Peak demand, consumer costs, and socioeconomic effects: Considerations for distributed generation and energy storage

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Abstract

Electrification is a key approach for reducing greenhouse gas emissions but will increase peak demand, challenging electricity systems. Distributed generation (DG) from solar photovoltaic (PV) panels and battery storage are often offered as potential solutions.

This study uses a previously validated agent-based model of residential electricity demand to assess the impact of solar DG on peak electricity demand, system costs, and consumer electricity costs in eight neighbourhoods with different incomes and across different locations in Aotearoa New Zealand.

Increasing solar PV capacity reduces grid energy use and peak demand, as expected. Peak demand reductions increase with battery storage, up to 0.17 kW (6%) per household. Average consumer electricity costs reduce between 25.20 NZD/month to 184.00 NZD/month. Highest savings of 1,364.00 NZD/year (net savings) are achieved with 10 kW PV panels, while greatest costs of -577.00 NZD/year (net cost) are incurred by 1 kW PV panels with 10 kWh battery. Greatest changes are in wealthier neighbourhoods in colder climates.

These results highlight the trade-off between seeking reductions in consumer costs and peak demand. A key finding is the suboptimality of battery storage for consumer cost reductions, suggesting incentives for battery storage, or reductions in cost, may be required to reduce peak demand. Incentives should consider uptake by lower-income households, which would reduce energy poverty without sacrificing energy system benefits.

Highlights

- Solar PV and battery storage reduce household energy demand and costs.
- Peak demand reductions up to 8.3 kW (6%) with battery storage and solar PV.
- Average whole-system net savings of up to 1364 NZD/year with 10 kW PV panels.
- Battery storage increases upfront costs, negating savings in some cases.
- Subsidies should consider peak reduction, socioeconomic disparity, energy poverty.

Keywords: Solar photovoltaic; Battery storage; Peak electricity demand; Energy poverty; Distributed generation

Word count: 6631

1. Introduction

Rapid emissions reductions are desired to reduce greenhouse gas (GHG) emissions and mitigate negative impacts due to climate change [1]. In general, electrification is considered a key component of climate change mitigation strategies [2], and many countries and regions have explicitly set targets for electrification [3–6]. In the residential sector, electrification is particularly important for reducing emissions from space heating [7–9] and transport (through the adoption of electric vehicles) [10–12].

However, increased electricity demand from electrification presents challenges, particularly for energy systems with constrained supply and aging networks. For example, electricity demand is expected to increase by 400-700% in the USA by 2050 [13,14], requiring new generation capacity to be built at up to six times the current rate. In Aotearoa New Zealand, electricity demand is expected to approximately double by 2050 [15], requiring up to 35 billion NZD of additional investment per decade in electricity transmission and distribution networks [16]. These values may increase further as energy demand for data centres expands to supply emerging digital industries [17,18].

These increases in infrastructure investment are driven primarily by increases in peak electricity demand, which dictates requirements for both security of supply, and transmission and distribution network capacities. Additionally, peak demand typically requires marginal electricity generation from gas, diesel, and/or coal-fired power plants [19], so GHG emissions are typically highest during peak demand periods [20–23]. Thus, reducing peak electricity demand acts to both reduce required investment and reduce GHG emissions through a reduction in fossil fuel use and by facilitating increased electrification without compromising energy security.

Methods for peak electricity demand reduction are typically categorised as either demand response or energy efficiency [24]. Demand response refers to intentional shifts in electricity demand in response to signals, such as price signals from electricity retail companies [25,26]. Energy efficiency refers to measures reducing electricity consumption without compromising outcomes, such as reducing space heating demand by increasing building insulation [27,28].

Distributed generation (DG), where electricity is generated close to the location of consumption, such as by residential solar photovoltaic (PV) panels, can also reduce the peak demand in electricity networks. For example, although the presence of solar PV panels does not affect electricity demand at a household level, in-house consumption of electricity generated by those panels (known as "self-consumption") reduces requirements for external supply, thus reducing distribution and transmission network load and marginal generation from centralised power plants. While DG can be from fossil fuels, such as diesel generators in off-grid communities [29,30], emissions reductions from renewable DG, such as solar PV, can augment emissions reductions from electrification by itself.

Governments in countries such as Germany [31,32], Australia [33,34], and the USA [35,36] have subsidised residential DG, primarily to support the energy transition. In Aotearoa New Zealand, such interventions are not subsidised, and a company offering a subscription-based finance model for households to install solar PV panels with no upfront costs failed in 2024 [37]. Approximately

50 MW of distributed solar generation capacity is installed annually in Aotearoa New Zealand [38], equivalent to approximately 0.025 kW/household [39] (although not all of this generation capacity is for residential rooftop solar). However, the high upfront cost of solar installation means uptake is skewed towards higher-socioeconomic households, due to greater access to capital [40]. Even when subsidised, the long payback periods of solar discourage uptake from rental home owners [41], where renters constitute approximately one third of Aotearoa New Zealand households [42] and are primarily in lower socioeconomic deciles [43]. As a result, the benefits are skewed socioeconomically, and the reductions obtained may not be as high as desired or possible.

Previous research on solar DG has shown its potential to reduce GHG emissions [44–46], peak electricity demand [47,48], and consumer electricity costs [49–51]. These benefits can be increased by batteries, which store energy generated during off-peak times, when demand is low, for use during peak times [52]. For example, a review conducted by the World Bank calculates consumer electricity costs can be reduced by 20-30% with distributed solar generation, and a further 10-15% with battery storage [53].

Disparities in solar DG uptake have also been the subject of previous research. Lukanov and Krieger [54] showed solar PV adoption in California, USA, has been persistently lower in disadvantaged communities, indicating California's DG subsidies may be increasing renewable electricity generation at the expense of energy equality. Similarly, Brown [55] showed California's battery storage adoption is concentrated in higher-income communities, despite a state fund targeting support for battery installation in lower-income households. Dorsey and Wolfson [56] assessed socioeconomic disparities using data from an online marketplace for solar auctions, and found solar purchases vary with income and ethnicity, and are lowest in households with low income and/or Black or Hispanic occupants. Sehic et al. [57] conducted telephone interviews, focus groups, and a national survey to assess challenges for energy storage uptake in Australia, and found financial and safety considerations are among households' top concerns. In Aotearoa New Zealand, DG is dominated by rooftop solar, which is typically more cost-effective than small-scale wind turbines [58], and electricity generation from solar DG in 2050 is expected to match generation from onshore and offshore wind combined [59].

To date, research has focused primarily on the effects of DG and energy storage on peak electricity demand, GHG emissions, and consumer energy costs. Where socioeconomic factors pertaining to DG and energy storage have been assessed, these studies have primarily related to the adoption of these technologies. However, research on the potential whole-system savings from DG and any associated storage, and the implications for variations in subsidies/incentives according to socioeconomic factors influencing these savings, has been limited.

This study models the uptake of solar DG, with and without battery storage, in residential neighbourhoods across a range of locations and socioeconomic situations in Aotearoa New Zealand. The effects of solar DG on peak electricity demand, electricity system costs, and consumer electricity bills are assessed, and the implications of these results for electricity system planning and the design of subsidies/incentives are discussed, including their potential effects on energy inequity and energy poverty.

2. Methods

Electricity demand is calculated with an agent-based model of residential electricity use, which has been validated against smart meter data from diverse neighbourhoods in previous work [60,61] and is described in full in the online supplemental file Appendix A. Thus, a short model overview is described here, with full details in supplemental Appendix A and the referenced prior work.

Household occupants are represented by individual agents, and electricity demand is calculated according to the following five sub-models:

- **General agent behaviour**: Decisions around waking, sleeping, and travel are made each day by each agent. Agents can be either asleep, away from home, or at home and awake (denoted “active”).
- **Appliance use**: The probability of active agents using appliances changes with appliance type and time of day [62–64]. When in use, appliances draw electrical power for the duration of their runtime (Appendix Table A1).
- **Lighting**: Lighting use for active agents is generated stochastically, increasing with the proportion of occupants in a household who are active and decreasing with increased outside light levels (Appendix Equation A2).
- **Space heating**: Active agents use heaters when inside temperature is below the household’s minimum heating temperature, which is decided collectively by the members of each household and is lower in lower-income households (Appendix Equation A4).
- **Water heating**: Hot water demand for houses with electric water heaters is generated stochastically with *DHWcalc* [65], a program for modelling domestic hot water use widely used in models where directly measured data are unavailable [66–69]. In houses with electric hot water cylinders, tank temperatures are updated according to a thermal model described in previous work [70,71].

Income affects electricity use in this model two ways: first, appliance use is lower in lower-income households; and second, space heating use is lower in lower-income households due to their reduced minimum heating temperatures and need to restrict costs. All modelled behaviours have been shown to be generalisable to a range of locations and socioeconomic levels in Aotearoa New Zealand, and the model's ability to accurately capture neighbourhood-level electricity demand has been validated across seasons and changes in demand behaviour [60].

2.1. Solar PV and battery storage

Electricity flows in households with PV panels and/or batteries are summarised in Figure 1. Electricity generation from solar PV panels is calculated:

$$P_{PV,i,t} = I_T \, A_{PV,i} \, \eta_{PV,i} \, (1 - P_{mpp,i}(T_{outside,t} - T_{rated,PV,i})) \tag{1}$$

where $P_{PV,i,t}$ is the power generated by panel i at time t [W]; $A_{PV,i}$ is the area of panel i [m^2]; I_T is the solar irradiance on the tilted PV panel [Wm^{-2}]; $\eta_{PV,i}$ is the rated efficiency of panel i; $P_{mpp,i}$ is the temperature coefficient of panel i [K^{-1}]; $T_{outside,t}$ is the outside temperature at time t [K]; and $T_{rated,PV,i}$ is the rated temperature of panel i [K]. In this work, η_{PV} is 20% at $T_{rated,PV}$ = 25 °C, and the temperature coefficient is P_{mpp} = 0.5%/K [72].

Electricity generated by the solar PV panel is preferentially used to meet household electricity demand ("self-consumption"). If full self-consumption is not possible because electricity is not being used in the household or use is minimal, the (excess) electricity generated from the PV panels is used to charge the household battery. If the household's battery is full or no battery is present, the electricity from the PV panels is sold to the grid at a fixed feed-in tariff. Batteries are charged and discharged:

$$SOC_{battery,i,t} = \begin{cases} SOC_{battery,i,t-1} + \eta_{battery} P_{PV,i,t} dt & \text{charging} \\ SOC_{battery,i,t-1} - P_{house,i,t} dt / \eta_{battery} & \text{discharging} \end{cases} \quad (2)$$

where $SOC_{battery,i,t}$ and $SOC_{battery,i,t-1}$ are the state of charge of battery i at time t and time t-1, respectively [J]; $\eta_{battery}$ is the efficiency of battery i, $P_{house,i,t}$ is the power from the battery used to meet demand of household i at time t [W]; and dt is the model timestep [s]. In this work, $\eta_{battery}$ of 90% is used for charging and discharging [73,74].

