Time shift: The peak reduction potential of demand response with simple time-of-use pricing

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This work is in review at Sustainable Energy, Grids and Network. This is a non-peer reviewed preprint submitted to EarthArXiv.

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Abstract

Increasing electrification of energy systems, required for greenhouse gas emissions reductions, poses challenges for electricity systems from increased peak demand. Demand response can reduce peak demand, but acceptability is limited by consumer concerns about effort, complexity, and lack of control. This study assesses the potential of simple demand response programs using existing electricity pricing structures for a median-income residential low-voltage distribution network in Auckland, Aotearoa New Zealand, and draws generalised conclusions applicable across a broad range of circumstances. Using an agent-based model validated against real transformer data, the electricity demand in 50 households is simulated under time-of-use electricity pricing structures, with participation varied between 0% and 100%. Time-of-use schedules without modified demand reduces household electricity costs by 14%, with further reductions of up to 35% through DR participation. Demand response can reduce peak electricity demand by up to 5.7%, but high levels of hot water cylinder (or "water heater") delayed heating can increase peak demand by up to 32.9%. These findings highlight the need for careful DR program design to avoid unintended peak demand increases and ensure equitable access to DR benefits. Regulators could consider facilitating the adoption of DR-capable technologies to enhance program effectiveness and support the energy transition.

Highlights

- Demand response of appliances and water heaters assessed with agent-based model.
- Simple time-of-use structures reduce complexity, and offer increased participation.
- Peak demand can increase or decrease, depending on the level of participation.
- Allocating households to separate peak schedules reduces overall peak demand.
- Careful program design is essential to avoid unintended peak demand increases.

Keywords: Demand side management; Residential energy use; Agent-based model; Peak electricity demand

Word count: 5168 (not including appendices, references)

1. Introduction

Countries and regions around the world are pursuing increased electrification as a primary method to mitigate climate change [1,2]. Electrification can reduce greenhouse gas (GHG) emissions by shifting energy use from fossil fuels to renewable forms of electricity [3–5]. At a household level, electrification initiatives are strongly focused on residential space heating [6–9], by reducing the combustion of fossil fuels and transitioning to efficient electrical heating appliances

However, electrification increases electricity demand, and peak demand in particular, creating challenges across the electricity system. For example, the average marginal cost of increasing peak electricity demand in Aotearoa New Zealand is estimated at 241 NZD/kW/year across electricity generation, transmission, and distribution [10]. Increased peak demand increases the required generation capacity in an electricity system, with the required capital formation for the construction of renewable power plants in high-electrification scenarios expected to be up to six times higher than current rates [11,12]. In the transmission and distribution sectors, increasing peak demand increases loads on network components, accelerating degradation and reducing infrastructure lifetime [13].

Therefore, managing peak electricity demand is critical to a successful transition to a low-GHG emissions/high electricity energy system [14]. Peak demand reduction strategies can be grouped into two broad categories: energy efficiency and demand response [15,16]. Energy efficiency directly reduces the electricity required for a given duty, such as by replacing low-efficiency lightbulbs with light emitting diodes or increasing insulation to reduce space heating use. Alternatively, demand response (DR, also known as “demand flexibility”) is the process of electricity consumers changing their consumption in response to signals, such as to utilise excess renewable generation or reduce loads on distribution networks [17]. Successful uptake of either method can reduce peak electricity demand, increasing the lifetime of network components and reducing GHG emissions both indirectly, by facilitating greater electrification, and directly, through the lower GHG emissions intensities of off-peak electricity generation [18–21].

However, consumer participation in DR can be limited by the effort required, complexity, and a perceived lack of control over energy use [22]. These issues can be addressed by DR programs employing relatively simple(r) signals, such as pre-determined variations in electricity price [23,24], to encourage consumers to shift demand away from peak periods. For example, so-called “time-of-use” (ToU) pricing schemes, in which electricity prices are increased and decreased during on- and off- peak periods, respectively, have been shown to elicit higher DR participation than more complicated methods of electricity pricing [25]. Thus, while higher-complexity DR programs have the potential to yield better results in the future, current peak demand reduction capacity is higher in simple programs due to improved consumer participation. For example, the start times of many modern whiteware appliances, such as washing machines, clothes driers, and dishwashers, can be delayed [26], and many hot water cylinders (HWCs) can be programmed not to turn on their heaters during peak periods [27], both of which have been shown to have considerable DR potential in Aotearoa New Zealand [28].

Residential DR has been the subject of a large body of research, particularly in terms of optimising the electricity demand of emerging technologies. Optimised charging has the potential to reduce peak electricity demand from electric vehicles, both at current [29,30] and projected future levels of adoption [31–33]. Optimised control of HWC heaters has the potential to reduce peak electricity demand without reducing hot water access [34–39], but implementation of these strategies in the majority of houses would require smart electricity metering infrastructure and control systems with capacities above those commonly installed. Similarly, the thermal storage capacity of buildings mean space heating timing could be optimised to reduce peak electricity demand without decreasing occupants' thermal comfort [40–42]. However, these methods require integration of real-time feedback control with external signals from electricity companies or demand aggregators, the availability of which is limited [22,43].

The DR potential of currently ubiquitous technologies has been less well studied. Pipattanasomporn et al. [44] characterise the electric load profiles of common household appliances in the USA and discuss the implications of these profiles for DR programs, but do not directly assess DR potential. While such load profiles have been used in many assessments of optimal appliance scheduling [45–48], the optimisation algorithms typically rely on "smart home" infrastructure and/or advanced scheduling controllers, which are not currently present in most homes. Similarly, assessments of the DR potential of electric HWCs have typically focused either on optimisation strategies requiring real-time bidirectional feedback [40–42], or methods such as ripple control [49,50], in which HWC heaters are switched off by electricity distributors during times of peak demand.

However, research focused on optimising the electricity demand of emerging technologies, such as electric vehicles, and requiring controllers not currently installed in most homes does not address the issues with consumer perception of, and limited participation in, DR [22]. While important for understanding the potential of DR in a future energy system, these assessments of optimised future scenarios do not consider the required evolution of DR from its current position of limited uptake, which is increasingly considered necessary for many aspects of the energy transition, including in the residential sector [51–53]. Thus, assessment of the DR potential of common technologies under existing electricity pricing structures, which may yield improved consumer engagement and thus better overall results, is an essential requirement, and the subject of this paper.

This paper assesses the DR potential of schedulable appliances and electric HWCs under currently available electricity pricing structures. Peak electricity demand, unmet hot water demand, and consumer electricity costs are assessed at varying levels of household participation in DR under current residential electricity price schedules for a low-voltage electricity distribution network in Aotearoa New Zealand. The implications of these results for regulators and the generalised design of DR programs, both now and for future technology adoption scenarios, are discussed.

2. Methods

2.1. Agent-based model

Electricity demand in this work is calculated using an agent-based model of residential energy use, which is presented and validated against smart meter data from a range of neighbourhoods in previous work [54,55]. This model uses high-level geographic and socioeconomic information from census data to simulate the behaviour of individual household occupants (agents) and the resulting electricity demand from their behaviour. The model is presented in full in Appendix A, so only the key features are described here.

For each modelled day, agents decide the times at which they wake up and go to sleep, and the times during which they will be away from home, according to the model of general behaviour described in Appendix A1. When at home and awake, agents are denoted “active”. Active agents use appliances according to the model described in Appendix A.2, where the probability of appliance use varies by appliance type and time of day (Figure A.2), based on real appliance use data from Italy [56], the United Kingdom [57,58], and Aotearoa New Zealand [59]. In the baseline model, appliances draw power immediately for the duration of their runtime, both of which vary by appliance type (Table A.1). Lighting use is generated stochastically and varies according to the total number of lightbulbs per house, the number of active agents, and the outside irradiance level (Appendix A.3). Electricity demand for lighting is highest when all household occupants are active and solar irradiance is low. Active agents turn on space heaters if the inside temperature is below the household’s “heating temperature”, which is lower in lower-income households, and house temperature is updated according to the thermal model described in Appendix A.4.

Hot water demand is generated using *DHWcalc* [60], which produces high-resolution profiles of hot water demand according to season and the total number of household occupants. HWC tank temperatures are updated according to a thermal model presented in previous work [61,62], which accounts for standing thermal losses and hot water use and is described in full in Appendix A.5. This model assumes HWCs are heated by electric resistive heaters, which are the norm in Aotearoa New Zealand, but is fully generalisable to alternative heating methods, such as hot water heat pumps, which are increasingly prevalent in other countries [63,64]. In the baseline model, HWCs are heated to a setpoint temperature, which is the most common method in Aotearoa New Zealand

[59], but the HWC model is generalisable to a range of control methods.

2.2. Case studies

The effects of DR with ToU electricity pricing schedules on residential electricity demand are assessed for three cases: (**i**) appliance scheduling; (**ii**) HWC delayed heating; and (**iii**) both appliance scheduling and HWC delayed heating. Modified appliance and HWC electricity demand models for households participating in DR programs are described in Sections 2.2.1 and 2.2.2, respectively.

Two schedules of on- and off- peak times are modelled:

- **Schedule 1**: on-peak times for all participating households are from 07:00-11:00 and 17:00-21:00.
- **Schedule 2**: participating households are divided evenly between two sets of on-peak times: (a) from 07:00-11:00 and 17:00-21:00; and (b) from 08:00-12:00 and 18:00-22:00.

