.8	-0.7%	257.9	-0.9%	235.1	-0.8%
-7.2	-150.0%	204.6	1.3%	177.1	2.5%	315.2	0.7%	264.1	1.5%	240.2	1.4%

Note: Colour scale indicates the lowest (green) to highest (red) demand values and percentage change.

Table 6.5 Sensitivity analysis for pipe lengths

Variable under sensitivity analysis: Pipe Length (L)		Demand without DW and WM				Demand with DW and WM				Average Total Diurnal Demand ($\ell/h/d$)	Average Demand change (%)
Variable Value ($^{\circ}C$)	Variable adjustment (%)	Winter		Summer		Winter		Summer			
		Total Demand ($\ell/h/d$)	Demand change (%)	Total Demand ($\ell/h/d$)	Demand change (%)	Total Demand ($\ell/h/d$)	Demand change (%)	Total Demand ($\ell/h/d$)	Demand change (%)		
25.0	30.0%	210.0	2.6%	176.5	1.3%	320.5	0.9%	267.1	1.2%	243.5	1.4%
23.0	20.0%	208.4	1.8%	176.2	1.2%	318.0	0.1%	266.4	0.9%	242.2	0.9%
21.0	10.0%	206.3	0.8%	174.9	0.4%	318.2	0.2%	264.8	0.3%	241.1	0.4%
19.0	base	204.6	0.0%	174.1	0.0%	317.7	0.0%	264.1	0.0%	240.1	0.0%
17.0	-10.0%	203.7	-0.4%	173.6	-0.3%	314.2	-1.1%	262.6	-0.5%	238.5	-0.7%
15.0	-20.0%	202.7	-1.0%	173.9	-0.1%	314.7	-0.9%	261.7	-0.9%	238.2	-0.8%
13.0	-30.0%	200.0	-2.3%	172.5	-0.9%	312.9	-1.5%	260.0	-1.5%	236.3	-1.6%
57.0	200.0%	218.0	6.5%	186.5	7.1%	338.3	6.5%	282.2	6.9%	256.2	6.7%

Note: Colour scale indicates the lowest (green) to highest (red) demand values and percentage change.

7 Conclusions and Recommendations

7.1 Summary of Findings

The heating of water for household consumption contributes significantly to energy demand in households. Previous DHW databases are available, but some were considered no longer representative of current demand patterns and new research, such as this thesis and future work on the topic, holds numerous benefits.

Various studies were reviewed for in-depth understanding of the factors that influence DHW demand. Tools and previous end-use models were reviewed, including the databases used and how the data was recorded. A successful stochastic residential end-use demand model by Scheepers (2012) was reviewed extensively. The model determined indoor water demand based on previously recorded data from the REUWS database by Mayer *et al.* (1999). A similar approach as that used by Scheepers (2012) was employed in this study to create a stochastic computer based model that used various factors to extract hot water demand from total domestic water demand end-use data. The factors included cold water inlet temperature, ambient temperature, water heater temperature settings, pipe flow heat loss and volume balances.

A stochastic end-use model was programmed in Java to estimate diurnal DHW demand on a temporal scale of one minute. End-uses were assumed to have a constant flow rate throughout the event duration, thus represented by rectangular demand pulses. A total of five DHW end-uses were modelled; namely, shower, bath, tap, dishwasher and washing machine. The model produced average demand profiles based on climate data for a particular month of the year, selected by the user.

The model used probability distributions describing end-use event characteristics which were based on measured end-use consumption from the REUWS database. The probability distributions were solved inversely to obtain realistic total water demand for

end-use events, which were then converted to DHW demand by the model. A single simulation of the model represented a DHW demand scenario for a single household. The number of iterations in the model is adjustable and multiple iterations results in an aggregation of diurnal demand profiles which can produce average DHW demand results and profiles.

7.2 Conclusion

The stochastic end-use model presented in this study produced good estimations for DHW demand when compared with results from previous studies. The diurnal demand profiles yielded by the model were similar to the most renowned existing profiles, such as the ASHRAE 90.2 profiles used in North America. The total average hot water demand volumes produced by the model were realistic and intuitively varied with seasonal change when different months of the year were simulated. Average per capita demands also agreed well with values cited from earlier research.

The number of occupants within a household was found to have a significant effect on DHW demand. The model included six household size categories but a household size of more than 5 PPH resulted in reduced total DHW demand, which was deemed nonsensical. The anomaly for the household size of larger than 5 PPH could be explained by the small sample of households that were this large in the original REUWS database (Mayer *et al.*, 1999). Furthermore, research has indicated that per capita demands are not the best method by which to determine DHW demand. According to the results of this study, per capita demand decreases logarithmically as the number of occupants per household increases.

By disaggregating DHW demand into per end-use demand, reasonable agreement was found when compared to previous studies. The bath, dishwasher and washing machine end-uses were considered to be overestimated by the model. The model included the option to specify that the dishwasher and washing machine end-use were connected to

the water heater and thus contributed to DHW demand in the households. Results indicate that exclusion of the dishwasher and washing machine end-uses leads to significant decreases in total diurnal DHW demand. In other words, hot water and thus energy can be saved by washing clothes in cold water instead of hot water, for example.

