

Peak loads, health, and energy equality: The effects of demand-side electricity efficiency interventions

Author details

Baxter Kamana-Williams ^{a,*}, R. J. Hooper ^b, Jamie Silk ^c, Daniel Gnoth ^d, J. Geoffrey Chase ^a

^a Department of Mechanical Engineering, University of Canterbury

Private Bag 4800

Christchurch 8140

New Zealand

^b Maidstone Associates Ltd.

2/17 Kahu Road

Christchurch 8140

New Zealand

^c Silk Advisory And Innovation Ltd.

PO Box 1

Oakura 4345

New Zealand

^d Ara Ake

8 Young Street

New Plymouth 4310

New Zealand

* Corresponding author: Baxter Kamana-Williams baxter.williams@pg.canterbury.ac.nz

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Abstract

Electrification is key for climate change mitigation but, if unmanaged, risks increasing energy poverty, inequalities, and peak electricity demand. While demand response to reduce peak electricity demand has been the subject of extensive research, the effects of energy efficiency interventions for wider health system and socioeconomic outcomes are less studied. This study assesses the impact of seven energy efficiency interventions on peak electricity demand in residential neighbourhoods in Aotearoa New Zealand, and compares these effects with wider system outcomes, including demonstrated direct health system costs. Using a validated agent-based model of energy use, electricity demand is simulated across socioeconomic and geographic conditions. Most energy efficiency interventions reduce peak electricity demand, with reductions of 0.08-1.64 kW/house (4-37%). Socioeconomic variations highlight the importance of targeting energy efficiency interventions to maximise whole-system outcomes. This study suggests increasing efficiency standards, accompanied by subsidies for low-income households, would enhance these benefits. However, average effects are skewed towards the highest-income neighbourhoods and do not represent the bottom 75% of neighbourhoods, meaning targeted subsidies would be preferable to avoid policy choices appearing biased towards wealthier segments, as well as being preferable in terms of economic efficiency and avoiding any increase in existing inequalities and energy poverty.

Highlights

- Energy efficiency interventions can reduce peak electricity demand.
- Heat pumps and insulation reduce peak demand by up to 1.64 kW per house (37%).
- Effects are larger in higher-income households and colder climates.
- Highest net savings are from retrofit insulation, due to improved health outcomes.
- Targeted interventions would maximise whole-system benefits and reduce inequality.

Keywords: Demand side management; Agent-based model; Energy policy; Just transition

Word count: 6594

1. Introduction

Rapid reductions in greenhouse gas (GHG) emissions are required for successful climate change mitigation (Intergovernmental Panel on Climate Change (IPCC), 2014). However, these efforts risk increasing inequality and/or reducing energy access by failing to consider implications for marginalised communities and across the socioeconomic spectrum (Markkanen and Anger-Kraavi, 2019). Electrification is a key component of GHG emissions reduction strategies (Sugiyama, 2012), with many countries incorporating electrification targets into national policies (Gold, 2021; Interim Climate Change Committee, 2019), but can decrease energy access for low-income consumers through increased upfront capital costs (Sovacool et al., 2019; Tarekegne, 2020). Further, strategies developed using average data risk increasing energy inequality across residential consumers, as households at the bottom end of the socioeconomic spectrum are often unable to benefit from electrification because money is limited, and additional energy spending reduces money available for other mandatory costs, such as housing, clothing, fuel, and food (Bardazzi et al., 2021; Huang et al., 2023).

Electrification of residential energy demand, primarily the replacement of natural gas for space and water heating and the increasing uptake of electric vehicles, will rapidly increase electricity demand, and peak demand in particular (Transpower, 2021). These increases in peak demand are expected to increase stress on existing electricity infrastructure and require considerable expenditure in network enhancements. In Aotearoa New Zealand, investment of 42 billion NZD per decade is expected to be required for electricity generation, transmission, and distribution infrastructure to meet this burgeoning demand (Tibi et al., 2022). Separate analyses estimate the total marginal cost per additional kW of peak electricity demand at 241 NZD per year, with

generation, transmission, and distribution accounting for 29%, 41%, and 31%, respectively (Reeve et al., 2021). This infrastructure spend is expected to increase pressure on electricity distribution businesses in particular (WEL Networks, 2022; Wellington Electricity, 2022), and ultimately increase energy costs for households. Additionally, GHG emissions from electricity generation are typically highest during periods of peak demand (Garcia and Freire, 2016; Hawkes, 2014; McCarthy and Yang, 2010; Siler-Evans et al., 2012), which typically require the use of responsive thermal plants (“peaking plants”) with high emissions intensities (Edenhofer et al., 2011).

Reducing peak electricity demand can thus reduce future energy system expenditure and GHG emissions. Methods for peak demand reduction can be categorised as either demand response or energy efficiency (Williams et al., 2023b). Demand response is the practice of electricity consumers responding to signals to adjust their consumption, such as shifting demand to match supply or reduce peak load (Mathieu et al., 2024; Williams and Bishop, 2024). Energy efficiency seeks to increase efficiency of electricity use, reducing demand without compromising desired outcomes (Gellings and Chamberlin, 1987).

Alongside peak demand reduction, many energy efficiency interventions have additional benefits for consumers. For example, increasing insulation in residential dwellings reduces overall energy use and peak electricity demand (Dortans et al., 2020; Maxim and Grubert, 2023), and reduces energy costs (Best and Sinha, 2021). Co-benefits include reduced GHG emissions, improved health outcomes, and improved thermal comfort and safety (Lima et al., 2020). On the basis of the health outcomes alone, many countries provide support for improving residential space heating and space cooling efficiency. For example, the *Warm Up New Zealand: Heat Smart* program

provided funding to retrofit insulation and install clean heating in 241,000 residential buildings in Aotearoa New Zealand between 2009 and 2013. The program's benefit-cost ratio was evaluated at 4:1, with over 99% of the benefits from improved health outcomes in the warmer, drier homes (Grimes et al., 2012), but much of Aotearoa New Zealand's housing stock remains insufficient to meet the thermal comfort and health needs of many occupants (Howden-Chapman et al., 2021). However, increased efficiency can increase overall energy use through the "rebound effect", as households in which space heating was previously ineffective may use heaters more, rather than less (Guerra Santin, 2013; Haas and Biermayr, 2000), which can increase peak electricity demand. Thus, assessments of energy efficiency should also consider potential rebound effects.

1.1. Literature review

There is a large body of research dedicated to demand response, including: quantifying the peak reduction (Silva et al., 2020; Uddin et al., 2018) and cost saving (Hussain et al., 2015; Yan et al., 2018) potential of demand response programs, calculating the demand response potential of countries and regions (Cai and Braun, 2019; Dortans et al., 2018; Gils, 2014), and identifying constraints and considerations for demand response implementation (Blanke et al., 2017; Gyamfi et al., 2013; O'Connell et al., 2014). Comparatively, there has been little research undertaken assessing the effects of energy efficiency interventions on peak electricity demand (Arteconi et al., 2012; Dyson et al., 2014), with previous research focused primarily on space heating/cooling efficiency. Maxim and Grubert (Maxim and Grubert, 2023) calculate the peak demand reduction potential from space heating efficiency interventions in residential buildings in South Dakota, USA, and find the required capital cost of insulation per kW of peak demand reduction to be comparable to capital costs for equivalent increases in generation capacity. Kunwar et al. (Kunwar

et al., 2023) assess the energy saving and peak demand response potential of active insulation, which combines insulation with a control system for thermal storage, in a residential building in the USA, where active insulation is shown to reduce peak power demand by up to 1 kW (38%). Bianchi et al. (Bianchi et al., 2007) use a numerical thermal model to compare the effects of ceiling insulation and high-reflectivity roofs on energy savings and peak energy demand in California, USA.

Alongside space heating/cooling interventions, previous research has assessed the demand reduction potential of lighting efficiency and general electricity efficiency improvements. Frick et al. (2019) use data on electricity efficiency programs from 36 electricity companies across nine states in the USA to calculate the “cost of saving peak demand”, the cost required by a program administrator to reduce peak electric power demand by a given amount. Costs are shown to vary more than four-fold between states, with an average cost of 1,483 USD per kW of peak reduction. Dortans et al. (2020) use a data-driven model to calculate energy efficient residential lighting could reduce winter peak electricity demand in Aotearoa New Zealand by 9%. However, the top-down nature of this approach means model results may not sufficiently represent behavioural dynamics and model results may show larger effects than would occur in reality. Taniguchi et al. (2016) use a model building approach to quantify the peak demand reduction potential of behavioural interventions, such as increasing setpoint temperature of air conditioners and turning off electric lights, and efficiency improvements, such as replacing air conditioners and installing high-efficiency lightbulbs in Japan, and show reduced use of electric lights has the highest peak reduction potential.

Efficiency interventions are typically assessed separately and in different countries/regions, meaning the effects of interventions in different studies are not readily comparable. For example, the differing methodologies for assessing the peak demand reduction potential of increased insulation in the USA (Maxim and Grubert, 2023) and reduced air conditioner use in Japan (Taniguchi et al., 2016) mean the two interventions cannot be readily compared with each other, or with the peak reduction potential of efficient residential lighting in Aotearoa New Zealand (Dortans et al., 2020). Additionally, although socioeconomic status affects residential energy use, with lower-income houses using less energy (Howden-Chapman et al., 2009; Losi et al., 2015), research to date has typically reported average peak demand reductions, without accounting for socioeconomic variation or assessing the differential effects of these interventions for households across the socioeconomic spectrum. These insights are the primary focus of the methodology employed in this work. Further, energy efficiency interventions are typically assessed according to their effects on energy system outcomes, such as electricity demand and energy costs, without reference to wider implications. To date, the authors are not aware of any research comparing the effects of a range of energy efficiency improvements, such as for appliances, lighting, and space heating, on peak electricity demand in households in varied socioeconomic and geographic circumstances, and comparing these effects with wider impacts, such as health system outcomes.

1.2. Contributions

This paper assesses the effects on peak electricity demand of a range of appliance, lighting, and space heating efficiency interventions in Aotearoa New Zealand, using a model of residential electricity use presented and validated in previous work across multiple seasons and behavioural disruptions. The change in peak electricity demand from seven interventions is assessed using a

validated agent-based modelling approach, in eight model neighbourhoods across two cities, representing a range of geographic and socioeconomic conditions. The financial benefits of these interventions are assessed, including savings for electricity distributors and consumers, and wider system effects are also quantified, where possible. The policy implications of these findings are discussed, including potential funding models considering the range of outcomes for government, businesses, and households across the socioeconomic spectrum.

2. Methods

An agent-based model of residential energy demand is used to calculate the effects of a range of demand-side energy efficiency improvements. An overview of the agent-based model, including its construction, validation, and key parameters, is presented in Section 2.1. Use of the agent-based model to simulate appliance, lighting, and space heating efficiency improvements, and the neighbourhoods in which these interventions are modelled, is described in Section 2.2. A framework for calculating the net financial and system-wide effects of these interventions is described in Section 2.3.

2.1. Modelling approach

Agent-based models simulate the behaviour of individual agents and the resulting emergent behaviours of groups, and are well suited for modelling residential electricity demand, due to their ability to capture the inherent variability of individual behaviour (Williams et al., 2023b). Electricity demand in this work is calculated using an agent-based model presented and validated in previous work, with agents representing the behaviour of individual household occupants. This

model is described in full in the online supplemental appendix and in previous work (Kamana-Williams et al., 2025a; Williams et al., 2025).

The agent-based model contains five sub-models, which are summarised here and in the flowchart in Figure 1, and described in full in the Appendix:

- **General behaviour:** Each day, agents decide when to wake up, sleep, and travel. Agents can be in one of three states: asleep, away from home, or active (at home and awake).
- **Appliance use behaviour:** Active agents use appliances according to probability distributions based on house- and appliance- level time-series datasets (Bizzozero et al., 2016; Isaacs et al., 2010; Kelly and Knottenbelt, 2015; Yilmaz et al., 2017), which are shown in Figure 2.
- **Lighting:** Lighting use is generated stochastically, with probability increasing with number of active occupants and decreasing with outside irradiance (Equation A2).
- **Space heating:** Active agents turn on heaters if inside temperature is below the household's minimum heating temperature. These minimum temperatures vary between households and are lower in lower-income households (Equation A4).
- **Water heating:** Hot water cylinders (HWCs) are the dominant form of water heating in Aotearoa New Zealand. Hot water use is generated using DHWcalc (Jordan and Vajen, 2005), and HWC internal temperature is updated according to a model described in previous work (Bishop et al., 2023b; Williams et al., 2023a), which accounts for hot water use and standing thermal losses (Equations A6-A9).