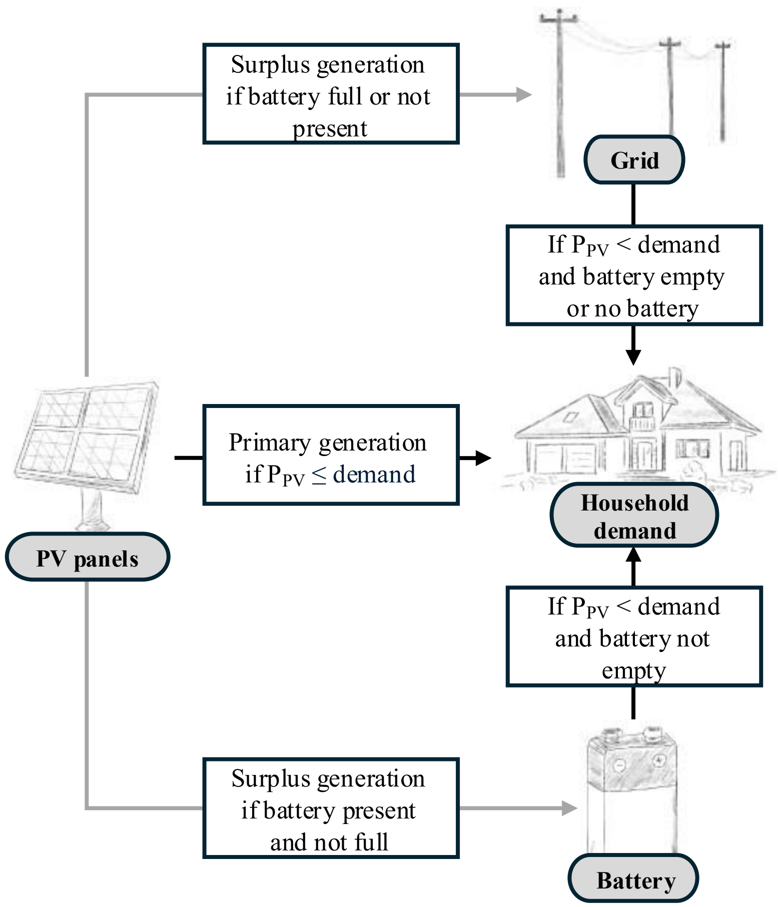

Figure 1. Flowchart showing interactions between PV panels, battery, household demand, and electricity grid. Black arrows indicate primary electricity flows, and grey arrows indicate flows of surplus electricity. Note P_{PV} is the electric power produced by the solar PV panel [W].

2.2. Analyses: Cases examined

Residential low-voltage electricity distribution transformers in Aotearoa New Zealand typically serve around 30-100 households [75]. In this work, neighbourhoods of 50 households, representing a single low-voltage network, are modelled in Auckland and Christchurch, the largest cities on the North and South Islands of Aotearoa New Zealand, respectively. Four neighbourhoods are modelled in each city (eight neighbourhoods total), each with identical model inputs except for their income, as shown in Table 1. Each neighbourhood is modelled in a reference case

("Baseline") with no solar PV panels or battery storage, and eight cases with varying solar PV and/or battery storage capacities, as shown in Table 2. These cases are intended to illustrate a range of plausible solar PV capacities for houses in Aotearoa New Zealand, and to illustrate the effects of varying battery capacity with smaller (1 kW) and larger (5 kW) solar PV panels. Model inputs are summarised in Table 3.

Table 1. Summary of modelled neighbourhoods. 50 houses are modelled in each neighbourhood, with average individual income matching deciles 1, 3, 7, or 10 in Aotearoa New Zealand [39], where decile 10 is the wealthiest and decile 1 the poorest.

Neighbourhood	Location	Average 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)

Table 2. Summary of cases.

Case	Installed capacity of solar PV panels [kW]	Battery storage capacity [kWh]
Baseline	0	0
1 kW PV	1	0
3 kW PV	3	0
5 kW PV	5	0
10 kW PV	10	0
1 kW PV 5 kWh battery	1	5
1 kW PV 10 kWh battery	1	10
5 kW PV 5 kWh battery	5	5
5 kW PV 10 kWh battery	5	10

Table 3. Summary of model inputs.

Variable	Value	Source
Number of houses	50	
Average annual income	See Table 1	
Mean heater power	5000 W	[76]
Mean preferred temperature (max)	24 °C	Estimated from [76]

Mean preferred temperature (min)	16 °C	Estimated from [76]
Mean house age	40 years	[77]
Mean house size	150 m^2	[78,79]
Mean number of floors	1.5	[78,79]
Story height	2.4 m	[78,79]
Mean window-wall ratio	0.22	[80]
Proportion of houses with heat pumps	19%	[76,81,82]
Proportion of houses with electric heaters	30%	[76]
Proportion of lighting from LED bulbs	14%	[76]
Mean trips /person /day	0.8	[83]
Mean wake time	0700 hrs	[84,85]
Mean sleep time	2200 hrs	[84,85]
Departure and arrival time	Varies	[83,86]
Proportion of electric hot water cylinders (HWCs)	86%	[76]
Average HWC thermostat setpoint (T_{set})	62 °C	[76]
HWC inlet temperature (T_{in})	15 °C	[87]
HWC outlet temperature (T_{out})	50 °C	
HWC ambient temperature (T_{amb})	18.1 °C	[76]
Average HWC heater power (P_{HWC})	1500 W	[76]
Average HWC volume (V_{HWC})	150 L	[88]
Average hot water demand	50 L/person/day	[89,90]
HWC thermal loss coefficient (K_{loss})	0.854 W/K	[70,71,76]
Solar PV generation capacity	See Table 2	
Battery storage capacity	See Table 2	
Solar PV panel rated temperature ($T_{rated,PV}$)	25 °C	[72]
Solar PV panel rated efficiency (η_{PV})	20%	[72]
Solar PV panel temperature coefficiency (P_{mpp})	0.5 %/K	[72]
Battery efficiency ($\eta_{battery}$)	90%	[73,74]
Maximum battery charging/discharging rate	10 kW	[91]
Timestep (dt)	60 seconds	
Electricity cost	0.25 NZD/kWh	[92,93]
Electricity feed-in tariff	0.125 NZD/kWh	[92,93]

2.3. Analyses: Implementation, impact assessments, and performance metrics

The model is implemented in MATLAB R2022b. All eight neighbourhoods are modelled in each of the nine cases for 30 days in southern hemisphere summer (January) and winter (June), for a total of 144 model runs. Temperature profiles are obtained from typical meteorological year profiles calculated for Auckland and Christchurch by the National Institute of Water and Atmospheric Research (NIWA) [94]. Irradiance on solar PV panels is obtained from NIWA's *solarview* tool (version 1.2.1: https://solarview.niwa.co.nz/) for North-facing panels tilted at the angle equivalent to the location's latitude (36.9 ° and 43.5 ° for Auckland and Christchurch, respectively) [95]. Average insolation on the tilted solar PV panels in summer and winter are shown in Figure 2. Electricity costs and feed-in tariffs are based on real pricing plans from retailers in Aotearoa New Zealand [92,96,97]. Note electricity costs are modelled as an average of 0.25 NZD/kWh, which is a representative average cost per kWh for residential consumers. Consumers typically also pay fixed charges per day, typically around 1 NZD/day [93], meaning total electricity costs are higher than the product of kWh consumed and cost per kWh.

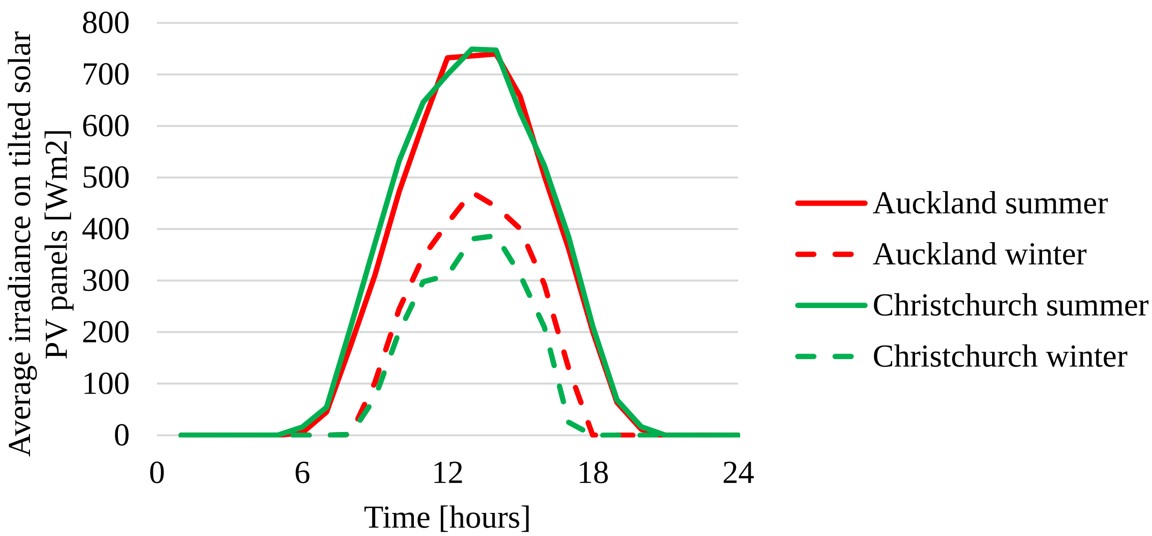

Figure 2. Average solar irradiance on tilted solar PV panels for Auckland and Christchurch in summer (January) and winter (June).

Median electricity demand profiles, peak electricity demand, solar PV generation not used for self-consumption ("unused PV generation"), and household electricity cost savings from feed-in tariffs and reduced consumption from the grid are calculated for each neighbourhood in each case, in summer and winter. Changes to electricity system costs are calculated at 241 NZD/year per additional kW of peak demand (41% of which is for electricity distribution [98]) for changes in winter peak demand, as Aotearoa New Zealand's peak electricity demand occurs in winter (June-August) [99]. Annual costs for solar PV panels and battery storage are calculated according to Table 4, and amortised costs for each intervention are compared with savings for consumers and the electricity system.

Table 4. Average cost and lifetime of solar PV panels and battery storage [100].

	Average installation cost [NZD]	**Lifetime [years]**
1 kW PV panel	3,500	25
3 kW PV panel	5,000	25
5 kW PV panel	11,000	25
10 kW PV panel	20,000	25
5 kWh battery	7,500	15
10 kWh battery	13,000	15

3. Results

Average electricity demand profiles in Decile 1 and 10 neighbourhoods in Auckland and Christchurch with increasing size of solar PV panels and increasing size of battery are shown for June (winter) in Figures 3 and 4 and for January (summer) in Figures 5 and 6. Average unused solar PV generation across all neighbourhoods is shown in Figure 7. Increasing size of solar PV panel increases distributed solar generation, which reduces grid electricity use. With solar PV panel size unchanged, adding a battery or increasing battery size with a sufficiently large solar PV capacity further reduces electricity demand by shifting energy from unused solar PV generation to times with lower generation. These reductions in electricity demand are larger in summer than winter, due to increased solar radiation, and larger in higher-socioeconomic neighbourhoods, due to increased electricity consumption and reduced unused solar PV generation. However, increasing battery capacity has little effect with a small solar PV capacity. For example, electricity production from a 1 kW PV panel is already effectively maximised by the 5 kWh battery, so there is no benefit from a larger battery, as shown in Figure 7.