Electricity prices for households participating in ToU pricing are 0.3125 NZD/kWh for electricity used during on-peak times and 0.1375 NZD/kWh for electricity used during off-peak times. For non-participating households, electricity costs 0.25 NZD/kWh at all times. Peak times and electricity prices are based on real residential pricing schedules available from electricity retailers in Aotearoa New Zealand [65–67], which include energy costs, taxes, carbon charges, transmission charges, and distribution charges. Total retail electricity prices are shown in Figure 1.

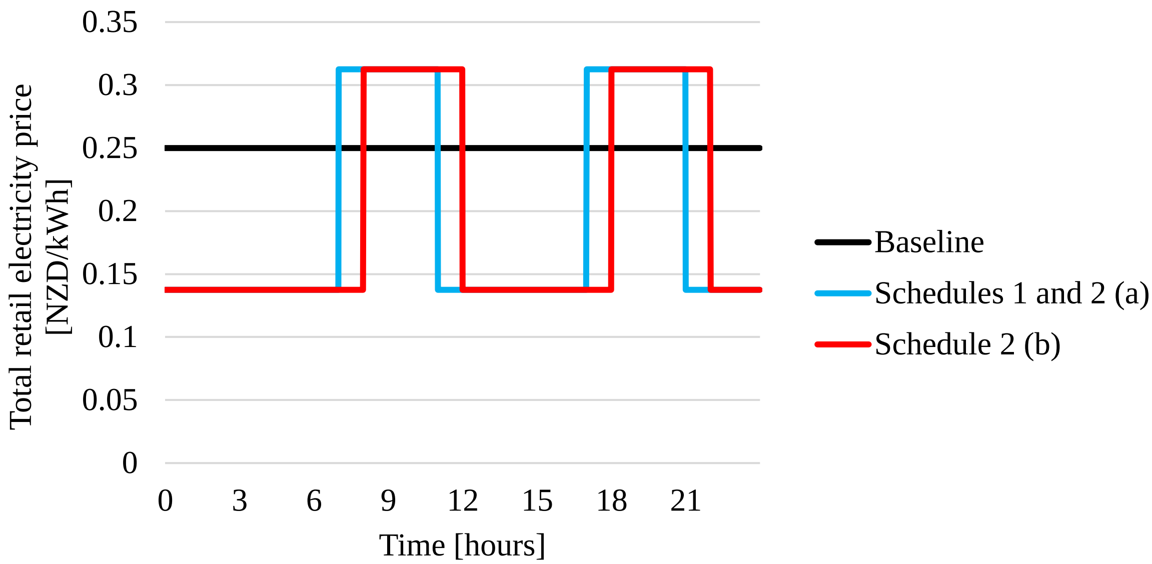

Figure 1. Total retail electricity prices for the baseline case (fixed) and Schedules 1 and 2 ToU prices. Note prices are identical in Schedules 1 and 2 (a).

2.2.1. Appliance scheduling

Schedulable household appliances are defined as those whose runtimes can be deferred without affecting desired consumer outcomes [28]. In this work, such appliances are dishwashers, washing machines, and clothes driers. In participating households, schedulable appliances, which would have part or all of their runtime during on-peak times, are delayed by the minimum integer number of hours to ensure all electricity demand occurs during off-peak times. For example, an agent in a household with on-peak times according to Schedule 1 and a washing machine with a runtime of 45 minutes would delay the washing machine's start by one hour if using it at 10:30, two hours if using it at 09:30, and five hours if using it at 06:30. All schedulable appliances are assumed to be capable of delaying their start time by up to six hours (i.e., their start can be delayed by 1, 2, 3, 4, 5, or 6 hours). Modelling delays by an integer number of hours is chosen to match current abilities of most schedulable appliances.

2.2.2. Hot water cylinder delayed heating

HWC heating in participating households is restricted to occur only during off-peak times. Thus, while hot water use and standing thermal losses can decrease HWC tank temperature during on-peak times, tank temperature can increase due to heating only during off-peak times. Water leaves the HWC at T_{HWC} and is mixed with cold water to T_{out}, so the hot water temperature experienced by household occupants reduces only when T_{HWC} is below T_{out}, as shown in Equation A-9.

Unmet hot water demand occurs when household occupants draw water from the HWC below the minimum temperature (50 °C in this work, to reflect regulations [68] and match previous work [61,62]). To reflect the greater discomfort of colder water, unmet hot water demand is defined:

$$\mathrm{UD} = \int_0^{t_n} \mathbb{H}(\dot{V})\mathbb{H}(T_{min} - T_{HWC})(T_{min} - T_{HWC})dt \qquad (1)$$

where UD is the total unmet hot water demand [K*min], t_n is the time in minutes, $\dot{V}$ is the flow rate of hot water from the HWC [L/s], T_{min} is the minimum HWC tank temperature [K], T_{HWC} is the HWC tank temperature [K], and $\mathbb{H}$ is the unitless Heaviside function, implemented in this case with $\mathbb{H}(0) = 0$.

2.3. Assessments

The model is implemented in MATLAB R2022b for a median-income (decile 5, 35,000 NZD [69]) neighbourhood in Auckland, the largest city in Aotearoa New Zealand. The neighbourhood is modelled with 50 houses, to represent a typical number of houses connected to a single low-voltage residential electricity distribution transformer [70]. Peak electricity demand in Aotearoa New

Zealand is in the winter [71,72], from June – August, so the effects of these DR interventions on overall peak demand are assessed by modelling this neighbourhood for 30 days in June, which corresponds to the peak of seasonal variation in the agent-based model. Model inputs are summarised in Table 1.

Table 1. Summary of inputs to the agent-based model.

Variable	Value	Source
Number of houses	50	
Average annual income	35,000 NZD	[69]
Mean electric space heater power	5000 W	[59]
Proportion of houses with heat pumps	19%	[73,74]
Proportion of houses with electric heaters	30%	[59]
Mean preferred temperature (max)	24 °C	Estimated from [59]
Mean preferred temperature (min)	16 °C	Estimated from [59]
Mean house age	40 years	[75]
Mean house size	150 m^2	[76,77]
Mean number of floors	1.5	[76,77]
Story height	2.4 m	[76,77]
Mean window-wall ratio	0.22	[78]
Average building loss coefficient (BLC)	265.2 WK^{-1}	
Mean trips /person /day	0.8	[79]
Mean wake time	0700 hrs	[80,81]
Mean sleep time	2200 hrs	[80,81]
Departure and arrival time	See Appendix A1	[79,82]
Proportion of households with electric HWCs	86%	[59]
Average HWC thermostat setpoint (T_{set})	62 °C	[59]
HWC inlet temperature (T_{in})	15 °C	[83]
HWC outlet temperature (T_{out})	40 °C	
HWC ambient temperature (T_{amb})	18.1 °C	[59]
HWC minimum outlet temperature (T_{min})	50 °C	[68]
Average HWC heater power (P_{HWC})	1500 W	[59]
Average HWC volume (V_{HWC})	150 L	[84]
Average hot water demand	50 L/person/day	[85,86]
K_{loss}	0.854 W/K	[59,61,62]
Timestep (dt)	60 seconds	

The model is run for a baseline case (no appliance scheduling or HWC delayed heating) and cases i-iii are modelled for both Schedules 1 and 2 of ToU electricity pricing, with participation varied between 0-100% of households. Median electricity demand profile over the modelled month, peak electricity demand, total unmet hot water demand, and average household electricity cost are recorded for each modelled case. Each case is also modelled for 30 days in January, which is the middle of summer in New Zealand, for both schedules of ToU electricity pricing at 100% participation, and average monthly electricity costs for participating households are calculated by averaging the total costs for each case in summer (January) and winter (June).

3. Results

Average electricity demand in June for the modelled neighbourhood in cases i-iii is shown in Figures 2-4, respectively. Increasing participation in ToU DR shifts more electricity demand away from typical peak times. However, it creates secondary peaks at previously off-peak times. These secondary peaks are larger with HWC delayed heating than with appliance scheduling and are higher than baseline peaks at high levels of participation. In all cases, overall peak demand is lower with pricing Schedule 2, as secondary peaks in half of participating households are shifted by one hour.