A sensitivity analysis was conducted on four variables in the model. The variables were the water heater temperature settings, the cold water inlet temperature, the ambient temperature and the pipe length between the water heater and end-uses. The model result was the most sensitive to the water heater thermostat temperature setting. A 20% decrease in the value of the variable resulted in a 25% increase in DHW demand. However, health and safety issues like legionella growth and scalding should be considered when selecting a water heater thermostat temperature setting. A temperature of 55°C or higher must be maintained to prevent legionella growth, but the temperature should not exceed 70°C to prevent scalding.

The variable that ranked second in the sensitivity analysis was the cold water inlet temperature. Results indicated that a 30% change to the variable resulted in demand fluctuations of approximately 8%. On the other hand, results for the ambient temperature and pipe lengths which were used in the pipe heat loss equation had insignificant influences on DHW demand.

Overall, the model was considered to be effective in estimating DHW demand and produced realistic DHW demand profiles based on a large database of previously recorded domestic water consumption. Various key DHW results were obtained by using the model in this study. When the dishwasher and washing machine were not connected to the water heater, average diurnal demands ranged between 171 ℓ /h/d in summer to 202 ℓ /h/d in winter. Per capita DHW demand, without the dishwasher and washing machine end-uses, ranged between 69 ℓ /c/d in summer and 81 ℓ /c/d in winter.

DHW demand increased when the dishwasher and washing machine end-uses were chosen to be connected to the DHW supply. In the connected case, average diurnal DHW

demands were found to range between 259 ℓ /h/d in summer to 313 ℓ /h/d in winter. Per capita DHW demand increased and ranged between 106 ℓ /c/d in summer and 127 ℓ /c/d in winter when the dishwasher and washing machine end-uses were connected to the water heater.

On a per-end-use basis, both the tap and dishwasher DHW demands did not fluctuate with seasonal change and were found to be approximately 49 ℓ /d and 31 ℓ /d, respectively. On the other hand, the shower DHW demand ranged from 80 ℓ /d in the summer to 100 ℓ /d in the winter. The bath DHW demand varied between 43 ℓ /d and 53 ℓ /d in summer and winter, respectively, while the same values for washing machine was 57 ℓ /d and 80 ℓ /d, respectively.

DHW demand profiles and per-end-use data produced by the model in this study can be helpful for identifying possible opportunities for domestic water and energy savings.

7.3 Suggestions for Further Research

Granted the success of the constructed end-use model, opportunities remain for enhancement and supplementary features. Numerous additions can be made to the model, such as including weekend and weekday variation, assigning a volume constraint to the water heater and including energy demand, based on the hot water demand. Thus the model could be used for applications related to hot water and energy demand. Additionally, the contribution of hot water demand to peak demands could be investigated.

The average diurnal demand of the bath, dishwasher and washing machine end-uses was overestimated by the model when compared with previous studies. The reason could be that the database used as a basis for model development included above average event volumes when compared to earlier research. Alternatively, previous studies might have underestimated the DHW demand of these events. Further research is required on certain

end-uses, especially appliances with cyclic demand like the dishwasher and washing machine. Extensive research into manufacturers, models, settings and cycles could reveal crucial information to help model DHW demand of these end-uses more accurately. It is important from the view point of the model in this study to investigate whether hot water is used from the water heater or heated internally. Additionally, the probability of households owning a dishwasher or washing machine could be studied.

In the absence of local large domestic water or hot water consumption data, the model presented in this study used North American total water consumption measurements. Therefore the probability distributions do not describe South African water demand. Future research into South African hot water demand would be valuable in the sense that this model could then be applied to local data. If a local data collection project was to be procured, certain measurements would be more important, especially for stochastic model as in this study. The most essential measurement is the cold water inlet temperature, since few data is available on this subject. Consequently, interesting results from a South African viewpoint could then be obtained.

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Appendix A – Event Frequencies

Table A.1 Shower diurnal event frequency cumulative relative frequency

Event Frequency	1 PPH	2 PPH	3 PPH	4 PPH	5 PPH	6 PPH
0	0.0433	0.0085	0.0164	0.0176	0.0424	0.1363
1	0.6532	0.4249	0.3013	0.2250	0.2183	0.2911
2	0.8826	0.7494	0.6082	0.5373	0.4264	0.4839
3	0.9630	0.8974	0.8185	0.7447	0.6457	0.6348
4	0.9836	0.9581	0.9184	0.8783	0.8067	0.7527
5	0.9937	0.9847	0.9617	0.9432	0.8972	0.8462
6	0.9976	0.9929	0.9815	0.9770	0.9504	0.9065
7	0.9981	0.9971	0.9925	0.9904	0.9780	0.9562
8	0.9986	0.9984	0.9961	0.9951	0.9888	0.9805
9	0.9995	0.9987	0.9973	0.9977	0.9944	0.9893
10	1.0000	0.9990	0.9982	0.9981	0.9954	0.9951
11		0.9991	0.9989	0.9991	0.9974	0.9990
12		0.9992	0.9991	0.9993	0.9990	1.0000
13		0.9994	0.9995	1.0000	0.9995	
14		0.9996	0.9998		1.0000	
15		0.9997	1.0000			
16		0.9999				
17		1.0000				