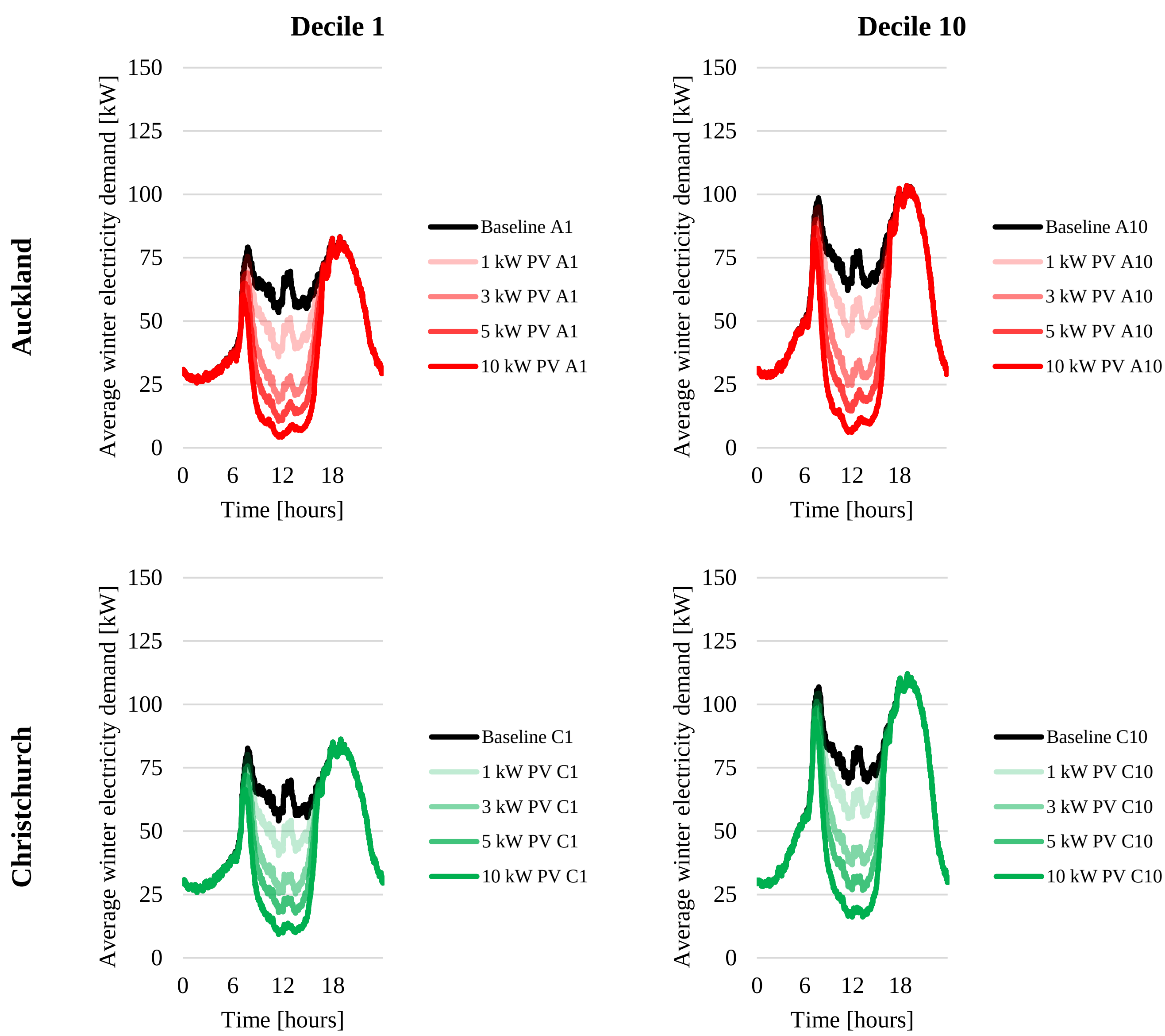

Figure 3. Average winter electricity demand in the baseline case (black line) and with 1 kW, 3 kW, 5 kW, or 10 kW solar PV panel in Decile 1 (left) and 10 (right) neighbourhoods in Auckland (top) and Christchurch (bottom) in the other lines. Cases are labelled as in Tables 1 and 2.

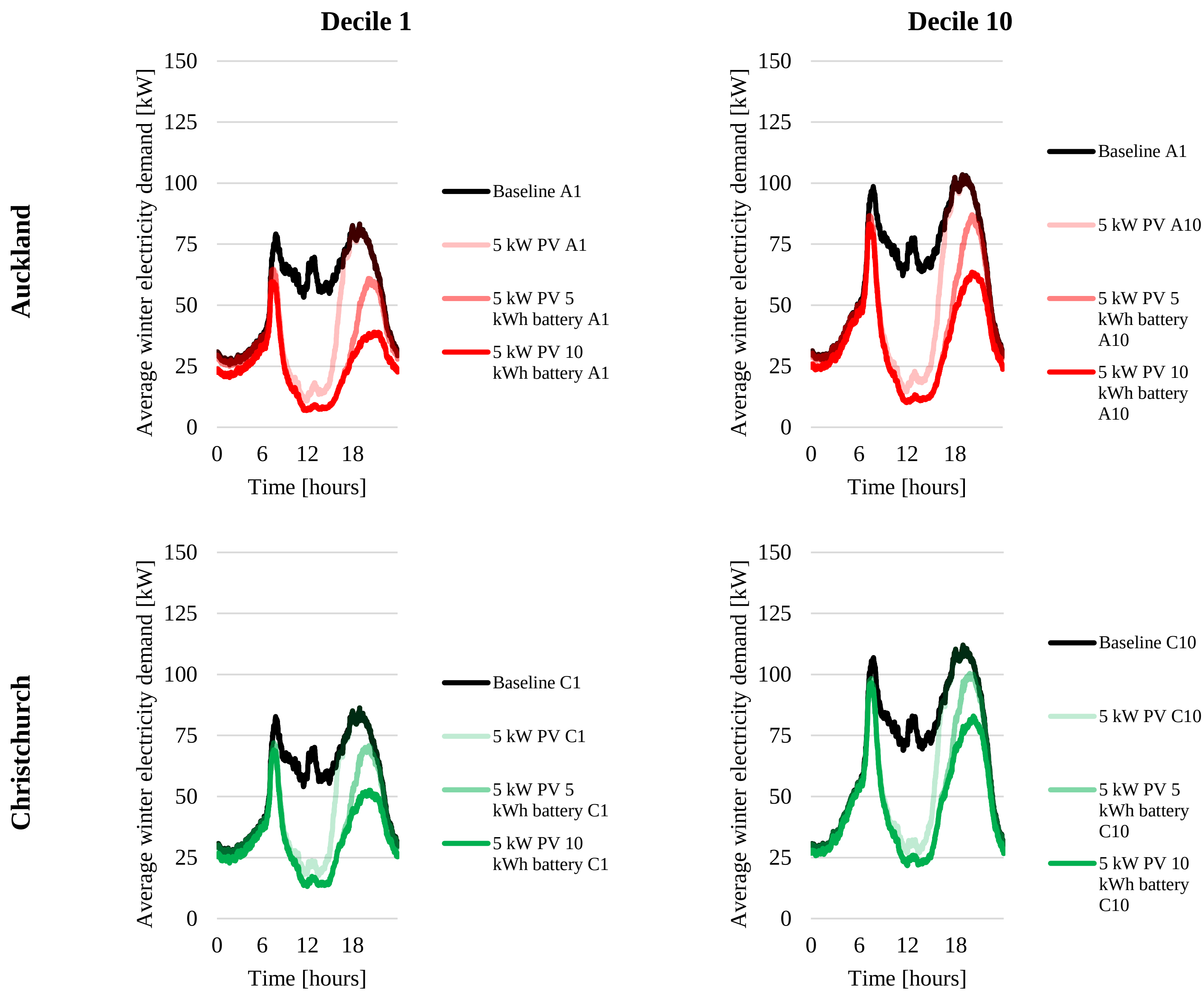

Figure 4. Average winter electricity demand in the baseline case (black line) and with a 5 kW solar PV panel and 5 kWh or 10 kWh battery in Decile 1 (left) and 10 (right) neighbourhoods in Auckland (top) and Christchurch (bottom) in other lines. Cases are labelled as in Tables 1 and 2.

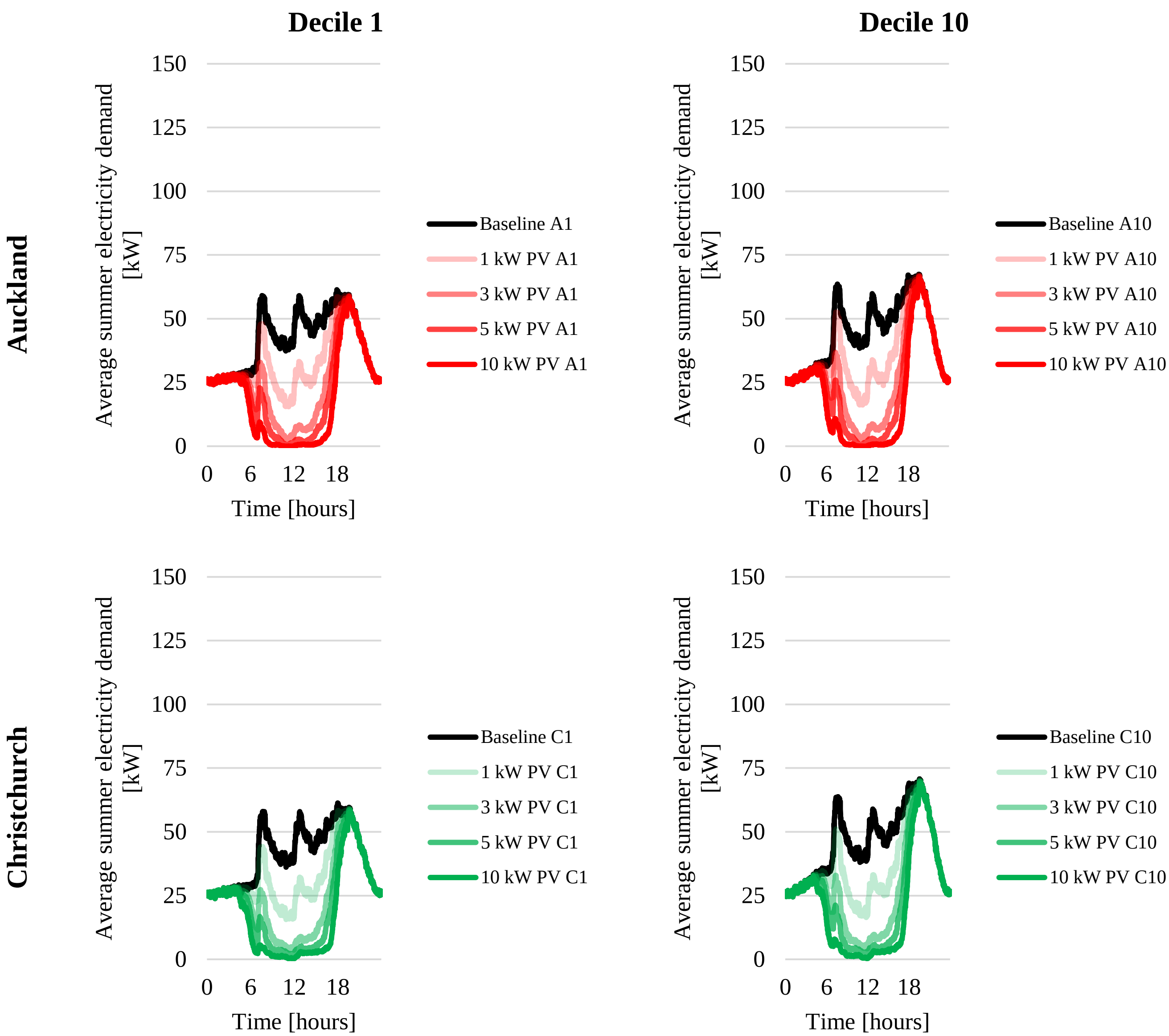

Figure 5. Average summer electricity demand with 1 kW, 3 kW, 5 kW, or 10 kW solar PV panel in Decile 1 (left) and 10 (right) neighbourhoods in Auckland (top) and Christchurch (bottom). Cases are labelled as in Tables 1 and 2.