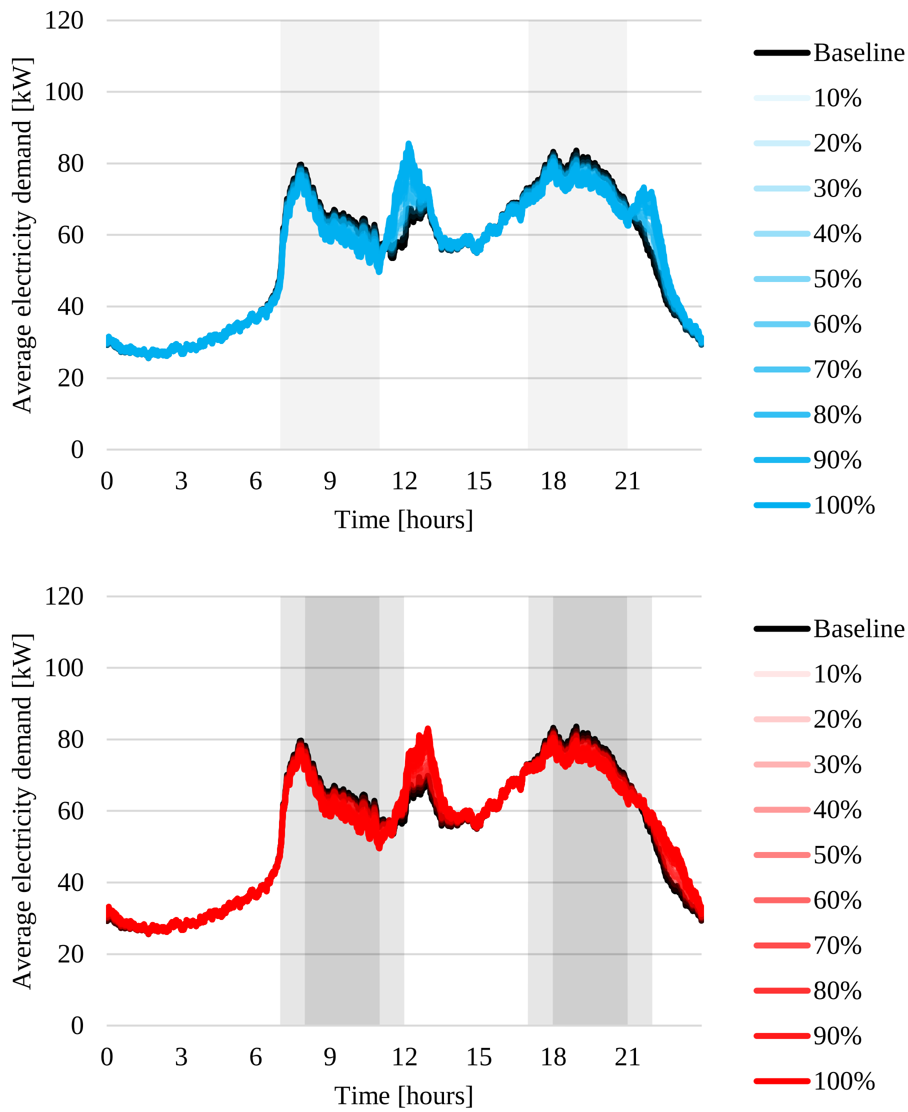

Figure 2. Average electricity demand in June for 50 houses in a Decile 5 neighbourhood in Auckland for appliance scheduling with peak electricity Schedules 1 (top) and 2 (bottom). Baseline demand (no DR) is shown in black, and demand with 10-100% of households participating in ToU shifting is shown in red. Shaded regions correspond to peak times.

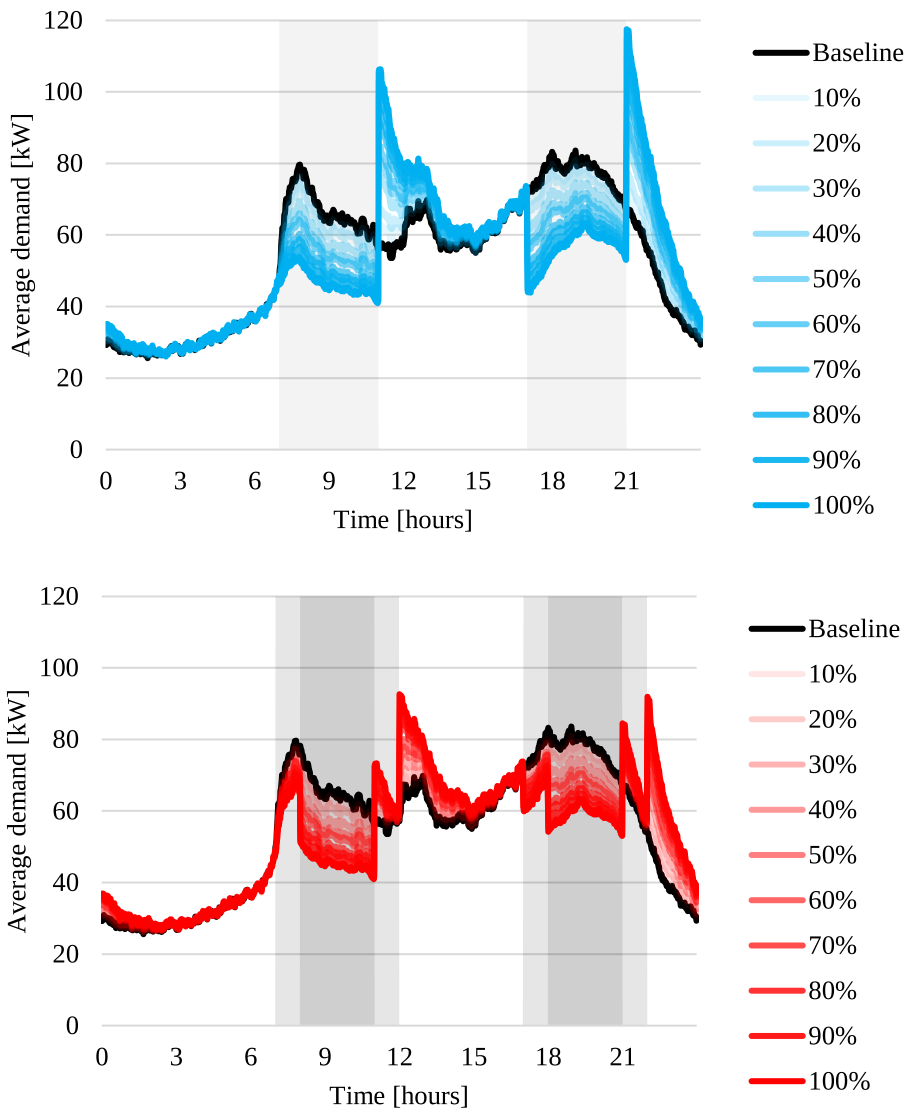

Figure 3. Average electricity demand in June for 50 houses in a Decile 5 neighbourhood in Auckland for delayed hot water cylinder heating with peak electricity Schedules 1 (top) and 2 (bottom). Baseline demand (no DR) is shown in black, and demand with 10-100% of households participating in ToU shifting is shown in red. Shaded regions correspond to peak times.

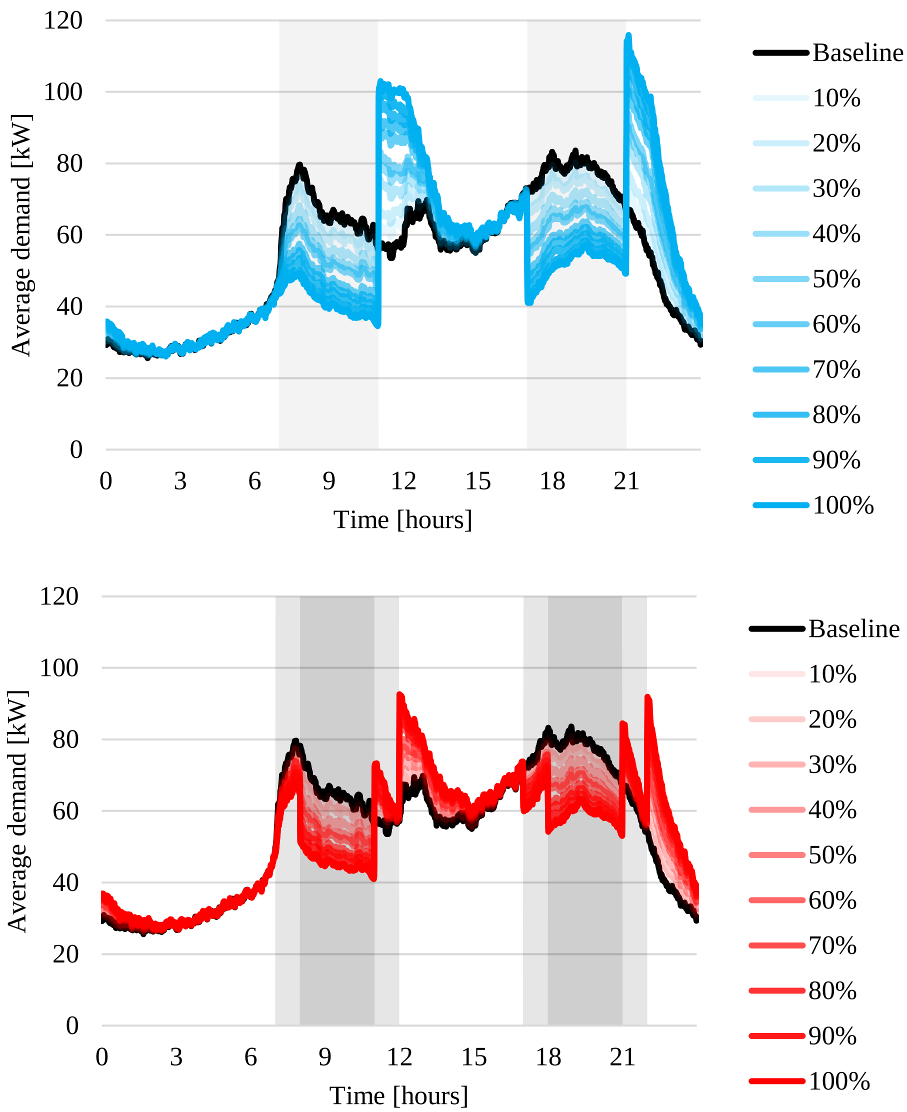

Figure 4. Average electricity demand in June for 50 houses in a Decile 5 neighbourhood in Auckland for appliance scheduling and delayed hot water cylinder heating with peak electricity Schedules 1 (top) and 2 (bottom). Baseline demand (no DR) is shown in black, and demand with 10-100% of households participating in ToU shifting is shown in red. Shaded regions correspond to peak times.

Changes in total winter peak electricity demand at different levels of participation of ToU schemes are shown in Figure 5. No change is observed in total peak demand at 10% participation in all cases. Peak demand reduces at low levels of participation, then increases at higher participation in every case except appliance scheduling according to Schedule 2, which reduces peak demand at all levels of participation above 10%. Maximum peak demand decrease for 50 households is 6.2 kW at 50% participation in HWC delayed heating under Schedule 2, and maximum increase is 35.5 kW at 100% participation in HWC delayed heating under Schedule 1. Increasing participation in hot water cylinder delayed heating increases unmet hot water demand, up to a maximum of 18,798 K*min and 18,712 K*min over the modelled month with one and two sets of peak times, respectively, as shown in Figure 6.