Table A.2 Bath diurnal event frequency cumulative relative frequency

Event Frequency	1 PPH	2 PPH	3 PPH	4 PPH	5 PPH	6 PPH
0	0.6121	0.1282	0.2192	0.0995	0.3301	0.5304
1	0.8772	0.7654	0.7861	0.7898	0.8010	0.8198
2	0.9612	0.9297	0.9580	0.9558	0.9450	0.9393
3	0.9914	0.9829	0.9895	0.9893	0.9871	0.9757
4	1.0000	0.9924	0.9974	0.9933	0.9903	0.9899
5		1.0000	0.9987	0.9973	0.9951	0.9939
6			1.0000	0.9987	0.9984	1.0000
7				1.0000	1.0000	

Table A.3 Tap diurnal event frequency cumulative relative frequency

Event Frequency	1 PPH	2 PPH	3 PPH	4 PPH	5 PPH	6 PPH
0	0.0134	0.0063	0.0153	0.0189	0.0571	0.1976
1	0.0239	0.0133	0.0220	0.0231	0.0641	0.2000
2	0.0331	0.0205	0.0287	0.0280	0.0667	0.2012
3	0.0445	0.0277	0.0325	0.0317	0.0712	0.2024
4	0.0650	0.0349	0.0378	0.0338	0.0756	0.2036
5	0.0819	0.0438	0.0451	0.0375	0.0763	0.2060
6	0.1027	0.0549	0.0518	0.0425	0.0840	0.2096
7	0.1225	0.0672	0.0598	0.0503	0.0846	0.2132
8	0.1447	0.0803	0.0675	0.0556	0.0878	0.2180
9	0.1710	0.0948	0.0791	0.0616	0.0910	0.2251
10	0.1955	0.1091	0.0906	0.0687	0.0936	0.2311
11	0.2223	0.1229	0.1013	0.0779	0.0955	0.2395
12	0.2449	0.1368	0.1147	0.0875	0.1019	0.2455
13	0.2704	0.1519	0.1277	0.0980	0.1083	0.2563
14	0.2914	0.1700	0.1407	0.1109	0.1154	0.2575
15	0.3122	0.1883	0.1563	0.1240	0.1237	0.2671
16	0.3377	0.2057	0.1707	0.1363	0.1301	0.2790
17	0.3620	0.2235	0.1837	0.1476	0.1436	0.2850
18	0.3816	0.2418	0.2024	0.1651	0.1609	0.2922
19	0.4034	0.2583	0.2229	0.1785	0.1660	0.2994
20	0.4227	0.2788	0.2399	0.1948	0.1763	0.3090
21	0.4454	0.3004	0.2609	0.2087	0.1872	0.3269
22	0.4686	0.3184	0.2831	0.2252	0.1974	0.3353
23	0.4900	0.3391	0.3005	0.2414	0.2096	0.3461
24	0.5098	0.3594	0.3209	0.2585	0.2212	0.3557
25	0.5314	0.3789	0.3393	0.2734	0.2346	0.3749
26	0.5483	0.3979	0.3565	0.2891	0.2462	0.3844
27	0.5666	0.4181	0.3750	0.3046	0.2583	0.4024
28	0.5843	0.4368	0.3956	0.3269	0.2737	0.4180
29	0.6003	0.4564	0.4119	0.3457	0.2929	0.4407
30	0.6203	0.4752	0.4308	0.3633	0.3122	0.4575
31	0.6372	0.4929	0.4516	0.3840	0.3256	0.4719
32	0.6540	0.5075	0.4690	0.4034	0.3487	0.4850