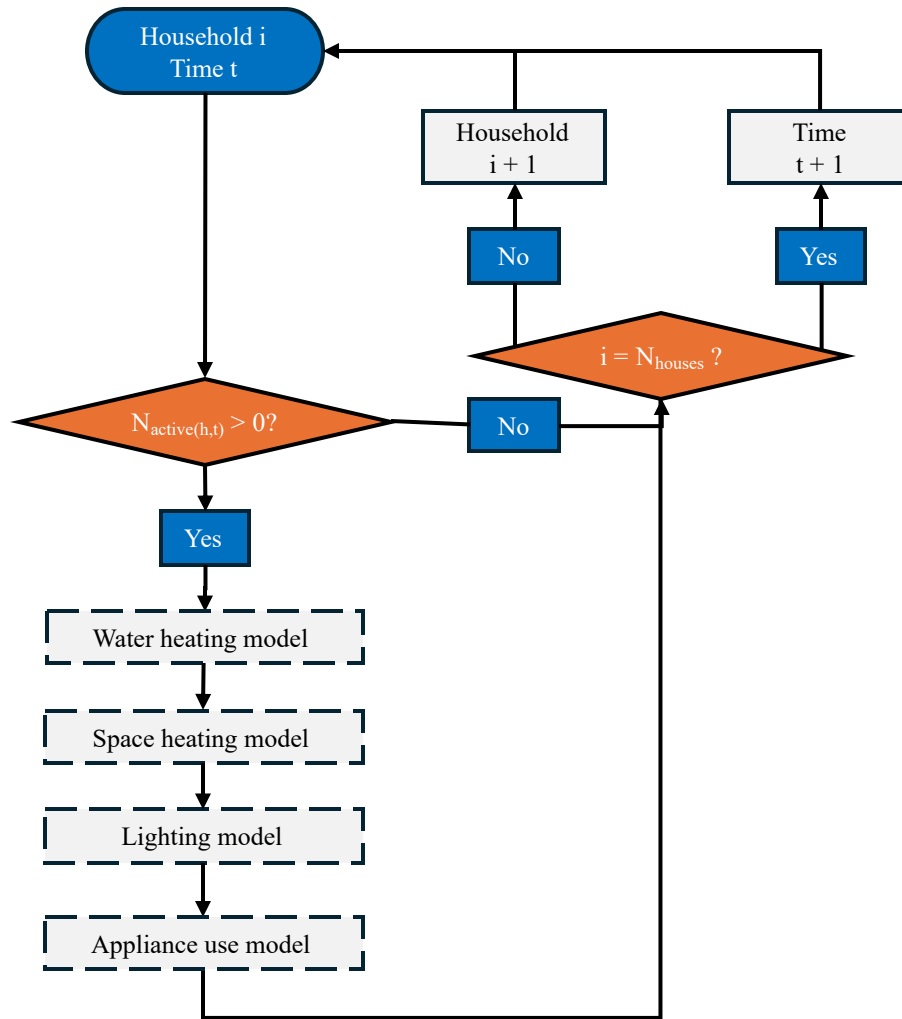


Figure 1. Flowchart describing overall model structure and sub-model locations. Flowcharts of sub-models for water heating, space heating, lighting, and appliance use are shown in Figures A2-A5.

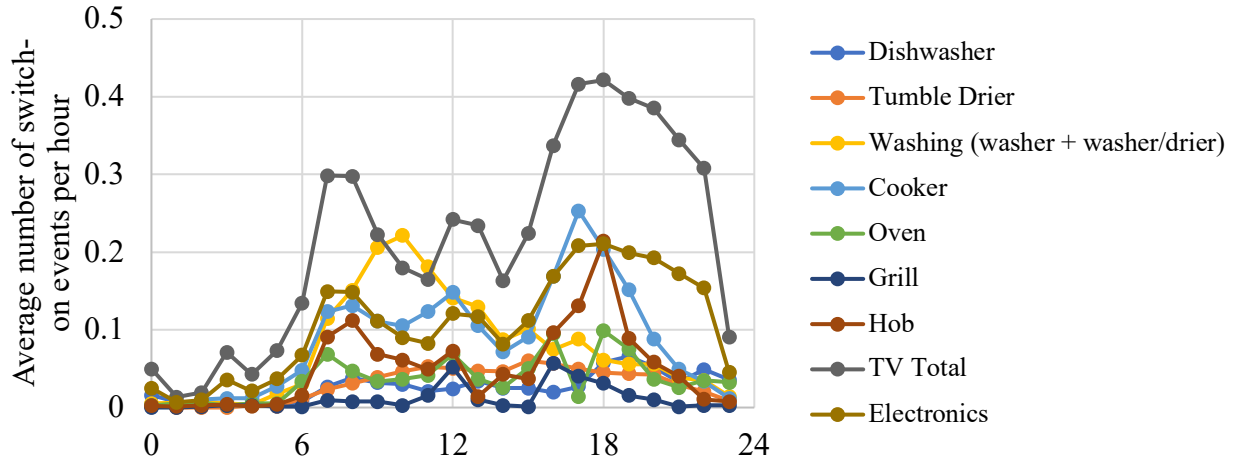


Figure 2. Variation of appliance use probability by appliance type and time of day (adapted from (Bizzozero et al., 2016; Isaacs et al., 2010; Kelly and Knottenbelt, 2015; Yilmaz et al., 2017), as described in (Kamana-Williams et al., 2025a)).

The model was validated by comparing modelled electricity demand with real electricity demand from low-voltage distribution transformers in Aotearoa New Zealand across a range of seasons and changes in aggregate behaviour. Correlation between modelled and real demand above 0.8 was calculated in over 80% of cases (Williams et al., 2025). In addition, total modelled energy demand from each load (appliances, lighting, space heating, and water heating) and contributions of each load to peak demand were compared with load-specific demand from appliance- and household- level measurements in households around Aotearoa New Zealand (Kamana-Williams et al., 2025a).

2.2. Analyses: Neighbourhoods and cases

Neighbourhoods of 50 houses, representing a typical number of houses connected to a single low-voltage electricity distribution transformer (Watson et al., 2014), are modelled for Auckland and Christchurch, two of the largest cities in Aotearoa New Zealand. In each location, four neighbourhoods are modelled, which are identical except for their average income (a total of eight

neighbourhoods).

Thus, baseline household configurations, house attributes, and appliance characteristics are unchanged between locations, and change only with income. While housing stock and household configurations vary between Auckland and Christchurch in reality (Isaacs et al., 2010), these differences could complicate calculations of the effects of efficiency improvements and are not included in these analyses. Thus, variation between Christchurch and Auckland in this work is limited to climate. Individual incomes of residents in each neighbourhood are assigned from a normal distribution with mean matching the average gross neighbourhood income, so each neighbourhood can include some households from across the socioeconomic spectrum. The modelled neighbourhoods are summarised in Table 1.

Table 1. Summary of modelled neighbourhoods. In each neighbourhood, 50 houses are modelled, with average gross individual income matching deciles 1, 3, 7, or 10 in Aotearoa New Zealand (Statistics New Zealand, 2018).

	Location	Average gross income [NZD]
A1	Auckland	15,000 (Decile 1)
A3	Auckland	25,000 (Decile 3)
A7	Auckland	50,000 (Decile 7)
A10	Auckland	100,000 (Decile 10)
C1	Christchurch	15,000 (Decile 1)
C3	Christchurch	25,000 (Decile 3)
C7	Christchurch	50,000 (Decile 7)
C10	Christchurch	100,000 (Decile 10)

Each neighbourhood is modelled in nine cases, representing a baseline (1), and the effects of appliance (2), lighting (3), and space heating (4-9) efficiency interventions, chosen to represent a range of realistic efficiency improvements in households in Aotearoa New Zealand:

1. **Baseline:** Reference case, with variables matching averages in Aotearoa New Zealand: appliance power demands as in Table A1, 14% of lighting from light emitting diode (LED)

bulbs (Isaacs et al., 2010), 30% of houses heated with electric heaters and 19% with heat pumps (Isaacs et al., 2010; Stephenson et al., 2018), and insulation according to minimum standards of the house's construction year (Table A2).

2. **Appliance efficiency:** 50% reduction in average appliance electricity demand from Baseline.
3. **Lighting efficiency:** Same as Baseline, but all lighting from LED bulbs.
4. **Insulation increase:** Increase in insulation of R-2 ($2 \text{ Wm}^{-2}\text{K}^{-1}$) from Baseline.
5. **0% electric heaters:** No electric space heating or heat pumps.
6. **100% electric heaters:** All space heating with electric heaters (no heat pumps).
7. **100% electric heaters + insulation increase:** All space heating with electric heaters (no heat pumps) and increase in insulation of R-2 ($2 \text{ Wm}^{-2}\text{K}^{-1}$) from Baseline.
8. **100% heat pumps:** All space heating with heat pumps.
9. **100% heat pumps + insulation increase:** All space heating with heat pumps and increase in insulation of R-2 ($2 \text{ Wm}^{-2}\text{K}^{-1}$) from Baseline.

Water heating efficiency interventions, such as the installation of hot water heat pumps (Hepbasli and Kalinci, 2009; Willem et al., 2017), are not included in these analyses because hot water cylinders in Aotearoa New Zealand are subject to different controls and constraints than other residential electricity loads, with heating curtailed by “ripple control” to reduce peak electricity demand (Energy Efficiency and Conservation Authority, 2020; Joish et al., 2014), so require separate analysis (Kamana-Williams et al., 2025b). Further, the increased difficulty of installation, particularly in houses without existing hot water cylinders, reduces the practicality of water heating interventions compared to the interventions assessed in this work.

Community-based trials have shown increasing insulation increases household interior temperature by approximately $0.25 \text{ }^{\circ}\text{C}$ for every $1 \text{ Wm}^{-2}\text{K}^{-1}$ increase of additional insulation (Howden-Chapman et al., 2007). Thus, in cases with increased insulation of $2 \text{ Wm}^{-2}\text{K}^{-1}$, the

minimum heating temperature (t_{heat} , the temperature below which all households turn on their heaters) increases by 0.5 °C. Modelled cases are summarised in Table 2, and all model inputs are summarised in Table 3.

Table 2. Summary of cases.

Case	Change in appliance electricity demand	Proportion of LED bulbs	Insulation increase	Proportion of houses with electric heaters	Proportion of houses with heat pumps
1	0	14%	0	30%	19%
2	-50%	14%	0	30%	19%
3	0	100%	0	30%	19%
4	0	14%	2 Wm ⁻² K ⁻¹	30%	19%
5	0	14%	0	0%	0%
6	0	14%	0	100%	0%
7	0	14%	2 Wm ⁻² K ⁻¹	100%	0%
8	0	14%	0	0%	100%
9	0	14%	2 Wm ⁻² K ⁻¹	0%	100%

Table 3. Summary of model inputs. Variables in this table are independent of income, including “mean preferred temperature”. Conversely, “minimum heating temperature”, the internal temperature below which household occupants turn on space heaters, varies with household income (from 9 °C to minimum comfort temperature), as described in Appendix A4.