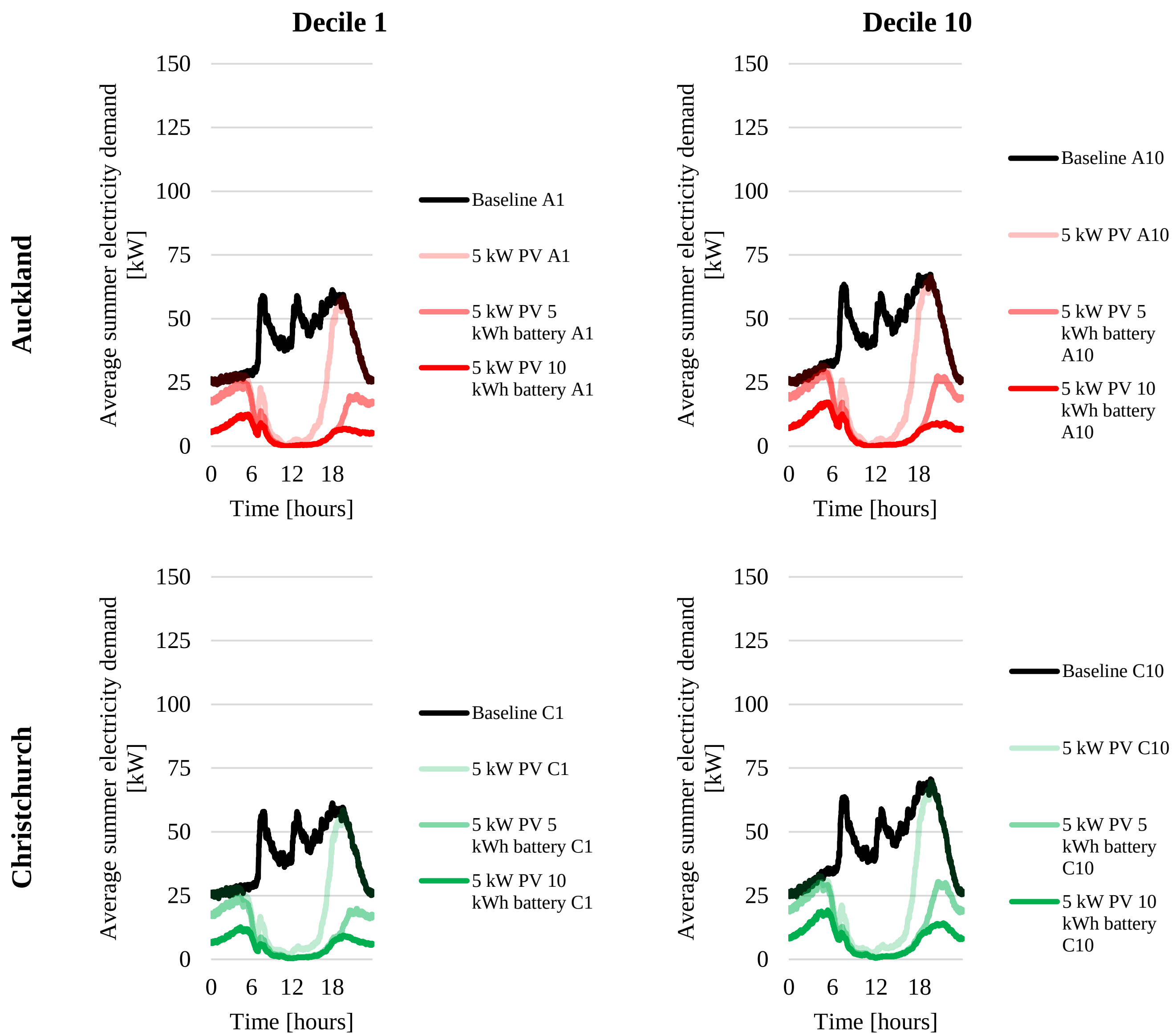

Figure 6. Average summer electricity demand with a 5 kW solar PV panel and 5 kWh or 10 kWh battery in Decile 1 (left) and 10 (right) neighbourhoods in Auckland (top) and Christchurch (bottom). Cases are labelled as in Tables 1 and 2.

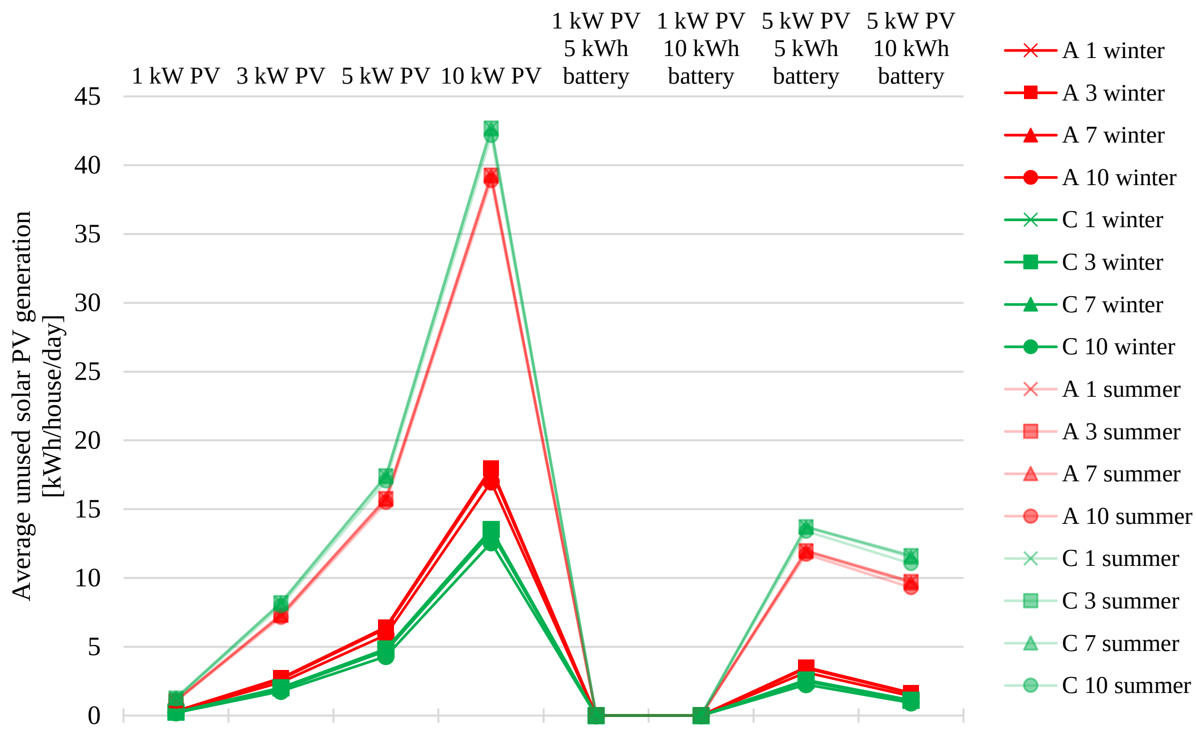

Figure 7. Average surplus solar PV generation exported to the grid in Decile 1, 3, 7, and 10 neighbourhoods in Auckland (red) and Christchurch (green) in winter (solid line) and summer (semi-transparent line). Note small differences between Deciles mean lines largely overlap for each combination of city and season.

Changes in winter peak electricity demand from the installation of solar PV panels and batteries in each neighbourhood are shown in Figure 8. Peak demand is unchanged with a 1 kW solar PV panel in neighbourhoods A10 and C7, and with a 1 kW solar panel and 5 kWh battery in neighbourhood C7. Peak demand reduces in all other cases, between 0.002 kW/house (0.09%) for 1 kW solar PV panels in neighbourhood A7 and 0.167 kW/house (6.39%) for 5 kW solar PV panels and 10 kWh batteries in neighbourhood C10. Peak demand reductions are typically larger in Auckland than Christchurch, due to increased solar radiation, and in higher-socioeconomic neighbourhoods, due to increased electricity consumption in higher-income households.

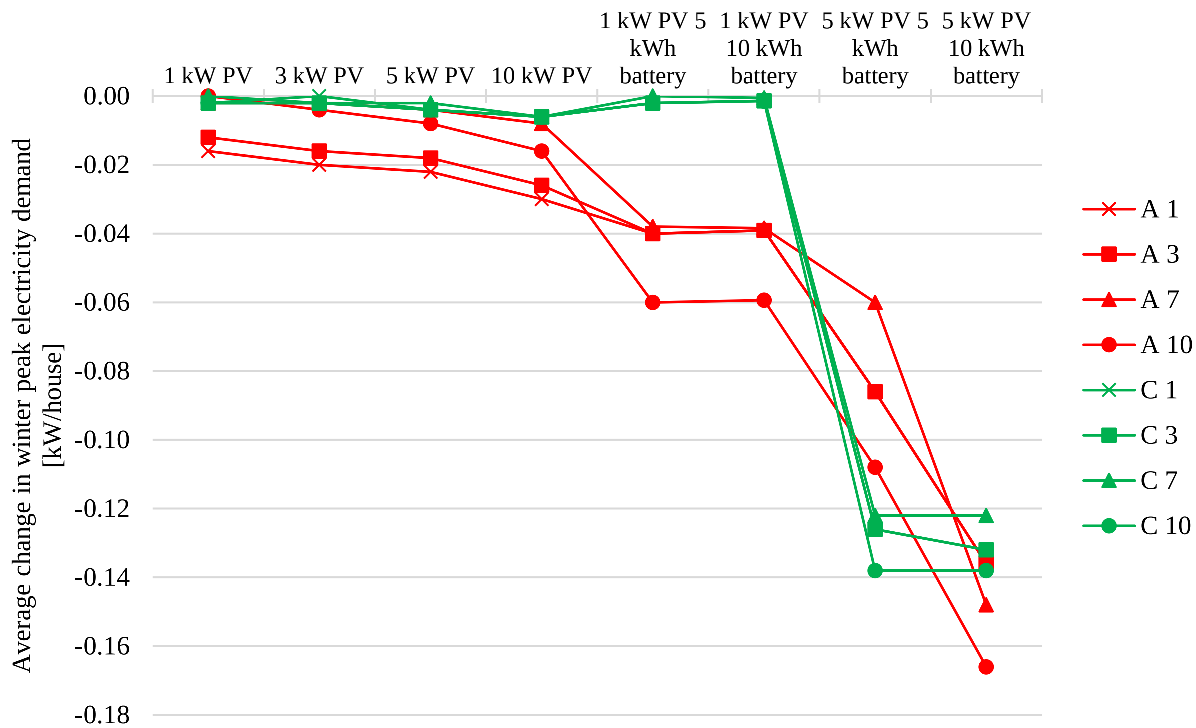

Figure 8. Average change in winter peak electricity demand with solar PV panels and batteries in Decile 1, 3, 7, and 10 neighbourhoods in Auckland and Christchurch. Baseline peak demand is 2.15-2.82 kW/house.