Event Frequency	1 PPH	2 PPH	3 PPH	4 PPH	5 PPH	6 PPH
33	0.6639	0.5283	0.4878	0.4181	0.3744	0.4982
34	0.6757	0.5465	0.5057	0.4364	0.3910	0.5102
35	0.6892	0.5633	0.5185	0.4509	0.4083	0.5210
36	0.7034	0.5792	0.5325	0.4684	0.4212	0.5305
37	0.7166	0.5962	0.5474	0.4841	0.4340	0.5473
38	0.7250	0.6136	0.5638	0.5030	0.4506	0.5593
39	0.7370	0.6302	0.5816	0.5208	0.4712	0.5665
40	0.7446	0.6435	0.5927	0.5429	0.4853	0.5808
41	0.7547	0.6576	0.6074	0.5578	0.5006	0.5880
42	0.7644	0.6703	0.6231	0.5751	0.5186	0.5988
43	0.7767	0.6837	0.6370	0.5887	0.5340	0.6084
44	0.7858	0.6970	0.6479	0.6058	0.5532	0.6204
45	0.7956	0.7076	0.6586	0.6202	0.5692	0.6323
46	0.8065	0.7208	0.6722	0.6354	0.5853	0.6419
47	0.8160	0.7316	0.6848	0.6511	0.5987	0.6551
48	0.8236	0.7442	0.6959	0.6682	0.6179	0.6683
49	0.8308	0.7540	0.7066	0.6815	0.6359	0.6778
50	0.8380	0.7661	0.7171	0.6938	0.6545	0.6922
51	0.8434	0.7774	0.7269	0.7106	0.6699	0.7042
52	0.8514	0.7887	0.7362	0.7211	0.6891	0.7186
53	0.8601	0.7974	0.7500	0.7358	0.7006	0.7257
54	0.8662	0.8070	0.7588	0.7465	0.7103	0.7341
55	0.8718	0.8151	0.7693	0.7586	0.7263	0.7461
56	0.8767	0.8229	0.7792	0.7706	0.7449	0.7581
57	0.8821	0.8321	0.7861	0.7822	0.7538	0.7665
58	0.8885	0.8402	0.7932	0.7924	0.7635	0.7689
59	0.8934	0.8461	0.8039	0.8039	0.7737	0.7808
60	0.8987	0.8516	0.8125	0.8142	0.7872	0.7844
61	0.9043	0.8599	0.8201	0.8244	0.7981	0.7916
62	0.9092	0.8665	0.8284	0.8341	0.8103	0.8060
63	0.9131	0.8721	0.8366	0.8417	0.8179	0.8144
64	0.9187	0.8783	0.8429	0.8493	0.8327	0.8228
65	0.9232	0.8840	0.8507	0.8582	0.8429	0.8335
66	0.9280	0.8888	0.8572	0.8650	0.8500	0.8455

Event Frequency	1 PPH	2 PPH	3 PPH	4 PPH	5 PPH	6 PPH
67	0.9331	0.8936	0.8660	0.8718	0.8609	0.8515
68	0.9376	0.8984	0.8719	0.8792	0.8667	0.8611
69	0.9405	0.9037	0.8792	0.8862	0.8718	0.8671
70	0.9446	0.9093	0.8867	0.8925	0.8776	0.8743
71	0.9467	0.9143	0.8935	0.8986	0.8859	0.8778
72	0.9490	0.9196	0.8995	0.9041	0.8942	0.8874
73	0.9516	0.9249	0.9056	0.9088	0.9026	0.8994
74	0.9557	0.9294	0.9111	0.9117	0.9096	0.9030
75	0.9578	0.9352	0.9153	0.9166	0.9179	0.9102
76	0.9617	0.9389	0.9203	0.9219	0.9231	0.9126
77	0.9636	0.9424	0.9262	0.9271	0.9269	0.9162
78	0.9673	0.9457	0.9304	0.9308	0.9321	0.9222
79	0.9695	0.9490	0.9327	0.9358	0.9372	0.9269
80	0.9714	0.9531	0.9371	0.9389	0.9417	0.9341
81	0.9735	0.9567	0.9409	0.9421	0.9455	0.9365
82	0.9753	0.9605	0.9451	0.9463	0.9481	0.9389
83	0.9763	0.9646	0.9480	0.9505	0.9526	0.9485
84	0.9778	0.9668	0.9507	0.9549	0.9558	0.9545
85	0.9788	0.9708	0.9547	0.9573	0.9590	0.9557
86	0.9794	0.9730	0.9606	0.9620	0.9622	0.9581
87	0.9805	0.9748	0.9637	0.9649	0.9654	0.9617
88	0.9825	0.9772	0.9685	0.9670	0.9679	0.9629
89	0.9858	0.9794	0.9711	0.9688	0.9712	0.9665
90	0.9874	0.9820	0.9750	0.9730	0.9724	0.9725
91	0.9891	0.9843	0.9773	0.9748	0.9744	0.9760
92	0.9907	0.9862	0.9801	0.9782	0.9769	0.9820
93	0.9932	0.9883	0.9826	0.9817	0.9795	0.9856
94	0.9938	0.9902	0.9847	0.9861	0.9840	0.9868
95	0.9951	0.9923	0.9872	0.9893	0.9853	0.9892
96	0.9965	0.9938	0.9910	0.9927	0.9891	0.9904
97	0.9977	0.9952	0.9933	0.9940	0.9923	0.9940
98	0.9984	0.9970	0.9956	0.9963	0.9949	0.9964
99	0.9992	0.9985	0.9977	0.9979	0.9974	0.9976
100	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Table A.4 Dishwasher diurnal event frequency cumulative relative frequency

Event Frequency	1 PPH	2 PPH	3 PPH	4 PPH	5 PPH	6 PPH
0	0.3779	0.0324	0.0781	0.0628	0.1722	0.4654
1	0.9666	0.9425	0.9437	0.9298	0.9004	0.9402
2	0.9982	0.9947	0.9947	0.9939	0.9865	0.0994
3	1.0000	1.0000	0.9985	1.0000	0.9975	1.0000
4			1.0000		0.9988	
5					1.0000	