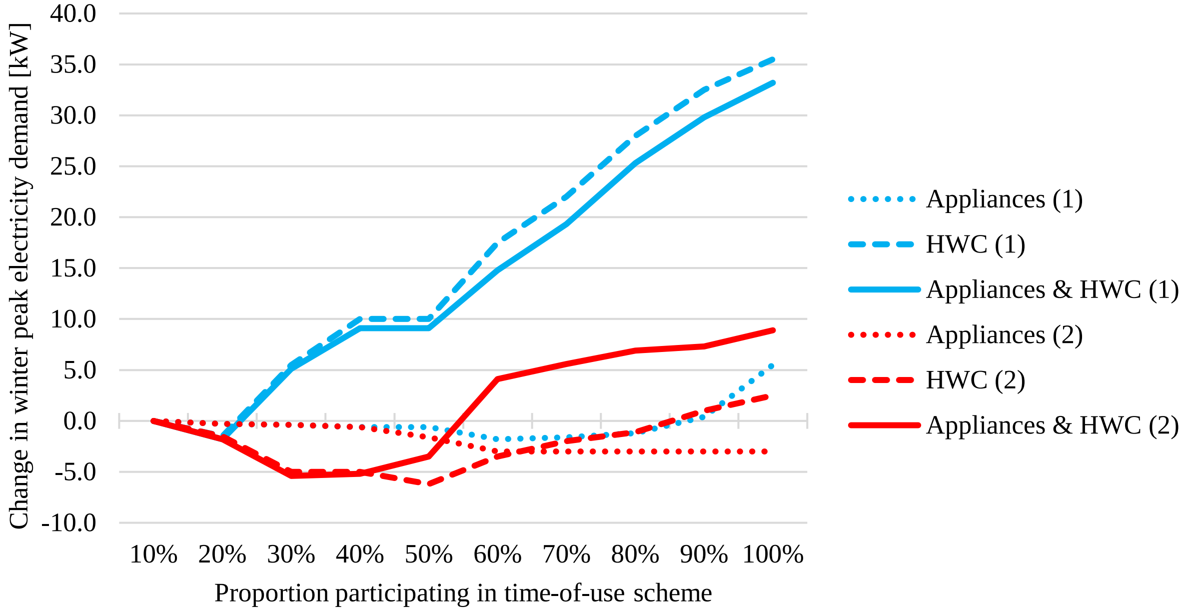

Figure 5. Change in winter peak electricity demand for 50 houses in a Decile 5 neighbourhood in Auckland, at different levels of participation in ToU scheduling of appliances and/or hot water cylinder delayed heating with peak electricity Schedules 1 (blue) and 2 (red).

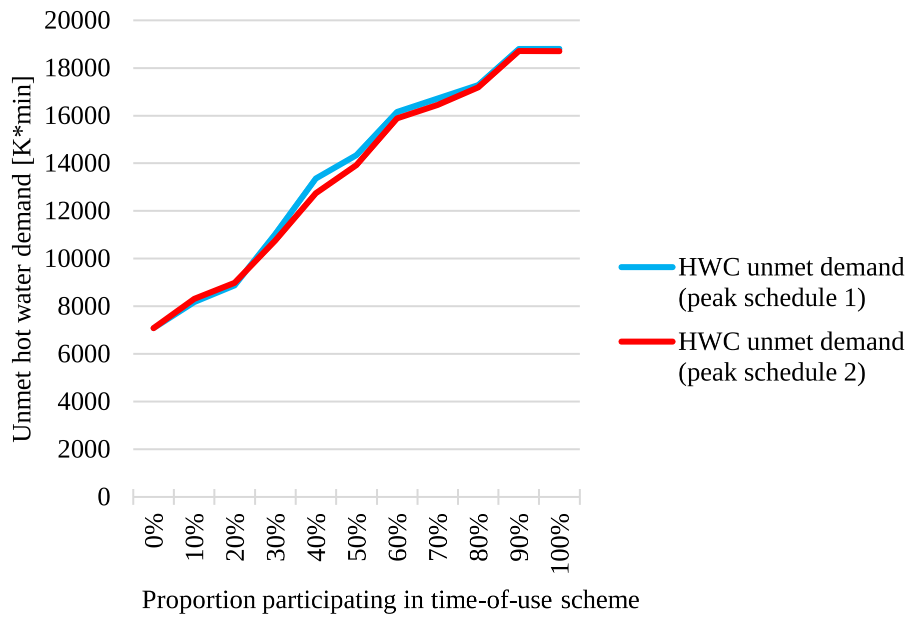

Figure 6. Total unmet hot water demand in June for 50 houses in a Decile 5 neighbourhood in Auckland, at different levels of participation in delayed heating of hot water cylinders in response to ToU prices with peak electricity Schedules 1 (blue) and 2 (red).

Average monthly electricity costs for participating households are shown in Figure 7. Costs are highest for non-participating households without ToU pricing (far left in Figure 7). Participation in appliance scheduling or HWC delayed heating reduces costs compared to baseline costs with and without ToU prices. Participating in both forms of DR reduces costs more than participating in either individually. However, savings from participating in both are lower than the sum of constituent savings. Cost saving variation between Schedules 1 and 2 is under 1.5% in all cases.

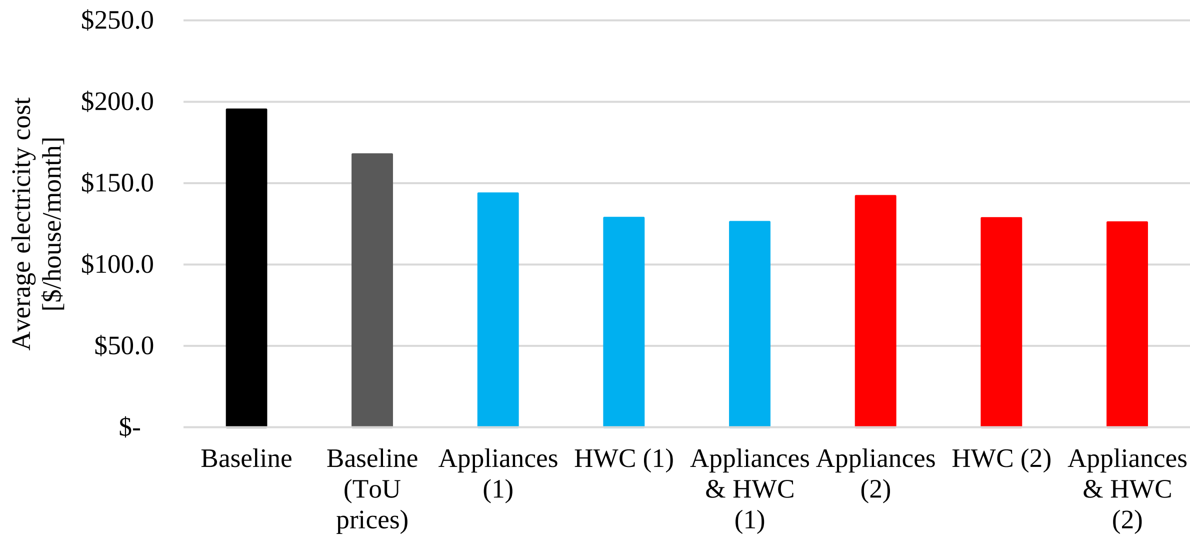

Figure 7. Average monthly electricity costs for households participating in appliance scheduling and/or hot water cylinder delayed heating according to schedules 1 (blue) and 2 (red) of ToU electricity prices, and for non-participating households (baseline) with and without ToU prices.

4. Discussion

DR with schedulable appliances and HWCs can reshape electricity demand profiles according to the ToU pricing schedules shown in Figure 1. Shifting demand away from peak times can reduce peaks but can create secondary peaks at previously off-peak times, as shown in Figures 2-4. The likelihood of these secondary peaks being higher than original peaks, and thus increasing overall peak demand, increases with increasing participation in the DR program. Secondary peaks, and thus overall peak demand, are highest in cases ii and iii, as delaying HWC heating causes all heaters to be turned on at the same time, as soon as peak times are over.

Allocating participating households to distinct peak schedules reduces overall peak electricity demand, as shown in Figure 5. In all cases and at all levels of participation, Schedule 2 produces lower peak demand than Schedule 1, as secondary peaks are split between two times. For example, HWC delayed heating with Schedule 1 increases overall peak demand from 20% participation, with a total increase of 35.5 kW (32.9%) at 100% participation, while the same intervention with Schedule 2 reduces overall peak demand at all levels of participation up to 90%, with a total increase of 2.5 kW at 100% participation. These reductions in peak demand from Schedule 2 do not considerably reduce savings in average electricity costs for individual consumers, as the difference in costs between Schedule 1 and Schedule 2 is less than 1.5% in all cases, as shown in Figure 7.

ToU pricing schemes can reduce household electricity costs, as shown in Figure 7. Even without any participation in DR, the lower off-peak prices reduce average household electricity costs by 27.5 NZD/month (14%) from baseline. Participation in DR can reduce electricity costs by 26%, 34%, and 35% for households participating in appliance scheduling, HWC delayed heating, and both, respectively. The higher savings from HWC delayed heating are due to the larger total amount of energy being shifted and the decreased HWC tank temperatures, and resulting lower thermal losses, during peak times. However, achieving these savings can increase unmet hot water demand.