Average changes in electricity costs for households in all neighbourhoods are shown in Figure 9. All interventions reduce electricity costs, with the smallest reductions with 1 kW solar PV panels (25.20 – 26.40 NZD/household/month in neighbourhoods C1 and A10, respectively) and the largest reductions with 10 kW solar PV panels (173.50 – 184.00 NZD/household/month). Batteries increase the magnitude of household cost reductions by 32-36% (increase in savings reduction from installing a 10 kWh battery in addition to existing 5 kW solar PV panels), with reductions increasing with battery size, but these increases are smaller for small solar PV panels with large batteries. Changes in consumer energy cost savings are driven more by location than by income.

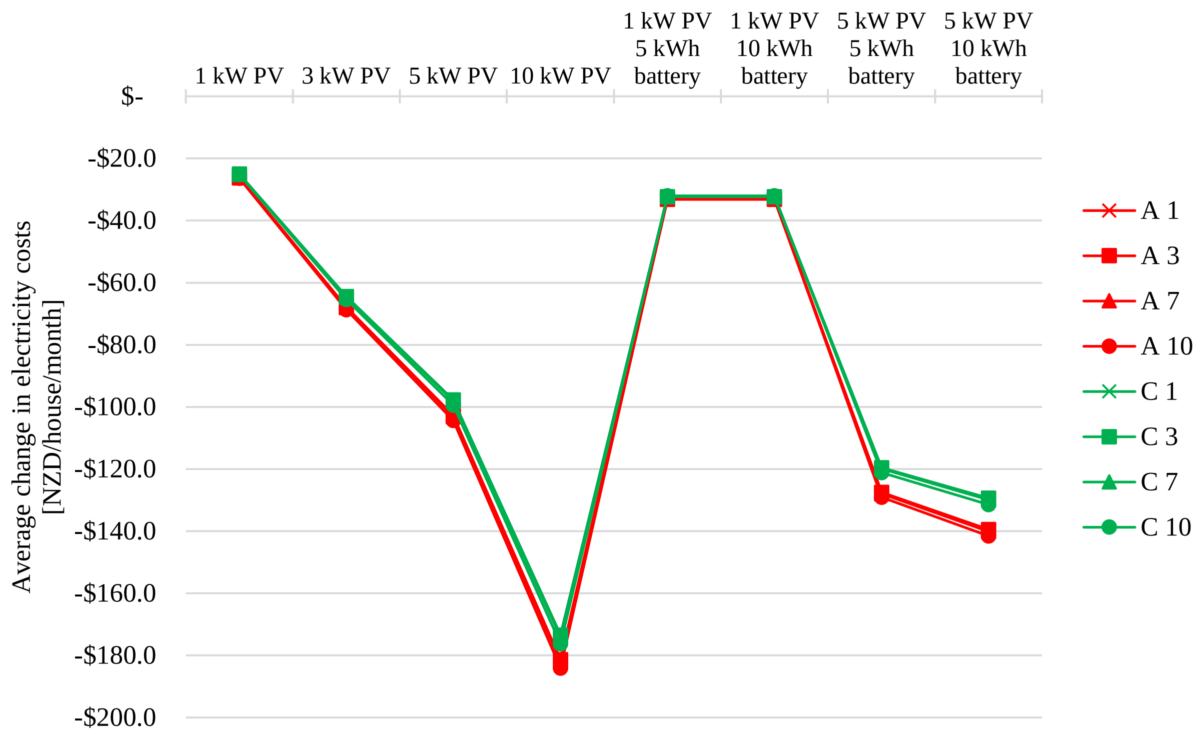

Figure 9. Average change in monthly electricity costs with solar PV panels and batteries, averaged for summer and winter in Decile 1, 3, 7, and 10 neighbourhoods in Auckland (red) and Christchurch (green). Note small differences between Deciles mean lines largely overlap for each city.

Average annual costs, savings, net benefits, and benefit-cost ratios of solar PV panels and batteries are shown in Figure 10. Highest annual net savings of 1364.00 NZD are for 10 kW solar PV panels, and greatest net costs of -577.00 NZD are for 1 kW solar PV panels and 10 kWh batteries, which also has the lowest benefit-cost ratio of 0.4 (net costs). Highest benefit-cost ratio of 4.1 is for the 3 kW solar PV panels case, notably without batteries. Savings are driven primarily by reductions in consumer electricity costs due to self-consumption of solar generated electricity, which contribute over 90% of gross savings in all cases, while costs are driven by battery storage. Total net savings (positive) and costs (negative) by neighbourhood are shown in Figure 11. Variations in the accumulated savings for solar PV panels alone are small, with a maximum variation of 10% across income and geographical location. Relative variations in the savings achieved for PV panels and batteries are larger: average savings for 5 kW PV panels and 10 kWh batteries in decile 10 households in Christchurch (147 NZD/household/year) are 63% greater than decile 1 households in Christchurch (90 NZD/household/year), and 32% lesser than decile 10 households in Auckland (216 NZD/household/year).

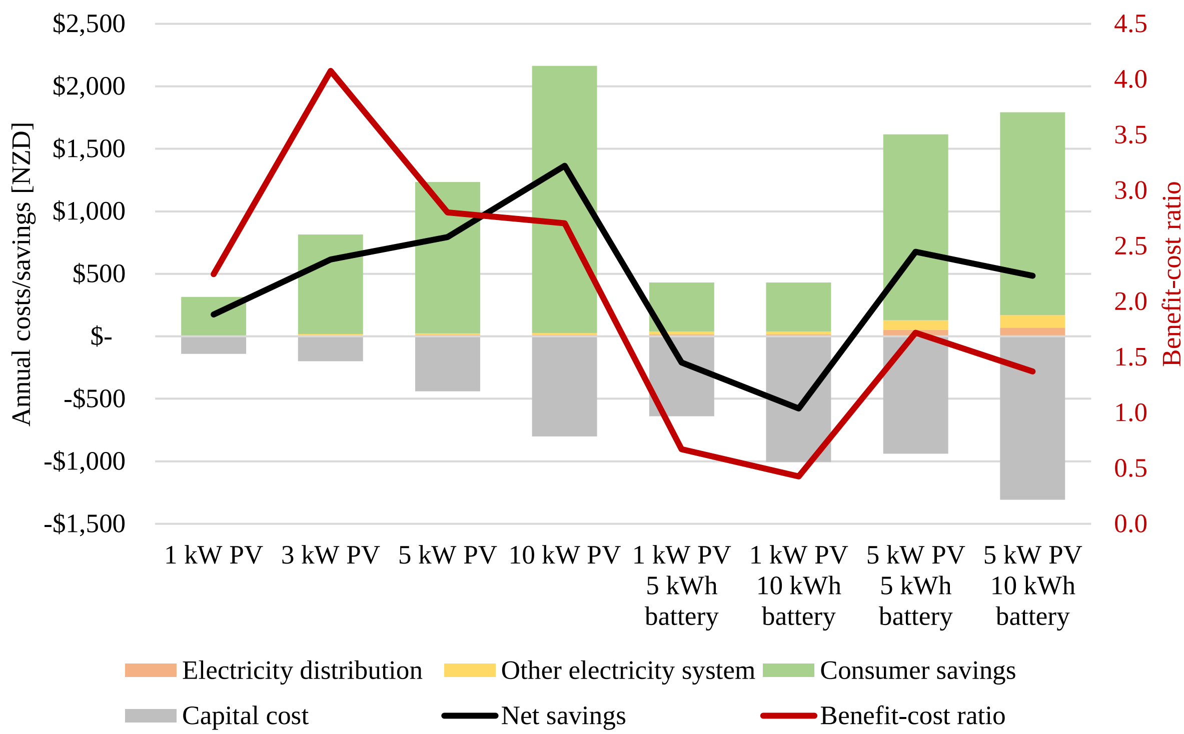

Figure 10. Average annual costs (negative) and savings (positive) from changes in peak electricity demand and consumer electricity bills with solar PV panels and batteries across all neighbourhoods.

Figure 11. Average annual costs (negative) and savings (positive) by neighbourhood: Decile 1 (top left), 3 (top right), 7 (bottom left), and 10 (bottom right) in Auckland (red) and Christchurch (green).

4. Discussion

In all neighbourhoods and all cases, increasing solar PV size reduces demand for electricity from the grid, as shown in Figures 3-6 and Figure 9. Adding battery storage capacity further reduces grid energy demand, as electricity generated by solar panels can be used for self-consumption even when generation exceeds household demand. Peak demand reductions are greater in summer than winter and in Auckland than Christchurch, due to higher insolation in summer and in Auckland. Differences in peak electric power demand are more varied (Figure 8), as peak solar generation does not line up with typical times of peak electricity demand (Figures 3 and 5). As such, winter peak demand is unchanged in three cases with distributed solar generation (1 kW PV in A10 and C7, 1 kW PV 5 kWh battery in C7). Peak demand reductions are largest in Auckland, due to higher insolation, and in cases with batteries, which allow storage of electricity generated by solar PV panels for use during peak periods. Batteries also increase self-consumption, with less than 0.1 kWh/house/day of unused solar PV generation in all neighbourhoods in cases with 1 kW solar PV capacity and 5 kWh or 10 kWh batteries, in summer and winter. Unused generation from a 5 kW solar PV panel is reduced by 21-24% and 27-32% by a 5 kWh and 10 kWh battery, respectively, in summer, and 45-48% and 83-92% by a 5 kWh and 10 kWh battery, respectively, in winter.

Income has little effect on consumer electricity cost reductions (Figure 9), as these reductions are directly proportional to total solar PV consumption, which varies little with income (Figure 7). Differences in peak demand changes across incomes are larger (Figure 8), as peak timing varies with income, likely because of the differing contributions of load types. For example, energy use for space heating is typically higher in higher-income households, leading to higher electricity demand later in winter evenings [60,61]. These socioeconomic differences are larger in Auckland than Christchurch, likely due to the increased evening insolation at Auckland's higher latitude. In cases with battery storage, these socioeconomic differences are smaller than those between cities, with peak demand reductions in Auckland typically larger than those in Christchurch.

Location also has a greater effect than household income on consumer electricity cost reductions, as shown in Figure 9. Differences in average consumer electricity cost reductions due to income in the same location are under 2% (although these changes are relatively much larger for lower-income households, as discussed in Section 4.1), while differences in average cost reductions between neighbourhoods with the same income in Auckland and Christchurch are between 2.6-7.3%. Consumer electricity cost savings increase with increasing self-consumption (Figures 7 and 9), as electricity cost savings on fixed-cost electricity price plans are directly proportional to reductions in total energy use. However, the peak demand reduction potential of batteries would increase the calculated consumer cost savings reported here for those households with time-of-use or real-time electricity price plans, in which electricity is more expensive during periods of peak demand.