Table A.5 Washing Machine diurnal frequency cumulative relative frequency

Event Frequency	1 PPH	2 PPH	3 PPH	4 PPH	5 PPH	6 PPH
0	0.1174	0.0166	0.0310	0.0298	0.0728	0.1868
1	0.6385	0.5074	0.4466	0.4214	0.3949	0.4188
2	0.8486	0.7505	0.6886	0.6884	0.6456	0.6265
3	0.9422	0.8757	0.8319	0.8340	0.7943	0.7552
4	0.9725	0.9453	0.9055	0.9106	0.8919	0.8654
5	0.9890	0.9781	0.9516	0.9555	0.9467	0.9188
6	0.9963	0.9900	0.9717	0.9759	0.9685	0.9524
7	0.9991	0.9940	0.9899	0.9883	0.9857	0.9733
8	1.0000	0.9978	0.9961	0.9959	0.9917	0.9884
9		0.9993	0.9977	0.9989	0.9977	0.9919
10		0.9998	0.9981	1.0000	0.9992	0.9942
11		1.0000	0.9988		1.0000	0.9965
12			0.9996			0.9988
13			1.0000			1.0000

Appendix B – Starting Hour Frequencies

Table B.1 Starting hour cumulative relative frequency

Hour	Shower	Bath	Tap	Dishwasher	Washing Machine
0	0.010	0.011	0.014	0.025	0.006
1	0.014	0.016	0.022	0.035	0.035
2	0.017	0.019	0.028	0.042	0.042
3	0.022	0.023	0.034	0.045	0.045
4	0.034	0.028	0.042	0.049	0.049
5	0.084	0.046	0.060	0.057	0.057
6	0.193	0.083	0.099	0.081	0.081
7	0.305	0.133	0.158	0.122	0.122
8	0.400	0.195	0.221	0.179	0.179
9	0.475	0.251	0.280	0.233	0.233
10	0.534	0.299	0.333	0.284	0.284
11	0.580	0.330	0.384	0.328	0.328
12	0.615	0.358	0.435	0.373	0.373
13	0.644	0.379	0.482	0.418	0.418
14	0.669	0.403	0.525	0.455	0.455
15	0.695	0.426	0.569	0.485	0.485
16	0.727	0.463	0.620	0.526	0.526
17	0.767	0.511	0.687	0.579	0.579
18	0.812	0.584	0.763	0.661	0.661
19	0.857	0.699	0.829	0.752	0.752
20	0.902	0.818	0.884	0.828	0.828
21	0.945	0.902	0.934	0.901	0.901
22	0.977	0.964	0.973	0.960	0.960
23	1.000	1.000	1.000	1.000	1.000

Appendix C – Number of Cycles

Table C.1 Number of cycles cumulative relative frequency

<u>Number of Cycles</u>	<u>Dishwasher</u>
1	0.0000
2	0.0040
3	0.0527
4	0.3196
5	0.6033
6	0.8338
7	0.9525
8	0.9865
9	0.9951
10	0.9987
11	0.9996
12	1.0000