Variable	Value	Source
Number of houses	50	
Average annual income	See Table 1	
Mean heater power	5000 W	(Isaacs et al., 2010)
Proportion of house with heat pumps	19%	(Buckett, 2007; French, 2008)
Mean preferred temperature (max)	24 °C	Estimated from (Isaacs et al., 2010)
Mean preferred temperature (min)	16 °C	Estimated from (Isaacs et al., 2010)
Mean house age	40 years	(Stats, 2020)
Mean house size	150 m ²	(Khajehzadeh and Vale, 2017, 2016)
Mean number of floors	1.5	(Khajehzadeh and Vale, 2017, 2016)
Story height	2.4 m	(Khajehzadeh and Vale, 2017, 2016)
Mean window-wall ratio	0.22	(Bishop et al., 2024)
House insulation level	See Table 2	
Proportion of houses with heat pumps	See Table 2	
Proportion of houses with electric heaters	See Table 2	
Proportion of lighting from LED bulbs	See Table 2	
Mean trips /person /day	0.8	(Lojowska et al., 2012)
Mean wake time	0700 hrs	(Dorofaeff and Denny, 2006; Galland et al., 2020)

Mean sleep time	2200 hrs	(Dorofaeff and Denny, 2006; Galland et al., 2020)
Departure and arrival time	Varies	(Anderson et al., 2020; Lojowska et al., 2012)
Proportion of electric HWCs	86%	(Isaacs et al., 2010)
Average HWC thermostat setpoint (T_{set})	62 °C	(Isaacs et al., 2010)
HWC inlet temperature (T_{in})	15 °C	(Bulleid, 2019)
HWC outlet temperature (T_{out})	40 °C	
HWC ambient temperature (T_{amb})	18.1 °C	(Isaacs et al., 2010)
Average HWC heater power (P_{HWC})	1500 W	(Isaacs et al., 2010)
Average HWC volume (V_{HWC})	150 L	(HeatingForce, 2017)
Average hot water demand	50 L/person/day	(Basson, 1983; Parker et al., 2015)
K_{loss}	0.854 W/K	(Bishop et al., 2023b; Isaacs et al., 2010; Williams et al., 2023a)
Timestep (dt)	60 seconds	
Electricity cost	0.25 NZD/kWh	(Genesis Energy, 2023; Ministry of Business Innovation and Employment, 2025)

2.3. Analyses: Implementation and assessments

Peak electricity demand in Aotearoa New Zealand occurs in the winter (June-August) (Kamana-Williams et al., 2023). Thus, to determine the effects of each intervention on peak electricity demand, all eight neighbourhoods are modelled for each of the nine cases (72 total, including the baseline for each) for the entire month of June. Median electricity demand profile, total peak demand, and average electricity cost per household are recorded for each case. The effects of each intervention on peak electricity demand per household is assessed in each neighbourhood, as follows:

- Appliance efficiency [**App**]: peak demand case 2 – peak demand case 1.
- Lighting efficiency [**LED**]: peak demand case 3 – peak demand case 1.
- Increasing the insulation of all houses in an average neighbourhood [**Ins(ave)**]: peak demand case 4 – peak demand case 1.
- Increasing the insulation of houses with electric heaters [**Ins(eH100)**]: peak demand case 7 – peak demand case 6.

- Replacing electric heaters with heat pumps [**HP(eH100)**]: peak demand case 8 – peak demand case 6.
- Increasing the insulation of houses with electric heaters and replacing those heaters with heat pumps [**Ins + HP(eH100)**]: peak demand case 9 – peak demand case 6.
- Increasing the insulation of houses with non-electric heaters and replacing those heaters with heat pumps [**Ins + HP(eH0)**]: peak demand case 9 – peak demand case 5.

2.3.1. Cost-benefit analysis

Annual costs of each intervention are calculated according to the values in Table 4. Health system savings for interventions including retrofit insulation are calculated according to the average total health system savings (7,494 NZD, after adjusting for inflation between 2013 Q1 and 2024 Q4) from the *Warm Up New Zealand: Heat Smart* study (Grimes et al., 2012), which accounted for reduced mortality and reductions in hospitalisation and pharmaceutical use from warmer homes, which reduce the incidence of respiratory and other illnesses (McCormack et al., 2016). In this work, “health outcomes” refers specifically to those related to indoor temperature, the health system savings of which are calculated for Aotearoa New Zealand in the *Warm Up New Zealand: Heat Smart* study (Grimes et al., 2012). These health system savings are amortised over the expected lifetime of 15 years for retrofit insulation (Building Performance, 2023).

Annual average electricity system savings from peak demand reductions across the eight modelled neighbourhoods are calculated for each intervention at 241 NZD/kW(peak)/year, 41% of which is attributed to the incumbent electricity distribution business (Reeve et al., 2021). Average net savings are calculated by subtracting total annual costs from total combined savings, and benefit-cost ratios are calculated as the ratio of gross savings to total costs.

Table 4. Average total cost and lifetime of energy efficiency interventions in Aotearoa New Zealand.

	Average total cost [NZD]	Lifetime [years]	Source
Heat pump installation	2,000	15	(Gen Less, 2025a; One Air, 2024)
Retrofit insulation	1,010	15	(Building Performance, 2023; Grimes et al., 2012)
LED bulbs replacement	414	14	(Gen Less, 2025b; Isaacs et al., 2010)
Appliance replacement	17,000	10	(Cahill, 2023)

3. Results

Change in average electricity demand in June for the selected neighbourhoods of 50 houses in Auckland and Christchurch from the installation of heat pumps and retrofitted insulation is shown for houses with non-electric heaters (i.e., replacing non-electric heaters with heat pumps) in Figure 3, and for houses with electric heaters (i.e., replacing electric heaters with heat pumps) in Figure 4. In all cases, total electricity demand increases (5% - 23% from Auckland Decile 1 to Christchurch Decile 10) when heat pumps replace non-electric heaters, such as gas fires, and decreases (27% - 37%) when heat pumps replace electric heaters. These differences are larger in Christchurch than Auckland, due to its colder climate, and larger in Decile 10 (highest-income) than Decile 1 neighbourhoods, due to increased heating use in higher socioeconomic households.

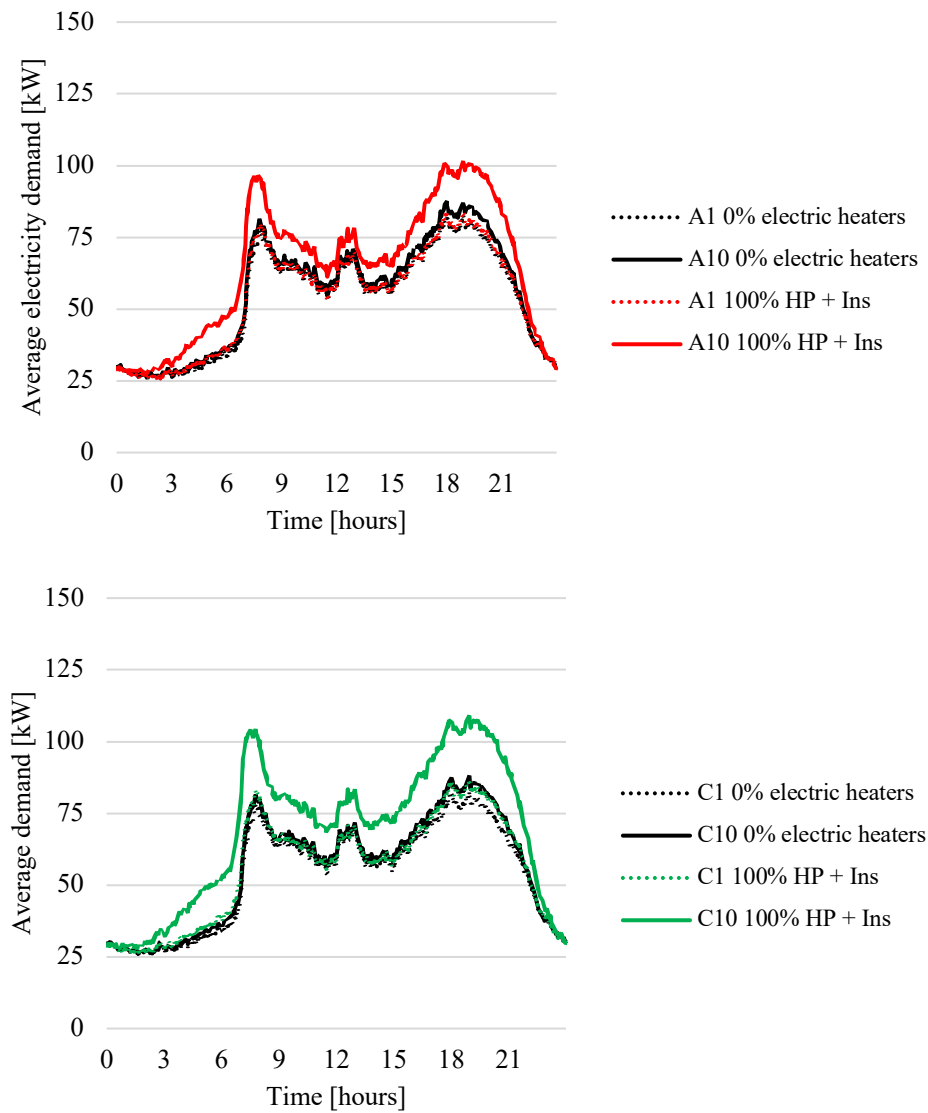


Figure 3. Total average electricity demand in June for Decile 1 and 10 neighbourhoods in Auckland (top) and Christchurch (bottom) in case 5 (0% electric heaters, black) and 9 (100% heat pumps + insulation, red/green).

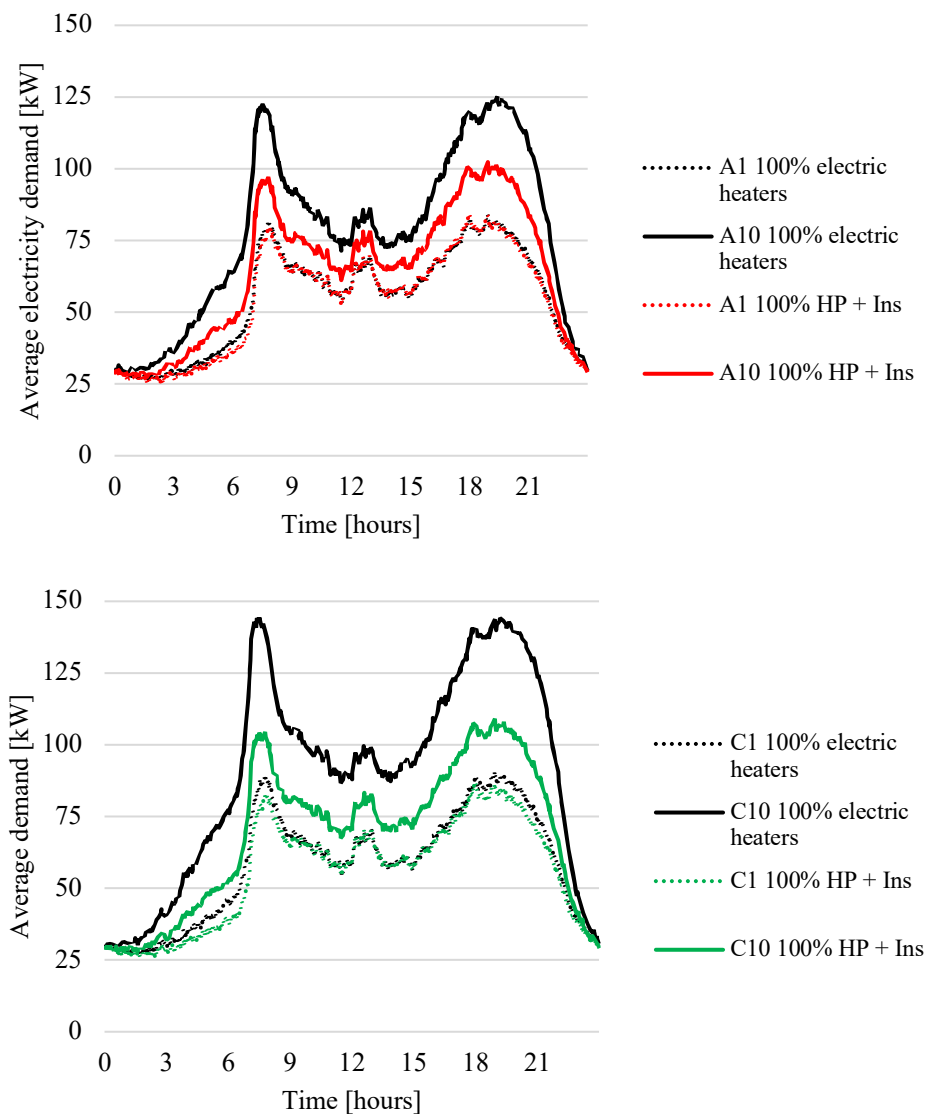


Figure 4. Total average electricity demand in June for Decile 1 and 10 neighbourhoods in Auckland (top) and Christchurch (bottom) in case 6 (100% electric heaters, black) and 9 (100% heat pumps + insulation, red/green).