Delayed heating of HWCs during peak times increases unmet hot water demand, as shown in Figure 6. Total unmet hot water demand in winter increases to more than 2.6 times baseline levels in the average participating house in both peak schedules. Unmet hot water demand results in reduced comfort, particularly when the water is used for baths or showers, so participation in DR programs which restrict HWC heating may be limited [87]. This effect is expected to be lower in houses with larger HWCs, as larger tanks have higher thermal storage and thus would experience lower unmet demand.

4.1. Implications for the design of demand response programs

In all cases, 100% participation in ToU DR does not yield the largest reductions in total peak electricity demand, as shown in Figure 5. The largest reduction in peak demand is 6.2 kW (5.7%), at 50% participation in HWC delayed heating according to Schedule 2. Even for appliance scheduling according to Schedule 2, in which total peak demand does not increase at higher levels of participation, the maximum peak reduction of 3.0 kW (2.8%) is achieved at participation levels of 60% and above. Thus, the best results for electricity companies are from ToU DR programs with participation under 100%, so these companies may seek to limit participation in these programs.

However, the best financial results for each household are from participating in DR (Figure 7), meaning design of such programs should carefully consider the interests of both electricity distributors and consumers. Additionally, higher-income households may have greater incentives, because of their higher electricity use [54,55], and be better equipped to participate in such DR programs through newer appliances and technology. Lower-income households, whose flexibility primarily stems from changes of routine, rather than technological capability [88,89], will thus be forced to change their routines to realise the financial benefits of DR programs. Thus, socioeconomic differences should be explicitly considered in the design of DR programs to avoid exacerbating existing inequalities, which is a recognised concern with some programs [90].

The peak demand reductions in Figure 5 show the potential effects of simple DR programs using existing electricity pricing structures and technologies currently available in most homes. While these programs are likely to be viewed more favourably by consumers than more complicated programs, the increased peak demand at higher levels of participation indicates these programs could be improved to better reduce peak demand. Some improvements could be made without requiring additional technology or complicated pricing structures by allocating households to alternative peak schedules. However, secondary peaks do not decay immediately (e.g., average demand after 15 minutes is within 3% of its midday peak with scheduling of HWCs and appliances in Schedule 2, as shown in Figure 4), so this disaggregation is unlikely to significantly reduce secondary peaks at high levels of participation, and further peak demand reductions are expected to require alternative measures, such as increased energy efficiency or more complex DR programs.

Further improvements in consumer perceptions of DR would allow the introduction of programs with higher complexity but greater peak demand reduction potential, such as real-time pricing [91–93] or centralised control [94–96]. The potential for these programs would be increased with greater uptake of smart appliances, which can more easily participate in dynamic load control [97,98]. Thus, regulators could consider incentivising uptake of DR-capable loads, such as by reducing the price of smart appliances through subsidies, to increase overall DR potential. Again, such programs should consider program design to understand and/or mitigate issues around equity.

A key takeaway for the design of DR programs is the larger magnitude of peak demand increases (up to 32.9%) than decreases (up to 5.7%), particularly increases apparent only at higher levels of participation. As such, caution is required in the design of DR programs, as even programs yielding peak reductions in pilot programs may increase overall peak demand if implemented at scale. Agent-based approaches like the one used in this work, which provide a low-cost method to accurately model realistic electricity consumption behaviour and the emergent effects of behavioural changes in multi-agent populations, can identify such issues and thus complement and/or provide a precursor to pilot studies in the design of DR programs.

4.2. Limitations and future work

This work assesses the impact of ToU-based DR programs in a single median-income neighbourhood in Auckland, Aotearoa New Zealand. Peak electricity demand could be driven by other factors in other situations, such as increased heating load in higher-socioeconomic households and colder climates. The capacity of consumers to adjust electricity consumption in response to ToU price schedules may also vary according to socioeconomic factors [90]. For example, lower-socioeconomic households may be more constrained by work schedules but may have higher incentives for participation in DR programs due to budget constraints. While socioeconomic and geographic variations are not considered in this work, the agent-based model is fully generalisable to other locations and demographics [54,55], and the effects of these variations on DR potential and outcomes are the subject of intended future work.

Full participation (i.e., 100% as modelled in this work) in DR programs is unlikely, both at the intra- and inter- household levels. For example, some households may choose not to participate even in simple DR programs, such as those assessed in this work, due to perceived effort and/or loss of control [22]. In participating households, full participation is also unlikely, as the importance of electricity cost in energy use decisions can vary [99]. For example, participation in HWC delayed heating could be reduced when the presence of guests increases hot water demand. In this work, uncertainty about participation in DR programs is addressed by varying participation between 0% and 100%, providing the full range of possible outcomes. DR program designers with information about likely participation levels in a given program, given geographic, socioeconomic, and other considerations, can use the data presented in Figure 5 to estimate the likely impact of the program in the target region.

Participation in DR programs can also be limited by technological capacity. At minimum, participation in ToU pricing schedules requires the presence of smart electricity meters with the ability to differentiate between energy consumed during on- and off- peak times. HWC delayed heating and appliance scheduling require the presence of water heaters and appliances with the capacity to delay electricity demand. While most households in Aotearoa New Zealand have smart electricity meters and schedulable appliances and/or HWC heaters [100], the availability of these technologies varies both within and between countries. DR participation can also be limited by behavioural factors, such as societal and family constraints on the timing of electricity demand [101]. However, as the data in Figure 5 are presented for the full range of participation levels, energy modellers and DR program designers can use the information relevant to their region of interest. Furthermore, the modelling approach presented in this work is fully generalisable to a range of technological and behavioural constraints.

The analyses presented in this work are intended to represent an average residential neighbourhood in Aotearoa New Zealand, with HWC heating from electric resistance heaters, as is the case in

86% of households [59], and minimal distributed electricity generation [102]. Peak reductions could be affected by changes to both variables, such as increased uptake of hot water heat pumps [63,64] or the integration of residential solar photovoltaic (PV) generation [103]. Particularly, increased electricity demand following the first period of peak times (11:00 for Schedules 1 and 2 (a), and 12:00 for Schedule 2 (b)) coincides with typical peak insolation, so considerable co-benefits could arise with the installation of solar PV generation or solar water heating. While not assessed in this work, the modelling approach used here is fully generalisable to such analyses, including the potential for DR programs to align demand with distributed renewable generation.

This work assesses the impacts of two types of response to ToU peak schedule: delaying the runtimes of schedulable appliances and preventing HWC heating during peak times. Residential electricity consumers may also respond to ToU electricity prices in other ways, such as by shifting mealtimes to further reduce on-peak appliance loads from food preparation and, where possible, shifting heating loads by utilising building thermal storage and/or reducing the number of rooms heated during peak times [16,28,104]. While these further behavioural changes are likely to be minimal in most households, future work could assess the effects of such coordinated reduction in demand.

DR participation in the assessments presented in this work results only from responses to the ToU electricity price changes. However, many electricity consumers state participation in DR programs could also be driven by non-financial considerations, such as avoiding blackouts or reducing GHG emissions from fossil fuel-powered generation [43,105]. The GHG emissions intensity of electricity generation and the likelihood of blackouts typically vary over minutes, rather than hours

[72], so their communication for DR would require more complicated signals than the ToU schedules assessed in this work. However, the validated agent-based model used in this work is fully generalisable to investigations of such cases.

5. Conclusions

Simple demand response (DR) interventions can effectively reshape electricity demand profiles by shifting demand away from peak times but can increase overall peak demand through the creation of secondary peaks, particularly at high levels of participation of hot water cylinder (HWC) delayed heating. Schedule 2, which allocates participating households evenly between two sets of peak times and reduces secondary peaks, reduces overall peak demand in all cases.

Maximum peak demand reduction for the 50 households modelled of 6.2 kW (5.7%) is observed at 50% participation in HWC delayed heating under Schedule 2, while maximum peak demand increases of 35.5 kW is observed at 100% participation in HWC delayed heating under Schedule 1. Time-of-use (ToU) pricing reduces average household electricity costs by 27.5 NZD/month (14%) from baseline, and participation in DR reduces costs by an average of 26%, 34%, and 35% for households participating in appliance scheduling, HWC delayed heating, and both, respectively. However, delayed heating of HWCs during peak times increases unmet hot water demand, up to 18,798 K*min over the modelled month.

The potential for increased peak demand through ToU price schedules highlights the importance of careful DR program design to avoid unintended consequences, particularly those observed only at high levels of participation, which may not be apparent in pilot programs. Allocating households to distinct peak schedules can better distribute demand over off-peak hours, mitigating these peak increases. DR program designers should also consider socioeconomic factors to ensure equitable access to DR programs and avoid exacerbating existing inequalities. Incentivizing the adoption of DR-capable technologies, such as smart appliances, can enhance the effectiveness of these programs and support the transition to a low-GHG emissions energy system. Future work could explore the impact of DR programs across diverse socioeconomic and geographic contexts, as well as the potential for more complex DR strategies, such as real-time pricing and centralized control.

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Appendix A: Description of the generalisable agent-based model of residential electricity demand

The agent-based model of residential electricity demand is constructed according to the architecture shown in Figure A.1. Electricity demand is calculated for each household, comprising a house and its occupants (agents). Agent behaviour is modelled by sampling random variables from distributions representing the spread of behaviours. Agents can be in one of three states: (i) asleep; (ii) away from home; or (iii) at home and awake, denoted “active”.