Appendix D – User Desired Temperature Database

Table D.1 Modified user desired temperature database

Participant Name	Location - Town	Location - Country	Date of reading	Type of end-use	T _h (°C)	T _a (°C)
Abrie	Stellenbosch	South Africa	18-Aug-14	Shower	41.90	20.10
Abrie	Stellenbosch	South Africa	19-Aug-14	Shower	42.10	18.60
Abrie	Stellenbosch	South Africa	19-Aug-14	Shower	41.80	18.20
Abrie	Stellenbosch	South Africa	20-Aug-14	Shower	41.90	17.60
Abrie	Stellenbosch	South Africa	21-Aug-14	Shower	40.30	16.00
Abrie	Stellenbosch	South Africa	21-Aug-14	Shower	42.70	15.10
Abrie	Stellenbosch	South Africa	22-Aug-14	Shower	41.90	15.60
Abrie	Stellenbosch	South Africa	22-Aug-14	Shower	42.00	15.50
Abrie	Stellenbosch	South Africa	23-Aug-14	Shower	42.10	15.80
Abrie	Stellenbosch	South Africa	23-Aug-14	Shower	42.10	15.70
Abrie	Stellenbosch	South Africa	24-Aug-14	Shower	42.00	16.50
Abrie	Stellenbosch	South Africa	24-Aug-14	Shower	41.40	16.40
Abrie	Stellenbosch	South Africa	25-Aug-14	Shower	42.10	15.50
Abrie	Stellenbosch	South Africa	25-Aug-14	Shower	41.90	18.00
Abrie	Stellenbosch	South Africa	26-Aug-14	Shower	42.00	17.70
Abrie	Stellenbosch	South Africa	26-Aug-14	Shower	41.50	17.90
Abrie	Stellenbosch	South Africa	27-Aug-14	Shower	42.50	16.00
Abrie	Stellenbosch	South Africa	28-Aug-14	Shower	42.80	13.40
Abrie	Stellenbosch	South Africa	29-Aug-14	Shower	41.50	13.50
Abrie	Stellenbosch	South Africa	29-Aug-14	Shower	42.60	14.10
Nicolaas	Aranos	Namibia	07-Aug-14	Shower	38.20	27.00
Nicolaas	Aranos	Namibia	08-Aug-14	Shower	38.80	27.20
Nicolaas	Aranos	Namibia	09-Aug-14	Shower	38.30	27.50
Nicolaas	Aranos	Namibia	10-Aug-14	Shower	38.60	26.70
Nicolaas	Aranos	Namibia	11-Aug-14	Shower	38.50	25.30
Nicolaas	Aranos	Namibia	12-Aug-14	Shower	38.60	26.80
Nicolaas	Aranos	Namibia	13-Aug-14	Shower	38.40	25.40
Nicolaas	Aranos	Namibia	14-Aug-14	Shower	38.10	25.50
Nicolaas	Aranos	Namibia	15-Aug-14	Shower	39.00	27.20
Nicolaas	Aranos	Namibia	16-Aug-14	Shower	38.50	20.50
Nicolaas	Aranos	Namibia	17-Aug-14	Shower	38.50	27.50
Nicolaas	Aranos	Namibia	18-Aug-14	Shower	38.90	27.50
Nicolaas	Aranos	Namibia	19-Aug-14	Shower	38.00	25.40
Nicolaas	Aranos	Namibia	20-Aug-14	Shower	39.20	24.00
Nicolaas	Aranos	Namibia	21-Aug-14	Shower	39.20	24.50
Nicolaas	Aranos	Namibia	22-Aug-14	Shower	38.10	24.60
Nicolaas	Aranos	Namibia	23-Aug-14	Shower	38.10	20.50
Nicolaas	Aranos	Namibia	24-Aug-14	Shower	38.90	20.70
Nicolaas	Aranos	Namibia	25-Aug-14	Shower	38.30	23.30
Nicolaas	Aranos	Namibia	26-Aug-14	Shower	38.40	25.50
Carla	Stellenbosch	South Africa	05-Aug-14	Shower	43.00	15.40
Carla	Stellenbosch	South Africa	05-Aug-14	Shower	43.60	16.80
Carla	Stellenbosch	South Africa	06-Aug-14	Shower	42.80	15.70
Carla	Stellenbosch	South Africa	07-Aug-14	Shower	42.30	16.40
Carla	Stellenbosch	South Africa	08-Aug-14	Shower	43.60	18.40
Carla	Stellenbosch	South Africa	09-Aug-14	Shower	42.60	19.00
Carla	Stellenbosch	South Africa	11-Aug-14	Shower	42.10	18.70
Carla	Stellenbosch	South Africa	11-Aug-14	Shower	43.60	19.20
Carla	Stellenbosch	South Africa	13-Aug-14	Shower	43.30	17.80
Carla	Stellenbosch	South Africa	13-Aug-14	Shower	42.10	17.10