Changes in winter peak electricity demand per house from appliance, lighting, and heating efficiency interventions are shown in Figure 5. Peak electricity demand is increased (5% - 23%) by the replacement of non-electric heaters with heat pumps, and decreased by all other interventions. Changes are larger in higher-decile neighbourhoods, and changes from heating interventions are larger in Christchurch than Auckland, due to Christchurch's colder climate. Peak

demand reductions range from -0.13 to -0.23 kW/house (6% to 8% reduction) for the installation of LED bulbs, to -0.80 to -1.64 kW/house (27% to 37% reduction) for the installation of heat pumps and retrofitted insulation in houses with electric heaters.

Changes in monthly winter electricity cost per house from appliance, lighting, and heating efficiency interventions are shown in Figure 6. Electricity cost increases by 3 to 47 NZD/house/month when heat pumps replace non-electric heaters (due to the replacement of non-electric heaters) and reduces for all other interventions. Monthly reductions range from 13 to 20 NZD/house for LED lightbulbs and 3 to 77 NZD/house for heat pumps and insulation. Changes in electricity costs are higher in higher-decile neighbourhoods, and the effects of space heating interventions are higher in Christchurch than in Auckland.

Distributions of change in peak electricity demand and consumer electricity costs by income are shown in Figures 7 and 8, respectively. Effects of space heating interventions in low- and medium-income neighbourhoods are typically clustered and lower than in high-income neighbourhoods. For example, installing heat pumps and retrofit insulation in houses with electric heaters reduces peak electricity demand in Decile 1-7 neighbourhoods in Christchurch by 0.75-0.90 kW/house (25% - 28% reduction) and by 1.64 kW/house (37%) in the Decile 10 neighbourhood, and mean peak reduction for this population (1.02 kW/house, 29% reduction) is at least 11-36% higher than for the Decile 1-7 neighbourhoods. As with peak electricity demand reductions, changes in household electricity costs for low- and middle- income households are clustered and are lower than those for high-income households. Similarly, mean cost advantage for Decile 10 households is typically higher than average cost change in Decile 1-7 households.

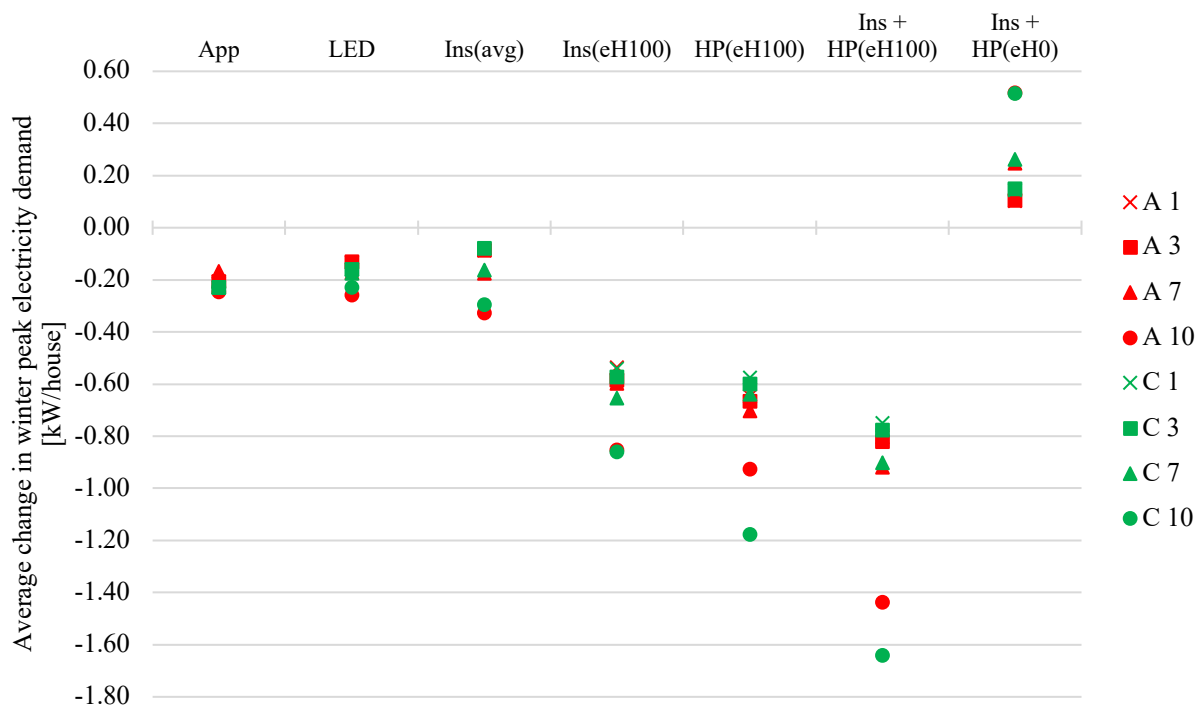


Figure 5. Average change in winter peak electricity demand per house for appliance, lighting, and heating efficiency cases.

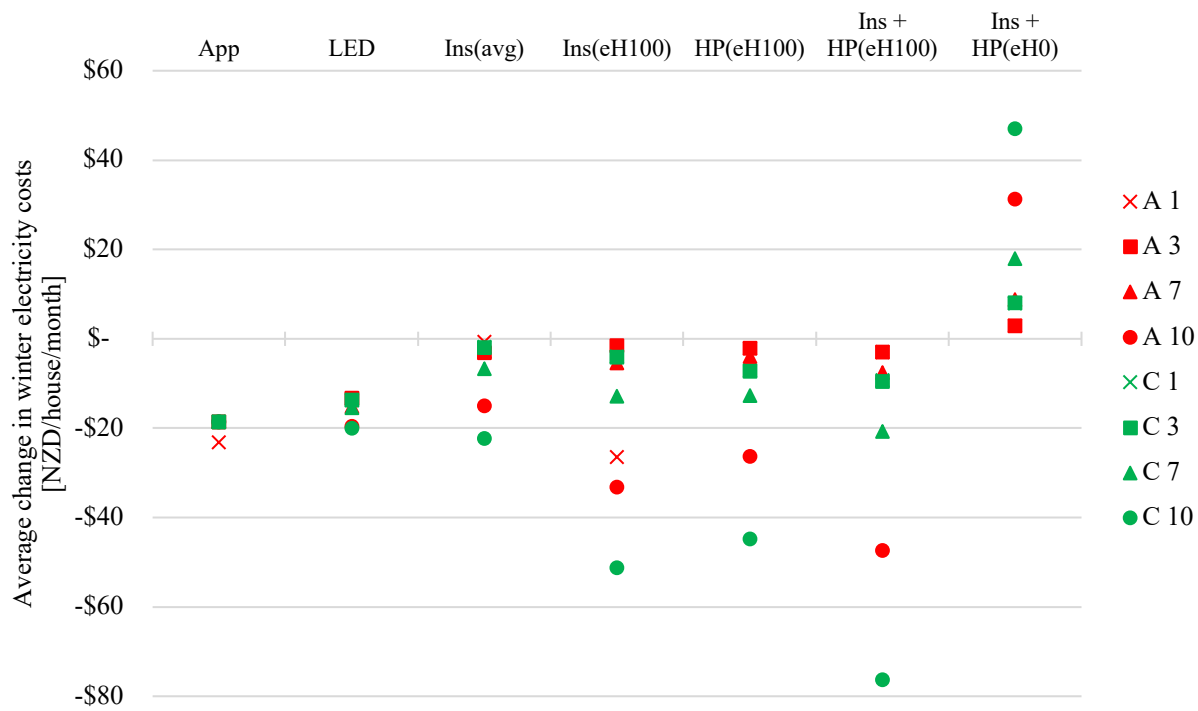


Figure 6. Average change in winter electricity cost per house for appliance, lighting, and heating efficiency cases.

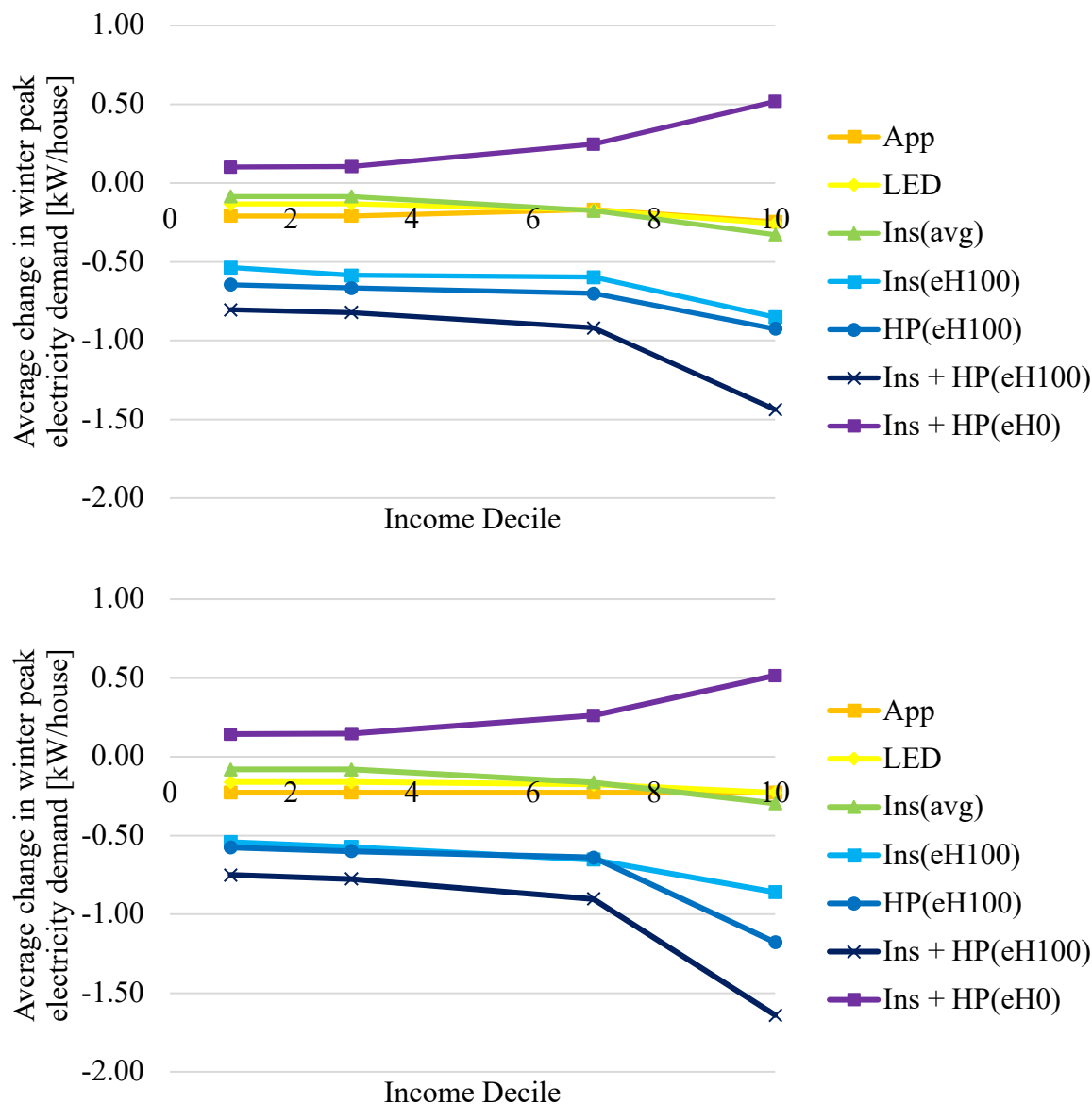


Figure 7. Average change in winter peak electricity demand by income in Auckland (top) and Christchurch (bottom).