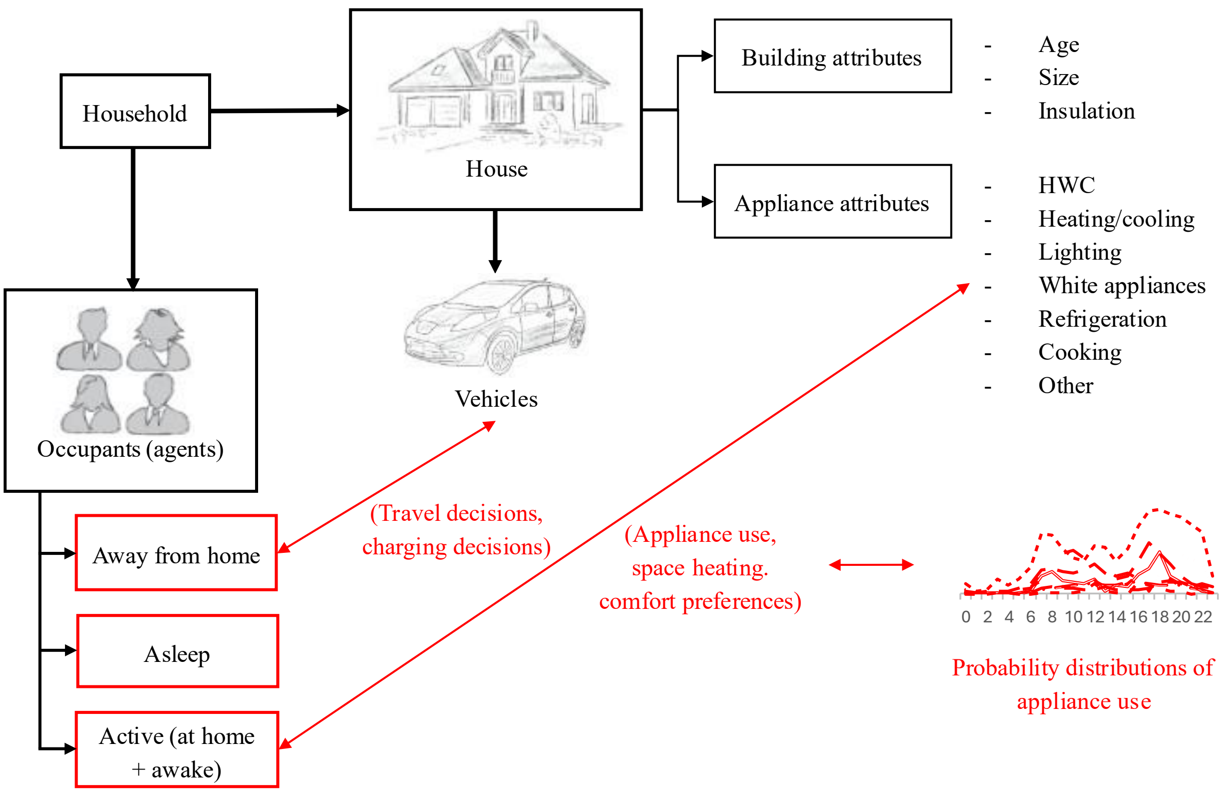

Figure A.1. Architecture of the agent-based model.

Individual incomes are randomly assigned from a normal distribution with mean matching the modelled area, and household incomes are the simple sum of occupant incomes. Household spending power is approximated by “wealth coefficient”:

$$WC_i = \begin{cases} 0 & I_{house,i}/N_{occupants,i} < I_{avg} \\ I_{house,i}/N_{occupants,i}/I_{avg} & I_{avg} < I_{house,i}/N_{occupants,i} < 2I_{avg} \\ 1 & 2I_{avg} < I_{house,i}/N_{occupants,i} \end{cases} \tag{A-1}$$

where WC_i, $I_{house,i}$, and $N_{occupants,i}$ are the wealth coefficient, income [NZD], and number of occupants of household i, and I_{avg} is the average individual income in Aotearoa New Zealand [NZD].

A.1. General behaviour

Agents rise from bed each day at t_{wake} and return to bed at t_{sleep}, both modelled with normal distributions matching average behaviour in Aotearoa New Zealand [80,81]. Travel behaviour is modelled as "house-to-house" trips. At the beginning of each day, agents determine travel behaviour according to four variables: number of trips (N_{trips}), distance per trip (dist), and beginning and end times of each trip (t_{leave} and t_{arrive}), as in previous work [106]. While data on the interdependence of these four variables are not publicly available in Aotearoa New Zealand, they have been shown to be partially independent in other countries [79]. In this model, these variables are generated from independent normal distributions matching average national patterns [82,107]. Agents not travelling are classified as "working from home" and modelled as remaining in bed for an average of one hour longer than those leaving the house.

A.2. Appliance use behaviour

Active agents interact with their surroundings. The probability of appliance use varies according to appliance type and time of day, with distributions shown in Figure A.2. These distributions are based on appliance- and household- level datasets in the United Kingdom [57,58] and a national time-use survey in Italy [56], and adjusted according to data from appliance prevalence and use in 397 randomly selected houses Aotearoa New Zealand [59].

An agent using an appliance is denoted a “switch-on event”, after which the appliance draws power for the duration of its runtime. While agents can use a maximum of one appliance per minute, they can begin another activity before appliances cease running. Thus, multiple appliances can draw power concurrently from the actions of a single agent. Standby loads and other non-behaviour dependent loads, such as TV standby and WiFi routers, are denoted “baseline” demand, which can occur without active agents. Average appliance power demands and runtimes are shown in Table A.1.

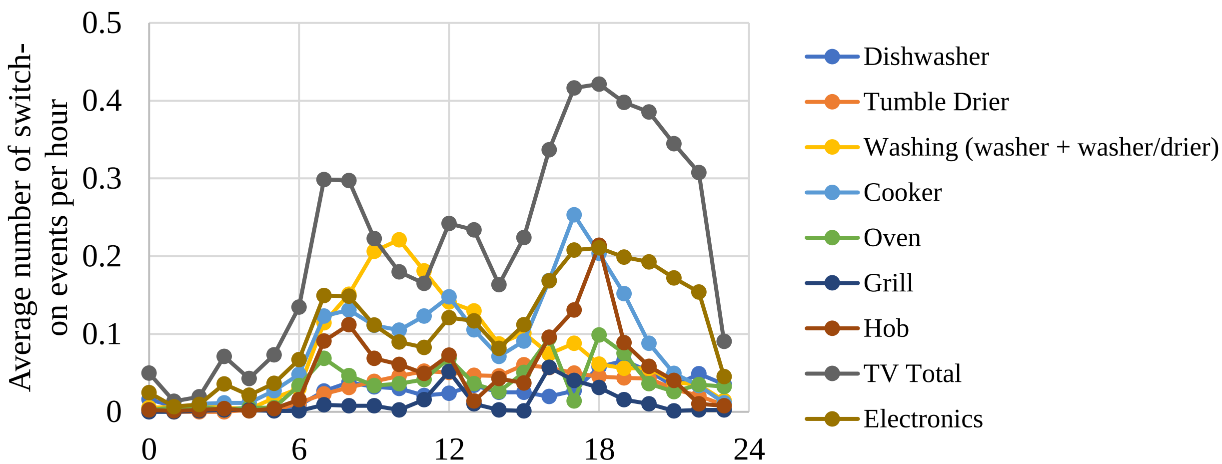

Figure A.2. Variation of appliance use probability by appliance type and time of day (adapted from [56–59]).

Table A.1. Mean appliance power demand and runtime (from [44,58,108,109]).

Appliance type	Average power [kW]	Average runtime [min]
Dishwasher	0.7	60
Tumble drier	1.1	60
Washing machine	0.7	45
Cooker	1.0	30
Oven	0.7	30
Grill	1.5	20
Hob	1.0	20

Television	0.1	120
Other electronics	0.8	30
Baseline	0.4	N/A

A flowchart summarising the appliance use sub-model is shown in Figure A.3.

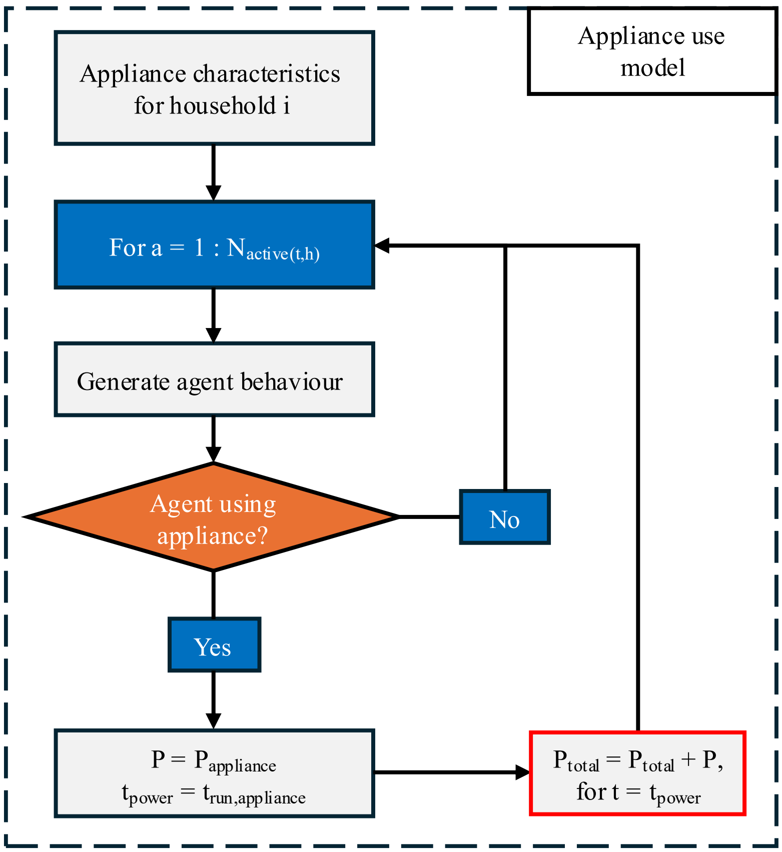

Figure A.3. Flowchart describing the appliance use model.