Net savings increase with increasing capacity of solar PV panels (Figure 10), as consumer cost savings from larger panels increase at a greater rate than the cost of those panels. Conversely, net savings decrease with the addition of batteries and with increasing battery storage capacity. Net savings are negative for 1 kW PV panels with 5 kWh and 10 kWh batteries, indicating payback periods exceeding expected system lifetime, and positive for all other cases, indicating payback periods within expected system lifetimes. Cost savings are driven by reductions in consumer costs in all cases, due to the small reductions in peak electricity demand, which yield limited electricity savings. However, electricity system savings are higher for cases with batteries, due to their ability to store electricity and reduce peak electricity demand. Net savings for solar PV panels alone vary little between neighbourhoods (Figure 11). Although relative variations are higher for interventions including batteries, with higher net savings in higher-income neighbourhoods and in Auckland, these larger relative variations are due to the smaller total savings, and absolute variations are under 150 NZD/household/year.

4.1. Key takeaways and implications

4.1.1. Impact of benefits vary between consumers and distributors

Electricity consumer and distributors have different outcomes of interest (electricity cost reduction and peak demand reduction, respectively), so are likely to consider different cases as the optimum. For example, consumers may prefer 10 kW or 3 kW PV panels for maximum net savings or maximum benefit-cost ratio, respectively, while electricity distribution companies may prefer those consumers to install 5 kW PV panels with battery storage for maximum peak reduction. Thus, while households with access to capital may opt to install distributed solar generation on its own economic merits, distributors would need to consider offering incentives for those households to also install battery storage, which can offer increased average peak demand reductions by 400-1500%, depending on location and the size of solar PV panels installed. These incentives could be developed in coordination with government, as reducing peak electricity demand can also reduce GHG emissions [101]. Equally, the added costs can be interpreted as the required price reduction in battery storage, the cost of which is expected to continue declining [102], before these choices become economic without subsidy.

4.1.2. Consumer benefits are unevenly socioeconomically distributed

Care should be taken to ensure any incentive/subsidy programs do not increase energy inequality. Variation in consumer cost savings across income levels is small, indicating high- and low- income households could similarly benefit from distributed generation and storage. Thus, equitable uptake of these technologies could reduce energy costs across the socioeconomic spectrum, reducing energy poverty in low-income households. However, adoption of solar DG and storage is limited by high capital costs, so higher-income households are currently more likely to realise these benefits [41,54,55]. Thus, subsidies designed to reduce capital costs could increase the equity of adoption of distributed generation and storage technologies, reducing energy poverty without sacrificing the benefits of peak demand reduction. In addition, subsidy/incentive design should consider the ways in which benefits are communicated, to ensure engagement with, and thus utilisation of subsidies/incentives by, a wide range of electricity consumers [103]. For example, Håkansson et al. suggest clearly communicating other effects alongside economic advantages, such as increased energy resilience, self-sufficiency, and environmental considerations, could increase the appeal of solar DG for women, who are typically not the target of advertising for rooftop solar panels [104].

4.1.3. The same benefits have greater economic impact for lower-income households

Variations in income mean the impact for households of equivalent consumer cost changes also varies with income. Changes in consumer electricity costs for a given intervention in a given location vary by under 2 NZD/household/month: the maximum difference by income is for 5 kW solar PV panels in Christchurch, which reduce average consumer electricity costs by 97.7 and 99.4 NZD/month for Decile 1 and 10 households, respectively. While the absolute values of these cost reductions are similar, they are equivalent to 7.8% of average monthly income for Decile 1 households, but only 1.2% of monthly income for Decile 10 households, meaning the effect on household finances of realising these changes is likely to be larger for lower-income households. Further, lower-income households typically have colder indoor temperatures, due to reduced insulation and reduced space heating usage, so the differences in these relative changes could be further amplified by their differential effects on energy poverty, which is high in low-income households and low (or non-existent) in high-income households [28,105]. However, without some form of intervention, differences in access to capital (and the cost of capital) means these savings are more likely to be realised in higher-income households, rather than the lower-income households who would most benefit.

4.1.4. Benefits may not outweigh other alternatives

However, while subsidies or other forms of intervention for solar DG and energy storage could reduce energy poverty, GHG emissions, and electricity system costs, these benefits must be compared with those of other potential demand-side interventions, such as energy efficiency and demand response. For example, increasing residential insulation can reduce peak electricity demand [106] and reduce health system costs by improving health outcomes [107,108], while demand response programs can also reduce peak demand with minimal additional costs [109,110]. Any subsidies or programs should thus be carefully compared with alternatives, to ensure optimal management of resources for the energy transition.

4.2. Limitations and future work

In this work, adoption of solar distributed generation and energy storage is assumed to be homogeneous within the modelled neighbourhoods, with all households assumed to have the same size and orientation of solar PV panels and the same capacity of battery storage. In reality, the adoption of these technologies and the orientation and size of installed solar PV panels are expected to vary within and between neighbourhoods. Further, the neighbourhoods modelled in this work are hypothetical averages not intended to represent any specific neighbourhood. As such, detailed data on building size and orientation, and surrounding vegetation or infrastructure, which affect the performance of solar PV panels, are not available. Thus, results should be considered representative of potential real outcomes and are presented on a per-house basis to facilitate ease of extrapolation for cases with varied sizes of solar PV panels.

Equally, while the agent-based model is representative, it is not perfect. However, it has been validated on real data from diverse neighbourhoods in Aotearoa New Zealand [60,61]. Thus, the modelling approach used in this work is fully generalisable to specific locations and capable of including more specific factors and uptake rates, where data are available. Further, the results shown can be modified in proportion to any expected uptake, where no uptake would be the baseline case.

Socioeconomic differences in peak electricity demand reduction are more pronounced in Auckland than in Christchurch (as shown in Figure 8), due to the varying importance of space heating for peak demand in the two cities' climates. Space heating is a larger contributor to winter peak demand in Christchurch, so the timing of peak demand is more consistent across different houses, as all houses experience the same outdoor temperature profile, which is colder in Christchurch. Conversely, in Auckland, space heating is a lower contributor, so the timing of peak demand also varies more between houses. As such, more households in Christchurch experience their peak demand at the same time (and thus also experience the same level of insolation), while peak demand timing (and thus the amount reduced by solar PV) in different Auckland neighbourhoods is more varied. All the sub-models of the ABM operate with a timestep of 60 seconds, meaning these variations, which may only be on the order of minutes, affect results. These differences in peak demand mean the reductions between neighbourhoods are not cumulative, as these reductions may occur at different times. However, the modelling approach used in this work is fully generalisable to assessing changes in peak demand at a given time, such as coinciding with national peak demand.

These analyses consider only DG from solar PV panels and energy storage with batteries. Alternative technologies are available for DG and energy storage, such as electricity generation from residential wind turbines [111] and biomass combustion [112], and residential hydrogen storage [113,114]. While solar accounts for over 90% of distributed generation in Aotearoa New Zealand [115] and these results are thus representative of current trends, this modelling approach is fully generalisable to other DG technologies, including wind and biomass generation and hydrogen storage.

Appliance ownership in the agent-based model is primarily based on data from the New Zealand Household Energy End-use Project (HEEP) [76], which is the most up-to-date study of representative residential energy use in Aotearoa New Zealand. However, the HEEP study was completed in 2004, since which time energy use [116] and appliance ownership [117,118] have changed. For example, ownership of heat pumps [39] and electric vehicles is increasing [119]. Thus, future electricity demand patterns may not match those in this work, which could affect the outcomes of DG and energy storage installation. However, the modelling approach adopted here is fully generalisable to these and other changes in electricity use.

Peak electricity demand is considered the primary outcome of interest for the electricity grid. Other effects from distributed generation, such as bidirectional electricity flows in distribution networks, are not considered. However, electricity networks are increasingly equipped for such effects, and guidelines and streamlined connection processes are available for the safe and efficient connection of distributed solar PV generation in Aotearoa New Zealand [120]. Future research could quantify the additional network investment required to facilitate the levels of solar PV adoption modelled in this work and assess the implications of this additional investment for economic viability.

Energy use in this work is unchanged by the presence of DG or energy storage. In reality, some households with solar PV panels may shift their energy use to reduce unmet solar generation, such as by choosing to run the washing machine during the middle of the day instead of the evening. These effects are likely to vary between households due to factors including access to shiftable loads [103] and timing constraints due to family and work schedules [121]. Thus, these factors are not included in this work to avoid further assumptions. However, the agent-based modelling approach used in this work is fully generalisable to modelling these shifts in energy consumption behaviour and can be readily modelled if the high-resolution data for these behaviours were available. Finally, the effects of load shifting on peak electricity demand are the subject of intended future research.

In this work, peak electricity demand reductions are assumed to reduce GHG emissions. While GHG emissions are typically correlated with peak demand [20–23], these correlations are currently weaker in Aotearoa New Zealand than in many other countries [122], primarily due to the dominance of hydroelectric electricity generation. However, emissions intensities of electricity generation in Aotearoa New Zealand are typically between 0.090-0.130 kg(CO_{2}-$_{e}$)/kWh [122], while direct emissions from distributed solar generation are effectively 0 kg(CO_{2}-$_{e}$)/kWh [123]. Thus, while the effects of reducing peak demand on GHG emissions are less direct in Aotearoa

New Zealand than in other countries, increasing utilisation of zero-emissions DG sources is still expected to reduce GHG emissions.

The presence of other electric loads could change typical profiles of residential demand, shifting peak demand times and altering load during peak periods of solar generation. For example, increasing adoption of electric vehicles is expected to create alternative peaks during previously off-peak time, but could also provide battery storage while at home during the day [124–126], particularly in high-income neighbourhoods, which typically have higher electric vehicle adoption [127–129]. While the proportion of electric vehicles is modelled as 0% in these analyses, the agent-based approach is fully generalisable to modelling a range of electric vehicle adoption levels and charging behaviours, as has been conducted in previous work [130], and future research could use this modelling framework to assess the interactions between electric vehicles, energy storage, and distributed solar generation.

Weather data in this work are from typical meteorological year profiles for Auckland and Christchurch, which use recent historical data to provide typical expected profiles based on time of day and time of year. However, insolation can be affected by global warming [131–133] or more rapid climatic changes [134], which could change the magnitude and shape of solar PV generation profiles. While these changes are not assessed in this work, the model is capable of conducting analyses, where sufficient data are available.

The model used in this work is also fully generalisable to assessing the impacts of alternative electricity pricing structures, including sensitivity to the magnitude of feed-in tariffs for residential

DG, and the impacts of electricity pricing on peak electricity demand are the subject of intended future research. Agent-based models are also well suited to studying non-economic incentives for technology adoption, such as social influence [135,136] and gamification [137,138], and this model is readily adaptable to such analyses. Further, distributed solar generation can increase energy resilience in natural disasters and other unexpected disruptions to electricity supply and distribution [139,140]. Thus, future work could use the modelling approach employed in this work, which has been shown to accurately simulate the effects of large-scale behavioural changes [60], to assess the effects of DG and battery storage on energy security.