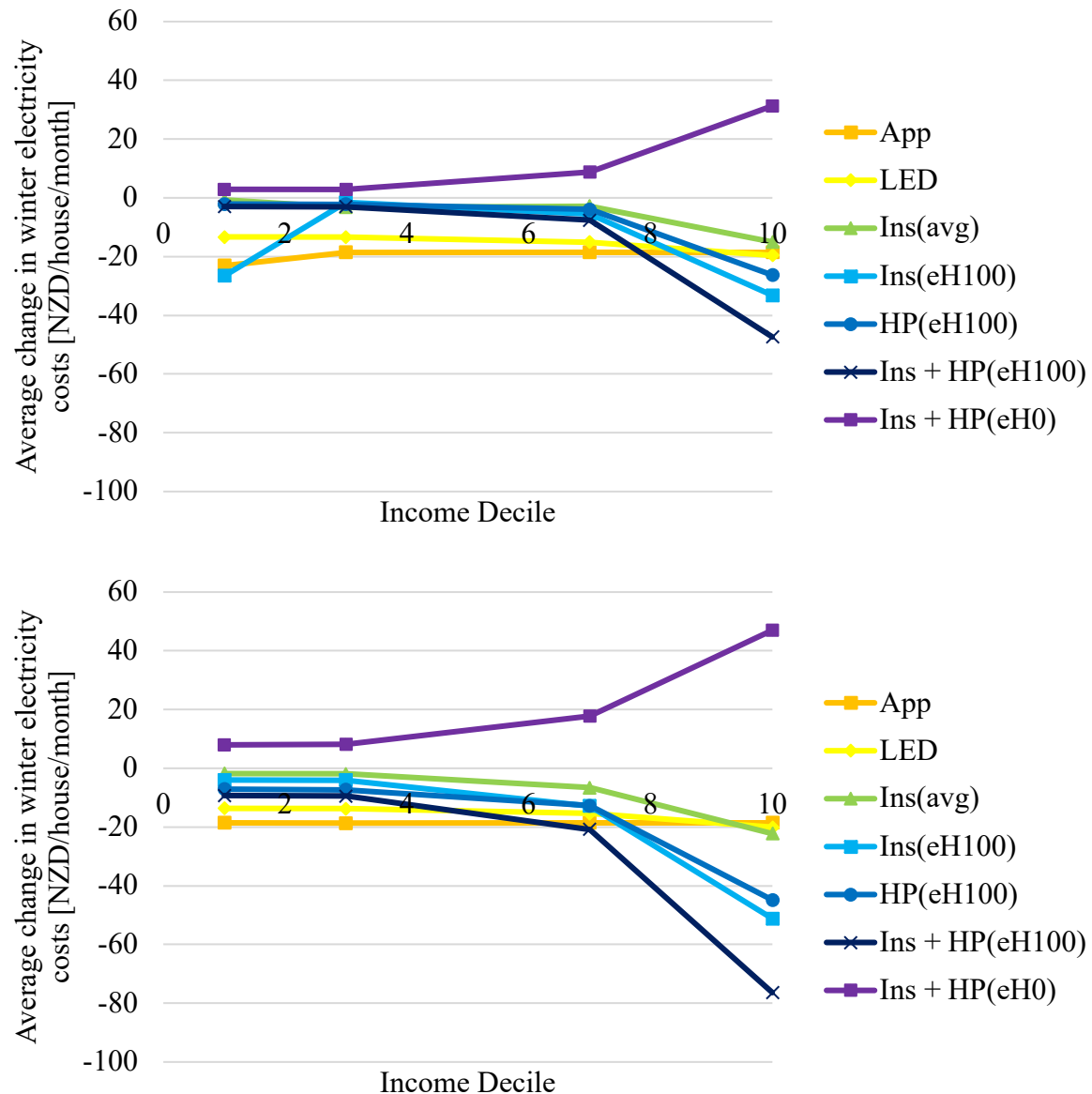


Figure 8. Average change in consumer winter electricity costs by income in Auckland (top) and Christchurch (bottom).

Average derived annual costs, savings, net benefits, and the benefit-cost ratio determined for appliance, lighting, and heating efficiency interventions are shown in Figure 9. The highest- and lowest- cost interventions are the installation of high-efficiency appliances and the replacement of all lightbulbs with LEDs, respectively. Highest net savings are for installing retrofit insulation and heat pumps in houses with electric heaters (807 NZD/year), followed by installation of retrofit

insulation (without heat pumps) in the same houses (797 NZD/year). Highest benefit-cost ratio is for installing retrofit insulation in houses with electric heaters (12.9:1), followed by installing retrofit insulation in all houses (9.2:1) and replacing lightbulbs with LEDs (7.75:1). Lowest benefit-cost ratio is for appliance efficiency (0.2:1), due to the high cost of appliance replacement, followed by installing heat pumps and insulation in houses with non-electric heaters (1.2:1). Results and cost-benefit are compared directly to the *Warm Up New Zealand: Heat Smart* study, which provides important context. In particular, average benefit-cost ratio calculated for the *Warm Up New Zealand: Heat Smart* study was 4:1 (Grimes et al., 2012). In general, interventions including installation of retrofit insulation have the highest net savings, due to demonstrated, large health system cost savings from improved health outcomes, which average 7,494 NZD (adjusted for inflation) per house with installed insulation, amortised over the expected lifetime of 15 years for retrofit insulation.

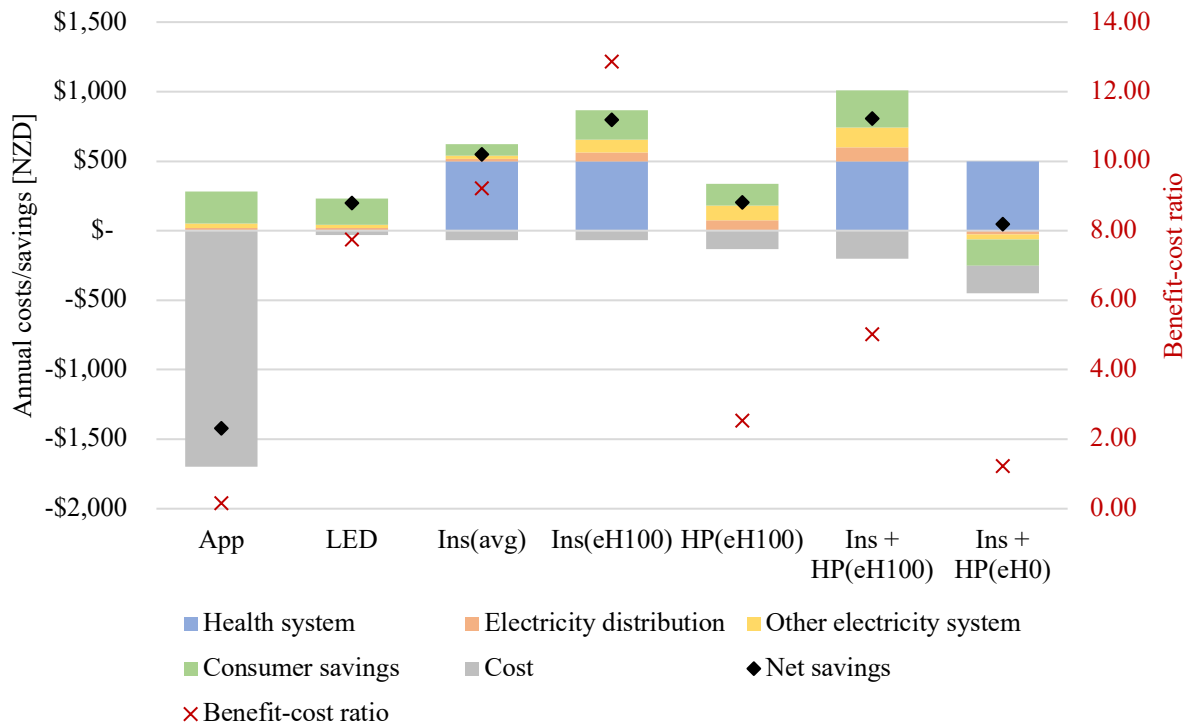


Figure 9. Average annual costs (negative) and savings (positive) from improved health outcomes, changes in peak electricity demand, and consumer electricity bills for appliance, lighting, and heating efficiency cases.

4. Discussion

Energy efficiency interventions can reduce peak electricity demand between 0.08-1.64 kW/house, equivalent to reductions of 4-37% as shown in Figure 5. Where high-efficiency electric loads replace non-electric loads, such as replacing non-electric heaters with heat pumps, peak electricity demand increases by between 0.1-0.52 kW/house, equivalent to increases of 5-24%. Effects on peak demand vary between interventions, with space heating-related interventions having a greater impact in higher-income households and when targeted to houses with electric heating. Space heating-related interventions are also more effective in colder climates, in which higher heating requirements increase the impact of equivalent interventions (Figure 3).

While consumer electricity cost savings for space heating interventions are higher in higher-income households, consumer savings from appliance and lighting efficiency interventions are more consistent across households with different incomes, as shown in Figure 6. In Decile 1 and 3 neighbourhoods in both locations, appliance and lighting efficiency interventions result in greater average cost savings than any space heating intervention. While consumer electricity costs in all neighbourhoods increase when replacing non-electric heaters with heat pumps (Figure 6), the higher efficiency of heat pumps, and of electrified heating in general, compared to combustion heating means total consumer energy costs for space heating will decrease in most cases where energy is purchased externally (Halvorsen and Larsen, 2013; Walker et al., 2022).

While these interventions are assessed in Aotearoa New Zealand, the trends from these analyses are generalisable to other countries and cities. Auckland and Christchurch both experience peak electricity demand in winter (Isaacs et al., 2010) and have oceanic climates, with average winter temperatures of 11 °C and 6 °C and average summer temperatures of 20 °C and 17 °C in Auckland and Christchurch, respectively (National Institute of Water and Atmospheric Research, 2025). Cities with similar climates and seasonality of peak electricity demand in the USA and Europe are San Francisco, CA, and Porto, Portugal, for Auckland and Astoria, OR, and Edinburgh, Scotland, for Christchurch. This modelling approach is also fully generalisable to these and other cities.

A sensitivity analysis is a key part of model validation and was undertaken in previous research validating the models used in this work (Kamana-Williams et al., 2025a). Key outcomes of this sensitivity analysis included: (i) changing behavioural profiles affects both peak demand and total

energy use; (ii) peak demand is more sensitive to behavioural variations than total energy use, with variations of +/-50% in behavioural profiles for each appliance type yielding changes of up to 10% in peak demand and 5.7% total demand; and (iii) magnitude of these changes depends on both the size of the load (shown in Table A1) and its baseline probability (shown in Figure 1). These results highlight the importance of behavioural profile accuracy, as these input profiles drive agent behaviour and electricity demand. Thus, this model's extensive validation (Kamana-Williams et al., 2025a; Williams et al., 2025), which included a full sensitivity analysis and showed the model's accuracy for matching real electricity demand, indicates the results presented here are robust to modelling and/or data errors.

4.1. Incentive design and targeted interventions

The installation of heat pumps reduces electricity demand when replacing electric heaters, due to heat pumps' increased coefficient of performance, but increases demand when replacing non-electric heaters (Figures 3-5). Thus, electricity distributors or retailers aiming to reduce peak demand could provide incentives for heat pumps to replace electric heaters, but not to replace non-electric heaters. Additionally, as peak demand reductions for space heating efficiency interventions are larger for houses in higher-socioeconomic neighbourhoods, those interested only in reducing peak electricity demand, such as some electricity companies, could consider targeting interventions towards higher-income households. In such situations, electricity price signals may be a sufficient incentive, as higher-income households typically have greater capacity and capital for upfront efficiency investments.