A.3. Lighting use

Lighting use is generated from the uniform distribution on the interval [0 $P_{light,max}$], where $P_{light.max}$ is defined in this model:

$$P_{light,max} = (N_{active,i}/N_{occupants,i})\,(1 - (L_{light}/L_{light,max,i}))\,P_{bulb,i}\,N_{bulbs,i} \qquad \text{(A-2)}$$

where $N_{active,i}$ is the number of active agents in household i, L_{light} is the current outside irradiance [Wm^{-2}], $L_{light,max,i}$ is the maximum annual irradiance in location i [Wm^{-2}], $P_{bulb,i}$ is the average power per lightbulb in household i [W], and $N_{bulbs,i}$ is the number of lightbulbs in household i.

A flowchart summarising the lighting use sub-model is shown in Figure A.4.

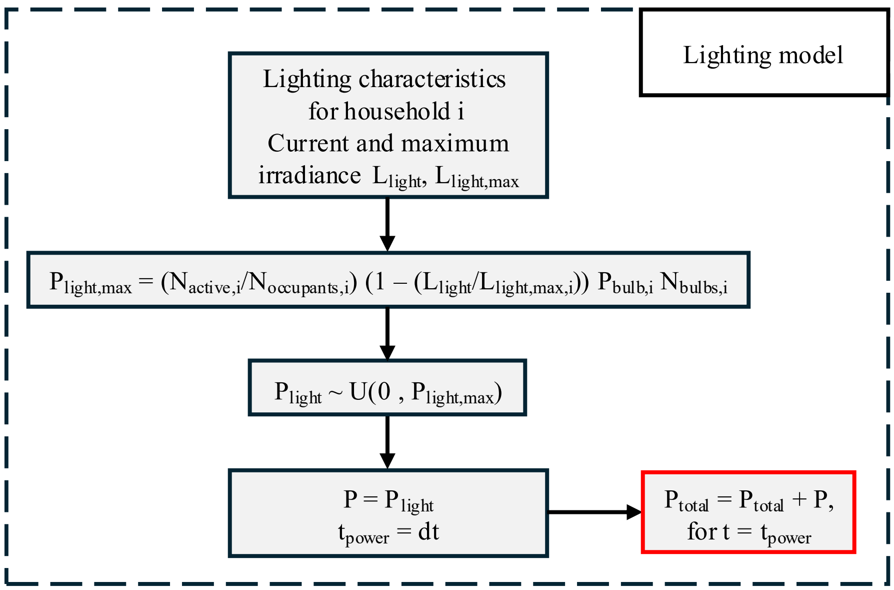

Figure A.4. Flowchart describing the lighting use model.

A.4. Space heating

Detailed building characteristics and geometries are unavailable in most neighbourhoods in Aotearoa New Zealand, so building ages and geometries in this model are characterised by four key parameters assigned from normal distributions matching the modelled population: age, number of floors, floor area, and average window-to-wall ratios. This simplified approach matches common strategies for large-scale energy models without building-specific information [78,110–112]. Insulation levels are assigned according to the minimum insulation requirements of the year in which the building was constructed, as shown in Table A.2.

Table A.2. Minimum insulation requirements by build year and zone [$Wm^{-2}K^{-1}$], from the Aotearoa New Zealand Building Codes 1978-2021 [113]. Higher zone indicates colder climate.

	Zone 1			Zone 2			Zone 3		
Year	**Walls**	**Floor**	**Roof**	**Walls**	**Floor**	**Roof**	**Walls**	**Floor**	**Roof**
1978-2000	0.9	0.9	1.9	0.9	0.9	1.9	0.9	0.9	1.9
2000-2007	1.5	1.3	1.9	1.5	1.3	1.9	1.5	1.3	1.9
2007-2021	1.9	1.3	2.9	1.9	1.3	1.9	2.0	1.3	3.3
2021 -	2.0	1.3	3.3	2.0	1.3	3.3	2.4	1.3	3.6

The building loss coefficient for each house is defined:

$$BLC = (A_{floor} / R_{floor}) + (A_{walls} / R_{walls}) + (A_{roof} / R_{roof}) + (A_{windows} / R_{windows}) \qquad \text{(A-3)}$$

where BLC is the building loss coefficient [WK^{-1}], and A_e [m^2] and R_e [WK^{-1}] are the surface area and R-value of element e, respectively.

Each agents' comfort bounds, the temperatures within which they are most comfortable, are assigned at the beginning of each model run. Household occupants then randomly select a range of preferred temperatures between their individual comfort bounds, which become the maximum and minimum comfort temperatures for the household. However, those in lower-income households typically heat their houses to temperatures below their comfort temperature [114,115]. Thus, household "heating temperature" ($T_{heat,i}$ [K]), the temperature below which occupants of household i turn on heating, is defined:

$$T_{heat,i} = T_{heat,min} + (T_{min,i} - T_{heat,min})WC_i \qquad \text{(A-4)}$$

where $T_{min,i}$ [K] is the minimum comfort temperature of household i and $T_{heat,min}$ [K] is the minimum temperature below which all agents turn on heating, which varies between regions in Aotearoa New Zealand [59].

Active agents turn on heating if the inside temperature is below the household heating temperature. In houses with air conditioning, the inverse is also true: active agents turn on air conditioning if the inside temperature is above the household cooling temperature. Inside temperature is then updated according to:

$$\dot{T}_{house} = (-(T_{house} - T_{outside}) * BLC + P_{heater}) / HC_i \qquad \text{(A-5)}$$

where $\dot{T}_{house}$ is the rate of change of inside temperature [K/s], T_{house} is the inside temperature [K], P_{heater} is the power output from internal heating [W], $T_{outside}$ is the external temperature at time t [K], and HC_i is the internal heat capacity of house i [J/K].

A flowchart summarising the space heating sub-model is shown in Figure A.5.

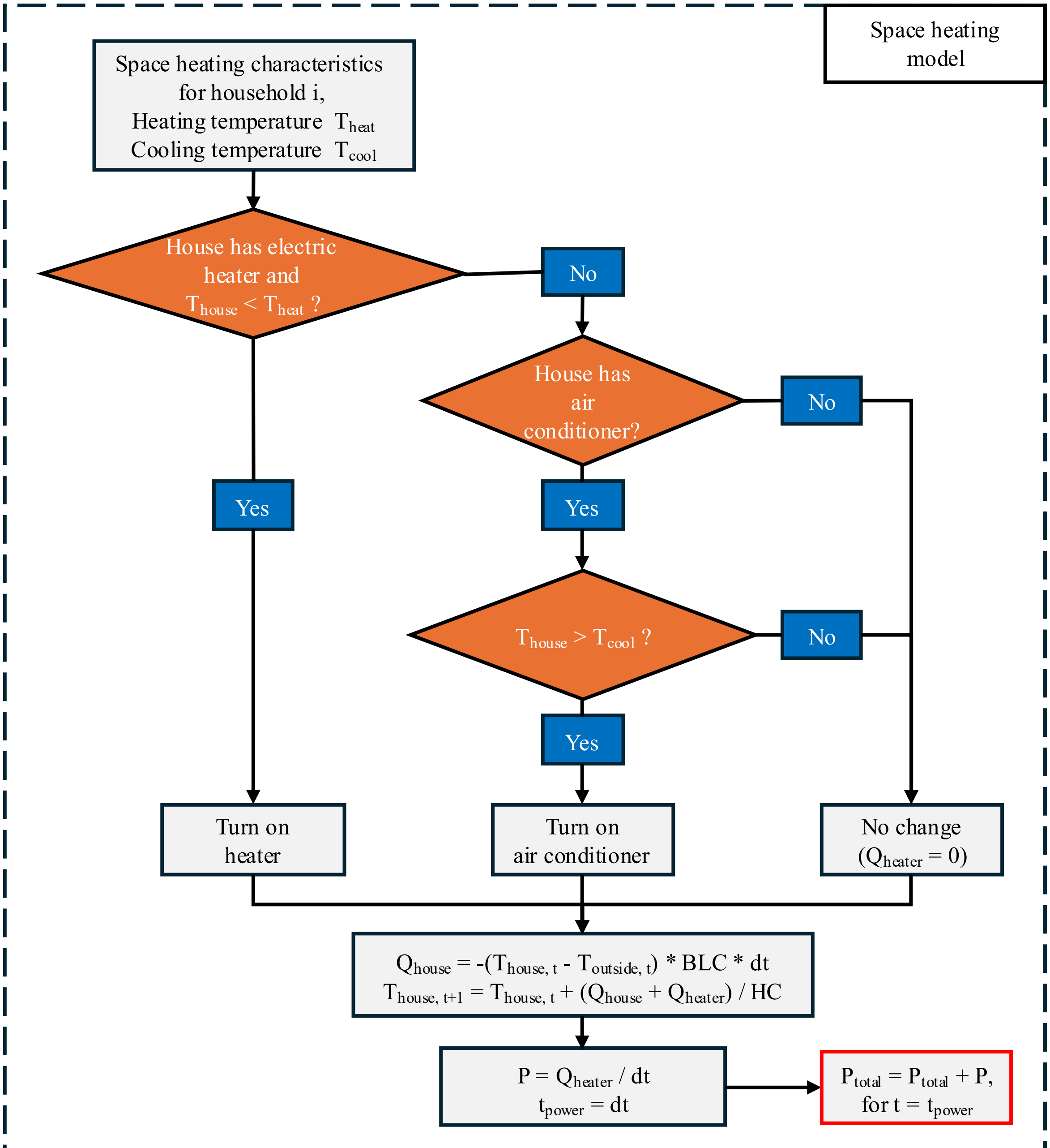

Figure A.5. Flowchart describing the space heating model.