5. Conclusions

Distributed generation from solar photovoltaic (PV) panels and battery storage is shown to reduce household grid-supplied electricity demand, and thus consumer electricity costs, across the socioeconomic spectrum in Auckland and Christchurch, although high upfront costs for battery storage mean total costs outweigh total savings in some cases. Demand for grid electricity is reduced by increased capacity of PV panels, and further reduced by the presence of battery storage. The misalignment of peak solar PV generation and peak electricity demand means peak demand reductions are highest in cases with batteries, which allows the storage of electricity for use during evening peak demand periods. Comparison of economic benefits for electricity consumers and distributors shows a trade-off between the two, as consumers are likely to prioritise electricity cost reductions (directly proportional to total electricity demand), while electricity companies prioritise peak demand reductions. Battery storage, which has a greater effect on peak demand than on total energy use, may thus require incentivisation for consumer adoption. While variation in consumer cost savings across income levels is small, suggesting both high- and low- income households could similarly benefit from these technologies, high capital costs limit adoption primarily to higher-income households. Subsidies or other interventions designed to increase equity of adoption could thus reduce energy poverty without sacrificing the benefits of peak demand reduction. Future research should consider the impacts of electric vehicles and other distributed generation (DG) technologies on peak demand and whole-system costs, and compare the benefits of solar DG with alternative demand-side interventions, such as energy efficiency and demand response.

Data availability

All direct data are presented in the Results section of this paper. Additional data supporting the conclusions made here will be made available on request.

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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".

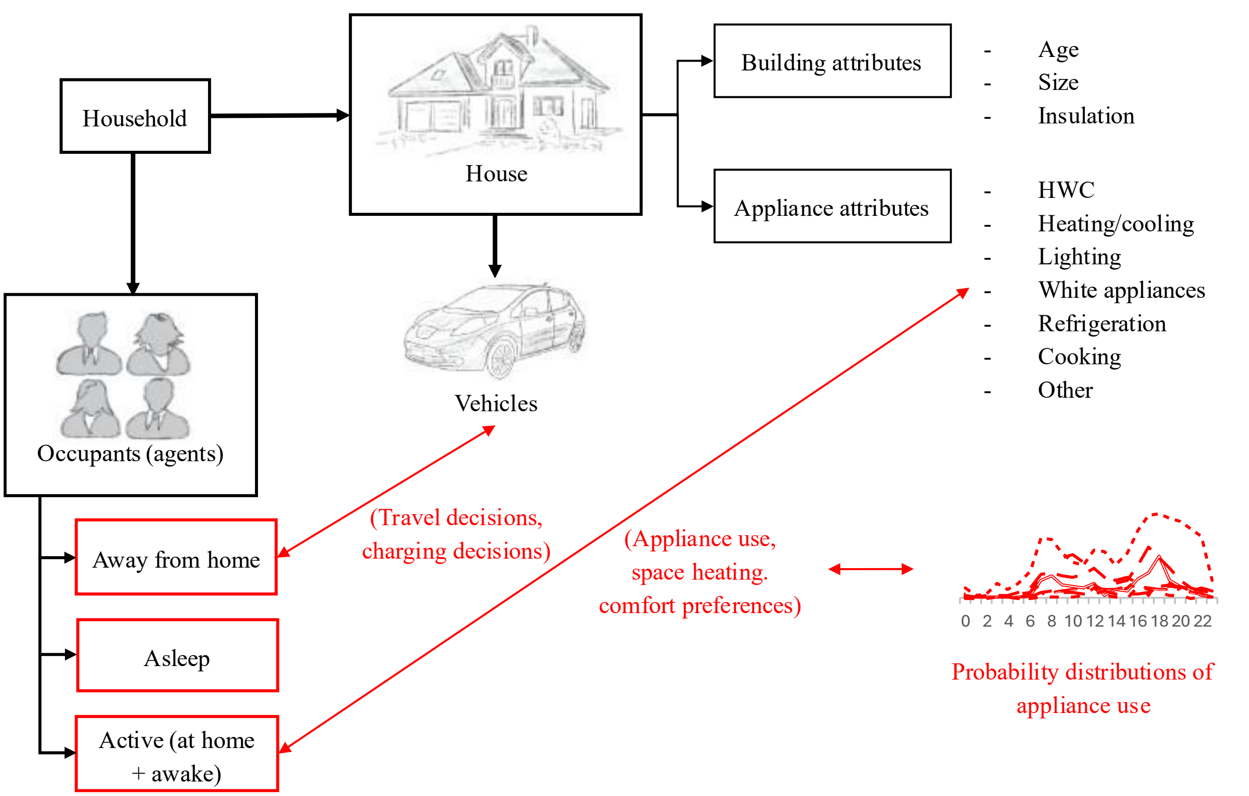

Figure A.1. Architecture of the agent-based model.

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":

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

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 [84,85]. 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 [130]. 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 [83]. In this model, these variables are generated from independent normal distributions matching average national patterns [86,141]. 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 [62,63] and a national time-use survey in Italy [64], and adjusted according to data from appliance prevalence and use in 397 randomly selected houses Aotearoa New Zealand [76].

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.

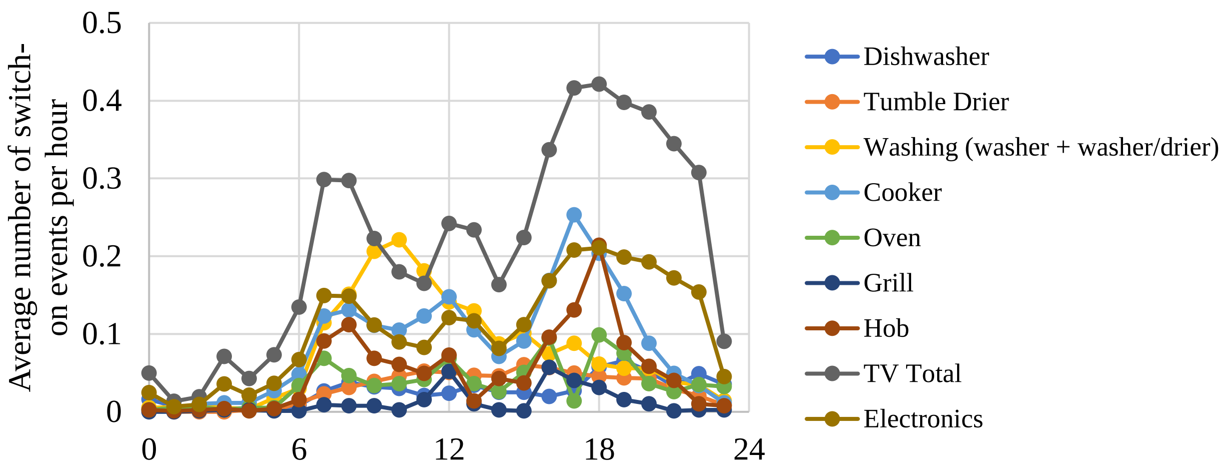

Figure A.2. Variation of appliance use probability by appliance type and time of day (adapted from [62–64,76]).

Table A.1. Mean appliance power demand and runtime (from [63,116,142,143]).

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.

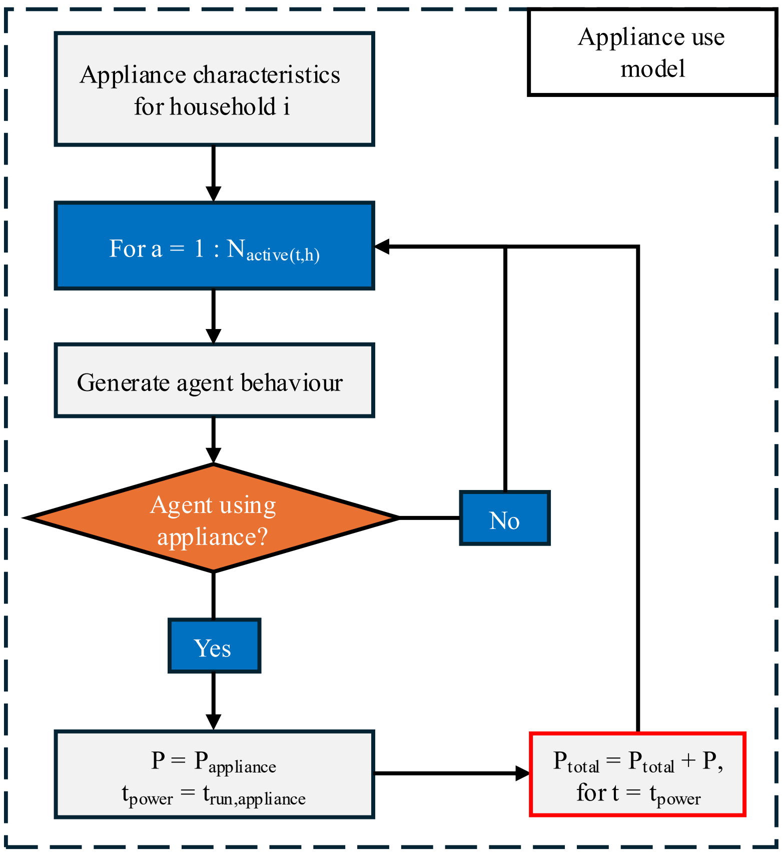

Figure A.3. Flowchart describing the appliance use model.

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.

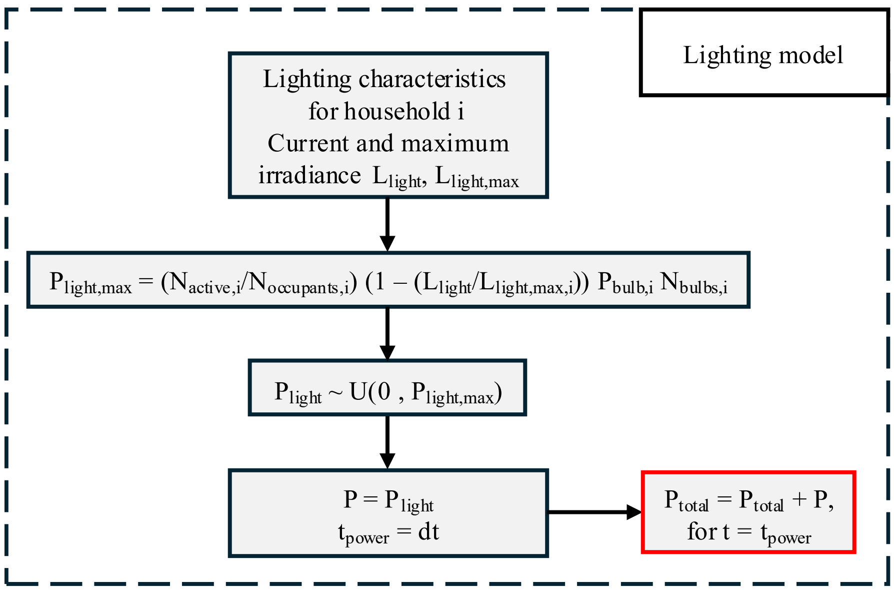

Figure A.4. Flowchart describing the lighting use model.

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 [80,144–146]. 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 [147]. 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:

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

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 [28,148]. Thus, household "heating temperature" ($T_{heat,i}$ [K]), the temperature below which occupants of household i turn on heating, is defined:

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

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 [76].

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.