However, targeted intervention towards Decile 1-7 households is likely to improve economic efficiency, as shown in Figures 7 and 8, and could also yield larger improvements in health outcomes and health system savings, which are higher in lower-income households (Grimes et al., 2012). Existing research also identifies solutions for public housing residents and other low-socioeconomic households (Copiello, 2015; Peralta et al., 2017), allowing the design of specific targets based on alternative supply arrangements with housing providers, such as governments or non-governmental organisations. Such policies could include subsidies for increased insulation and/or heat pumps for tenants, public housing residents, and other marginalised communities.

Without such targeted interventions, generalised policy to reduce peak electricity demand could increase energy and health inequalities, as higher-income households typically already have warmer, drier homes (Howden-Chapman et al., 2012). Additionally, although peak demand reductions and savings for electricity companies are higher in higher-income neighbourhoods, health system savings are larger contributors to overall cost savings (Figure 9). Even for the intervention with the largest peak demand reduction (installing heat pumps and retrofit insulation in houses with electric heaters), annual health system savings for the Aotearoa New Zealand cases examined here are more than twice those of the average electricity system savings.

Further, improved health outcomes and health system savings from retrofit insulation are higher in lower-income households, due to typically lower insulation levels and lower heating use (Grimes et al., 2012), so interventions to reduce whole-system costs would be better targeted towards installing insulation in lower-income households, despite the lower electricity system savings. In such a case, the primary beneficiary of these interventions would likely be the health

system, highlighting the imperative to consider whole-system effects, even for interventions residing primarily in a sector, such as electricity, which is not immediately connected to other sectors, such as health. These health system direct cost savings and their dominance also show the difficult and narrow range of achieving net profitable interventions based on direct system costs alone, where gaps show the cost range which needs to be covered by incentives, subsidies, or other savings.

Equally, these results show the potential difficulty in creating incentive schemes where the primary beneficiary may not be directly involved in the electricity purchase-consumption transaction. In these cases, co-funding platforms and/or public health funding could encourage cross-sector collaboration to increase indoor air temperatures and address the causes of poor health. Alternatively, where feasible, governments could increase insulation and clean heating standards for housing, particularly for rental and public housing, which is typically of lower quality than owner-occupied properties (Lang et al., 2022). Such funding models are not considered here but are an important direction for future research.

All space heating interventions have net positive average annual savings, as shown in Figure 9, including the replacement of electric heaters with heat pumps, which does not provide the health system benefits of increased insulation. Average benefit-cost ratio is highest for interventions only involving retrofit insulation (9.2:1 for Ins(avg) and 12.9:1 for Ins(eH100)), due to the low cost of retrofit insulation and high health system benefits of warmer homes. Benefit-cost ratio for the interventions involving heat pumps and/or insulation across all households is between 1.2:1 to

12.9:1, compared to an average of 4:1 calculated for the *Warm Up New Zealand: Heat Smart* study (Grimes et al., 2012).

The only energy efficiency intervention with benefit-cost ratio less than 1:1, indicating higher costs than benefits, is appliance efficiency (Figure 9). Average total cost to replace home appliances is estimated at 17,000 NZD (Cahill, 2023), including capital and labour costs, meaning upfront cost and capital required to purchase higher-efficiency appliances is more than eight times higher than for any other intervention assessed in this work, which will further increase barriers to energy efficiency for lower-income households. This higher cost assumes the purchase price would be attributed entirely to the higher efficiency of new appliances, while in most houses, higher-efficiency appliances would likely be purchased when replacing existing appliances for other reasons. While high-efficiency appliances can have higher upfront costs than lower-efficiency alternatives (McNeil and Bojda, 2012; Olatunde et al., 2024), the total marginal cost of installing high-efficiency appliances will be lower than 17,000 NZD per household. However, installing high-efficiency appliances only when replacing existing appliances would only gradually reduce peak electricity demand, and these reductions could thus reduce the peak demand increases from current trends in increasing size and number of appliances (Cabeza et al., 2018). Thus, meaningful reductions in peak electricity demand are only expected to occur with increased appliance efficiency standards, although these increases will likely increase average appliance replacement costs, which would increase financial burdens for low-income households. Additionally, any perceived benefits could be outweighed by the proliferation of larger appliances (Cabeza et al., 2018; Jones and Lomas, 2016; Statista, 2024) and/or the addition of new appliances, such as electric vehicles (Liasi and Golkar, 2017; Ramadhani et al., 2021; Su et al., 2019). Other non-fiscal

approaches may be necessary to overcome such barriers, such as incentivisation of appliances with greater demand flexibility, including times and delay functions.

Improving lighting efficiency requires the lowest costs of any intervention assessed in this work (Figure 9), with an average cost of 414 NZD to replace all lightbulbs, assuming a cost of 18 NZD per lightbulb (Gen Less, 2025b) and 23 lightbulbs in an average house in Aotearoa New Zealand (Isaacs et al., 2010), and an average lifetime of 14 years (Gen Less, 2025b). However, as with appliance replacements, the marginal cost of installing LED bulbs would be lower if LEDs were installed only when already replacing existing lightbulbs. To encourage installation of LED lightbulbs over lower-efficiency alternatives, efficiency standards for lighting could also be increased, particularly for new constructions.

Increasing efficiency standards for appliances, lighting, insulation, and heaters would likely disadvantage lower socioeconomic households, due to the increased cost of higher-efficiency alternatives (Solà et al., 2021). Thus, to ensure uptake across the socioeconomic spectrum, interventions to reduce peak electricity demand would likely need to be incentivised by electricity retailers or distributors. Demand aggregators, which are increasingly prevalent in electricity markets around the world, could also consider incentivising energy efficiency improvements. This study points to the need for some form of direct subsidy for low-income households, who would otherwise be unable to afford the improvements.

While energy companies know when and where network improvements are required, they will not benefit from the improved health outcomes or improved energy equality. Thus, for interventions

involving increased household insulation, subsidies could consider the health system benefits and could thus be offered in conjunction with government social programmes, rather than solely by energy companies. Consideration of the full range of system-wide benefits from energy efficiency interventions could thus increase access to these improvements, reducing peak electricity demand and consumer electricity costs as well as improving health outcomes and reducing health system costs.

The design of any subsidies or incentives must consider the likely effects for the full range of households and should not rely solely on mean or average outcomes. Differential space heating behaviour, with lower-income households heating their houses to lower temperatures, means the effects of space heating interventions on electricity demand and consumer costs vary across the socioeconomic spectrum. As shown in Figures 7 and 8, the effects of space heating interventions for Decile 1-7 neighbourhoods are clustered, and are considerably lower than both the mean effect and the measured effect in Decile 10 neighbourhoods. As house sizes are unchanged between neighbourhoods, these changes are direct results of differences in heating behaviours.

Hence, if subsidies were designed according to the mean or average benefit in these figures, their implementation would disproportionately benefit high-income households. In particular, even Decile 7 households, which may be considered high-income by policymakers, would benefit considerably less than Decile 10 households, and publicly funded subsidies would constitute an indirect transfer of wealth from low- to high- income households. Thus, accounting for skew in the expected results of energy efficiency interventions, particularly those involving space heating,

would reduce the potential for real and perceived inequality in such programs and better reduce energy poverty in low-income households.

4.2. Limitations and future work

Socioeconomic variation is assessed by varying the average income of households in the modelled neighbourhoods to match income deciles 1, 3, 7, and 10 in Aotearoa New Zealand. In the agent-based model, this variation of income affects a household's wealth coefficient (WC), a proxy of spending power, which in turn affects energy use through mechanisms such as lower heating use in households with lower wealth coefficients. In reality, heating use is affected by additional factors than just spending power, which in turn can be affected by more than just household income. While further research could investigate the impact of other socioeconomic variables on energy use, such as benefit status and availability of savings, validation of the agent-based model shows income to be a sufficient proxy for socioeconomic variations at the neighbourhood level (Kamana-Williams et al., 2025a; Williams et al., 2025).

Baseline insulation in all neighbourhoods is the same, regardless of socioeconomic status, and the same amount of insulation ($2 \text{ Wm}^{-2}\text{K}^{-1}$) is added to all houses in retrofit insulation cases. Higher-income households typically have better-insulated houses than lower-income households (Howden-Chapman et al., 2024; Wyatt, 2013), so these assumptions are likely simplifications, as higher-income households may be less likely to install retrofit insulation and insulation. However, across the socioeconomic spectrum in Aotearoa New Zealand, houses are typically under-insulated (Howden-Chapman et al., 2021; Leardini and Van Raamsdonk, 2010), and excess winter mortality rates are among the highest in the world [92]. Thus, although higher-income households typically

live in better-insulated houses, households across the socioeconomic spectrum in Aotearoa New Zealand are likely to benefit from increased insulation, so the effects of these assumptions are expected to be minimal.

Costs, benefits, net savings, and benefit-cost ratios for each intervention are calculated using average values, which do not account for socioeconomic or geographic variations. Peak demand reductions and consumer electricity savings from appliance and lighting efficiency interventions are not strongly dependent on income (Figures 5 and 6), so the effects of these assumptions are expected to be minimal for appliance and lighting interventions. While the peak demand reductions from space heating interventions are higher in higher-income households (Figures 5 and 6), the health system benefits from improved health outcomes in houses with retrofit insulation area greater in lower-income households (Grimes et al., 2012), so the net effects of these assumptions in space heating interventions may also be minimal.

The effects of appliance efficiency are assessed using a 50% reduction in average appliance electricity demand. While appliance efficiency trends continue to improve (Energy Efficiency Strategies, 2015), differences in electricity demand of 50% are among the highest currently available from existing appliance efficiency improvements (McNeil and Bojda, 2012). Thus, while future efficiency improvements may exceed these amounts, the appliance efficiency improvement interventions presented in this work should be considered representative of a realistic upper bound on the effects achievable by installing currently available high-efficiency appliances. As discussed in Section 4.1, incentivising appliances with high demand flexibility, such as delayed-start timers, could further reduce peak electricity demand.

The agent-based model used in this work calculates total neighbourhood electricity demand at each timestep as the simple sum of demand in constituent households. As such, grid constraints, such as distribution transformer load limits, are not explicitly considered. However, neighbourhoods are modelled as 50 households to represent a typical number of residential connections to a single low-voltage distribution transformer (Watson et al., 2014) and to match levels used in model validation, which yielded peak loads well below transformer rated capacities (Kamana-Williams et al., 2025a; Williams et al., 2025). Further, as the neighbourhoods considered in this work are intended to be representative, rather than to match any particular real neighbourhoods, explicit consideration of grid constraints is excluded to ensure the generalisability of results to a range of potential implementation cases. Thus, the choice of 50 households per neighbourhood implicitly considers network constraints by limiting loads to those typically seen in a typical low-voltage distribution network, without compromising model generalisability. In addition, the model used in this work is fully generalisable to considering different neighbourhood sizes, transformer types, and network configurations, such as modelling demand in medium-voltage transformers and the effects of specific grid constraints, where sufficient data and computing power are available.

Heat pump coefficient of performance (COP) in this work is assumed to be unchanged between cities. In reality, heat pump COP varies between cities based on climatic factors and is typically higher in Auckland than Christchurch (Page, 2009), so the increased electricity demand for space heating in Christchurch compared to Auckland may be larger than modelled in these analyses. However, COP also varies with many other factors, such as heat pump model, refrigerant, size, and cycle type (Chua et al., 2010; Staffell et al., 2012), the inclusion of which would considerably

increase model complexity and limit generalisability. Further, validation of the underlying agent-based model shows this assumption of constant COP does not hinder the model's ability to accurately capture heating demand and aggregate electricity demand in multiple locations and seasons in Aotearoa New Zealand (Kamana-Williams et al., 2025a; Williams et al., 2025).

Increasing lighting efficiency by installing LED bulbs is expected to reduce peak electricity demand by 0.13-0.26 kW/house, equivalent to total reductions of 270-520 MW (~3-8% of total (Kamana-Williams et al., 2023)) across Aotearoa New Zealand's 2.03 million households (Statistics New Zealand, 2018). These national estimates are lower than in other research with top-down modelling, which estimates a lower bound of 500 MW peak reductions from increased residential lighting efficiency in Aotearoa New Zealand (Dortans et al., 2020). However, the bottom-up nature of the model in this work, which accounts for behavioural differences within and between households, means it is better able to capture the potential non-linearities of such efficiency interventions, which may limit the practical scalability of simple calculations for peak load reduction. In other words, this model, unlike top-down models, can account for the fact not all households use the same amount of lighting at the same time, and thus contribute differing amounts to peak demand reduction.