A.5. Water heating

Electric hot water cylinders (HWCs) are present in over 85% of houses in Aotearoa New Zealand [59], but this proportion varies by neighbourhood. For houses with electric HWCs, cylinder sizes are assigned according to industry-standard recommendations for occupancy level [84]. Hot water demand profiles are generated using DHWcalc [60] with average daily hot water use of 50 L per person [85,86]. DHWcalc stochastically generates domestic hot water demand profiles according to household occupancy levels, and is widely use where hot water demand data are unavailable [38,116–118]. HWC temperatures are calculated at each timestep according to a model presented in previous work [61,62]:

$$\dot{T}_{HWC} = (P_{HWC} - Q_{DHW} - Q_{loss})/(C_p * V_{HWC}) \qquad \text{(A-6)}$$

$$Q_{DHW} = K_{mix} * \dot{V} * C_p * \rho \, (T_{HWC} - T_{in}) \qquad \text{(A-7)}$$

$$Q_{loss} = K_{loss} \, (T_{HWC} - T_{house,i}) \qquad \text{(A-8)}$$

where T_{HWC} is the temperature of the HWC [K], P_{HWC} is the power supplied by the heating element [W], Q_{DHW} is the heat loss from standing thermal losses [W], ρ is the density of water [kgm^{-3}], C_p is the specific heat of water [$Jkg^{-1}K^{-1}$], V_{HWC} is the volume of the HWC [L], $\dot{V}$ is the flow rate of hot water from the HWC [L/s], T_{in} is the water inlet temperature [K], $T_{house,i}$ is the internal temperature of house i [K], K_{loss} is an empirically tuned coefficient to a first order approximation of thermal losses [W/K], and K_{mix} is a factor to account for a thermostatic mixing valve, defined:

$$K_{mix} = \begin{cases} (T_{out} - T_{in})/(T_{HWC} - T_{in}), & T_{HWC} \geq T_{out} \\ 1, & T_{HWC} < T_{out} \end{cases} \qquad \text{(A-9)}$$

where T_{out} is the water outlet temperature [K]. HWCs are heated if $T_{HWC} < T_{set}$, the cylinder setpoint temperature [K].

A flowchart summarising the water heating model is shown in Figure A.6.

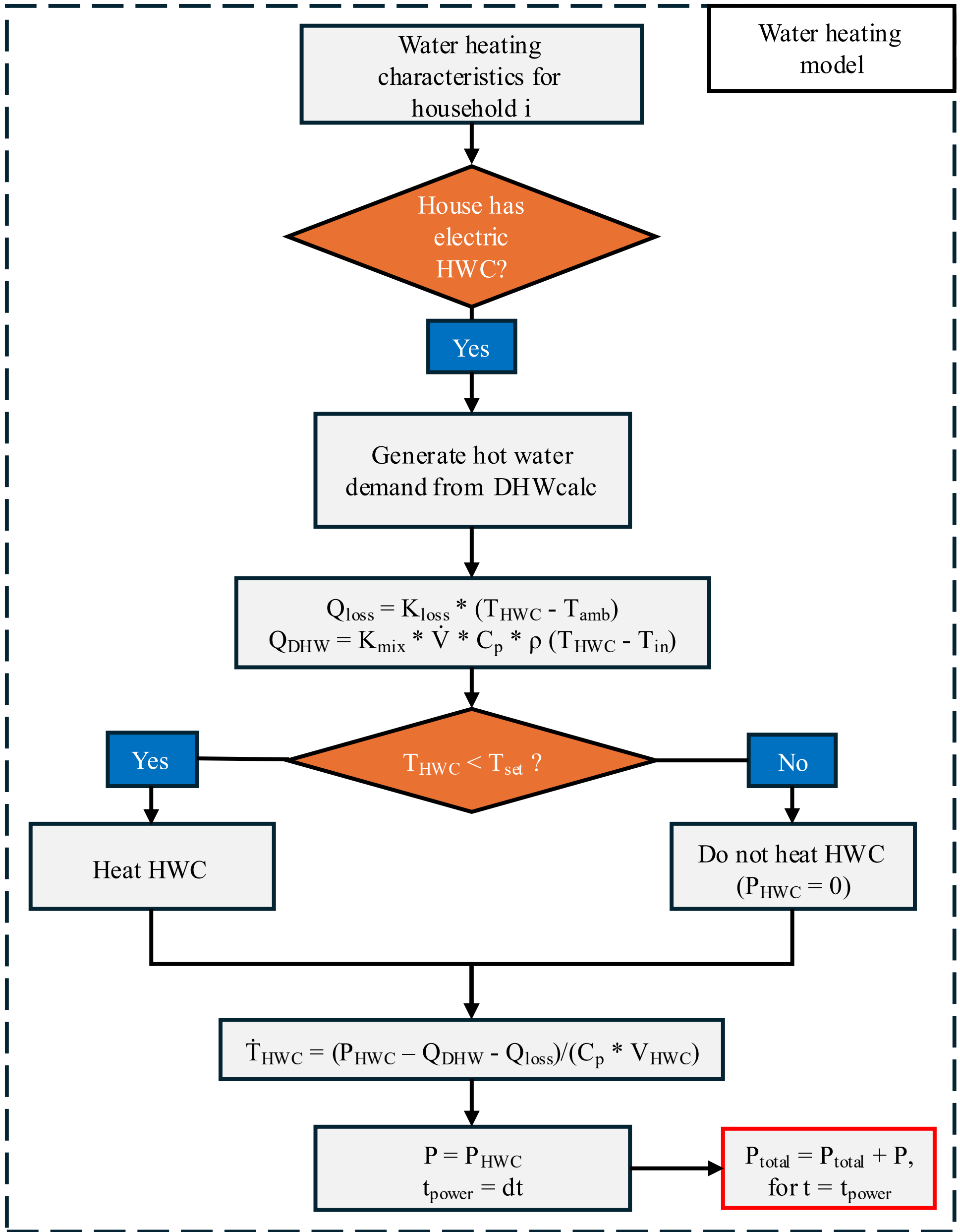

Figure A.6. Flowchart describing the water heating model.

A.6. Model summary

A flowchart summarising the overall model is shown in Figure A.7.

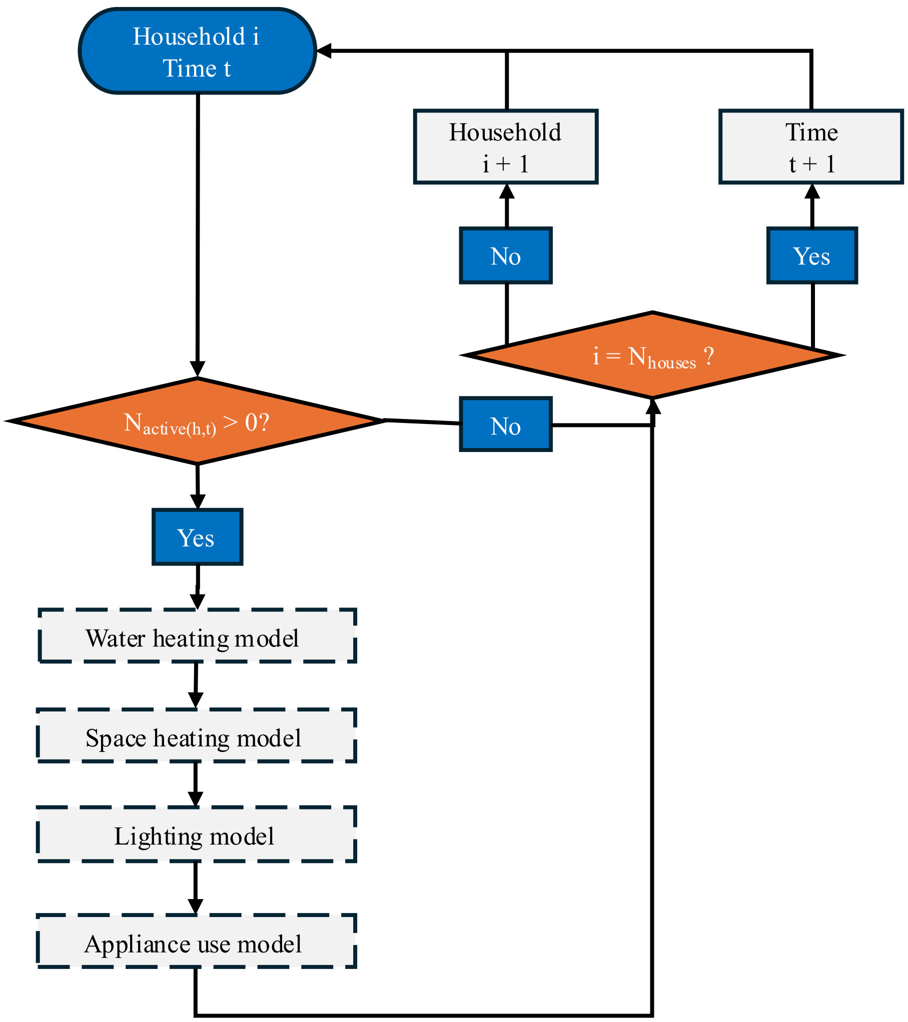

Figure A.7. Flowchart describing overall model structure and sub-model locations.