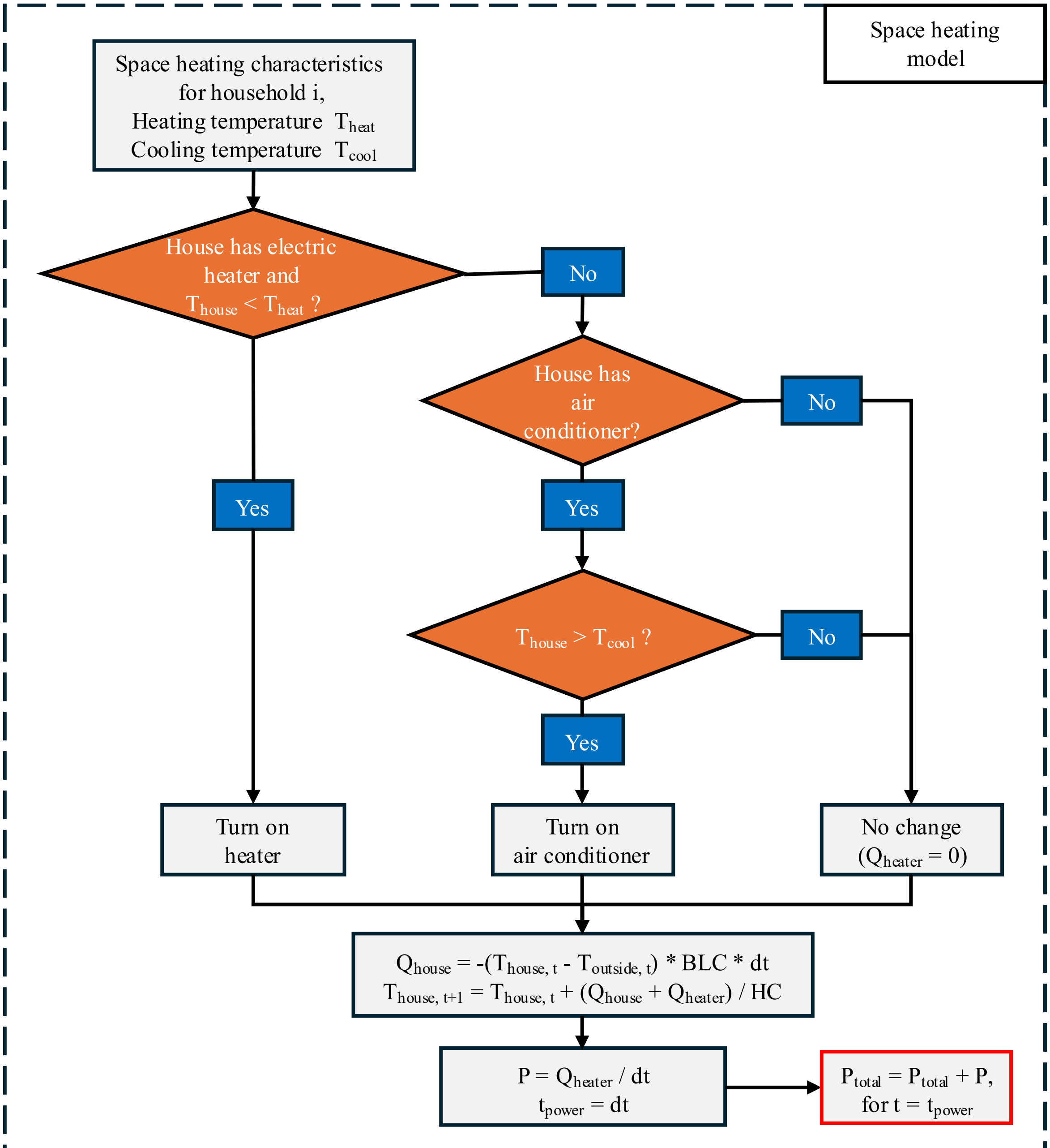

Figure A.5. Flowchart describing the space heating model.

A.5. Water heating

Electric hot water cylinders (HWCs) are present in over 85% of houses in Aotearoa New Zealand [76], but this proportion varies by neighbourhood. For houses with electric HWCs, cylinder sizes are assigned according to industry-standard recommendations for occupancy level [88]. Hot water demand profiles are generated using DHWcalc [65] with average daily hot water use of 50 L per person [89,90]. DHWcalc stochastically generates domestic hot water demand profiles according to household occupancy levels, and is widely use where hot water demand data are unavailable [66–69]. HWC temperatures are calculated at each timestep according to a model presented in previous work [70,71]:

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

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

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

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:

$$K_{mix} = \left| \begin{array}{ll} (T_{out} - T_{in})/(T_{HWC} - T_{in}), & T_{HWC} \geq T_{out} \\ 1, & T_{HWC} < T_{out} \end{array} \right. \tag{A-9}$$

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.

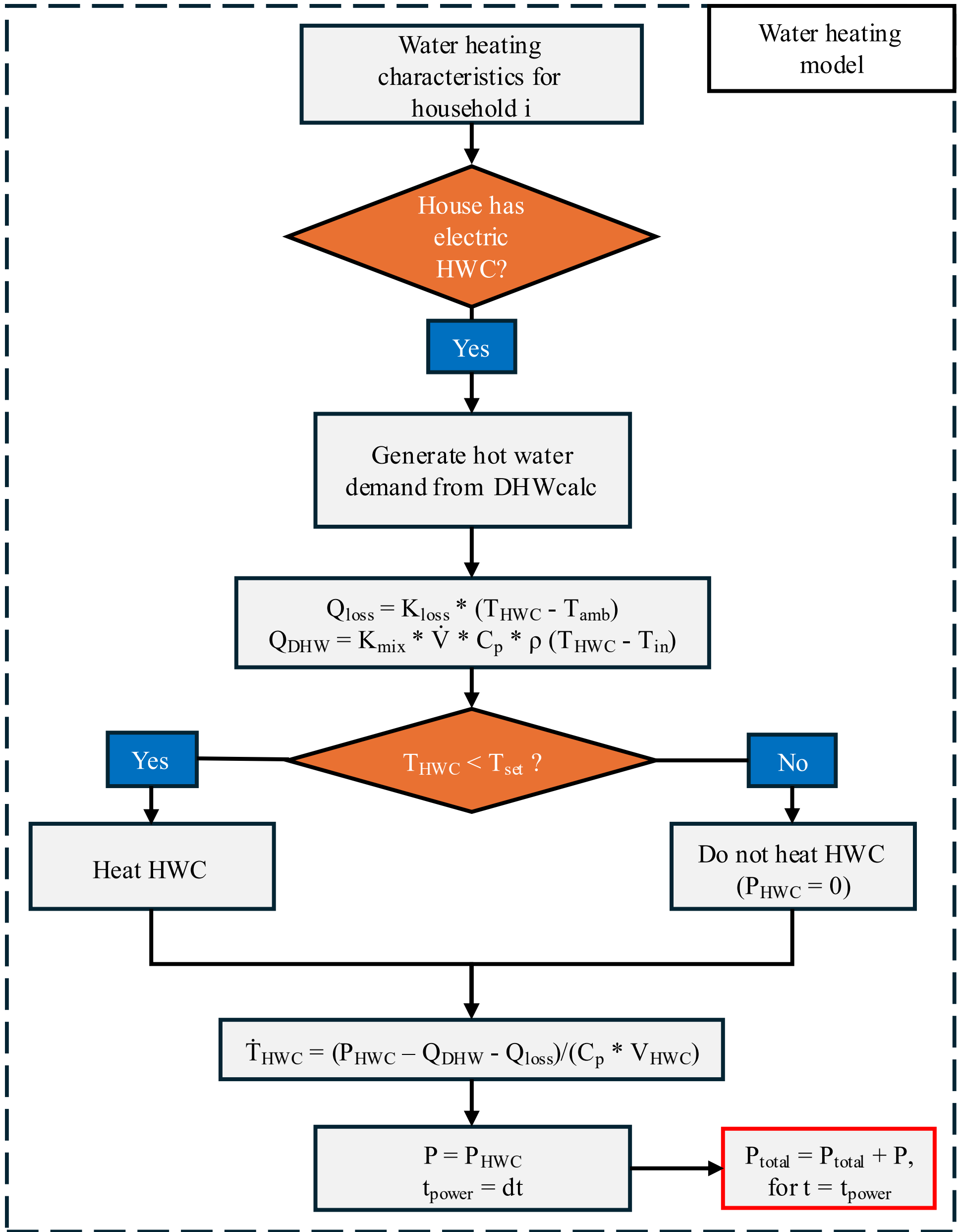

Figure A.6. Flowchart describing the water heating model.

A.6. Model summary

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

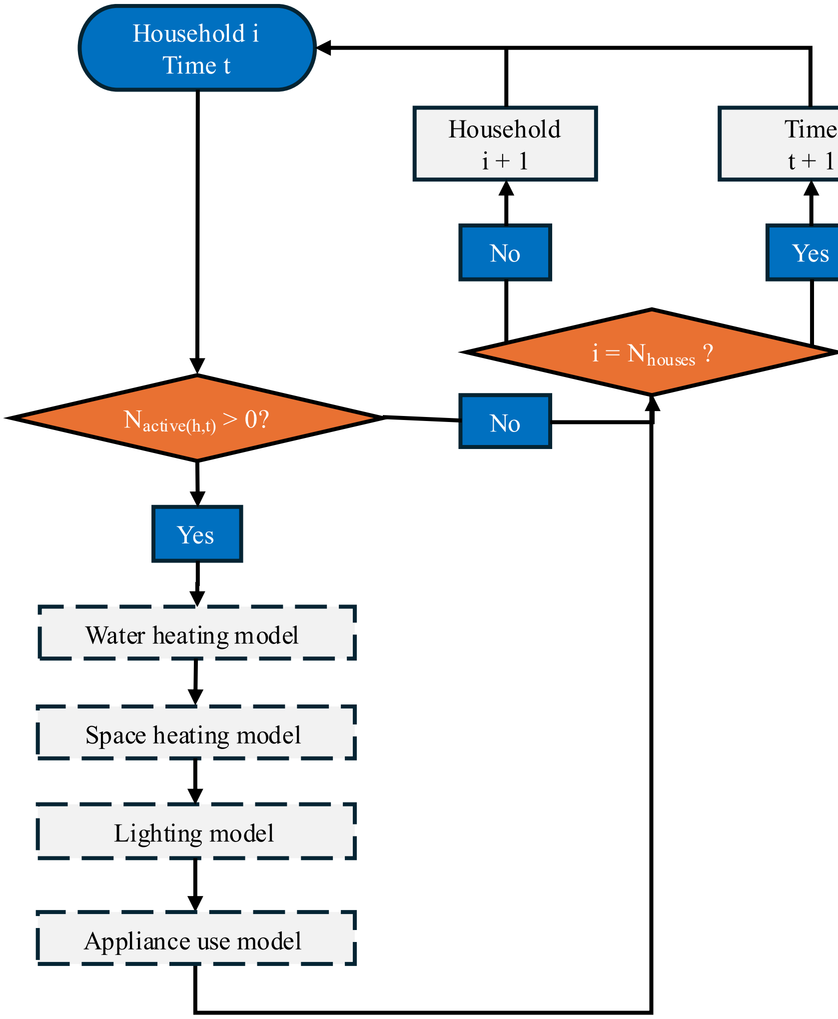

Figure A.7. Flowchart describing overall model structure and sub-model locations.