Effects of the interventions assessed in this work on peak electricity demand are assessed for current demand scenarios, as calculated by the agent-based model. Thus, peak demand reductions are for current peak times. However, the adoption of new technologies and behaviours, such as electric vehicle smart charging, has the potential to change times of overall peak electricity demand (Daina et al., 2017; Morais et al., 2014). The results of these analyses may not be applicable to

situations in which electricity demand curves, and thus the times of peak demand, fundamentally change. However, the modelling approach presented in this work is applicable to such situations, and the underlying agent-based model is readily generalisable to a range of electricity demand scenarios, including widespread adoption of electric vehicles, due to its consideration of the fundamental drivers of energy use behaviour (Kamana-Williams et al., 2025a; Williams et al., 2025).

Rebound effects in these analyses are assessed using an average space heating setpoint increase of 0.25 °C for every 1 Wm⁻²K⁻¹ increase of additional insulation, matching average outcomes measured in community trials of increased insulation (Howden-Chapman et al., 2007). Other rebound effects, such as increased lighting use with efficient LED bulbs, are not assessed, as sufficient data on these effects are unavailable. Thus, while not considered in this work, increases in lighting and appliance efficiency could increase use, which could negate the energy and power demand reductions of the efficiency improvements. Additionally, the economic analyses presented in this work do not consider motivations which could drive uptake outside of the standard rational economic model, such as gamification (Hamari et al., 2014; Lee et al., 2024) or uptake among peers (Moglia et al., 2018). However, agent-based models are considered ideal tools for assessing both gamification (Ahrweiler et al., 2024) and social influence (Nguyen et al., 2021; Olszewski et al., 2019), and the approach used in this work is fully generalisable to these cases and to other behavioural changes, such as rebound effects, the effects of which could be the subject of future research.

The cases assessed in this work cover a range of appliance, lighting, and space heating efficiency interventions but are not an exhaustive list of potential energy efficiency interventions. The effects on peak electricity demand and system-wide costs/benefits of other energy efficiency interventions, such as improvements to HWC insulation or hot water heat pumps, could also be assessed. These assessments, and the effects of other non-efficiency related interventions, such as the installation of solar panels, house- and neighbourhood- level energy storage, and the adoption of demand response programs, are the subject of intended future research.

5. Conclusions

The effects on peak electricity demand and whole-system costs and benefits of seven appliance, lighting, and space heating efficiency interventions in eight residential neighbourhoods in Aotearoa New Zealand are assessed using an agent-based model. Energy efficiency interventions can reduce peak electricity demand, with reductions of 1.64 kW per house (37% reduction) from the installation of heat pumps and retrofitted insulation in houses with electric heaters. Peak demand changes from space heating-related interventions are larger in higher-income neighbourhoods and larger in Christchurch than Auckland, due to the colder climate. Space heating interventions also have the largest financial benefits, with the highest net savings and benefit-cost ratios observed for retrofit insulation, due to health system savings from improved health outcomes. These results show targeting energy efficiency interventions to maximise both economic and health outcomes is key to ensure whole-system benefits.

Higher-income households show greater peak demand reductions from space heating interventions, while lower-income households benefit more from health system savings due to

typically lower insulation levels and heating use. Policies and incentives should consider these variations to ensure positive whole-system outcomes and avoid exacerbating existing energy and health inequalities. Increasing efficiency standards for appliances, lighting, and insulation could further enhance the benefits of these interventions. Such standards could be accompanied by subsidies or incentives for low-income households to ensure widespread adoption and energy equality.

Overall, energy efficiency interventions have the potential to reduce peak electricity demand and consumer electricity costs, and improve health outcomes, but support for adoption of these interventions should be carefully targeted to improve energy access and equality, and whole-system outcomes. Agent-based models can incorporate a range of consumer behaviour, including intra- and inter- consumer variability, and can be used to inform such efforts.

Future work could test the utility of wider socioeconomic drivers of energy use and assess the impacts of a wider range of energy efficiency and demand response interventions on peak electricity demand and system cost/benefits. Benefit would also come from further development of the model to take full account of national demographic data and thus enable such a tool to be used for national benefit analysis and the assessment of policy interventions targeted towards improving the wellbeing of disadvantaged groups.

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Appendix: 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 A1. 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”.

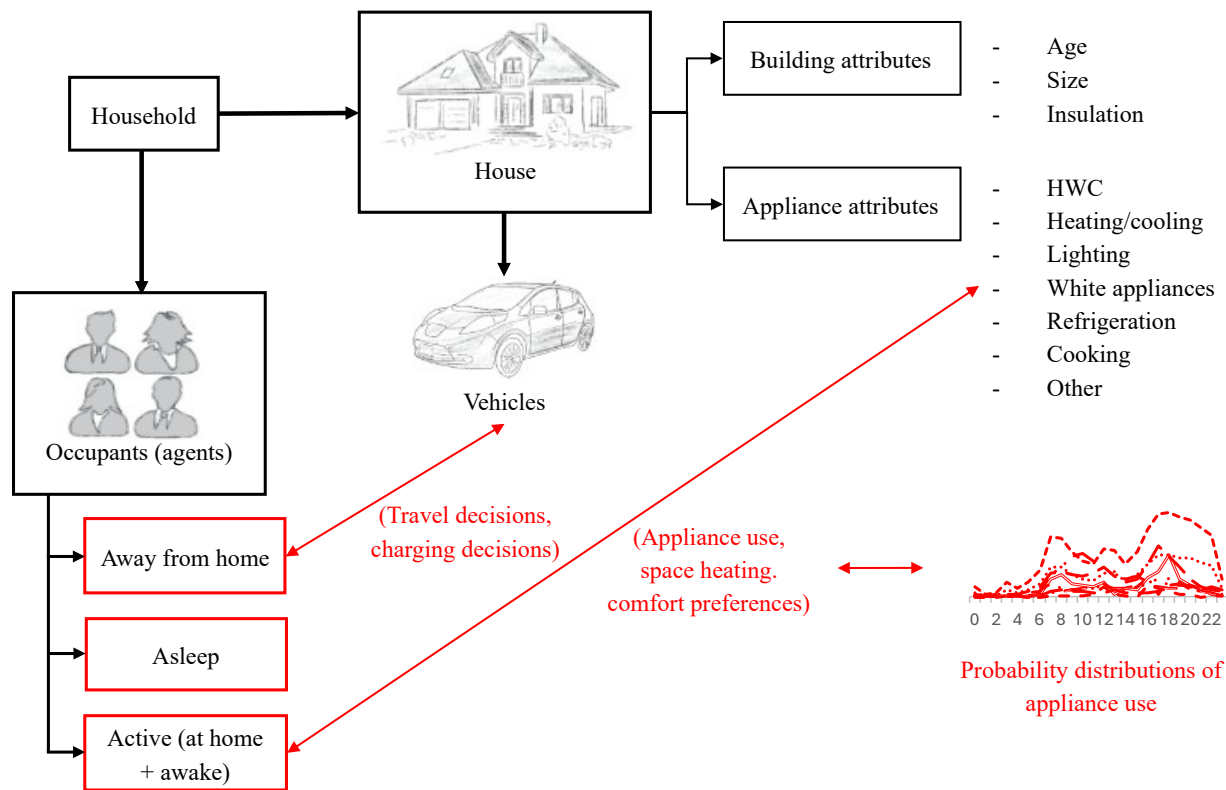


Figure A1. Architecture of the agent-based model.

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”:

$$WC_i = \begin{cases} 0 & I_{house,i}/N_{occupants,i} < I_{avg} \\ I_{house,i}/N_{occupants,i}/I_{avg} & I_{avg} < I_{house,i}/N_{occupants,i} < 2I_{avg} \\ 1 & 2I_{avg} < I_{house,i}/N_{occupants,i} \end{cases} \quad (A1)$$

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].

A1. 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 (Dorofaeff and Denny, 2006; Galland et al., 2020). 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 (Kamana-Williams et al., 2024). 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 (Lojowska et al., 2012). In this model, these variables are generated from independent normal distributions matching average national patterns (Anderson et al., 2020; Ministry of Transport, 2022). 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.

A2. Appliance use behaviour

Active agents interact with their surroundings. The probability of appliance use varies according to appliance type and time of day. These distributions are based on appliance- and household- level datasets in the United Kingdom (Kelly and Knottenbelt, 2015; Yilmaz et al., 2017) and a national

time-use survey in Italy (Bizzozzero et al., 2016), and adjusted according to data from appliance prevalence and use in 397 randomly selected houses Aotearoa New Zealand (Isaacs et al., 2010).

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 A1.

Table A1. Mean appliance power demand and runtime (from (Cetin et al., 2014; Dortans et al., 2019; Kelly and Knottenbelt, 2015; Pipattanasomporn et al., 2013)).

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 A2.

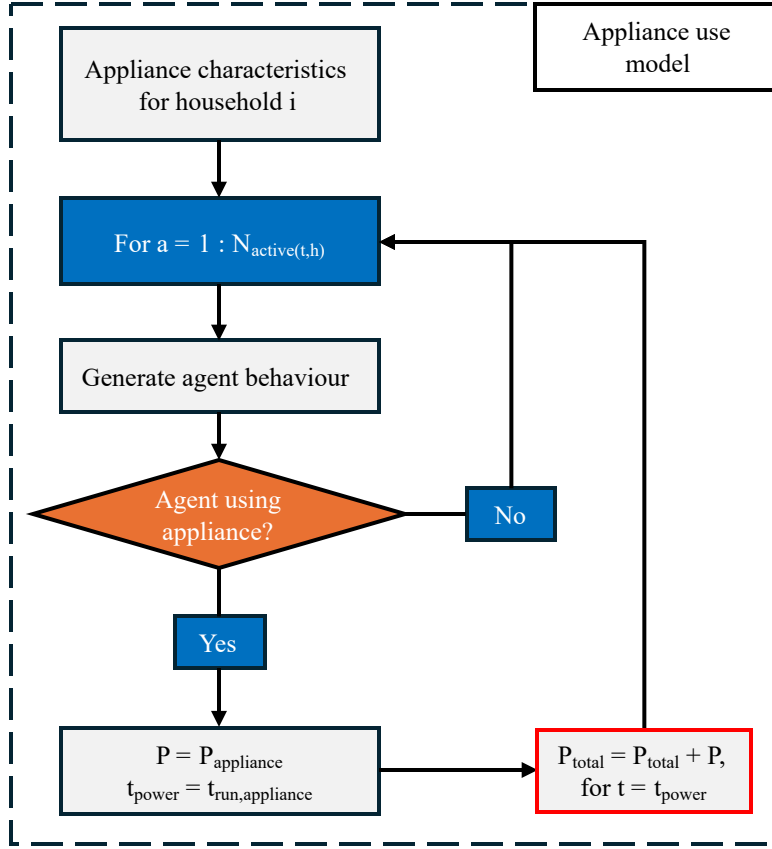


Figure A2. Flowchart describing the appliance use model.

A3. Lighting use

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

$$P_{\text{light,max}} = (N_{\text{active},i}/N_{\text{occupants},i}) (1 - (L_{\text{light}}/L_{\text{light,max},i})) P_{\text{bulb},i} N_{\text{bulbs},i} \quad (\text{A2})$$

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

A flowchart summarising the lighting use sub-model is shown in Figure A3.