Participant Name	Location - Town	Location - Country	Date of reading	Type of end-use	T _h (°C)	T _a (°C)
Carla	Stellenbosch	South Africa	15-Aug-14	Shower	44.70	15.30
Carla	Stellenbosch	South Africa	15-Aug-14	Shower	44.10	17.60
Carla	Stellenbosch	South Africa	17-Aug-14	Shower	42.80	19.90
Carla	Stellenbosch	South Africa	18-Aug-14	Shower	43.30	20.80
Carla	Stellenbosch	South Africa	19-Aug-14	Shower	45.00	17.20
Carla	Stellenbosch	South Africa	20-Aug-14	Shower	45.70	15.60
Carla	Stellenbosch	South Africa	21-Aug-14	Shower	43.90	15.00
Carla	Stellenbosch	South Africa	22-Aug-14	Shower	45.40	16.10
Carla	Stellenbosch	South Africa	23-Aug-14	Shower	45.00	14.70
Carla	Stellenbosch	South Africa	24-Aug-14	Shower	45.60	13.80
Stefan	Stellenbosch	South Africa	05-Aug-14	Shower	40.80	14.60
Stefan	Stellenbosch	South Africa	05-Aug-14	Shower	41.20	15.60
Stefan	Stellenbosch	South Africa	06-Aug-14	Shower	41.60	14.90
Stefan	Stellenbosch	South Africa	07-Aug-14	Shower	42.70	17.50
Stefan	Stellenbosch	South Africa	08-Aug-14	Shower	41.20	18.20
Stefan	Stellenbosch	South Africa	09-Aug-14	Shower	40.70	17.90
Stefan	Stellenbosch	South Africa	10-Aug-14	Shower	41.20	20.80
Stefan	Stellenbosch	South Africa	10-Aug-14	Shower	41.47	19.40
Stefan	Stellenbosch	South Africa	11-Aug-14	Shower	41.20	14.40
Stefan	Stellenbosch	South Africa	12-Aug-14	Shower	41.30	17.30
Stefan	Stellenbosch	South Africa	13-Aug-14	Shower	43.40	17.60
Stefan	Stellenbosch	South Africa	14-Aug-14	Shower	40.50	19.20
Stefan	Stellenbosch	South Africa	16-Aug-14	Shower	42.20	23.20
Stefan	Stellenbosch	South Africa	17-Aug-14	Shower	40.40	20.70
Stefan	Stellenbosch	South Africa	18-Aug-14	Shower	42.50	17.10
Stefan	Stellenbosch	South Africa	19-Aug-14	Shower	42.80	15.20
Stefan	Stellenbosch	South Africa	21-Aug-14	Shower	41.10	14.40
Stefan	Stellenbosch	South Africa	22-Aug-14	Shower	43.00	13.50
Stefan	Stellenbosch	South Africa	23-Aug-14	Shower	42.60	19.10
Stefan	Stellenbosch	South Africa	24-Aug-14	Shower	43.40	17.60
Albie	Stellenbosch	South Africa	04-Aug-14	Shower	41.20	15.80
Albie	Stellenbosch	South Africa	05-Aug-14	Shower	41.20	16.70
Albie	Stellenbosch	South Africa	06-Aug-14	Shower	41.60	15.90
Albie	Stellenbosch	South Africa	07-Aug-14	Shower	40.20	17.90
Albie	Stellenbosch	South Africa	08-Aug-14	Shower	40.40	18.80
Albie	Stellenbosch	South Africa	09-Aug-14	Shower	41.30	19.30
Albie	Stellenbosch	South Africa	10-Aug-14	Shower	41.70	20.50
Albie	Stellenbosch	South Africa	11-Aug-14	Shower	41.10	19.00
Albie	Stellenbosch	South Africa	12-Aug-14	Shower	40.70	20.40
Albie	Stellenbosch	South Africa	13-Aug-14	Shower	41.00	17.30
Albie	Stellenbosch	South Africa	14-Aug-14	Shower	41.50	17.70
Albie	Stellenbosch	South Africa	15-Aug-14	Shower	41.40	17.80
Albie	Stellenbosch	South Africa	16-Aug-14	Shower	40.70	23.50
Albie	Stellenbosch	South Africa	17-Aug-14	Shower	42.70	20.80
Albie	Stellenbosch	South Africa	18-Aug-14	Shower	42.80	17.30
Albie	Stellenbosch	South Africa	19-Aug-14	Shower	43.30	15.40
Albie	Stellenbosch	South Africa	20-Aug-14	Shower	42.30	15.50
Albie	Stellenbosch	South Africa	21-Aug-14	Shower	42.10	15.50
Albie	Stellenbosch	South Africa	22-Aug-14	Shower	42.80	15.30
Albie	Stellenbosch	South Africa	23-Aug-14	Shower	42.40	15.10
Albie	Aranos	Namibia	07-Sep-14	Shower	41.70	25.60
Albie	Aranos	Namibia	08-Sep-14	Shower	41.80	25.40