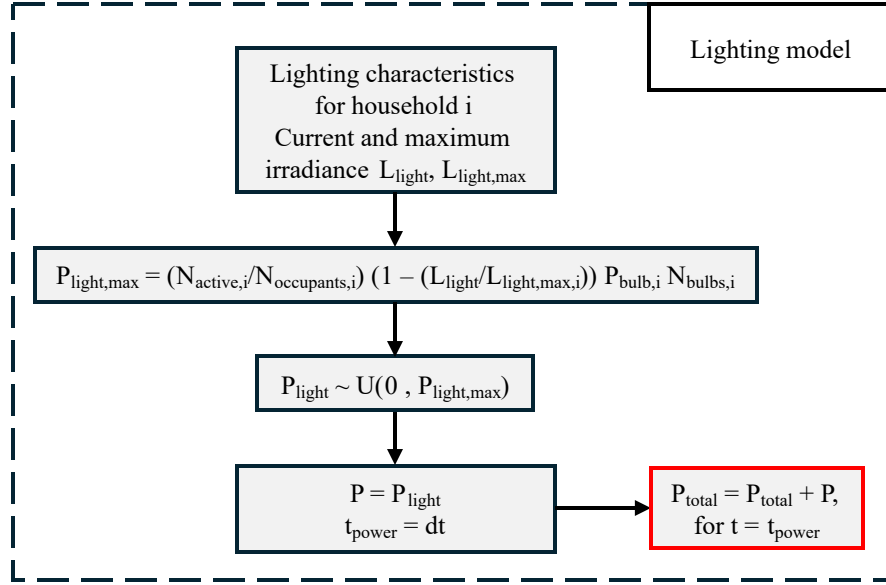


Figure A3. Flowchart describing the lighting use model.

A4. 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 (Battini et al., 2023a, 2023b; Bishop et al., 2024, 2023a). Insulation levels are assigned according to the minimum insulation requirements of the year in which the building was constructed, as shown in Table A2.

Table A2. Minimum insulation requirements by build year and zone [$\text{Wm}^{-2}\text{K}^{-1}$], from the New Zealand Building Codes 1978-2021 (Ministry of Business Innovation and Employment, 2021). Higher zone indicates colder climate.

Year	Zone 1			Zone 2			Zone 3		
	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:

$$\text{BLC} = (A_{\text{floor}} / R_{\text{floor}}) + (A_{\text{walls}} / R_{\text{walls}}) + (A_{\text{roof}} / R_{\text{roof}}) + (A_{\text{windows}} / R_{\text{windows}}) \quad (\text{A3})$$

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 (Howden-Chapman et al., 2024, 2009). Thus, household “heating temperature” ($T_{\text{heat},i}$ [K]), the temperature below which occupants of household i turn on heating, is defined:

$$T_{\text{heat},i} = T_{\text{heat,min}} + (T_{\text{min},i} - T_{\text{heat,min}})WC_i \quad (\text{A4})$$

where $T_{\text{min},i}$ [K] is the minimum comfort temperature of household i and $T_{\text{heat,min}}$ [K] is the minimum temperature below which all agents turn on heating, which varies between regions in Aotearoa New Zealand (Isaacs et al., 2010).

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:

$$\dot{T}_{\text{house}} = -(T_{\text{house}} - T_{\text{outside}}) * \text{BLC} + P_{\text{heater}} / \text{HC}_i \quad (\text{A5})$$

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 A4.

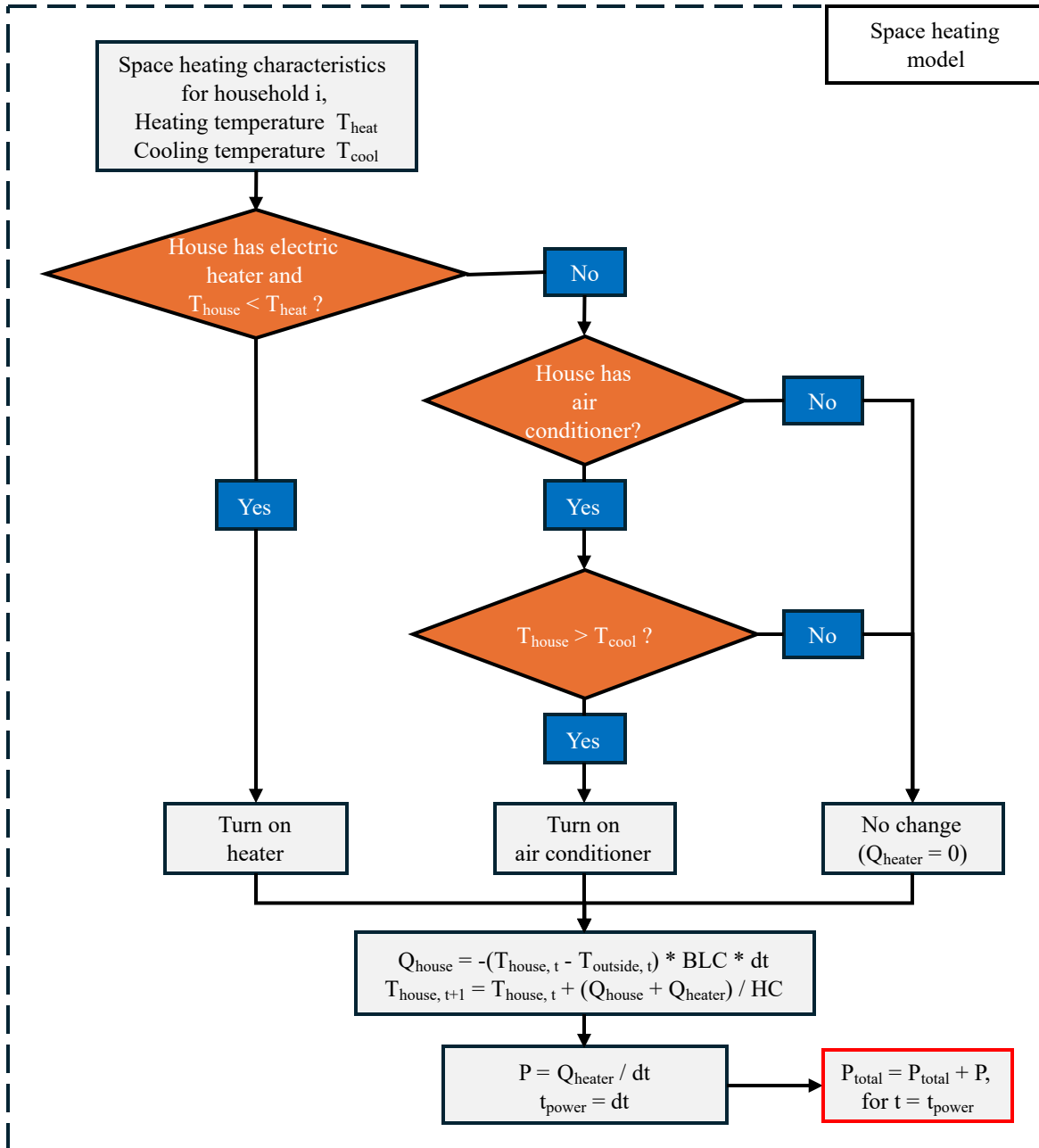


Figure A4. Flowchart describing the space heating model.

A5. Water heating

Electric hot water cylinders (HWCs) are present in over 85% of houses in Aotearoa New Zealand (Isaacs et al., 2010), but this proportion varies by neighbourhood. For houses with electric HWCs, cylinder sizes are assigned according to industry-standard recommendations for occupancy level

(HeatingForce, 2017). Hot water demand profiles are generated using DHWcalc (Jordan and Vajen, 2005) with average daily hot water use of 50 L per person (Basson, 1983; Parker et al., 2015). DHWcalc stochastically generates domestic hot water demand profiles according to household occupancy levels, and is widely use where hot water demand data are unavailable (Braas et al., 2020; Kepplinger et al., 2015; Ochs et al., 2020; Pulkkinen and Louis, 2021). HWC temperatures are calculated at each timestep according to a model presented in previous work (Bishop et al., 2023b; Williams et al., 2023a):

$$\dot{T}_{HWC} = (P_{HWC} - Q_{DHW} - Q_{loss}) / (C_p * V_{HWC}) \quad (A6)$$

$$Q_{DHW} = K_{mix} * \dot{V} * C_p * \rho (T_{HWC} - T_{in}) \quad (A7)$$

$$Q_{loss} = K_{loss} (T_{HWC} - T_{house,i}) \quad (A8)$$

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 [$\text{Jkg}^{-1}\text{K}^{-1}$], 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:

$$K_{mix} = \begin{cases} (T_{out} - T_{in}) / (T_{HWC} - T_{in}), & T_{HWC} \geq T_{out} \\ 1, & T_{HWC} < T_{out} \end{cases} \quad (A9)$$

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 A5.

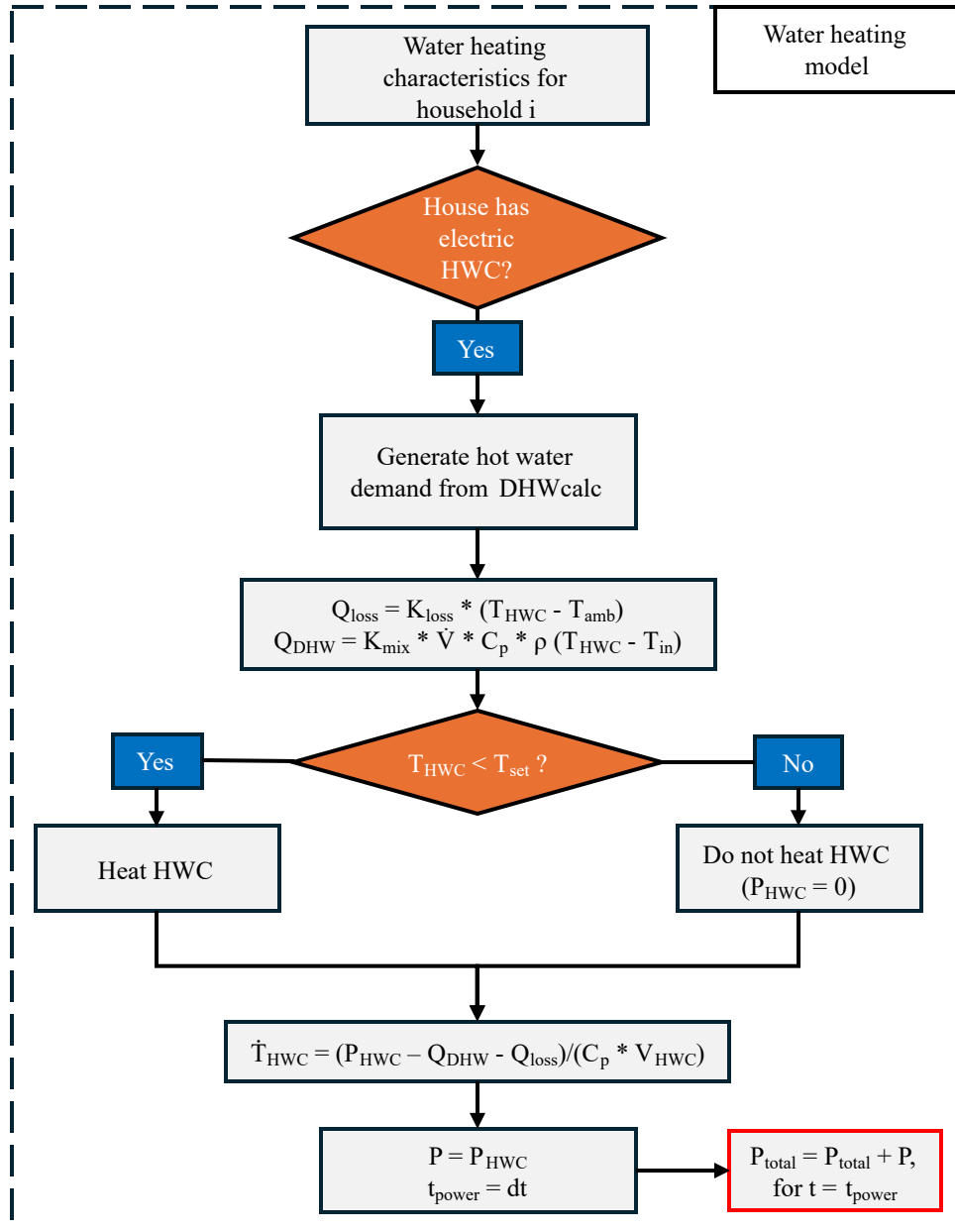


Figure A5. Flowchart describing the water heating model.