Participant Name	Location - Town	Location - Country	Date of reading	Type of end-use	T _h (°C)	T _a (°C)
Albie	Aranos	Namibia	09-Sep-14	Shower	40.20	25.10
Albie	Aranos	Namibia	10-Sep-14	Shower	40.90	27.50
Albie	Aranos	Namibia	11-Sep-14	Shower	41.20	22.50
Albie	Aranos	Namibia	12-Sep-14	Shower	40.90	27.10
Albie	Aranos	Namibia	13-Sep-14	Shower	41.90	22.90
Albie	Aranos	Namibia	14-Sep-14	Shower	41.90	27.00
Albie	Aranos	Namibia	15-Sep-14	Shower	42.10	26.30
Albie	Aranos	Namibia	16-Sep-14	Shower	41.50	25.10
Carla	Aranos	Namibia	08-Sep-14	Bath	40.80	23.80
Carla	Aranos	Namibia	09-Sep-14	Bath	40.60	25.20
Carla	Aranos	Namibia	10-Sep-14	Bath	40.00	26.10
Carla	Aranos	Namibia	11-Sep-14	Bath	40.60	22.80
Carla	Aranos	Namibia	12-Sep-14	Bath	41.00	25.70
Carla	Aranos	Namibia	13-Sep-14	Bath	40.70	23.60
Carla	Aranos	Namibia	14-Sep-14	Bath	40.70	26.30
Carla	Aranos	Namibia	15-Sep-14	Bath	40.90	26.20
Carla	Aranos	Namibia	16-Sep-14	Bath	40.70	23.00
Carla	Aranos	Namibia	17-Sep-14	Bath	40.70	25.70
Christa	Aranos	Namibia	08-Sep-14	Bath	42.50	23.10
Christa	Aranos	Namibia	09-Sep-14	Bath	42.90	22.20
Christa	Aranos	Namibia	10-Sep-14	Bath	43.10	23.40
Christa	Aranos	Namibia	11-Sep-14	Bath	42.20	23.90
Christa	Aranos	Namibia	12-Sep-14	Bath	41.30	25.80
Christa	Aranos	Namibia	13-Sep-14	Bath	41.20	24.40
Christa	Aranos	Namibia	14-Sep-14	Bath	41.20	24.90
Christa	Aranos	Namibia	15-Sep-14	Bath	41.80	23.90
Christa	Aranos	Namibia	16-Sep-14	Bath	42.10	22.50
Christa	Aranos	Namibia	17-Sep-14	Bath	42.90	26.90
Elize	Aranos	Namibia	08-Sep-14	Bath	42.50	27.00
Elize	Aranos	Namibia	09-Sep-14	Bath	42.80	27.20
Elize	Aranos	Namibia	10-Sep-14	Bath	42.20	27.50
Elize	Aranos	Namibia	11-Sep-14	Bath	42.30	22.30
Elize	Aranos	Namibia	12-Sep-14	Bath	41.20	25.30
Elize	Aranos	Namibia	13-Sep-14	Bath	41.80	26.80
Elize	Aranos	Namibia	14-Sep-14	Bath	41.70	25.40
Elize	Aranos	Namibia	15-Sep-14	Bath	42.10	26.20
Elize	Aranos	Namibia	16-Sep-14	Bath	42.30	28.20
Elize	Aranos	Namibia	17-Sep-14	Bath	41.90	20.30
Morne	Stellenbosch	South Africa	09-Feb-15	Shower	40.30	25.20
Morne	Stellenbosch	South Africa	10-Feb-15	Shower	40.20	22.30
Morne	Stellenbosch	South Africa	11-Feb-15	Shower	39.90	24.30
Morne	Stellenbosch	South Africa	12-Feb-15	Shower	39.90	24.60
Morne	Stellenbosch	South Africa	13-Feb-15	Shower	40.70	23.80
Morne	Stellenbosch	South Africa	16-Feb-15	Shower	40.70	26.10
Morne	Stellenbosch	South Africa	18-Feb-15	Shower	40.70	26.30
Morne	Stellenbosch	South Africa	19-Feb-15	Shower	40.10	24.30
Morne	Stellenbosch	South Africa	20-Feb-15	Shower	40.30	24.50
Morne	Stellenbosch	South Africa	23-Feb-15	Shower	40.10	23.60
Morne	Stellenbosch	South Africa	24-Feb-15	Shower	40.50	25.60
Morne	Stellenbosch	South Africa	25-Feb-15	Shower	40.70	26.40
Morne	Stellenbosch	South Africa	26-Feb-15	Shower	39.80	26.60
Morne	Stellenbosch	South Africa	27-Feb-15	Shower	40.50	25.70

Participant Name	Location - Town	Location - Country	Date of reading	Type of end-use	T _h (°C)	T _a (°C)
Ronel	Paarl	South Africa	08-Mar-15	Shower	38.70	26.60
Ronel	Paarl	South Africa	09-Mar-15	Shower	41.20	24.10
Ronel	Paarl	South Africa	10-Mar-15	Shower	41.30	23.90
Ronel	Paarl	South Africa	11-Mar-15	Shower	41.10	24.10
Ronel	Paarl	South Africa	11-Mar-15	Shower	36.40	28.20
Ronel	Paarl	South Africa	13-Mar-15	Shower	41.20	24.30
Ronel	Paarl	South Africa	14-Mar-15	Shower	40.10	26.10
Ronel	Paarl	South Africa	15-Mar-15	Shower	40.20	25.20
Ronel	Paarl	South Africa	16-Mar-15	Shower	39.80	22.60
Ronel	Paarl	South Africa	17-Mar-15	Shower	40.20	22.80
Ronel	Paarl	South Africa	18-Mar-15	Shower	38.80	24.10
Ronel	Paarl	South Africa	19-Mar-15	Shower	40.10	23.70
Ronel	Paarl	South Africa	20-Mar-15	Shower	40.30	23.80
Ronel	Paarl	South Africa	21-Mar-15	Shower	36.50	27.10
Deon	Paarl	South Africa	10-Mar-15	Shower	38.80	27.80
Deon	Paarl	South Africa	11-Mar-15	Shower	37.60	26.20
Deon	Paarl	South Africa	12-Mar-15	Shower	36.60	27.60
Deon	Paarl	South Africa	13-Mar-15	Shower	39.20	24.70
Deon	Paarl	South Africa	14-Mar-15	Shower	38.20	27.80
Deon	Paarl	South Africa	15-Mar-15	Shower	40.20	26.00
Deon	Paarl	South Africa	16-Mar-15	Shower	38.20	29.80
Deon	Paarl	South Africa	17-Mar-15	Shower	39.20	27.60
Deon	Paarl	South Africa	18-Mar-15	Shower	39.20	25.20
Deon	Paarl	South Africa	19-Mar-15	Shower	38.30	29.30
Deon	Paarl	South Africa	20-Mar-15	Shower	38.10	26.50
Deon	Paarl	South Africa	21-Mar-15	Shower	39.20	25.20
Deon	Paarl	South Africa	22-Mar-15	Shower	38.20	25.80
Deon	Paarl	South Africa	23-Mar-15	Shower	38.10	25.20

Note: All measurement from 2015 was conducted as part of this study, the rest was recorded by Smith (2014).